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ABSTRACT

This paper analyses and compares the morphology of knowledge spillover networks based on green versus non-green technologies to assess whether one of the two domains diffuses more widely, travels farther in the geographical space, and connects more extensively otherwise distant technological fields. We employ various metrics based on forward citations to measure knowledge spillovers from patented technologies. Our sample includes bibliometric data of 3,809,214 patent applications filed at the European Patent Office from 1981 to 2020, of which 316,897 (8.32%) are classified as green. Results show that green patents receive more citations – both directly and indirectly – from follow-on inventions than non-green ones, thus contributing to a greater knowledge diffusion throughout the entire spillover network. We also find that the spectrum of sectors to which a green knowledge spillover network is targeted tends to be broader. Lastly, the inherent nature of green technologies, along with their potential to act as boundary spanners, results in knowledge transmission within the green do-main being less geographically localized than for non-green technologies.

1. Introduction

Green innovation, which is increasingly at the centre of policy action, is seen as a crucial means to pursue sustainable development and offset the negative externalities resulting from the polluting outputs of production processes (De Marchi, 2012).[1] Several works have focused on discussing how policy interventions can contribute to the generation, adoption, and diffusion of green technologies (Acemoglu et al., 2012; Fischer and Newell, 2008; Hoppmann et al., 2013).

A comprehensive analysis of how public intervention can generate long-term societal value through the promotion of green innovation requires examining how such knowledge is created and the mechanisms through which knowledge spillovers from green technologies (i.e., both direct and indirect) disseminate (Martin and Verhoeven, 2022). Knowledge spillovers constitute a subset of knowledge flows: they occur when knowledge is transmitted in ways that are non-contractual, unpriced, and not fully appropriable by the original creator. As they generate unintentional benefits for third parties, spillovers represent important externalities and provide a rationale for public intervention.

Knowledge spillovers are critical drivers of technological advancement, as they enable subsequent inventions and may lead firms to pursue open innovation strategies in rapidly evolving and knowledge-intensive sectors. By absorbing external knowledge through spillover channels, firms strengthen their innovative capacity and facilitate the exchange and recombination of ideas across organizational boundaries (Bogers et al., 2020; Chesbrough and Di Minin, 2014; Schoenmakers and Duysters, 2010; Collevecchio et al., 2024).

The study of knowledge spillovers from technologies is therefore crucial for understanding the broader impact of green innovation, as they play a dual role. On the one hand, they amplify the impact of core technological solutions in sustainable development, thereby defining the path of green innovation knowledge diffusion (Zhang et al., 2023). On the other hand, as positive externalities, they create a misalignment between public and private incentives, reflecting a market failure that justifies the implementation of corrective policy measures. Within the more general process of knowledge diffusion, knowledge spillovers constitute unintentional but measurable mechanisms through which knowledge is transmitted across actors, regions, or technological fields.

A long-standing academic tradition has exploited forward patent citations (i.e., citations by follow-on patents over time) as an empirical

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[1] While acknowledging that no technology is perfectly clean, in line with Jee and Srivastav (2024), we define “green technologies” as those developed with the aim of mitigating greenhouse gas emissions, as opposed to “non-green technologies” that instead contribute to such emissions.

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proxy to measure knowledge spillovers from technologies. These citations provide observable evidence of how knowledge generated by one invention is used in subsequent innovations, thereby making knowledge spillovers measurable. The seminal works of Griliches (1990), Jaffe et al. (1993), and Trajtenberg (1990) initiated a research strand that has since flourished, offering both rich theoretical discussions (see Jaffe and De Rassenfosse, 2017, for a review) and empirical confirmations (among the most recent studies, see Arora et al., 2018; Corsino et al., 2019; Kuhn et al., 2020). Patent citations are considered not only a key metric for measuring the economic value of innovation, since high-quality technologies tend to be cited more often (Griliches, 1990; Trajtenberg, 1990), but also a reliable indicator of the transfer of knowledge from the cited to the citing invention. In other words, citation links identify the antecedents on which an invention is built, or the background knowledge that is relevant to it.

The transmission of knowledge as evidenced by patent citations has been the focus of extensive research aimed at understanding the underlying mechanisms that contribute to the formation and success of regional innovation clusters (Audretsch, 1998). Patent citations have been employed in many works to map the diffusion of knowledge through knowledge spillovers across geographical boundaries and technological fields (Bacchiocchi and Montobbio, 2010; Bottazzi and Peri, 2003; Breschi and Lissoni, 2009; Criscuolo and Verspagen, 2008; Jaffe et al., 1993; Peri, 2005). Collectively, this body of work shows that knowledge spillovers can extend beyond local clusters, depending on the technological characteristics of innovations, the frequency of contact between the parties involved, and the absorptive capacities of the receivers.

Building on this literature, various arguments – ranging from the specific nature of the externalities involved to the novelty and complexity of the technologies themselves – suggest that green and non-green technologies may rely on distinct mechanisms of knowledge diffusion (Barbieri et al., 2020; De Marchi, 2012; Horbach, 2008; Popp and Newell, 2012). In particular, green technologies exhibit higher levels of complexity and novelty, which affects their greater spillover potential and the channels through which such knowledge spillovers materialize. Moreover, their common value proposition and the inherent nature of the externalities they generate often require broader technological complementarities and more extensive collaboration networks. Finally, because the development of green technologies is closely intertwined with public policy, regulatory changes, and geopolitical conditions, the associated spillovers are especially sensitive to institutional contexts, policy dynamics, and the spatial unevenness of innovation investments.

While empirical studies have extensively investigated the production of green knowledge (see Section 2.1), research on the diffusion, structural characteristics, technological pathways, and spatial dynamics of knowledge spillovers from green technologies remains limited. In particular, the extant literature has yet to determine whether the distinctive features of green technologies (i.e., greater novelty and complexity, stronger externalities, and closer ties to public policy) translate into specific patterns of knowledge transfer, including whether such diffusion occurs along technologically closer or more distant trajectories, whether spillovers are more pervasive or more technologically cohesive, and whether they extend more broadly across the geographical space and serve as boundary spanners than those originating from non-green inventions. Consistent with the previous discussion, we use patent citations as a privileged empirical tool for tracing both direct and indirect knowledge spillovers.

Our contribution to the existing literature is twofold. First, we contribute to the body of research that offers insights into characterizing the green knowledge base (Aghion et al., 2016; Aldieri et al., 2020; De Marchi, 2012; Montresor and Quatraro, 2019) and to the works that examine the ex-post impact of green technologies (Barbieri et al., 2020; Dechezleprêtre et al., 2014; Jee and Srivastav, 2024; Popp and Newell, 2012). These papers have found that the novelty and the emerging nature of green technologies induce larger spillover effects on subsequent inventions compared to non-green technologies. However, previous studies have mainly focused on a limited number of technology fields (e.g., energy, transport), while our approach is more comprehensive and takes into account the full spectrum of green domains, as in Barbieri et al. (2020).

Second, we provide finer-grained evidence on knowledge spillovers from green inventions. Using widely accepted measures of technological distance, we map the technological proximity of green inventions with citing patents in the knowledge space and dig deeper into their pervasiveness at sectoral level. We are also interested in whether knowledge from green inventions flows more easily over long geographical distances than over short ones compared to non-green inventions. In addition, our contribution offers a foundation for advancing the field of open innovation (Bogers et al., 2020; Chesbrough and Di Minin, 2014; Collevecchio et al., 2024) to explore how firms that access external knowledge via spillover channels can enhance their innovative capacity and facilitate the exchange and recombination of ideas across organizational boundaries.

The results of our empirical analysis reveal that green patents are not only associated with a higher number of forward citations, but they also contribute to a greater knowledge diffusion throughout the entire knowledge spillover network. Furthermore, our findings suggest that the range of industries targeted by green knowledge spillover networks is broader. Lastly, the inherent nature of green technologies, along with their potential to serve as boundary spanners, results in knowledge transmission within the green domain being less geographically localized than for non-green technologies.

The remainder of the paper is organised as follows. Section 2 puts forward some testable hypotheses in the context of prior research. Section 3 describes the sample and the main variables employed for the empirical analysis. Section 4 presents the model and the econometric specification, whereas the results of the estimations are discussed in Section 5. Section 6 provides some concluding observations.

2. Theory

2.1. Background literature

A long-standing tradition in the economics of innovation and technological change, rooted in earlier studies (Usher, 1954), has seen technological innovation as the result of knowledge recombination and transfer processes. The inherent nature of knowledge as a public good implies that an inventor's original idea can become prior art for new technologies developed by other firms, potentially affecting other sectors or technological domains. Knowledge from an invention can spill over to other inventions, technologically close or distant, within the same field or to unrelated ones, giving rise to intra-technology, inter-technology, and external-technology spillovers. This flow of knowledge from one invention to another helps trigger future technological developments (Schoenmakers and Duysters, 2010) and may also incentivize firms to engage in open innovation strategies, particularly in fast-evolving and knowledge-intensive technological domains (Collevecchio et al., 2024). By leveraging external knowledge through spillover channels, firms can enhance their innovative capacity and facilitate the exchange and recombination of ideas across organizational boundaries, thereby establishing knowledge spillovers as key mechanisms within open innovation dynamics (Bogers et al., 2020; Chesbrough and Di Minin, 2014).

A well-established literature has shown how patent citations can be considered a meaningful indicator of the “learning trail” from one inventor to another in knowledge transfer processes. The usefulness of patent citation networks in mapping and exploring knowledge spillovers as a subset of knowledge flows has been recognized in numerous studies (Corsino et al., 2019; Jaffe et al., 1993, 2000; Lanjouw and Schankerman, 2004; Trajtenberg, 1990).

Knowledge generation and learning processes derived from existing technologies serve as an interpretive framework for identifying geographically or technologically bounded or unbounded knowledge spillover networks. The potential for knowledge spillovers to drive the development of innovation and shape knowledge spillover networks (potentially transcending geographical boundaries) is in fact largely acknowledged. The generation and transmission of knowledge form the foundation around which innovation systems develop. These systems play a key role in advancing core technological solutions. As complex adaptive systems – constantly evolving in response to ongoing challenges and uncertainties (Neto et al., 2024) – a growing body of literature has examined how their existence and structure are shaped by the pathways of knowledge diffusion (Adner and Kapoor, 2010; Granstrand and Holgersson, 2020).

The broader and more diverse combination of technological knowledge that characterizes more complex or novel technologies, such as green technologies, is likely to generate larger spillover effects (Schoenmakers and Duysters, 2010). Coming to the comparison of green versus non-green technologies, previous studies – often focused on specific sectors – have found that the former generally give rise to more densely interconnected knowledge spillover networks. Using citation data for renewable technology patents filed at 18 patent offices of EU member states from 1978 to 2006, Noailly and Shestalova (2017) report that renewable energy technology sectors generate more spillovers than fossil fuel power generation sectors, thereby advocating for larger cleantech R&D subsidies. More in general, Popp and Newell (2012) and Dechezleprêtre et al. (2014) have found that green technologies exhibit more knowledge spillovers than other technologies, providing a rationale for policy intervention in favour of environmentally friendly innovations. Dechezleprêtre et al. (2014) and then Martin et al. (2020) and Guillard et al. (2021) also show that there are significant differences in spillover rates between different clean technology types and different countries.

Empirical evidence has also shown limited knowledge spillovers between green and non-green technologies, suggesting that they do not share significant overlaps in their knowledge bases (Aghion et al., 2016; Dugoua and Gerarden, 2023; Jee and Srivastav, 2024). For example, Jee and Srivastav (2024), using USPTO patent citations between 1976 and 2020, find that less than one-tenth of green technologies directly cite non-green ones, while most are indirectly linked to them via intermediate patents.

Finally, the propensity of firms to innovate in clean technologies appears to be especially stimulated by their own history of clean innovations (Aghion et al., 2016). In other words, path dependence in the direction of technical change seems more pronounced in green technologies.[2]

In support of this empirical evidence, the literature suggests some conceptual reasons to explain them.

First, the novelty and the greater complexity associated with the emerging nature of green technologies makes them more likely to be breakthroughs. Popp and Newell (2012), and then Barbieri et al. (2020) have demonstrated the impact of ex-ante characteristics of knowledge recombination on the spillover potential of green technologies and explained how their greater impact on subsequent technological developments depends on their degree of complexity and novelty.

Secondly, green innovations are considered to be different from other innovations in terms of their common value proposition and the character of the externalities they produce, as their systemic and complex nature. This implies a wider diffusion and the activation of wider R&D cooperation with external partners (De Marchi, 2012; Horbach, 2008). Common values and an intrinsic higher propensity to cooperation might explain a stronger path dependence and the more connected spillover network.

Third, there is a more subtle and endogenous effect connecting green innovations and public interventions. Innovation in clean technologies is a typical case of 'directed technical change' à la Acemoglu (2002), i.e., not neutral, since the direction of innovation is largely driven by some factors of production more than others, and here the direction is often clearly 'directed' by policy intervention. Acemoglu et al. (2012) and Gans (2012) study models in which a (carbon) tax increases innovation in clean energy-augmenting technologies. This suggests that green innovation is particularly sensitive to economic policy uncertainty and geopolitical risk (Attílio, 2025), which may account for the temporal and spatial clustering of innovation investments. Such clustering can, in turn, lead innovation trajectories of firms to be more influenced by local knowledge spillovers (stronger path dependence) and to create stronger incentives for cooperation aimed at diversifying and pooling these risks.

2.2. Research hypotheses

Prior research has found that green patents generate more knowledge spillovers (i.e., receive more citations from subsequent inventions) than non-green ones. The theoretical mechanism underlying this observed pattern rests on the role of green technologies in addressing large-scale environmental problems, which creates strong incentives for their broad diffusion and adaptation across sectors. Because green inventions often build on general-purpose technologies and they can be applied in different technological and industrial domains, their associated knowledge is more widely transferable and becomes foundational for a broader range of downstream inventive activities. Since the most frequently cited patents are indicative of their greater relevance and thus their greater value to society (Lanjouw and Schankerman, 2004; Malerba et al., 2013; Maurseth and Verspagen, 2002; Schoenmakers and Duysters, 2010), it is widely maintained that green patents establish prior art, thereby expanding the scope of future innovative activity. However, simply counting direct spillovers using conventional forward-citation-based indicators does not fully capture this broader diffusion mechanism. Green technologies generate both direct and indirect spillovers, jointly shaping the overall structure and dynamics of knowledge diffusion.

In this context, our analysis examines if green innovations generate more spillovers than non-green ones, considering not only direct citations but also their overall contribution to the structure of the spillover network. This is operationalised using the novel indicator described in Paragraph 3.1.2, which more precisely measures this dimension of patent importance. The following hypothesis is therefore proposed:

H1. Green patents receive more citations – both directly and indirectly – from follow-on inventions than non-green patents.

The notion that green innovation generates larger and denser spillover networks aligns with a view of innovation as more complex and less incremental, grounded in globally shared values, and often shaped by public policies of varying degrees of localization. This framework is expected to foster greater cooperation among innovators. These characteristics are likely to produce distinctive spillover network structures and to shape unique forms of investment path dependence. However, the structure of green knowledge spillover networks and the specific patterns of path dependence remain underexplored in the literature. Moreover, conceptual predictions do not readily translate into empirical ones. In this vein, the following three research hypotheses aim to elucidate how the spillover network for green technologies develops.

Previous research has also investigated the source of knowledge spillovers by developing metrics to capture the "close or distant" nature of technological knowledge to reflect how technologically similar the patents linked by a citation are (Jaffe and De Rassenfosse, 2017;

[2] Consistently, Montresor and Quatraro (2019) find that specialization of European regions in new green technologies can be driven by previous related knowledge, both green and non-green. However, the grade of relatedness of pre-existing knowledge is less binding for non-green than for green knowledge, thus suggesting a higher need of cognitive proximity for green specialization.

Trajtenberg et al., 1997). Several authors have argued that greater knowledge spillovers are generated by innovations that are closer to a particular technology field, due to the benefits that may arise when learning from "near" prior art compared to "distant" ones, reflecting the cumulative nature of knowledge within a particular technological trajectory (Cohen and Levinthal, 1990; Dosi, 1982; Nemet and Johnson, 2012).

Since the cost of searching the knowledge space is high – especially when dealing with more complex technologies – understanding what is cognitively closer amplifies the recombinant possibilities generated by innovation. The systemic and complex nature of green technologies implies that knowledge spillovers originating from them are more effectively absorbed from subsequent innovations within same or closer technological trajectories. Put differently, consistent with the assonant evidence reported by Montresor and Quatraro (2019) showing greater cognitive compactness in green innovations, the processes of identifying, assimilating, and exploiting knowledge spillovers are expected to occur along technologically closer trajectories for green innovations than for their non-green counterparts. This argument leads to the following hypothesis:

H2. Green patents are cited by patents that are more technologically similar (closer in the technology space) than non-green patents.

The concept of pervasiveness of a technology refers to the variety of applications or sectors it affects. We argue that the knowledge that spills over from green patents to general innovation can target a broader set of sectors, serving as building blocks for complementary innovations across different domains (Ardito et al., 2016; Barbieri et al., 2020). This stems from the systemic and transformational nature of green technologies.

Previous research in the energy domain has explored whether knowledge generated by green energy innovation diffuses into a broad or narrow range of technological applications. Noailly and Shestalova (2017) report mixed evidence across energy technologies: a substantial share of innovations in solar energy and storage find applications beyond the power generation sector, whereas innovations in wind technologies tend to remain more sector-specific.

The systemic and complex character of green innovations makes them relevant to several challenges, allowing inventors in different technology areas to reuse or build upon this knowledge. In other words, green knowledge is likely to spill over to a broader set of domains because its combinatorial features make it more transferable and applicable across fields than knowledge from non-green patents.

The assumption that knowledge from green patents tends to spill over to a wider range of sectors with a broader set of applications than non-green technologies, leads to the following hypothesis:

H3. Green patents are cited by patents that are linked with a more diversified (less concentrated) set of domains than non-green patents.

Also note that the technological features of green patents may give rise to a specific configuration of knowledge spillovers, whereby the sectors that benefit from such externalities are simultaneously diverse and technologically close to the focal invention. Put differently, while green patents may exert their influence across a wide range of technological domains (i.e., high generality), these fields may be located within a relatively compact area of the knowledge space (i.e., higher technological proximity). Such a pattern could stem from the systemic nature of green innovations, which require the integration of complementary technologies and coordinated efforts by firms operating across related industrial domains. As a result, green knowledge spillovers may not only be more pervasive but also more technologically cohesive than those originating from non-green inventions.

The geographic localization of knowledge spillovers has been explained by the higher absorptive capacity of co-located actors with similar and complementary competencies (Audretsch, 1998). If such a spatial concentration effect actually exists and synergies arise from physical co-location, knowledge will then accumulate within a geographical area and the resulting spillovers may be confined within its limits, leading to a clustering of innovation activities. In summary, a well-established body of research consistently shows that patent citations decline sharply with distance (Almeida and Kogut, 1999; Audretsch and Feldman, 2004; Henderson et al., 2005; Peri, 2005; Alcacer and Gittelman, 2006; Thompson, 2006; Agrawal et al., 2008; Belenzon and Schankerman, 2013; Singh and Marx, 2013; Murata et al., 2014) and that the effects of distance do not diminish over time.

This traditional, place-based view of knowledge spillovers is expected to hold true even for green innovations, as evidenced, for example, by Corradini (2019) and Quatraro and Scandura (2019). However, it is unclear whether geographical distance and borders impose weaker or stronger constraints on knowledge transmission for green than for non-green technologies. One might argue for green innovations that policy shocks, on the one hand, encourage more local cooperation, thereby making knowledge exchanges more delimited, while, on the other hand, complexity, risk-pooling needs, and the global diffusion of sustainability values tend to produce less localized knowledge spillovers.[3]

The economic literature has yet to provide a definitive conclusion regarding the geographic extension of knowledge networks in the green domain and their potential to act as boundary spanners compared to non-green sectors. Consequently, we leave the validation of the following hypothesis to empirical analysis:

H4. Green patents are cited by patents that are developed by more geographically distant innovators than non-green patents.

3. Data

We exploit data from the Worldwide Patent Statistical Database (PATSTAT).[4] Patents are categorized as either green or non-green based on the Cooperative Patent Classification (CPC).[5] In doing so, we rely on prior work conducted by the EPO and the USPTO, which have recently developed a patent classification system for "*Technologies related to climate change mitigation and adaptation*" (for more details on how this system was developed, see Veefkind et al., 2012).

Our final sample includes bibliometric information of 3,809,214 patent applications filed at the EPO in the four decades between 1981 and 2020, of which 316,897 (8.32%) are classified as green technologies. Table 1 and Table 2 provide a breakdown of the patents in our sample by application year and origin country, also distinguishing between green and non-green patents.

Green and non-green patents exhibit notable differences in application year and origin country. Regarding the temporal distribution, green patents are more recent, since almost half of them (47.66%) were filed at the patent office after 2010, while the same percentage for non-green patents drops to 33.78%, as confirmed by the chi-square test (significant at the 1% confidence level). Regarding the geographical

[3] Aghion et al. (2016), for example, in the auto industry find that "*a firm's propensity to innovate in clean technologies appears to be stimulated by its own past history of clean innovations (and vice versa for dirty technologies). […] Our [further] finding is that a firm's direction of innovation is affected by local knowledge spillovers. We measure this using the geographical location of its inventors. More specifically, a firm is more likely to innovate in clean technologies if its inventors are located in countries where other firms have been undertaking more clean innovations (and vice versa for dirty technologies)*" (p. 3).

[4] This repository is managed by the EPO and contains more than 100 million patent documents from 90 different patent issuing authorities.

[5] We classify patents as green when they bear one or more CPC subclasses in "Y02". This choice facilitates replication and comparability with the recent literature. Prior studies have also relied on the Green Inventory developed by the Committee of Experts of the International Patent Classification Union or hybrid approaches that are based on semantic and classification searches.

Table 1
Patents by application year and green domain.

Sample	Green patents		Non-green patents		All patents	
Application year	Count	Percent	Count	Percent	Count	Percent
From 1981 to 1990	20,661	6.52	404,050	11.57	424,711	11.15
From 1991 to 2000	41,605	13.13	719,924	20.61	761,529	19.99
From 2001 to 2010	103,588	32.69	1,188,587	34.03	1,292,175	33.92
From 2011 to 2020	151,043	47.66	1,179,756	33.78	1,330,799	34.94
Total	**316,897**	**100.00**	**3,492,317**	**100.00**	**3,809,214**	**100.00**

Table 2
Patents by top origin country and green domain.

Sample	Green patents		Non-green patents		All patents	
Origin country	Count	Percent	Count	Percent	Count	Percent
United States	83,801	26.53	987,286	28.37	1,071,087	28.22
Germany	57,152	18.09	667,089	19.17	724,241	19.08
Japan	59,814	18.93	561,703	16.14	621,517	16.37
France	22,923	7.26	257,513	7.40	280,436	7.39
United Kingdom	15,233	4.82	191,073	5.49	206,306	5.44
Italy	8,601	2.72	128,408	3.69	137,009	3.61
Switzerland	7,123	2.25	108,904	3.13	116,027	3.06
Netherlands	7,626	2.41	103,275	2.97	110,901	2.92
South Korea	14,455	4.58	92,765	2.67	107,220	2.82
China	9,049	2.86	89,517	2.57	98,566	2.60
Sweden	6,635	2.10	77,844	2.24	84,479	2.23
Canada	6,289	1.99	59,333	1.71	65,622	1.73
Austria	4,929	1.56	48,643	1.40	53,572	1.41
Belgium	4,349	1.38	48,128	1.38	52,477	1.38
Finland	3,133	0.99	37,213	1.07	40,346	1.06
Spain	3,783	1.20	33,403	0.96	37,186	0.98
Denmark	5,588	1.77	30,559	0.88	36,147	0.95
Israel	2,209	0.70	31,252	0.90	33,461	0.88
Australia	2,783	0.88	28,307	0.81	31,090	0.82
Taiwan	2,175	0.69	23,976	0.69	26,151	0.69
Others	8,577	2.71	89,246	2.56	97,823	2.57
Missing	4,280	1.35	40,488	1.16	44,768	1.18
Total	**316,897**	**100.00**	**3,492,317**	**100.00**	**3,809,214**	**100.00**

The residual category includes Bulgaria, Croatia, Cyprus, Czechia, Estonia, Greece, Hungary, India, Ireland, Latvia, Lithuania, Luxembourg, Malta, Norway, Poland, Portugal, Romania, Slovakia, and Slovenia.

distribution, several countries show a higher propensity to develop green inventions than non-green ones (e.g., Denmark, South Korea, Japan, or Spain) while others show the opposite (e.g., Switzerland, Italy, Israel, or Netherlands). The list of patent classifications used to identify green and non-green inventions is shown in Table 3. The most represented categories in green patents are: "*Technologies related to energy generation, transmission or distribution*" (37.79%), "*Technologies related to the production or processing of goods*" (23.62%), and "*Technologies related to transportation*" (22.94%).

Table 3
Patents by green subdomain.

Green subdomain	Count	Share on green	Share on sample
Adaptation to climate change (Y02A)	34,336	10.84	0.90
Buildings (Y02B)	31,602	9.97	0.83
Capture, storage, sequestration or disposal of greenhouse gases (Y02C)	4,648	1.47	0.12
ICT aiming at the reduction of their own energy use (Y02D)	20,041	6.32	0.53
Energy generation, transmission or distribution (Y02E)	119,771	37.79	3.14
Production or processing of goods (Y02P)	74,843	23.62	1.96
Transportation (Y02T)	72,683	22.94	1.91
Wastewater treatment or waste management (Y02W)	16,932	5.34	0.44
Total	**316,897**	**100.00**	**8.32**

Patents may be associated to more than one green subdomain; they are on average linked to 1.19 fields (17.67% of them report multiple technological areas in Y02).

3.1. Knowledge spillover measures

This study compares the knowledge spillovers generated by green and non-green innovations. To this end, we proxy the intensity of knowledge externalities with several alternative measures, which are described in the following sub-sections.

3.1.1. Received citations

We first measure knowledge spillovers by means of citations that are reported in patent documents. A well-established literature argues that patent citations witness the presence of knowledge spillovers or a form of "learning trail" among inventors. Since we are interested in where knowledge from green technologies flows to, we focus on forward citations, i.e., the references made over time by subsequent patents, which reflect the knowledge spillover from a patent to follow-on inventions. As Griliches (1990) describes them, patent citations are "pure knowledge spillovers".

Patent citations address the legal requirement to define the scope of an inventor's claim to novelty, serving as a connection to the pre-existing knowledge that the invention builds upon. Essentially, a citation implies that the information in the referenced document has contributed to the development of the new invention, thus representing a flow of knowledge (Collins and Wyatt, 1988). For all these reasons, a long-standing tradition has used patent forward citations to measure knowledge spillovers from technologies (Arora et al., 2018; Corsino et al., 2019;

Table 4
Received citations by green domain.

Green patents	Count	Mean	Median	SD	Min	Max
Count of received citations	81,684	2.927	2.000	6.819	1.000	758.000
Count of received citations after ten years	52,960	2.675	2.000	3.129	1.000	246.000
Count of received citations after five years	51,506	2.034	1.000	1.998	1.000	91.000
Count of received citations after three years	35,781	1.657	1.000	1.418	1.000	79.000
Non-green patents	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Count of received citations	959,445	2.834	2.000	5.558	1.000	1,414.000
Count of received citations after ten years	707,762	2.431	2.000	2.605	1.000	259.000
Count of received citations after five years	583,086	1.955	1.000	1.874	1.000	104.000
Count of received citations after three years	395,797	1.642	1.000	1.390	1.000	82.000

Jaffe et al., 1993, 2000; Lanjouw and Schankerman, 2004; Trajtenberg, 1990).

In our dataset, 1,041,129 patents (27.33% of the total sample) receive at least one citation.[6] The percentage of cited patents is lower for green patents (25.78%) than for non-green ones (27.47%). This slight difference according to the chi-square test (significant at the 1% confidence level) suggests that green patents have a lower probability to be cited than non-green ones.[7]

In Table 4, we show the average values of forward citations for cited patents by disentangling between green and non-green patents. According to Table 4, cited green patents obtain an average of 2.927 references over their lifetime, while non-green ones receive slightly less, averaging 2.834 citations (−3.18%). Table 5 shows the result of the univariate analysis comparing the difference in mean received citations. The difference in mean received citations by green and non-green patents is statistically significant at the 1% confidence level.

However, a major issue with this straightforward comparison is that green patents had less time to accumulate citations because they are generally newer. On average, green and non-green patents are respectively 16.792 and 19.935 years old (with median values of 14.510 and 18.685 years). To address this truncation issue, we also observe the number of citations received within the first ten, five, and three years after the filing date of each patent (as recommended by Hall et al., 2001).[8] When looking at shorter time frames, as reported in Table 5, the difference between green and non-green innovations becomes less pronounced: green patents receive 9.14%, 3.87%, and 0.93% more citations within the first ten, five, and three years, respectively. This provides a first confirmation to our research hypothesis H1.

Table 5
Differences in mean received citations by green domain.

Time window	All years	Ten years	Five years	Three years
Green patents	2.927	2.675	2.034	1.657
Non-green patents	2.834	2.431	1.955	1.642
Difference	0.093***	0.245***	0.079***	0.015**
	(0.025)	(0.014)	(0.009)	(0.008)
Observations	1,041,129	760,722	634,592	431,578

We test differences in received citations in each sample of cited green and non-green patents by regressing the variables on the green dummy and the constant term. We report standard errors robust to heteroskedasticity in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

3.1.2. Patent importance

In addition to measuring the citation count received by a patent, we also aim to estimate the relevance of the spillovers generated by a patent by resorting to a measure of "importance", defined by the amount of knowledge spillovers originated by the patent, including direct and indirect ones. More in detail, we use a new measure introduced by Buzzacchi and De Marco (2024), which is based on a micro-founded network centrality indicator. Specifically, this importance measure proxies the amount of knowledge spillovers generated by a patent with a weighted forward citation count, where each reference is recursively scaled by the importance of the citing patent (which, however, is discounted by a constant factor).[9] Consequently, both direct and indirect spillovers generated by a patent contribute to its importance, with the latter receiving lower weights.

In Table 6, we report the average values of importance for cited patents (i.e., considering total citations and citations within their first ten, five, and three years after the application date of each patent) by disentangling between green and non-green patents. Again, we show, in Table 7, the results of the univariate analysis comparing the difference in mean importances.

According to Table 6, cited green patents have a mean importance related to the citations received over their lifetime equal to 7.922, while non-green ones show a much higher value (i.e., 9.404). This difference is statistically significant at the 1% confidence level.

This evidence does not hold true after correcting for truncation biases: green patents exhibit significantly higher values of importance associated with the citations received within the first ten years (4.362 and 4.222, respectively) and non-significantly different importances at

[6] Note that we have excluded self-citations from our dataset, which obviously do not represent any knowledge spillovers. However, we cannot identify self-citations defined with respect to the perimeter of the innovating company or inventor owing to the well-known disambiguation problems regarding patentee names.

[7] The value of the Pearson test statistic with one degree of freedom is 421.16.

[8] To address biases related to differential time exposures of patent cohorts, we compute three-year, five-year, and ten-year counts of received citations starting from the application date in addition to the corresponding lifetime values (Hall et al., 2001). Consistent truncation restricts the cohorts to applications filed by 2017, 2015, and 2010, yielding samples of 3,506,575, 3,203,581, and 2,478,415 observations, respectively.

[9] The discount factor is equal to 0.6 in our case. To get an idea, the importance of a non-cited patent is 0; the importance of a patent cited by a non-cited patent is 1; the importance of a patent cited by a patent that is, in turn, cited by a non-cited patent is 1.6.

Table 6
Patent importance by green domain.

Green patents	Count	Mean	Median	SD	Min	Max
Patent importance	81,684	7.922	2.000	42.494	1.000	3,227.511
Patent importance after ten years	52,960	4.362	2.000	8.634	1.000	372.371
Patent importance after five years	51,506	2.437	1.000	3.200	1.000	179.042
Patent importance after three years	35,781	1.795	1.000	1.852	1.000	101.680
Non-green patents	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Patent importance	959,445	9.404	2.200	79.290	1.000	25,995.055
Patent importance after ten years	707,762	4.222	2.000	12.805	1.000	2,674.568
Patent importance after five years	583,086	2.424	1.000	3.915	1.000	658.757
Patent importance after three years	395,797	1.795	1.000	2.001	1.000	184.194

Table 7
Differences in mean patent importances by green domain.

Time window	All years	Ten years	Five years	Three years
Green patents	7.922	4.362	2.437	1.795
Non-green patents	9.404	4.222	2.424	1.795
Difference	−1.482***	0.140***	0.013	0.000
	(0.169)	(0.040)	(0.015)	(0.010)
Observations	1,041,129	760,722	634,592	431,578

We test differences in patent importance in each sample of green and non-green patents by regressing the variables on the green dummy and the constant term. We report standard errors robust to heteroskedasticity in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

both five (2.437 and 2.424, respectively) and three years (1.795 and 1.795, respectively). This seems partially consistent with our research hypothesis H1.[10]

3.1.3. Technological proximity

In order to test our H2 related to the “close or distant” nature of technological knowledge generated by green patents, we need to resort to a metric reflecting how technologically similar the patents linked by a citation are. Our measure is derived from the technological proximity indicator proposed by Hidalgo et al. (2007), which gauges the closeness between two sectors from zero to one, the former value being the proximity of the sectors furthest apart and the latter being the distance of a sector from itself. We computed the distance between each pair of technological fields (at the third level of the IPC system) so that we could assign a proximity to each citation. We then calculated the mean and median of the technological proximity distribution of all citations obtained by each patent as well as the share of citing patents in the same patent field with respect to the focal cited patent.

Table 8
Technological proximities from citing patents by green domain.

Green patents	Count	Mean	Median	SD	Min	Max
Average technological proximity	81,646	0.723	0.690	0.195	0.049	1.000
Median technological proximity	81,646	0.729	0.693	0.200	0.049	1.000
Share of citing patents in the same field	81,646	0.939	1.000	0.207	0.000	1.000
Non-green patents	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Average technological proximity	959,259	0.753	0.735	0.206	0.040	1.000
Median technological proximity	959,259	0.759	0.735	0.211	0.040	1.000
Share of citing patents in the same field	959,259	0.936	1.000	0.211	0.000	1.000

In Table 8, we report the values of the technological proximity measures for cited patents by disentangling green and non-green patents. Again, we show, in Table 9, the result of the univariate analysis comparing the difference in mean and median technological proximities of received citations as well as the difference in the shares of citing patents that belong to the same technological class as the cited patent.

Table 9 shows that green patents receive a slightly but statistically significant higher proportion of citations from closely related patent areas. At the same time, green inventions exhibit significantly lower technological proximity to citing patents than non-green inventions. This suggests that, despite a higher share of close citations, green knowledge spillovers may also contribute to the development of more technologically distant innovations. Overall, these findings provide mixed evidence on the technological cohesion of green versus non-green innovation. Therefore, research hypothesis H2 can neither be accepted nor rejected.

3.1.4. Patent generality

In H3, we argue that the knowledge generated by green patents should be better suited to fertilize innovation activities in a more diverse range of technological domains. Our assumption is that knowledge from green patents tends to spill over to a broader set of applications than non-green ones. In fact, since green technologies are relatively newer, we assume that they might offer more opportunities for “fundamental” research, whereas older non-green technologies might focus more on developing new incremental applications in their technological domain. Note that if green inventions have broader applications, this could also explain why they tend to receive more citations, i.e., they appear to generate larger knowledge spillovers, adding further motivation to

[10] This evidence seems to be mainly due to a truncation bias, since the standardized measures at three and five years are not significantly different; in other words, more recent green patents have not yet had sufficient time to accumulate indirect citations at levels comparable to those of generally older non-green patents.

Table 9
Differences in mean and median technological proximities from citing patents by green domain.

Variable	Average tech proximity	Median tech proximity	Same patent field share
Green patents	0.723	0.729	0.939
Non-green patents	0.753	0.759	0.936
Difference	−0.030***	−0.030***	0.002***
	(0.001)	(0.001)	(0.001)
Observations	1,040,905	1,040,905	1,040,905

We test differences in technological proximity in each sample of green and non-green patents by regressing the variables on the green dummy and the constant term. We report standard errors robust to heteroskedasticity in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 10
Patent generality by green domain.

Green patents	Count	Mean	Median	SD	Min	Max
Patent generality	81,646	0.452	0.500	0.304	0.000	0.957
Non-green patents	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Patent generality	959,259	0.419	0.500	0.310	0.000	0.970

H1.[11]

The commonly used measure of generality, i.e., the breadth of the technological range to which the knowledge spillovers of a patent are addressed, has been proposed by Trajtenberg et al. (1997) and is defined as one minus the (Herfindahl) concentration of citations through technological sectors. Therefore, an originating patent with generality approaching one has citations that are widely dispersed across patent classes, while zero generality corresponds to all citations in a single class. The generality of a patent is thus calculated as:

$$generality_i = 1 - \sum_{j}^{n_i} s_{ij}^2$$

where s_{ij} is the share of patent citations received by patent i that belong to patent class j (defined at the level of three-digit IPC entities), out of n_i patent classes. In Table 10, we report the average values of generality for cited patents by disentangling between green and non-green patents.

Green patents have a significantly higher mean generality compared to non-green ones, thus providing a first confirmation to our research hypothesis H3.[12]

3.1.5. *Geographical distance*

Hypothesis H4 posits that spillovers from green technologies are less geographically localized than those from non-green technologies. If confirmed, this could help explain why green patents generate more extensive knowledge spillovers. To test H4, we use a metric that measures the geographical distance between citing and cited patents. More specifically, we computed the geodetic distance between the locations specified in the addresses of all inventors listed on the cited and the citing patents.[13] For each focal patent in our sample, we derived the mean and median geographical distance of its forward references. We also measured the proportion of received citations originating from either the same country or province as the cited patent.[14]

In Table 11, we report the average values of the geographical distance measures for the entire citation set (i.e., the average and median geodetic distances as well as the shares of citing patents in the same province and country) by disentangling between green and non-green cited patents. Again, we show, in Table 12, the result of the univariate analysis comparing the difference in geographical distances of citations.

According to Table 12, green patents exhibit a significantly higher geographical distance from their received citations than non-green ones and, correspondingly, are associated with a significantly lower share of received citations from the same country and province, in line with our research hypothesis H4.

4. Empirical models

The preliminary descriptive statistics illustrated in the previous sections provide a first confirmation of our research hypotheses. This simple comparison might be confounded by several ex-ante patent characteristics. We consequently resort to a multivariate analysis in which the different facets of knowledge diffusion in green and non-green knowledge spillover networks can be properly compared. The general model to be estimated is then:

$$spillovers_i = \beta green_i + X_i\Gamma + \varepsilon_i$$

where the dependent variable $spillovers_i$ measures the different characteristics of the knowledge spillovers generated by patent i, proxied by the different metrics described in the previous section (i.e., received citations, patent importance, technological proximity, patent generality, and geographical distance). The $green_i$ dummy variable indicates whether patent i is green, X_i are controls, and ε_i is the error term. Our main coefficient of interest, β, captures the difference between green and non-green patents, all other things being equal. We include in all specifications various control variables to purge the estimates from as many potential confounding factors as possible.

More in details, we include the co-assigned dummy, which equals one if the patent has multiple applicants and the count of inventors to control for the size of the research team. The triadic dummy equals one when the family of the focal patent includes filings at the USPTO, EPO, and JPO, that is, when the invention is protected at all the three major patent authorities. In line with the literature (e.g., Dernis and Khan, 2004; Criscuolo, 2006), this is commonly interpreted as a costly signal of higher quality and broader international market intent. The count of patent sectors measures the breadth of the technological scope in terms of its classification across different patent fields. The count of backward citations, which define the legal boundaries of the patented technology relative to the prior art, captures the extent of reliance on pre-existing technologies: more trivial inventions are more extensively rooted in what has come before, while more fundamental inventions are less incremental (i.e., more radical) in nature and therefore have fewer identifiable antecedents (Trajtenberg et al., 1997).

We also include a dummy indicating whether the patent has been

[11] Note that both the structure and granularity of the categories listed in each branch of the IPC system can significantly influence the measurement of technological proximity and generality. Since more detailed taxonomies represent finer patent domains, results might vary depending on the hierarchical depth and consistency across technical areas of the classification scheme adopted.

[12] The result of this univariate analysis is not reported in the text for the sake of brevity. The test confirms that the difference in mean generalities (i.e., 0.033) between green patents and non-green ones is statistically significant at the 1% confidence level.

[13] Geographical distances have been computed only when at least one of the inventors listed on the citing patent is located within the selected EU member states. Consequently, this metric is available for a subset of links in the citation network.

[14] This variable reflects the hypothesis that administrative borders may act as discontinuities in the relationship between geographic distance and citation probability (see Maurseth and Verspagen, 2002; Arora et al., 2018). We use the third level of the nomenclature of territorial units for statistics (NUTS) which identifies, for instance, 'provinces' in Italy and Spain, 'prefectures' in Greece, 'landkreise' in Germany, and 'departments' in France.

Table 11
Geographical distances from citing patents by green domain.

Green patents	Count	Mean	Median	SD	Min	Max
Average geographical distance	27,688	616.373	493.121	555.459	0.000	8,618.162
Median geographical distance	27,688	603.243	468.686	568.706	0.000	8,618.162
Share of citing patents in the same country	27,693	0.529	0.500	0.447	0.000	1.000
Share of citing patents in the same province	27,693	0.238	0.000	0.383	0.000	1.000
Non-green patents	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Average geographical distance	360,832	567.557	448.022	530.370	0.000	8,955.254
Median geographical distance	360,832	557.268	430.332	542.974	0.000	8,955.254
Share of citing patents in the same country	360,910	0.543	0.600	0.449	0.000	1.000
Share of citing patents in the same province	360,910	0.258	0.000	0.394	0.000	1.000

Table 12
Differences in mean and median geographical distances from citing patents by green domain.

Variable	Average geo distance	Median geo distance	Same country share	Same province share
Green patents	616.373	603.243	0.529	0.238
Non-green patents	567.557	557.268	0.543	0.258
Difference	48.816***	45.975***	−0.014***	−0.020***
	(3.453)	(3.535)	(0.003)	(0.002)
Observations	388,520	388,520	388,603	388,603

We test differences in geographical distances in each sample of green and non-green patents by regressing the variables on the green dummy and the constant term. We report standard errors robust to heteroskedasticity in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

granted by the receiving patent office. This information must be considered as an indicator of quality, as it signals that an invention is officially recognized as fulfilling the three patentability requirements of novelty, inventive step, and industrial applicability.[15] Finally, the inclusion of year dummies corrects for differences related to the filing year of the patent, while technological field dummies account for differences that may affect the specific patent classes (e.g., differences in terms of propensity to patent or policy support across technological fields).[16] See Table 13 for descriptive statistics of the variables used in our models and Table A1 of the Appendix for the correlation matrix.

5. Results

In Table 14 we report the results of models using received citations as dependent variable. Given the count data nature of the dependent variable, we resort to a negative binomial model.[17] Models from (1) to (4) use total received citations as well as citations in the first ten, five, and three years.[18]

All the control variables are significant at the 1% level, take the expected sign and exhibit economically meaningful magnitudes. More complex and redeployable patents with a larger team of inventors receive more citations (Yoshikane, 2013). Similarly, granted and triadic patents are associated with higher impact (Dechezleprêtre et al., 2014).

Regarding our main independent variable, results indicate that, considering all patents (with or without received citations), being green increases the expected number of citations by a factor (i.e., the exponential of the green dummy coefficient) ranging between 1.22 and 1.23, holding other covariates constant. Specifically, the green premium translates into an increase of 23.8% in the expected number of lifetime received citations. In levels, the corresponding average marginal effect of being green amounts to extra 0.182 lifetime references on a non-green baseline of about 0.765 expected received citations. When we use a consistent truncation window across patent cohorts, the marginal effects of green patents are still valuable even though reduced (i.e., an increase of about 0.164 at ten years, 0.082 at five years, and 0.041 at three years after filing, respectively). Such attenuation reflects shorter exposure times of examined patents rather than weaker proportional effects. These results provide confirmation to our H1.[19]

When considering the importance of patent citations, we resort to an OLS model using the measure described in Paragraph 3.1.2.[20] Patent

[15] We also estimate a variant of the baseline that includes the number of claims (where available) and its interaction with the grant status dummy. Results remain directly comparable to those in the baseline: the claim count is positively associated with forward citations, while the interaction term is significantly negative, implying a smaller marginal citation return to additional claims for granted patents (consistent with examiner-induced post-grant narrowing of patent scope).

[16] As a robustness check, we augment our baseline specifications with fixed effects for the inventor-address country – proxying for the geographical locus of R&D – and results remain qualitatively unchanged with respect to those presented in Section 5. These estimates are not reported in the text for the sake of brevity but are available from the authors upon request. Furthermore, by restricting attention to EPO citations only, we mitigate heterogeneity stemming from jurisdiction-specific citation practices. We nevertheless recognize that the geographic composition of green patenting may affect diffusion patterns and explicitly acknowledge this as an avenue for further work.

[17] We also resort to a Poisson model obtaining similar results. According to the test on overdispersion (i.e., p-value of alpha), results indicate that the negative binomial model is preferable. Results of Poisson estimations are not reported in the text for the sake of brevity but are available from the authors upon request.

[18] Given the predominance of patents without citations in our sample, we also estimate these models by resorting to zero-inflated negative binomial regressions. The inflate equations in zero-inflated negative binomial estimations model whether the patent has no citations. We obtain a positive and significant coefficient of the green dummy indicating that being green affects the occurrence of the excess zero counts (i.e., green patents are less likely to be cited). Results of these estimations, in line with those discussed in Section 5, are not reported in the text for the sake of brevity but are available from the authors upon request.

[19] We estimate the same model by subperiods (from 1981 to 1990, from 1991 to 2000, from 2001 to 2010, and from 2011 to 2020). These estimates, shown in Tables A2 and A3 of the Appendix confirm that green patents tend to receive more citations than non-green ones, especially in more recent periods, particularly after 2000. This result suggests an increasing attention to sustainable innovation over time.

[20] Since patent importance assumes only positive values, we also estimate, as a robustness check, Tobit models and obtain results that are in line with those discussed in Section 5. Results of Tobit estimations are not reported in the text for the sake of brevity but are available from the authors upon request.

Table 13
Descriptive statistics of the dependent variables, regressors, and controls.

Dependent variables	Count	Mean	Median	SD	Min	Max
Received citations	1,041,129	2.842	2.000	5.667	1.000	1,414.000
Received citations after ten years	760,722	2.448	2.000	2.645	1.000	259.000
Received citations after five years	634,592	1.962	1.000	1.884	1.000	104.000
Received citations after three years	431,578	1.643	1.000	1.393	1.000	82.000
Patent importance	1,041,129	9.288	2.200	77.042	1.000	25,995.055
Patent importance after ten years	760,722	4.232	2.000	12.560	1.000	2,674.568
Patent importance after five years	634,592	2.425	1.000	3.862	1.000	658.757
Patent importance after three years	431,578	1.795	1.000	1.989	1.000	184.194
Average technological proximity	1,040,905	0.750	0.731	0.205	0.040	1.000
Median technological proximity	1,040,905	0.757	0.731	0.211	0.040	1.000
Share of citing patents in the same field	1,040,905	0.937	1.000	0.211	0.000	1.000
Generality	1,040,905	0.422	0.500	0.310	0.000	0.970
Average geographical distance	388,520	571.036	451.480	532.344	0.000	8,955.254
Median geographical distance	388,520	560.545	433.285	544.975	0.000	8,955.254
Share of citing patents in the same country	388,603	0.542	0.600	0.449	0.000	1.000
Share of citing patents in the same province	388,603	0.256	0.000	0.393	0.000	1.000
Main regressors and controls	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Green dummy	3,809,214	0.083	0.000	0.276	0.000	1.000
Co-assigned dummy	3,809,214	0.062	0.000	0.241	0.000	1.000
Granted dummy	3,809,214	0.532	1.000	0.499	0.000	1.000
Triadic dummy	3,809,214	0.497	0.000	0.500	0.000	1.000
Inventor count	3,809,214	2.662	2.000	1.941	0.000	133.000
Patent field count	3,809,214	1.565	1.000	0.802	1.000	13.000
Backward reference count	3,809,214	0.794	0.000	1.367	0.000	215.000

The green dummy is a binary variable that equals one if the patent is associated with one subdomain in the list of "*Technologies related to climate change mitigation and adaptation*" and zero otherwise. The co-assigned dummy is a binary variable that equals one if the patent has multiple applicants and zero otherwise. The granted dummy is a binary variable that equals one if the patent has been granted by the receiving patent office and zero otherwise. The triadic dummy is a binary variable that equals one if the patent has been filed jointly at the EPO, the USPTO, and the JPO and zero otherwise. The count of inventors, patent classes, and backward citations are discrete non-negative variables that measure respectively the size of the research team, the breadth of the technological scope, and the extent of reliance on pre-existing technologies.

importance can be interpreted as a sum of direct and indirect received citations, so that it is still zero for non-cited patents. In other words, zero values predominate also for patent importance.[21] In Table 15, results of OLS estimations are reported using as dependent variable the total patent importance in Model (1), the patent importance after the first ten, five, and three years in Models (2), (3), and (4) respectively.

All models exhibit a positive and significant coefficient of the green dummy, this confirming that green patents are not only associated to a higher number of forward citations, but they also generate more knowledge diffusion in the entire knowledge spillover network. Moreover, while the univariate comparison (reported in Table 7) indicates that green patents exhibit significantly higher mean importance than non-green patents only when the citation window is restricted to ten years after the filing date – and no significant or even negative differences are instead observed when shorter or non-truncated observation periods are used – the multivariate regression analysis offers a more robust understanding of the relationship by accounting for potential confounding factors. Indeed, the econometric models (presented in Table 15) show that, once ex-ante patent features have been partialled out, green patents display a consistently positive and significant association with technological importance across the four different specifications. Such a finding suggests that the higher importance of green

Table 14
Negative binomial regressions on the number of received citations.

Model	(1)	(2)	(3)	(4)
Time window of the dependent variable	All years	Ten years	Five years	Three years
Green dummy	0.214***	0.210***	0.202***	0.196***
	(0.007)	(0.007)	(0.007)	(0.008)
Co-assigned dummy	−0.091***	−0.067***	−0.090***	−0.137***
	(0.008)	(0.007)	(0.007)	(0.008)
Granted dummy	0.371***	0.321***	0.287***	0.309***
	(0.003)	(0.003)	(0.003)	(0.004)
Triadic dummy	0.045***	0.109***	0.147***	0.173***
	(0.003)	(0.003)	(0.003)	(0.004)
Inventor count	0.037***	0.041***	0.039***	0.044***
	(0.001)	(0.001)	(0.001)	(0.001)
Patent field count	0.040***	−0.036***	−0.120***	−0.177***
	(0.007)	(0.008)	(0.009)	(0.010)
Backward reference count	0.181***	0.200***	0.203***	0.205***
	(0.001)	(0.001)	(0.001)	(0.002)
Filing year and patent field dummies	Yes	Yes	Yes	Yes
Constant	0.131***	−0.500***	−1.040***	−1.614***
	(0.015)	(0.012)	(0.014)	(0.016)
Logarithm of the dispersion parameter	1.033***	1.070***	1.291***	1.460***
	(0.003)	(0.003)	(0.003)	(0.004)
Observations	3,809,214	2,478,415	3,203,581	3,506,575
Pseudo R-squared	0.088	0.029	0.036	0.046
Log-likelihood	−3,739,096	−2,690,197	−2,354,761	−1,692,860
Marginal effect of the green dummy	0.182***	0.164***	0.082***	0.041***
	(0.009)	(0.006)	(0.003)	(0.002)

The dependent variable is the total number of received citations in Model (1), the number of received citations after ten, five, and three years in Models (2), (3), and (4) respectively. The main regressor is the green dummy. All specifications include filing year and patent field dummies as well as the constant term. The marginal effect of the green dummy has been computed using the results of the corresponding Poisson models. Standard errors robust to heteroskedasticity are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

[21] In order to deal with this evidence, as a robustness check, similarly to what we did for zero-inflated negative binomial model, we also resort to an Heckman model in which, in the first stage, we estimate the probability of receiving at least one citation (that means having an importance greater or equal than one) and, in the second stage, we estimate the importance of the patent, i.e., its centrality in the network of citation flows. Again, in the first stage, we obtain a positive coefficient of the green dummy indicating that being green affects the occurrence of the excess zero counts (i.e., the probability not to be cited). Results of these estimations, in line with those discussed Section 5, are not reported in the text for the sake of brevity but are available from the authors upon request.

Table 15
Ordinary least squares regressions on patent importance.

Model	(1)	(2)	(3)	(4)
Time window of the dependent variable	All years	Ten years	Five years	Three years
Green dummy	0.552***	0.269***	0.085***	0.036***
	(0.041)	(0.013)	(0.004)	(0.002)
Co-assigned dummy	0.082	0.015	−0.032***	−0.025***
	(0.093)	(0.030)	(0.005)	(0.002)
Granted dummy	1.366***	0.505***	0.155***	0.070***
	(0.034)	(0.008)	(0.002)	(0.001)
Triadic dummy	0.702***	0.309***	0.114***	0.055***
	(0.040)	(0.008)	(0.002)	(0.001)
Inventor count	0.147***	0.078***	0.026***	0.012***
	(0.010)	(0.003)	(0.001)	(0.000)
Patent field count	−0.547***	−0.188***	−0.067***	−0.035***
	(0.038)	(0.010)	(0.003)	(0.002)
Backward reference count	0.641***	0.358***	0.112***	0.050***
	(0.022)	(0.012)	(0.003)	(0.001)
Filing year and patent field dummies	Yes	Yes	Yes	Yes
Constant	17.293***	1.705***	0.591***	0.285***
	(1.264)	(0.076)	(0.021)	(0.009)
Observations	3,809,214	2,478,415	3,203,581	3,506,575
Adjusted R-squared	0.013	0.023	0.035	0.036

The dependent variable is the total importance in Model (1), the importance after ten, five, and three years in Models (2), (3), and (4) respectively. The main regressor is the green dummy. All specifications include filing year and patent field dummies as well as the constant term. Standard errors robust to heteroskedasticity are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

patents is not merely a consequence of age bias or truncation effects but rather indicates an intrinsic feature of their role in the knowledge spillover network. The average marginal effects equal 0.552, 0.269, 0.085, and 0.036 units over lifetime, ten-year, five-year, and three-year observation windows, respectively. Since the non-green baseline importance amounts to approximately 2.493, the implied relative change is 22.1% for lifetime received citations. These results also mirror the exposure-related scaling observed for count outcomes.

Overall, these findings support our H1 that green patents receive more citations from subsequent inventions than non-green ones. Furthermore, since more important patents generate more knowledge flows in the whole knowledge spillover network and, consequently, greater societal value, we suggest that green patents serve as foundational prior art for a broader range of future innovations within knowledge spillover networks.

In order to test our H2, we estimate baseline models by using the technological proximity variables as dependent variables and we resort to a fractional logit model estimations since all variables are distributed between zero and one. Regression results are reported in Table 16.

Model (1) and (2) include respectively the average and median technological proximities as dependent variables, while the dependent variable in Model (3) is the share of citing patents in the same technological field with respect to the focal cited patent.

As anticipated in the discussion of the descriptive statistics, the results reported in Table 16 provide only weak support for hypothesis H2. When technological proximity is measured using continuous indicators, green patents are associated with lower technological proximity, as indicated by the negative and statistically significant coefficients for both the mean and median measures. At the same time, green patents display a significantly higher share of citations within the same technological field, suggesting that the estimated effect depends on the proximity measure adopted. The final row of Table 16 reports the marginal effects of the green dummy. While the baseline average technological proximity for non-green patents is 0.75, the corresponding value for green patents is 0.74, implying an average marginal effect of approximately −1.0%. A similar pattern emerges for median technological proximity. By contrast, the within-class citation share for green patents is about 0.2 percentage points higher. Even though all these effects are statistically significant, their magnitude is negligible, indicating only minor differences in technological compactness between green and non-green patents. Overall, the evidence remains rather inconclusive with respect to H2. At most, it offers weak indications in two partially offsetting directions. On the one hand, citations to green

Table 16
Fractional logit regressions on technological proximity.

Model	(1)	(2)	(3)
Dependent variable	Average tech proximity	Median tech proximity	Same patent field share
Green dummy	−0.042***	−0.034***	0.033**
	(0.004)	(0.004)	(0.015)
Co-assigned dummy	−0.037***	−0.039***	−0.071***
	(0.004)	(0.004)	(0.015)
Granted dummy	0.057***	0.065***	0.129***
	(0.002)	(0.002)	(0.007)
Triadic dummy	0.012***	0.014***	0.215***
	(0.002)	(0.002)	(0.008)
Inventor count	−0.006***	−0.005***	0.003
	(0.001)	(0.001)	(0.002)
Patent field count	−0.650***	−0.670***	0.294***
	(0.005)	(0.005)	(0.018)
Backward reference count	0.014***	0.017***	0.077***
	(0.001)	(0.001)	(0.003)
Filing year and patent field dummies	Yes	Yes	Yes
Constant	2.220***	2.296***	2.330***
	(0.008)	(0.008)	(0.031)
Observations	1,040,905	1,040,905	1,040,905
Marginal effect of the green dummy	−0.007***	−0.006***	0.002**
	(0.001)	(0.001)	(0.001)

The dependent variable is respectively the average and the median technological proximities in Model (1) and (2), the share of citing patents in the same patent field in Model (3). The main regressor is the green dummy. All specifications include filing year and patent field dummies as well as the constant term. The average marginal effect of the green dummy is reported at the bottom of the table. Standard errors robust to heteroskedasticity are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 17
Fractional logit regressions on patent generality.

Model	(1)
Green dummy	0.129***
	(0.005)
Co-assigned dummy	0.031***
	(0.005)
Granted dummy	−0.036***
	(0.003)
Triadic dummy	0.015***
	(0.003)
Inventor count	0.022***
	(0.001)
Patent field count	0.205***
	(0.007)
Backward reference count	0.024***
	(0.001)
Filing year and patent field dummies	Yes
Constant	−0.854***
	(0.010)
Observations	1,040,905
Marginal effect of the green dummy	0.030***
	(0.001)

The dependent variable is patent generality. The main regressor is the green dummy. All specifications include filing year and patent field dummies as well as the constant term. The average marginal effect of the green dummy is reported at the bottom of the table. Standard errors robust to heteroskedasticity are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

patents appears to be slightly more dispersed across technological classes. On the other hand, they are weakly associated to higher within-class citation share. This mixed pattern is consistent with prior literature suggesting that the technological distribution of knowledge spillovers in green innovations varies substantially across domains (see, for example, Noailly and Shestalova, 2017, in the context of renewable energy generation). This lack of clear-cut evidence suggests that the measures of technological proximity employed in this study are likely to mask substantial heterogeneity in citation patterns across specific technological fields and stages of the innovation process. In this sense, the observed effects should be interpreted as broad aggregate tendencies rather than as uniform features of green innovation.

As to H3, we refer to the estimates of fractional logit regressions reported in Table 17 using generality as dependent variable since also this variable assumes values between zero and one.

Table 18
Ordinary least squares and fractional logit regressions on geographical proximity.

Model	(1)	(2)	(3)	(4)
Dependent variable	Average geo distance	Median geo distance	Same country share	Same province share
Green dummy	68.729***	64.961***	−0.149***	−0.199***
	(3.662)	(3.750)	(0.012)	(0.015)
Co-assigned dummy	50.176***	50.757***	−0.147***	−0.133***
	(3.524)	(3.609)	(0.012)	(0.015)
Granted dummy	−101.360***	−105.035***	0.371***	0.446***
	(1.908)	(1.948)	(0.007)	(0.008)
Triadic dummy	−61.639***	−62.442***	0.211***	0.448***
	(1.966)	(2.019)	(0.007)	(0.008)
Inventor count	−6.527***	−7.460***	0.085***	0.114***
	(0.613)	(0.634)	(0.002)	(0.002)
Patent field count	28.222***	24.579***	−0.148***	−0.306***
	(3.451)	(3.524)	(0.012)	(0.015)
Backward reference count	−12.145***	−13.075***	0.031***	0.035***
	(0.575)	(0.592)	(0.002)	(0.002)
Filing year and patent field dummies	Yes	Yes	Yes	Yes
Constant	691.339***	685.321***	−0.565***	−2.035***
	(6.270)	(6.413)	(0.023)	(0.027)
Observations	388,520	388,520	388,603	388,603
Adjusted R-squared	0.048	0.046		
Marginal effect of the green dummy	68.729***	64.961***	−0.036***	−0.034***
	(3.662)	(3.750)	(0.003)	(0.002)

The dependent variable is respectively the average and the median geographical proximities in Model (1) and (2), the share of citing patents in the same country and province in Models (3) and (4). The main regressor is the green dummy. All specifications include year and patent field dummies as well as the constant term. The average marginal effect of the green dummy is reported at the bottom of the table. Standard errors robust to heteroskedasticity are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Results presented in Table 17 support our H3, showing that green patents are associated with higher generality than non-green ones. Again, the last row of Table 17 refers to the estimation of the marginal effects of the green dummy, thus providing an idea about the economic impact exerted by the variable of interest. Specifically, the non-green baseline is 0.42, whereas green patents reach 0.45. The implied average marginal effect is 0.03 percentage points, corresponding to an increase of about 7.1% relative to its reference value.

We then confirm that the knowledge spilling over from green patents to general innovation can impact a wider set of technological domains, making it particularly valuable for driving innovation. Due to their widespread nature and broad applications, green technologies can serve as foundational elements across different technology sectors. The inherent complexity and novelty of green innovations suggest that knowledge spillovers from these technologies have the potential to influence a wide range of industries. This result suggests that the spectrum of sectors to which a green knowledge spillover network is targeted tends to be broader.

When considering geographical distance from citing patents, we first resort to an OLS model using the measure described in Paragraph 3.1.5.[22] We finally resort to a fractional logit model when estimating the geographical proximity share since this variable assumes values between zero and one, as described in Paragraph 3.1.5. Results are shown in Table 18.

Model (1) and (2) refer to OLS estimations in which the dependent variable is respectively the average and the median geographical proximities, while Model (3) and (4) refer to fractional logit estimations in which the dependent variable is the share of citing patents in the same country and province with respect to the focal cited patent. For the average geographic distance, the non-green baseline amounts to 566.1 km, while green patents reach 634.9 km, implying an increase of approximately 68.7 km. Compared with the baseline, this corresponds to a relative change of about 12.1%. Results for the median distances are closely aligned. Moreover, the within-area share is lower by about 3.6 and 3.4 percentage points when defined at the country and the province level, respectively.

All models confirm our H4 with a positive and significant coefficient of the green dummy associated with the geographical distance of citing patents as well as a negative and significant coefficient associated with the share of citing patents in the same country and province. This confirms that the nature of green technologies and their potential as boundary spanners leads to knowledge transmission in the green field being less geographically localized than for non-green technologies.

Note that these results, taken together with those reported for H2 and H3, describe a clear picture of the morphology of the knowledge spillovers network based on green versus non-green technologies. They suggest that the spectrum of industries to which a green knowledge spillovers network is targeted tends to be broader and more geographically scattered, but, at the same time, the recipient industries show technological cohesion alongside greater cross-field dispersion.

6. Conclusion

In this paper, we examine the morphology of knowledge spillover networks for both green and non-green patents. Building on a long-standing empirical literature that uses patent data to trace knowledge spillovers through forward citations (e.g., Corsino et al., 2019; Jaffe et al., 1993; Jaffe et al., 2000; Lanjouw and Schankerman, 2004; Trajtenberg, 1990), we provide finer-grained evidence on the patterns of knowledge spillover networks, with a specific focus on green technologies. While it is well established that green patents typically generate more spillovers than non-green ones (Dechezleprêtre et al., 2014; Noailly and Shestalova, 2017; Popp and Newell, 2012), prior research has largely relied on direct citation counts. Consequently, a comprehensive understanding of the structure of green knowledge spillover networks and the patterns of path dependence in knowledge

[22] Since geographical distance assumes only positive values, we also estimate, as a robustness check, Tobit models and obtain results that are in line with those discussed in Section 5. As further robustness check, since the geographical distance of citations is known only for patents receiving at least one forward citation, we also resort to a Heckman model in which, in the first stage, we estimate the probability of receiving at least one citation and, in the second stage, we estimate the geographical distance of citations received. Results of these additional estimations, in line with those discussed in Section 5, are not reported in the text for the sake of brevity but are available from the authors upon request.

accumulation remains limited.

Our study advances the extant literature in several ways. First, we extend the understanding of how knowledge generated by green technologies can serve as a foundational prior for future innovations (Barbieri et al., 2020; Popp and Newell, 2012; Dechezleprêtre et al., 2014), thus filling a critical gap in the current discourse on sustainable development and technology management. Unlike previous studies that focus on specific domains, such as sustainable energy, our approach considers the full spectrum of green technologies, offering a richer characterization of the green knowledge base and its underlying spillovers. We thus contribute to the literature on the characterization of the green knowledge base (Aghion et al., 2016; Aldieri et al., 2020; De Marchi, 2012; Montresor and Quatraro, 2019), as well as to studies examining the *ex post* impact of green technologies (Barbieri et al., 2020; Dechezleprêtre et al., 2014; Jee and Srivastav, 2024; Popp and Newell, 2012), by adopting a broader perspective that covers the full spectrum of green technological domains.

Second, we provide a more nuanced analysis of the morphology and relevance of knowledge spillovers and how the distinctive features of green technologies (i.e., greater novelty and complexity, stronger externalities, and closer ties to public policy) translate into distinctive patterns of knowledge diffusion. Specifically, we examine not only the amount of knowledge spillovers, including both direct and indirect ones, but also how knowledge diffusion unfolds, along technological trajectories, across structural and sectoral patterns, and over geographic boundaries. We suggest that green innovations serve as foundational elements within broader technological networks, enhancing the potential for future advances in different sectors. Indeed, our empirical findings suggest that green patents not only receive on average a greater number of citations – both direct and indirect – from subsequent inventions but also facilitate more extensive knowledge diffusion throughout the network compared to their non-green counterparts. This evidence highlights the critical role that green technologies play in shaping collaborative networks and facilitating knowledge exchange within knowledge spillover networks.

Third, our research underscores the critical importance of green patents in fostering innovation, enhancing knowledge spillovers, and contributing to societal value through their unique characteristics and systemic interactions within the broader technological landscape. We provide more detailed insights into the mechanisms of knowledge transfer from green inventions to subsequent technological developments, by mapping the technological proximity between green inventions and their citing patents within the knowledge space and exploring their pervasiveness at sectoral level.

We document that knowledge spillovers associated with green patents exhibit a technologically cohesive yet heterogeneous structure, combining a relatively broad cross-field reach with a stronger concentration within the same technological domains. This suggests that knowledge externalities originating from green innovations are not confined to technologically close areas, but instead reflect a nuanced interplay of domain-specific knowledge reuse and knowledge integration across technological areas. Our results also show that the knowledge embedded in green patents has a broad impact across different sectors, underscoring their value in fostering innovation beyond their own domain and amplifying their impact on wider knowledge spillover networks. Our findings thus contribute to the open innovation literature (Bogers et al., 2020; Chesbrough and Di Minin, 2014; Collevecchio et al., 2024) by highlighting how firms can leverage knowledge spillovers to enhance innovation capacity and promote the exchange and recombination of ideas beyond organizational boundaries. Finally, our empirical models confirm that knowledge spillovers are less geographically localized for green technologies than for their non-green counterparts, highlighting the role of green innovations as boundary spanners in knowledge spillover networks.

This paper has important implications for practice and policy. From a policy perspective, the reported evidence that green patents generate denser and wider networks of positive externalities, suggests that market failures and thus sub-optimal private investments in green technologies should be more severe. Targeted policy interventions in this area can therefore yield higher returns when they stimulate innovation, thus providing opportunities to create and capture value from new markets, also in hard-to-decarbonize sectors. Incentivizing partnerships and fostering an environment conducive to collaboration between different stakeholders within knowledge spillover networks should help internalizing externalities and stimulating innovation investments. This will clearly depend on the persistence of political will and societal commitment to sustainability. In periods or geographical areas where environmental and social priorities face a backlash or decline in prominence, the momentum behind green innovation may weaken. In such contexts, consistent policy support becomes even more critical to maintaining innovation efforts around green technologies. Future research should therefore investigate whether the spillover advantage of green technologies remains robust over time and across varying policy environments.

Furthermore, the finding that knowledge spillovers from green patents to general innovation can affect different but technologically cohesive sectors could have implications for the design of such policy support. Policies will be particularly effective if they facilitate the diffusion and recombination of green knowledge across a wider range of industrial applications. Finally, the broader geographical reach of these networks implies that policy measures should be scaled accordingly – potentially at a supranational level – to effectively internalize the positive externalities. From a managerial and firm-level perspective, our findings underline the importance of fostering firm-level collaboration within knowledge spillover networks to maximize the benefits of green technologies. Firms should actively engage in partnerships in order to internalize knowledge externalities and leverage their technological complementarities, while facilitating knowledge sharing across sectors.

Our paper is not without limitations. First, there is some consensus that patent citations, although widely used in empirical research to measure knowledge transmission, are imperfect and "noisy" indicators of technology spillovers (Jaffe et al., 2000; Roach and Cohen, 2013). There are several reasons for this, ranging from the institutional setting of patent filings (e.g., in some jurisdictions, citations are added by patent attorneys or examiners; see Criscuolo and Verspagen, 2008), the technological nature of inventions (e.g., applicants in complex product technologies tend to be less active in prior art searches), strategic motives of patentees (e.g., applicants might intentionally omit prior art to secure a broader patent scope or reduce the risk of application rejection; see Atal and Bar, 2010; Lampe, 2012; Langinier and Marcoul, 2016; Sampat, 2010), and the level of political support for specific technological domains, where attention and public focus may be more pronounced than in others. Second, patent citations can only capture those flows of technological knowledge that lead to a patentable technology (Griliches, 1990) and thus may underestimate the true extent of knowledge spillovers. Future research could extend our work by exploring the interconnectedness of knowledge spillovers both within and outside the patent system and investigating alternative channels of knowledge transfer that are not accounted for by patent citations. Finally, another limitation is that we classify patents as green and non-green using existing international classifications such as the Cooperative Patent Classification (CPC). More realistically, the "greenness" of innovations is likely to be more pervasive and non-boolean, and in this sense future research should improve green patent categorization by analysing data from patent abstracts, titles, and claims using machine learning and other AI techniques.

CRediT authorship contribution statement

Luigi Buzzacchi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Annalisa Croce:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Antonio De Marco:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Elisa Ughetto:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Conflict of interest

The authors declare that they have no known conflict of interests that could have appeared to influence the work reported in this paper.

Appendix

Table 19
Correlation matrix

Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Green dummy	1.0000						
(2) Co-assigned dummy	0.0145	1.0000					
(3) Grant dummy	−0.0076	−0.0163	1.0000				
(4) Triadic dummy	0.0060	0.0112	0.1119	1.0000			
(5) Inventor count	0.0348	0.1172	−0.0159	0.1263	1.0000		
(6) Patent field count	0.0446	0.0234	0.0196	0.1565	0.0760	1.0000	
(7) Backward reference count	0.0071	−0.0123	0.0687	0.0311	0.0404	0.0280	1.0000

Table A2
Negative binomial regressions on the number of received citations by subperiod

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subperiod	From 1981 to 1990				From 1991 to 2000			
Time window of the dependent variable	All years	Ten years	Five years	Three years	All years	Ten years	Five years	Three years
Green dummy	0.119***	0.058***	0.062***	0.048***	0.193***	0.167***	0.159***	0.153***
	(0.019)	(0.012)	(0.014)	(0.017)	(0.013)	(0.013)	(0.015)	(0.017)
Co-assigned dummy	−0.046***	−0.031***	−0.029**	−0.039***	−0.072***	−0.074***	−0.084***	−0.100***
	(0.014)	(0.010)	(0.012)	(0.014)	(0.018)	(0.012)	(0.013)	(0.015)
Granted dummy	0.349***	0.360***	0.352***	0.329***	0.309***	0.238***	0.214***	0.212***
	(0.007)	(0.006)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)	(0.008)
Triadic dummy	0.072***	0.208***	0.282***	0.345***	0.081***	0.141***	0.219***	0.291***
	(0.007)	(0.005)	(0.006)	(0.008)	(0.006)	(0.006)	(0.007)	(0.008)
Inventor count	0.071***	0.073***	0.082***	0.088***	0.065***	0.066***	0.068***	0.068***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Patent field count	−0.006	−0.165***	−0.241***	−0.304***	0.032***	−0.090***	−0.198***	−0.251***
	(0.012)	(0.013)	(0.016)	(0.021)	(0.012)	(0.012)	(0.015)	(0.019)
Backward reference count	0.202***	0.230***	0.252***	0.264***	0.178***	0.187***	0.201***	0.209***
	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Filing year and patent field dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.027*	−0.714***	−1.340***	−1.909***	−0.068***	−0.539***	−1.149***	−1.749***
	(0.014)	(0.012)	(0.015)	(0.018)	(0.014)	(0.011)	(0.012)	(0.015)
Observations	424,711	424,711	424,711	424,711	761,529	761,529	761,529	761,529
Pseudo R-squared	0.025	0.032	0.040	0.045	0.018	0.020	0.025	0.028
Log-likelihood	−797,815	−618,012	−464,080	−337,048	−1,130,967	−923,941	−694,388	−496,235

The dependent variable is the total number of received citations in Models (1) and (5), the number of received citations after ten years in Models (2) and (6), the number of received citations after five years in Models (3) and (7), and the number of received citations after three years in Models (4) and (8) respectively. Models from (1) to (4) refer to the group of years from 1981 to 1990, Models from (5) to (8) refer to the group of years from 1991 to 2000. The main regressor is the green dummy. All specifications include filing year and patent field dummies as well as the constant term. Standard errors robust to heteroskedasticity are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A3
Negative binomial regressions on the number of received citations by subperiod

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subperiod	From 2001 to 2010				From 2011 to 2020			
Time window of the dependent variable	All years	Ten years	Five years	Three years	All years	Ten years	Five years	Three years
Green dummy	0.215***	0.228***	0.248***	0.221***	0.166***	-	0.131***	0.166***
	(0.011)	(0.010)	(0.011)	(0.013)	(0.011)	-	(0.013)	(0.015)
Co-assigned dummy	−0.054***	−0.046***	−0.056***	−0.113***	−0.149***	-	−0.121***	−0.216***

(*continued on next page*)

Table A3 (*continued*)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subperiod	From 2001 to 2010				From 2011 to 2020			
Time window of the dependent variable	All years	Ten years	Five years	Three years	All years	Ten years	Five years	Three years
	(0.011)	(0.011)	(0.013)	(0.016)	(0.018)	-	(0.021)	(0.024)
Granted dummy	0.357***	0.317***	0.245***	0.253***	0.431***	-	0.307***	0.385***
	(0.006)	(0.005)	(0.006)	(0.007)	(0.008)	-	(0.009)	(0.010)
Triadic dummy	0.041***	0.061***	0.100***	0.115***	0.009	-	0.029***	0.011
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	-	(0.009)	(0.010)
Inventor count	0.022***	0.022***	0.023***	0.028***	0.028***	-	0.024***	0.035***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	-	(0.002)	(0.002)
Patent field count	0.108***	0.058***	−0.030**	−0.082***	−0.056***	-	−0.101***	−0.155***
	(0.012)	(0.012)	(0.014)	(0.018)	(0.017)	-	(0.021)	(0.023)
Backward reference count	0.169***	0.174***	0.180***	0.185***	0.155***	-	0.152***	0.149***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	-	(0.003)	(0.003)
Filing year and patent field dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.708***	−1.009***	−1.540***	−2.141***	−1.476***	-	−1.853***	−2.542***
	(0.011)	(0.011)	(0.012)	(0.015)	(0.014)	-	(0.016)	(0.018)
Observations	1,292,175	1,292,175	1,292,175	1,292,175	1,330,799	0	725,166	1,028,160
Pseudo R-squared	0.020	0.017	0.018	0.021	0.078	-	0.018	0.022
Log-likelihood	−1,225,260	−1,112,664	−802,763	−530,117	−536,091	-	−362,994	−306,929

The dependent variable is the total number of received citations in Models (9) and (13), the number of received citations after ten years in Models (10) and (14), the number of received citations after five years in Models (11) and (15), and the number of received citations after three years in Models (12) and (16) respectively. Models from (9) to (12) refer to the group of years from 2001 to 2010, Models from (13) to (16) refer to the group of years from 2011 to 2020. The main regressor is the green dummy. All specifications include filing year and patent field dummies as well as the constant term. Standard errors robust to heteroskedasticity are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Data availability

The authors do not have permission to share data.

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