JOURNAL OF
BUSINESS CHEMISTRY

Vol.23, Iss.1, February 2026

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

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

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

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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

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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

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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

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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

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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**

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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

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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:

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DOI: 10.17879/70918521284

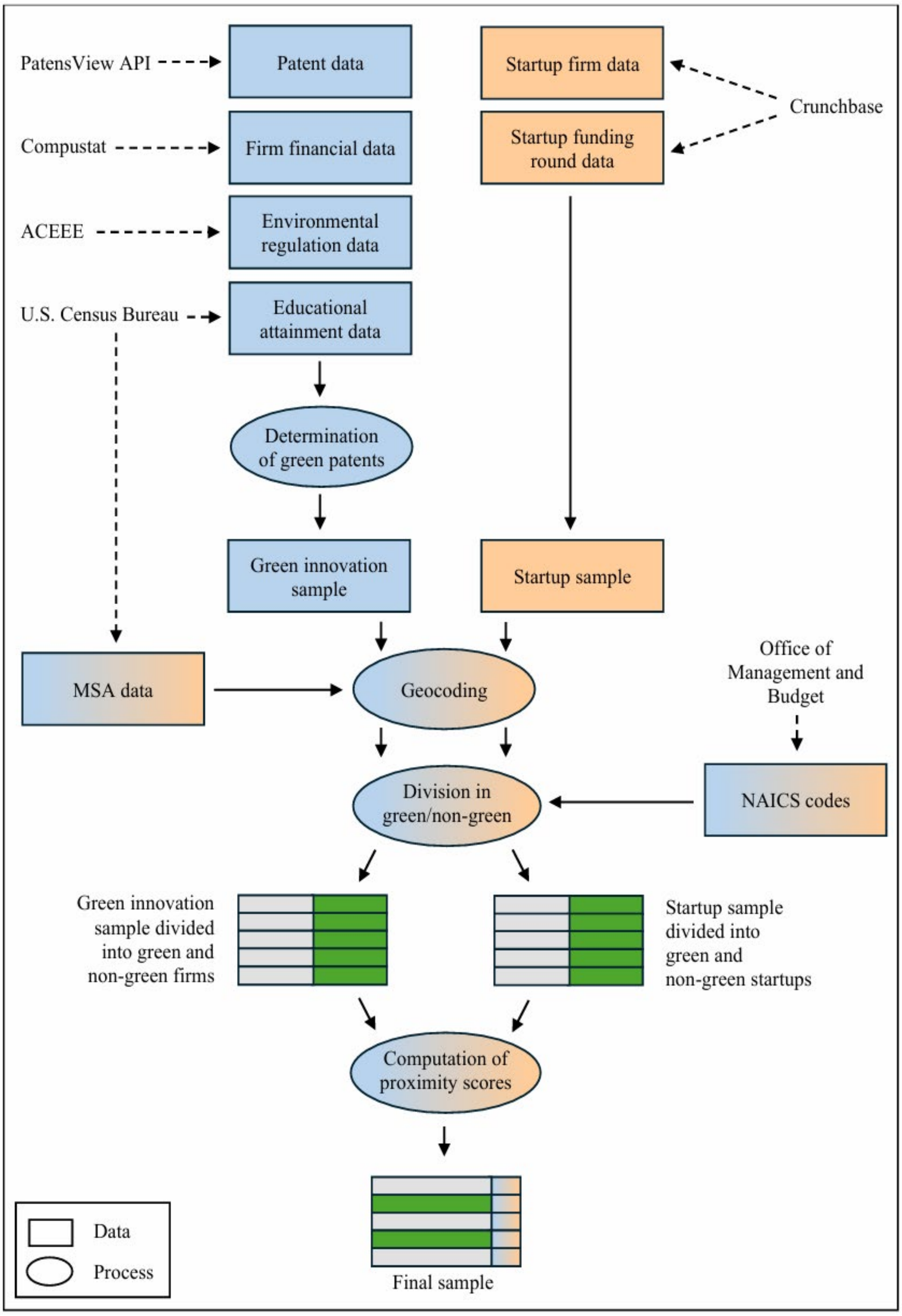

Figure 1: Visualization of the Sample Genreration Process

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

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

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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

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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.

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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.

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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.

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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.

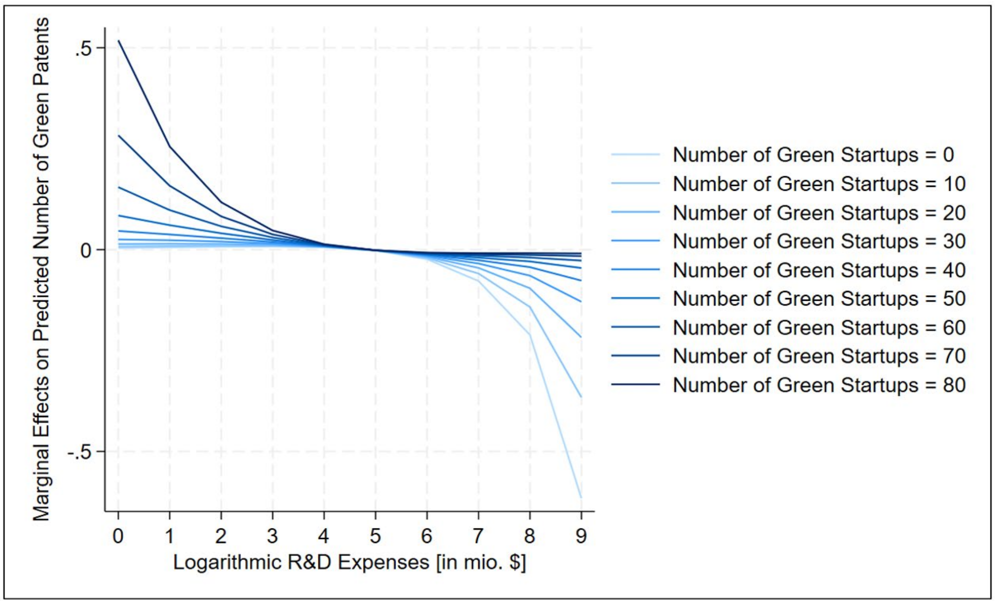

Figure 2: The Marginal Effect of an Increase of Each Green Startup for Different R&D Budgets and Green Startup Densities

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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

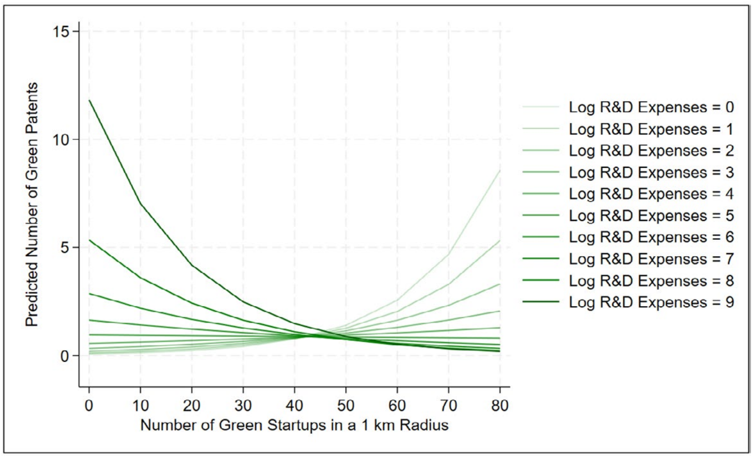

Figure 3: Impact of the Number of Proximate Green Startups on Green Innovation for Different Levels of R&D Expenses

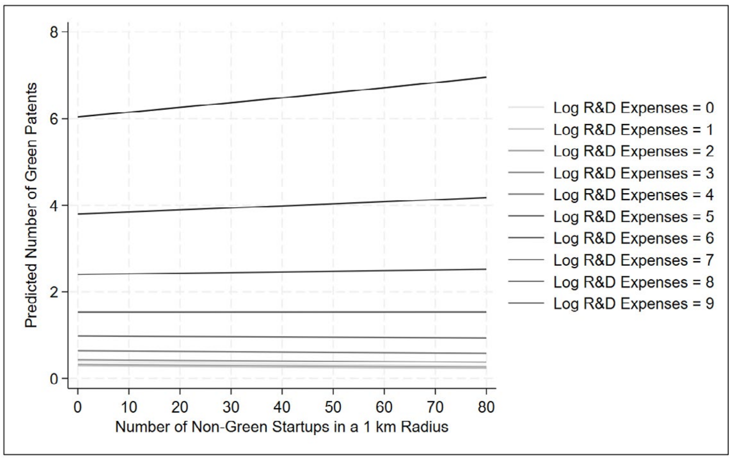

Figure 4: Impact of the Number of Proximate Non-Green Startups on Green Innovation for Different Levels of R&D Expenses

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= -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.

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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 ($\beta = 0.1021$; $p < 0.1$ and $\beta = 0.0969$; $p < 0.1$). 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 ($\beta = 0.2003$; $p < 0.001$) and lowest for incumbents from non-green industries ($\beta = 0.0224$; $p > 0.05$). The coefficient of all incumbents lies in the middle but closer to the one for incumbents from non-green industries ($\beta = 0.0605$; $p < 0.01$), 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 ($\beta = -0.0099$; $p < 0.001$), lowest for a incumbent from a non-green industry ($\beta = -0.0020$; $p > 0.05$) and in the middle for all incumbents ($\beta = -0.0035$; $p < 0.01$). 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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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*** (2.68)	0.2003*** (3.99)	0.0224 (0.90)			
GreenStartupDensity_5km				0.0459** (2.28)	0.1507*** (3.10)	0.0193 (0.88)
OtherStartupDensity_1km	-0.0035*** (-3.17)	-0.0099*** (-3.65)	-0.0020 (-1.62)			
OtherStartupDensity_5km				-0.0030*** (-2.94)	-0.0077*** (-3.05)	-0.0020* (-1.69)
RDExp.	0.4980*** (6.71)	0.3917*** (2.95)	0.5377*** (5.83)	0.4937*** (6.79)	0.3960*** (3.00)	0.5320*** (5.91)
GreenStartupDensity_1km x RDExp.	-0.0125*** (-2.76)	-0.0317*** (-3.45)	-0.0081 (-1.52)			
GreenStartupDensity_5km x RDExp.				-0.0112*** (-2.72)	-0.0263*** (-2.88)	-0.0078 (-1.64)
OtherStartupDensity_1km x RDExp.	0.0006** (2.43)	0.0015** (2.93)	0.0004 (1.46)			
OtherStartupDensity_5km x RDExp.				0.0006** (2.45)	0.0012** (2.44)	0.0005* (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.

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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

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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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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

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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

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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.

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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.

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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.

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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.

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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.

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

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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.

