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Editorial Board

Aim and Scope

The Journal of Business Chemistry (JoBC) focuses on current developments and insights at the intersection of management and chemistry, biotechnology or pharmacy.

The JoBC provides an international forum for researchers and practitioners in companies, research institutes, public authorities, consultancies or NGOs to present and discuss current challenges as well as potential solutions in an interdisciplinary manner. Thus, the JoBC aims to foster the dialog between science and business, to support management practice in the chemical and pharmaceutical industry and to indicate where further research from academia is needed. The JoBC offers high quality publications with academic standards, a fast publishing process and global reach. With this multidisciplinary and boundary-spanning approach, the JoBC intends to become the leading journal for decision makers in the chemical and pharmaceutical industry.

Publisher

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Contents

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JOURNAL OF
BUSINESS CHEMISTRY

Letter from the Editors

Systemic Transformation in Process Industries: Innovation, Circularity and Competitiveness

With this first issue of the Journal of Business Chemistry in 2026, we continue to explore how chemical, pharmaceutical and energy-related industries are navigating an era of profound structural change. Across sectors, firms are confronted with the simultaneous challenges of ecological transformation, technological acceleration and increasing competitive pressure. The contributions brought together in this issue illustrate that responding to these challenges requires more than isolated technological advances. Instead, it demands a rethinking of business models, innovation processes and the broader ecosystems in which firms operate.

We open this issue by a Call for Papers for a forthcoming Special Issue of the Journal of Business Chemistry focusing on Innovation and Production Management in the Process Industries. The Special Issue invites conceptual and empirical contributions that address the close interconnection between product and process innovation, particularly in the context of eco-industrial transformation. By encouraging interdisciplinary perspectives and collaborative contributions from academia and practice, the Call for Papers highlights the journal's continued commitment to fostering dialogue on systemic innovation challenges in process industries.

The research section is complemented by a contribution in the Practitioner's Section. In "Accelerating Industrial Innovation under Time Pressure: Platform-Based Lessons from Specialty Chemicals", Heiko Brunner presents an anonymized case study from the specialty chemicals industry. The article examines how companies can respond when critical inputs suddenly become unavailable and development timelines are severely constrained. The analysis highlights the limitations of strictly sequential Stage-Gate® models in such contexts and shows how parallelized development structures and modular platform strategies can enable faster and more resilient innovation processes. By focusing on organizational design and managerial decision-making rather than technical details, the contribution provides practical insights for managing innovation under conditions of uncertainty, high interdependence and acute time pressure.

We then turn to the first research paper of this issue. In "Actors and Supply Chain Strategies in the Circular Economy: A Guideline for Circular Business Model Design and Innovation", Jannis Wesselkämper and Sina Mortazavi address a central yet underexplored question in circular economy research. The authors develop a comprehensive conceptual framework that links different actor roles within circular ecosystems to distinct supply chain strategies. By deriving nine circular business model patterns and complementing them with innovation approaches that vary in openness and intensity, the article offers a structured orientation for companies seeking to reposition themselves in emerging circular value networks. The illustration of the framework through the transformation of the electric vehicle battery industry further underlines its practical relevance and demonstrates how circularity fundamentally alters established business logics.

The following contribution shifts the focus to industrial competitiveness and cost structures. In "Profitability and Cost Structure in the Battery Cell Industry: A Comparative Analysis of CATL and Key Competitors", Jan-Hendrik Richter, Tim Niklas Franke and Simon Lux analyze why certain battery cell manufacturers remain economically resilient despite global overcapacities, declining prices and intensified international competition. By examining differences in cost structures, production locations, vertical integration and market exposure, the article sheds

ISSN 1613-9623

light on the strategic and structural factors that shape profitability in one of today's most capital-intensive and strategically important industries. The analysis offers valuable insights for both industry practitioners and policymakers concerned with the future of battery value chains.

The issue concludes with a contribution that highlights the importance of spatial contexts for sustainable innovation. In "Does Geographic Proximity to Startups Drive Green Innovation?", Alexandra Wenning and Jan-Luca Evers examine how local startup environments influence the green innovation activities of established firms. Drawing on proximity theory and the knowledge spillover literature, the authors provide a nuanced empirical analysis showing that the effects of geographic closeness are far from uniform. While proximity to green startups can stimulate green innovation for firms with lower R&D intensity, it may also intensify competition and appropriation concerns for firms with higher R&D intensity. By differentiating between green and non-green startups and by considering first-time green patenting, the study deepens our understanding of how regional ecosystems, firm capabilities and sustainability-oriented innovation interact.

Taken together, the contributions in this issue demonstrate that contemporary industrial transformation is inherently systemic. Circular economy strategies reshape supply chains and business models, regional innovation ecosystems influence the direction and intensity of green innovation, organizational choices determine the speed of technological response, and global market structures condition economic viability. The articles underline that sustainable and competitive industrial development depends on aligning technological innovation with thoughtful managerial and strategic design.

We hope you enjoy reading this issue of the Journal of Business Chemistry. Should you have any comments or suggestions, please feel free to contact us at contact@businesschemistry.org. For ongoing updates and insights, we invite you to follow us on LinkedIn (www.linkedin.com/company/jobc) and subscribe to our newsletter.

We sincerely thank all authors, reviewers and readers for their continued support and engagement.

Warm regards,

Friederike Fontes (geb. Woltmann)
(Executive Editor)

Sabrina Duswald
(Executive Editor)

A call for papers for a Special Issue in the Journal of Business Chemistry

Innovation and Production Management in the Process Industries

Submission deadline: 15 September 2026

This Special issue (SI) invites papers that shed light on enhanced models and practices for managing on-going and future eco-industrial transformations in the "family" of process industries. We particularly encourage papers that not only explore the close interconnection between product and process innovation but also adopt an interdisciplinary perspective on "Innovation and Production Management". Both conceptual and empirical contributions that enrich a fundamental understanding of these topical areas are welcome. While we are especially interested in contributions from the chemical, petrochemical, biotechnological, and pharmaceutical industrial sectors, we also invite submissions from other sectors of the process industries, fostering a cross-sectoral learning and knowledge exchange. Please observe that the Journal of Business Chemistry (JoBC) has a special Practitioner's Section, and in reference to the topical area for this Special issue, collaborative papers together with academic scholars and industry practitioners are especially appreciated.

Guest editors:

- Prof. Dr. Dr. Thomas Lager (corresponding Guest Editor), Department of Industrial Economics, Blekinge Institute of Technology, Sweden
- Dr. Eva Lövstål, Department of Industrial Economics, Blekinge Institute of Technology, Sweden
- Dr. Wen Pan Fagerlin, Department of Industrial Economics, Blekinge Institute of Technology, Sweden

Special issue information:

In assembly-based industries, the components in a product largely remain unchanged during and after the production process. In contrast, materials in the process industries are subjected to a transformative production process that convert them into completely different entities. These products are typically homogeneous (Lager and Simms, 2023), and their functionalities in customer use are primarily determined by their internal structural properties (Kuwashima and Fujimoto, 2023). In essence, in "assembly-based" production systems, the product largely defines the configuration of subsequent production system, whereas in the process industries – characterized as "transformation-based" production systems - the production process defines both the product and its final product specifications (Lager, 2024 p.30). Barnett and Clark (1996) argued early that innovation in process industries is primarily enabled by process innovation, which simultaneously constitute the most constraining factor for product innovation. Consequently, an in-depth understanding of the production system is critical for success in both product and process innovation. Moreover, in the pursuit of new pathways in eco-industrial transformations (Fagerlin et al., 2019), a reengineering system approach (Hammer, 1990) combinded with a shift toward more radical corporate process innovation is most likely a necessary road to follow (Sandberg and Aarikka-Stenros, 2014, Radnejad et al., 2020).

Given that product innovation in the process industries is fundamentally an outcome of successful innovation of new process technology (Lager, 2024), and considering that CO_2 emissions from production processes often constitutes the major company environmental challenge, an integrative approach in managing innovation and production technology is desirable. Such an approach incentivizes an exploration of new pathways and inter-organizational solutions for eco-industrial transformations. Furthermore, the ability to create intra-organizational value chains through an interlinkage of production plants, infrastructures, by-products, and energy flows in large-scale global

ISSN 1613-9623

operations – referred to as "Verbund" in the BASF company (2026) – is an interesting approach in the perspective of industrial symbiosis (Heck et al., 2024). Conversely, the strongly integrated and asset-intensive industrial infrastructure is unfortunately often hindering an ability to respond to environmental changes (Samuelsson and Lager, 2019).

In conclusion, process innovation (Lager, 2010) has become an increasingly critical concern for the "family" of process industries, since the production process is a major contributor to greenhouse gas emissions and the necessary interconnectedness between product and process innovation in all stages of product innovation (Wittfoth et al., 2022, Rammer, 2023, Lager, 2024). Consequently, the complex and idiosyncratic environment of process industries crave intertwined product, process, and raw materials innovation in a concurrent view on all these areas in a systemic innovation approach (Storm et al., 2013). Such "Systemic Innovation" (Teece, 1986, Midglay and Lindhult, 2021) is emerging not only as a vital mechanism for establishing a more dynamic integration of different categories of innovation but also as the establishment of a "collaborative playground" for necessary novel eco-industrial experimental networks.

Tentative research questions:

- How can cross-sectoral organizational learning and knowledge exchange be facilitated and stimulated in a process-industrial context?
- In the context of eco-industrial transformation of corporate unit process technology - sometimes encompassing whole production systems -, how can such a "re-engineering" corporate perspective be institutionalized and applied?
- What novel conceptual and practical frameworks are necessary for future industrial supply and value chain configurations in eco-industrial transformations in the process industries?
- How can early-stage integration of equipment suppliers, technology providers, and intermediaries in the process-industrial eco-system enhance systemic innovation and sustainability outcomes?
- Given the experimental nature and longtime horizons of process innovation in eco-industrial transformation, how can the process development work be accelerated to meet the urgency of fossil-free technology development?
- What kinds of organizational and work process reconfigurations are necessary to enable more radical process innovation in eco-industrial transformations in the process industries?

Manuscript submission information:

As a continuation of a series of international workshops on the overall theme "Innovation and Production Management in the Process Industries", the 5th invitational workshop IMP2026 will be convened at Blekinge Institute of Technology (BTH) in May 2026, in Karlskrona, Sweden (www.bth.se/ipm2026). Authors that intend to submit a paper to this Special Issue are invited to present their papers at the workshop. **However, workshop participation is not a prerequisite for submission to the Special issue and will not influence the selection of SI papers for full peer review.**

- March 2026 — Submission starts for Special issue
- 22 March — Deadline for submission of abstracts for the workshop (thomas.lager@bth.se)
- 29 March — Notification of acceptance and request for working papers for the workshop
- 17 April — Deadline for submission of working papers together with registration
- 23 April — Final full workshop program and book of abstracts available for delegates
- **6-7 May — Two-day workshop**
- 15 September — Submission deadline for Special issue

All manuscripts for the Special issue should be submitted to contact@businesschemistry.org.

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ISSN 1613-9623

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JOURNAL OF
BUSINESS CHEMISTRY

Vol.23, Iss.1, February 2026

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Practitioner’s Section

Heiko Brunner[a]

Accelerating Industrial Innovation under Time Pressure: Platform-Based Lessons from Specialty Chemicals

Innovation in the specialty chemicals industry is increasingly constrained by shortened product life cycles, rising regulatory complexity, and strong dependencies on critical functional components. When essential inputs become unavailable, companies must rapidly develop substitutes while maintaining performance, scalability, compliance, and economic viability. This article presents an anonymized industrial case study showing how additive and formulation development under severe time pressure can be accelerated through parallelized development structures and modular platform strategies. Focusing on process architecture and managerial decision-making rather than technical specifics, the contribution derives practical insights for innovation managers in process-oriented industries. Project risk is shown to be strongly influenced by early parallel R&D resource allocation rather than by capital investment decisions alone, highlighting the importance of development process architecture under severe time pressure.

Keywords: Innovation Management, Stage-Gate® Process, Parallel Development, Platform-based Development, Chemical Industry

1. Introduction

Innovation is a critical driver of competitiveness in the specialty chemicals industry, where differentiation is often achieved through highly specific functional additives and tailored process solutions. At the same time, innovation activities are increasingly constrained by shortened product life cycles, rising regulatory complexity, and growing global competition. As a result, chemical companies are required not only to innovate effectively but also to bring new solutions to market within increasingly narrow time windows.

A particular challenge arises when established products or processes depend on critical components that become unavailable due to external factors such as supply chain disruptions, regulatory changes, or strategic shifts by upstream suppliers. In such situations, companies are forced to substitute essential components while ensuring equivalent or improved performance, industrial scalability, regulatory compliance, and economic viability. Failure to do so may result in significant revenue losses and erosion of market position.

Classical linear gated development models, such as Stage-Gate® type processes, are widely used in the chemical industry to structure innovation activities and manage technical and commercial risks. While these models provide transparency and control, they often rely on sequential execution of development phases. This sequential logic can become a limiting factor when multiple interdependent development streams such as substance development, process scale-up, sourcing, regulatory approval, and market preparation must progress simultaneously under high time pressure.

This article presents an anonymized industrial case study from the specialty chemicals industry that illustrates how innovation can be accelerated when

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classical sequential development models are replaced or complemented by parallelized development structures. The case focuses on the substitution of a critical functional additive in an established industrial application, where time-to-market constraints necessitated a departure from traditional development logic.

The objective of this article is threefold. First, it analyzes the limitations of linear gated development models in highly time-critical innovation scenarios. Second, it demonstrates how principles of Simultaneous Engineering and modular platform strategies can be applied in an industrial chemical context to enable parallelization of development activities. Third, it derives practical lessons learned and managerial implications for innovation managers facing similar challenges in process-oriented industries.

By abstracting technical and economic details and focusing on organizational design and decision-making logic, this contribution aims to provide transferable insights for practitioners and researchers interested in accelerating innovation under conditions of uncertainty and time pressure.

Importantly, the case is not a one-to-one replacement of a single molecule. The legacy additive was embedded in multiple formulations and process variants, which required a modular substitution strategy and the development of two new proprietary additives. In this context, innovation is reflected less in isolated molecular novelty than in the successful alignment of (i) conceptual novelty, (ii) industrial applicability, and (iii) market viability. Both additives are protected by intellectual property rights and were implemented at industrial scale, demonstrating that the case exceeds a purely technical substitution and represents an industrial innovation under severe time constraints.

2. Main Part

2.1 Development Challenge and Industrial Context

2.1.1 Business-Critical Substitution under Time Pressure

The case presented in this article originates from a situation in which a multinational specialty chemicals company faced the imminent unavailability of a critical functional additive used across multiple established formulations and industrial processes. The additive represented a key performance component, and its substitution was mandatory to ensure continued market participation and business continuity. In addition to the limited remaining availability of the legacy raw material, the situation was further exacerbated by a pronounced dependency on a single external supplier, which significantly increased supply chain risk and reduced strategic flexibility. The challenge was therefore not driven by exploratory innovation or market expansion, but by the necessity to redesign an existing solution architecture under severe time constraints.

Due to the broad range of applications in which the legacy additive was embedded, the substitution problem could not be addressed through a simple one-to-one molecular replacement. Instead, the development ultimately required two new proprietary additives to cover the functional requirements of the existing formulation and process landscape. Consequently, the innovation task comprised two tightly coupled development streams: (i) the synthesis, scale-up, and industrial production of new additives, and (ii) their integration into existing formulations and applications, requiring reformulation and validation at system level.

The remaining availability of the legacy raw material defined a fixed and non-negotiable development window of approximately three years. This constraint fundamentally shaped the innovation strategy, as it effectively ruled out extended sequential exploration or radical chemical novelty. To meet the time-to-market requirements, the project relied on a modular substitution logic based on established additive classes and shared synthesis intermediates. Several intermediates had already been developed and industrialized for related products, while only a limited number of additional precursors required further development.

This modular architecture enabled reuse of existing manufacturing routes, analytical and quality control methods, and qualified toll manufacturing capabilities. Beyond accelerating development, the approach reduced regulatory uncertainty and positively affected cost structures, which is particularly relevant in specialty chemical contexts characterized by low substance volumes and stringent registration requirements. Although performance improvement was not the primary objective, the resulting additives exhibited improved stability and robustness in application, further supporting their industrial and commercial viability.

Vol.23, Iss.1, February 2026
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2.1.2 Boundary Conditions and Constraints

The development challenge was shaped by a set of non-negotiable boundary conditions that significantly constrained the range of feasible innovation strategies. First, the fixed time window imposed by the limited remaining availability of the legacy raw material eliminated the option of extended sequential exploration. Delays or late-stage failures would have directly translated into business interruption rather than postponed market entry.

Second, the substitution affected an existing and commercially active process landscape. Unlike exploratory innovation projects, the case required compatibility with established formulations, production infrastructure, customer qualification routines, and regulatory frameworks. As a result, the project could not rely on trial-and-error experimentation or radical departures from known chemical classes without incurring disproportionate technical and regulatory risks.

Third, the specialty chemical context introduced additional constraints related to substance volumes, cost sensitivity, and regulatory compliance across multiple regions. As the additive was used globally, registration requirements extended beyond REACH to include additional national and regional regulatory regimes with differing timelines, data requirements, and approval procedures. Late structural changes would have multiplied regulatory effort and uncertainty across jurisdictions, thereby strongly favoring reuse of known intermediates, established toxicological profiles, and proven substance classes.

Combined, these boundary conditions favored an innovation strategy based on modular recombination of existing technological assets rather than radical novelty. Platform-based additive classes, shared synthesis intermediates, and established analytical and manufacturing capabilities provided a sufficiently robust solution space to enable early parallelization while maintaining acceptable risk exposure. Under these constraints, the primary innovation challenge shifted from molecular discovery to the orchestration and synchronization of tightly coupled development activities.

2.2 Limitations of Linear Stage-Gate® Development

2.2.1 Role and Strengths of Linear Stage-Gate® Models

Classical linear gated development models, such as Stage-Gate® type processes, are widely used in the chemical industry to structure innovation activities and manage technical and commercial risks. By dividing development projects into sequential phases separated by formal decision gates, these models provide transparency, clear accountability, and structured decision-making, and have become a dominant framework for managing innovation projects (Cooper, 1990; Cooper, 2008; Smolnick and Bergmann, 2020). In the chemical industry, such gated development processes are widely applied to balance technical risk, regulatory requirements, and resource allocation across development stages (Cooper, 1990; Cooper, 2008; Leker et al., 2018).

In the present case, the linear gated model initially provided a useful orientation, especially for framing the overall project scope and defining high-level milestones. As a governance framework, it offered a common language for cross-functional coordination and supported alignment between technical development and management oversight.

However, as the project requirements became clearer, several structural limitations of the sequential development logic emerged. These limitations were not inherent flaws of the gated approach itself, but rather the result of a mismatch between the process architecture and the specific constraints of a highly time-critical substitution scenario. The classical Stage-Gate® logic assumes that uncertainty can be reduced stepwise and that downstream activities can be postponed until upstream phases have been completed. Under severe time pressure and strong interdependence between development streams, this assumption proved increasingly restrictive.

2.2.2 Mismatch Between Sequential Processes and Time-Critical Substitution Projects

In the present case, several structural limitations of the sequential development logic became apparent as project requirements crystallized. These limitations were not inherent flaws of the gated approach itself but resulted from a mismatch between the process

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Vol.23, Iss.1, February 2026

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DOI: 10.17879/70918526846

architecture and the constraints of a highly time-critical substitution scenario.

A key challenge arose from the strong interdependence between multiple development streams. The project required simultaneous advancement of substance development, process scale-up, sourcing of raw materials and intermediates, regulatory preparation, and market-facing activities. In a strictly sequential model, downstream functions such as procurement, regulatory compliance, and production would only be formally engaged after completion of earlier development phases. Under severe time pressure, this sequencing would have postponed critical activities and concentrated technical, regulatory, and supply chain risks into late project stages.

Furthermore, the linear gated model implicitly assumes a relatively stable problem definition during early phases, with uncertainty gradually reduced before subsequent activities commence. In the present case, however, uncertainty was distributed unevenly across the project timeline. While early-stage technical screening could be performed rapidly based on prior knowledge and platform elements, uncertainties related to industrial scalability, cost structures, supply chain robustness, and global regulatory requirements could not be resolved without early involvement of downstream functions. The sequential logic therefore created artificial waiting times that did not reflect the actual information needs of the project.

This misalignment is particularly critical in chemical development contexts, where cost-relevant parameters are often fixed early in the innovation process. Prior work on cost management in R&D-intensive industries has highlighted that late discovery of unfavorable cost structures significantly constrains corrective action (Murjahn, 2004). Under severe time pressure, postponing cost, sourcing, and regulatory assessments until late development stages increases the likelihood that economically or operationally infeasible solutions are identified only when remaining time and degrees of freedom are already exhausted.

As a result, effective risk management in such projects requires early synchronization of technical, economic, and regulatory considerations rather than late-stage control. This observation motivated the transition toward a parallelized development approach, which is

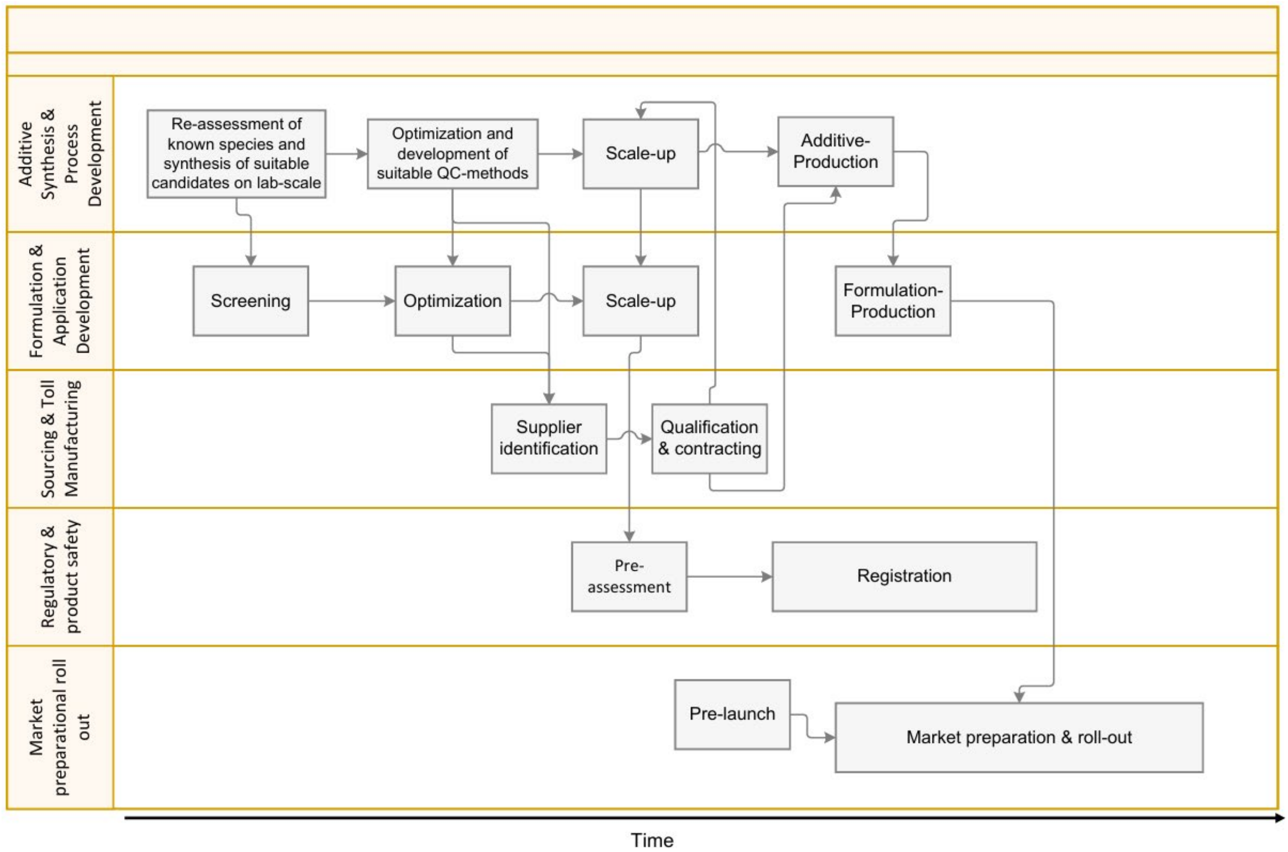

Figure 1. Simplified and anonymized development timeline illustrating parallelized innovation activities

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918527720
DOI: 10.17879/70918526846

discussed in the following section.

2.3 Parallelized Development and Platform-Based Strategies

2.3.1 Transition to Parallelized Development

In response to the limitations of a strictly sequential development logic, the project organization was deliberately reconfigured toward a parallelized development approach inspired by principles of Simultaneous Engineering. Prior research has shown that overlapping development activities and early cross-functional integration can significantly accelerate innovation processes in time-critical environments (Eisenhardt and Tabrizi, 1995; Bender and Gericke, 2016). The objective of this transition was not to abandon structured governance altogether, but to decouple critical activities from a rigid phase sequence and enable controlled concurrency across organizational functions.

The transition was initiated once a sufficiently robust solution space had been established through early technical screening. Existing knowledge of additive classes, synthesis routes, and application behavior allowed the project team to narrow down viable solution candidates at an early stage. This early convergence enabled downstream activities to be launched based on provisional but reliable information, rather than waiting for full technical validation as implied by a classical Stage-Gate® logic (Cooper, 1990; Cooper, 2008).

To illustrate the underlying logic of the parallelized development approach, Figure 1 provides a simplified and anonymized development timeline highlighting the deliberate overlap of key activities. Rather than following a strictly sequential progression, additive synthesis and process development, formulation and application development, sourcing and toll manufacturing, regulatory preparation, and market-related activities were advanced concurrently. This overlap reduced idle time and allowed interdependencies between development streams to be addressed early, thereby preventing late-stage bottlenecks under severe time pressure.

The conceptual differences between a classical sequential Stage-Gate® process and a parallelized development approach are summarized in Table 1, highlighting shifts in process logic, risk exposure, and early-stage resource commitment under conditions of severe time pressure. As illustrated in Table 1, parallelization redistributes risk toward earlier project phases and increases upfront R&D resource commitment, while reducing the likelihood that critical technical, regulatory, or sourcing constraints are identified only at a point where remaining time and degrees of freedom are already exhausted.

The feasibility of this early parallelization was further supported by established analytical and quality control routines. As key synthesis intermediates and additive platforms had already been characterized in prior development activities, analytical methods and quality specifications were largely available from the outset. This reduced uncertainty and enabled early decision-making without disproportionately increasing technical or regulatory risk.

2.3.2 Role of Modular Platform Strategies

In addition to organizational parallelization, the acceleration of the development process was strongly enabled using a modular platform strategy. Platform-based development approaches aim to reuse existing technological building blocks across multiple innovation projects to reduce uncertainty, increase learning efficiency, and enable faster downstream decision-making (Meyer and Lehnerd, 1997; Gebhart et al., 2016). In the present case, the platform strategy did not represent a long-term product family initiative, but a pragmatic response to severe time pressure and regulatory constraints.

Rather than developing a single replacement compound, the substitution challenge required the development of two new proprietary additives to cover the functional requirements of multiple existing formulations and process variants. Both additives were deliberately designed using a modular synthesis architecture with shared intermediates. Several of these intermediates had already been developed and industrialized for related products, while only a limited number of additional precursors required further development and scale-up. This modularity significantly reduced technical uncertainty and enabled parallel progress across synthesis, formulation, sourcing, and regulatory activities.

From an innovation management perspective, the platform-based approach facilitated early convergence on a robust solution space. Familiarity with synthesis routes, analytical characterization, quality control

Vol.23, Iss.1, February 2026

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DOI: 10.17879/70918526846

Table 1. Conceptual comparison of Stage-Gate® and simultaneous engineering approaches in additive and formulation development

Dimension	*Stage-Gate® process (sequential)*	*Simultaneous Engineering (parallel)*
Process logic	Sequential phases separated by formal decision gates	Overlapping and parallelized development activities
Functional involvement	Gradual, function-by-function activation	Early simultaneous involvement of multiple functions
Dominant early-stage cost driver	Individual experiments and focused tests	Number of functions involved and parallel activities
Primary source of risk	Late technical failure within individual disciplines	Early mis-selection of development direction
Character of cost exposure	Gradually increasing over project phases	Early bundled allocation of R&D resources
R&D budget exposure	Limited in early phases due to selective progression	Elevated due to early parallel resource commitment
Cost of wrong direction	Relatively contained	Significantly amplified by parallel resource commitment.
Flexibility of project termination	High	Reduced
Learning and iteration logic	Sequential and focused	Parallel, but less reversible
Role of CAPEX in early stages	Typically, marginal	Typically, marginal
Relevance of OPEX considerations	Addressed at later stages	Implicitly shaped earlier but still limited.
Typical application focus	Explorative search and option generation	Targeted optimization of defined concepts
Suitable for additive and formulation development	Resource-efficient selection under uncertainty	Faster integration at the expense of higher R&D risk.

methods, and qualified toll manufacturing partners allowed downstream functions to engage early based on provisional but reliable substance definitions. This was a critical enabler for parallelization, as it reduced the risk that late-stage feasibility constraints would emerge after substantial time and resources had already been committed.

Beyond speed advantages, the modular platform strategy contributed to risk mitigation and economic viability across multiple dimensions. Reuse of shared synthesis intermediates reduced development effort, supported cost efficiency in low-volume specialty chemical contexts, and simplified global regulatory activities by leveraging existing toxicological and registration knowledge. In addition, the availability of established analytical and quality control routines further stabilized development execution and reduced coordination effort across organizational interfaces.

From an operational and quality perspective, both newly developed additives were protected by comprehensive intellectual property rights, underscoring their strategic relevance and long-term applicability. Compared to the legacy additive, the new compounds exhibited higher chemical stability and improved reproducibility of the synthesis and scale-up processes. This, in turn, facilitated more robust analytical characterization and quality control, contributing to enhanced process stability and reduced variability in industrial production. These properties further supported reliable global deployment and reduced operational risk across the value chain. In the context of specialty chemicals, functional additives are typically embedded in complex formulation and process systems, where stability, reproducibility, and robust analytical characterization are critical

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918527720
DOI: 10.17879/70918526846

prerequisites for reliable industrial application (Fink, 2017). Beyond improved chemical stability and enhanced reproducibility, the two newly developed additives also generated structural advantages along the value chain and within the supply network. Their modular synthesis architecture enabled, in principle, in-house production and thus increased internal value creation. At the same time, the availability of alternative qualified toll manufacturers facilitated a flexible allocation or relocation of production capacity without fundamental changes to the process architecture.

In contrast, the legacy additive had been manufactured exclusively by a single external supplier on a dedicated production line, resulting in a pronounced sole-source dependency. In addition, significant quality fluctuations were repeatedly observed, which required continuous formulation adjustments to ensure consistent product performance. Such variability was not encountered with the newly developed additives, further contributing to operational robustness and supply chain resilience.

Taken together, the platform strategy functioned as a structural enabler rather than an isolated methodological choice. By stabilizing early assumptions and reducing uncertainty across technical, regulatory, and economic dimensions, it allowed the project team to deliberately accept higher early R&D resource commitment in exchange for protecting time-to-market and business continuity under fixed external constraints.

2.3.3 Parallelization versus Front Loading

Both parallelized development and front-loading approaches aim to improve innovation performance under uncertainty by shifting activities toward earlier project phases. Front loading has been discussed in the context of engineering design and innovation management as a strategy to increase the amount of information generated early in the development process, thereby enabling earlier optimization and more informed downstream decisions (Bender and Gericke, 2016). This approach assumes that uncertainty can be sufficiently reduced through early analysis, experimentation, and knowledge generation.

In contrast, the platform-based parallel development approach applied in this case focused less on early convergence and optimization, and more on preserving decision optionality. Rather than committing prematurely to a single solution, multiple development activities were advanced concurrently on the basis of provisional but sufficiently stable assumptions. This logic allowed technical, economic, and regulatory uncertainties to be explored in parallel, without forcing early irreversible decisions.

This distinction is particularly relevant in innovation contexts characterized by high irreversibility of downstream decisions, such as industrial chemical development with global regulatory requirements and fixed time windows. In such settings, late-stage changes to substance structures, synthesis routes, or sourcing strategies typically entail disproportionate cost and regulatory effort (Loch et al., 2006). Parallelization therefore served not as a means of early optimization, but as a risk management mechanism to prevent critical feasibility constraints from emerging only after remaining time and degrees of freedom had already been exhausted.

From a management perspective, the degree of parallelization represents a deliberate decision variable that directly affects early R&D resource commitment and risk exposure. While front loading seeks to reduce uncertainty through early information generation, parallelization redistributes uncertainty across organizational functions and project phases. In the present case, this trade-off was consciously accepted in order to protect time-to-market and business continuity under fixed external constraints.

2.4 Risk Management and Organizational Implications

2.4.1 Managing Risk through Reversible and Irreversible Decisions

The transition toward a parallelized development approach fundamentally altered the project's risk profile. While sequential development processes aim to defer uncertainty to later stages, parallelized development redistributes uncertainty across the project timeline and requires earlier managerial engagement with incomplete information. As a result, risk management shifted from late-stage control toward proactive orchestration of assumptions, dependencies, and decision points.

A central element of this risk management approach was the explicit differentiation between reversible and irreversible decisions. Managing innovation under high uncertainty requires careful attention to the degree of irreversibility associated with early commitments

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918527720
DOI: 10.17879/70918526846

(Loch et al., 2006). In the present case, activities with low irreversibility—such as exploratory formulation work, preliminary sourcing assessments, and regulatory pre-evaluations—were deliberately advanced early to preserve schedule flexibility. In contrast, decisions associated with high sunk costs or long-term commitments, including final process investments or binding supplier contracts, were postponed until sufficient technical and regulatory confidence had been achieved.

This differentiated treatment of decision types enabled the project team to accept higher early R&D resource allocation without disproportionately increasing overall project risk. By consciously delaying irreversible commitments while advancing reversible activities, the organization maintained strategic flexibility despite severe time pressure.

2.4.2 Coordination, Governance, and Communication

Parallel execution of interdependent development activities significantly increased coordination and communication requirements. Multiple organizational functions operated simultaneously on partially provisional assumptions, increasing the risk of misalignment and information asymmetry. To manage this complexity, explicit coordination and governance mechanisms were required.

Rather than relying exclusively on formal gate decisions, the project organization emphasized frequent cross-functional synchronization. Regular alignment meetings ensured transparency regarding progress, assumptions, risks, and interdependencies across synthesis development, formulation, sourcing, regulatory preparation, and market-facing activities. Importantly, the objective was not to eliminate uncertainty, but to make it explicit, shared, and manageable at an early stage.

From a managerial perspective, this required a shift from gatekeeping toward active orchestration. Decision-making focuses less on pass/fail judgments at predefined milestones and more on continuously reassessing assumptions and updating priorities as new information emerged. This adaptive governance approach proved essential for maintaining coherence and momentum in a parallelized development environment.

At the managerial level, several transferable implications emerge from the case.

First, development process architecture should be treated as a situational design choice rather than a standardized template. In time-critical substitution scenarios with high interdependence between development streams, parallelization may provide superior risk control compared to strictly sequential approaches.

Second, early parallelization requires explicit decision rules regarding reversibility and resource commitment. Without such rules, parallel execution risks degenerating into uncontrolled resource consumption. Platform-based strategies and established organizational knowledge play a critical role in stabilizing early assumptions and enabling informed concurrency.

Finally, accelerated innovation under time pressure is less a function of individual technical breakthroughs than of organizational design and managerial decision-making. The case demonstrates that maintaining strategic flexibility, aligning cross-functional activities early, and consciously managing irreversibility can significantly improve innovation outcomes when time-to-market constraints are externally imposed.

2.5 Results and Lessons Learned from Practice

2.5.1 Development Speed and Economic Effects

The implementation of a parallelized development approach in combination with a modular platform strategy resulted in measurable improvements in development speed and coordination efficiency. Compared to comparable innovation projects following a strictly sequential development logic, the overall development timeline was reduced by approximately 20–25%. This reduction was primarily driven by the early overlap of synthesis development, formulation work, sourcing activities, and regulatory preparation, which significantly reduced idle time between development phases.

From an economic perspective, early parallelization shifted cost exposure toward earlier project stages, primarily through increased upfront R&D resource allocation. However, this increase was offset by reduced late-stage rework, earlier identification of infeasible solution paths, and improved transparency regarding cost drivers. In particular, early visibility into sourcing options, regulatory implications, and scale-up feasibility

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918527720
DOI: 10.17879/70918526846

enabled informed trade-offs between performance optimization, economic viability, and time-to-market. This observation is consistent with prior findings on early fixation of cost-relevant parameters in chemical development, which emphasize the limited corrective potential once unfavorable cost structures are discovered at later project stages (Murjahn, 2004).

Especially in the context of specialty chemicals characterized by low substance volumes, the reuse of shared synthesis intermediates and established analytical routines contributed to cost efficiency and reduced overall development risk. While the approach required higher early coordination effort, it prevented the accumulation of technical and regulatory risks at late project stages, where corrective actions would have been significantly more costly or infeasible.

2.5.2 Managerial Lessons Learned

Several transferable lessons emerge from the case. First, development process architecture should be treated as a situational design choice rather than a standardized template. Under severe time pressure and high interdependence between development streams, strictly sequential processes may amplify rather than mitigate risk.

Second, early parallelization requires disciplined management of assumptions, decision reversibility, and resource allocation. Parallel execution is not inherently superior to sequential development but becomes effective when supported by platform-based strategies, established organizational knowledge, and explicit coordination mechanisms.

The case further illustrates that supply chain structure should be treated as an integral design parameter of the innovation process rather than as a downstream operational concern. Strong dependencies on single suppliers or dedicated production assets significantly amplify project risk under time pressure, as they reduce strategic degrees of freedom and increase the consequences of late-stage failure.

Platform-based development and early parallel engagement with sourcing and manufacturing functions can mitigate such risks by preserving make-or-buy optionality and enabling flexible allocation of production responsibilities. From a managerial perspective, reducing sole-source dependencies is therefore not merely a procurement objective, but a strategic lever for increasing innovation robustness and organizational resilience in time-critical development projects.

Third, the case highlights that accelerated innovation under time pressure is less driven by individual technical breakthroughs than by organizational design and managerial decision-making. The ability to recombine existing technological, regulatory, and organizational assets in a modular way proved to be a critical enabler for maintaining strategic flexibility while meeting externally imposed time constraints.

Finally, the findings underline the importance of distinguishing between analytical generalization and statistical generalization in practice-based research. While the insights derived from this single case are shaped by its specific industrial context, the underlying mechanisms—early parallelization, modular platform use, and explicit management of irreversibility—are transferable to other process-oriented industries facing similar time-critical innovation challenges.

3. Conclusion

Innovation in the specialty chemicals industry is increasingly shaped by external constraints such as shortened product life cycles, global regulatory requirements, and fragile supply chains. In this context, innovation challenges often arise not from the pursuit of radical novelty, but from the necessity to redesign existing solution architectures under severe time pressure. This article analyzed such a boundary case using an anonymized industrial case study and focused on development process architecture rather than technical detail.

The case demonstrates that classical sequential Stage-Gate® models, while effective in many innovation contexts, may reach their limits when multiple tightly coupled development streams must progress simultaneously within a fixed and non-negotiable time window. Under such conditions, development process architecture and early cross-functional synchronization become critical managerial levers—not only to accelerate time-to-market, but also to reduce structural vulnerabilities arising from supply chain dependencies. Thus, platform-based parallel development provides a viable alternative by enabling early synchronization of synthesis development, formulation work, sourcing, regulatory preparation, and market-related activities. Rather than eliminating uncertainty, this approach

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918527720
DOI: 10.17879/70918526846

redistributes and manages it proactively across the project timeline.

Importantly, the innovation character of the case does not primarily reside in isolated molecular novelty, but in the successful alignment of three core dimensions of industrial innovation: conceptual novelty, practical applicability, and market viability. The development of two new proprietary additives based on a modular platform architecture fulfilled all three dimensions. The underlying idea was technically novel and protected by intellectual property rights, the additives were industrially producible and robustly characterizable, and their application in existing formulations and processes was successfully implemented at commercial scale. In this sense, the case illustrates a Schumpeterian understanding of innovation as the realization of new combinations rather than mere invention.

The findings indicate that innovation success and project risk are less a function of individual technical breakthroughs than of early managerial decisions regarding parallel R&D resource allocation, process architecture, and the orchestration of interdependent development activities.

As with all practice-based analyses, the insights derived from this single case are shaped by its specific organizational, regulatory, and market context and should be interpreted accordingly. Nevertheless, the underlying mechanisms identified—a modular platform use, controlled parallelization, and proactive risk orchestration—are transferable to other process-oriented industries facing time-critical innovation challenges. When applied selectively and in alignment with contextual constraints, platform-based parallel development can complement established Stage-Gate® processes and contribute to more resilient and successful innovation outcomes. Hence, development process architecture should be treated as a strategic management variable rather than as a purely procedural choice.

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Research Paper

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Actors and supply chain strategies in the circular economy: A guideline for circular business model design and innovation

The circular economy transforms fundamental, well-known business logics. To remain competitive and seize new business opportunities, companies are forced to implement innovative, circular business models. However, the current literature on circular business models still lacks a comprehensive perspective on options for companies to engage in various positions and functions along circular supply chains and how to develop corresponding business models. Therefore, a major challenge for companies remains in the identification of business opportunities, i.e., the positioning within emerging circular economy ecosystem, and how to adapt business models accordingly. Addressing this gap, this article provides a novel conceptual framework for circular business model patterns. First, the framework proposes three key actors (manufacturer, integrator, enabler) and three key supply chain strategies (creating, stretching, sustaining cycles) within a circular economy to derive nine circular business model patterns. Second, based on innovation strategies (closed, open) and intensities (low, high), this article characterizes four novel approaches to circular business model innovation. Finally, the framework is illustrated using the case of the emerging electric vehicle battery industry shifting towards a circular economy.

Introduction

For the past few years, companies have been increasingly facing a fundamentally transformative, socio-economic challenge: Sustainable values defined by environmental and social dimensions increasingly complement the dominant economic dimensions and drive the transformation of industries (Boons and Lüdeke-Freund, 2013; Joyce and Paquin, 2016; Lüdeke-Freund et al., 2018). Therefore, companies need to adapt internal business processes to provide innovative and sustainable products and services to customers, and align stakeholders with adapted strategies. In particular, established companies in manufacturing industries have been systematically introducing new strategies aimed at increasing sustainable value within the company and beyond (Kortmann and Piller, 2016). Regulations on sustainability and customer demand alike are forcing established companies and start-ups to innovate in order to seize upcoming market opportunities. A focus of corporates' innovative thinking and acting is the creation of a circular economy (Kirchherr et al., 2017; Kirchherr et al., 2023a; Kirchherr et al., 2023b). Compared to previous linear economies, the circular economy is based on a fundamental paradigm shift in economics and reflects new business logics for a more sustainable development (Stahel, 2016; Geissdoerfer et al., 2017).

Take, make, use, dispose - this is the conventional way in which companies 'do business' (Bocken et al., 2016), or simpler – "bigger, better, faster" (Geissdoerfer et al., 2017). The underlying paradigm of economic growth accomplished by increased production and consumption is linked to the irreversible and destructive exploitation of global finite resources, the increasing production of waste, and, eventually, the loss of material value. A circular economy can make economic growth

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Vol.23, Iss.1, February 2026
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independent of consumption and depletion of resources (Ellen MacArthur Foundation, 2013). The circular economy provides companies with new business opportunities by new value creation logics using alternative resources, such as waste, and alternative processes, such as repairing or reusing (Bocken et al. 2016; Lüdeke-Freund et al., 2018).

The relevance of a future sustainable economy has resulted in the circular economy receiving increasing interest from society, academia and industry, and has influenced policymaking (Bocken et al. 2016; Kirchherr et al., 2017). For example, caused by the fact that 40 million tons of waste ended up in landfills in California solely in 2019 (CalRecycle, 2019), the government of California initiated a comprehensive waste management program including recycling, reuse and reduce of waste. Similarly, to handle the current 2.2 billion tons of annual produced waste sustainably, the EU decided to intensify and expand waste management regulations towards a circular economy until 2050 (European Commission, 2023).

However, even if the regulatory foundations to engage in the circular economy have been laid, companies still struggle with seizing business opportunities and identifying strategies within circular supply chains across industries (Geissdoerfer et al., 2020; Bocken and Ritala, 2022). Thus, both start-ups and existing companies face challenges and opportunities for **re-positioning** and **re-aligning** in re-defined industries with innovative, circular business models. However, scholarly literature on circular business models still lacks a perspective on various actors - characterized by functions in supply chains - and supply chain strategies. Thus, so far, prior studies do not offer sufficient guidance for **re-positioning** in the circular economy and **re-aligning** business models.

The framework provided in this article addresses this gap and proposes two guidelines for strategic decision-making in developing and innovating business models within emerging circular economy ecosystem of a company's partners and stakeholders. First, we identify three key actors (manufacturer, integrator, enabler) and three key supply chain strategies (creating, stretching, sustaining cycles) within a circular economy and derive nine circular business model patterns that support companies in **re-positioning**. Second, by mapping innovation strategies (closed, open) and intensities (low/high), we propose a systematic guideline for companies to **re-align** based on four circular business model innovation approaches. Finally, we illustrate the derived framework of circular business model patterns and innovation approaches using a prominent case: the circular economy transformation of the electric vehicle (EV) battery industry.

Literature background: Supply chain strategies and actors in the circular economy and the emergence of circular business model concepts

Business models and the necessity to innovate them

The concept of the business model has been widely discussed and addressed in the literature in the past, and a large variety of definitions and characteristics have emerged as the concept has gained increasing interest (Zott et al., 2011). In general, a business model describes how a company "does" its business characterized by offering a convincing narrative to customer (customer value proposition) and achieving profitable numbers to sustain a business (Magretta, 2002). Fundamentally, every business model consists of three main elements: value proposition, value creation and delivery, and value capture (Richardson, 2008). By reflecting and realizing a company's strategies (Casadesus-Masanell and Ricart, 2010), the business model may be a main source of sustainable, competitive advantage (Magretta, 2002; Afuah, 2004; Teece, 2010). Thus, the development of an appropriate business model is essential for capturing new customer value for companies, thus, in achieving advantageous firm performances through the implementation of innovation (Chesbrough and Rosenbloom, 2002; Teece, 2010; Chesbrough, 2010). While established companies need to regularly assess and re-think current business models to sustain a competitive advantage through innovation (Chesbrough, 2010), for start-ups the business model represents "a core building block of the entrepreneurial enactment process" (George and Bock, 2011, p. 102). Therefore, to seize market opportunities, creating a business model is key in the entrepreneurial process. For example, Zott and Amit (2007) found that the performance of an entrepreneurial firm is enhanced by novelty-centered business models.

Vol.23, Iss.1, February 2026
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DOI: 10.17879/70918524339

Besides the strategic importance for companies, the business model can function as a unit of systematic analysis and external communication (Zott et al., 2011). Due to its importance but abstract and theory derived definition, several practical frameworks emerged to systemize and analyze business models for practitioner, such as the **Business Model Canvas** presented by Osterwalder and Pigneur (2010) consistent of nine building blocks, or the **four-boxes-framework** proposed by Johnson et al. (2008).

Although developing new business models pose many challenges for companies, business model innovation is important to capture value of innovative technologies by adapting existing business model and seize new business opportunities by creating new business models (Chesbrough, 2010; Osterwalder and Pigneur, 2010; Amit and Zott, 2012). Business model innovation is defined as "the search for new logics of the firm and new ways to create and capture value for its stakeholders; it focuses primarily on finding new ways to generate revenues and define value propositions for customers, suppliers, and partners" (Casadesus-Masanell and Zhu, 2012, p. 464). Institutionalized business model innovation processes can provide companies with a sustainable competitive advantage, enable companies to react on technology and market developments, and prevent disruption by other companies (Chesbrough, 2010; Osterwalder and Pigneur, 2010; Amit and Zott, 2012; Foss and Saebi, 2017). However, business model innovation gained a lot of attention from researchers and practitioners recently, but still lacks unified conceptualization and definition (Foss and Saebi, 2017). In industries and sectors shifting towards new customer value defined be environmental, social, and economic factors, business model innovation is crucial for companies to maintain competitive advantage by re-configuring internal capabilities to create, deliver and capture sustainable value (Boons and Lüdeke-Freund, 2013; Geissdoerfer et al., 2020). Thus, business model innovation is critical to leverage and implement the circular economy on an organizational business level (Rashid et al., 2013).

Circular economy

The circular economy is an "industrial system that is restorative or regenerative by intention and design. It replaces the 'end-of-life' concept with restoration, shifts towards the use of renewable energy, eliminates the use of toxic chemicals, which impair reuse, and aims for the elimination of waste through the superior design of materials, products, systems, and, within this, business models" (Ellen MacArthur Foundation, 2013, p. 7). The development towards a circular economy represents a fundamental, disruptive economic shift that changes the established model of production and consumption (Esposito et al., 2018). In the scholarly literature, numerous definitions of the circular economy emerged with different components such as supply chains strategies (Kirchherr et al., 2017). In general, the concept of circular economy is closely connected to sustainability, but fundamentally represents a means to enhance the sustainable transition of an economy or industry (Geissdoerfer et al., 2017). Thus, circular economy principles are widely applied in sustainability strategies by policymakers and companies to create a more sustainable economy towards separating economic growth from the consumption of natural resources (Ellen MacArthur Foundation, 2013), act in accordance with economic, social, and environmental value (Geissdoerfer et al., 2018), and address international sustainability guidelines, such as the 17 Sustainable Development Goals defined by the UN (United Nations, 2023).

All definitions imply the fundamental logic of eventually closing resource loops (Kirchherr et al. 2017; Geissdoerfer et al., 2017). However, individual definitions of the circular economy also include perspectives on systematic economy thinking to improve sustainability by including further principles, such as intelligent decentralization to increase systematic efficiency (Stahel, 2016), dematerialization by digitization of products to services to reduce material demand (Geissdoerfer et al., 2020), long-lasting products to enhance product value (Bocken et al., 2016), or sharing models to increase material usage efficiency (Geissdoerfer et al., 2020). Through these definitions, the range of supply chain strategies within the circular economy is broad. Next to recycling of waste and end-of-life (EoL) products and materials, other functions such as testing and determining product and material quality after use, remanufacturing, reuse, repair or repurpose provide companies with various options for implementing circular economy principles. In addition, new circular material flows require logistics from decentralized customers to centralized circular economy product or service providers to be re-thought to increase efficient linking of various stakeholders. However, the various strategies and functions pose

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918524956
DOI: 10.17879/70918524339

managers and policymakers with issues of decision-making and prioritization, which is not sufficiently addressed by research so far either. First approaches by policy and research are based on prioritizing logics of waste reduction and recovery at the end of a products' life cycle resulting in a cascading of consecutive supply chain strategies, such as reducing, reusing, repairing, remanufacturing, and finally recycling (Achterberg et al., 2016; Campbell-Johnston et al., 2020; Kirchherr et al., 2023a).

By providing a broad variety of emerging supply chain strategies for use and EoL management of products and materials, the circular economy entails both challenges and opportunities for companies. First, new supply chain strategies result in emerging actors with new functions within value chains in circular economy ecosystems. The circular economy poses threats of disruption of existing industries by creating new circular technologies and processes (Kirchherr et al., 2023c) (e.g., repairing, reusing, or recycling instead of mining and processing raw materials). Therefore, successfully (re)positioning of companies is required to sustain competitive advantages. However, due to the nascent stage of the circular economy in many industries, it is still unknown what actors take on new tasks of reverse logistics, recycling, reusing, repairing or remanufacturing, and what partners and competitors will emerge based on different business models. Finally, companies face strategic issues of new positioning or integrating several value chain steps in existing and new industries or entering partnerships with emerging actors. Thus, new concepts for business models are required including various actors and supply chain strategies within a circular economy to inform strategic decision-making of managers on designing suitable business models.

Second, seizing new business opportunities within a circular economy requires adaptation of business models according to new supply chain strategies and actors. In the business model innovation process towards implementing circular economy supply chain strategies, companies are faced with numerous challenges, such as deciding on whether to adapt existing business models by considering individual business model elements or developing new business models. Furthermore, against the background of emerging actors in a circular economy, new cooperations and partnerships with suppliers and customers may be required that can influence business model innovation processes. Thus, concepts for business model innovation approaches in the circular economy based on innovation intensity and involvement of external partners are required further to inform managers on how to (re)align business models, which is not yet addressed by research in detail.

Circular business models and circular business model innovation

The term of circular business model emerged from the sustainable business model literature and raised interest of numerous scholars and practitioners, recently (Geissdoerfer et al., 2018; Bocken et al., 2014). A circular business model is defined as "how an organisation creates, delivers, and captures value in a circular economic system" (Den Hollander and Bakker, 2016, p. 2). Previous studies primarily showed different circular business model strategies and archetypes of circular business models and categorize them into frameworks (Geissdoerfer et al., 2020). The results conceptualize the term of circular business model theoretically, but also offer companies practical guides to develop circular business models, and thus support in engaging of circular value chains. For example, Stahel (2016) differentiated circular business model strategies into two types: the recovery of materials through recycling and the continued utilization of products through reuse, remanufacture, repair, upgrades, and retrofits. Bocken et al. (2016), however, defined three resource strategies for a circular economy (slowing, closing, and narrowing resource loops) and proposed different circular business models to implement these circular resource strategies, for example extending resource value or industrial symbiosis for closing resource loops. More recent frameworks also refer to the basic definitions and frameworks of the business model itself to realize circular strategies. Based on Osterwalder and Pigneur (2010), Lewandowski (2016) introduced the circular business model canvas which defines eleven key elements of a circular business models without showing circular strategies. Besides the nine building blocks of the Business Model Canvas, take-back system and adoption factors are proposed as further elements of a circular business model (Lewandowski, 2016). In contrast, based on a comprehensive review, Geissdoerfer et al. (2020) introduced four circular strategies (cycling, intensifying, extending, and dematerialising) and corresponding business models.

JOURNAL OF
BUSINESS CHEMISTRY

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918524956
DOI: 10.17879/70918524339

In addition to categorizing circular business models, different approaches for practitioners to innovate their circular business model have been investigated initially. Circular business model innovation "incorporates principles or practices from circular economy as guidelines for business model design" (Geissdoerfer et al., 2020, p. 8). However, solely initial research on circular business model innovation has been conducted that primarily focused on different outcomes of circular business model innovation. For example, Geissdoerfer et al. (2020) proposed four types of circular business model innovation. Whereas processual perspectives on circular business model innovation primarily focus on the transformation of large and established firms towards circular economy (Frishammar and Parida, 2019; Suchek et al., 2022), and do not sufficiently provide various approaches of circular business model innovation for different actors and supply chain strategies in the circular economy.

Thus, prior research has focused on the developing of circular business model and circular business model innovation frameworks as practical guidelines for companies from a holistic view but neglect individual perspectives of various actors within the circular economy and designing and developing appropriate circular business models according to different supply chains strategies. Although the influence of circular economy characterizations, such as national and international policies, on different actors in circular value chains have been investigated (Ranta et al., 2018), there is still a lack of design and innovation of circular business models resulting in companies struggling to create business models according to positions and functions within a circular economy. This article aims to address this theoretical gap and managerial problem by providing a guideline for companies to support the design and innovation of corresponding circular business models.

Circular business model patterns: Mapping key actors and supply chain strategies

As shown, so far, established concepts and frameworks of circular business models lack a perspective on company functions or positions in circular economy supply chains. Based on initial differentiation between actors in the literature (Ranta et al., 2018), we define three key actors within the circular economy: **manufacturer, integrator** and **enabler** (Figure 1).

Manufacturers are companies that increase the value of materials and products that are ultimately delivered to the customer through processing. Manufacturers include various companies along a value chain that produce materials or manufacture intermediate and final products. **Integrator** refers to companies that take over EoL or waste products and, through various processes, guarantee the further use in form of products, individual components, or materials. These products, components, or materials can be integrated back into the value chain to manufacturers or users (customers). **Enablers** represent firms that support and enable the realization of a circular economy by providing key complementary services, for example, logistics or digital services. Compared to a linear economy, where service suppliers along value chains are also crucial for a profitable business model, the circular economy

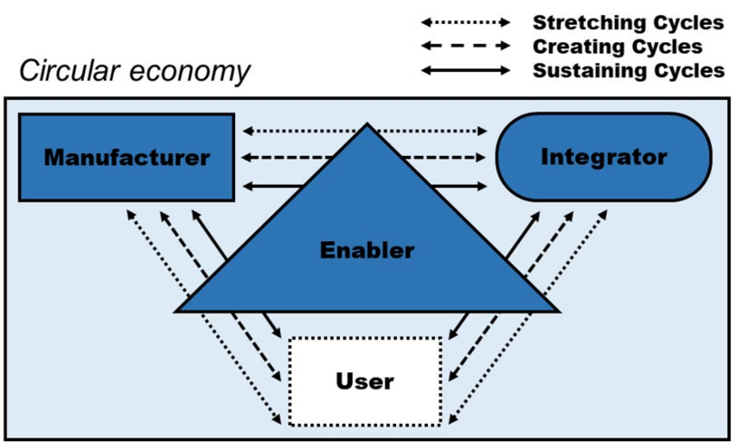

Figure 1: Key circular economy actors (manufacturer, integrator, enabler) and supply chain strategies (stretching, creating, sustaining cycles).

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918524956
DOI: 10.17879/70918524339

poses additional challenges such as necessary reverse material streams back from decentralized customers, intensified collaboration, additional organizational efforts, and required data streams across actors that need to be supported by enablers.

Next to functions or positions, companies can engage in a circular economy by pursuing various strategies. Based on previous definition of circular economy strategies (Bocken et al., 2016; Geissdoerfer et al., 2020; Frankenberger et al., 2021; Morseletto, 2020), we propose three supply chain strategies: **creating, stretching,** and **sustaining cycles** (Figure 1).

The supply chain strategy of **creating cycles** refers to the different ways of finally returning EoL and waste materials and products back into value chains. EoL and waste materials and products can be reintroduced to manufacturer at various points along the entire value chain. In recycling, products are broken down into individual materials in order to serve as basic resources for products of equal or other applications and industries (so-called 'upcycling' or 'downcycling'). In remanufacturing, products are rebuilt for the same use. For this purpose, discarded products are broken down into sub-products, which are then reassembled to the original product by combining them with new or repaired individual components. In contrast to recycling, in the remanufacturing process products are not fully broken down to a material level but disassembled into components. Thus, remanufactured products are returned to manufacturers located further downstream in the value chain compared to recycled products or materials (Achterberg et al., 2016). Finally, in refurbishing, products are subjected to a quality-assuring overhaul and restoration for the purpose of further use and remarketing. Refurbishing also includes the reconditioning and renovation of individual defects in the functions or characteristics of products that are rather simple to remove.

Stretching cycles includes reusing, repairing, and prolonging as well as guaranteeing an intentionally long life (longevity) of products or individual components. Reusing is the process of continuing to use products in similar applications or other applications of similar functional models after they have been deployed in a first-life application. Reusing is often preceded by a quality check to determine optimal options for further use. During repairing, in particular, the cycles of individual components are stretched. Defective individual components or products are processed by means of repairing to ensure further use in the intended application. In repairing, as in reusing, products and individual components are not returned to the value chain but are returned or sold directly to users or customers. Prolonging focuses on long use through optimal utilization. The principles of prolonging include maintenance and monitoring of the functions and performance of individual components or products in order to extend their service life and maximize efficiency. Longevity, on the other hand, refers to the intentionally long-lasting design of products and the avoidance of defects by ensuring quality assurance in advance.

Sustaining cycles refers to strategies that support, improve, and ensure existing cycles. Strategic options include reducing, regenerating, restoring, co-using, digitalizing, and connecting. Existing cycles are dependent on the flow of materials and the reintegration of products. Cycles can be stabilized and made more sustainable by reducing the number of materials used or related factors such as energy requirements. The principle of reducing is a cornerstone of sustainable strategies and is considered as a fundamental strategy of the circular economy (Kirchherr et al., 2017; Geissdoerfer et al., 2017; Ellen MacArthur Foundation, 2013). Regenerating and restoring primarily relate to strategies for balancing or absorbing linear depletion through reverse linear processes (Salonen et al., 2025). In these strategies, materials are partially extracted from existing cycles and reintegrated as a natural reserve. This concept, which is still in its early stages, can primarily be found in energy (e.g., water/hydrogen) and biological (re-planting) cycles. Co-using intends to increase the efficiency of use of products and materials and thus save additional necessary resources. Classic sharing, reservation, or multi-way models are examples of co-using for both individual users and companies. Digitalizing aims to replace physical transactions and activities with digital services and processes. Digitalizing not solely allows material and product requirements to be reduced, but also helps to map and support complex inter-actor processes in a circular economy. Finally, connecting describes the support of processes within the circular economy in order to link individual activities and actors within one or more cycles and, thus, make product and material cycles more efficient and sustainable.

JOURNAL OF
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Vol.23, Iss.1, February 2026
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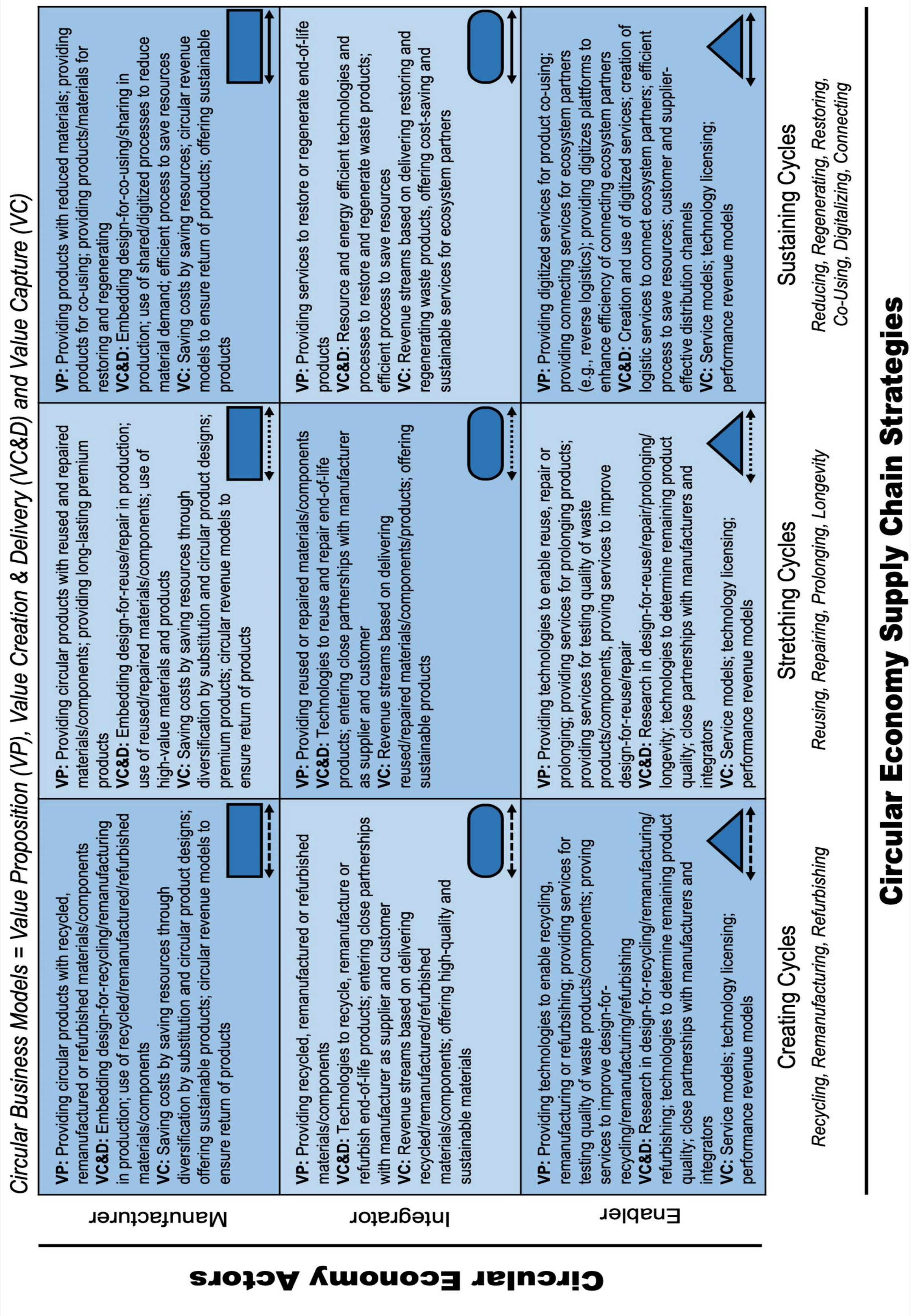

Figure 2: Nine circular business model patterns.

Vol.23, Iss.1, February 2026
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By mapping actors and supply chain strategies, we propose a novel concept of nine circular business model patters, shown in Figure 2. These patterns provide a practical guideline to develop suitable circular business models defined by various value proposition and logics for value creation and delivery and value capture (Chesbrough and Rosenbloom, 2002; Richardson, 2008; Osterwalder and Pigneur, 2010).

Furthermore, the nine circular business model patterns demonstrate which types of circular business models and corresponding characteristics of their elements are suitable in the respective circular economy strategies (creating, stretching, and sustaining cycles) for key actors (manufacturer, integrator, and enabler) in the circular economy. However, companies may opt for developing multiple business models and, thus, are not limited to individual strategies and functions within the circular economy. For example, companies may pursue multiple supply chain strategy options to capture value, such as recycling and reuse, depending on remaining quality and inherent value. In addition, vertical and horizontal integration of companies into positions and strategies within the circular economy leads to the integration of new circular business models and diversification of an existing business model portfolio through the design options of circular business models shown in Figure 2.

Four strategic options for circular business model innovation

Although the derived circular business model patterns show various outcomes for business model development processes, it does not yet contain a perspective on how companies may innovate their business model to adopt a suitable circular business model pattern. Companies can develop a circular business model applying various options of circular business model innovation. We derive options for circular business model innovation by answering two key questions: (1) 'How intensively should or must the business model be adapted towards a circular economy?' and (2) 'Should a company approach innovation from resources within the company or should external partners be involved in the innovation process?' Thus, we categorized circular business model innovation by **circular business model innovation intensity** (1) and **circular business model innovation strategy** (2).

Circular business model innovation intensity refers to how radically the business model is to be adapted. The business model is a configuration of the different elements or building blocks of value proposition, value creation and delivery, and value capture. Within these elements, further sub-elements or characteristics can be defined - for example, cost structure and revenue streams within value capture or key resources and partners within value creation elements (Osterwalder and Pigneur, 2010). A low-intensity, or incremental, circular business model innovation can therefore relate to individual elements or characteristics of these elements. High-intensity, or radical, circular business model innovations, on the other hand, may affect the entire architecture of elements in an existing business model. The advantages of low-intensity circular business model innovations are, for example, low risk and the efficient reuse of internal resources and knowledge, whereas high-intensity business model innovations offer access to new markets and may provide further profit and growth opportunities.

Circular business model innovation strategy comprises two fundamental approaches to innovation: closed and open. The concept of open innovation developed by Chesbrough (2003) is characterized by the inclusion of external stakeholders in the innovation process. In contrast to closed innovation, in which companies carry out the innovation process internally without external partners, the results of open innovation are usually not limited to individual companies but are rather intended to be used across firm boundaries (Chesbrough, 2003; Chesbrough, 2010). Closed innovation primarily offers companies control over processes (Bocken and Ritala, 2022), whereas open innovation promises more efficient incorporation of customers' and partners' demand as well as stable integration into complex emerging ecosystems such as a circular economy.

Figure 3 maps circular business model innovation intensity and strategy to derive four options for circular business model innovation: **circular re-configuration, circular re-design, circular co-configuration,** and **circular co-design**.

Circular re-configuration, as proposed here, corresponds to the internal reorganization of the business model by adapting individual business model elements to implement circular economy principles. Circular re-

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918524956
DOI: 10.17879/70918524339

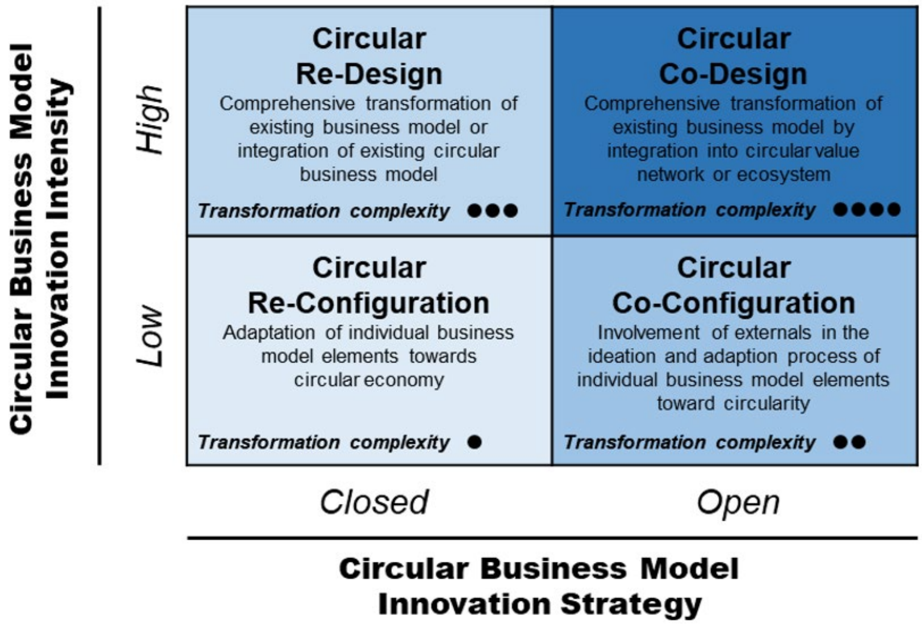

Figure 3: Four strategic options for circular business model innovation.

configuration, for example, can be realized within value creation and delivery by replacing linear resources with circular materials from recycling or reuse. Another option is to convert revenue streams within the value capture towards access or leasing models to ensure the return flow of products. Individual elements can generally be adapted incrementally using the options outlined in the circular business model positioning framework in Figure 2.

Circular re-design represents the holistic and comprehensive transformation of the business model, in which all the elements of value proposition, value creation and delivery, and value capture of a business model are newly defined and tailored simultaneously towards the circular economy through internal processes. In addition, circular business models can also be integrated into the existing business model portfolio through a company‘s own activities in spin-offs (diversification) or acquisitions (Geissdoerfer et al., 2020).

Circular co-configuration refers to the involvement of individual external participants in a circular economy, such as customers or partners, in the active development of new business model elements. Accordingly, the customer can be involved in the circular business model innovation process in order to redefine and adapt the value proposition, often also referred to as customer co-creation (O'Hern and Rindfleisch, 2010). Furthermore, for example, circular co-configuration can be used to redefine value creation by suppliers of materials in terms of circular principles and find joint solutions. Organizational forms of circular co-configuration can include, for example, the establishment of joint ventures.

Circular co-design, in contrast to circular co-configuration, involves the adaptation of the entire business model with partners and stakeholders in one or more circular supply chains and therefore requires the adaptation and integration of the business model into a circular value network or ecosystem. Due to the complex structures and difference of various players, the circular business model innovation as circular co-design takes place holistically and with the involvement of various actors and stakeholders in the value network (Zott and Amit, 2010; Centobelli et al., 2020) or ecosystem (Murray et al., 2017; Adner, 2017; Konietzko et al., 2020; Pietrulla and Frankenberger, 2020).

The case of the electric vehicle battery industry: A transformation towards circular economy

A prominent example for an emerging industry shifting towards a circular economy is the EV battery industry. The EV battery industry is rapid developing by technology adoption, corporate strategies, and shifting external boundaries, while new actors and supply

JOURNAL OF
BUSINESS CHEMISTRY
Vol.23, Iss.1, February 2026
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DOI: 10.17879/70918524339

chain strategies emerge to increase sustainability by integrating circular economy principles. Although product life cycle studies generally show that electrified mobility is environmentally beneficial compared to combustion-engine vehicles, the current linear sourcing of battery raw materials still pose major challenges for a sustainable industry (Wesselkaemper et al., 2024).
Today, battery raw material mining is associated with social issues for local workers and residents (e.g., artisanal cobalt mining in DR Congo (Nature, 2021; Baars et al., 2021), requires vast amounts of water (e.g., lithium mining in South America (Nature, 2021; Haddad et al., 2023), and consumes considerable energy in global transportation (e.g., most refining process and capacities in battery production are currently located in China (Cheng et al., 2024). Moreover, raw materials are main battery (Wesselkaemper et al., 2026; Gutsch and Leker, 2024) and EV cost drivers (Mauler et al., 2021), caused by rising and fluctuating prices (e.g., the nickel price exploded in March 2022 due to the Ukraine-invasion of Russia, a large nickel producer (Nature, 2021).
To improve the sustainability of EVs, policymakers and companies increasingly adapt a circular economy of EV batteries and their materials. Circular economy principles such the remanufacturing, recycling, and reuse of batteries make battery supply chains less dependent on environmentally, socially, and economically critical raw materials like lithium, cobalt, and nickel (Wesselkaemper et al., 2025). Global regulations, such as the Inflation Reduction Act in the US (Trost and Dunn, 2023), electrification and recycling targets in California (Wesselkaemper et al., 2025), or the updated EU Battery Directive (European Union, 2023), are promoting EV sales, while supporting an EV battery circular economy and corresponding circular business models. Driven by the shift of the cost-sensitive EV industry towards a circular economy, established companies, such as German car producer Volkswagen, Belgium recycler Umicore, Swiss mining giant Glencore, Chinese EV battery production market leader CATL, or US-based manufacturer GM, are trying to re-organize and re-define positions by exploiting innovative, circular business models. In addition, due to emerging market opportunities, the industry faces a vast majority of entrants, including numerous Chinese EV and battery manufacturers like Nio and BYD, emerging recyclers like Ascend Elements (US), Cylib (Germany), or Brunp (China), and companies integrating multiple steps in circular supply and value chains like Redwood Materials (US), which tries to couple recycling and reuse with its battery production business model. Furthermore, new market opportunities attract innovative business models like platforms (e.g., offered by the German start-up Circunomics) supporting efficient circular material flows by linking waste supplier and customers, and required reverse logistics systems after use phase to guarantee the reintegration of waste materials back into the value chain. These examples underline the ongoing development of business models suitable for a circular battery economy, despite of companies facing major challenges in innovating circular business models in emerging circular economy ecosystems (Wesselkaemper and von Delft, 2024).
Given this transformation, in the following, the case EV battery industry is used to illustrate companies' positioning strategies in an evolving circular economy, corresponding circular business models patterns (see Figure 2), and applied circular business model innovation options as derived in this study (see Figure 3).

Nine circular business model patterns in the EV battery industry

Creating cycles in the EV battery industry is currently primarily focused on the recycling of batteries as an influential shift in value proposition, value creation and delivery, and value capture of various business models. Large EV manufacturers such as Tesla and VW, as well as EV battery manufacturers such as CATL, LG Chem and Panasonic, are continuously integrating recycling as circular economy strategies into their own business models. Tesla and VW, for example, are currently building own battery factories (so-called gigafactories) that produce EV batteries in which production follows a design-for-recycling approach to simplify battery disassembly and recycling after use. In this way, manufacturer transform their value proposition. Additionally, in new key processes within the value creation logic, battery materials are planned to be increasingly sourced from recycling, which is why recyclers have been identified as key suppliers by manufacturers, strengthening collaboration with both integrators and enablers as key partners in a circular economy. Even though many manufacturers strategically aim to integrate recycling into their own portfolio, which offers extended value propositions

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918524956
DOI: 10.17879/70918524339

and value creation and delivery, a large proportion of spent EV battery materials are received by recycling companies (integrators). Recycling integrators such as Ascend Elements or Redwood Materials offer value propositions to suppliers and customers characterized by services for handling and recycling spent batteries to secondary materials such as lithium, cobalt and nickel supplied to their customers, i.e., manufacturers. By implementing new, circular revenue streams such as recycling-as-a-service, value capture and delivery is enhanced. Similarly, partially defective batteries are dismantled and remanufactured as part of value proposition and creation of integrators such as Redwood Materials, or manufacturers such as Nissan. By reassembling, batteries can be sold directly to EV manufacturers without passing manufacturing, saving costs and supporting the value capture logics of various stakeholders. Next to manufacturer and integrator, enabler emerge. For example, the Luxembourg-based start-up Circu Li-Ion supports creating cycles of batteries through an automated technology that tackles current challenges of complex spent battery disassembly. By providing a so-called machine-as-a-service, Circu Li-Ion acts as an enabler with its value proposition of providing technology to manufacturer to remanufacture batteries, and to integrators to recycle batteries more efficiently. Next to disassembly, another operating challenge in circular material flows is the transport of hazardous batteries after EV life from customers to manufacturers and integrators. Driven by varying regulations, this requires special knowledge on spent batteries and logistics, which offers new value proposition opportunities for actors. Both integrators and enablers are approaching this challenge and try to seize opportunities with innovative business models. Various recyclers partner with local reverse logistics provider to transport decentralized customers' EV batteries to recycling plants. For example, though having filed bankruptcy recently, Li-Cycle has approached an innovative value creation model, the so-called spoke-and-hub model, by regionally splitting the recycling value chain supporting value capture by reducing costs.

Stretching cycles in the EV battery industry is mainly characterized by reuse strategies and design strategies for long-life EV batteries (longevity). Various battery manufacturers, such as Tesla or the Chinese start-up Nio, increasingly focus value propositions on long-life battery technologies. For example, Nio supports longevity with new value creation and delivery and value capture logics that involve exchanging discharged with charged batteries with bespoke swapping infrastructure. By regularly checking the batteries after replacement, battery lifetimes can be extended (prolonging) and battery parts can be replaced through repairing if necessary. The integration of design-for-longevity of batteries and battery technologies into the value proposition and value creation also often implies a prolonged usability of batteries after EV life. In the reuse of EV batteries, 2nd use, batteries that no longer meet the performance requirements of EVs at the end of their life cycle are reused in applications with lower performance requirement profiles. These include applications in balancing and absorbing grid loads, in stationary home storage systems or in charging infrastructures. Manufacturers, integrators and enablers alike have implemented reuse in existing business models or are currently developing new business models for reuse. As an EV manufacturer, Renault, for example, offers new leasing models in the value capture logic that guarantee the return of batteries to the manufacturer, which, in turn, supports value delivery. Discarded batteries are sold by Renault generating new revenue streams and installed in large-scale energy storage systems to capture business opportunities driven by growing applications in grid usage and stationary energy storage. In addition, Renault diagnoses its own returning batteries to be able to repair individual defective parts of the battery, thereby continuing to stretch cycles by applying new value creation logics. In the B2U, integrators act as users of stationary battery storage systems who increasingly rely on the application of spent batteries. One example is the Finnish company Fortum, which aims to use energy storage system solutions from spent EV batteries to store energy from hydropower plants, relieving grid loads while generating revenue. The battery industry is seeing an upswing in new enablers whose business model consists of taking old EV batteries, testing them, and repurposing and selling them for reuse in large-scale applications. Particularly young start-ups, such as Voltfang from Germany or B2U Energy Solutions and RePurpose Energy from the US, are developing business models to profit from stretching EV battery cycles through reuse by new value propositions and value capture and delivery logics. The German start-up Betteries, for example, reuses EV batteries to produce mobile stationary storage systems for usage in remote

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918524956
DOI: 10.17879/70918524339

locations around the world. In addition, Betteries ensures recycling in the end of the reused battery life by a battery-as-a-service revenue model.

Finally, **sustaining cycles in the EV battery industry** is characterized by a diverse strategy field in which manufacturers, integrators and enablers operate through a variety of business models. Potentially, with sufficient supply of secondary materials from recycling, companies may consider restoring and regenerating of critical battery materials, but business models for these strategies are comparatively unexplored and not yet being applied. However, other strategies in sustaining cycles, reducing, co-using, digitizing and connecting, are found in the EV battery industry. The reduction of materials used in batteries is particularly important among manufacturers. Many of the materials are either very expensive (e.g., cobalt, nickel, lithium) or hazardous, which effects value capture. Therefore, manufacturers are looking for novel production methods to reduce materials and minimize waste through cyclical material flows in production implying new circular value creation logics. Besides reducing the extensive use of water through capturing and reusing, one example of this is the reduction of expensive, toxic and environmentally harmful liquid solvents in the process, which can be drastically reduced by so-called dry coating methods, such as explored by VW, innovating value creation logics. Next to reducing, several manufacturers have implemented co-using business models by car-sharing models in urban areas to intensify and optimize the material usage and requirements of charging infrastructure by applying new revenue streams in the value capture logic. This may be further optimized through innovative value propositions and additional revenue streams such as vehicle-to-grid solutions, in which the EV battery is source of power for grid loads, and which manufacturer like VW investigate. Services provided by manufacturers, enablers and integrators are also increasingly being made more efficient through digitalization and become attractive for customer. EV manufacturer Porsche, for example, uses digital twins of vehicles to optimize maintenance and design processes and, thus, save resources in key processes of value creation. As an enabler, Circunomics creates digital battery twins that contain information along the value chain to sustain other circular strategies such as recycling or reuse, thereby offering new value propositions and value creation and delivery logics. In addition, Circunomics sustains cycles by connecting material cycles of batteries. Using a platform business model, Circunomics connects suppliers and customers of used batteries (value proposition) to optimize the efficient reuse of batteries between multiple stakeholders along the battery value chain. As enabler, besides the disassembly technology, Circu Li-Ion also provides a battery diagnosis technology for sustaining battery cycles, saving resources and increasing efficiency.

Four circular business model innovation options in the EV battery industry

Circular re-configuration in the EV battery industry often is the first step to integrate circular economy principles into their business models of established companies. As mentioned in numerous examples above, individual elements of the business model are realigned to realize a circular economy. Examples of this include the circular re-configuration of value capture logics at Renault by switching to a leasing model and generating new revenue streams from the sale of discarded batteries to reuse integrators and enablers. Other cases of circular re-configuration are the switching to the use of circular, recycled materials, and the establishment of material cycles in the production of EV and battery manufacturers.

Primarily, examples of **circular re-design in the EV battery industry** can be identified in the large number of new integrator and enabler start-ups that are tailoring the entire business model to a circular economy by establishing a new circular business model. However, start-ups such as Cylib or Redwood Materials, as well as established companies such as Tesla, Daimler, and VW, are also integrating new circular business models through diversification, as they aim to recycle batteries independently in the future. Redwood, which is currently primarily active in the reuse and recycling of batteries, intends to produce battery materials itself from the recycled materials in future, thereby independently establishing and integrating an integrated business model in the battery cycle. Redwood also provides an illustrative case of business model innovation by acquisitions. By acquiring the German recycler Redux, Redwood diversified the company into new markets in Europe, in the course of which new circular business models are being integrated into the company.

Circular co-configuration in the EV battery industry is currently a common approach for companies

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Vol.23, Iss.1, February 2026
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DOI: 10.17879/70918524339

to integrate circular principles into their business model and participate in a newly emerging circular economy. In particular, joint ventures are emerging from a wide variety of partners to create synergies and share knowledge to remodel individual elements of business models. For example, the US-based recycler Redwood, General Motors, and the South Korean battery manufacturer LG Energy Solutions formed a partnership to jointly recycle battery production waste in an energy-efficient manner. Another example is Fortum, which, as mentioned above, reuses batteries to store energy from hydropower. On organizational level, this is realized through a joint venture with EV manufacturer Volvo Cars and the cleantech company Comsys.

Finally, **Circular co-design in the EV battery industry** has not yet been realized. Main reasons are complex circular systems around EV batteries and their redefinition of material flows through reuse, repair, remanufacture or recycling, for example, have yet to be established and mature in the next decades. Companies that want to participate in this complex system of multiple cycles in the future through a corresponding business model will be forced to coordinate their business model with varying players to be able to deliver added value to the value network or ecosystem.

Discussion and implications

Theoretical implications

This article offers theoretical contributions on circular business models and circular business model innovation. Business model innovation is a key driver for sustaining competitive advantages in known industries, realizing successful strategies in emerging industries, and creating value for companies and customer from new technologies and product innovations. As shown, thus, the new economic logic and paradigm of circular economy forces companies to create innovative, circular business models to implement circular strategies and introduce new processes, products or services based on new customer value. A circular economy offers a wide variety of strategies based on the fundamental aim of efficient and sustainable cycling of EoL products, intermediate components, or raw materials. The economic cycling principle requires new value chain activities that emerge and, therefore, offer companies new integration and market opportunities. Although academic research has addressed this issue with first practical guidelines of circular business model development, a key perspective on different actors and supply chain strategies within a circular economy and corresponding resulting business models has been lacking so far. As a result, although initial circular business model patterns emerge in industries, companies still struggle in developing business models according to new positions and functions based on different circular supply chain strategies. This study takes on this gap and offers a practical guide for the development of circular business models by providing a value-chain positioning perspective of actors and strategies. Three fundamental circular economy strategies (creating, stretching, and sustaining cycles) and three key actors (manufacturer, integrator, and enabler) are identified and mapped to derive novel circular business model patterns. This guideline provides nine patterns of circular business models, and their element characterization options for value proposition, value creation and delivery, and value capture. Furthermore, strategic options for companies to approach circular business model innovation are proposed. Based on different circular business model innovation strategy (open, closed) and intensity (low, high), four circular business model innovation options are defined: circular re-configuration, circular re-design, circular co-configuration, and circular co-design.

Managerial Implications

The conceptual guideline for circular business model design and innovation presented in this article have several practical implications for managers and practitioners of established companies as well as for entrepreneurs and start-up managers. The business model patterns and innovation strategies improves managers' understanding of business model options offered by the circular economy based on different functions of actors and supply chain strategies. The guideline presented can be applied by firms that face major industrial transformations to a circular economy or aim to seize new business opportunities in an emerging circular economy. However, the application of the framework has different implications for managers and companies, dependent on whether the circular business model development process of an established company or a start-up is aimed at.

Primarily, an established company must develop circular business models in mainly two scenarios. First, companies adapt their established business

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DOI: 10.17879/70918524339

model according to current positions in the industry to further sustain their competitive advantage in a circular economy by, for example, manufacturing products or intermediate components. The proposed guideline offers several implications for the development of the circular business model. On the one hand, it proposes circular business model transformation outcomes by providing business models element options characterized through value proposition, value creation and delivery, and value capture. On the other hand, it supports strategic decision-makers in the understanding of how other players in the industry can develop their business models based on current or future position and functions in value chains. This supports companies in identifying suitable position within the circular economies, and, furthermore, provides a guideline to inform whether strategies and business models of former partners are aligned with the targeted circular business model, laying the foundation to identify new partners and stakeholders that fit to business models, which is required to succeed in complex networks and ecosystems of emerging circular economies.

In the second scenario, established companies seek to integrate circular value chain steps or functions (e.g., integration of enabler or integrator activities by a manufacturer) or supply chain strategies (integration of stretching and creating cycles through reusing and recycling of materials simultaneously). In this scenario, the presented guideline offers a structured approach to assess current business models and mapping new circular business model options based on the integration of additional functions or supply chain strategies. This article informs managers and practitioners about business model patterns, what elements characterize them, and which beneficial or disadvantageous capability, stakeholder and resource allocation potentials arise to improve outlining integration strategies and derive requirements for horizontal and vertical integrations.

In both scenarios, understanding circular business models patterns of the focal firm, partners and competitors is essential. In addition, the proposed four circular business model innovation options (circular re-configuration, circular re-design, circular co-configuration, and circular co-design) offer a strategic guideline on how to tackle circular business model development. A transforming as well as an integrating company face circular business model innovation challenges that arise from key issues of closed or open business model innovation and incremental (low intensity) or radical (high intensity) business model innovation diversity. The guideline identifies different options for managers and practitioners and characteristics of these options along with transformation complexity. Thus, the proposed guideline supports the transitions leading from circular re-configuration to circular co-creation.

Finally, this article supports entrepreneurs with the creation of new start-ups in a circular economy by providing nine circular business model patterns. These patterns serve as a tool to categorize different actors and supply chain strategies in the industry and support the assessment of potential competitors and partners in order to successful engage in an industry shifting towards a circular economy. Against the background of transformation and integration challenges of established companies, managers of start-ups can design business models according to different positions and supply chain strategies within the new circular economy from the outset.

Outlook

As new principles and business logics arise from the circular economy, companies are still struggling to position themselves in new circular economies and to develop suitable circular business models accordingly. In this article, we derive nine circular business model patterns based on three key actors (manufacturer, integrator, and enabler) and three key supply chain strategies (creating, stretching, sustaining cycles) in a circular economy. Further, we propose four approaches to circular business model innovation considering innovation intensity (low, high) and strategy (open, closed): circular re-configuration, circular re-design, circular co-configuration, and circular co-design. In doing so, this article aims to inform managers and practitioners in strategic decision-making of circular business model development processes. Although, as shown, these patterns and innovation options are found in current industries transforming towards the circular economy, such as the EV battery industry, they are not mutually exclusive and can be integrated in several ways by established companies and start-ups that try to seize new business opportunities.

Overall, the guideline presented in this article contribute

Vol.23, Iss.1, February 2026

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DOI: 10.17879/70918524339

to academic literature that results in managerial problems by providing a perspective on different actors engaging in different supply chain functions and corresponding business models based on supply chain strategies, as well as a approaches to circular business model innovation. However, the early status of the emerging circular economy in various industries is constantly facing scholars and practitioners with challenges and opportunities. Thus, the provided patterns should be applied in the strategic circular business model development process and further integrate established and emerging concepts against the background of the rapidly developing, reactionary, and complex networks within circular economies.

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JOURNAL OF
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Research Paper

Jan-Hendrik Richter*[a], Tim Niklas Franke[a], Simon Lux[ab]

Profitability and Cost Structure in the Battery Cell Industry: A Comparative Analysis of CATL and Key Competitors

The battery market currently faces significant challenges for market participants. European and American EV sales stagnated during 2023 and 2024 (IEA, 2025). At the same time, dramatic overcapacities of Chinese companies increase pressure on prices and margins. Ultimately, several battery cell manufacturing companies face economic difficulties. Nevertheless, a few remain in a stronger economic position than the majority. This analysis compares Contemporary Amperex Technology Limited's (CATL) business performance based on publicly available data from the early 2023 through the first half of 2025 with three major competitors in the battery cell market China Aviation Lithium Battery (CALB), LG Energy Solution (LGES) and Samsung SDI (SDI). Besides location-based differences, CATL's efforts to establish own supply chains and potential economic benefits were also considered.

1. Introduction

Presently, the manufacturing of battery cells faces numerous challenges. Especially European companies are encountering difficulties in establishing local cell production. The insolvency of *Northvolt AB*, the postponement of *ACC*'s battery cell plants in Italy and Germany, and recent decision of *Porsche AG* to cancel the *Cellforce GmbH* project to establish its own cell production illustrate the capital-intensity and challenge of maintaining an industrial-scale battery cell manufacturing successfully (batterienews.com, 2025; BatteryIndustry.net, 2024; Carla Westerheide, 2025; Julian Baumann, 2025; Porsche AG, 2025).

Moreover, intense price competition is ongoing due to a substantial mismatch between battery cell capacity expansion and current demand in China. As a result, battery cell market prices have declined by approximately 60% since 2022 (Fabrice Renard and Christophe Pillot, 2025). Additional overcapacities for cathode active material reinforced prices and margins pressure along the entire supply chain (Fabrice Renard and Christophe Pillot, 2025; Wu et al., 2025). Consequently, battery cell manufacturers are forced to reduce sales prices, potentially eroding margins and earnings.

On the one hand, this development may have certain positive implications for customers and the automotive industry. In the context of intensifying competition, cell sales prices are decreasing, which reduces purchasing costs enabling automotive manufacturers and other customers to procure cells at lower prices.

On the other hand, to maintain economic viability, cell manufacturers need to decrease production costs. This price competition poses risks for market players that are unable to cut prices and maintain competitiveness simultaneously. Furthermore, the current situation is preventing new market participants from entering this challenging market. Nevertheless, some firms continue to perform strongly despite these adverse conditions.

An initial review of operating margins indicates that CATL and CALB were able to keep margins stable. Nevertheless, CATL exhibits significantly higher profitability (Figure 1).

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Vol.23, Iss.1, February 2026
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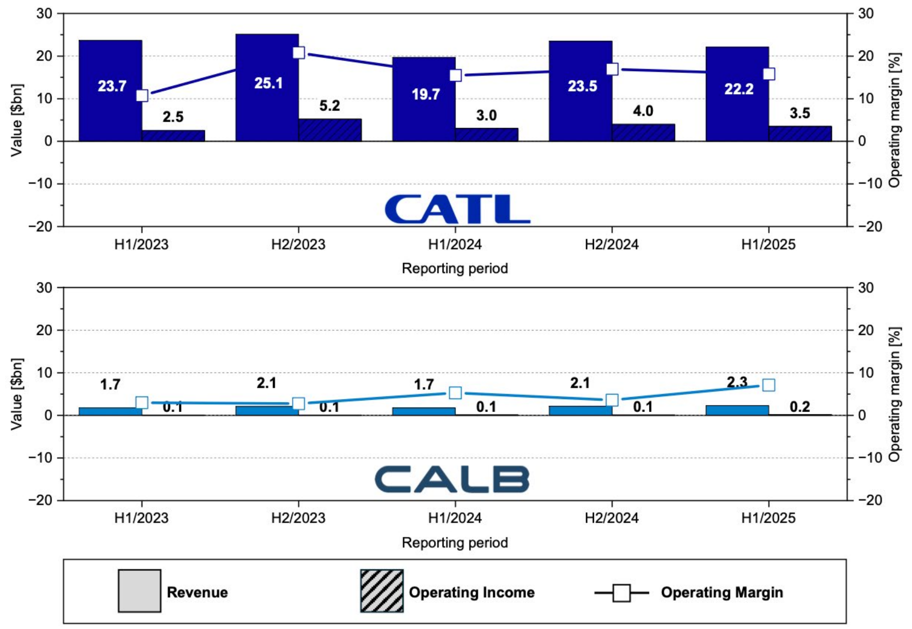

Figure 1: Revenue and operating income comparison of Chinese companies CATL and CALB between second half of 2023 to first half of 2025. The analysis considers only revenue and operating profit or loss associated with cell & battery manufacturing and its sales (CALB, 2024, 2025a, 2025b, 2025c; Contemporary Amperex Technology Co. Limited (CATL), 2023, 2024a, 2024b, 2025b, 2025d).

In comparison, the economic performance of two major Korean competitors, LGES and SDI, displays a significantly different picture.

Both are facing operating loss since at least two reporting periods if subsidies granted through *Inflation-Reduction-Act* are neglected (Figure 2).

The fundamental question arising from this observation is why Chinese manufacturers, especially CATL, are able to maintain high profitability despite global overcapacity and intense price competition, while other competitors

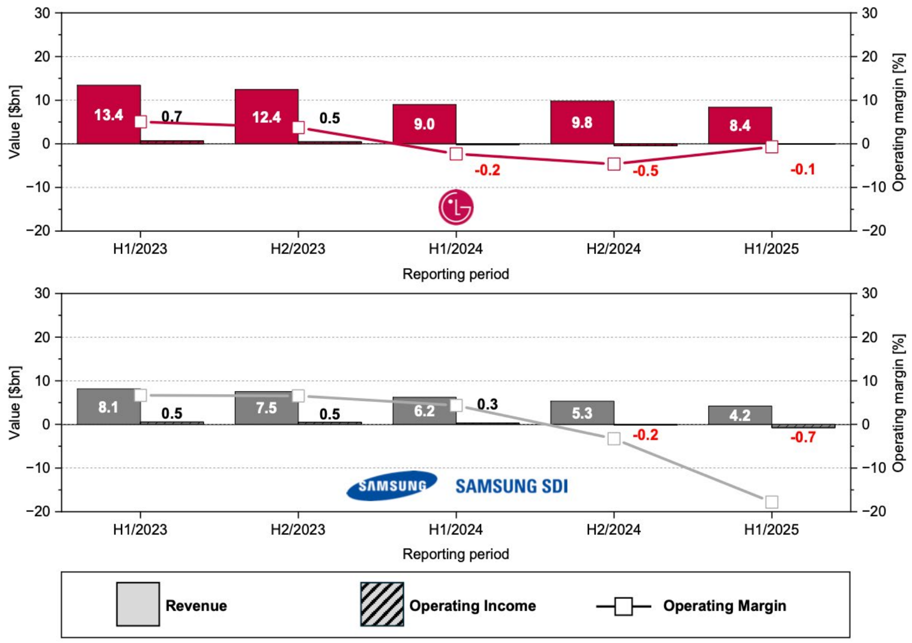

Figure 2: Revenue and operating income comparison of Korean companies Samsung SDI and LGES between second half of 2023 to first half of 2025. For LGES and SDI other operational income from *Inflation-Reduction-Act* of the U.S. government is excluded. The analysis considers revenue and operating profit or loss associated with cell & battery manufacturing and its sales (LG Energy Solution, 2023, 2024b, 2024c, 2025b, 2025c; Samsung SDI, 2023, 2024a, 2024b, 2025a, 2025b).

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918523415
DOI: 10.17879/70918522810

incur operating losses or achieve only low profitability. The existing literature provides limited insight into this question, although CATL has been examined in several studies:

Whitfield et al. examine the technological catch-up of BYD and CATL at the company level. The study assesses how BYD and CATL became leading firms in the EV and battery cell manufacturing sectors. The author ultimately identifies early corporate investments and technology efforts, as well as government policies, as key drivers of their success. (Whitfield and Wuttke, 2026)

Zhang et al. conducted a study on CATL's profit model, including financial metrics. However, their analysis focuses primarily on customer and market perspectives. In addition, competitors are not assessed. (Zhang and Yang, 2023).

Fan et al. assessed the profitability of CATL's business, evaluating it from a variety of perspectives. This assessment also includes a brief evaluation of the major domestic competitor. Nevertheless, financial assessment is exclusively available for CATL. Nevertheless, the author arrived at the conclusion that the decline in the margin of CATL was substantial and was the result of increased domestic competition (Fan, 2022).

Therefore, the subsequent analysis evaluates CATL's business model and examines possible drivers for its resilience and profitability compared to key competitors. Within this analysis, the following hypotheses were assessed:

H1: In general, Chinese companies benefit from a significant cost advantage due to lower energy costs and wages associated with domestic production.

H2: As the global leading battery cell manufacturer, CATL benefits from economies of scale arising from its large manufacturing capacity.

H3: CATL benefits from vertical integration into the battery raw material supply chain and from significant acquisitions of related companies.

2. Method

For the data analysis, semi-annual and annual reports of the battery cell manufacturers CATL, CALB, LGES and SDI from 2023 to the first half of 2025 were analyzed and evaluated. The selection of these companies was based on three key criteria.

First, their business activities include battery cell production which is globally relevant. Accordingly, all companies analyzed rank among the top ten in battery volumes sold in 2024. Second, required financial reporting data were accessible. Third, the companies' major business activity needed to be directly related to battery cell production.

It would also have been appropriate to include BYD, the world's second-largest battery cell manufacturer, in this comparison. However, from an external perspective, the battery business cannot be assessed independently of BYD's automotive business and other corporate activities.

To conduct this analysis, original Chinese and Korean reports were translated by using DeepL.com Pro-Version. The analysis focused on key financial indicators – as revenue, operating income and operating margin – consistent with prior studies (Fan, 2022). Additionally, raw material costs were encompassed to assess CATL's raw material strategy. Net income was excluded, due to varying tax rates and government incentives. Several key performance indicators were considered, including sales volume, production capacity and production output. All currencies were converted to USD using an average currency exchange rate for the respective year (ExchangeRates.org.uk).

Subsidies or government grants, such as *Inflation Reduction Act* (IRA) by U.S. government or Chinese governmental funding were subtracted wherever possible. In the *Statement of Profit or Loss* of both companies, the amount and type of funding become not immediately obvious. Therefore, it cannot be confirmed that government subsidies were fully excluded from the following analysis. (CALB, 2025a; 2025).

In addition to battery-related businesses, CATL and SDI generated revenues from other activities. For SDI, the production of semiconductors and displays contribute between 5% to 10% of total revenue. CATL generated approximately 10% to 15% of total revenue by businesses related to raw materials, battery materials, recycling and further businesses summarized under Others. For both companies, revenues and incomes from those activities were excluded to enable a more precise analysis of their battery-related businesses. Therefore, CATL's indirect expenses (Overhead, sales expenses, R&D expenses, etc.), which are not immediately attributable to the battery related business, were allocated based on the revenue share of the battery-related business units.

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3. Results and discussion

3.1. Company profiles

CATL is a Chinese company headquartered in Ningde, Fujian. The company has extensive experience in battery cell manufacturing and in battery cell development for electric vehicle applications (xEVs), energy storage systems (ESS), and niche applications such as power tools and e-bikes. In addition, CATL actively acquires and invests in domestic and international projects to secure direct access to battery raw materials and to expand recycling activities for production scrap and end-of-life batteries. CATL operates lithium mining in China and has been identified as a stakeholder in a nickel mining project in Indonesia and a cobalt mining project in the Democratic Republic of Congo (BatteryIndustry.net, 2024; Contemporary Amperex Technology Co. Limited (CATL), 2021, 2022, 2025c; Tom Daly, 2022).

CATL supplies numerous well-known customers, nationally and internationally, including *Volkswagen AG*, *Stellantis N.V.* and *Ford Motor Company*. The company operates a total of 13 production facilities. Furthermore, several subsidiaries or equity investments in Joint Ventures are owned by to the company (Contemporary Amperex Technology Co. Limited (CATL), 2025a). One of the largest subsidiaries is *Guangdong Brunp Recycling Technology*, which is involved in recycling and raw material sourcing activities (Guangdong Brunp Recycling Technology, 2023).

In 2024, CATL generated revenue of approximately \$50 billion while the annual production volume reached approximately 516 gigawatt-hours (GWh). Of this, 475 GWh were sold. CATL is undoubtedly the global leader in battery cell production for xEVs and ESS, its market share in these segments is approximately 37.9% respective 36.5%, while it surpasses the second-largest producer *BYD* by 20.7% and 23.3%, respectively (Contemporary Amperex Technology Co. Limited (CATL), 2025b). CATL supplies battery cells, modules and complete packs to its customers. However, a precise breakdown across specific markets and products is not disclosed. Nevertheless, due to the description in the semi-annual report in 2025 it is assumed that revenue und sales volumes are mainly attributable to xEV or heavy-truck applications rather than niche applications. Relevant chemistries are nickel-manganese-cobalt-oxide (NMC), lithium iron-phosphate (LFP) and sodium-ion (SIB).

CALB, the second company included in this analysis, is also a Chinese battery cell manufacturer. In contrast to CATL, CALB produces almost exclusively for the

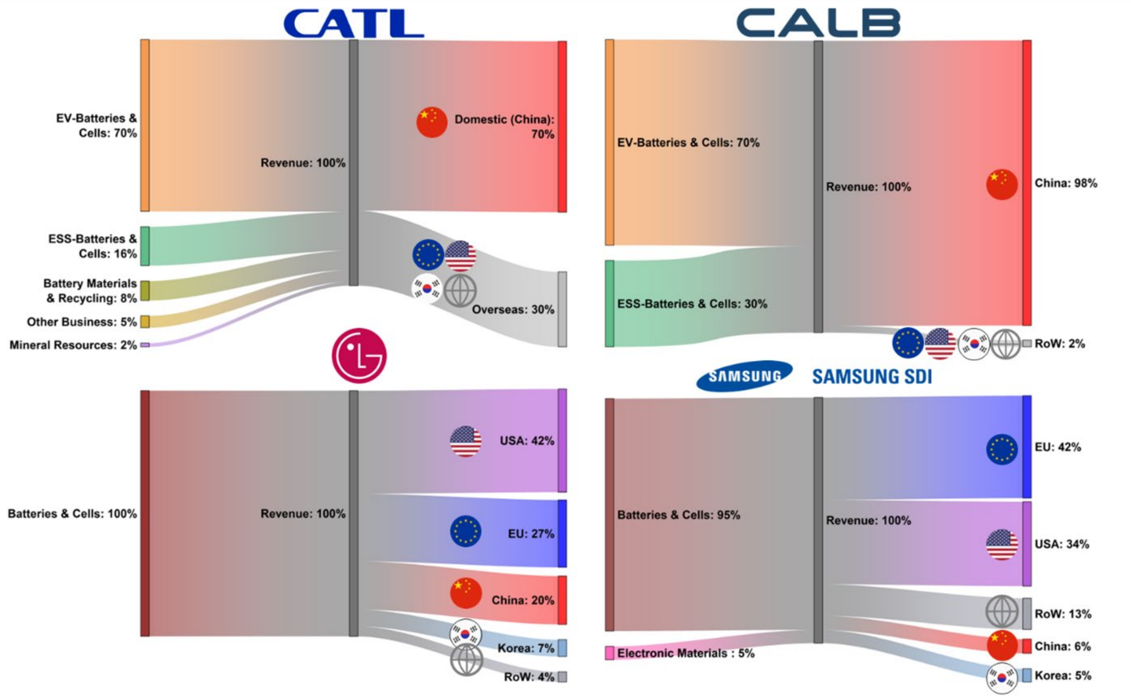

Figure 3: Revenues streams and revenue distribution of CATL, CALB, LGES and SDI for the year 2024 (CALB, 2025a; Contemporary Amperex Technology Co. Limited (CATL), 2025b; LG Energy Solution, 2025b; Samsung SDI, 2025a).

JOURNAL OF
BUSINESS CHEMISTRY

Vol.23, Iss.1, February 2026
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domestic market. Approximately 98% of CALB's revenue is generated in China (Figure 3) (CALB, 2025a; Contemporary Amperex Technology Co. Limited (CATL), 2025b). A production plant in the European Union is currently in planning stage (Reuters, 2025b). Compared with LGES, SDI and CATL, CALB's revenue is smaller, but its business growth rate is significantly larger (Figure 1).

LGES and SDI are Korean companies operating production facilities in Asia and the European Union. In addition, both also manufacture in the United States. Currently, LGES maintains two joint ventures and one subsidiary, while two additional joint ventures are in the construction phase. SDI started its mass production at joint venture *Star Plus Energy* by the end of 2024 (Samsung SDI). Furthermore, SDI aims to start production at a second joint venture with *General Motors* as of 2027 with an annual capacity of 27 GWh (Samsung SDI).

All companies produce cells for xEV and ESS applications. LGES, SDI and CATL, to some extent, provide cells for minor and niche applications (Contemporary Amperex Technology Co. Limited (CATL), 2025b; Fabrice Renard and Christophe Pillot, 2025; LG Energy Solution, 2025a; Samsung SDI). Additionally, SDI produces battery cells for portable electronic devices, such as smartphones, wearables and laptops.

Lastly, Figure 3 illustrates the revenue distribution across business segments and regions of all competitors. Comparing revenue streams and regions is important to understand location dependencies.

When comparing revenue streams, it becomes evident that the Chinese manufacturers CATL and CALB are primarily exposed to the Chinese market, with CALB being particularly dependent on it. By contrast, LGES and SDI have only a minor presence in China and therefore rely more heavily on the U.S. and European markets (Figure 3).

3.2. Production regions and capacity

In a comparative analysis of production costs, the location of production represents a crucial factor. Differences in location-related salaries and energy costs affect battery cell production cost significantly (Degen and Krätzig, 2024; Ruppert et al., 2025). Therefore, the subsequent overview illustrates companies' production capacities, their production regions and a qualitative estimation about the corresponding production share. Additionally, it shows where current capacity expansions or new production site developments accessing new regions are ongoing (Figure 4):

It is evident that the Chinese companies CALB and

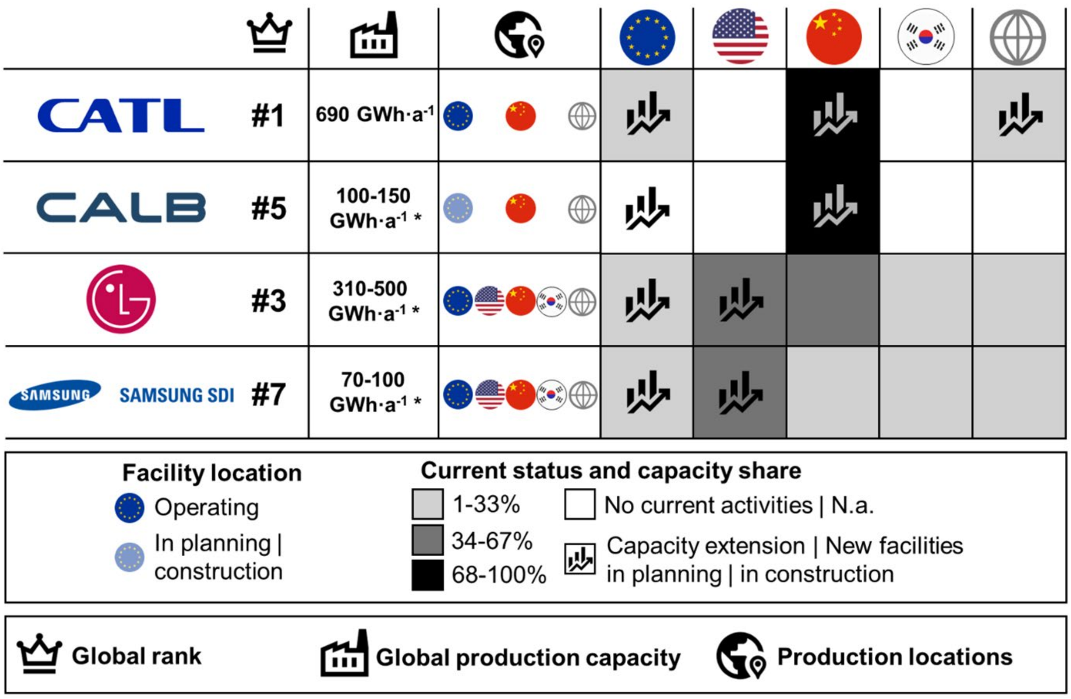

Figure 4: Production locations, capacity and capacity shares across various major regions(Contemporary Amperex Technology Co. Limited (CATL), 2025d). *Production capacities of LGES, CALB and SDI are estimated based on company information, news and announcements for (CALB, 2022; Florian Treiß, 2025; LG Energy Solution; LG Energy Solution, 2025a;

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918523415
DOI: 10.17879/70918522810

CATL mainly produce in China. Currently, neither CATL nor CALB has made official announcements regarding future production plants in the United States or Korea. CATL's production facility in Germany has a capacity of approximately 14 GWh·a^{-1}. The Hungarian factory aims to reach a capacity up to 100 GWh·a^{-1}. Consequently, the estimated production capacity share of CATL in Europe is below 34% of total capacity.

Currently, CALB does not maintain production facilities outside of China. However, a factory in Portugal is in the planning stage. The intended capacity is 15 GWh·a^{-1} and start of production is planned in 2028 (Reuters, 2025b).

In contrast, LGES and SDI maintain a significant share of their production capacity in the European Union and the United States. Both companies also operate manufacturing facilities in China, but the capacity share in this region is below 25% of their total capacity. In addition, LGES has announced plans to increase annual production capacity in North America to up to 250 GWh·a^{-1} and to raise the region's share up to 50% to 60% of its global production capacity. As noted above, LGES and SDI generate a larger share of their revenue from the U.S. and European markets than from China (Figure 3) (LG Energy Solution, 2024a).

Both LGES and SDI maintain large shares of their production capacity in the European Union and the United States, where average wages and energy costs are considerably higher, particularly in Europe. This leads to higher production costs. Consequently, LGES and SDI face a structural cost disadvantage associated with local manufacturing in the European Union and the United States. Their ability to reduce prices while remaining profitable is therefore more limited.

Additionally, transportation costs are a crucial factor that must be considered. Higher production costs in the European Union and the United States can be offset, by lower logistics costs resulting from shorter transport routes when supplying the European or American domestic market. However, these savings are generally limited and therefore only partially compensate higher production costs (Thomsen and Lux, 2025).

In conclusion, the geographic distribution of CATL's and CALB's production locations support hypothesis H1. However, CATL's manufacturing sites in Europe refute a purely location-based explanation. Otherwise, CALB would exhibit superior financial performance, due to exclusive domestic production. Hence, while production location confers a cost advantage for CATL and for CALB, it is unlikely to be sufficient to explain the observed divergence in economic results.

This interpretation is further supported by the limited contribution of manufacturing costs to total battery costs, which is estimated at approximately 10% to 30% (Degen and Krätzig, 2024; Ruppert et al., 2025). A comparative assessment between China (low-cost case) and Germany (high-cost case) reports a cost differential of 5.8 \$·kWh^{-1} for LFP pouch-cell production at a scale of 20 GWh·a^{-1}, corresponding to a 35% decrease in manufacturing costs and approximately 3% to 10% decrease of total battery cost (Ruppert et al., 2025). While LGES and SDI predominantly manufacture in the United States (comparable wages, lower energy cost compared to Germany) or other European countries (lower costs compared to Germany), a smaller location-driven cost differential appears plausible. Accordingly, the performance gap is likely explained by a combination of factors rather than by production location alone.

3.3. Capacity and production development

In general, producing larger volumes decreases manufacturing costs per kilowatt-hour through economies of scale (Mauler et al., 2021). However, capacity extensions are capital-intensive, which may also affect profitability. Moreover, if capacity utilization is low, higher production costs per unit occur in comparison to a smaller production facility operating at higher capacity utilization (Mauler et al., 2021).

For the analysis of production and sales volume, relevant data from all companies on a semi-annual basis were evaluated (Figure 5). On the one hand, the comparison of sales volumes reveals a substantial gap between CATL and the three competitors (Figure 6). This suggests that CATL may face lower manufacturing costs through economies of scale, thereby supporting thesis H2. On the other hand, LGES, as the second-largest producer by sales volumes exhibited the weakest income performance in 2024, which in turn contradicts thesis H2 (Figure 1).

Moreover, the cost reduction attributable to economies of scale appears quantitatively limited. For an illustrative LFP pouch-cell facility, increasing annual capacity from 20 GWh·a^{-1} to 100 GWh·a^{-1} reduces manufacturing costs by only 1.8 \$·kWh^{-1} (fully utilization is assumed) corresponding to -16% of production cost or approximately -2% to -5% of total battery cost (Ruppert et al., 2025). Consequently, an in-depth assessment of

JOURNAL OF
BUSINESS CHEMISTRY

Vol.23, Iss.1, February 2026
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DOI: 10.17879/70918522810

installed capacity and utilization is required.

From the second half of 2023 to the first of 2024, CATL's capacity utilization shrinks from 70% to 65%. In the subsequent reporting periods, both production volume and utilization increased significantly, while capacity extension – particularly in the first half of 2025 – slowed down (Contemporary Amperex Technology Co. Limited (CATL), 2024b, 2025b). Finally, CATL achieved the highest capacity utilization rate in comparison with LGES and SDI of approximately 90%. Between the second half of 2023 and first half of 2025, its annual production capacity increased by approximately 25%, while production volume rose by about 32% (Contemporary Amperex Technology Co. Limited (CATL), 2024a, 2024b, 2025b, 2025d).

LGES and SDI disclosed their production capacity in monetary terms or units rather than in gigawatt-hours. Consequently, a direct comparison to CATL is not feasible. The reported values indicate a substantial decline in capacity – for LGES from $42.6 billion for 2023 to $28.6 billion for 2025 and for SDI from 2.721 to 2.450 billion units during the same period (2025 capacities are estimated by doubling value received from semi annual reports). Reasons for the reported decline in production capacity are not disclosed. For LGES, it is unclear whether this reflects a real reduction in capacity or lower average battery prices, which would reduce the reported capacity value. A shift in product mix toward lower-cost chemistries could have a similar effect. However, the capacity utilization rate is the more comparable and relevant metric. While CATL managed to increase utilization, LGES experienced a decline from 74.8% in first half of 2023 to 51.3% in the first half of 2025 (Figure 5). It remains unclear whether this trend reflects accelerated capacity expansion relative to production volumes or a contraction in demand. Due to the general ongoing market situation and overcapacities, a shrinking demand is more plausible than an accelerated capacity extension, which is also indicated during comparison of cell production capacities. In addition, there are announcements that LGES decided to reduce spending on investment for 2024 to address global overcapacities. Furthermore, sales volumes decreased between 2023 and 2024 (Figure 6) (Lee Min-Jo, 2024).

SDI's capacity utilizations rate draws a similar picture as LGES. Between the first half of 2023 and 2024, SDI maintained the highest capacity utilization rate of all companies in scope. Later in 2024 and first half of 2025 it shrinks to 44.2%. Surprisingly, this development is comparable to operating margin development. Between first half of 2023 and 2024, margin was stable, later it turned to an operative loss.

For CALB, no precise information about capacity utilization is disclosed. Due to the fast-growing sales and revenue of CALB in comparison to the other companies and even to CATL, a high utilization is assumed.

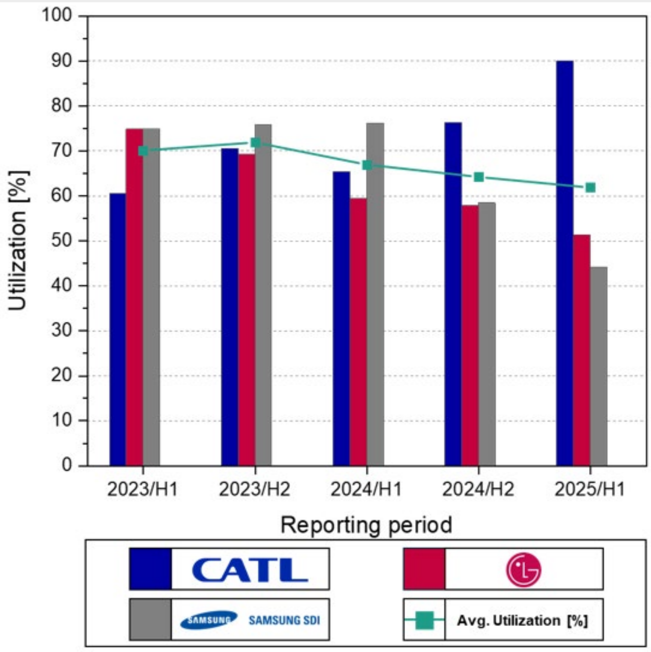

Figure 5: Production capacity utilization of CATL, LGES and SDI and average utilization across these companies. CALB does not disclose values related to capacity utilization.

JOURNAL OF
BUSINESS CHEMISTRY

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918523415
DOI: 10.17879/70918522810

If manufacturing continuously and the ability to shut down equipment is limited (e.g. dry room), the production cost measured per kilowatt-hour nearly doubles at a utilization rate of approximately 50%. Ultimately, relative to full utilization, this may increase total battery costs by approximately 10% to 30%.

Overall, production capacity and capacity utilization have a significant impact on production cost. Capacity expansions are cost-intensive and extent production capacities operating at lower utilization results in higher cost per unit. As shown in the reports, CATL maintains the largest production capacity operating at the highest utilization rate compared with its competitors. Therefore, CATL may benefit significantly from its high capacity utilization and large-scale production.

Nevertheless, a central question remains: How is CATL able to increase its utilization, while LGES and SDI face significant decline? A possible explanation could be a considerably lower sales price in comparison to LGES and SDI, offering CATL a significant advantage against its competitors. Furthermore, a demand shift in preferred cell chemistry is also a potential reason. According to *SNE Research*, the significant decline in sales volumes of the Korean companies LGES and SDI between 2023 and 2024 are attributable to a shift in demand from NMC to LFP cell chemistry. LFP is predominantly supplied by Chinese manufacturers such as CATL, BYD and CALB (Shanghai Metal Markets, 2025a; SNE Research, 2025).

3.4. Sales volumes and income development

Relevant information such as cell sales composition by type or chemistry were not disclosed. In particular, the cost of NMC, NCA or LCO battery cells is considerably higher than LFP battery cells due to more expensive raw materials (Fabrice Renard and Christophe Pillot, 2025; Ruppert et al., 2025).

The sales volumes comparison highlights CATL's dominance as the global market leader (Figure 6). LGES ranks third globally, with annual sales volumes equivalent to approximately 25% of CATL's value. CALB and SDI are positioned at 5. and 7. rank, respectively.

From 2023 to 2024, only Chinese companies CATL and CALB were able to increase sales volumes by approximately 20% respective 50%. Simultaneously, LGES and SDI experienced a sales volumes decline of 6% and 18%, respectively. As previously referenced, this development may be attributable to the accelerated distribution of LFP technology in ESS and xEV applications (Shanghai Metal Markets, 2025a; SNE Research, 2025). Recently, American automotive manufacturer *General Motors* has requested its suppliers, SDI and LGES, to produce LFP cells at its North American production facilities for its vehicle models (Sang-Hoon Sung, 2025).

Conversely, the average revenue per kilowatt-hour shows a divergent trend. In general, it declined

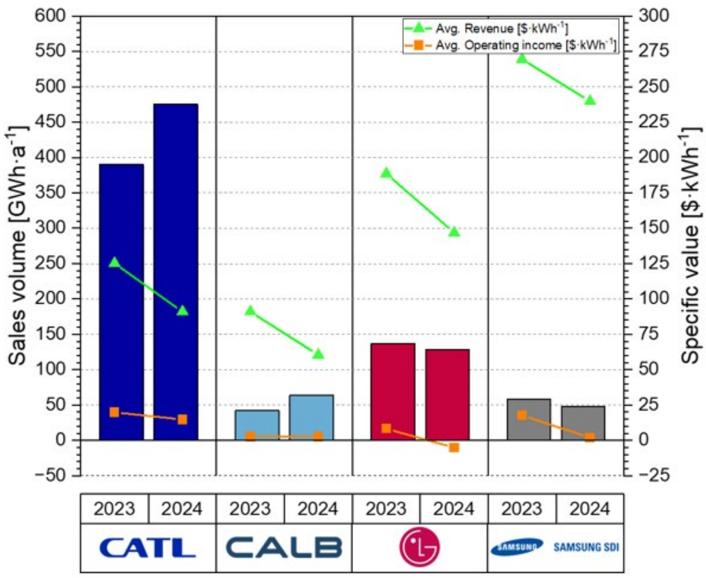

Figure 6: Sales volumes, average revenue and operating income per kilowatt-hour for 2023 and 2024. For LGES and SDI, IRA funds are excluded.(CALB, 2024, 2025a; Contemporary Amperex Technology Co. Limited (CATL), 2024a, 2025b; LG Energy Solution, 2024b, 2025b; Samsung SDI, 2024a, 2025a; SNE Research, 2025)

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918523415
DOI: 10.17879/70918522810

from 2023 to 2024 ranging from 20 $·kWh⁻¹ to 40 $·kWh⁻¹. Due to overcapacities and price competition in the battery cell market, companies decreased prices. It is noteworthy that SDI, with the highest revenue of approximately 269 $·kWh⁻¹, exhibited the smallest decrease, amounting to approximately 29 $·kWh⁻¹ to 240 $·kWh⁻¹. However, it needs to be considered that SDI also produces a significant quantity of small-scale cells for smartphones and further portable electric devices, containing lithium cobalt oxide (LCO) which is more expensive. For those battery cells, the price per kilowatt-hour is considerably higher than for NMC or LFP chemistry due to higher cobalt share. Ultimately, this increases average revenue measured per kilowatt-hour. As the average revenue for both LGES and SDI decreases, the average operating income per kilowatt-hour for these entities also experiences a significant decline. It is noteworthy that LGES's ability to generate operating profit in previous reporting periods was primarily attributable to IRA subsidies from the U.S. government (Stan Lee, 2024c). In contrast, CALB and CATL face a smaller decline in income per kilowatt-hour compared to LGES and SDI. Consequently, both had the opportunity to compensate for shrinking revenue per kilowatt-hour by implementing cost optimization strategies.

Furthermore, it is important to note that Chinese government frequently provides significant subsidies to domestic companies. It subsidized the EV and battery industry with approximately $231 billion between 2009 and 2023 (Scott Kennedy, 2024). Therefore, CATL as one of the largest recipients of governmental subsidies benefited significantly during the last years. Those fundings offer a boost to promote domestic companies and gain competitive advantages in an emerging market. According to public announcements, CATL received $0.76 billion of subsidies in 2023 and approximately $0.53 billion during the first half of 2024 (Kenji Kawase, 2025; Nikkei Asia, 2024).

For CATL and CALB, neither the type nor the amount of funding obtained was immediately disclosed. However it is important to note, that values may be subject to alteration if the amount of funding is precisely identified and deducted (Kenji Kawase, 2024, 2025; Nikkei Asia, 2024).

Nevertheless, summarizing results from previous analysis, the lower capacity utilization for LGES and SDI may be attributable to diminishing sales volumes in 2023 and 2024. That may be caused due to weaker demand and intensified competition with companies such as CATL, which has demonstrated a significant cost advantage. Surprisingly, the lowest average revenue per kilowatt-hour was shown by CALB.

Assuming CATL and CALB benefit from a production cost advantage due to their domestic manufacturing in China and that both increased their sales volumes in response to higher demand for LFP cells, it remains unclear why CATL – despite operating production facilities in the European Union – achieves a considerably higher operating margin. Could CATL's endeavors to establish its own raw material supply chains provide a potential explanation for this competitive advantage?

3.5. Impact of raw material prices and vertical integration

Raw material accounts for the largest share of battery cell cost of 70% to 90% depending on the cell chemistry (Degen and Krätzig, 2024; Ruppert et al., 2025). Procuring or accessing raw material at the cost of production enables a potential advantage especially during periods of increasing material prices.

As demonstrated by preceding studies, supply chain of battery raw materials is predominantly controlled by Chinese companies (Greitemeier et al., 2025). Evidence suggests that CATL undertakes direct investments and strategic partnerships to secure raw material access. The company maintains activities in almost all steps along the supply chain. The present activities encompass the extraction and processing of raw materials, in addition to recycling end-of-life cells and production scrap by its subsidiary *Guangdong Brunp Recycling Technology* (Contemporary Amperex Technology Co. Limited (CATL), 2021, 2022, 2025c; Guangdong Brunp Recycling Technology, 2023; Reuters, 2025a).

LGES maintain also some projects with partners to secure raw material (Carrie Hampel, 2025). It is evident that only minor activities have been disclosed by SDI and CALB, at least in official announcements.

The subsequent illustration summarizes the present activities being undertaken by CATL, CALB, LGES and SDI along the battery cell supply chain: The categories encompass *Raw Material Mining and Processing*, *precursor CAM/CAM Production*, *Battery Cell Manufacturing and Recycling* (Figure 7). The figure refers to the three most expensive raw materials, namely lithium, cobalt and nickel.

JOURNAL OF
BUSINESS CHEMISTRY

Vol.23, Iss.1, February 2026

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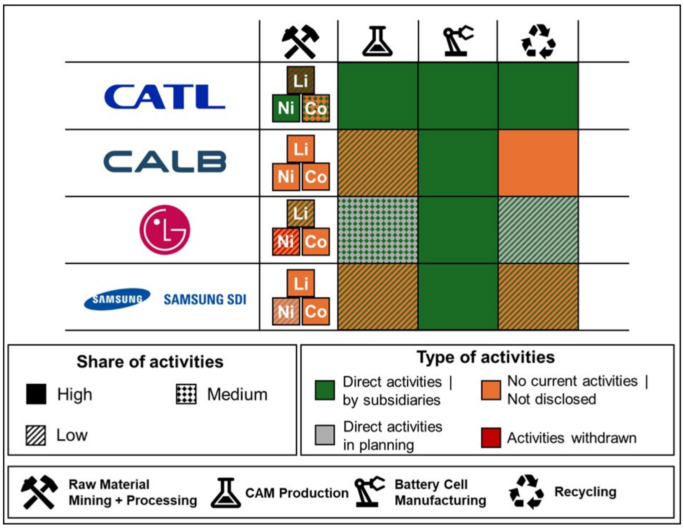

Figure 7: Overview of supply chain activities of CATL, LGES, CALB and SDI based on assumptions and public announcements of the companies (Carrie Hampel, 2025; Contemporary Amperex Technology Co. Limited (CATL), 2022, 2025c; Guangdong Brunp Recycling Technology, 2023; Jin-Won Kim, 2024; Matthias Bartmann, 2025; pandaily.com, 2023; Reuters, 2025a; Stan Lee, 2024a, 2024b; Tang Shihua, 2025).

As mentioned earlier, besides raw material security, financial benefits of self-sufficient raw material production become particularly evident during periods of elevated or rising material prices. A decline in the prices of relevant raw materials such as lithium, nickel and cobalt salts has been observed since 2023 (Fabrice Renard and Christophe Pillot, 2025). If the difference between the raw material market price and incurring cost of production is minimal, vertical integration might not offer a significant commercial benefit.

Finally, a raw material cost analysis was conducted. Reported direct material costs from financial reports were obtained and evaluated (Figure 8). In accordance with the diminishing market price for primary raw materials such as lithium, nickel and cobalt, all companies have exhibited a significant decrease in average raw material cost per kilowatt-hour from 2023 to 2024.

It becomes evident that CATL reports a lower average raw material cost per kilowatt-hour than LGES and SDI. This difference may be attributable to CATL's activities along the battery cell supply chain or, as noted earlier, to differences in product composition (Chapter 3.4). This initially supports thesis H3. However, the average

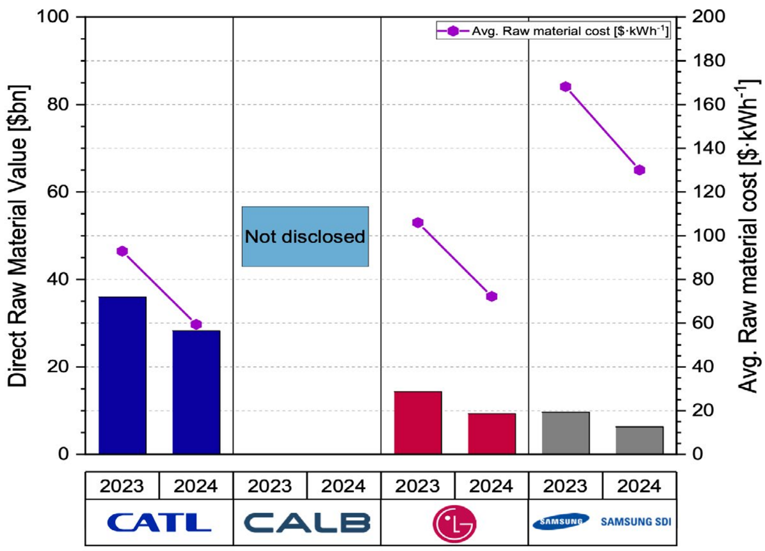

Figure 8: Total cost of raw material and cost per kilowatt-hour (For SDI, only battery cell related raw materials amount is considered | For CATL, encompassing raw material amount related to all business units) (Contemporary Amperex Technology Co. Limited (CATL), 2024a, 2025b; LG Energy Solution, 2024b, 2025b; Samsung SDI, 2024a, 2025a).

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918523415
DOI: 10.17879/70918522810

production cost of CALB as a difference of revenue and operating income (Figure 6) highlights an average cost encompassing production cost and material cost of 57 $\$\cdot kWh^{-1}$ which is lower than CATL average raw material cost of 59 $\$\cdot kWh^{-1}$ in 2024 (Figure 8). Accordingly, it is assumed that CALB incurred lower average raw material costs than CATL in 2024.

The magnitude of the commercial advantage derived from CATL's raw material access strategy remains unclear. CALB may have a higher share of LFP batteries, driven by its focus on the Chinese domestic market, partially explain observed cost differences (Figure 3). In contrast, CATL serves several international customers that continue to demand NMC batteries, particularly automotive manufacturers in mid-range and premium segments.

Lastly, CATLs reported direct raw material costs encompassed all business segments. Considering that around 15% of its revenue is obtained from at least non battery manufacturing activities, it is feasible that a minor share of raw material cost is related to other business units which are not attributable to CATL's manufacturing business. Therefore, the average raw material cost might be even lower than illustrated in Figure 8.

The current market prices of relevant raw materials may conceal the benefits of maintaining its own supply chains if the difference between cost of production and market prices is small. In the following, a calculation is conducted to evaluate the potential economic benefit between the cost of production and raw material spot prices:

Gallagher et al. conducted a scenario analysis to compare cost of production of battery grade lithium salt derived from brine or ore under different assumptions (Gallagher et al., 2025). For production from ore, costs range from 7.1 $\$\cdot kg^{-1}$ (mining & refining in China) and 17.2 $\$\cdot kg^{-1}$ (mining & refining in Australia) (Gallagher et al., 2025). In contrast, production from brine displays lower costs, ranging from 3.4 $\$\cdot kg^{-1}$ for extraction and refining in China to 6.6 $\$\cdot kg^{-1}$ for extraction in Chile followed by refining in China (Gallagher et al., 2025). *Avicenne Energy* reported comparable conversion costs for lithium salts in the range of 5 to 15 $\$\cdot kg^{-1}$ (Fabrice Renard and Christophe Pillot, 2025). Compared with current market prices for battery grade lithium hydroxide or carbonate – ranging from 9.5 to 10.2 $\$\cdot kg^{-1}$ in November 2025 (Shanghai Metal Markets, 2025b) – the immediate commercial benefit of CATL's vertically integrated supply chain appears limited, aside from improved raw material access and supply security (Shanghai Metal Markets, 2025b).

In 2024, average lithium salt prices were slightly higher at approximately 12.4 $\$\cdot kg^{-1}$ (Georgia Williams, 2024). The Jianxiawo mine, one of the world's largest lithium ore mines, is located in China and owned by CATL. Assuming the reported production cost of 7.1 $\$\cdot kg^{-1}$ for domestic mining and refining in China, a potential cost advantage of approximately 5.3 $\$\cdot kg^{-1}$ lithium carbonate or 42.7% could be derived in 2024.

Assuming a lithium salt demand of 0.6 to 0.7 $kg_{LCE}\cdot kWh^{-1}$ of cell capacity (Ruppert et al., 2025), this corresponds to a total cost advantage of approximately 3.2 to 3.8 $\$\cdot kWh^{-1}$ or roughly 3% to 4% when compared with CATL's average revenue of 91 $\$\cdot kWh^{-1}$ in 2024 (Figure 6). In comparison, a theoretical calculation indicates that an LFP/graphite pouch cell (38 Ah) produced in China at a scale of 20 $GWh{*}a^{-1}$ would cost approximately 59.0 $\$\cdot kWh^{-1}$ (Ruppert et al., 2025). Raw materials account for 42.3 $\$\cdot kWh^{-1}$, which corresponds to roughly 72% of total costs (Ruppert et al., 2025). In this case, the lithium cost advantage would translate into a total cost reduction of approximately -5% to -7%. This supports thesis H3, that CATL significant benefits from maintaining own supply chain activities.

Surprisingly, the calculated cost value aligns well with CALB's average revenue for 2024, for which exclusively domestic production in China and a high LFP share are assumed (Figure 6).

This raw material estimate assumes full self-sufficiency in lithium carbonate production within China. Consequently, the actual economic benefit for CATL is likely somewhat lower. For this initial comparison, focusing on lithium salts is sufficient, given their relevance across multiple lithium-ion cell chemistries.

Nevertheless, if overcapacities decline and raw material prices rise due to supply shortages or a substantial demand increase in the future, CATL may achieve significantly higher cost advantages over its competitors (Wu et al., 2025). Procuring raw materials at production cost rather than at market prices provides resilience against price volatility driven by market developments.

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918523415
DOI: 10.17879/70918522810

4. Conclusion

This study compared four battery cell manufacturers with differing production capacities, locations, and target markets. Overall, the results indicate several key drivers of CATL's superior profitability and resilience. Three hypotheses were analyzed and critically discussed.

First, the Korean competitors LGES and SDI face significantly higher location-based production costs due to their major manufacturing presence in Europe and the United States, which supports thesis H1. However, this factor alone does not explain the observed performance differences. Otherwise, CALB due to its exclusively domestic production in China would be expected to be in the strongest economic position. The potential reduction in total battery costs attributable to location effects is estimated at approximately -3% to -10%.

Economies of scale remain essential for reducing manufacturing costs. CATL has the largest production capacity, suggesting that it benefits most from economies of scale, which support H2 (Figure 4). However, economies of scale gains are most pronounced at smaller plant sizes, particularly below 10 $GWh \cdot a^{-1}$. All companies in scope operate large-scale production facilities. Therefore, a limited contribution is expected. To illustrate this effect, a comparison between two large-scale plant sizes indicates a potential total cost reduction of approximately 2% to 6%, which is smaller than the estimated impact of production location.

Additionally, LGES and SDI companies have experienced declining utilization rates and shrinking sales volumes, which increase production costs per unit. Under continuous operation constraints with limited ability to temporarily shut down equipment, this can increase total battery costs by approximately 10% to 30% relative to full utilization. Consequently, economies of scale, as proposed in H2, remain relevant. In this case, however, the adverse cost impact of low utilization appears to outweigh the potential cost reductions associated with larger installed capacities. Under this interpretation, H2 is supported only when considering installed capacity alone. In this case, cell chemistry may play decisive role in competitiveness. LGES and SDI rely heavily on nickel-based technologies faced stagnating demand due to lower sales of EVs from European and American car manufactures since 2023. Over the same period, CATL and CALB have benefited from the growing adoption of LFP chemistry across various applications such as entry- to mid-class EVs and ESS (Orangi et al., 2024). Their ability to produce LFP cells at lower cost while meeting market demand has reinforced their competitive advantage and strengthened their overall market position. However, a margin discrepancy remains evident when comparing CATL and CALB, both of which primarily operate in China.

Lastly, the supply chain strategies of all competitors were compared. Although CATL maintains its own supply chain activities, the entire benefits of these investments are not immediately evident. CATL shows a lower raw material cost per kilowatt-hour than LGES and SDI, while CALB appears to be in a similar cost range. However, it is not possible to clearly distinguish whether this advantage results from supply chain integration or from differences in product portfolio.

An estimate based on the gap between production costs and market prices suggests a total battery cost decreasing potential of -5% to -7% per kWh, assuming full self sufficiency in lithium salt production located from China, which supports thesis H3. Both CATL and CALB likely have a higher share of LFP chemistry, which further reduces the average raw material cost per kilowatt-hour. In addition, current lithium spot prices are close to production costs, assuming a Chinese raw material mining a refining. As a result, the near-term commercial benefits of proprietary supply chains appear limited, which contradicts thesis H3. In conclusion, CATL's supply chain activities represent a distinctive cost lever, even if their short-term impact is less pronounced than that of capacity utilization.

In summary, low capacity utilization of LGES and SDI has substantial potential to increase unit costs relative to CATL and CALB, assuming high utilization for CALB. Production location and supply chain integration of CATL provide an intermediate contribution to reducing total battery costs. By contrast, in this case the cost reduction potential from economies of scale is limited, particulalry under the assumption of full capacity utilization.

Nevertheless, if raw material prices rise due to supply constraints or increasing demand, companies such as CATL that maintain vertically integrated supply chains could gain substantial additional cost advantages over their competitors. Procuring raw materials at production cost rather than at market prices provides resilience against price volatility and reinforces cost

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918523415
DOI: 10.17879/70918522810

leadership. At the same time, such developments would undermine the competitiveness of manufacturers that already face production-cost disadvantages and would additionally be exposed to rising raw material prices. This perspective underscores the strategic importance of raw material procurement and supply chain integration for battery cell manufacturers seeking to safeguard long-term competitiveness and ensure the viability of their business model.

Finally, it will be important to monitor how the current situation evolves. Recent announcements indicate that LGES improved its business performance in the third quarter of 2025 (LG Energy Solution, 2025d). Furthermore, SDI and LGES aim to start LFP cell production in the short term (LG Energy Solution). In addition, xEV demand in the European Union and U.S. markets increased compared with 2024 (Amir Orusov, 2025; European Environment Agency, 2025). However, several challenges for a European- or U.S-localized battery cell production industry remain. These include substantial overcapacity in China and resulting in dumping prices, lack of supply chain activities, structural cost disadvantages, and uncertainty regarding future demand and cell chemistry.

5. Acknowledge

The author`s utilized ChatGPT to enhance readability during the preparation of this work. After employing this tool, we thoroughly reviewed and edited the content as necessary, assuming full responsibility for the final publication.

6. Declaration of Internets

There are no conflicts of interest to declare

7. CRediT Authorship contribution statement

Jan-Hendrik Richter: Conceptualization, Methodology, Data Curation, Analysis, Visualization, Software, Writing – Original Draft. **Tim Niklas Franke:** Methodology, Data Curation, Analysis. **Simon Lux:** Conceptualization, Supervision.

8. Data availability

The authors declare that the data which were used for this analysis derived public available source. Further questions regarding the calculations and evaluation can be addressed directly to the corresponding author.

Vol.23, Iss.1, February 2026
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Research Paper

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Does Geographic Proximity to Startups Drive Green Innovation?

As environmental challenges intensify, green innovation has emerged as a critical component of sustainable growth. Startups are often viewed as important sources of rapid change and green technological advancement. Drawing on the proximity literature and the knowledge spillover theory, this study examines whether the geographic proximity to startups, particularly to green startups, affects the green innovation output of incumbents. Using a panel dataset of 5,569 incumbents and 77,022 startups, we find strong heterogeneity in green innovation outcomes by incumbents' R&D intensity. Geographic proximity to green startups increases green innovation among incumbents with low R&D spending, which is consistent with knowledge spillover mechanisms. In contrast, proximity to green startups is negatively associated with green innovation among R&D-intensive incumbents, consistent with intensified competition for scarce resources, concerns about knowledge leakage, and crowding-out effects. Moreover, we show that these results are more pronounced for subsequent innovation activities than for first-time green patents and are amplified when incumbents share an environmental orientation with nearby green startups.

Keywords: Green Innovation, Startup Proximity, Geographic Proximity, Knowledge Spillover, Appropriability Paradigm

1. Introduction

Achieving sustainable economic growth is one of the central challenges facing modern economies, as continued economic development must be reconciled with environmental protection and the preservation of natural resources (Teixeira et al., 2025). Rising carbon emissions, climate change, and scarce resources cause severe and potentially irreversible damage to ecosystems and the environment (Solomon et al., 2009), while also threatening long-term growth prospects and social welfare (Farajzadeh et al., 2023). Accordingly, firms are facing growing pressure from investors, customers, and regulators to innovate sustainably while remaining competitive (Mady et al., 2024). A central way in which firms pursue sustainable growth is to develop and adopt green innovations. Green innovation refers to the generation, adoption, or implementation of new products, processes, services, or management practices that reduce environmental impact over their life cycle compared to conventional alternatives (Kemp & Pearson, 2008). This is particularly relevant in R&D-intensive industries characterized by complex production processes and substantial environmental challenges, such as the chemical and pharmaceutical industries (Jiménez-González & Overcash, 2014; Schuhmacher et al., 2023). Despite the growing importance of green innovation, firms differ significantly in their ability to develop and adopt environmentally friendly technologies, as green innovation often requires integrating new technologies and external knowledge into their existing operations (Aboelmaged & Hashem,

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2019). This study examines whether geographic proximity to startups, particularly green startups, affects incumbents' green innovation outcomes.

Although closer proximity to startups could be expected to facilitate incumbents' green innovation outcomes through localized spillover effects in knowledge and talent, this relationship is not self-evident. Proximity to startups may intensify competition, increase appropriation risks, and reduce incentives for incumbent firms to invest in R&D, which could lead to crowding out of the incumbents (Crowley & Jordan, 2018; Devarakonda et al., 2018; Duguay et al., 2026). Empirical evidence on proximity-based effects remains mixed. For example, prior studies document limited or no influence, for instance of spatially close universities, on firms' green innovation outcomes (Petruzzelli, 2011). It is therefore still an empirical question whether, and under which conditions, geographic proximity to startups truly fosters incumbents' green innovation outcomes.

We build on existing research on geographic proximity and knowledge spillovers as drivers of incumbents' green innovation. Geographic proximity facilitates the transfer of knowledge by increasing opportunities for face-to-face interactions, informal exchanges, and observations, which enhance the diffusion of tacit and codified knowledge. Knowledge spillover theory suggests that firms benefit from external knowledge generated by nearby actors, as spatial proximity reduces communication barriers, lowers search and communication costs, and improves firms' abilities to recognize, assimilate, and apply new knowledge. Prior empirical evidence suggests that geographic proximity to external actors, such as environmental NGOs (Hu et al., 2021), science parks (F. Zhang & Zhu, 2019), or industrial agglomerations (Antonioli et al., 2016), can facilitate green innovation by enabling localized knowledge spillovers and learning processes that enhance firms' absorptive capacity and their technological capabilities.

We aim to contribute to this literature and examine the effect of proximity to startups. Startups are frequently highlighted as central drivers of new green technology due to their agility, technological focus and relatively high tolerance for risk (Bergset & Fichter, 2015; Sharma & Subba, 2025). Compared to incumbents, startups may also gain access to targeted financial or operational resources that allow them to scale their green innovations without being immediately constrained by short-term financial performance (Aldrich & Auster, 1986). Importantly, startups differ substantially in their technological orientation, with some being explicitly focused on environmental technologies (green startups), while others operate in non-green technological domains (non-green startups). These differences may have important implications for the collaboration between incumbents and startups as well as the type and relevance of knowledge spillovers generated for incumbent firms' green innovation activities (Hockerts & Wüstenhagen, 2010).

Accordingly, we expect that greater geographic proximity to green startups facilitates incumbents' green innovation by enabling localized knowledge spillovers through repeated interactions, labor mobility, and collaboration with nearby startups. These channels reduce the costs of accessing and absorbing external knowledge and are particularly relevant in the context of green innovation.

We address this question by examining the relationship between changes in startup proximity and incumbents' green innovation outcomes. To capture startup proximity, we count all startups surrounding a firm within a given radius per year. We explicitly differentiate between green and non-green startups based on their industry affiliation, allowing us to assess how the technological orientation of proximate startups shapes knowledge spillovers. To capture firms' green innovation outcomes, we retrieve firm-level patent data and identify green patents using common patent classification frameworks. Furthermore, we measure green innovation outcomes by calculating the number of green patents per firm-year.

In our main analysis, we find substantial cross-sectional heterogeneity. First, we show that the effect of green startup proximity on green innovation outcomes depends on incumbents' R&D intensity. Geographic proximity to green startups increases green innovation among firms with low R&D spending, which is consistent with knowledge spillover mechanisms. In contrast, proximity to green startups is negatively associated with green innovation among R&D-intensive incumbents consistent with intensified competition for scarce resources, concerns about knowledge leakage and lock-in effects. This asymmetric relationship emphasizes existing theory by demonstrating that geographic proximity does not uniformly create spillover effects but also induces local competitive pressures, appropriation races and crowding-out. Second, we show that our main

Vol.23, Iss.1, February 2026
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findings are more pronounced for subsequent innovation activities than for first-time green patents. Last, we find that our results are amplified when incumbents exhibit a common environmental orientation with nearby green startups.

Our study makes three important contributions to the literature. First, we expand the literature on geographically close actors as external drivers of green innovation. To the best of our knowledge, we are the first to integrate the research on geographically proximate actors, such as universities (Anselin et al., 1997; Bu et al., 2025; Petruzzelli, 2011), industry agglomerations (Antonioli et al., 2016) and environmental NGOs (Hu et al., 2021), on green innovation with studies examining how startups influence traditional innovation (Crowley & Jordan, 2018). We close the research gap if neighboring startups strengthen or hinder green innovation drawing on the proximity framework and the knowledge spillover theory.

Second, we contribute to green innovation literature by differentiating between stages of green innovation. We show that spatial proximity is substantially weaker for first-time green patents than the overall green patent count. This suggests that knowledge spillover effects are more relevant for subsequent green innovation projects once firms have already developed a minimum level of environmental knowledge. In contrast, entry into green innovation appears to be constrained by limited absorptive capacity, which reduces the incumbents' ability to recognize, adapt and exploit external green knowledge. By drawing on knowledge spillover theory, we thus refine existing theory that treats green innovation as a homogenous process and highlights the conditional nature of geographic knowledge spillovers.

Third, our study supports the Marshall-Arrow-Romer model within the knowledge spillover theory that outlines the importance of regional similarity for innovation. Also, including the proximity framework, we highlight that a shared ecological alignment between startups and incumbents strengthens the positive effects of geographic proximity while dissimilarity reinforces the negative impacts. This moderating role underscores that geographic proximity yields better results if complemented with other proximity dimensions, such as cognitive or technological relatedness.

The rest of the paper is structured as follows. Section 2 summarizes prior literature, Section 3 derives hypotheses, Section 4 describes the data and the empirical methodology, Section 5 presents the results and Section 6 concludes.

2. Theoretical Background

2.1 Green Innovation

While innovation in the traditional sense has been well established since Schumpeter (1911), the concept of green innovation remains less uniformly defined in the scientific literature (Lampikoski et al., 2014, p. 92). Instead, scholars and practitioners use a wide range of terminology, such as green innovation, environmental innovation, sustainable innovation, and eco-/ ecological innovation, which are commonly treated as synonymous (Schiederig et al., 2011). What distinguishes green innovation from general innovation is the explicit integration of environmental considerations into the innovation process.

Green innovation refers to the development, adoption and exploitation of novel products, services, processes or business models that yield significant environmental benefits (Driessen & Hillebrand, 2002; Fussler & James, 1996; Kemp & Pearson, 2008; OECD & Statistical Office of the European Communities, 2005; Oltra & Saint Jean, 2009). Throughout its life cycle, green innovation aims to reduce or entirely avoid negative environmental impact or improve resource efficiency compared to conventional alternatives (Favot et al., 2023; Hojnik & Ruzzier, 2016; Kemp & Pearson, 2008; Schiederig et al., 2011). Green innovation includes saving energy, preventing pollution, waste recycling, corporate environmental management, or green product designs (Chen et al., 2006). The environmental benefits generated by such green practices are independent of whether firms pursue them for ecological or economic reasons (Carrillo-Hermosilla et al., 2010). Thus, green innovation can be a strategy for firms to pursue sustainable development while strengthening their competitive advantage (Bu et al., 2025).

The literature on green innovation has become a widely explored topic in recent years (Karimi Takalo et al., 2021). One of the main research streams focuses on the analysis of drivers of green innovation, which can be divided into external and internal drivers (Bu et al., 2025). Among external drivers, research has particularly examined the role of geographically proximate actors (e.g. universities, science parks, environmental NGOs) as catalyst of green

Vol.23, Iss.1, February 2026
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DOI: 10.17879/70918521284

innovation through knowledge spillovers (Anselin et al., 1997; Hu et al., 2021; Petruzzelli, 2011; Y. Zhang & Ding, 2024). Importantly, such geographically proximate actors also include startups, which may represent a particularly dynamic and technologically specialized source of external knowledge.

2.2 Geographic Startup Proximity

We define a startup as a small firm (Cockayne, 2019) that is no older than ten years (Davila & Foster, 2005; Kollmann et al., 2016), still operating, and has neither been acquired nor gone public through an IPO (Ferrati et al., 2021; Moon & Suh, 2021). As young firms operating under conditions of uncertainty and rapid growth, often dependent on external capital to finance development and scaling, startups often pursue novel and technologically advanced solutions, including in environmentally relevant domains (Cockayne, 2019; Granlund & Taipaleenmäki, 2005; Skala, 2019). These characteristics make startups a distinct and potentially powerful source of localized knowledge for incumbent firms.

Geographic startup proximity refers to the degree of spatial closeness between incumbents and such startups in absolute (e.g. kilometres) or relative (e.g. travel time) terms (Boschma, 2005a). Higher proximity implies a greater density of startups in the vicinity of an incumbent. Geographic proximity between incumbents and startups may therefore shape innovation dynamics in ways that differ from other proximate actors. Prominent innovation clusters such as Silicon Valley illustrate how spatial concentration of startups can foster rapid knowledge exchange and technological advancement (Coenen et al., 2015).

To better understand these dynamics, we draw on Boschma's (2005a) proximity framework, which has been widely used to explain how inter-organisational collaboration contributes to innovation (e.g. Knoben & Oerlemans, 2006; Steinmo & Rasmussen, 2016). The central idea is that (geographic, organisational, cognitive, institutional or social) proximity between firms or employees mitigates uncertainty and coordination difficulties, which in turn promotes trust and mutual understanding (Boschma, 2005a). Ultimately, this leads to the exchange of ideas, knowledge and interactive learning which facilitates innovation (Addy & Dubé, 2018; Boschma, 2005a; Howells, 2002).

However, geographic proximity also entails several potential drawbacks. High spatial closeness may lead to lock-in effects, where firms become overly specialized or committed to existing local partners, reducing openness to new ideas and limiting innovative capacity (Boschma, 2005b, 2005a; Garcia Martinez et al., 2025). Additionally, geographic proximity can cause information overload and increased competition due to scarce resources like skilled labor, input materials, funding or research infrastructure. This, in turn, may drive up costs and even push less competitive actors out of the market, also referred to as crowding-out effect (Duguay et al., 2026; Lang, 2009; Pandit et al., 2018).

2.3 Knowledge Spillovers and Appropriability in Innovation

While geographic startup proximity has been defined within the proximity framework, it also closely relates to well-established theories and ideas in economic geography literature, namely the knowledge spillover theory and the concept of the appropriability paradigm (Jaffe et al., 1993; Teece, 1986). These perspectives offer further insights into how spatial closeness may foster or hinder knowledge diffusion and innovation.

Knowledge spillover theory belongs to the economics of innovation and entrepreneurship and argues that innovation is strengthened through the diffusion of ideas and expertise between proximate actors (Arrow, 1962; Audretsch & Feldman, 1996; Jaffe et al., 1993; Marshall, 1890; Romer, 1990). Planned or random face-to-face interactions as well as frequent collaboration enable the exchange of codified and tacit knowledge and thus subsequent innovative activities (Addy & Dubé, 2018; Aldieri et al., 2018; Coenen et al., 2015; Feldman & Audretsch, 1999). Underlying mechanisms include observations, rumors and gossip (Henry & Pinch, 2000), licensing and patent or technology transfer (Hu et al., 2021) as well as labor mobility (Almeida & Kogut, 1999). The effectiveness of such external knowledge spillovers depends on the absorptive capacity of the receiving firm, which is the ability to recognize valuable external knowledge, understand and process it, and then turn it into value-creating outputs (Cohen & Levinthal, 1989). Two contrasting streams exist regarding which environments maximize spillovers: The Marshall-Arrow-Romer model emphasizes intra-industry clustering and similarity (Arrow, 1962; E. L. Glaeser et al., 1992; Griliches, 1992; Marshall, 1890; Romer, 1990), while Jacobs (1969) highlights the benefits of inter-industry

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

diversity for generating complementary knowledge and innovation opportunities (E. L. Glaeser et al., 1992).

The appropriability paradigm emphasizes the potential downsides of knowledge spillovers. Because knowledge is largely nonrival and can be replicated or advanced by geographically proximate competitors, firms may face difficulties in fully appropriating the benefits of their research and development (R&D) investments (Arrow, 1962; Teece, 1986). Consequently, spillovers can reduce expected returns on innovation and weaken incentives to invest in in-house R&D (Teece, 1986). To mitigate these appropriation risks, firms rely on various preventative strategies, such as patent filings (Laursen & Salter, 2014; Teece, 1986), R&D secrecy (Arundel, 2001; Teece, 1986), or strategic shifts toward acquiring external knowledge through partnerships, licensing agreements, or acquisitions (Arrow, 1962; Gans & Stern, 2017; Hall & Lerner, 2010). While these mechanisms can limit unwanted spillovers in the short run, overly defensive strategies and limited R&D spending leads to fewer innovative ideas, declining absorptive capacity and an overall weaker ecosystem for knowledge spillovers and long-term innovative performance (Audretsch & Belitski, 2022; Cassiman & Veugelers, 2002; Cohen & Levinthal, 1990; Laursen & Salter, 2014).

3. Hypotheses

3.1 Geographic Startup Proximity and Green Innovation

As previously outlined, scientific literature offers contrasting theoretical perspectives on the effects of geographic startup proximity on innovation. In the specific context of green innovation, it is important to distinguish between green and non-green startups in the local environment, as their knowledge bases and competitive dynamics are likely to differ substantially.

First, geographic proximity to green startups can be expected to foster incumbents' green innovation output. According to knowledge spillover theory, spatial proximity facilitates the transfer of tacit and complex knowledge through informal interactions, labor mobility, and embedded networks (Feldman & Audretsch, 1999; Jaffe et al., 1993). Since green startups specialize in environmentally relevant technologies and sustainability-oriented business models, their knowledge is therefore thematically aligned with ecological objectives and can complement incumbents' existing green innovation activities. Moreover, the regional presence of green startups may reinforce sustainability-oriented norms and institutional pressures, further stimulating incumbents' engagement in environmental innovation (Leendertse & van Rijnsoever, 2025). From a proximity perspective, short geographic distances enhance opportunities for collaboration, monitoring, and mutual learning, thereby increasing the likelihood that incumbents can access and integrate environmentally relevant knowledge (Boschma, 2005a). Taken together, these arguments suggest a positive association between geographic proximity to green startups and incumbents' green innovation.

In contrast, geographic proximity to non-green startups is expected to exert a negative effect on incumbents' green innovation. Non-green startups operate in technological domains unrelated to environmental objectives. As a result, the knowledge they generate is often thematically misaligned with incumbents' green innovation activities. Such misalignment can increase search and coordination costs and limit the usefulness of potential spillovers for ecological innovation (Boschma, 2005a; Garcia Martinez et al., 2025). Furthermore, proximity to non-green startups may intensify competition for scarce regional resources such as skilled labor, research infrastructure, and financial capital (Lang, 2009; Pandit et al., 2018). This heightened competitive pressure can crowd out incumbents' investments in green innovation or redirect attention toward conventional technological trajectories (Duguay et al., 2026). From an appropriation perspective, firms may also moderate their own R&D efforts to reduce the risk of unintended knowledge leakage in dense local environments (Teece, 1986). Overall, the negative mechanisms associated with misaligned knowledge bases, resource competition, and crowding-out effects are likely to lead to a negative impact of non-green startup proximity on incumbents' green innovation output.

When considering overall geographic startup proximity without differentiating between green and non-green startups, the expected effect on incumbents' green innovation represents a net effect of these opposing mechanisms. While green startups may generate environmentally relevant spillovers that stimulate green innovation, non-green startups may introduce misaligned knowledge dynamics and competitive

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

pressures that hinder such activities. Given the predominance of non-green startups in our sample mirroring most regional ecosystems, the aggregate effect of overall startup proximity is therefore expected to be negative. Thus, we deduce the following hypotheses:

H1a. *Geographic proximity to green startups is positively associated with green innovation of incumbents.*

H1b. *Geographic proximity to non-green startups is negatively associated with green innovation of incumbents.*

H1c. *Overall geographic startup proximity is negatively associated with green innovation of incumbents.*

3.2 The Moderating Role of R&D Expenditures

R&D spending constitutes a key contingency factor when examining the influence of knowledge spillovers on green innovation (Audretsch et al., 2021; Audretsch & Feldman, 1996; Cohen & Levinthal, 1990). Prior research emphasizes that the level of R&D investments influences incumbents' absorptive capacity and, consequently, the effectiveness of knowledge spillovers from geographically proximate startups (Cohen & Levinthal, 1990). Consequently, we argue that the influence of geographic startup proximity depends on incumbents' internal innovation capabilities.

With regard to proximity to green startups, high R&D spending may lessen the positive effects of proximity. Incumbents with substantial internal R&D resources possess skilled employees, internal knowledge, and structured innovation processes that enable them to generate and implement green innovations independently (Cohen & Levinthal, 1990). As a result, although such firms may exhibit high absolute levels of green innovation, marginal gains attributable to an increase in green startup proximity diminish.

Moreover, extensive internal R&D engagement can produce an inward-oriented focus that limits responsiveness to external knowledge sources. When firms operate numerous internal projects, managers and employees are primarily focused on their own development activities. Cognitive attention, time, and organizational resources become increasingly absorbed by internal initiatives. This internal focus may crowd out the recognition and integration of external knowledge impulses. In particular, limited managerial attention and the "Not Invented Here" syndrome can lead to the systematic neglect or devaluation of ideas originating outside the firm (Audretsch et al., 2021). Consequently, although geographic proximity to startups provides access to potentially valuable knowledge spillovers, high internal R&D intensity may weaken the extent to which incumbents benefit from such external stimuli.

In contrast, R&D expenditures may mitigate the negative effects of proximity to non-green startups. A high level of absorptive capacity, which can result from high R&D expenses, enables incumbents not merely to imitate non-green knowledge, but to filter, recombine, and transform it for an ecological use (Cohen & Levinthal, 1990). Rather than being diverted toward conventional technological trajectories, firms with strong internal R&D capabilities may selectively integrate external knowledge in ways that support their green innovation objectives.

Additionally, proximity to non-green startups may intensify competitive and price pressures, particularly as environmentally friendly practices are often associated with higher costs (Lang, 2009; Pandit et al., 2018). Incumbents with substantial R&D budgets are better positioned to withstand such pressures and to use their environmental activities for differentiation. In this way, internal R&D investments may buffer the potentially adverse consequences of non-green startup proximity. Accordingly, we propose the following two hypotheses:

H2a. *A high level of incumbents' R&D expenditures weakens the positive association of geographic proximity to green startups on green innovation of incumbents.*

H2b. *A high level of incumbents' R&D expenditures weakens the negative association of geographic proximity to non-green startups on green innovation of incumbents.*

3.3 Geographic Startup Proximity and First-Time Green Patents

Another point of examination is whether the geographic proximity to startups increases the probability that an incumbent publishes its first overall green patent. Either because the incumbent previously has had no patents

JOURNAL OF
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at all or only non-green patents. From a knowledge spillover theory perspective, one can argue that green startups make green technologies and environmental knowledge more visible and accessible. Consequently, the startups' knowledge might spill over to the incumbents. This might move incumbents to begin ecological projects. Thus, we derive that incumbents might profit from surrounding green startups and might be more prone to publish their first green patent.

H3. *The geographic proximity to green startups is positively associated with first-time green patents of incumbents.*

3.4 Influence of a Shared Environmental Orientation

Lastly, we analyse if there is a difference of effects between incumbents that are embedded in a green industry and those that are not. In accordance with the EU Taxonomy, an industry is considered green if it has a direct, measurable benefit to at least one ecological objective such as climate change mitigation, circular economy, pollution control, etc. (European Union, 2020, p. 17). From a theoretical perspective, arguments from both points of view exist, as provided in Subchapter 2.3. In short, either similarity helps in recognising and applying knowledge, or different viewpoints and opinions provide a broader range of knowledge. In this study, we propose that the effects of similarity between incumbents and startups dominate. Firms which have a green environmental orientation have a more suitable absorptive capacity to notice and utilize knowledge that is thematically related to their own knowledge. As a result, spillovers from green start-ups should be stronger and more readily exploited by incumbents that have a green environmental profile than those that have a non-green one. Thus, similarity dominates.

H4. *The effect of the geographic proximity to green startups is more pronounced for incumbents that have an environmental orientation than those that do not have an environmental orientation.*

4. Methods

4.1 Sample Selection

Startup Dataset

We retrieve the startup data from Crunchbase (https://www.crunchbase.com), one of the largest and most widely used databases for information on innovative startup companies worldwide (Moon & Suh, 2021; Pisoni & Onetti, 2018; Savin et al., 2023). The downloaded data consist of Crunchbase funding round data matched with Crunchbase company data to supplement missing firm information, such as founding years. Since the platform not only contains startups but also more mature companies that do not need funding (Savin et al., 2023), only U.S. firms with at least one funding round between 2000 and 2023 are included (Deias & Magrini, 2023). The downloaded dataset contains firm name, founding year, startup location (city, state, country), funding type, funding amount, the startups' industries and details

Table 1: Crunchbase Sample Construction

	Observations
Crunchbase funding round data	289,882
Less:	
Not matched to company data (e.g. missing firm name)	(11,107)
Funding type is atypical for startups or undisclosed	(13,194)
Duplicates or firms with multiple funding rounds per year	(47,915)
Expanded:	
Inclusion of all startup years without funding round acording to each defined lifespan	321,783
Final Startup Sample	**539,449**

JOURNAL OF
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about the startups' status of operation (active, closed, went public or was acquired). We include firms from 2000 to 2023, tracking each from its founding year (or from 2000, if founded earlier) to the end of its active lifespan. That is, up to a maximum of ten years, unless the firm was closed, exited, acquired, or went public, whichever occurred first (Ferrati et al., 2021, p. 313; Moon & Suh, 2021, pp. 5, 9).

We obtained a total of 289,882 funding rounds, out of which 278,775 were successfully matched to the corresponding company data. In the cleaning process (summarized in Table 1), firms with funding types atypical for startups (e.g. post-IPO debt/equity or secondary market), undisclosed funding types or funding amounts were excluded as well as duplicates (Ferrati et al., 2021, p. 313; Shi et al., 2020, p. 92). Among the observations, we ensured that each founding and funding date precedes the corresponding exit date and that entities such as universities, schools, and cities are excluded (Krankovits et al., 2024, p. 4). Finally, we expanded the dataset to include startups across all relevant years within their previously defined lifespan, not just the years in which funding occurred. This leads to a final sample of 539,449 startup-year observations, covering 77,022 distinct startups.

We classify these startups as either "green" or "non-green" startups based on their industry. Crunchbase provides its own system of industry classifications, which we manually reviewed and assigned to either the green or non-green category. Since startups in Crunchbase are often associated with multiple industries, a startup is considered "green" if at least one of its listed industries falls into a green category. Overall, 42,511 (7,88%) startup observations are classified as green, while 496,938 (92,12%) are considered non-green startup observations.

Green Innovation Dataset

In accordance with numerous academic studies (e.g. Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Johnstone et al., 2010; Li et al., 2017; Petruzzelli, 2011), we measure green innovation by the green patent count. We retrieved the patent data from the PatentSearch API from PatentsView in April 2025. The data, compiled from the endpoint 'Patent', specifically, comprise all patents with at least one U.S. inventor from 2000-2024. Further information includes the patent year, the patent type (only utility patents are accumulated), the number of forward citations per patent, the inventor and assignee organisation name, the assignee and inventor location (city, state, country) as well as both CPC (Cooperative Patent Classification) and IPC (International Patent Classification) codes. Patents often list several inventors but only one inventor name or location could be entered. Thus, we selected the first listed inventor, assuming they represent the primary contributor (Mowery & Ziedonis, 2001; Tietze, 2023; USPTO, 2024).

We matched each patent to firm financial information from the Compustat database using fuzzy string matching. Values above 90-95 are commonly considered reasonably accurate (Schölzel, 2024). For this research, we included all scores above 95 in the dataset along with scores between 90 and 95, if the headquarter from Compustat was identical to the assignee organisation location. In total, 864,742 out of 1,757,504 patents were successfully matched and retained.

Next, we classified all patents as green or non-green by means of the classification frameworks ENV-Tech (Haščič & Migotto, 2015), the Y02/Y04S-tagging scheme (Angelucci et al., 2018; EPO, 2016) and the IPC Green Inventory (WIPO, 2012), which make use of the CPC and IPC classification codes. As noted by Favot et al. (2023) as well as Ghisetti and Quatraro (2017), the classification systems are considered complements and should, consequently, be applied in conjunction for best results. This study follows Favot et al., who provide a method to obtain all relevant green IPC and CPC codes, which can then be matched to the PatentsView dataset. A patent is considered a green patent (coded as 1), if at least one classification code is included in one of the three frameworks mentioned above, and a non-green patent (coded as 0) otherwise (Barbieri et al., 2020). If no IPC or CPC codes are available, these observations are deleted.

Further cleaning steps include removing data if neither inventor nor assignee address are American and if the organisation name contains special characters. Lastly, we aggregate all patents on a firm-year level. We include firm years 2000 (unless the company was founded later) until 2024. Years without patent records in PatentsView are taken as evidence of zero patenting activity by the incumbent. Consequently, we set both the total number of patents and the number of green patents to zero. We then merge all remaining data with state-level data on environmental regulation strength and educational attainment. The latter was retained from the U.S. Census Bureau (Kresowik et al., 2025) and the environ-mental legislation data from the ACEEE, the American Council

Vol.23, Iss.1, February 2026
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Table 2: Green Innovation Sample Construction

	Observations
Patents collected from Patents View (2000-2024)	1,757,504
Less:	
Patents not matched to Compustat firm	(892,762)
Patents without available CPC/ IPC codes	(42,335)
Neither (first) inventor nor assignee address are American	(8,983)
Assignee name contains special characters	(12)
Aggregated:	
Aggregation on firm-year-level	=29,463
Inclusion of firm-year combinations with zero patents	42,835
Final Green Innovation Sample	**=72,298**

for an Energy-Efficient Economy (Manson et al., 2024). Table 2 provides an overview of the construction of the green innovation dataset.

For the analysis of a shared environmental orientation, we classify all incumbents as a green or non-green incumbent. Based on the EU Taxonomy, a firm is considered green if its industry provides a direct, measureable benefit for the environment with the objectives of climate change adaption or mitigation, sustainable water use, circular economy, pollution prevention and the protection of biodiversity (European Union, 2020, p. 17). The final green innovation dataset entails 72,298 firm-year observations, covering 5,569 unique firms. Green patents account for 68,840 (8.52%) of the total 808,350 patents.

Final Dataset

We integrate the Crunchbase startup dataset with the PatentsView green innovation dataset, as illustrated in Figure 1. The linkage is based on geographic proximity between startups and incumbents. Therefore, we geocode all city-level location data into longitude and latitude coordinates of each city's centroid using OpenStreetMap. In accordance with Ardito et al. (2019) and Petruzzelli (2011), for the location of the incumbents, we choose their respective R&D site over their headquarter location, as innovation activities typically occur where research is conducted. The inventor's address serves as a proxy for the R&D site, assuming inventors reside near (and commute to) their workplace. For each incumbent, we identify the most frequent inventor city and assignee city and map them to Metropolitan Statistical Areas (MSAs) (U.S. Census Bureau, 2023). If both cities belong to the same MSA, the assignee city is used for geocoding. If they differ, or if assignee information is missing, the inventor city is used instead.

Based on geocoded latitude and longitude data, we calculate the yearly geographic proximity between each incumbent and their surrounding startups. In accordance with proximity calculations in scientific research (e.g. Arena & Dewally, 2012; Hu et al., 2021; Uysal et al., 2008), we apply the Haversine formula to determine spherical distances between coordinates.

4.2 Research Design and Variable Definitions

We examine the relation between geographic startup proximity and green innovation using the following baseline regression specification:

JOURNAL OF
BUSINESS CHEMISTRY

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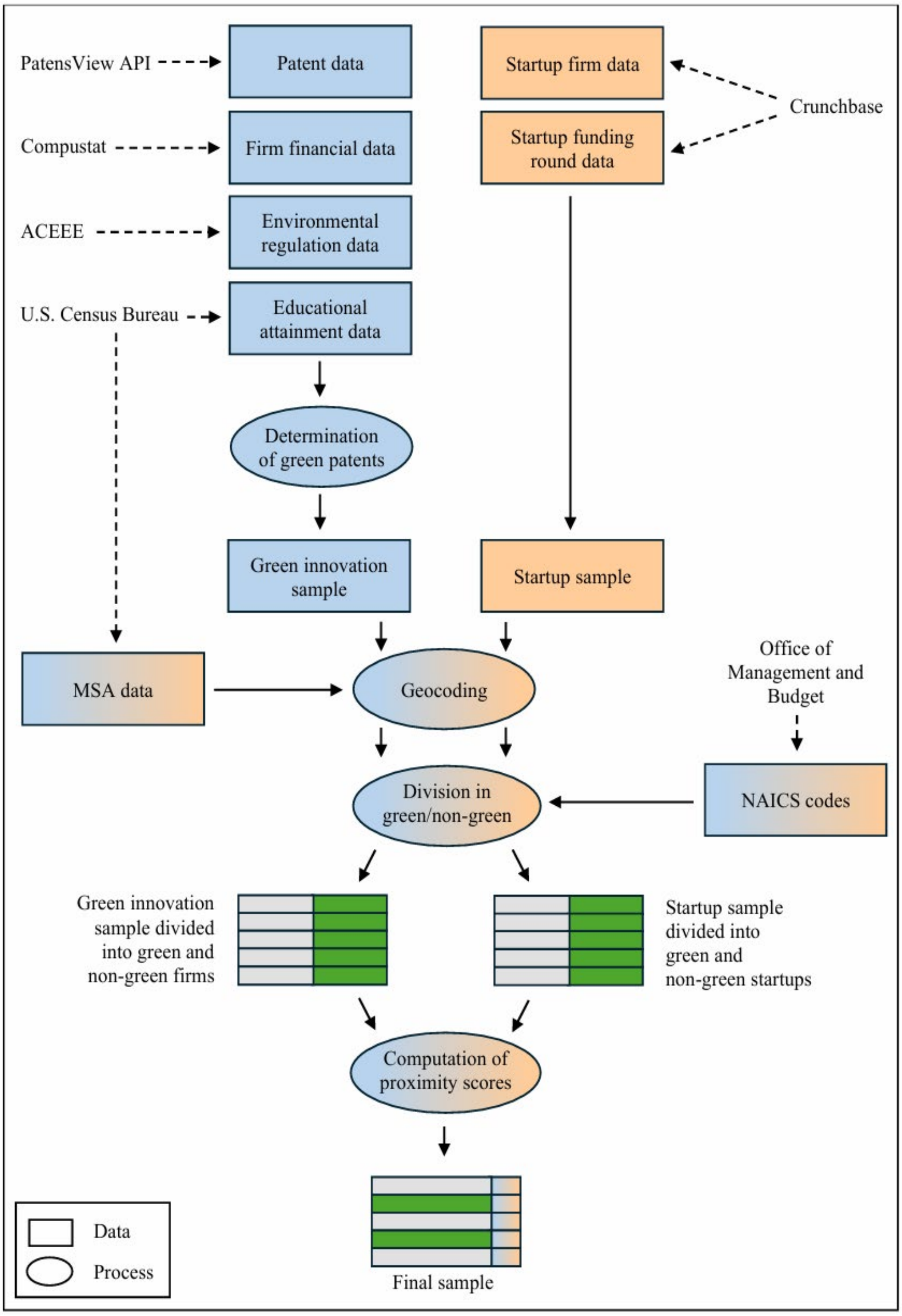

Figure 1: Visualization of the Sample Gerneration Process

$$ln(E[GreenPatents_{i,t}]) = \beta_0 + \beta_1 \cdot StartupDensity_{j,t-5} + \sum \beta_n \cdot Control_{n,t-5} + \gamma_t + \delta_i + \varepsilon_{i,t} \quad (1)$$

To capture geographic proximity to startups, we construct a measure of startup density, which is defined as the number of startups located within a 1-km (5-km) radius around each incumbent in a given year (e.g. Abramovsky & Simpson, 2011, p. 9). Startup counts are computed for all startups in total (*StartupDensity_1km* and *StartupDensity_5km*), for green startups (*GreenStartupDensity_1km* and *GreenStartupDensity_5km*), and for non-green start-ups (*OtherStartupDensity_1km* and

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

OtherStartupDensity_5km). These are employed as independent variables.

For the dependent variable, we select the absolute number of green patents per firm-year (*GreenPatents*) as a proxy for green innovation. It is assumed that innovation unfolds over time (Cohen & Levinthal, 1990) since research and development initiatives take time. Further, the average delay between patent application and publication is an additional 1.5 years (USPTO, 2022). Thus, we employ a time lag of five years.

To test our hypotheses, we use panel data in which the dependent variable, the number of green patents, is a count variable. The distribution of this variable is highly skewed, with many firm-year observations recording zero patents, while few observations exhibit high green patent counts. Since the dependent variable is hence non-continuous and non-normally distributed, standard linear regression techniques like ordinary least squares regression are inappropriate in this setting. Instead, a count models such as Poisson or negative binomial regressions are more appropriate. Given the clear overdispersion in the dependent variable (mean = 0.45, variance = 1.97), we employ a negative binomial regression model (Corrocher & Mancusi, 2021; Zhenhong et al., 2021).

In accordance with relevant proximity and green innovation literature (e.g. S. Glaeser & Lang, 2024; Hu et al., 2021; Sheng & Ding, 2024), we control for the average age of startups included in the respective radius (*StartupAge_1km* and *StartupAge_5km*), as well as the average size of startups included in the specific radius, measured as the natural logarithm of the startup's last funding in U.S. dollars (*StartupSize_1km* and *StartupSize_5km*) to control for the characteristics of the local startup ecosystem. We further account for characteristics of incumbent to control for possible effects of firm-level economic factors on green innovation: Age (*FirmAge*), size, measured as the natural logarithm of the number of employees (*FirmSize*), return on assets (*ROA*), asset-liability ratio (*Leverage*), market-to-book ratio (*MarketToBook*), cash-to-current-assets ratio (*CashToCurrentAssets*), net income (*NetIncome*), and logarithmic R&D expenses (*RDExp*). Finally, to account for institutional and human capital conditions, additional control variables include the state-level regulation strength (*EnvStateScore*) and the state-level educational attainment (*EduStateScore*), which have been shown to shape firms' incentives and capabilities for green innovation. We include year and industry fixed effects as γ_t and δ_i, respectively. Here, *i* indexes incumbents, *j* indexes startups, and the time *t* denotes the year. The error term of the regression equation is reflected by $\varepsilon_{i,t}$. Finally, standard errors are clustered on the firm level. All continuous variables are winsorized at the 1st and 99th percentiles and are provided in Appendix A.

In Hypothesis 2a and 2b, we evaluate the interaction between R&D expenses and geographic startup proximity, specifically, the proximity to green startups and to non-green startups. Thus, we include interaction effects, e.g. between *GreenStartupDensity_1km* and *RDExp* as well as *OtherStartupDensity_1km* and *RDExp*. The third hypothesis examines first-time green patents per incumbent. The regression remains similar to the baseline model, except that we apply a logistic regression for panel data since *FirstGreenPatent* is an indicator variable. It is coded as 1 for the year in which an incumbent publishes its first green patent, and 0 otherwise.

To test Hypothesis 4, whether green incumbents from green industries benefit more from spatially close green startups, we reapply our main model. The variable *EnvIndustry* is an indicator variable coded as 1 for all incumbents in an environmental industry, and 0 otherwise. To compare the subgroups, we first enter all incumbents in the regression, in a second step only those incumbents from a green industry (*EnvIndustry=1*), and lastly, only those incumbents not from a green industry (*EnvIndustry=0*). All variables are defined in Appendix A.

5. Results

5.1 Descriptive Statistics

Table 3 shows the descriptive statistics for all variables used in this study. In total, the data set includes 808,350 patents out of which 68,840 (8.52%) are classified as green patents. Each incumbent publishes an average of 6.31 patents per year. 0.45 (7.13%) of the overall number of patents qualify as green patents.

Out of all 77,022 distinct startups, 5,818 are classified as green, and 71,352 are considered as non-green. Accordingly, this represents a share of 7.55% green startups related to all startups. Within a 1-km radius around each incumbent, an average of 107.04 total startups, 5.71 green startups and 101.32 non-green

JOURNAL OF
BUSINESS CHEMISTRY

Vol.23, Iss.1, February 2026

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Table 3: Descriptive Statistics

Variables	N	Mean	Median	SD	Min.	Max.
Depentent variables						
GreenPatents	72,298	0,45	0	1.97	0	15
FirstGreenPatent	72,298	0.03	0	0.16	0	1
TotalPatents	72,298	6.31	0	23.44	0	476
GreenPatentCitations	72,298	1.28	0	5.92	0	44.25
Indepentent variables						
StartupDensity_1km	72,298	107.04	6	386,49	0	3784
StartupDensity_5km	72,298	118.40	8	393.67	0	3845
GreenStartupDensity_1km	72,298	5.71	0	17.47	0	162
GreenStartupDensity_5km	72,298	6,43	0	18.19	0	164
OtherStartupDensity_1km	72,298	101.33	5	369.90	0	3624
OtherStartupDensity_5km	72,298	111.97	7	376.54	0	3684
Moderator varible						
RDExp.	55,858	3.37	3.23	2.12	0	8.77
Control Variables						
StartupAge_1km	49,796	4.94	4.83	1.79	0	23
StartupAge_5km	52,741	4.96	4.85	1.80	0	23
StartupSize_1km	49,796	15.83	16.11	1.31	6.91	23.72
StartupSize_5km	52,741	15.84	16.11	1.29	6.91	23.43
FirmAge	72,298	19.66	14	17.37	0	70
FirmSize	70,934	6.19	6.13	2.83	-0.95	12.46
EOA	70,820	-0.24	0.01	0.84	-6.03	0.34
Leverage	70,764	3.35	2.04	3.79	0.12	24.51
MarketToBook	64,692	3.51	2.27	8.20	-30.18	50.75
CashToCurrentAssets	68,652	0.46	0.43	0.31	0.01	0.99
NetIncome	70,874	397.31	2.76	1,448.47	-1,408	9,856
EnvStateScore	71,020	12.61	15.1	8.49	1.01	22.63
EduStateScore	67,838	0.31	0.31	0.06	0.15	0.63

Notes: This table provides descriptive statistics for all variables used in this paper. All continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in Appendix A.

Vol.23, Iss.1, February 2026
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DOI: 10.17879/70918521284

startups are located. In a 5-km radius, an average of 118.40 total startups, 6.43 green startups, and 111.97 non-green startups are situated.

The incumbents' mean R&D expenditure amounts to 298.90 $m, which is 3.37 $m after applying the natural logarithm. For further analysis, we separate the incumbents into green and non-green incumbents based on their environmental orientation. 1031 distinct incumbents are considered environmentally friendly, which amounts to 18.15%. 4539 distinct incumbents are classified as non-green.

5.2 Influence of Geographic Startup Proximity on Green Innovation

First, we explore if the geographic proximity to green and non-green startups, individually, affects green innovation. The results are presented in Columns (1) and (2) of Table 4. Geographic proximity to green startups exhibits positive coefficients, consistent with our theoretical expectation that environmentally specialized startups may generate relevant knowledge spillovers. However, the effect is not statistically significant at conventional levels. Thus, we do not find sufficient empirical support to conclude that proximity

Table 4 : Influence of the Geographic Proximity of Total, Green, and Non-green Startups on Green In-novation of Incumbents

Variables	GreenPatents (1)	GreenPatents (2)	GreenPatents (3)	GreenPatents (4)
GreenStartupDensity_1km	0.0016 (0.16)			
GreenStartupDensity_5km		0.0059 (0.64)		
OtherStartupDensity_1km	-0.0008 (-1.47)			
OtherStartupDensity_5km		-0.005 (-1.16)		
StartupDensity_1km			-0.0007*** (-3.45)	
StartupDensity_5km				-0.0007*** (-3.60)
RDExp	0.4859*** (6.48)	0.4875*** (6.69)	0.4863*** (6.49)	0.4864*** (6.68)
Observations	20,990	22,340	20,990	22,340
Control variables	Yes	Yes	Yes	Yes
Firm,year, industry FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.1171	0.1161	0.1171	0.1161

Notes: This table presents the results of a negative binomial regression model testing the influence of startup proximity on green innovation (*GreenPatents*). The influence of the proximity to all startups in a 1-km radius (*StartupDensity_1km*) and a 5-km radius (*StartupDensity_5km*) is presented in columns (1) and (2), the influence of the proximity to green startups in a 1-km radius (*GreenStartupDensity_1km*) and a 5-km radius (*Green-StartupDensity_5km*) in columns (3) and (4), and the influence of the proximity to non-green startups in a 1-km radius (*OtherStartupDensity_1km*) and a 5-km radius (*OtherStartupDensity_5km*) in columns (5) and (6). All variables are defined in Appendix A. The z-statistics based on heteroscedasticity-robust standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Vol.23, Iss.1, February 2026

URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

Table 5: Interaction of the Geographic Proximity to Green and Non-green Startups with R&D Expenditures

Variables	GreenPatents (1)	GreenPatents (2)	GreenPatents (3)	GreenPatents (4)	GreenPatents (5)	GreenPatents (6)
GreenStartupDensity_1km	0.0458*	0.0503*	0.0605***			
	(1.88)	(1.91)	(2.68)			
GreenStartupDensity_5km				0.0307	0.0395*	0.0459**
				(1.48)	(1.71)	(2.28)
OtherStartupDensity_1km	-0.0027**	-0.0029**	-0.0035***			
	(-2.26)	(-2.16)	(-3.17)			
OtherStartupDensity_5km				-0.0021**	-0.0026**	-0.0030**
				(-2.04)	(-2.17)	(-2.94)
RDExp.	0.5403***	0.4577***	0.4980***	0.5407***	0.4484***	0.4937***
	(21.74)	(7.90)	(6.71)	(21.61)	(7.66)	(6.79)
GreenStartupDensity_1km x RDExp.	-0.0060	-0.0063	-0.0125***			
	(-1.26)	(-1.27)	(-2.76)			
GreenStartupDensity_5km x RDExp.				-0.0048	-0.0057	-0.0112***
				(-1.13)	(-1.32)	(-2.72)
OtherStartupDensity_1km x RDExp.	0.0003	0.0003	0.0006**			
	(1.19)	(1.07)	(2.43)			
OtherStartupDensity_5km x RDExp.				0.0003	0.0003	0.0006**
				(1.16)	(1.23)	(2.45)
Observations	34,956	20,990	20,990	34,956	20,340	22,340
Control variables	No	Yes	Yes	No	Yes	Yes
Firm, year, industry FE	No	No	Yes	No	No	Yes
Pseudo R-squared	0.0531	0.0557	0.1176	0.0529	0.0547	0.1166

Notes: This table presents the results of a negative binomial regression model testing the influence of green and non-green startup proximity on green innovation (*GreenPatents*) with R&D expenses (*RDExp*) as a moderator. Column (1) presents the baseline regression results within a 1-km radius, column (2) includes fixed effects, column (3) includes control variables, and column (4) includes fixed effects and control variables. The regression results with fixed effects and control variables in a 5-km radius are presented in column (5). All variables are defined in Appendix A. The z-statistics based on heteroscedasticity-robust standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

to green startups systematically enhances incumbents' green innovation.

In contrast, geographic proximity to non-green startups is associated with negative coefficients, in line with our argument that misaligned knowledge bases, increased competition for local resources, and potential crowding-out effects may hinder incumbents' green innovation activities. Yet, similar to the results for green startups, this relationship is statistically insignificant. Therefore, the evidence does not indicate a robust negative effect of non-green startup proximity when considered in isolation.

When combining both types of startups into an overall measure of geographic startup proximity, the results reveal a negative association with incumbents' green innovation, which is highly significant at the 1% level. This finding, which are presented in columns (3) and (4) suggests that, on aggregate, spatial proximity to startups is associated with lower levels of green innovation among incumbents. The negative overall effect can be attributed to the composition of the local startup environment in our sample. Non-green startups clearly dominate in number, which implies that the aggregate proximity measure largely reflects the exposure to those startups. As a result, the potentially beneficial spillovers from green startups are outweighed by the misalignment, competitive pressures, and crowding-out mechanisms associated with non-green startups. The significant negative overall coefficient therefore represents a net effect driven primarily by the predominance of non-green startups in the sample.

5.3 The Moderating Role of R&D Expenditures

In our second analysis, we examine the effect of incumbents' R&D investments as a moderator of the relationship between geographic startup proximity and incumbents' green innovation output. The results are shown in Table 5. Columns (1) – (3) show findings for a 1-km radius, while columns (4) – (6) report results for a 5-km radius. The full models reveal significant main and interaction effects. Within a 1 km-radius, the main effect of the green startup density is positive and significant at the 1% level ($\beta = 0.0605$; $p < 0.01$). This indicates that an increase of one additional green startup in the 1km range is associated with a 6.2% increase in green patents, assuming the incumbent's R&D expenses are zero. In a 5-km radius, analogously, proximate green startups have a significant positive effect ($\beta = 0.0459$; $p < 0.05$), corresponding to a 4,7% increase in green patents. Moreover, the incumbent's R&D expenses exhibit a strong and highly significant positive main effect on green innovation for both the 1 km ($\beta = 0.4980$; $p < 0.01$) and the 5 km ($\beta = 0.4937$; $p < 0.01$) radii. These coefficients imply that a one-unit increase in logarithmic R&D spending is associated with a 65.5% increase in green patent output when no green startups are situated within 1 km, and a 63.8% increase for a 5-km radius.

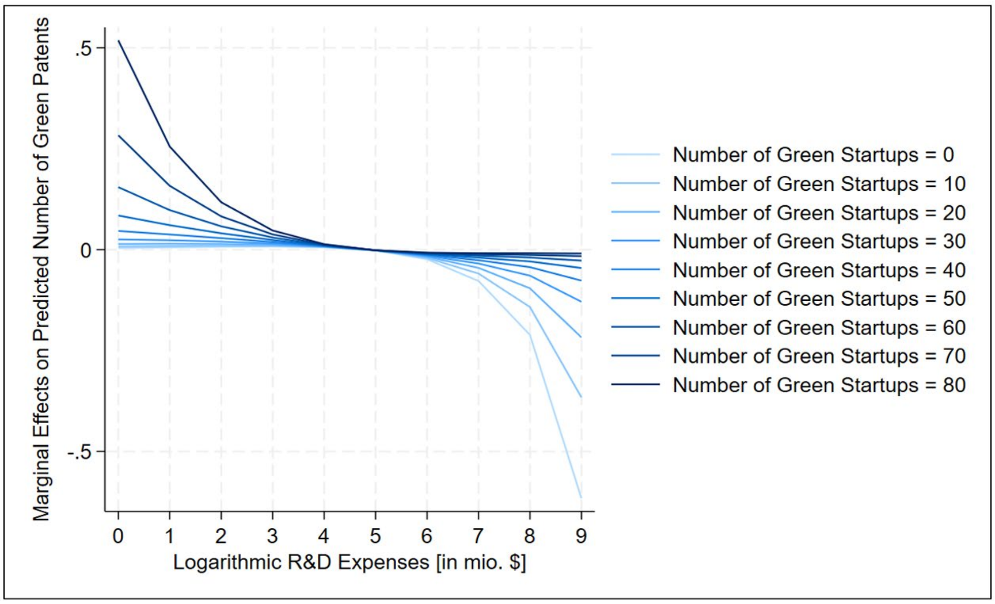

Figure 2: The Marginal Effect of an Increase of Each Green Startup for Different R&D Budgets and Green Startup Densities

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

In contrast, the interaction between green startup proximity and the incumbent's R&D budget is negative and significant. This suggests that the positive impact of proximate green startups diminishes exponentially as R&D increases and eventually turns negative. The turning point occurs at an R&D budget of 126.8 \$m per year (RDExp = 4.84). Below this threshold, marginal effects of a rising green startup density remain positive, above it, marginal effects become negative. This pattern is illustrated in Figure 2. In this dataset, 77% of all firm-year observations fall below this R&D threshold, while 23% exceed it.

Two key insights emerge from this analysis: First, incumbents with lower R&D budgets (< 126.8 \$m; *RDExp* < 4.84) benefit from a large number of green startups in their operating area. Second, incumbents with higher R&D budgets (>126.8 \$m; *RDExp* > 4.84) experience a negative impact when surrounded by many green startups. Figure 3 visualizes these patterns, showing how the number of proximate green startups affects the green patent output across different R&D budgets. Lines representing lower-budget incumbents (Log R&D expenses = 0 – 4) slope upward as the green startup density increases, illustrating how knowledge spillovers are associated with higher patent counts. In contrast, lines for high-budget incumbents (Log R&D expenses = 5 – 9) slope downward, indicating that additional green startups reduce expected patents for R&D-intensive incumbents.

For non-green startups, the effect is inverted. In a 1-km radius, the main effect of the startup density is significantly negative (β = -0.0035 $p < 0.01$), corresponding to a 0.35% decrease in green patents for each additional non-green startup when R&D expenses are zero. Within a 5-km radius, the decrease amounts to 0.30% (β = -0.0030 $p < 0.01$), analogously. For both distances, the interaction between the number of non-green startups and R&D expenses is significantly positive (β = 0.0006; $p < 0.05$), indicating that higher R&D expenses mitigate and eventually counteract the negative effect. However, since these effect sizes are much smaller compared to the effect of R&D expenses (β = -0.4980 $p < 0.001$ and β

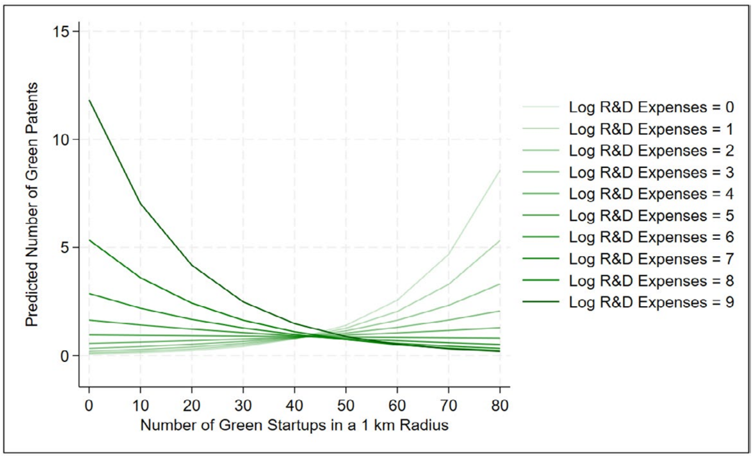

Figure 3: Impact of the Number of Proximate Green Startups on Green Innovation for Different Levels of R&D Expenses

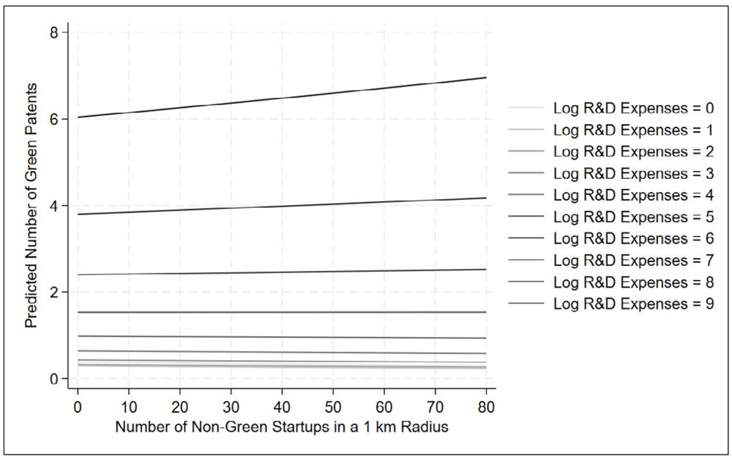

Figure 4: Impact of the Number of Proximate Non-Green Startups on Green Innovation for Different Levels of R&D Expenses

Vol.23, Iss.1, February 2026

URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

= -0.4937 $p < 0.001$), the effect of proximate non-green startups on green patents is quantitively small. This is depicted in Figure 4.

All in all, Hypothesis H2a, that incumbent's R&D expenses weaken the positive impact of proximate green startups on green innovation, is supported. This finding aligns with relevant theory, which suggests that while knowledge spillover effects from geographically proximate startups enhance incumbents' subsequent green innovation output, they are often constrained by intensified competitive pressures, technological lock-in, and crowding-out effects. In particular, high R&D investments may reinforce existing technological trajectories and organizational routines, thereby limiting the extent to which incumbents can flexibly absorb and capitalize on external green knowledge.

The findings are further in line with H2b, that incumbent's R&D expenses weaken the negative impact of proximate non-green startups on green innovation. Higher R&D intensity enhances an incumbent's ability

Table 6: Influence on First-Time Green Patents

Variables	**FirstGreenPatent (1)**	**FirstGreenPatent (2)**
GreenStartupDensity_1km	0.1021* (1.95)	
GreenStartupDensity_5km		0.0969* (1.92)
OtherStartupDensity_1km	-0.0031 (-1.05)	
OtherStartupDensity_5km		-0.0033 (-1.11)
RDExp.	0.1124 (0.72)	0.1706 (1.14)
GreenStartupDensity_1km x RDExp.	-0.0158 (-1.32)	
GreenStartupDensity_5km x RDExp.		-0.0179 (-1.55)
OtherStartupDensity_1km x RDExp.	0.0001 (0.14)	
OtherStartupDensity_5km x RDExp		0.0004 (0.53)
Observations	4,097	4,435
Control Variables	Yes	Yes
Firm FE	Yes	Yes

Notes: This table presents the results of a logistic binomial regression model with panel data testing the influ-ence of green and non-green startup proximity on first-time green patents (*FirstGreenPatent*) with R&D expens-es (*RDExp*) as a moderator. The number of green startups within a 1-km radius (*GreenStartupDensity_1km*) and 5 km (*GreenStartupDensity_5km*) radius are presented in columns (1) and (2). All variables are defined in Ap-pendix A. The z-statistics based on heteroscedasticity-robust standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

to identify, assimilate, and exploit external knowledge. Therefore, when exposed to proximate non-green startups, firms with strong R&D capabilities are better positioned to reinterpret or recombine non-green knowledge in ways that stimulate green innovation, thereby offsetting the potential disadvantages arising from cost-competitive and efficiency-driven non-green technologies introduced by nearby competitors.

5.4 Influence of Geographic Startup Proximity on First-Time Green Patents

The second section analyses the effect of geographic startup proximity on first-time green patents rather than on overall green patent counts. H3 presumes that the density of green geographically proximate startups leads to more first-time patents because of knowledge spillovers. The results shown in Table 6 provide only marginal to no support for H2. Although the effect sizes show similar directions and slightly larger magnitudes compared to the original model featuring subsequent patents, the results lack statistical significance. Only the main effects of green startup proximity are significant on a 10% level (β = 0.1021; $p < 0.1$ and β = 0.0969; $p < 0.1$). This indicates a fainter and less robust proximity effect at the entry stage of green innovation. Consequently, H3 can neither be rejected nor fully supported.

The reasoning might be that incumbents must first develop a certain level of internal ecological expertise before venturing into green innovation. Thus, geographic spillovers alone are more unlikely to lead to the first green patent. Once that level of expertise is achieved, local knowledge flows can more reliably drive further green patents. Further, labor contracts in startup environments often include non-compete clauses, which means that employees who decide to switch to another firm are prohibited from working in the same thematical field for usually one to two years (Marx, 2022, p. 1759).

5.5 Examination of a Shared Environmental Orientation

The third part of the analysis explores if similarity in form of a common environmental orientation influences the association between spatial proximity and green innovation. The results for the influence of the green startup density depending on environmental alignment in a 1-km radius are presented in columns (1) – (3) of Table 7. In accordance with H4, the coefficient of the green startup density is highest for incumbents from green industries (β = 0.2003; $p < 0.001$) and lowest for incumbents from non-green industries (β = 0.0224; $p > 0.05$). The coefficient of all incumbents lies in the middle but closer to the one for incumbents from non-green industries (β = 0.0605; $p < 0.01$), which seems intuitive since it is a mixture of incumbents from green and non-green industries but dominated by non-green industries. Further, the interaction effect with a incumbent's R&D expenses is also largest for a incumbent working in a green industry (β = - 0.0099; $p < 0.001$), lowest for a incumbent from a non-green industry (β = - 0.0020; $p > 0.05$) and in the middle for all incumbents (β = - 0.0035; $p < 0.01$). Noticeable is that for non-green incumbents, only non-green startups seem to influence the incumbent green patents but not the green startups. It further underlines that similarity strengthens proximity effects. The results for the 5-km radius are analogous.

5.3 Robustness Tests

Given that our main finding lies in the heterogenous effects of green startup proximity conditional on incumbents` R&D intensity, the robustness analyses focus primarily on confirming the results of these interaction effects tested in Hypothesis 2a and 2b. These robustness tests include (1) the variation of employed time lags, (2) the variation of distances that count as geographic startup proximity, (3) exchanging the number of green patents with the number of their forward citations as the dependent variable, (4) exchanging the proximity measure and (5) an analysis of reverse causality.

First, we reestimate our regression model using alternative time lags instead of the five-year lags employed in the baseline model. The corresponding results for startup density within a 1 km radius are presented in Appendix C. Regression output for different radii for startup density report similar results. Overall, the findings remain robust across similar time lags, as for example time lags of six or seven years lead to similar, even more significant results. In contrast, shorter time lags lead to weaker or statistically insignificant results, suggesting that the effects require time to unfold.

The second robustness check applies different radii as cutoff points when measuring proximity. In the original models, we employ a 1-km and a 5-km radius.

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Vol.23, Iss.1, February 2026

URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

Table 7: Influence of a Shared Environmental Orientation

Variables	GreenPatents (1)	GreenPatents (2)	GreenPatents (3)	GreenPatents (4)	GreenPatents (5)	GreenPatents (6)
Incumbents' environmental orientation	all	green	non-green	all	green	non-green
GreenStartupDensity_1km	0.0605***	0.2003***	0.0224			
	(2.68)	(3.99)	(0.90)			
GreenStartupDensity_5km				0.0459**	0.1507***	0.0193
				(2.28)	(3.10)	(0.88)
OtherStartupDensity_1km	-0.0035***	-0.0099***	-0.0020			
	(-3.17)	(-3.65)	(-1.62)			
OtherStartupDensity_5km				-0.0030***	-0.0077***	-0.0020*
				(-2.94)	(-3.05)	(-1.69)
RDExp.	0.4980***	0.3917***	0.5377***	0.4937***	0.3960***	0.5320***
	(6.71)	(2.95)	(5.83)	(6.79)	(3.00)	(5.91)
GreenStartupDensity_1km x RDExp.	-0.0125***	-0.0317***	-0.0081			
	(-2.76)	(-3.45)	(-1.52)			
GreenStartupDensity_5km x RDExp.				-0.0112***	-0.0263***	-0.0078
				(-2.72)	(-2.88)	(-1.64)
OtherStartupDensity_1km x RDExp.	0.0006**	0.0015**	0.0004			
	(2.43)	(2.93)	(1.46)			
OtherStartupDensity_5km x RDExp.				0.0006**	0.0012**	0.0005*
				(2.45)	(2.44)	(1.66)
Observations	20,990	5,260	15,730	22,340	5,550	16,790
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm, year, industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.1176	0.0835	0.1334	0.1166	0.0807	0.1325

Notes: This table presents the results of a negative binomial regression model testing the influence of green and non-green startup proximity on green innovation (*GreenPatents*) with R&D expenses (*RDExp*) as a moderator. The number of green startups within a 1-km radius (*GreenStartupDensity_1km*) is presented in columns (1) - (3). The number of green startups within a 5-km radius (*GreenStartupDensity_5km*) is presented in columns (4) - (6). Columns (1) and (4) present the regression results featuring all incumbents, columns (2) and (5) featuring the subset of all incumbents that exhibit an environmental orientation, and columns (3) and (6) featuring the subset of all incumbents that exhibit a non-environmental orientation. All variables are defined in Appendix A. The z-statistics based on heteroscedasticity-robust standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

Now, these are expanded to a 10-km radius and a 25-km radius. The results are shown in Appendix D. All tested proximate radii prove significant, although their effect sizes decrease slightly as the radius increases. This is in accordance with established theories and further economic studies, in which it is stressed that knowledge spillovers decline with decreasing proximity (Jaffe et al., 1993, p. 577).

As a third robustness test, we exchange the dependent variable *GreenPatents*, the number of green patents per firm-year, with *GreenPatentCitations*. This variable measures all U.S. forward citations to these green patents. Appendix E shows the corresponding regression results. Our results hold for the forward citations as independent variable. We notice that the effect sizes are slightly higher than in the original model, which might indicate that the geographic startup proximity affects not only the quantity of green patents but even more strongly their quality or technological relevance. Proximate green startups might create conditions like improved networks or stronger absorptive capabilities that foster more impactful green innovations rather than merely increasing output (Anton-Tejon et al., 2024; Buzard et al., 2020; Cohen & Levinthal, 1990).

In the fourth robustness check, we replace the count-based proximity measure with a distance-based measure, assigning greater weight to shorter distances than to longer distances within the specified radii. Appendix F shows the according results, which prove analogous to our main model, thus supporting our study's findings.

The final robustness check, presented in Appendix G, inspects potential reverse causality. Specifically, innovative incumbents may attract green startups to locate nearby, rather than benefiting from startup proximity. To assess this possibility, we reverse the roles of the dependent and independent variables. The results show no significant effects, suggesting that incumbents' prior green innovation does not drive subsequent green startup clustering. This finding supports the proposed direction of influence from startup proximity to incumbents' green innovation, particularly for incumbents with low R&D intensity.

6. Conclusion

Firms face growing pressure to innovate sustainably without sacrificing competitiveness, making their positioning within regional innovation ecosystems a critical strategic question. The results of our study disentangle the effects spatially close startups have on green innovations of incumbents. We show that the impact of geographic proximity is contingent on incumbents' internal R&D investments, highlighting a systematic moderation effect. Proximity to green startups increases green innovation among incumbents with low R&D intensity but is associated with fewer future green patents for incumbents with high R&D expenditures like many incumbents from chemical or pharmaceutical industries. By contrast, proximity to non-green startups exhibits the reverse pattern. This asymmetric relationship underscores that geographic proximity entails both knowledge spillovers and competitive forces, and that high absorptive capacity is essential for incumbents to offset crowding out, appropriation risks, and technological lock-in.

Moreover, our results emphasize that spatial proximity plays a markedly weaker role for first-time green patents than for subsequent green innovation activities, suggesting that localized knowledge spillovers become more relevant once incumbents have developed a minimum level of environmental knowledge and absorptive capacity. Finally, we demonstrate that shared characteristics between startups and incumbents amplify the effects of geographic proximity, highlighting the value of regional similarities for green innovation outcomes.

Our study enhances the understanding of spatial proximity effects as a driver of green innovation, particularly by considering how incumbents' R&D intensity and homogenous characteristics moderate these effects. Furthermore, our contribution lies in thoroughly disentangling the beneficial role of knowledge spillovers and absorptive capacity opposed to the constraining effects of local competitive pressures and appropriation risks. The results encourage managers of incumbents and startups to strategically localize their R&D activities and select suitable partners for cooperation. Moreover, the results suggest that policy makers as well as investment funds should prioritize the development of regional innovation ecosystems that facilitate collaboration, promote knowledge exchange and accelerate the adoption of sustainable technologies. Future research could further unpack the mechanisms underlying startup proximity by incorporating richer measures of technological and organizational

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

relatedness between startups and incumbents. Such analyses would allow for a more direct test of the argument that similarity facilitates knowledge spillovers.
Moreover, extending the analysis beyond geographic startup proximity by considering additional dimensions of proximity could provide a more precise understanding of the mechanisms that drive knowledge spillovers.

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Vol.23, Iss.1, February 2026

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Vol.23, Iss.1, February 2026
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Vol.23, Iss.1, February 2026

URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

Appendix

Appendix A (1): Variable Definitions

Variables	Definition	Data Source
GreenPatents	Number of green patents per firm-year observation	PatentsView
FirstGreenPatent	An indicator variable coded as 1 if a firm published its first-time green patent overall in this year, 0 otherwise	PatentsView
TotalPatents	Number of total patents per firm-year observation	PatentsView
GreenPatentCitations	Number of all U.S. forward citations per green patents	PatentsView
StartupDensity_1km	Total number of all startups surrounding a firm in a 1-km radius per year	Crunchbase
StartupDensity_5km	Total number of all startups surrounding a firm in a 5-km radius per year	Crunchbase
GreenStartupDensity_1km	Number of green startups surrounding a firm in a 1-km radius per year	Crunchbase
GreenStartupDensity_5km	Number of green startups surrounding a firm in a 5-km radius per year	Crunchbase
GreenStartupDensity_10km	Number of green startups surrounding a firm in a 10-km radius per year	Crunchbase
GreenStartupDensity_25km	Number of green startups surrounding a firm in a 25-km radius per year	Crunchbase
GreenStartupProximityIndex_1km	Proximity score for green startups surrounding the firm in a 1-km radius per year measured as the weighted sum of the inverse distances	Crunchbase
GreenStartupProximityIndex_5km	Proximity score for green startups surrounding the firm in a 5-km radius per year measured as the weighted sum of the inverse distances	Crunchbase
OtherStartupDensity_1km	Number of non-green startups surrounding a firm in a 1-km radius per year	Crunchbase
OtherStartupDensity_5km	Number of non-green startups surrounding a firm in a 5-km radius per year	Crunchbase
OtherStartupDensity_10km	Number of non-green startups surrounding a firm in a 10-km radius per year	Crunchbase
OtherStartupDensity_25km	Number of non-green startups surrounding a firm in a 25-km radius per year	Crunchbase
OtherStartupProximityIndex_1km	Proximity score for non-green startups surrounding the firm in a 1-km radius per year measured as the weighted sum of the inverse distances	Crunchbase
OtherStartupProximityIndex_5km	Proximity score for non-green startups surrounding the firm in a 5-km radius per year measured as the weighted sum of the inverse distances	Crunchbase
RDExp	The natural logarithm of a firm's research and development expenses per year in millions of U.S. dollars	Compustat
StartupAge_1km	Average age of all startups in a 1-km radius around the respective firm per year	Crunchbase
StartupAge_5km	Average age of all startups in a 5-km radius around the respective firm per year	Crunchbase

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

Appendix

Appendix A (2): Variable Definitions

StartupAge_10km	Average age of all startups in a 10-km radius around the respective firm per year	Crunchbase
StartupAge_25km	Average age of all startups in a 25-km radius around the respective firm per year	Crunchbase
StartupSize_1km	Average size of all startups in a 1-km radius around the respective firm measured as the natural logarithm of the startup's last funding in U.S. dollars	Crunchbase
StartupSize_5km	Average size of all startups in a 5-km radius around the respective firm measured as the natural logarithm of the startup's last funding in U.S. dollars	Crunchbase
StartupSize_10km	Average size of all startups in a 10-km radius around the respective firm measured as the natural logarithm of the startup's last funding in U.S. dollars	Crunchbase
StartupSize_25km	Average size of all startups in a 25-km radius around the respective firm measured as the natural logarithm of the startup's last funding in U.S. dollars	Crunchbase
FirmAge	Firm age in years.	Compustat
FirmSize	A firm's natural logarithm of their employee number per year	Compustat
ROA	A firm's return on assets per year	Compustat
Leverage	A firm's ratio of total liabilities to total equity per year	Compustat
MarketToBook	A firm's ratio of the market value of equity to the book value of equity per year	Compustat
CashToCurren-tAssets	A firm's cash-to-current-assets ratio per year	Compustat
NetIncome	Net profit per firm-year in millions of U.S. dollars calculated by subtracting all expenses from total revenue	Compustat
EnvStateScore	State-level environmental regulation strengths measured as a total score given by the ACEEE	ACEEE
EduStateScore	State-level educational attainment, which is the ratio of people aged 25 and older that have at least completed a bachelor's degree or equivalent	U.S. Census Bureau
EnvIndustry	An indicator variable coded as 1 if an incumbent firm works in an environmentally friendly industry, 0 otherwise	Office of Manage-ment and Budget

JOURNAL OF BUSINESS CHEMISTRY
Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

Appendix B: Bivariate Correlation Coefficients

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) GreenPatents	1.00														
(2) Startup-Density_1km	-0.01*	1.00													
(3) Startup-Density_5km	-0.01**	0.99***	1.00												
(4) Green-StartupDensity_1km	0.00	0.95***	0.94***	1.00											
(5) Green-StartupDensity_5km	0.00	0.93***	0.94***	0.98***	1.00										
(6) Other-StartupDensity_1km	-0.01*	0.99***	0.99***	0.95***	0.93***	1.00									
(7) Other-StartupDensity_5km	-0.01**	0.99***	0.99***	0.94***	0.94***	0.99***	1.00								
(8) RDExp	0.26***	0.08***	0.09***	0.10***	0.11***	0.08***	0.09***	1.00							
(9) StartupAge_1km	0.00	-0.08***	-0.09***	-0.08***	-0.08***	-0.08***	-0.09***	-0.03***	1.00						
(10) StartupAge_5km	0.00	-0.09***	-0.09***	-0.08***	-0.09***	-0.09***	-0.09***	-0.03***	0.94***	1.00					
(11) StartupSize_1km	-0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.02***	0.02***	0.02***	1.00				
(12) StartupSize_5km	0.01	0.00	0.01	0.01**	0.01*	0.00	0.01	0.02***	0.02***	0.02***	0.99***	1.00			
(13) FirmAge	0.16***	-0.04***	-0.05***	-0.03***	-0.04***	-0.04***	-0.05***	0.30***	0.05***	0.06***	-0.01***	-0.01**	1.00		
(14) FirmSize	0.18***	0.06***	0.05***	0.06***	0.06***	0.05***	0.05***	0.78***	0.00	0.01**	0.01	0.01	0.46***	1.00	
(15) ROA	0.06***	-0.01*	-0.01***	-0.01*	-0.01***	-0.01*	-0.01**	0.26***	0.01**	0.01**	0.00	0.00	0.22***	0.50***	1.00
(16) Leverage	-0.04***	0.00	0.01**	0.00	0.01**	0.00	0.01**	-0.14***	-0.03***	-0.03***	0.00	0.00	-0.20***	-0.21***	0.08***
(17) MarketToBook	0.03***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.09***	-0.03***	-0.03***	0.00	0.00	-0.02***	0.03***	0.09***
(18) CashTo-CurrentAssets	-0.02***	0.12***	0.14***	0.13***	0.15***	0.13***	0.13***	0.04***	-0.01***	-0.07***	0.01**	0.01**	-0.37***	-0.28***	-0.19***
(19) NetIncome	0.16***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.47***	0.00	0.001	0.00	0.00	0.29***	0.47***	0.13***
(20) EnvStateScore	0.01***	0.21***	0.23***	0.19***	0.21***	0.21***	0.24***	0.10***	-0.07***	-0.07***	0.02***	0.03***	-0.14***	-0.07***	-0.04***
(21) EduStateScore	0.01***	0.19***	0.21***	0.23***	0.27***	0.19***	0.21***	0.13***	0.03***	0.03***	0.02***	0.03***	0.01***	0.02***	-0.04***

Notes: This table presents the pairwise Pearson correlation coefficients among the main variables used in the analysis. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Variables	(16)	(17)	(18)	(19)	(20)	(21)
(1) GreenPatents						
(2) StartupDensity_1km						
(3) StartupDensity_5km						
(4) GreenStartupDensity_1km						
(5) GreenStartupDensity_5km						
(6) OtherStartupDensity_1km						
(7) OtherStartupDensity_5km						
(8) RDExp						
(9) StartupAge_1km						
(10) StartupAge_5km						
(11) StartupSize_1km						
(12) StartupSize_5km						
(13) FirmAge						
(14) FirmSize						
(15) ROA						
(16) Leverage	1.00					
(17) MarketToBook	0.01***	1.00				
(18) CashToCurrentAssets	0.41***	0.10	1.00			
(19) NetIncome	-0.01***	0.05***	-0.08***	1.00		
(20) EnvStateScore	0.09***	0.06***	0.28***	0.01***	1.00	
(21) EduStateScore	0.04**	0.06***	0.23***	0.07***	0.43***	1.00

Notes: This table presents the pairwise Pearson correlation coefficients among the main variables used in the analysis. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

Appendix C: Regression Results with Different Time Lags

Variables	GreenPatents				
	(1)	(2)	(3)	(4)	(5)
Time lag [in years]	5	3	4	6	7
GreenStartupDensity_1km	0.0605***	0.0199	0.0383*	0.0883***	0.1123***
	(2.68)	(1.02)	(1.73)	(3.59)	(4.19)
OtherStartupDensity_1km	-0.0035***	-0.0015*	-0.0026**	-0-0048***	-0.0056***
	(-3.17)	(-1.67)	(-2.43)	(-3.74)	(-3.93)
RDExp	0.4980***	0.4309***	0.4804***	0.4660***	0.4458***
	(6.71)	(6.27)	(6.61)	(6.09)	(5.55)
GreenStartupDensity_1km x RDExp	-0.0125***	-0.0047	-0.0082*	-0.0174***	-0.0215***
	(-3.70)	(-1.14)	(-1.81)	(-3.62)	(-4.14)
OtherStartupDensity_1km x RDExp	0.0006**	0.0002	0.0004*	0.0008***	0.0009***
	(2.43)	(1.22)	(1.86)	(3.05)	(3.22)
Observations	20,990	26,240	23,465	18,728	16,646
Control variables	Yes	Yes	Yes	Yes	Yes
Firm, year, industry FE	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.1176	0.1184	0.1186	0.1155	0.1153

Notes: This table presents the results of a negative binomial regression model testing the influence of green startup proximity on green innovation (*GreenPatents*) with R&D expenses (*RDExp*) as a moderator. Column (1) presents the original model with a time lag of 5 years, columns (2) – (6) show time lags of 3, 4, 6, and 7 years, respectively. All variables are defined in Appendix A. The z-statistics based on heteroscedasticity-robust standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Vol.23, Iss.1, February 2026
URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

Appendix D: Regression Results with Different Radii as Proximity Measurements

Variables	GreenPatents			
	(1)	(2)	(3)	(4)
Radius [in km]	1	5	10	25
GreenStartupDensity_1km	0.0605*** (2.68)			
GreenStartupDensity_5km		0.0459** (2.28)		
GreenStartupDensity_10km			0.0358** (2.54)	
GreenStartupDensity_25km				0.0212** (2.43)
OtherStartupDensity_1km	-0.0035*** (-3.17)			
OtherStartupDensity_5km		-0.0030*** (-2.94)		
OtherStartupDensity_10km			-0.0021** (-2.35)	
OtherStartupDensity_25km				-0.0015** (-2.57)
RDExp	0.4980*** (6.71)	0.4937*** (6.79)	0.4726*** (6.66)	0.4128*** (5.92)
GreenStartupDensity_1km x RDExp	-0.0125*** (-2.76)			
GreenStartupDensity_5km x RDExp		-0.0112*** (-2.72)		
GreenStartupDensity_10km x RDExp			-0.0084*** (-2.94)	
GreenStartupDensity_25km x RDExp				-0.0060*** (-3.25)
OtherStartupDensity_1km x RDExp	0.0006** (2.43)			
OtherStartupDensity_5km x RDExp		0.0006** (2.45)		
OtherStartupDensity_10km x RDExp			0.0005** (2.40)	
OtherStartupDensity_25km x RDExp				0.0004*** (2.84)
Observations	20,990	22,340	24,273	26,636
Control variables	Yes	Yes	Yes	Yes
Firm, year, industry FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.1176	0.1166	0.1152	0.1175

Notes: This table presents the results of a negative binomial regression model testing the influence of green startup proximity on green innovation (*GreenPatents*) with R&D expenses (*RDExp*) as a moderator. Columns (1) and (2) present the original models with a radius of 1 km and 5 km, respectively. Columns (3) and (4) show a 10-km radius and a 25-km radius, respectively. All variables are defined in Appendix A. The z-statistics based on heteroscedasticity-robust standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Vol.23, Iss.1, February 2026

URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

Appendix E: Regression Results with Forward Citations as Dependent Variable

Variables	GreenPatentCitations	
	(1)	(2)
GreenStartupDensity_1km	0.1070*** (3.24)	
GreenStartupDensity_5km		0.0833*** (2.97)
OtherStartupDensity_1km	-0.0074*** (-3.79)	
OtherStartupDensity_5km		-0.0057*** (-3.58)
RDExp	0.2445*** (3.02)	0.2539*** (3.40)
GreenStartupDensity_1km x RDExp	-0.0221** (-2.24)	
GreenStartupDensity_5km x RDExp		-0.0176*** (-2.98)
OtherStartupDensity_1km x RDExp	0.0014*** (3.56)	
OtherStartupDensity_5km x RDExp		0.0011*** (3.28)
Observations	20,990	22,340
Control variables	Yes	Yes
Firm, year, industry FE	Yes	Yes
Pseudo R-squared	0.0766	0.0754

Notes: This table presents the results of a negative binomial regression model testing the influence of green startup proximity on green innovation (*GreenPatentCitations*) with R&D expenses (*RDExp*) as a moderator. Columns (1) and (2) present the geographic startup proximity with a radius of 1 km and 5 km as independent variables, respectively. All variables are defined in Appendix A. The z-statistics based on heteroscedasticity-robust standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

JOURNAL OF
BUSINESS CHEMISTRY

Vol.23, Iss.1, February 2026

URN: urn:nbn:de:hbz:6-70918521805
DOI: 10.17879/70918521284

Appendix F: Regression Results with a Distance-Weighted Proximity Measure

Variables	GreenPatents	
	(1)	(2)
GreenStartupProximityIndex_1km	0.0317**	
	(1.97)	
GreenStartupProximityIndex_5km		0.0291*
		(1.84)
OtherStartupProximityIndex_1km	-0.0021**	
	(-2.50)	
OtherStartupProximityIndex_5km		-0.0020**
		(-2.40)
RDExp	0.4957***	0.4937***
	(6.64)	(6.79)
GreenStartupProximityIndex_1km x RDExp	-0.0068**	
	(-2.01)	
GreenStartupProximityIndex_5km x RDExp		-0.0067**
		(-1.99)
OtherStartupProximityIndex_1km x RDExp	0.0003*	
	(1.84)	
OtherStartupProximityIndex_5km x RDExp		0.0003*
		(1.84)
Observations	20,990	22,340
Control variables	Yes	Yes
Firm, year, industry FE	Yes	Yes
Pseudo R-squared	0.1175	0.1164

Notes: This table presents the results of a negative binomial regression model testing the influence of green startup proximity on green innovation (*GreenPatents*) with R&D expenses (*RDExp*) as a moderator. Columns (1) and (2) present the geographic startup proximity based on a distance-weighted proximity measure within a radius of 1 km and 5 km as independent variables, respectively. All variables are defined in Appendix A. The z-statistics based on heteroscedasticity-robust standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Vol.23, Iss.1, February 2026

URN: urn:nbn:de:hbz:6-70918521805

DOI: 10.17879/70918521284

Appendix G: Reverse Causality Analysis

Variables	(1) Startup-Density_1km	(2) GreenStartup-Density_1km	(3) GreenStartup-Density_1km	(4) OtherStartup-Density_1km	(5) OtherStartup-Density_1km
GreenPatents	0.0064	0.0097	0.0375	0.0063	0.0485
	(0.41)	(0.67)	(0.68)	(0.40)	(0.81)
RDExp	0.0023	-0.0030	0.1116***	0.0041	0.1418***
	(0.05)	(-0.08)	(2.62)	(0.10)	(2.88)
GreenPatents x RDExp			-0.0011		-0.0019
			(-0.13)		(-0.22)
Observations	29,701	29,701	29,701	29,701	29,701
Control variables	Yes	Yes	Yes	Yes	Yes
Firm, year, industry FE	No	No	Yes	No	Yes
Pseudo R-squared	0.0152	0.0176	0.1143	0.0158	0.0749

Notes: This table presents the results of negative binomial regression models testing the influence of green innovation (*GreenPatents*) on overall, green and non-green startup proximity without R&D expenses (*RDExp*) as a moderator in columns (1) – (3) and with R&D expenses (*RDExp*) as a moderator in columns (4) – (5). Further variations (radii, time lags, etc.) were tested with analogous results. All variables are defined in Appendix A. The z-statistics based on heteroscedasticity-robust standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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