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Exploring Technological Originality and Self-Citation in Wind Energy Innovation: Implications for Technological Impact

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Abstract: Technological innovation is paramount for accelerating climate change mitigation efforts within sectors characterized by low technological diffusion. This study examines the role of self-citation and technological novelty on the technological impact of wind energy technologies (2010–2023). Using USPTO patent data and a negative binomial regression analysis, the results reveal an inverse relationship between self-citation and technological impact and a positive relationship between technological originality and technological impact. Specifically, a 1% increase in the self-citation rate is associated with an 11.2% decrease in technological impact, while a 1% increase in technological originality leads to a 5.2% increase in technological impact. These findings highlight the need for policies that incentivize technological diversity and foster knowledge exchange and collaboration among firms to enhance innovation diffusion. By providing insights into firms' innovation strategies, this study offers practical guidance for policymakers aiming to accelerate renewable energy adoption and achieve long-term sustainability goals.

Keywords: technological impact; self-citation; technological originality; wind energy sector; negative binomial regression; patent analysis; renewable energy innovation

JEL Classification: O31; O33; Q42

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1. Introduction

Addressing climate change and achieving sustainable development goals underscore the need for global transition to renewable energy [1–3]. Wind power has demonstrated considerable cost competitiveness as a leading renewable energy technology [4–6] and plays a pivotal role in advancing global sustainability goals due to its potential to significantly reduce greenhouse gas emissions and reliance on fossil fuels. As one of the fastest-growing renewable energy sources, wind energy is essential for achieving carbon neutrality and mitigating the impacts of climate change. Projections indicate that it may meet up to 35% of global electricity demand by 2050. Notwithstanding its technological advancement and economic feasibility, the dissemination of wind energy technology lags behind that of other renewable energy sources, such as solar photovoltaics [6–12]. This is largely attributable to complex technological demands, substantial capital investment, and a concentrated market [9,13–15]. Given the urgent need for climate change mitigation, understanding the dynamics of technological innovation in the wind energy sector is critical.

Low technological diffusion sectors are characterized by the adoption and widespread application of new technologies and face significant barriers, including high capital costs, long research and development (R&D) cycles, regulatory constraints, high technological uncertainty, and limited knowledge spillovers [16–18]. Examples of such sectors include offshore wind energy, carbon capture and storage, nuclear energy, and hydrogen fuel technology, where technological advancements are critical; however, progress is often hindered by high infrastructure costs and policy uncertainties [8,17,18]. Wind energy falls into this category because, while it has experienced growth, its adoption and technological diffusion remain slower than those of other renewables, such as solar photovoltaics. Unlike solar energy, which benefits from modular and rapidly deployable technologies, wind energy requires large-scale infrastructure, grid integration, and specialized expertise, contributing to its lower diffusion rate [13]. The low diffusion rate inherent to wind energy technologies necessitates a closer examination of how firms' innovation strategies, specifically knowledge acquisition via self-citation and integration via technological novelty, impact technological advancements and wider adoption [11,13,19,20].

While prior studies have extensively examined macro-level factors influencing renewable energy innovation, they often fail to address the micro-level strategies employed by firms. Specifically, the role of self-citation and technological originality in shaping the dissemination and impact of wind energy technologies remains insufficiently explored. Self-citation, defined in this study as a firm's reliance on prior patents, reflects its dependence on internal knowledge building. Although self-citation can foster incremental innovation by consolidating existing expertise, excessive reliance on it may hinder external knowledge integration, reduce external recognition, and slow down the dissemination of technological advancement. These challenges are particularly critical in the wind energy sector, where collaboration and knowledge diffusion are essential for driving innovation and achieving sustainability goals [21,22].

Moreover, the wind energy sector faces a relatively slow pace of technological diffusion, which can be exacerbated by firms' tendency to focus on refining existing technologies rather than integrating diverse external advancements. This phenomenon, often referred to as knowledge lock-in, highlights the risks associated with overreliance on internal expertise. To overcome this challenge, fostering interdisciplinary collaboration, such as integrating advancements from materials science, artificial intelligence, and meteorology, can help break the cycle of knowledge lock-in and accelerate innovation in the sector. Similarly, although technological originality, defined as the integration of diverse and innovative knowledge sources, is widely recognized as a driver of breakthrough innovations, its role in advancing wind energy technologies remains under-researched [11,13]. These gaps in the literature underscore the need for a deeper understanding of how firm-level innovation strategies influence the diffusion and impact of wind energy technologies.

To address these gaps, this study investigates the following research questions: (1) To what extent does self-citation affect the technological impact and dissemination of wind energy innovations? (2) What role does technological originality play in enhancing the diffusion and impact of wind energy technologies? By exploring these questions, this study provides novel insights into firms' micro-level innovation strategies and their implications for technological dissemination in low-diffusion renewable energy sectors, offering a fresh perspective on the dynamics of innovation in the wind energy industry.

To answer these research questions, a robust analysis was conducted on a dataset comprising 19539 wind energy patents filed worldwide from 2000 to 2020 by prominent manufacturers and technology developers. Our findings reveal that, while self-citation negatively affects technological impact, technological originality significantly enhances the diffusion of wind energy innovations. These findings make several important contributions

to innovation theory and practices. First, they extend our understanding of knowledge recombination in the renewable energy sector by revealing the dual effects of internal knowledge utilization. Second, they provide empirical evidence of the role of technological originality in promoting breakthrough innovations in wind energy technology. These insights offer valuable guidance for firms seeking to optimize their innovation strategies and for policymakers aiming to accelerate the diffusion of renewable energy technologies.

The remainder of this paper is organized as follows. Section 2 develops our hypotheses. Section 3 describes the data collection process, variable definitions, and empirical methods. Section 4 presents the empirical results and robustness checks. Section 5 discusses the implications of the findings in the context of the existing literature, highlighting their theoretical and practical significance. Section 6 concludes this study by summarizing the key findings, offering policy recommendations and addressing methodological limitations while suggesting directions for future research.

2. Theoretical Background and Research Hypothesis

2.1. Sectoral System of Innovation for Wind Energy Technologies

Technological innovation in the wind energy sector is deeply embedded within a complex and specialized innovation system [13]. This system is distinguished by its interdisciplinary reliance on wind energy technologies, which necessitates the integration of expertise in mechanical engineering, materials science, meteorology, and electrical systems [13,23]. Wind energy technology development is significantly influenced by the sector's dependence on extensive infrastructure, protracted R&D periods, and considerable capital expenditures [13,24–26]. The confluence of these factors results in a comparatively low diffusion rate within the sector, in contrast to other renewable energy technologies such as solar photovoltaics.

Technological innovation in the wind energy sector is largely concentrated in a selected group of firms [27]. The global wind energy market is dominated by Vestas, Siemens Gamesa, and GE Renewable Energy, which collectively hold most of the field's patents [28]. The observed market concentration is a consequence of high barriers to entry, primarily due to the considerable capital investment demands of R&D, manufacturing, and deployment [29,30]. The development of offshore wind turbines requires sophisticated technological capabilities and significant financial investment for their design, testing, and deployment in demanding marine settings [13]. Consequently, smaller companies and newcomers frequently encounter difficulties in competing, resulting in a market structure in which innovation is primarily concentrated among a limited number of dominant firms [31,32]. This concentration significantly affects the dissemination of wind energy technologies, as established corporations may favor proprietary information and iterative advancements to preserve their competitive edge, thereby hindering widespread knowledge exchange and collaborative efforts [10].

The high capital costs associated with wind energy technologies contribute to the sector's slow adoption rate. In contrast to modular and scalable technologies that support solar energy, wind energy requires substantial infrastructure investment including wind farms, grid integration, and maintenance resources. The substantial initial investment required restricts the adoption and adaptation of wind energy technologies by smaller companies and developing nations, thereby hindering the global dissemination of innovation [33]. Furthermore, the financial hazards inherent in wind energy ventures frequently incentivize companies to prioritize the optimization of current technologies over high-risk, potentially high-yield innovations. This risk-averse behavior is evident in the high frequency of self-citations within the industry as companies utilize their previous patents to enhance and optimize their technological advancements. Although this strategy fosters internal

knowledge growth, it may also lead to path dependency and restrict the exploration of innovative technological solutions.

The concentration of innovation within large firms and the capital-intensive nature of the sector also influence the role of originality in shaping technological impact. Integrating diverse and novel knowledge sources, which constitute originality, is crucial for overcoming the technological and economic challenges inherent in the wind energy sector [21]. For instance, the development of floating offshore wind platforms necessitates the integration of marine engineering, materials science, and renewable energy system expertise, marking a substantial divergence from conventional fixed-bottom turbine designs. Such highly original innovations have the potential to break existing technological trajectories and expand the applicability of wind energy technologies to new environments such as deep-water locations. The significant expenses and risks associated with such innovations often discourage firms from pursuing them, thereby hindering the sector's adoption rate.

In conclusion, the wind energy sector's innovation ecosystem is characterized by its interdisciplinary composition, concentration of technological advancements within major corporations, and substantial capital investment demanded for research, development, and implementation. The sector's low diffusion rate is attributable to firms prioritizing incremental advancements and internal knowledge retention over broader knowledge dissemination and high-risk innovation [34]. This analysis emphasizes the crucial roles of self-citation and originality in determining technological outcomes. Firms' self-citations indicate dependence on internal expertise for technological optimization, whereas originality signifies the capacity to integrate diverse knowledge bases and generate groundbreaking innovations [21]. Collectively, these elements establish a framework for comprehending how businesses address the difficulties inherent in innovation within a low-diffusion sector such as wind energy.

2.2. The Role of Self-Citation on Technological Impact in the Wind Energy Sector

The strategic orientation of firms in wind energy innovation is reflected in self-citation patterns, which focus on the optimization of existing technological pathways [35]. For example, prominent wind turbine manufacturers often reference their intellectual property rights when designing improvements to specific components, including blade design optimization, gearbox efficiency enhancement, and advanced control systems [4,29,36]. Internal knowledge accumulation, while enhancing competitive advantage within specific technological niches, may concurrently restrict the exploration of novel technological possibilities [37–40]. Path dependency in the offshore wind energy sector often constrains firms' ability to pursue breakthrough innovations, particularly when they rely extensively on their existing knowledge base through self-citation [41,42]. To overcome this limitation, fostering interdisciplinary collaboration can help firms integrate external advancements from diverse fields, such as materials science, artificial intelligence, and meteorology, thereby breaking the cycle of knowledge lock-in and enabling transformative innovation.

The structural features of the wind energy industry exacerbate the detrimental consequences of self-citation [21]. The interdisciplinary nature of this sector, which encompasses mechanical engineering, materials science, electrical systems, and environmental technologies, requires the integration of diverse expertise for innovation. Reliance on internally generated patents may prevent firms from leveraging technological advancements in related areas [43]. A wind turbine manufacturer that restricts its focus to internal expertise risks overlooking advancements in composite materials, artificial intelligence, and grid stabilization technologies with the potential to substantially improve product performance and market competitiveness.

Moreover, the slow diffusion of wind energy technologies exacerbates the limitations imposed by the high self-citation rates. Renewable energy technologies, including wind power, face significant barriers to knowledge dissemination owing to their long development cycles, substantial capital requirements, and complex regulatory frameworks [8,44,45]. Firms that rely heavily on self-citations may isolate their innovations from broader technological ecosystems. For instance, patents on floating offshore wind platforms might remain confined within a single firm's development pipeline rather than being adapted and improved through external collaboration and knowledge exchange.

The empirical evidence from our study supports these theoretical arguments, revealing a negative relationship between self-citation rates and technological impact in the wind energy sector. This analysis indicates that patents with higher self-citation rates tend to receive fewer forward citations, which suggests reduced external recognition and limited knowledge diffusion. Based on these theoretical arguments and empirical observations of the wind energy sector, we propose our first hypothesis.

Hypothesis 1 (H1). *Higher self-citation is negatively related to technological impact.*

2.3. The Role of Technological Originality on Technological Impact in the Wind Energy Sector

Technological originality represents a firm's capability to integrate diverse knowledge sources into the innovation process, which is particularly crucial in the wind energy sector owing to its inherently interdisciplinary nature [13,46]. Technological advancement fundamentally stems from novel combinations of existing knowledge components [40,47,48]. This theoretical foundation suggests that innovations incorporating diverse technological elements are more likely to generate breakthrough advancements than incremental improvements [49–52].

Wind energy innovations require the integration of knowledge from multiple disciplines including mechanical engineering, materials science, meteorology, and electrical systems [13,23]. This multidisciplinary nature creates opportunities for novel knowledge combinations that can lead to significant technological breakthroughs [27,36]. For instance, the development of direct-drive wind turbines represents a breakthrough innovation that has emerged from combining electromagnetic principles with advanced materials science, eliminating the need for traditional gearbox systems and significantly improving turbine reliability [53].

Integrating diverse knowledge sources in wind energy innovation enhances the technological impact through several mechanisms [4]. First, knowledge integration enables firms to develop more comprehensive solutions to complex technological challenges [54–57]. When patents draw upon diverse technological domains, they are more likely to address multiple aspects of wind energy systems simultaneously, such as combining aerodynamic optimization with advanced control systems to enhance energy capture efficiency [58,59]. This comprehensive approach increases the likelihood of creating valuable innovations that attract attention from various technological domains [60–62].

Furthermore, technological originality facilitates the creation of novel solutions that transcend traditional technological boundaries [62,63]. In the context of wind energy, this might involve incorporating insights from aerospace engineering into blade design or applying advanced materials science to develop more durable components. Interdisciplinary innovations of this nature frequently constitute substantial technological progress, thereby attracting citations from a wider array of ensuing innovations [4]. This aligns with the findings of innovation studies, which suggest that breakthrough innovations often emerge at the intersection of different knowledge domains [49,51,64].

Technological originality is especially critical for wind energy innovation given the sector's difficulties with technological diffusion [65]. As a low-diffusion sector, wind en-

ergy technology requires significant breakthroughs to overcome existing technological limitations and achieve wider adoption [29]. Original innovations that successfully integrate diverse knowledge sources are more likely to address these challenges effectively, leading to higher citation rates and broader technological impact [66]. This is evidenced by the success of innovations that combine multiple technological domains such as smart wind farm management systems that integrate artificial intelligence, IoT technologies, and traditional wind energy engineering.

Moreover, technological originality enhances the potential for knowledge spillovers across technological domains [67–72]. When wind energy patents incorporate diverse knowledge sources, they create new technological combinations that are valuable for innovations in related fields such as other renewable energy technologies or grid integration solutions [67,73]. This broader applicability increases the likelihood of a patent being cited by subsequent innovations, thereby enhancing its technological impact. This phenomenon is particularly relevant in the renewable energy sector, where technological advances often have implications beyond their immediate application domains [44,74,75]. Therefore, we formulate the following second hypothesis:

Hypothesis 2 (H2). *Higher technological originality is positively related to technological impact*.

Based on this hypothesis, Figure 1 presents the conceptual framework underlying this study, which examines the relationship between firms' citation strategies and their technological impacts in the wind energy sector.

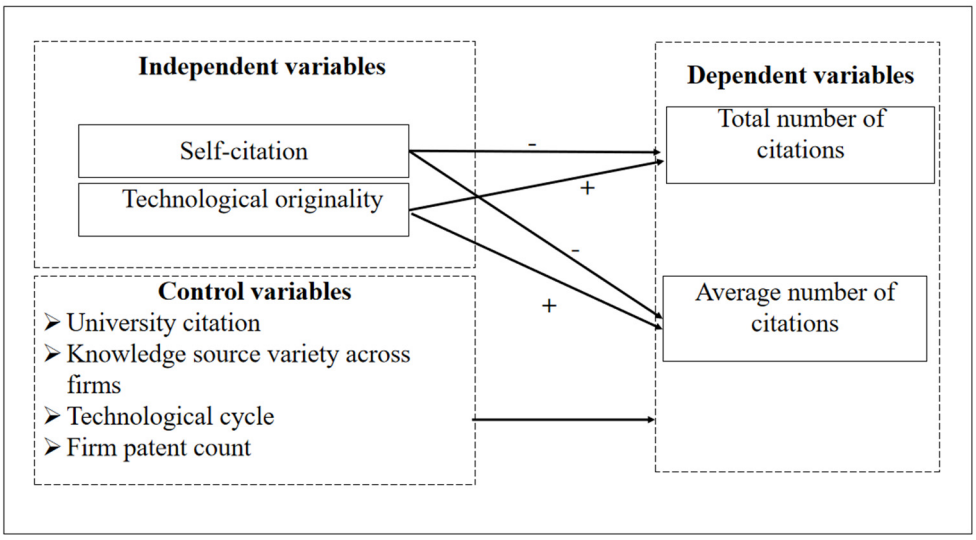


Figure 1. Conceptual framework of the study.

3. Methodology

3.1. Sample and Data

This study investigated the impact of self-citation and technological originality on wind energy technological flows. Patent data serve as a formal and standardized record of innovation, encompassing detailed information on new technological developments, inventors, and applications [76,77]. These data effectively capture the knowledge base of technological advancements, highlight their novelty and utility, and provide a reliable proxy for evaluating the impact of technological innovation. The United States Patent and Trademark Office (USPTO) serves as the primary source of patent data for this study. As one of the world's largest and most frequently referenced sources, this database is an important tool for examining technological breakthroughs and innovation tendencies. This study employed two sources of data: USPTO bulk data (https://bulkdata.uspto.gov) and

Google Patent public data on Google's cloud console (https://console.cloud.google.com). These two databases are well known and useful for academic studies.

Table 1 shows the IPC and CPC search queries used to collect the empirical data. To enhance accuracy and reduce inconsistencies, citation lag was calculated, and those with a positive time lag were selected. The assignee names for the wind energy patents were standardized. Only companies with more than 30 patents were included in the analysis to focus on the most impactful contributors to wind energy innovation. Firms that filed fewer than ten patents per year were dropped. Following the filtering process, the final dataset contained 23 companies with 5244 patents from 2010 to 2023.

Table 1. Search queries.

IPC	Field Description
B63H9	Marine propulsion provided directly by wind power (wind motors driving underwater propulsive elements B63H0013000000)
B63H13	Marine propulsion by wind motors driving water-engaging propulsive elements
B64U50/36	By wind turbines, e.g., ram air turbines (RATs)
B60L53/52	Wind-driven generators
B03B4	Separating via pneumatic tables or via pneumatic jigs
CPC	
B60K2016/006	Wind power driven
B03B4	Separating by pneumatic tables or by pneumatic jigs
B60L53/52	Wind-driven generators
B63B2209/20	Wind energy
B63H9	Marine propulsion provided directly by wind power (wind motors driving underwater propulsive elements B63H13/00)
F03D	Wind motoes
F04B17/02	Driven by wind motors
F05B2240/21	For wind turbines
F16C2360/31	Wind motors (in general F03D)
F16H2057/02078	For wind turbines
F16N2210/025	Wind turbines
F21S9/043	Driven by wind power, e.g., by wind turbines.
F21S9/026	Rechargeable using wind power, e.g., using wind turbines.
F24D2101/20	Wind turbines
F24D2200/15	Wind energy
G06F2113/06	Wind turbines or wind farms
G05B2219/2619	Wind turbines
H02J3/386	Wind energy (wind motors F03D).
H02J2300/28	The renewable source being wind energy (wind motors F03D)
H02K7/183	Wherein the turbine is a wind turbine (adaptation of a wind turbine to an electric generator F03D9/25).
H02P2101/15	For wind-driven turbines
H02S10/12	Hybrid wind–PV energy systems
Y02A20/141	Wind power
Y02B10/30	Wind power
Y02E10/70	Wind energy
Y02W10/33	Using wind energy

3.2. Variables

3.2.1. Dependent Variables

Technological impact refers to the extent to which a firm's patents contribute to its future technological development. In the wind energy sector, technological impact reflects the ability of firms to drive innovation and contribute to the broader adoption of renewable energy technologies. Given the sector's low diffusion rate and reliance on breakthrough innovations, understanding technological impact is critical for identifying strategies that enhance knowledge dissemination and innovation diffusion. We chose two distinct yet interconnected dependent variables.

Total number of forward citations for each firm (TFC): Patent forward citation counts have long been regarded as indicators of technological impacts [78,79]. The total number of forward citations received by a firm's patents represents its influence on subsequent innovation. A higher TFC indicates technological advancement. The variable is expressed in Equation (1):

$$TFC = \sum_{i=1}^{N} FC_i \quad (1)$$

where FC_i represents the number of forward citations for each patent i, N is the total number of patents granted to each company. Many forward citations have indicated that this technology is widely recognized.

Average number of citations (AC): This was measured as the average number of forward citations for each company each year. This can be expressed using Equation (2).

$$AC = \frac{TFC}{N} \quad (2)$$

This metric reduces the skewness commonly observed in citation distributions.

3.2.2. Independent Variable

Self-citation rate (SCR): Self-citation refers to instances in which a firm cites its prior patents in a subsequent innovation. This reflects the extent to which a firm builds upon its internal knowledge base rather than integrating external technological advancements, which indicates how a firm's innovative activities will contribute to future innovation [79,80]. This rate is expressed in Equation (3).

$$SCR = \frac{\sum_{i=1}^{N} \frac{SR_i}{TN_i}}{N} \quad (3)$$

where SR_i is the number of self-citations for each patent, and TN denotes the total number of backward citations.

Higher self-citation rates reflect a strong internal knowledge base and the potential for continual innovation, implying that organizations effectively utilize their accumulated knowledge and experience to drive discoveries [79,81,82]. In the wind energy sector, self-citation reflects a firm's reliance on internal knowledge. While this can foster incremental innovation, excessive self-citation may lead to knowledge lock-in, limiting external collaboration and technological diffusion. This is particularly important in a sector where interdisciplinary collaboration is essential for overcoming technological and economic barriers.

Technological originality (TO): This variable represents the extent to which a firm's knowledge base is dispersed across the technological classes. To calculate it for each patent and at the firm level, we use Equation (4).

$$TO = \sum_{i=1}^{N} \frac{1 - \sum_{t=1}^{T} \left(\frac{TCITE_t}{TN} \right)^2}{N} \quad (4)$$

where t represents the primary IPC codes, and $TCITE_t$ denotes the total number of citations to a given patent in each technological field t.

A higher TO indicates the combination of diverse technological domains. A greater distribution of IPC codes among a company's cited patents indicates greater reliance on knowledge from diverse technological domains. Originality is crucial in the wind energy sector, where integrating diverse knowledge domains (e.g., materials science, mechanical engineering, and meteorology) can lead to breakthrough innovations. High originality fosters interdisciplinary solutions, which are essential for addressing the sector's challenges, such as high capital costs and complex infrastructure requirements.

3.3. Control Variables

University Citation Rate (UCR): This variable captures the extent to which a firm cites inventions granted by universities and public research institutions. It is calculated using Equation (5).

$$UCR = \frac{\sum_{i=1}^{N} \frac{UC_i}{TN_i}}{N} \tag{5}$$

where UC_i is the number of university citations for each patent i. A higher proportion of such citations reflects a strong engagement with the scientific community [83,84]. By leveraging knowledge from academic institutions, companies gain access to novel ideas, specialized expertise, and a broader perspective on technological advancements, potentially accelerating innovation. University citations indicate engagement with cutting-edge scientific research, which can enhance innovation quality. In the wind energy sector, collaboration with academic institutions is vital for accessing novel ideas and specialized expertise, particularly in areas like advanced materials and grid integration.

Knowledge source variety across firms (KSV): This variable examines the distribution of citations among different citing firms [84]. It is calculated using a similar equation as TO; thus,

$$KSV = 1 - \frac{\sum_{i=1}^{N} \sum_{f=1}^{F} \left(\frac{FCITE_f}{TN_i}\right)^2}{N} \tag{6}$$

where f represents the patent of the citing firm, and $FCITE_f$ denotes the total number of citations by the patent of the citing firm. A higher index value suggests that firms integrate external knowledge from various sources, thereby supporting a dynamic innovation process. This is particularly relevant in the wind energy sector, where external collaboration can mitigate the risks of technological isolation and foster broader knowledge spillovers.

Technological cycle. This was calculated as the average time difference between the filing date of a focal patent and the publication date of a reference patent at the technological level. We then computed the average backward citation lag for all patents associated with a specific company over a designated period to measure the technological cycle at the firm level. It is expressed as

$$TC = \frac{\sum_{i}^{N} \sum_{j=1}^{TN} \frac{FD_i - PD_j}{TN}}{N} \tag{7}$$

where FD_i denotes the filing date of patent i, and PD_j represents the publication date of referenced patent j. A shorter technology cycle indicates that a company actively integrates cutting-edge knowledge into its R&D, demonstrating a dynamic and agile approach to innovation [78,81,85–89]. This is critical in the wind energy sector, where rapid technological progress is needed to address pressing sustainability goals.

Firm patent count (FC): It captures the scale of a firm's innovative activities as measured by the number of patents granted annually. This variable plays a crucial role in understanding the extent to which a firm's innovation size affects its technological impact.

Firms with more patent filings are likely to receive more citations because of their broader visibility within the patent landscape. Additionally, a higher patent count often indicates greater investment in research and development (R&D), which enhances a firm's capacity for innovation and increases the likelihood of producing patents with a substantial technological impact.

Certain variables, such as regional policy differences or market concentration, were excluded due to data limitations or the study's focus on firm-level innovation strategies. While these factors undoubtedly influence technological impact, the analysis prioritizes variables that directly capture firms' internal and external knowledge dynamics. Future research could incorporate these broader contextual factors to provide a more comprehensive understanding of innovation in the wind energy sector.

3.4. Econometric Modeling and Specification

While Poisson regression is commonly used for count data, it assumes that the mean and variance of the dependent variable are equal. This assumption often does not hold in real-world data, particularly in cases where overdispersion is present. This study employs a negative binomial regression (NBR) model to examine the relationship between self-citation, technological originality, and technological impact in the wind energy sector. The dependent variable, the number of forward citations received by a patent, is the count data characterized by overdispersion in the dataset and requires an appropriate regression model. The NBR model effectively addresses overdispersion, leading to more accurate coefficient estimates, standard errors, and an improved model fit. This approach enhances the reliability of hypothesis testing and the interpretation of results in econometric modeling and specification; however, our preliminary analysis revealed that the variance of forward citations was significantly greater than the mean, indicating the presence of overdispersion.

The negative binomial regression model is an extension of the Poisson model that incorporates an additional dispersion parameter, allowing for greater variance than the mean and making it better suited for handling dispersed count data. Using NBR helps avoid the underestimation of standard errors and biasing coefficient estimates, ensuring more reliable inferences. Furthermore, NBR is widely used in similar studies, particularly in analyzing count-based data such as patent citations, where overdispersion is a common issue.

3.4.1. Negative Binomial Regression Model

This study investigated the relationship between self-citation, originality, and technological impact in the field of wind energy. We focus on two primary metrics of technological advancement. The metrics under consideration exhibit the characteristics of count data, manifesting as non-negative integers. Furthermore, these metrics are distinguished by overdispersion, a statistical property in which the observed variance exceeds the expected mean. Overdispersion commonly arises in patent analysis because of the irregular nature of innovation, in which firms may exhibit bursts of self-referencing or produce original inventions at varying rates.

Standard Poisson models, which assume that the mean and variable of the count data are equal, are unsuitable for this type of data because they do not account for overdispersion. In the Poisson model, the expected total citation counts for firm i at time t is expressed as

$$E(Y_{it}|X_{it}) = \mu_{it} = exp(X_{it}\beta) \tag{8}$$

where Y_{it} is the number of cited patents; X_{it} represents the independent variables, and β is the vector of coefficients. However, Poisson models assume that $Var(Y_{it}|X_{it}) = \mu_{it}$, which does not hold in our case due to the significant variance across firms' patenting activities.

To account for overdispersion, we employ the negative binomial regression (NBR) model, which introduces a dispersion parameter that allows the variance to exceed the mean. Specifically, the NBR model assumes that the conditional variance is

$$Var(Y_{it}|X_{it}) = \mu_{it} + \alpha\mu_{it}^2 \tag{9}$$

where α is the dispersion parameter. When $\alpha > 0$, the variance accommodates the observed overdispersion in the data, making it more appropriate for analyzing the irregular and punctuated nature of innovative activities of firms.

The NBR model can be understood as a Poisson–Gamma mixture, where the mean count μ_{it} follows a Gamma distribution, providing flexibility to address the unobserved heterogeneity among firms. The probability function of the NBR is

$$P(Y_{it} = y_{it}) = \frac{\Gamma\left(y_{it} + \alpha^{-1}\right)}{\Gamma(y_{it}+1)\Gamma(\alpha^{-1})}\left(\frac{\mu_{it}}{\alpha^{-1}+\mu_{it}}\right)^{y_{it}}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu_{it}}\right)^{\alpha^{-1}} \tag{10}$$

where α^{-1} is the inverse of the dispersion parameter. The flexibility of this model allows us to capture the irregular nature of innovation better, where firms may exhibit varying levels of patenting activity over time. The gamma function $\Gamma(.)$ adjusts for the count distribution. The likelihood function for this model is

$$LnL(\beta, \alpha) = \sum_{i=1}^{N}\sum_{t=1}^{T}(-\exp(X_{it}\beta) + Y_{it}X_{it}\beta - \ln(Y_{it}!)) \tag{11}$$

Combining the counts across firms and periods, this function is maximized using maximum likelihood estimation (MLE) to estimate both the regression coefficient β and the dispersion parameter α. This approach enables a robust analysis of how factors such as the self-citation rate and technological originality influence innovation outcomes and the technological positioning of firms relative to industry leaders.

In summary, the NBR model provides a more accurate representation of the data by accommodating the overdispersion inherent in patent counts, allowing us to draw meaningful conclusions on the impact of citation strategies on firm-level innovation performance.

Building on the conceptual framework derived from the theoretical discussion, we formally specify the NBR models used to analyze the relationship between citation practices and technological impact. According to the negative binomial distribution, the expected count μ_{it} is modeled as an exponential function of the independent variables:

$$E(Y_{it}|x_{it}) = \mu_{it} = \exp(x_{it}\beta + \epsilon_{it}) \tag{12}$$

$$\log(\mu_{it}) = x_{it}\beta + \epsilon_{it} \tag{13}$$

This specification ensures that the expected count μ_{it} remains positive for all possible values of the covariates. The error term ϵ_{it} accounts for unobserved heterogeneity across firms.

3.4.2. Model Specification

The dependent variable is each firm's total number of citations per year. The independent variables include the self-citation rate and technological originality. Additionally, we control for a set of firm-level factors that have been shown to influence the dependent variable, namely, university citation (UCR_{it}), knowledge source variety across firms

(KVS_{it}), citation lag, and firm patent count (FC_{it}). The negative binomial regression model is as follows:

$$log(TFC_{it}) = \beta_0 + \beta_1 SCR_{it} + \beta_2 TO_{it} + \gamma_1 UCR_{it} + \gamma_2 KVS_{it} + \gamma_3 TC_{it} + \gamma_4 FC_{it} + \epsilon_{it} \quad (14)$$

The model specification accounts for the expected number of forward citations $log(TFC_{it})$ at year t for firm i, with coefficients β_1 and β_2 representing the effects of self-citation and technological originality, respectively. The coefficients for the control variables are represented by coefficients γ_1, γ_2, γ_3, and γ_4, respectively. ϵ_{it} is the error term accounting for unobserved heterogeneity.

We introduce Poisson regression for comparison with the negative binomial regression model in the robustness check. In addition, we used the average number of citations (AC) as the dependent variable. The regression equation is shown in Equation (15).

$$log(AC_{it}) = \beta_0 + \beta_1 SCR_{it} + \beta_2 TO_{it} + \gamma_1 UCR_{it} + \gamma_2 KVS_{it} + \gamma_3 TC_{it} + \gamma_4 FC_{it} + \epsilon_{it} \quad (15)$$

4. Results

4.1. Statistics and Description

Table 2 presents the descriptive statistics for the key variables. Firms receive an average of 149 citations per annum, although this varies significantly (0–2475 citations), highlighting the substantial disparities in their innovative contributions. The average value of AC was 3.01, with a standard deviation of 2.89. Although some firms hold highly recognized patents, others possess patents with negligible technological impact, thereby highlighting the uneven distribution of technological influence within the sector. These data reveal significant variations in technological impact across firms, highlighting the uneven distribution of recognition and valuation of wind energy innovations in subsequent inventions.

Table 2. Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
TFC	117	148.829	301.131	0	2475
AC	117	3.007	2.893	0	12.692
SCR	117	0.107	0.072	0	0.253
TO	117	0.583	0.072	0.38	0.761
UCR	117	0.021	0.016	0	0.108
KSV	117	0.793	0.053	0.536	0.919
TC	117	8.123	2.076	5.212	17.151
FC	117	44.821	42.116	10	195

The average self-citation rate of the sample is 0.107, with a standard deviation of 0.072. However, this proportion exhibits variability across firms, with certain entities exhibiting greater reliance on internal sources than others do. The maximum self-citation rate is 0.253, which reflects significant reliance on internal knowledge in some cases, and some firms do not engage in self-citation. The mean technological originality (TO) score is 0.583, with a standard deviation of 0.072. The originality scores of the dataset range from 0.761 to 0.38, indicating variation in the degree to which firms' innovations draw on diverse technological bases.

Table 3 presents the correlation matrix for the key variables. No pairwise correlation coefficients surpassed 0.7, suggesting a minimal risk of multicollinearity within the dataset.

Table 3. Correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) TFC	1							
(2) AC	0.635 *	1						
(3) SCR	0.254 *	−0.090	1					
(4) TO	0.196 *	0.309 *	−0.026	1				
(5) UCR	−0.036	−0.148	−0.004	0.012	1			
(6) KSV	−0.154	−0.098	−0.283 *	0.175	0.535 *	1		
(7) TC	0.082	0.263 *	−0.193 *	0.129	−0.108	0.131	1	
(8) FC	0.613 *	0.116	0.616 *	0.056	0.094	−0.080	−0.126	1

Notes: After Bonferroni adjustment, a star (*) is added to correlations significant at a 5% level.

4.2. Econometric Results and Analysis

Table 4 reports the results of the negative binomial regression analysis using the total number of forward citations (TFC) as the dependent variable. Column (1) includes only the control variables. Column (2) adds the independent variable self-citation to the control variables. Column (3) introduces technological originality along with the control variables. Column (4) presents all the independent and control variables. This model exhibited a chi-square value of 107.67, surpassing all other specifications and signifying optimal data congruence.

Table 4. The regression results with the number of cited patents as the dependent variable.

	(1)	(2)	(3)	(4)
SCR		−11.894 ***		−11.195 ***
		(1.779)		(1.633)
TO			5.216 ***	5.168 ***
			(1.313)	(1.209)
UCR	−11.570 *	−5.713	−9.139	−3.155
	(6.550)	(5.614)	(6.153)	(5.026)
KSV	3.138	−1.402	0.252	−2.503
	(2.384)	(1.920)	(2.235)	(1.706)
TC	0.075 **	0.033	0.069 **	0.009
	(0.035)	(0.031)	(0.034)	(0.030)
FC	0.005 *	0.016 ***	0.007 ***	0.016 ***
	(0.003)	(0.002)	(0.003)	(0.002)
_cons	−2.870	2.232	−3.619 **	0.294
	(1.786)	(1.498)	(1.543)	(1.373)
ln_r	0.585	0.193	0.757 *	0.280
	(0.416)	(0.328)	(0.438)	(0.318)
ln_s	4.132 ***	2.876 ***	4.221 ***	2.804 ***
	(0.637)	(0.510)	(0.651)	(0.478)
Chi-Squared	10.594	69.782	26.977	107.668
p-value	0.032	0.000	0.000	0.000
Log-likelihood	−646.556	−624.796	−638.196	−615.124
Observations	117	117	117	117

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A negative SCR coefficient indicates an inverse relationship between self-citation and subsequent citations. Several mechanisms can explain this phenomenon. First, prevalent self-citation suggests that innovation is largely based on a firm's established technological path, possibly signifying incremental advancements rather than groundbreaking discoveries. Furthermore, elevated self-citation rates may indicate a restricted technological focus, constraining a patent's significance and utility in diverse technological fields. Technological isolation can diminish a patent's perceived novelty, influence external inventors, and reduce the citation rates.

This shows a positive correlation between technological originality and the subsequent citation counts. This outcome can be attributed to the combination of these factors. Superior technological novelty often indicates that a patent integrates knowledge from multiple technological fields rather than relying primarily on prior inventions from a limited range of areas. Therefore, these patents are more likely to attract wider interests, resulting in increased citation counts. Second, groundbreaking innovations, as opposed to incremental improvements, are often characterized by significant technological advancements. Such patents may facilitate novel research and development avenues, thereby enhancing the citation impact. Notably, patents that demonstrate exceptional originality can enhance a firm's reputation for innovation, thereby attracting increased scrutiny from its industry counterparts and patent officials.

4.3. Robustness Check

To evaluate the robustness of our findings, we conducted two robustness checks. First, we employed the Poisson regression method. Table 5 presents the results. Second, we used an alternative dependent variable, the average number of cited patents (AC), as detailed in Table 6.

Table 5. Robustness check with Poisson regression.

	(1)	(2)	(3)	(4)
SCR		−15.691 ***		−14.443 ***
		(0.305)		(0.316)
TO			7.550 ***	4.248 ***
			(0.256)	(0.266)
UC	−22.593 ***	−8.427 ***	−13.167 ***	−4.841 ***
	(1.152)	(1.175)	(1.163)	(1.177)
KSV	−4.587 ***	−5.582 ***	−5.582 ***	−6.457 ***
	(0.340)	(0.356)	(0.343)	(0.360)
TC	0.251 ***	0.017 ***	0.218 ***	0.021 ***
	(0.005)	(0.006)	(0.005)	(0.006)
FC	0.013 ***	0.014 ***	0.014 ***	0.014 ***
	(0.000)	(0.000)	(0.000)	(0.000)
_cons	6.099 ***	10.189 ***	2.319 ***	8.028 ***
	(0.340)	(0.401)	(0.354)	(0.416)
lnalpha	−0.125	0.517 **	−0.249	0.416 *
	(0.268)	(0.249)	(0.271)	(0.252)
Chi-Squared	6372.030	8461.042	7258.121	8772.191
p-value	0.000	0.000	0.000	0.000
Log-likelihood	-4.0×10^3	-2.6×10^3	-3.6×10^3	-2.5×10^3
Observations	117	117	117	117

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Robustness check with the average number of cited patents as the dependent variable.

	(1)	(2)	(3)	(4)
SCR		−9.508 ***		−8.249 ***
		(2.297)		(2.241)
TO			4.724 ***	4.202 ***
			(1.292)	(1.443)
UCR	−11.704	−5.950	−8.587	−5.193
	(7.118)	(7.275)	(6.713)	(6.849)
KSV	0.774	−2.008	−1.422	−3.082
	(2.082)	(2.060)	(2.018)	(1.998)
TC	0.147 ***	0.084 **	0.118 ***	0.078 **
	(0.037)	(0.039)	(0.039)	(0.038)
FC	−0.001	0.005 *	0.002	0.006 **
	(0.003)	(0.003)	(0.003)	(0.003)

Table 6. *Cont.*

	(1)	(2)	(3)	(4)
_cons	−0.181	3.896 **	−1.257	1.967
	(1.587)	(1.840)	(1.467)	(1.814)
ln_r	2.178 ***	1.930 ***	3.119 **	2.181 ***
	(0.548)	(0.500)	(1.294)	(0.524)
ln_s	1.770 ***	0.774	2.822 *	1.161 *
	(0.617)	(0.513)	(1.542)	(0.596)
Chi-Squared	23.964	49.999	29.806	53.608
p-value	0.000	0.000	0.000	0.000
Log-likelihood	−248.446	−238.449	−242.391	−234.216
Observations	117	117	117	117

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The regression coefficients for self-citation and technological originality maintained their signs and statistical significance. This consistency reinforces the reliability of the original results, suggesting that the observed relationships between these variables and patent citations are stable and are not driven by model specification or variable choice.

5. Discussion

The results of our study provide significant insights into the relationship between self-citation, technological originality, and technological impact within the wind energy sector. Specifically, our findings indicate that higher self-citation rates are associated with reduced technological impacts. This suggests that while self-citation can enhance internal knowledge accumulation, it may also limit the exploration of novel technological possibilities and restrict knowledge transfer to external entities. This aligns with previous research that highlights the potential drawbacks of path dependency and incremental innovation strategies [39–42]. Path dependency often constrains firms' ability to explore alternative technological trajectories, particularly in sectors with high capital intensity and long innovation cycles such as wind energy [41,42].

The negative impact of self-citation on the technological impact can be attributed to several factors. First, high self-citation rates may indicate that firms primarily focus on optimizing existing technological trajectories, which can lead to incremental advancements rather than groundbreaking discoveries. This internal focus can limit the exploration of novel technological possibilities and reduce the likelihood of significant technological breakthroughs. Additionally, extensive self-citation may signal a lack of engagement with external knowledge sources, thereby restricting the potential for knowledge spillover and collaborative innovation [21,22]. This finding is consistent with the broader literature on innovation management, which emphasizes the importance of external knowledge acquisition in overcoming technological lock-ins and fostering radical innovation [68,70].

On the contrary, the positive coefficient for technological originality underscores the importance of integrating diverse knowledge sources to foster significant technological advancements. This result aligns with theories suggesting that breakthrough innovations often emerge from a combination of disparate technological elements [47,49,50,68]. In the context of wind energy, original innovations that transcend traditional technological boundaries are more likely to attract citations and achieve broader technological impacts. For instance, the development of floating offshore wind platforms, which integrate knowledge from marine engineering, materials science, and renewable energy systems, exemplifies how interdisciplinary approaches can lead to transformative innovation [4,13]. By integrating knowledge from multiple technological domains, firms can develop robust and versatile solutions that are likely to attract wider interest and recognition. Furthermore, original

innovations often create new technological pathways, facilitating further advancements and enhancing overall technological impact [4].

This study also contributes to the theoretical understanding of innovation dynamics in low-diffusion sectors. The findings suggest that self-citation, while beneficial for reinforcing internal knowledge bases, may inadvertently hinder a firm's ability to engage with external knowledge networks and explore novel technological opportunities. This aligns with the concept of "exploration versus exploitation" in organizational learning, where excessive focus on exploitation can limit the capacity for exploration and radical innovation [54]. By contrast, the positive relationship between technological originality and technological impact highlights the value of knowledge diversity and interdisciplinary collaboration in overcoming these limitations. This finding is consistent with the knowledge recombination perspective, which posits that integrating diverse knowledge elements can lead to the creation of novel and impactful innovations [51].

Furthermore, the broader implications of these findings extend to other low-diffusion sectors such as marine energy and advanced nuclear technologies [74]. Similar to the wind energy sector, these industries face significant barriers to technological dissemination owing to high capital costs, complex technological demands, and market concentration [13,15]. The negative impact of self-citation and the positive influence of technological originality observed in this study suggest that firms in these sectors may benefit from strategies that prioritize knowledge diversity and interdisciplinary collaboration. For example, the integration of knowledge from adjacent fields such as materials science and artificial intelligence could facilitate the development of innovative solutions to address the unique challenges faced by these industries.

In addition to internal dynamics such as self-citation and knowledge lock-in, external influences, including governmental policies and market forces, play a critical role in shaping technological originality and impact [90]. For instance, government subsidies and regulatory frameworks can incentivize firms to pursue breakthrough innovations, while market competition and demand fluctuations may drive firms to adapt and integrate external advancements. A comprehensive framework that incorporates both internal and external dynamics provides a more holistic understanding of the factors influencing innovation in the wind energy sector.

By situating these findings within the broader theoretical and empirical literature, this study contributes to a deeper understanding of the complex interplay among self-citation, technological originality, and technological impact. This underscores the importance of balancing internal knowledge accumulation with external knowledge engagement to foster impactful innovation, particularly in sectors characterized by low technological diffusion.

6. Conclusions, Policy Recommendations, and Limitations

6.1. Conclusions and Policy Recommendations

Addressing climate change and transitioning to sustainable energy systems are among the most pressing global challenges driving increasing attention to low-diffusion energy technologies. This study investigates the role of self-citation and technological originality on the technological impact within the wind energy sector, a field characterized by low technological diffusion but a high potential for sustainable energy solutions. The analysis reveals that self-citation has a negative effect on technological impact. Technological originality has a positive effect on technological impact.

Based on these findings, several targeted policy recommendations have been proposed to enhance the technological diffusion and innovation impact in the wind energy sector and other low-diffusion energy industries. First, policymakers should foster collaboration among firms, universities, and research institutions to encourage knowledge exchange

and interdisciplinary innovation. For instance, establishing innovation hubs and research alliances, such as those seen in Denmark's wind energy sector, can serve as effective models. Public–private partnerships and shared R&D facilities can reduce reliance on internal knowledge and mitigate the negative effects of self-citation, while joint patent development platforms can further facilitate the dissemination of knowledge and accelerate breakthrough innovations. Second, financial incentives, such as grants, subsidies, and tax credits, should prioritize high-risk, high-reward research projects that emphasize technological originality. For example, supporting cross-sector R&D initiatives in offshore wind technologies or hybrid renewable systems can nurture startups and small firms working on disruptive innovations, thereby increasing the diversity of technological solutions in the wind energy sector. Third, promoting international cooperation is essential to accelerate the global diffusion of wind energy technologies. Harmonizing technical standards and intellectual property regulations across major patent offices can reduce barriers to adoption and facilitate cross-border licensing agreements. International knowledge-sharing platforms, such as the International Renewable Energy Agency (IRENA), and collaborative R&D programs can further enhance the dissemination of wind energy innovations, particularly in developing countries where adoption rates remain low. Finally, aligning R&D funding with net-zero emission targets is critical for ensuring that public investments prioritize technologies with high originality and diffusion potential. Subsidies should focus on projects that contribute significantly to decarbonization efforts, such as offshore wind technologies and hybrid renewable energy systems. By integrating these targeted measures, policymakers and industry stakeholders can address the structural challenges faced by the wind energy sector, enhance technological diffusion, and accelerate the transition toward sustainable energy systems. These recommendations also provide a framework for fostering innovation in other low-diffusion energy sectors, such as hydrogen and marine energy, where similar challenges and opportunities exist.

6.2. Limitations and Future Research Direction

This study had several limitations that should be addressed in future research. First, the reliance on patent data, while a widely used and valuable source for analyzing technological innovation, may introduce biases related to the quality and scope of patent filings. For instance, not all innovations are patented, and the significance of patents can vary across industries and regions. Future studies could complement patent analyses with alternative indicators of technological impact, such as scientific publications, industry reports, and expert surveys, to provide a more comprehensive understanding of innovation dynamics.

Second, this study focuses exclusively on the wind energy sector, which may limit the generalizability of the findings to other low-diffusion sectors. Future research could extend this analysis to other renewable energy technologies, such as nuclear energy, hydrogen energy, and solar photovoltaics, to identify common patterns and sector-specific differences. Comparative studies across these sectors could provide deeper insights into how self-citation and technological originality influence innovation in various technological and market contexts.

Third, this study does not consider regional differences in technological diffusion and innovation strategies. Regional innovation ecosystems, policy environments, and cultural factors can significantly influence the relationships between self-citation, technological originality, and technological impact. Future research could explore these regional variations to better understand how local contexts influence innovation outcomes and the diffusion of renewable energy technologies.

In addition, future studies could adopt advanced patent analysis methods to enhance the robustness of the findings. For example, a main path analysis can be employed to trace

the evolution of key technological trajectories and identify critical innovations within the wind energy sector and beyond. Such methods can provide a more nuanced understanding of how knowledge flows and accumulates over time.

In conclusion, this study highlights the critical roles of self-citation and technological originality in determining the technological impact within the low-diffusion wind energy sector. By fostering knowledge diversity and reducing reliance on internal knowledge, firms can enhance their capacity for groundbreaking innovations and accelerate the diffusion of new technologies. Future research should address the limitations identified in this study, explore the broader implications of these findings for other renewable energy sectors, and leverage advanced analytical methods to deepen our understanding of the innovation dynamics in low-diffusion industries.

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