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The diffusion of energy technologies. Evidence from renewable, fossil, and nuclear energy patents

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A B S T R A C T

Technology innovation is widely recognised as a critical means in tackling climate change and fulfilling energy policy objectives. The objective of this paper is twofold: first, to provide a descriptive analysis of innovation in energy technology across countries and sectors and over time; and second, to explore the determining factors of patented knowledge diffusion of energy technologies by distinguishing between renewables and other energy patents, i.e., fossil and nuclear patents) thorough a regression analysis. The data employed in this paper consists of an original database on renewables and other energy patents applied by firms in the period 1990–2015 and contained in PATSTAT. By drawing on patent citations as an indicator of knowledge diffusion and focusing on characteristics extracted from patent documents, a set of econometric models is estimated. Our results show that those patents containing more citations to previous scientific literature and patents attain greater diffusion. Joint patents with other firms or universities exert a negligible effect on technology regarding renewables. Co ownership with universities has a negative effect on the diffusion of other types of energy technology. Several policy implications can be determined from our results: for example, the justification for policies oriented to wards enhancing the incorporation of scientific knowledge and co-inventorship in energy innovation.

Keywords: Patent quality,Renewable energy technologies, Fossil technologies Nuclear technologies Co-ownership Forward citations

1. Introduction

Technology innovation is widely recognised as a critical means in tackling climate change and attaining energy policy objectives, including those of increasing energy access and reducing air pollution (IEA, 2020). Mitigating the harmful effects of climate change involves working towards the best use of clean energy and encouraging the transition of the world energy system towards electricity generation from low-carbon sources and other gasses (IEA, 2017). Due to increasing concerns over the environmental consequences of greenhouse gas emissions from fossil fuels, renewable energy has emerged as a substitute energy source, since the reduction of CO_2 emissions and the control of climate change must include the reorganization of the energy sector (Abulfotuh, 2007; Apergis and Payne, 2012; Balsalobre-Lorente et al., 2018). It is clear that the energy sector will only reach net-zero emissions through a global effort for innovation (IEA, 2020). Furthermore, investing in renewable energy sources can contribute towards other public-policy objectives, such as greater energy security, in the face of the uncertain markets of fossil fuels (Johnstone et al., 2010). Furthermore, this sector constitutes a driving force for innovation, since it exerts a significant impact on other sectors that are indirectly affected, such as transport and waste management (Schmidt et al., 2012).

Previous research has revealed the importance of external knowledge sourcing and knowledge diffusion across sectors (Nemet, 2012; Duch-Brown and Costa-Campi, 2015), and geography (Binz and Ana don, 2018; Gosens et al., 2015; Li et al., 2021). It has also shown the relevance of collaboration for green innovation (Ghisetti et al., 2015; Araújo and Franco, 2021) and in general for innovation, which is in line with the open innovation paradigm. Additionally, there is an observed increase towards the incorporation of science into energy patents, especially in renewables (Hötte et al., 2021; Perrons et al., 2021).

This paper addresses two limitations of the extant literature. First, previous contributions on the diffusion of energy technology using patent data have focused on the effect of policy incentives in inducing innovation (Battke and Schmidt, 2015; Noailly and Shestalova, 2017; Popp, 2006; Johnstone et al., 2010; Miremadi et al., 2019; Hötte, 2020) or in the international or regional knowledge flows (Binz and Anadon, 2018; Gosens et al., 2015; Li et al., 2021). Second, the literature exploring the effect of in-text patent indicators on knowledge diffusion has not focused on the energy sector and extant non-specific energy sector reserch provides mixed evidence on the effect of scientific link ages, backward citations, and co-ownership on the diffusion of technology (e.g., see Acosta et al., 2009 for environmental technologies; Schmid, 2018 for military technologies; and Belderbos et al., 2014, Briggs, 2015, and Peeters et al., 2020 for general evidence).

This paper aims to fill these gaps by providing a comprehensive analysis of patented energy technology generation and of the factors affecting its diffusion based on patent data. Firstly, a description is provided of the temporal evolution of patented energy technology over the period 1990–2015, and of its distribution across technological fields. Light is also shed on which countries lead the process of patented technology in the energy sector. Additionally, descriptive statistics enable comparisons between renewables and other energy technologies. Secondly, a set of econometric models is estimated to identify the factors that determine the diffusion of renewable energy technologies and other energy technologies, which includes scientific linkages, backward citations, and co-ownership of patents. For this purpose, two technological sectors are distinguished: renewable technologies, and other technologies producing energy. Renewable energy technologies include *Wind, Solar, Geothermal, Marine, Hydro, Biomass, Waste,* and *Storage* technologies. Other technologies producing energy include Fossil *Fuels* and *Nuclear* technologies. Our analysis is based on the number of citations a patent receives in subsequent patents, that is, forward citations, as a proxy for knowledge diffusion.

The consequences of patent diffusion make this research relevant both from the firms' and policy-makers' perspectives. At the firm level, empirical literature has shown a strong relationship between patent diffusion (e.g., the impact of a patent on subsequent patented inventions) and several indicators of firm performance (Chen and Chang, 2010; Hall and MacGarvie, 2010; Hall et al., al., 2005; Harrigan et al., al., 2018; Hirschey and Richardson, 2004; Patel and Ward, 2011): for example, stock prices (Hall and MacGarvie, 2010), market value (Hall et al., 2005; Kim et al., 2018 for the renewables sector), and reputation for technological innovation, which in turn correlate with the firm's competitive advantage (Henard and Dacin, 2010; Höflinger et al., al., 2018). Furthermore, patent diffusion promotes innovation by reducing transaction costs and coordinating R&D efforts between rivals (Sag and Rohde, 2007; Thomas, 2002). From the policy-makers' perspective, understanding innovation and diffusion of energy technologies become essential for efficient energy and environmental policy design, and may contribute towards explaining why certain existing technological solutions in the market diffuse slowly, even when they are technologically superior (Hötte, 2020). These crucial consequences of patent quality for the firm and for society trigger political and academic interest in understanding the factors affecting patent diffusion in the energy sector.

2. Theoretical background

Broadly speaking, comprehension of the mechanisms underlying knowledge creation and diffusion is essential for economic growth to be understood (Silverberg et al., 1988; Klarl, 2014; Andergassen et al., 2017). In one of the seminal contributions of knowledge diffusion, Rogers (1962, p. 5) defined diffusion as "a process by which an innovation is communicated through certain channels over time among the members of a social system". This concept of diffusion conveys both market and non-market channels. However, in this paper, a more con strained concept of diffusion is adopted, which is centered on knowledge spillovers. These can be defined as external knowledge sources upon which organisations are built and in which there is no compensation, or said compensation lies below the actual value of the knowledge (Jaffe, 1998; Korres, 2012). From a macroeconomic viewpoint, knowledge diffusion through spillovers plays a key role in the literature on endogenous economic growth (Grossman and Helpman, 1991, 2018; Griliches, 1992; Aghion and Howitt, 1992; Acemoglu and Akcigit, 2012). From a microeconomic viewpoint, technological diffusion pro vides a key factor for productivity growth (Baumol, 1991). Furthermore, the identification and understanding of the processes of technological knowledge diffusion and acquisition is essential in the design of successful business strategies (Bonesso et al., 2011; Momeni and Rost, 2016). However, the process of knowledge diffusion is not automatic, as shown by a large set of studies initiated by Jaffe et al. (1993), but instead depends on agents' absorptive capacity (Cohen and Levinthal, 1990; Lane et al., 2006).

2.1. The diffusion of technology in the energy sector

Although not precisely focused on the factors affecting knowledge diffusion, a growing number of studies rely on patent data to examine innovation and knowledge sourcing in the energy sector and provide relevant clues for this research.

Motivated by the fact that technological change is considered accumulative process in which new technologies result from the recombination of existing knowledge in innovative ways (Arthur, 2007), several papers have provided evidence on knowledge flows through the analysis of backward patent citations within/across technological sectors (Nemet, 2012; Duch-Brown and Costa-Campi, 2015) or geography (Binz and Anadon, 2018; Gosens et al., 2015; Li et al., 2021). In the case of renewables, evidence has revealed that energy innovation depends on a broad range of knowledge sources since it usually involves the combination of diversified and complex knowledge areas (Nemet, 2012; Garrone et al., 2014; Noailly and Smeets, 2015;

Popp, 2017). This highlights the importance of external knowledge sourcing to foster innovation and diffusion. However, the rate of diffusion depends on the type of technology. For example, green technologies exert a higher impact on future inventions (Barbieri et al., 2020). Overall, patents in wind, storage, and solar technologies tend to be more frequently cited than other renewable technologies (Noailly and Shestalova, 2017).

Additionally, previous research has found that energy innovation increasingly relies on science (Hötte et al., 2021; Perrons et al., 2021), particularly in the case of renewable energies (Perrons et al., 2021; Persoon et al., 2020), which may indicate an increasing dependence of invention on scientific research over time.

From an institutional point of view, open innovation becomes a relevant paradigm (see Lacerda and Van den Bergh, 2020 for renewable technologies). The open innovation perspective stresses the value of external knowledge by arguing it is a necessary strategy to increase R&D productivity in the face of growing competition and faster technology development cycles. Nevertheless, successful environmental innovations are highly dependent on the participation of different stake holders in their development/uptake, that is, they are likely to result from the cooperation between the public sector, academia, and business (Carrillo-Hermosilla et al., 2010). However, it has been found that universities play a less important role in wind research than they do for solar and biofuels, which the authors interpret as being wind energy research at a more applied stage where commercialization and final product development has become more important than basic research (Hötte et al., 2021). In particular, green energy innovations rely on technologies developed outside the field of power generation (Noailly and Ryfish, 2015) and often require the combination of various items of knowledge developed by different actors in different countries (Corrocher and Mancussi, 2021), which exemplifies the relevance of open innovation.

Despite the importance of building upon previous extant techno logical, scientific knowledge and cooperation for energy innovation, their effect on diffusion has yet to be explored. Therefore, in the sub sequent section, the non-specific energy empirical evidence on the determinants of patent diffusion is reviewed.

2.2. Determinants of patent diffusion

The cumulative nature of knowledge and path dependancy make it crucial to rely on previous knowledge for innovation. Two prominent sources of knowledge are those of previous codified knowledge (either in patent or non-patent literature), and R&D cooperation (either with universities or firms). In this section, our hypotheses are derived, as summarised in Fig. 1.

2.2.1. Citations to non-patent literature

Scientific research has been largely discussed as being relevant for technological innovation (e.g., Bush, 1945; Brooks, 1994; Godin, 2006; Balconi et al., 2010 ; Fleming et al., 2019) Fleming & Sorenson (2004.) suggested that science functions as a map of the technological landscapes that can guide private research towards useful combinations, thereby avoiding dead-end research efforts. Furthermore, the growth of markets for technology including those from academia, implies that firms have access to a larger scientific pool than ever (Marx and Fuegui, 2020).

Several papers have found a close relationship between scientific citations and the value of patented inventions (e.g., Sorenson and Fleming, 2004; Branstetter, 2005; Gambardella et al., 2005; Ahmadpoor and Jones, 2017; Poege et al., 2019 provide non-specific sector evidence; see, Harhoff et al. (2003), for pharmaceutical and chemical patents). However, the empirical evidence remains mixed. For example, Harhoff et al. (2003) found a positive effect of citations to the non-patent literature and the value of pharmaceutical and chemical patents, but not in other technical fields Cassiman et al. (2008). found that references to scientific publications are not relevant in explaining forward citations in patents from a set of technological classes, which they justify because patents citing science may be uncovering knowledge of a more complex and fundamental nature, which is less readily diffused or remains far from market applications Petruzzelli et al. (2015)., using a sample of biotechnology patents, found that the use of scientific knowledge varies in its impact depending on the level of analysis of knowledge diffusion. According to their results, non-patent citations do not affect the number of forward citations, nor do patent citations from the same technology domain, nor the number of citations from other assignees. However, they did find a negative effect of scientific citations on a patent’s impact on subsequent patents outside the biotechnology industry, and they found a positive effect of the technological relevance of the patent for the assignee’s future inventions.

On the whole, the empirical evidence on the effect of scientific linkages of technological innovations remains largely unclear, although it does seem to remain dependent on the technological sector under analysis, whereby it has greater relevance in technologically complex sectors. The widely discussed relationship between science and technology, and the increasing importance of science for energy innovations (Hötte et al., 2021; Perrons et al., 2021), motivates the following hypothesis:

H1. More scientific knowledge sourcing exerts a positive effect on energy patent diffusion.

2.2.2. Backward patent citations

Backward citations have been used in other studies as a proxy for spillover effects and show a positive effect on the market value of firms (e.g., non-specific sector evidence available in Harhoff et al., 2003; Duguet and Macgarvie, 2005; Gay and Le Bas, 2005).

Backward citations can be directed towards patents owned by others or to self-owned patents. In the specific case of self-citations, these are a measure of path-dependent technologies (Sørensen and Stuart, 2000 for high-tech industry; Song et al., 2003 for non-specific sector evidence). Interestingly, Hall et al. (2005) provided general empirical evidence that self-citations have an even stronger effect on market value than do other citations. Liu et al. (2008) found that US pharmaceutical and biotechnology patents that are part of sequential inventions show increased technological value. Thus, the higher the number of self-citations included in a patent, the higher the expected number of forward citations, since it signals that the firm maintains greater accumulated technological knowledge (Gay et al., 2005).

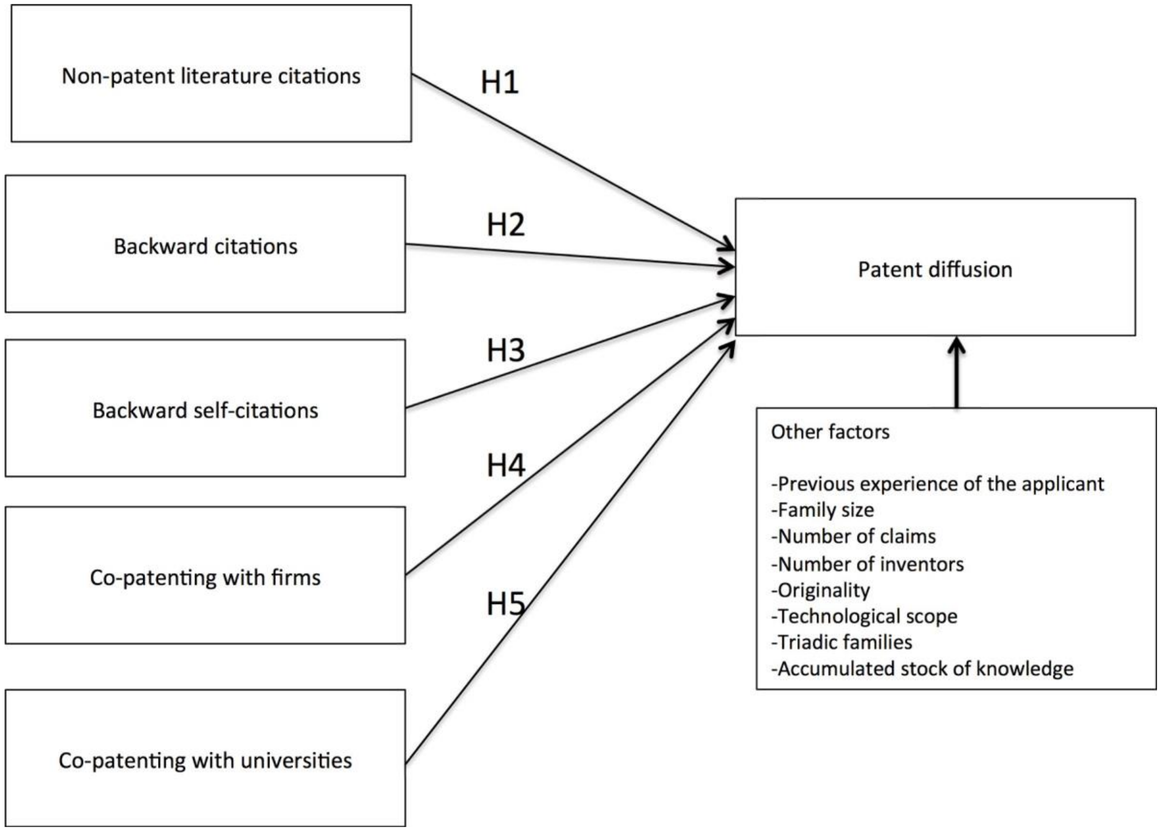

Fig. 1. Research model and hypotheses.

In consideration of the positive effect of citations and self-citations on innovation performance and diffusion, we advance the following hypothesis:

H2. More citations to the patents of others exerts a positive effect on the diffusion of energy patents.

H3. More citations to one's own patents exerts a positive effect on the diffusion of energy patents.

2.2.3. R&D collaboration and co-patenting

Collaboration with external organisations is generally viewed as positive for the firm's innovation because it provides access to resources, especially knowledge, that the focal firm lacks (Un et al., 2010). In the particular case of industry-university collaboration, universities can provide the scientific basis for technological progress and basic research (Peeters et al., 2020). Co-patenting implies the joint ownership of collaborative outcomes and has been used as an instrument to analyze the effect on value creation and appropiation (Belderbos et al., 2014). However, co-patenting creates uncertainty over the control that each co-owner possesses of the co-owned patent (Hagedoorn, 2003).

Empirical evidence on the effect of co-ownership reveals mixed re sults. Belderbos et al. (2014) find that co-ownership between firms re ceives more forward citations than do single-owned patents, while co-ownership with a university yields no statistical difference in the number of forward citations received compared to single-owned patents. With respect to the latter, Briggs (2015) obtained similar results when using forward patent citations within three years, but found a positive effect of co-ownership with universities on quality when using the total number of forward citations over the whole life of the patent. Recently, Peeters et al. (2020) found a positive effect of co-ownership with uni versities in exploratory trajectories, but a negative effect on forward citations for exploitative trajectories. They justify this result by stating that the more 'certain' exploitative trajectories are developed in-house, whereas the more uncertain types are more likely to be outsourced.

Given the distinct benefits of collaborating with different types of partners, we consider that in-depth studies are needed into the effect of co-ownership with universities and firms on patent diffusion in the "era of open innovation" (Enkel et al., 2009). This leads us to advance the following hypotheses:

H4. Co-patenting with other firms has a positive effect on the diffusion of energy patents.

H5. Co-patenting with universities has a positive effect on the diffusion of energy patents.

3. Methods and data

3.1. Measuring knowledge diffusion through the forward citations of patents

This paper relies on patent citations as an indicator of technological diffusion. Patent applicants are required to cite all "prior art" related to the invention (Criscuolo and Verspagen, 2008; Jaffe et al., 2000). Thus, patent citations are added to the patent documents if the knowledge in the cited patent is relevant to the citing patent. In other words, if patent B cites patent A, then it may be indicative of a knowledge flow from patent A to B (Hall et al., 2001). Following this reasoning, there is a large body of research using citation indicators of technological relations between the citing and cited patents (see, for example, Jaffe et al., 1993; Jaffe and Trajtemberg, 1999; Hall et al., 2001; Hu and Jaffe, 2003; Maurseth, 2005; Gay et al., 2005; Liu and Roseau, 2010; Schmid, 2018). However, patent citations fail to constitute a perfect measure of tech nological diffusion for two basic reasons (Verspagen, 2000). First, they depend on the consideration of patents as a reliable indicator of innovation. Thus, in sectors where inventions are less prone to be patented, patent citations provide a limited indicator of diffusion. Second, patent citations serve a legal purpose by limiting the claims that can be made on the invention: on recognizing previous technology, they narrow the innovativeness of the invention. For this reason, it is the ultimate responsibility of the patent examiner to determine which references should be included. It can happen, therefore, that the inventor remains unaware of the cited patent[1] (Alcácer and Gittelman, 2006; Cockburn et al., 2002). Several studies have focused on the validation of patent citations as indicators of knowledge flows (for a review, see Jaffe and de Rassenfosse, 2017). The overall conclusion of these studies is that patent citations are an accurate, though noisy, indicator of actual knowledge flows. Nevertheless, they constitute "the most widely employed measure of knowledge flows in the economics, management, and policy literatures" (Roach and Cohen, 2013).

From this literature, a number of studies have built upon the use of forward citations to measure technological diffusion (Sorenson and Fleming, 2004; Hoetker and Agarwal, 2007; Schmid, 2018). In addition, forward patent citations can be considered a measure of patent quality and hence a proxy for the economic value of a patent and its diffusion. An increased count of forward citations (citation of a patent in subsequent patents) means that the patent contributes with relevant knowledge to other inventions (e.g., Trajtenberg, 1990; Gambardella et al., 2008; Fischer and Leidinger, 2014; Briggs and Wade, 2014; Abrams et al., 2018). The relationship between forward patent citations and economic value suggests that patents related to a significant new technical knowledge receive more citations than other patents, which in turn reveals a close association between citations and the socioeconomic value of innovations (Carpenter et al., 1981; Albert et al., 1991; Harhoff et al., 2003; Lanjouw and Schankerman, 2004; Gay et al., 2005).

3.2. Variables, model, and data

3.2.1. Variables

A regression analysis of patent families (hereinafter referred to as "patents") is conducted.

Table 1 summarises variables and definitions. Our dependent variable (***forward_citations_5years***) is the count of citations that an invention (i.e., patent family) receives within a 5-year window from the first publication date (for more details, see de Rassenfosse et al., 2014; Squicciarini et al., 2013).The mechanisms generating applicant and examiner citations differ widely (see discussions regarding the role of the examiner in Alcácer et al., 2009; Chen, 2017; Azagra-Caro and Tur, 2018). Examiner citations are excluded since the inventor might remain unaware of the cited patents and may fail to utilize them for the creation of inventions and therefore may fail to truly indicate knowledge diffusion (Jaffe et al., 2000) .[2] Self-citations (i.e., citations made by an assignee to their own previous patents[3]) have also been excluded from the dependent variable (see, for example, Acosta et al., 2012). Further to factors mentioned in Section 2.2, other factors have also been identified as determinants of forward patent citations:

- *Previous experience of the applicant.* Given the path dependancy nature of knowledge creation, it is assumed that inventors that have previously innovated are more likely to develop relevant patents than inventors with no experience (Gambardella et al., 2005).
- *Family size.* The number of different jurisdictions where the same invention has been filed positively affects forward citations (e.g., Duch-Brown and Costa-Campi, 2015 for the oil and gas industries). The main argument explaining this relationship is that applying for protection is costly, therefore applicants are more likely to apply for protection in multiple countries for their most valuable inventions (Harhoff et al., 2003; Lanjouw and Schankerman, 2004 for manufacturing firms; Sampat, 2005).
- *Number of claims.* Each claim represents a distinct inventive contribution (Tong and Frame, 1992). Patents with more claims delimit broader property rights and thus are expected to be more frequently cited (see Bessen, 2008 for a set of technological sectors; Nemet, 2012 for energy technologies).
- *Number of inventors.* Increased team size increases richness of the knowledge involved in the patent and the access to a wider and more heterogeneous network (for non-energy specific evidence, see: Guellec and Van Pottelsberghe de la Potterie, 2001; Lee et al., 2007; Singh, 2008; Cassiman et al., 2008; Sun et al., 2020).
- *Originality.* Patent originality refers to the breadth of the fields of technology upon which a patent relies (Squicciarini et al., 2013). It is expected that the most original patents receive, on average, more citations since a broader search is the base for a broader range of subsequent innovations (Petruzelli et al., 2015 provide evidence for biotechnology). However, it has also been argued that searching widely is a risky process that conveys uncertainty regarding the outcomes (Petruzelli et al., 2015).
- *Technological scope.* A higher frequency of citations is expected when the patent family is assigned to a broader range of technological fields (Trajtenberg et al., 1997).
- *Triadic families.* It has been shown that EP patents simultaneously applied to US and Japan receive, on average, a higher number of citations than EP-only patents (Criscuolo, 2006 for a set of technological sectors, but not specific to energy).
- *Accumulated stock of knowledge.* The number of citations also depends on the number of opportunities to be cited: a large number of patents in a given technological domain indicate more inventors working on related technologies and thus the increased propensity of a given patent to be diffused (Acosta et al., 2013, and Schmid, 2018, for military technologies).
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[1] An analysis of the influence of citations included by the inventor and by the examiner, and the deviation generated in the determination of technological flows can be found in Alcácer & Gittelman (2006) and Thompson (2006).

[2] Following the recommendation of one anonoymous reviewer, we replicated our mainstream models using examiner citations as the dependent variable. Similar conclusions are reached regarding our hypotheses testing, except for Hypothesis 5. For brevity, the results are not displayed here but they are available from the authors upon request.

[3] To identify self-citations, we first harmonise companies' names. To this end, we consider two applicants as being the same applicant if they have the same name (even if they have different legal forms) and belong to the same country (Callaert et al., 2011).

Table 1
Variables and definitions.

Variable	Definition
Dependent variable	
Forward_citations_5years	No. of forward citations within the window of 5 years
Independent variables	
Non_patent_literature	No. of citations to non-patent literature
Backward_others_citations	No. of backward citations
Backward_self_citations	No. of backward self-citations
Collaboration_firm	Dummy: 1 indicates collaboration with a firm,0 otherwise
Collaboration_university	Dummy: 1 indicates collaboration with a university,0 otherwise
Previous_experience	No. of total inventions in energy technologies of the firms owning the patent in the previous ten years before the application date of the patent (as a logarithm)
Family_size	No. of different patent jurisdictions in the patent family
Claims	No. of claims in the patent family
Inventors	Maximum number of inventors in the patent family
Original	Originality index based on Trajtenberg et al. (1997). If all cited patents belong to exactly the same set of technologies, then the originality index is 0. A large "originality" value indicates broader technological roots of the invention
Scope	No. of different 4-digit IPC subclasses
US_JP	Dummy: 1 indicates protection in the US and JP, 0 otherwise
Stock	No. of inventions that already exist in the particular technological field over the last 10 years (as a logarithm)
Control variables	
Year dummies	Year effects: Dummy variable from 1990 to 2005, taking 2006 as base category
Field dummies	Field effects: Dummy variable. Renewables (*Wind, Solar, Geothermal, Marine, Hydro, Biomass, Waste* and *Storage*) and other technologies (*Fossil* and *Nuclear*)

Source: Author's own based on Patstat data.

All regressions control for year and field effects by including dummies. The year's fixed effects capture differences in the quality of patents relative to the last year in the sample. Similarly, several dummies capture possible differences between technological sub categories in the energy sector, both in renewables (*Wind, Solar, Geothermal, Marine, Hydro, Biomass, Waste,* and *Storage*) and other technologies (*Fossil* and *Nuclear*) (see Noailly and Shestalova, 2017, and Albino et al., 2014 for the list of IPC codes identifying each category). Each variable takes the value of 1 if the corresponding technological field appears in the group of IPC classification assigned to the patent family, and 0 otherwise.

Table 2 shows the frequencies of citations over 5 years for the whole sample. Our data shows that 74.45% of the patents in our sample do not receive citations in a 5-year window and 8.16% receive only one citation.

3.2.2. Model specification

As mentioned above, in order to estimate the influence of the various factors on the diffusion of knowledge in the energy sector, we estimate a model using the count data of forward citations over a 5-year window as a dependent variable (***forward_citations_5years***). The nature of the data implies the formulation and estimation of a counting model (Poisson or Negative Binomial), since estimates obtained from linear regression can be inconsistent, inefficient, and biased (Amano and Fujita, 1970; Long, 1997). Similar to many other studies, a baseline specification is assumed following a Poisson distribution with non-linear form. However, one restriction of the Poisson model is that it assumes the mean and variance of the dependent variable to be equal. When the dependent variable shows over-dispersion, (i.e., when the variance of the dependent vari able is greater than the mean), then negative binomial models are preferred (for details, see Cameron and Trivedi, 1986). Given the large number of zeros in our sample (as shown in Table 2, almost 75% of the patents in our sample fail to receive citations in a 5-year window), zero-inflated negative binomial regression models could be considered. However, these models assume that there is a mixed distribution composed of the two processes, one representing the count (Poisson or NB) and the other the excess of zeros (e.g., a logistic function). Following Bornmann and Leydesdorff (2015), since there is no known difference in the mechanism for the first citation and the later citations, zero-inflated negative binomial models are not used in this paper Thelwall and Wilson (2014). recommended the use of the generalised linear model with lognormal residuals for scientific citation data, although they recognize limitations to their study that probably provoke the over estimation of the unreliability of negative binomial regression for citations. Despite these limitations, and given the similarities in the distribution of patent and scientific citations, ordinary least squares models based on logarithmised citation data were additionally calculated to test the robustness of our results.[4]

Table 2
Frequency of 5-year forward citations (1990–2015).

No. of forward citations	No. of patents	Cumulative count	% of patents over total	Cumulative %
0	40,632	40,632	74.45	74.45
1	4451	45,083	8.16	82.60
2	2566	47,649	4.70	87.30
3	1681	49,330	3.08	90.38
4	1138	50,468	2.09	92.47
5	864	51,332	1.58	94.05
6	673	52,005	1.23	95.29
7	460	52,465	0.84	96.13
8	375	52,840	0.69	96.82
9	284	53,124	0.52	97.34
10	220	53,344	0.40	97.74
>10	1234	54,578	2.26	100

Source: Author's own based on Patstat data.

3.2.3. Data

The empirical data consists of 54,578 energy patent families applied for by firms and which includes at least one application to the European Patent Office (EPO) in the period 1990–2015, considering the earliest filing year of the family, that is, the priority date. The source of data is the *EPO Worldwide Patent Statistical Database (Patstat, autumn 2017 edition)*. In order to uniquely identify patent applicants, the OECD HAN database is employed together with manual harmonization. The OECD HAN database provides harmonised patent applicants' names, but it is only available for patent applicants at the EPO. Hence, our sample is limited to families of patents that include at least one application at the EPO. We follow the classification scheme based on the International Patent Classification Codes (IPC) as proposed in Noailly & Shestalova (2017) for renewables and fossil technologies, and in Albino et al. (2014) for nuclear technologies.

The DOCDB simple patent family concept is employed to build families, that is, a collection of patent documents that share identical technical content and are considered to protect a single invention. Our data is obtained from patent families instead of individual patents for several reasons (see Martínez, 2011, for a discussion on patent families). Since the same invention can be patented in multiple offices (Popp,

2005), in order to avoid duplication, patent families are used as an inventive integral unit, instead of using the individual counting of appli cations (Martínez, 2011). Furthermore, patent families can be associated to a unique priority filing (i.e., the earliest priority date), which should be that closest to the invention (Bastianin et al., 2021). From the side of citations, the focus on families prevents the multiple counting of citations (Fischer and Leidinger, 2014; Nesta et al., 2014). Moreover, if an application of the family receives a citation, it is just as valid as that received directly to the initial application (Bakker et al., 2016). Given these benefits of patent families, it is not unusual that they are increasingly used as the unit for counting patents (e.g., Baruffaldi and Shimeth, 2020; Bastianin et al., 2021), and examining knowledge diffusion across sectors (Nemet, 2012; Duch-Brown and Costa-Campi, 2015) or geographical areas (e.g., Li et al., 2021, for energy technologies).

Since citations can continue accumulating over a patent's life, the count of patent citations presents a truncation problem. Additionally, since older patents have had more time to be cited, they are expected to have received more citations. In accordance with previous contributions, we deal with these issues by using citations within a five-year time window (Petruzzelli et al., 2015) subsequent to when the invention was first published (Hall and Helmers, 2013; Moaniba et al., 2018).

However, our data is still truncated for two reasons. First, there is a publication delay: an application takes 18 months to be published after the initial filing date. Second, many EP applications are increasingly based on earlier PCT applications. For PCT applications, the applicant has 31 months to decide whether or not the application becomes a European application. In this paper, families with at least one EP application with priority date between 1990 and 2015 are considered, and hence the analysis of the data beyond 2011, which is the latest comprehensive year in our sample, should be approached with caution. In order to deal with these data truncation issues in regression analysis,

[4] Whereby 1 is added to the citation data, the logarithm is taken, and ordinary least squares regression is used.

the time frame of our sample is limited to enable the citation window to be completed. For example, the main set of econometric models is estimated using data for 1990–2006 patents to have complete information for the 5-year citation window.

4. Results

In this section, the results of our descriptive analysis are provided together with the estimation of an econometric model to identify the factors affecting forward citations of patented energy technology. Separate models for renewables and other technologies are estimated. In so doing, allowances are made for differences in the factors that encourage the diffusion of renewables and other technologies.

4.1. Descriptive analysis

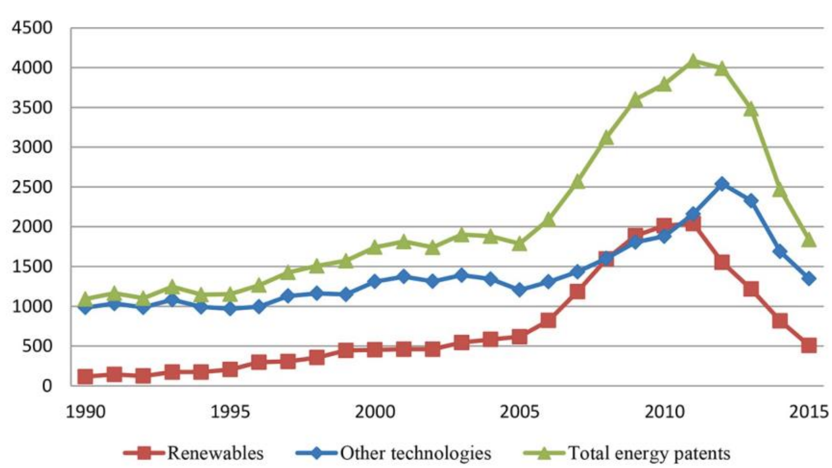
For the purpose of contextualization, a brief description is presented of patent families in our sample to provide insights into innovation in energy over time and its distribution across technological fields. Regarding the temporal evolution, Fig. 2 shows the number of patents related to renewable energy, related to other types of energy, and the total number of energy patents. For the joint series of renewables and other types of technologies, a consistent increase in the number of patents is observed from 1990 to 2011, and a decay from 2012 onwards. With the focus on renewables, the data reveals the catching up of innovation in renewable energies rising from 117 in 1990 to 2040 in 2011 (a 1643.59% increase), while other technologies rise from 984 in 1990 to 2160 in 2011 (119.51%). In 2011, renewable patents represented 49.95% of the total number of patented energy technologies. As in Haščič et al. (2015), the drop in recent years is likely to be due to a temporary phenomenon whereby certain batches of new data are included with a time lag.

Fig. 3 depicts the number of 5-year forward citations to energy patents, which shows an increasing trend from 1990 to 2007, but a notable decrease from 2008. This result can be explained: since citations are computed at the family level, and recent patent families might still be incomplete in that further applications might be expected to be added to the family. Moreover, it is worth mentioning that the number of citations that an invention receives becomes 0 in 2015, because these patents have not had enough time to be cited (5-year window not completed). Comparing these two types of energy technologies, Fig. 3 confirms the relevance of renewable energy technologies as having inventions that are more frequently cited for the generation of electricity since 2004.

Finally, by focusing on 5-year forward citations per patent over time, Fig. 4 shows a major increase in renewable energies, which surpass other technologies.

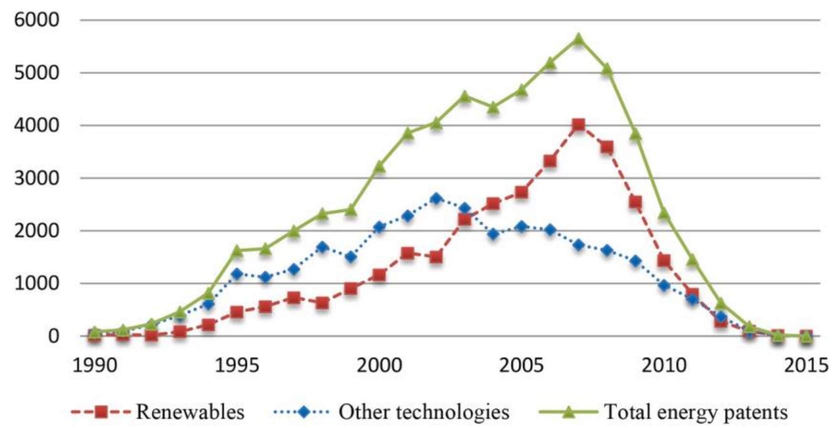
Table 3 reports the distribution of patent families and forward citations per technological field. Our results show that other technologies account for the largest share of total patents in the energy sector (65.25%). However, renewable energy technologies are cited more often than other traditional technologies for the generation of electricity (the former accounts for 51.58% of 5-year forward citations in the energy sector). Focusing on technological fields, our results also reveal that *Solar* (12.22%), *Wind* (11.63%), and *Storage* (6.37%) technologies account for the largest number of patents among the renewable energy technologies. These are also the fields with the largest share of citations in the energy sector. Furthermore, the minor importance of nuclear technologies in terms of patents and citations can be observed in comparison to fossil fuel technologies. The last column in Table 3 depicts information regarding citations over 5 years per patent family, once again revealing a higher impact of renewable energies (1.67) than for other technologies (0.84). *Wind, Biomass,* and *Storage* are the fields that receive more citations per patent family.

In order to shed light on which countries lead the process of knowledge generation in the energy sector, Table 4 presents the top ten countries with the highest number of energy inventions in the European Patent Office. Our data shows that 60.31% of the inventions in total energy originate from the United States, Germany, and Japan, with a high concentration in a few countries. This value falls to 57.19% in renewables, led by Germany, and rises to 62.07% in other technologies, led by the US. Regarding citations over 5 years per invention, Table 4 also shows the importance of the US as the leader of 5-year forward citations and 5-year citations per patent in renewables, other technologies, and total energy. Our data confirms the concentration of innovation activity in energy (for evidence on renewable technologies, see Garrone et al., 2014; Haščič and Migotto, 2015; Noailly and Ryfisch, 2015). When focusing on 5-year citations per patent, the best performing countries are Spain (1.39) and Republic of Korea (1.32) in renewable energy technologies, Japan in other technologies (0.73), and Denmark in total energy (1.06).



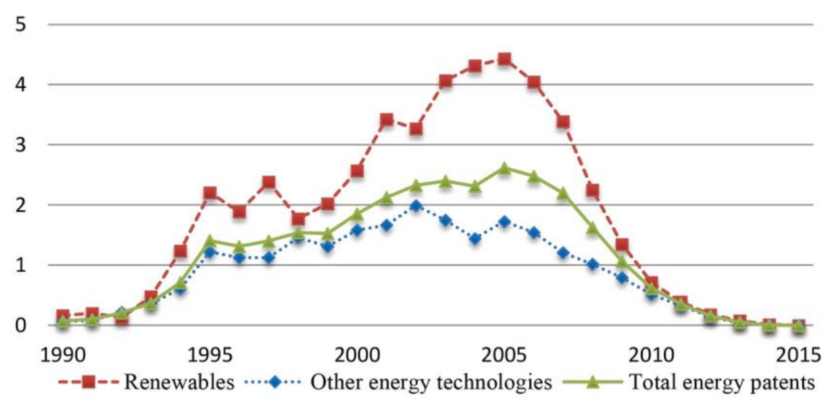
Source: Authors' own based on Patstat data.

Fig. 2. Number of inventions per type of energy technology (1990–2015), Source: Authors' own based on Patstat data.



Source: Authors' own based on Patstat data.

Fig. 3. Number of 5-year-window forward citations (1990–2015).



Source: Authors' own based on Patstat data.

Fig. 4. Number of 5-year forward citations per patent (1990–2015), Source: Authors' own based on Patstat data.

Table 3
Distribution of patent families and forward citation per technological field (1990–2015).

Technological field	A. No. of patent families	No. of patent families per field /total no. of energy patents (%)	B. No. of 5-year forward citations	No. of 5-year forward citations per field/ total no. of energy 5-year forward citations	B/A5-year forward citations per patent family
Wind	6565	11.63	11,445	18.00	1.74
Solar	6901	12.22	10,357	16.28	1.50
Geothermal	274	0.49	300	0.47	1.09
Marine	878	1.55	1049	1.65	1.19
Hydro	522	0.92	792	1.25	1.52
Biomass	310	0.55	540	0.85	1.74
Waste	573	1.01	489	0.77	0.85
Storage	3597	6.37	7834	12.32	2.18
Renewables	19,620	34.75	32,806	51.58	1.67
Fossil	33,493	59.31	29,465	46.33	0.88
Nuclear	3355	5.94	1330	2.09	0.40
Other technologies	36,848	65.25	30,795	48.42	0.84
Total energy	56,468	100	63,601	100	1.13

Note that a patent family may be related to more than one technological sector. For this reason, the sum of patent families is greater than the total sample. Source: Authors' own based on Patstat data.

Table 4
Top 10 countries with the highest number of patent families and their 5-year forward citations (1990–2015).

	Renewables					Other technologies					Total energy				
Rank	Country	Patent families	% Patent famlies over total	5-year forward Citations	5-year forward citations/ patents	Country	Patent families	% Patent families over total	5-year forward Citations	5-year forward citations/ patents	Country	Patent families	% Patent families over total	5-year forward Citations	5-year forward citations/ patents
1	DE	5240	23.38	5041	0.96	US	11,707	29.50	11,727	1.00	US	15,882	25.57	20,369	1.28
2	US	4175	18.63	8933	2.14	DE	8591	21.65	3101	0.36	DE	13,831	22.27	8117	0.59
3	JP	3405	15.19	3915	1.15	JP	4334	10.92	3153	0.73	JP	7739	12.46	7067	0.91
4	DK	1528	6.82	1825	1.19	FR	3201	8.07	1672	0.52	FR	4142	6.67	2552	0.62
5	FR	941	4.20	884	0.94	CH	2187	5.51	1314	0.6	CH	2820	4.54	1819	0.65
6	GB	885	3.95	1240	1.4	GB	1775	4.47	977	0.55	GB	2660	4.28	2212	0.83
7	ES	673	3.00	936	1.39	IT	1423	3.59	428	0.3	IT	1995	3.21	763	0.38
8	CH	633	2.82	517	0.82	SE	769	1.94	273	0.36	DK	1804	2.90	1920	1.06
9	IT	572	2.55	335	0.59	NL	760	1.91	465	0.61	NL	1303	2.10	1277	0.98
10	KR	569	2.54	749	1.32	AT	708	1.78	230	0.32	SE	1109	1.79	502	0.45
	Others	3795	16.93	5434	1.43	Others	4232	10.66	2568	0.61	Others	8818	14.20	8756	0.99
	Total	22,416	100	29,809	1.33	**Total**	39,687	100.00	25,908	0.65	Total	62,103	100	55,354	0.89

AT: Austria CH: Switzerland DE: Germany DK: Denmark ES: Spain FR: France GB: United Kingdom IT: Italy JP: Japan KR: Republic of Korea NL: Netherlands SE: Sweden US: United States.
*Note that one invention may be counted in two or more countries. For this reason, the number of inventions is greater than the total sample.

4.2. Main estimation results

Table 5 reports the descriptive statistics for all the explanatory variables, including patents from renewable energy technologies and other technologies. Renewable energy patents receive more citations on average than do other technologies (3.0573 vs. 1.1864). Several of the most notable differences are subsequently highlighted. Renewable energy patents are more prone to cite previous patents (*Back ward_others_citations* and *Backward_self_citations*). The mean number of inventors and claims is also higher for renewable energy patents than for other technologies. On the other hand, average previous experience and scope is larger for other technologies than for renewables. Interestingly, co-ownership with other firms is more usual for other technologies than for renewable energy patents (0.3259 vs. 0.3080, respectively), while co-ownership with universities is more frequent in renewable energy technologies than in other technologies (0.0102 vs. 0.0018, respectively).

As explained above, the dependent variable is the number of times that a patent family is cited as being the relevant state of the art in subsequent patent families filed within 5 years after the first publication of the patent family, excluding examiner citations and self-citations (*Forward_citations_5years*). According to Table 5, the variance (square of standard deviation) is greater than the mean. This difference suggests that over-dispersion is present and that a Negative Binomial model would be appropriate.

Table 6 shows the main econometric results using Negative Binomial models. Models 1, 3, and 5 explain knowledge diffusion in the renewable sector and include binary variables for each field. Models 2, 4, and 6 are estimated for other technologies and include two binary variables to control for nuclear and fossil energy innovations. In all the regressions, we also control for temporal effects. Patents that share codes from both renewables and other technologies are excluded. Furthermore, since *Backward_self_citations* and *Backward_others_citations* are components of the total backward citations, and despite not showing high linear cor relations to each other and the fact that the VIFs are low, we estimate our Negative Binomial model by including *Backward_others_citations* and omitting *Backward_self_citations* (and vice versa). Given the space limitations herein, only the results of Negative Binomial regressions for these separated regressions are included in Table 6, which are the preferred models, given the over-dispersion of citations.

The results show certain similarities in the variables in the explanation of the diffusion of renewables and other technologies. In all models, backward citations to other patents show a positive and significant coefficient, which emphasises the importance of knowledge sourcing for knowledge diffusion. Backward self-citations are also significant in all models, thus supporting the cumulative nature of knowledge. Co-ownership with other firms is not relevant in any model. The number of inventors, claims, scope, originality, and previous experience in the development of innovations exert a positive and significant effect on enhancing knowledge diffusion. Non-patent literature citations are only relevant for renewable energy technologies, but they also become significant for other technologies when omitting *Back ward_self_citations* or *Backward_others_citations* from the main regression (see Models 4 and 6). While being wary of encountering a possible multicollinearity problem, we conclude that scientific knowledge is relevant for innovations in the energy sector, both in renewables and other technologies.

Additionally, several differences across renewables and other technologies are also observed. There is a negative effect of co-ownership with universities and a positive effect of triadic families on knowledge diffusion within 5 years for other energy technologies, but this effect does not hold for renewable energy technologies. The stock of knowledge in the energy sector is only relevant in fossil and nuclear technologies, which exerts a negative effect on the number of citations thus suggesting that the competition effect for citations is greater than the size effect. In contrast, family size only increases the impact of renew able patented technologies since it is not relevant for the diffusion of other energy technologies.

Table 5
Descriptive statistics (1990–2006).

	RENEWABLES				OTHER TECHNOLOGIES			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Forward_citations_5years	3.0573	6.1617	0	99	1.1864	3.6416	0	186
Non_patent_literature	2.5193	12.2941	0	300	0.9785	7.5843	0	374
Backward_others_citations	6.4541	14.6875	0	176	3.6455	10.4930	0	197
Backward_self_citations	0.8803	2.8636	0	65	0.6937	2.3606	0	88
Collaboration_firm	0.3080	0.4617	0	1	0.3259	0.4687	0	1
Collaboration_university	0.0102	0.1003	0	1	0.0018	0.0419	0	1
Previous_experience	2.7610	2.3586	0	9.5613	3.8262	2.5453	0	10.0459
Family_size	5.4917	3.0381	1	30	5.4201	3.3320	1	33
Claims	16.8781	15.5567	0	199	14.1813	11.3574	0	373
Inventors	2.7742	1.9072	0	20	2.5751	1.7979	0	26
Original	0.6177	0.2443	0	0.9731	0.6990	0.2019	0	0.9750
Scope	2.3607	1.6393	1	23	2.9768	1.5925	1	26
US_JP	0.4583	0.4983	0	1	0.4487	0.4974	0	1
Stock	8.7658	0.5643	5.8579	10.0685	11.1509	0.4754	9.3248	11.6006
No. Obs. (year<=2006)	5900				19,343			

Table 6
Negative binomial estimations. Dependent variable: 5-year forward citations (1990–2006).

	Negative Binomial		Negative Binomial *Backward_self_citations* omitted		Negative Binomial *Backward_others_citations* omitted	
	Renew.(1)	Other(2)	Renew.(3)	Other(4)	Renew.(5)	Other(6)
Non_patent_literature	0.0047**	0.0024	0.0055***	0.0032*	0.0126***	0.0092***
	(0.0021)	(0.0016)	(0.0021)	(0.0017)	(0.0023)	(0.0019)
Backward_others_citations	0.0111***	0.0152***	0.0123***	0.0170***		
	(0.0018)	(0.0020)	(0.0018)	(0.0019)		
Backward_self_citations	0.0231***	0.0445***			0.0318***	0.0568***
	(0.0060)	(0.0079)			(0.0065)	(0.0080)
Ccollaboration_firm	0.0720	−0.0860	0.0725	−0.0879	0.0731	−0.0778
	(0.0570)	(0.0568)	(0.0567)	(0.0569)	(0.0567)	(0.0565)
Collaboration_university	0.3676*	−0.8377**	0.3651*	−0.8840**	0.3041	−0.7812**
	(0.2207)	(0.3957)	(0.2175)	(0.3964)	(0.2104)	(0.3945)
Previous_experience	0.0511***	0.0686***	0.0569***	0.0791***	0.0468***	0.0602***
	(0.0109)	(0.0096)	(0.0107)	(0.0093)	(0.0109)	(0.0093)
Family_size	0.0468***	−0.0004	0.0469***	0.0005	0.0517***	0.0009
	(0.0092)	(0.0088)	(0.0092)	(0.0088)	(0.0092)	(0.0088)
Claims	0.0187***	0.0320***	0.0189***	0.0329***	0.0204***	0.0353***
	(0.0019)	(0.0022)	(0.0019)	(0.0021)	(0.0019)	(0.0021)
Inventors	0.0449***	0.0503***	0.0451***	0.0511***	0.0490***	0.0524***
	(0.0145)	(0.0119)	(0.0145)	(0.0119)	(0.0145)	(0.0116)
Original	0.5039***	1.0320***	0.5201***	1.0376***	0.5170***	1.0979***
	(0.1289)	(0.1462)	(0.1283)	(0.1465)	(0.1284)	(0.1457)
Scope	0.0490***	0.0625***	0.0501***	0.0613***	0.0515***	0.0704***
	(0.0153)	(0.0160)	(0.0153)	(0.0160)	(0.0152)	(0.0157)
US_JP	0.0809	0.6745***	0.0741	0.6801***	0.1012	0.6904***
	(0.0933)	(0.0731)	(0.0931)	(0.0730)	(0.0936)	(0.0735)
Stock	0.0340	−2.7247***	0.0404	−2.7627***	−0.0127	−2.6944***
	(0.2117)	(0.6258)	(0.2117)	(0.6260)	(0.2126)	(0.6173)
_cons	−1.4396	23.1848***	−1.4969	23.5537***	−1.0962	22.8783***
	(1.6464)	(5.9100)	(1.6457)	(5.9110)	(1.6491)	(5.8284)
Time dummies	YES	YES	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES	YES	YES
lnalpha	1.2641***	1.6633***	1.2667***	1.6672***	1.2723***	1.6734***
	(−0.0302)	(−0.0243)	(−0.0301)	(−0.0243)	(−0.0301)	(−0.0241)
No. obs.	5900	19,343	5900	19,343	5900	19,343
pseudo R^2	0.044	0.058	0.043	0.058	0.043	0.057
Log-likelihood	−10,825.3080	−21,385.0997	−10,828.4833	−21,396.5387	−10,836.3758	−21,409.9299
Wald chi2	1147.9718***	1759.5052***	1136.2801***	1695.8557***	1079.6083***	1705.5769***

Standard errors are given in parentheses.
$^{*}p < 0.1$.
$^{**}p < 0.05$.
$^{***}p < 0.01$.

4.3. Robustness checks

In addition to the sensitivity analysis provided in the previous section, we estimate the models using the number of 3-year forward patent citations as a dependent variable (Table 7). Given the shorter 3-year citation window, we extend the period of the sample used in the estimations until 2009. The results of the alternative specifications included in Table 7 largely mirror the results from the main models in Table 6 regarding the principal conclusions. However, one notable result can be observed: the coefficient of co-ownership (either with universities or firms) is negative and significant in other energy patents, which strongly supports the conclusion that co-patenting with other companies or universities significantly hinders the diffusion of knowledge in the 3 year shorter run for fossil and nuclear technologies. The effect of co ownership on the diffusion of renewable patented technologies remains insignificant. Table 8 presents ordinary least squares regression models based on logarithmised citations, both for 5-year forward citations and 3-year forward citations. Due to the limited space, only the re-calculation of models 1, 2, 7, and 8 are presented (those including Back ward_self_citations and Backward_others_citations). The comparison of the results of these models with those of the negative binomial regression models largely confirms the robustness of our results.

Table 7 Negative binomial estimations. Dependent variable: 3-year forward citations (1990–2008).

	Negative Binomial		Negative Binomial *Backward_self_citations* omitted		Negative Binomial *Backward_others_citations* omitted	
	Renew.(7)	Other(8)	Renew.(9)	Other(10)	Renew.(11)	Other(12)
Non_patent_literature	0.0051**	0.0044*	0.0056**	0.0053**	0.0151***	0.0111***
	(0.0021)	(0.0023)	(0.0022)	(0.0023)	(0.0023)	(0.0023)
Backward_others_citations	0.0119***	0.0164***	0.0135***	0.0185***		
	(0.0020)	(0.0028)	(0.0020)	(0.0027)		
Backward_self_citations	0.0265***	0.0497***			0.0388***	0.0645***
	(0.0086)	(0.0117)			(0.0086)	(0.0116)
Collaboration_firm	0.0848	−0.2808***	0.0767	−0.2738***	0.0960	−0.2683***
	(0.0724)	(0.0902)	(0.0721)	(0.0903)	(0.0722)	(0.0897)
Collaboration_university	0.4288	−1.5744***	0.4162	−1.6640***	0.3765	−1.4455**
	(0.3205)	(0.6093)	(0.3203)	(0.5993)	(0.3137)	(0.6225)
Previous_experience	0.0248*	0.0576***	0.0306**	0.0698***	0.0202	0.0468***
	(0.0134)	(0.0146)	(0.0133)	(0.0140)	(0.0134)	(0.0140)
Family_size	0.0441***	0.0088	0.0446***	0.0086	0.0474***	0.0090
	(0.0114)	(0.0169)	(0.0114)	(0.0169)	(0.0114)	(0.0169)
Claims	0.0186***	0.0310***	0.0189***	0.0319***	0.0209***	0.0355***
	(0.0024)	(0.0032)	(0.0023)	(0.0032)	(0.0024)	(0.0031)
Inventors	0.0613***	0.0828***	0.0608***	0.0831***	0.0650***	0.0847***
	(0.0186)	(0.0172)	(0.0186)	(0.0173)	(0.0185)	(0.0170)
Original	0.5433***	1.3965***	0.5511***	1.3878***	0.5694***	1.4685***
	(0.1632)	(0.2392)	(0.1624)	(0.2401)	(0.1629)	(0.2381)
Scope	0.0766***	0.0986***	0.0786***	0.0975***	0.0810***	0.1040***
	(0.0188)	(0.0236)	(0.0188)	(0.0235)	(0.0186)	(0.0233)
US_JP	−0.0313	0.5014***	−0.0405	0.5074***	−0.0082	0.5247***
	(0.0967)	(0.1096)	(0.0972)	(0.1097)	(0.0961)	(0.1096)
Stock	−0.1859	−2.0636**	−0.1752	−2.0957**	−0.2129	−2.0958**
	(0.1975)	(0.9137)	(0.1967)	(0.9206)	(0.1969)	(0.8987)
_cons	−0.1174	16.0783*	−0.2027	16.4102*	0.0608	16.2942*
	(1.5700)	(8.5704)	(1.5639)	(8.6335)	(1.5655)	(8.4271)
Time dummies	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
lnalpha	2.0534***	2.7004***	2.0552***	2.7031***	2.0605***	2.7096***
	(0.0297)	(0.0308)	(0.0296)	(0.0308)	(0.0296)	(0.0304)
No. obs.	8559	22,256	8559	22,256	8559	22,256
pseudo R^2	0.0371	0.0460	0.0368	0.0456	0.0363	0.0451
Log-likelihood	−10,496.1332	−13,775.3583	−10,498.5317	−13,781.0434	−10,504.6038	−13,789.0086
Wald chi2	37,333.4499***	936.0816***	34,582.4743***	890.6581***	37,490.0924***	916.8443***

Robust standard errors are given in parentheses.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

Table 8 Ordinary least squares regression models based on logarithmised citation data.

	Dependent variable: 5-year forward citation		Dependent variable: 3-year forward citation	
	Renew.(13)	Other(14)	Renew.(15)	Other(16)
Non_patent_Literature	0.0040**	0.0038***	0.0048***	0.0033***
	(0.0017)	(0.0009)	(0.0018)	(0.0010)
Backward_others_citations	0.0089***	0.0081***	0.0062***	0.0045***
	(0.0013)	(0.0009)	(0.0012)	(0.0007)
Backward_self_citations	0.0264***	0.0187***	0.0134**	0.0092***
	(0.0050)	(0.0047)	(0.0054)	(0.0028)
Collaboration_firm	0.0007	−0.0166	−0.0251	−0.0260***
	(0.0269)	(0.0107)	(0.0204)	(0.0077)
Collaboration_university	0.0987	−0.2105*	−0.0170	−0.1285*
	(0.1542)	(0.1098)	(0.1148)	(0.0703)
Previous_experience	0.0332***	0.0272***	0.0153***	0.0111***
	(0.0056)	(0.0022)	(0.0039)	(0.0016)
Family_size	0.0187***	−0.0059***	0.0106***	−0.0033***
	(0.0045)	(0.0016)	(0.0035)	(0.0011)
Claims	0.0082***	0.0091***	0.0048***	0.0047***
	(0.0010)	(0.0008)	(0.0009)	(0.0006)
Inventors	0.0165**	0.0146***	0.0171***	0.0120***
	(0.0071)	(0.0031)	(0.0055)	(0.0024)
Original	0.1201**	0.0974***	0.0781**	0.0552***
	(0.0511)	(0.0205)	(0.0377)	(0.0142)
Scope	0.0415***	0.0217***	0.0289***	0.0141***
	(0.0094)	(0.0040)	(0.0074)	(0.0029)
US_JP	0.0513	0.1244***	−0.0088	0.0503***
	(0.0364)	(0.0112)	(0.0260)	(0.0080)
Stock	0.1724**	0.2482***	0.1165**	0.1414***
	(0.0819)	(0.0487)	(0.0524)	(0.0286)
_cons	−1.8292***	−2.4501***	−1.0180***	−1.4699***
	(0.5577)	(0.4736)	(0.3607)	(0.2788)
Time dummies	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES
No. obs.	5900	19,343	8559	22,256
R2	0.2165	0.1593	0.1302	0.0803
F test	54.53***	126.14***	39.78***	52.25***

Robust standard errors are given in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

6. Conclusions and policy implications

Innovation in energy technologies is required for the reduction of the environmental impact of power production. Therefore, ascertaining the factors that affect the diffusion of technology is essential. This paper contributes towards identifying the factors that affect the diffusion of patented technology in the energy sector. The empirical analysis is based on forward patent citations.

Our descriptive analysis shows an increasing trend towards innovation in renewable energy technologies from 1990 to 2011, the latest full year of our sample. Our data also confirms the relevance of renewable technologies in terms of the number of forward citations. Since inventions from renewable energy technologies are more frequently cited than other technologies, their knowledge is better distributed and environmental improvement is therefore encouraged.

The objective of our econometric model is to determine the factors affecting knowledge diffusion in the energy sector, by focusing on the role of non-patent literature citations, backward patent citations, and co ownership of patents. Certain similarities are found in the factors affecting forward citations between renewables and other patented technologies: backward citations to other patents, backward self citations, co-inventorship, claims, scope, originality, previous experience of the applicant in energy technologies, and non-patent literature all exert a positive effect on knowledge diffusion. However, certain differences across sectors can also be found. Family size is a significant variable in enabling the diffusion of renewable energy technologies, while triadic families exert a positive effect only in the diffusion of other technologies. An accumulated stock of knowledge negatively affects the number of forward citations of patented inventions in fossil and nuclear technologies. Interestingly, we find that co-ownership with other firms or universities is not significant for the diffusion of renewable energy technologies. In contrast, when focusing on other technologies, co ownership with universities hinders the diffusion of innovations. It is also found that co-ownership with other firms negatively affects the diffusion of other energy technologies but only in the shorter 3-year term.

The analysis offered several practical implications for policy-makers and firms. Our results show that patents more extensively based on scientific knowledge diffuse more readily, thereby enhancing the development of future innovations. For firms, this result highlights the importance of strengthening their scientific base through, for example, the incorporation of scientists into their research teams. Innovation policies could therefore be oriented towards creating incentives for this incorporation. Furthermore, this result, together with the positive effect of backward citations to other patents, justify initiatives oriented towards the creation of knowledge pools of patents and scientific papers related to research on energy technologies in order to enhance knowledge accessibility and the retrieval of potentially interesting information in this line of research. For example, the IPC Green Inventory, which facilitates searches for patent information relating to Environmentally Sound Technologies (ESTs), constitutes a well-justified initiative according to our results. Similar initiatives could also be addressed for the creation of a pool of publicly available scientific papers that would provide a scientific base for the development of further clean technologies.

Our results also show that co-ownership with other firms or universities may hinder the diffusion of fossil and nuclear patented technologies, while it exerts a negligible effect on the diffusion of renewable energy technologies. From the perspective of the firm, this finding is relevant because technological impact of the research is related to firm performance (e.g., Kim et al., 2018). Additionally, our results do not provide support for public or firm initiatives supporting co-patenting strategies if the objective involves the enhancement of the diffusion of patented technologies. In contrast, the role of co-inventorship is clear both in renewables and other technologies, and hence company strategies and policies oriented towards the formation of research teams are preferred over the facilitation of the R&D co-patenting strategies.

This paper presents several limitations. First, despite the widespread use of patent citations as indicators of knowledge diffusion, its use is not without limitations since knowledge diffusion is a complex process that can be measured through a variety of indicators. Second, not all collaborative efforts result in the co-ownership of a patent, and hence the conclusions cannot be extended to include all collaboration in R&D. Third, the geographical or sectoral profile of the co-assignee remains to be analysed, which could shed light on the characteristics of collabo rations of a more successful nature. Fourth, data on knowledge diffusion is truncated (citations are measured at a point in time) and diffusion in longer time windows has yet to be explored. These limitations could be addressed in further research.

CRediT authorship contribution statement

Ana María Fernández: Conceptualization, Methodology, Writing – original draft, Writing – review & editing.
Esther Ferrándiz: Conceptualization, Methodology, Writing – original draft, Writing – review & editing.
Jennifer Medina: Data curation, Methodology.

References

Abrams, D.S., Akcigit, U., Grennan, J., 2018. Patent Value and citations: Creative destruction Or Strategic disruption? (No. w19647). National Bureau of Economic Research, New York.

Abulfotuh, F., 2007. Energy efficiency and renewable technologies: the way to sustainable energy future. Desalination 209 (1–3), 275–282.

Acemoglu, D., Akcigit, U., 2012. Intellectual property rights policy, competition and innovation. J. Eur. Econ. Assoc. 10 (1), 1–42.

Acosta, M., Coronado, D., Fernández, A., 2009. Exploring the quality of environmental technology in Europe: evidence from patent citations. Scientometrics 80 (1),131–152.

Acosta, M., Coronado, D., Martínez, M.A., 2012. Spatial differences in the quality of university patenting: do regions matter? Res. Policy 41 (4), 692–703.

Acosta, M., Coronado, D., Marín, R., Prats, P., 2013. Factors affecting the diffusion of patented military technology in the field of weapons and ammunition. Scientometrics 94 (1), 1–22.

Aghion, P., Howitt, P., 1992. A model of growth through creative destruction. Econometrica 60, 323–351.

Ahmadpoor, M., Jones, B.F., 2017. The dual frontier: patented inventions and prior scientific advance. Science 357 (6351), 583–587.

Andergassen, R., Nardini, F., Ricottilli, M., 2017. Innovation diffusion, general purpose technologies and economic growth. Struct. Change Econ. Dynam. 40, 72–80.

Albert, M.B., Avery, D., Narin, F., McAllister, P., 1991. Direct validation of citation counts as indicators of industrially important patents. Res. Policy 20, 251–259.

Albino, V., Ardito, L., Dangelico, R.M., Petruzzelli, A.M., 2014. Understanding the development trends of low-carbon energy technologies: a patent analysis. Appl. Energy 135, 836–854.

Alcacer, J., Gittelman, M., 2006. Patent citations as a measure of knowledge flows: the influence of examiner citations. Rev. Econ. Stat. 88 (4), 774–779.

Alcácer, J., Gittelman, M., Sampat, B., 2009. Applicant and examiner citations in US patents: an overview and analysis. Res. Policy 38 (2), 415–427.

Amano, K., Fujita, M., 1970. Long run economic effect analysis of alternative transportation facility plans-regional and national. J. Reg. Sci. 10, 297–323.

Apergis, N., Payne, J.E., 2012. Renewable and non-renewable energy consumption growth nexus: evidence from a panel error correction model. Energy Econ. 34 (3),733–738.

Araújo, R., Franco, M., 2021. The use of collaboration networks in search of eco innovation: a systematic literature review. J. Clean Prod., 127975

Arthur, W.B., 2007. The structure of invention. Res. Policy 36 (2), 274–287.

Azagra-Caro, J.M., Tur, E.M., 2018. Examiner trust in applicants to the european patent office: country specificities. Scientometrics 117 (3), 1319–1348.

Bakker, J., Verhoeven, D., Zhang, L., van Looy, B., 2016. Patent citation indicators: one size fits all? Scientometrics 106 (1), 187–211.

Balconi, M., Brusoni, S., Orsenigo, L., 2010. defence of the linear model: an essay. Res.Policy 39 (1), 1–13.

Barbieri, N., Marzucchi, A., Rizzo, U., 2020. Knowledge sources and impacts on subsequent inventions: do green technologies differ from non-green ones? Res. Policy 49 (2), 103901.

Baruffaldi, S.H., Simeth, M., 2020. Patents and knowledge diffusion: the effect of early disclosure. Res. Policy 49 (4), 103927.

Bastianin, A., Castelnovo, P., Florio, M., Giunta, A., 2021. Big science and innovation:gestation lag from procurement to patents for CERN suppliers. J. Technol. Transf.1–25.

Battke, B., Schmidt, T.S., 2015. Cost-efficient demand-pull policies for multi-purpose technologies–The case of stationary electricity storage. Appl. Energy 155, 334–348.

Baumol, W.J. (1991). Technological imperatives, productivity and insurance costs. Geneva Papers on Risk and Insurance. Issues and Practice, 154–165.

Belderbos, R., Cassiman, B., Faems, D., Leten, B., Van Looy, B., 2014. Co-ownership of intellectual property: exploring the value-appropriation and value-creation implications of co-patenting with different partners. Res. Policy 43 (5), 841–852.

Bessen, J., 2008. The value of U.S. patents by owner and patent characteristics. Res.Policy 37 (5), 932–945.

Binz, C., Anadon, L.D., 2018. Unrelated diversification in latecomer contexts: emergence of the Chinese solar photovoltaics industry. Environm. Innov. Societal Trans. 28,14–34.

Bonesso, S., Comacchio, A., Pizzi, C., 2011. Technology sourcing decisions in exploratory projets. Technovation 31 (10–11), 573–585.

Bornmann, L., Leydesdorff, L., 2015. Does quality and content matter for citedness? Acomparison with para-textual factors and over time. J. Informetr. 9 (3), 419–429.

Branstetter, L., 2005. Exploring the link between academic science and industrial innovation. Ann. Econ. Stat. 79 (80), 119–142.

Briggs, K., Wade, M., 2014. More is better: evidence that joint patenting leads to quality innovation. Appl. Econ. 46, 4370–4379.

Briggs, K., 2015. Co-owner relationships conducive to high quality joint patents. Res.Policy 44 (8), 1566–1573.

Brooks, H., 1994. The relationship between science and technology. Res. Policy 23 (5), 477–486.

Bush, V., 1945. Science, the Endless Frontier: A report to the President. GovernmentPrinting Office, Washington.

Callaert, J., Plessis, M.D., Grouwels, J., Lecocq, C., Magerman, T., Peeters, B., Song, X., Looy, B.V., Vereyen, C., 2011. Patent statistics at eurostat: methods for regionalisation, sector allocation and name harmonisation. Eurostat Methodol. Working Papers.

Cameron, A., Trivedi, P., 1986. Econometrics Models Based on Count Data: comparisons and Applications of Some Estimators and Tests. J. Appl. Econom. 1 (1), 29–53.

Carpenter, M.P., Narin, F., Wolf, P., 1981. Citation rates to technologically important patents. World Patent Inform. 3, 160–163.

Carrillo-Hermosilla, J., Del Río, P., Könnölä, T., 2010. Diversity of eco-innovations: reflections from selected case studies. J. Clean Prod. 18, 1073–1083.

Cassiman, B., Veugelers, R., Zuniga, P., 2008. In search of performance effects of (in) direct industry science links. Indust. Corporate Change 17 (4), 611–646.

Chen, Y.S., Chang, K.C., 2010. The relationship between a firm's patent quality and its market value—The case of US pharmaceutical industry. Technol. Forecast Soc. Change 77 (1), 20–33.

Chen, L., 2017. Do patent citations indicate knowledge linkage? The evidence from text similarities between patents and their citations. J. Informetr. 11 (1), 63–79.

Cockburn, I.M., Kortum, S., Stern, S., 2002. Are all patent examiners equal? The impact of examiner characteristics. National Bureau Econ. Res. (No. w8980).

Cohen, W.M., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Adm. Sci. Q 128–152.

Corrocher, N., Mancusi, M.L., 2021. International collaborations in green energy technologies: what is the role of distance in environmental policy stringency? Energy Pol. 156, 112470.

Criscuolo, P., 2006. The 'home advantage' effect and patent families. A comparison of OECD triadic patents, the USPTO and the EPO. Scientometrics 66 (1), 23–41. Criscuolo, P., Verspagen, B., 2008. Does it matter where patent citations come from? Inventor vs. examiner citations in European patents. Res. Pol. 37 (10), 1892–1908.

De Rassenfosse, G., Dernis, H., Boedt, G., 2014. An Introduction to the Patstat database with example queries. Austral. Econ. Rev. 47 (3), 395–408.

Duch-Brown, N., Costa-Campi, M.T., 2015. The diffusion of patented oil and gas technology with environmental uses: a forward patent citation analysis. Energy Pol. 83, 267–276.

Duguet, E., Macgarvie, M., 2005. How well do patent citations measure flows of technology? Evidence from french innovation surveys. Econ. Innov. New Technol. 14 (5), 375–393.Enkel, E., Gassmann, O., Chesbrough, H.W., 2009. Open R&D and open innovation: exploring the phenomenon. R&D Management 39, 311–316.

Fischer, T., Leidinger, J., 2014. Testing patent value indicators on directly observed patent value An empirical analysis of ocean tomo patent auctions. Res. Policy 43 (3), 519–529.

Fleming, L., Greene, H., Li, G., Marx, M., Yao, D., 2019. Government-funded research increasingly fuels innovation. Science 364 (6446), 1139–1141.

Fleming, L., Sorenson, O., 2004. Science as a map in technological search. Strategic Manag. J. 25 (8–9), 909–928.

Gambardella, A., Harhoff, D., & Verspagen, B. (2005). The value of patents. Universita Bocconi, Ludwig-Maximiliens Universitaet, and Eindhoven University, Working Paper: http://www.creiweb.org/activities/sc_conferences/23/papers/gambardella.pdf.

Manag. Rev. 5 (2), 69–84.
Garrone, P., Piscitello, L., Wang, Y., 2014. Innovation performance and international knowledge spillovers: evidence from the renewable energy sector in OECD countries. Industry Innov. 21 (7–8), 574–598.
Gay, C., Le Bas, C., 2005. Uses without too many abuses of patent citations or the simple economics of patent citations as a measure of value and flows of knowledge. Econ. Innov. New Technol. 14 (5), 333–338.
Gay, C., Le Bas, C., Patel, P., Touach, K., 2005. The determinants of patent citations: an empirical analysis of French and British patents in the US. Econ. Innov. New Technol. 14 (5), 339–350.
Ghisetti, C., Marzucchi, A., Montresor, S., 2015. The open eco-innovation mode. An empirical investigation of eleven european countries. Res. Pol. 44 (5), 1080–1093.
Godin, B., 2006. The linear model of innovation: the historical construction of an analytical framework. Sci., Technol., Human Values 31 (6), 639–667.
Gosens, J., Lu, Y., Coenen, L., 2015. The role of transnational dimensions in emerging economy 'Technological Innovation Systems' for clean-tech. J. Clean Prod. 86, 378–388.
Griliches, Z., 1992. The Search for R&D Spillovers. Scandinavian J. Econ. 94, 29–47. Grossman, G.M., Helpman, E., 1991. Innovation and growth in the global economy. MIT press.
Grossman, G.M., Helpman, E., 2018. Growth, trade, and inequality. Econometrica 86 (1), 37–83.
Guellec, D., Van Pottelsberghe de la Potterie, B., 2001. The internationalization of technology analysed with patent data. Res. Pol. 30, 1253–1266.
Hagedoorn, J., 2003. Sharing intellectual property rights—An exploratory study of joint patenting amongst companies. Indust. Corp. Change 12 (5), 1035–1050.
Hall, B.H., MacGarvie, M., 2010. The private value of software patents. Res. Policy 39, 994–1009.
Hall, B.H., Helmers, C., 2013. Innovation and diffusion of clean/green technology: can patent commons help? J. Environ. Econ. Manage 66 (1), 33–51.
Hall, B., Jaffe, A., Trajtenberg, M., 2001. The NBER patent citation data file: lessons, insights and methodological tools. NBER Working Paper 8498.
Hall, B.H., Jaffe, A., Trajtenberg, M., 2005. Market value and patent citations. RAND J. Econ. 36, 16–38.
Harhoff, D., Scherer, F.M., Vopel, K., 2003. Citations, family size, opposition and the value of patent rights. Res. Policy 32 (8), 1343–1363.
Harhoff, D., Wagner, S., 2009. The duration of patent examination at the European Patent Office. Manage Sci. 55 (12), 1969–1984.
Harrigan, K.R., Di Guardo, M.C., Marku, E., 2018. Patent value and the Tobin's q ratio in media services. J. Technol. Transf. 43 (1), 1–19.
Haščič, I., Migotto, M., 2015. Measuring environmental innovation using patent data. OECD Environ. Working Paper 89.
Haščič, I., Silva, J., Johnstone, N., 2015. The Use of Patent Statistics For International Comparisons and Analysis of Narrow Technological Fields. OECD, Paris. Henard, D.H., Dacin, P.A., 2010. Reputation for product innovation: its impact on consumers. J. Prod. Innov. Manag. 27 (3), 321–335.
Hirschey, M., Richardson, V.J., 2004. Are scientific indicators of patent quality useful to investors? J. Empirical Fin. 11 (1), 91–107.
Hoetker, G., Agarwal, R., 2007. Death hurts, but it isn't fatal: the postexit diffusion of knowledge created by innovative companies. Acad. Management J. 50 (2), 446–467.
Höflinger, P.J., Nagel, C., Sandner, P., 2018. Reputation for technological innovation: does it actually cohere with innovative activity? J. Innov. Knowledge 3, 26–39. Hötte, K., 2020. How to accelerate green technology diffusion? Directed technological change in the presence of coevolving absorptive capacity. Energy Econ. 85, 104565. Hötte, K., Pichler, A., Lafond, F., 2021. The rise of science in low-carbon energy technologies. Renew. Sustain. Energy Rev. 139, 110654.
Hu, A.G., Jaffe, A.B., 2003. Patent citations and International Knowledge flow: the cases of Korea and Taiwan. Intern. J. Indust. Organiz. 21, 849–880.
IEA, 2017. Energy Technology Perspectives 2017. IEA. Paris. https://www.iea.org/repo rts/energy-technology-perspectives-2017.
IEA, 2020. Energy Technology Perspectives 2020. IEA. Paris. https://www.iea.org/repo rts/energy-technology-perspectives-2020.
Jaffe, A.B., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. the. Quart. J. Econ. 108 (3), 577–598.
Jaffe, A.B., 1998. The importance of "spillovers" in the policy mission of the advanced technology program. J. Technol. Transf. 23 (2), 11–19.
Jaffe, A., Trajtenberg, M., 1999. International knowledge flows: evidence from patent citations. Econ. Innov. New Technol. 8, 105–136.
Jaffe, A.B., Trajtenberg, M., Fogarty, M.S., 2000. Knowledge spillovers and patent citations: evidence from a survey of inventors. Am. Econ. Rev. 90 (2), 215–218.
Jaffe, A.B., De Rassenfosse, G., 2017. Patent citation data in social science research: overview and best practices. J. Assoc. Inf. Sci. Technol. 68 (6), 1360–1374.
Johnstone, N., Häscic, I., Popp, D., 2010. Renewable energy policies and technological innovation evidence based on patent counts. Environmen. Resource Econ. 45 (1), 133–155.
Kim, D., Kim, N., Kim, W., 2018. The effect of patent protection on firms' market value: the case of the renewable energy sector. Renew. Sustain. Energy Rev. 82, 4309–4319.
Klarl, T., 2014. Knowledge diffusion and knowledge transfer revisited: two sides of the medal. J. Evolut. Econ. 24 (4), 737–760.
Korres M, G, 2012. Inside Entrepreneurship and Innovation Activities. Knowledge Management and Drivers of Innovation in Services Industries. IGI Global, pp. 67–76.
Lacerda, J.S., Van den Bergh, J.C, 2020. Effectiveness of an 'open innovation' approach in renewable energy: empirical evidence from a survey on solar and wind power. Renew. Sustain. Energy Rev. 118, 109505.
Lane, P.J., Koka, B.R., Pathak, S., 2006. The reification of absorptive capacity: a critical review and rejuvenation of the construct. Acad. Manag. Rev. 31 (4), 853–863.
Lanjouw, J.O., Schankerman, M., 2004. Patent quality and research productivity: measuring innovation with multiple indicators. Econ. J. 114 (495), 441–465.
Lee, Y.G., Lee, J.D., Song, Y.I., Lee, S.Y., 2007. An in-depth empirical analysis of patent citation counts using zero-inflated count data model: the case of KIST. Scientometrics 70 (1), 27–39.
Lee, J., Sohn, S.Y., 2017. What makes the first forward citation of a patent occur earlier? Scientometrics 113 (1), 279–298.
Li, D., Heimeriks, G., Alkemade, F., 2021. Knowledge flows in global renewable energy innovation systems: the role of technological and geographical distance. Technol. Anal. Strat. Manage. 1–15.
Liu, K., Arthurs, J., Cullen, J., Alexander, R., 2008. Internal sequential innovations: how does interrelatedness affect patent renewal? Res. Policy 37 (5), 946–953.
Liu, Y., Rousseau, R., 2010. Knowledge diffusion through publications and citations: a case study using ESI-fields as unit of diffusion. J. Am. Soc. Inform. Sci. Technol. 61 (2), 340–351.
Long, J.S., 1997. Regression Models For Categorical and Limited Dependent Variables (Vol. 7). Sage Publications, Thousand Oaks, CA.
Martínez, C., 2011. Patent families: when do different definitions really matter?Scientometrics 86, 39–63.
Marx, M., Fuegi, A., 2020. Reliance on science: worldwide front-page patent citations to scientific articles. Strateg. Manag. J. 41 (9), 1572–1594.
Maurseth, P.B., 2005. Lovely but dangerous: the impact of patent citations on patent renewal. Econ. Innov. New Technol. 14 (5), 351–374.
Miremadi, I., Saboohi, Y., Arasti, M., 2019. The influence of public R&D and knowledge spillovers on the development of renewable energy sources: the case of the nordic countries. Technol. Forecast Soc. Change 146, 450–463.
Moaniba, I.M., Su, H.N., Lee, P.C., 2018. Knowledge recombination and technological innovation: the important role of cross-disciplinary knowledge. Innovation: management. Pol. Practice 20 (4), 326–352.
Momeni, A., Rost, K., 2016. Identification and monitoring of possible disruptive technologies by patent-development paths and topic modelling. Technol. Forecast Soc. Change 104, 16–29.
Nemet, G.F., 2012. Inter-technology knowledge spillovers for energy technologies. Energy Econ. 34 (5), 1259–1270.
Nesta, L., Vona, F., Nicolli, F., 2014. Environmental policies, competition and innovation in renewable energy. J. Environ. Econ. Manage 67 (3), 1–16.
Noailly, J., Smeets, R., 2015. Directing technical change from fossil-fuel to renewable energy innovation: an application using firm-level patent data. J. Environ. Econ. Manage 72, 15–37.
Noailly, J., Ryfisch, D., 2015. Multinational firms and the internationalization of green R&D: a review of the evidence and policy implications. Energy Pol. 83, 218–228. Noailly, J., Shestalova, V., 2017. Knowledge spillovers from renewable energy technologies: lessons from patent citations. Enviromen. Innov. Soc. Trans. 22, 1–14. Patel, D., Ward, M.R., 2011. Using patent citation patterns to infer innovation market competition. Res. Policy 40 (6), 886–894.
Peeters, H., Callaert, J., Van Looy, B., 2020. Do firms profit from involving academics when developing technology? J. Technol. Transf. 45 (2), 494–521.
Perrons, R.K., Jaffe, A.B., Le, T., 2021. Linking scientific research and energy innovation: a comparison of clean and dirty technologies. Energy Res. Soc. Sci. 78, 102122. Persoon, P.G., Bekkers, R.N., Alkemade, F., 2020. The science base of renewables. Technol. Forecast Soc. Change 158, 120121.
Petruzzelli, A., Rotolo, D., Albino, V., 2015. Determinants of patent citations in biotechnology: an analysis of patent influence across the industrial and organizational boundaries. Technol. Forecast Soc. Change 91, 208–221.

Poege, F., Harhoff, D., Gaessler, F., Baruffaldi, S., 2019. Science quality and the value of inventions. Sci. Adv. 5 (12), eaay7323.
Popp, D., 2005. Lessons from patents: using patents to measure technological change in environmental models. Ecol. Econ. 54 (2–3), 209–226.
Popp, D., 2006. International innovation and diffusion of air pollution control technologies: the effects of NOX and SO2 regulation in the US, Japan, and Germany. J. Environ. Econ. Manage. 51 (1), 46–71.
Popp, D., 2017. From science to technology: the value of knowledge from different energy research institutions. Res. Policy 46 (9), 1580–1594.
Roach, M., Cohen, W.M., 2013. Lens or prism? Patent citations as a measure of knowledge flows from public research. Manage Sci. 59 (2), 504–525.
Rogers, E.M., 1962. Diffusion of Innovations. Free Press, New York.
Sag, M., Rohde, K., 2007. Patent reform and differential impact. Minnesota J. Law, Sci.Technol. 8 (1), 1–93.
Sampat, B., 2005. Determinants of Patent Quality: An Empirical Analysis. Columbia. University, New York.
Schmid, J., 2018. The diffusion of military technology. Defence Peace Econ. 29 (6), 595–613.
Schmidt, T.S., Schneider, M., Hoffmann, V.H., 2012. Decarbonising the power sector via technological change differing contributions from heterogeneous firms. Energy Pol. 43, 466–479.
Silverberg, Gerald, Dosi, Giovanni, Orsenigo, Luigi, et al., 1988. Innovation, diversity and diffusion: a self-organisation model. The Economic Journal 98 (393), 1032–1054.
Singh, J., 2008. Distributed R& D, cross-regional knowledge integration and quality of innovative output. Res. Policy 37 (1), 77–96.
Song, J., Almeida, P., Wu, G., 2003. Learning-by-hiring: when is mobility more likely to facilitate interfirm knowledge transfer? Manage Sci. 49 (4), 351–365
Sørensen, J.B., Stuart, T.E., 2000. Aging, obsolescence, and organizational innovation. Adm. Sci. Q 45 (1), 81–112.
Sorenson, O., Fleming, L., 2004. Science and the diffusion of knowledge. Res. Policy 33 (10), 1615–1634.
Squicciarini, M., Dernis, H., & Criscuolo, C. (2013). Measuring patent quality. OECD science, technology and industry working papers (03).
Sun, Y., Zhang, C., Kok, R.A., 2020. The role of research outcome quality in the relationship between university research collaboration and technology transfer: empirical results from China. Scientometrics 122 (2), 1003–1026.
Thelwall, M., Wilson, P., 2014. Distributions for cited articles from individual subjects and years. J. Informetr. 8 (4), 824–839.
Thomas, J.R., 2002. The responsibility of the rule maker: comparative approaches to patent administration reform. Berkeley Technol. Law J. 17, 727–761.
Thompson, P., 2006. Patent citations and the geography of knowledge spillovers: evidence from inventor and examiner-added citations. Rev Econ. Stat. 88 (2), 383–388.
Tong, X., Frame, J.D., 1992. Measuring national technological performance with patent claims data. Res. Policy 23, 133–141.
Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. Rand J. Econ. 21, 172–187.
Trajtenberg, M., Jaffe, A., Henderson, R., 1997. University versus corporate patents: a window of the basicness of invention. Econ. Innovat. New Technol. 5 (1), 19–50.
Un, C.A., Cuervo-Cazurra, A., Asakawa, K., 2010. R&D collaborations and product innovation. J. Product Innovation Manag. 27 (5), 673–689.
Verspagen, B., 2000. The role of large multinationals in the Dutch technology infrastructure. A patent citation analysis. Scientometrics 47 (2), 427–448.