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Green patents and green trademarks as indicators of green innovation

Jörn Block [a,b,c,*], Darius Lambrecht [a], Tom Willeke [a], Marco Cucculelli [d], Damiano Meloni [d]

[a] Faculty of Management, Trier University, Universitätsring 15, 54296 Trier, Germany
[b] Centre for Family Entrepreneurship and Ownership (CEFEO), Jönköping International Business School, Sweden
[c] Wittener Institut für Familienunternehmen (WIFU), Universität Witten/Herdecke, Alfred-Herrhausen-Straße 48, Witten, Germany
[d] Department of Economics and Social Science, Università Politecnica delle Marche, Piazzale Martelli 8, 60121 Ancona, Italy

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ABSTRACT

Identifying green innovations and the firms that generate them is crucial for understanding the role of technology and innovation in the transition to a green economy. Information from intellectual property rights, particularly patent and trademark data, offer an objective, transparent, fast and cost-effective way to identify green innovations, especially when compared to traditional survey-based methods. However, the validity of this identification method is not yet fully established. Not all innovations can be protected through intellectual property rights and some firms may deliberately choose not to pursue formal protection. This study uses patent, trademark and survey data from two distinct samples of SMEs and mid-cap firms from Germany and Italy to investigate whether green patents and green trademarks can effectively identify green innovative firms. The findings reveal that relying solely on patent- and trademark-based measures of green innovation leads to the exclusion of many green innovative firms. In the larger and more representative Italian sample, we observe that only about 1 % of firms have filed a green patent, and 1.65 % have registered a green trademark in the five years prior to the survey. While green trademarks remain a valuable indicator of various types of green innovation, green patents do not prove to be a strong measure of green innovation—at least in a broad industry sample. The predictive power of green trademarks is strongest for identifying green product innovation, particularly within samples of small yet established firms. In contrast, the predictive value of green patents diminishes when considering a firm's total patent portfolio. The findings of our study are relevant for policymakers and investors seeking to identify green innovative firms.

1. Introduction

Green innovations encompass any type of innovation—whether in products, processes, services, or business models—that either reduces an organization's negative impact on the natural environment or generates a positive environmental effect. These innovations are essential for the transition to a green economy, while also creating market opportunities and enhancing firms' competitive advantage.

To examine the determinants, diffusion, and impact of green innovations, it is essential to identify the innovating and adopting firms. The conventional method for measuring green innovation involves surveys that ask key informants within firms to evaluate their innovation outputs. However, this approach has limitations, particularly when working with large datasets. The data collected may not be representative, and low response rates can further reduce the reliability of the findings. Moreover, surveys are susceptible to biases, such as social desirability bias, which can significantly affect the accuracy of the data. Intellectual property rights (IPR) data, particularly patents and trademarks, offer a promising alternative to survey data by providing an objective, transparent, efficient, and cost-effective method for assessing firms' innovation activities. This alternative approach is valuable for policymakers and investors seeking to identify green firms. Additionally, companies can use IPR data to benchmark their green innovations against those of their competitors and distinguish themselves from firms making unsubstantiated claims about their environmental sustainability.

Prior research suggests that patents and trademarks can be used as indicators for innovation input and output (Acs et al., 2002; Burhan et al., 2017; Mendonça et al., 2004), irrespective of whether the innovation is green or not. Some scholars have started to use patents (but so far not trademarks) to identify green innovation and green innovative firms using different approaches (e.g., Haščič and Migotto, 2015; León

* Corresponding author at: Faculty of Management, Trier University, Universitätsring 15, 54296 Trier, Germany.
E-mail address: block@uni-trier.de (J. Block).

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et al., 2018; Wagner, 2007). Due to the growing interest in green innovation and technology, the number of studies using patent data to capture green innovation and its diffusion has grown substantially (e.g., Aiello et al., 2021; Bermúdez-Edo et al., 2017). Morales et al. (2022) investigate the role of patents, trademarks, and other appropriation mechanisms in sustainable innovation and find that both patents and trademarks show no association with commercial success. They explain this result through high (patenting) costs, ineffectiveness for appropriation, reputational critiques, and obstructing diffusion. They argue that trademarks typically protect the firm name rather than the product name, and that for products alternatives such as eco-marks or certifications are often used to indicate product-specific environmental attributes. Vimalnath et al. (2022), use a sample of green innovations and their inventors recognized by the European Inventor Award and study the use of intellectual property (IP) throughout the different phases of the innovation process. They find that established firms tend to adopt closed IP models across all phases, whereas startups and universities do so only in early phases. In later stages of the innovation process, they often share their IPRs through licensing with the goal to accelerate its diffusion and ecological impact.

To effectively use green patents and trademarks as indicators of green innovation, it is crucial to assess the validity of this measurement approach, which may be questioned for several reasons. Not all innovations are eligible for protection through formal IPRs, and some firms may deliberately choose not to seek IPR protection due to its potential ineffectiveness, high costs, lengthy application processes, or the risk of disclosing critical knowledge (Arundel, 2001; Cohen et al., 2000; Hall et al., 2014). Moreover, the concept of green innovation is multidimensional and used in various contexts with different meanings resulting in different terminologies and definitions (Carrillo-Hermosilla et al., 2009). True and impactful green innovation often involves systemic changes, collaborative efforts, and non-technological innovations. IPRs such as patents or trademarks may not be effective protection mechanisms or could potentially hinder the diffusion of green innovation (Morales et al., 2022; Morales et al., 2024a). In some cases, IPRs might even conflict with societal environmental goals. This has sparked a recent debate whether IPRs are working for society (or not) (Castaldi et al., 2024).

Apart from the more general question of whether IPRs can be used to predict green innovation, particularly little knowledge exists about the role of trademarks in this regard. Unlike patents, which protect technological innovations, trademarks are designed to protect soft, non-technological innovations, such as those in service, marketing, or business models (Flikkema et al., 2019). These types of innovations are essential for the transition to a green economy. For small and medium-sized enterprises (SMEs), incorporating trademarks into the measurement of innovation can enhance the identification of innovations (Morales et al., 2024b). From a market and commercialization perspective, trademark data can also help researchers track the actual adoption and diffusion of green innovations.

In summary, it is an open question whether, when and to what extent IPR-based measures can be used as indicators for green innovation. Focusing on SMEs and mid-cap firms, we examine how effectively green patents and trademarks identify, or potentially overlook, various types of green innovation. Our research addresses the following questions: (1) To what extent can green patents and trademarks identify firms involved in green innovation? (2) Which types of green innovation—such as product, process, business model, or service—can be detected? (3) How do firm size, age, and industry affect the applicability of green patents and trademarks as indicators of green innovation?

Our study focuses on SMEs and mid-cap firms, which represent a substantial segment of the economy. These firms collectively contribute significantly to industrial pollution, prompting governments to support their efforts in reducing emissions while maintaining economic stability. SMEs and mid-cap firms provide an intriguing context for using trademark measures to assess innovation. Generally, these firms have a lower propensity to patent, and their innovations are often underestimated when relying solely on patent-based metrics (Blind et al., 2006; Leiponen and Byma, 2009; Thomä and Bizer, 2013). Moreover, as suppliers to larger firms, SMEs and mid-cap firms are increasingly pressured by large firms to enhance their environmental sustainability ("trickledown effect"). Consequently, green innovation is not merely a desirable attribute for these firms but a crucial factor for their survival. Green innovation can often be carried out with limited resources and is frequently independent of formal R&D activities (Lee and Walsh, 2016; Rammer et al., 2009). SMEs and mid-caps face unique challenges and constraints compared to large firms, making their approach to green innovation distinct (Marin et al., 2015). Finally, SME's agility and potential for disruptive innovation can drive scalable environmental solutions.

To analyze our research questions, we combine survey, patent, and trademark data from two characteristically different firm samples from Germany and Italy and use approaches by the OECD, WIPO, EPO and EUIPO to capture green patents and trademarks. The resulting patent and trademark measures are then matched with survey-based information about green innovation. The results show that many green innovative firms are overlooked when only patent and trademark data are used. For the larger and more representative Italian sample, we find that only about 1 % (1.65 %) percent of firms have filed a green patent (green trademark) in the 5 years preceding the survey. While green trademarks remain a valuable indicator of various types of green innovation, green patents do not prove to be a strong measure of green innovation—at least in a broad industry sample. The predictive power of green trademarks is strongest for green product innovation and for small (but established) firms. In contrast, the predictive value of green patents diminishes when considering a firm's total patent portfolio. Finally, when comparing various methods for identifying green patents, only minor differences are observed.

Our findings contribute to the literature on the identification of green innovation (e.g. Cheng and Shiu, 2012; Haščič and Migotto, 2015; Wagner, 2007). Previous studies have mostly relied on surveys to identify green innovation activities of firms (e.g., Antonioli et al., 2013; Cainelli et al., 2012; Chang, 2011). Our study provides deeper insights into the applicability and validity of green patents and trademarks as indicators of green innovation. In particular green trademarks have predictive power and are associated with green innovation. The prediction works best for product innovations in small (but established) firms. In contrast, the predictive power of green patents is generally weak and diminishes when considering a firm's total patent portfolio. Additionally, our research reveals that many green innovations are overlooked when relying solely on patent and trademark metrics, suggesting that researchers, policymakers, and investors should be cautious about depending exclusively on these indicators. Next to advancing the general literature on measuring green innovation, our study also contributes to the specific discussion on using patents as a measure of green innovation, an area where several competing classification systems are currently in use. We find that the patents identified by the OECD, WIPO, and EPO classification systems show qualitatively and quantitatively similar correlations with our survey-based measures of green innovation.

Our study contributes to the literature on trademarks as a measure of innovation (e.g., Flikkema et al., 2014, 2019; Gotsch and Hipp, 2012; Mendonça et al., 2004). Previous research suggests that trademarks are an indicator of innovation in the creative and cultural industries (Castaldi, 2018), the pharmaceutical industry (Nasirov, 2020), but also in the service sector (Mendonça et al., 2004; Gotsch and Hipp, 2012). Our study shows that trademark measures can also help to identify green innovation, as suggested by Castaldi (2021). Specifically, green trademarks are more effective at identifying green product innovation compared to green process, business model, and service innovations. However, similar to patents, trademark measures should be used with caution, as our study reveals that many green innovations are overlooked when relying solely on green trademarks. Additionally, our study is among the first to utilize the European Union Intellectual Property Office (EUIPO)'s (2021) green trademark classification, and our descriptive results regarding the absolute and relative numbers of green trademarks align with their data.

2. Background

The background chapter starts with a brief review of the concept of green innovation. In the next step, we introduce patents and trademarks as measures of innovation followed by a brief discussion how they can be used to identify *green* innovations.

2.1. Concept of green innovation

Green innovation, also known as environmental or ecological innovation, refers broadly to the development and implementation of new ideas, processes, products, or technologies with the goal or intention to reduce a firm's negative impact on the natural environment or create a positive impact in this regard. Kemp and Pearson (2007, p. 7) define green innovation as "the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organization (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives". Carrillo-Hermosilla et al. (2009) state that the term green innovation is used in various contexts with different underlying connotations resulting in a variety of definitions. These definitions focus either on the ecological, green or sustainable intention of the innovator (Rennings, 2000) or on the actual positive green outcome or impact of the innovation (Carrillo-Hermosilla et al., 2010; European Commission, 2007; Oltra and Saint Jean, 2009).

Green innovation can occur on various levels encompassing individuals, households, organizations, associations, regions, industries, and societies. The focus of our study is on firms as organizations. Here, we distinguish between different objects of innovation, specifically a firm's products, processes, services, and business models. Next to distinguishing between different objects of innovation, we also make a distinction regarding the level of (perceived) novelty. Incremental (less novel) green innovations are those innovations that bring about gradual modifications to an existing mechanism, resulting in component addition or optimization, while radical (more novel) green innovations are innovations that cause discontinuous changes or disruptive technologies that do not blend with the existing mechanisms, resulting in the introduction of completely new systems (Hazarika and Zhang, 2019). In practice, the distinction between incremental and radical green innovation is often a matter of perception that depends on the perspective of the innovator or adopter.

2.2. Identification of innovation via patents and trademarks

Patents and trademarks are widely recognized as indicators of innovation activity. Particularly patents are often used as a proxy for (intermediate) innovation output as they protect new technological inventions (Archibugi, 1992; Chang, 2012; Peeters and Pottelsberghe de la Potterie, 2007). Yet, the identification of innovations through patents has limitations, since not all inventions are patented or patentable (Acs et al., 2002; Arundel and Kabla, 1998). Furthermore, patents are in many contexts and situations not the most important mechanism to protect the IP of a firm, as firms may prefer informal mechanisms, for example secrecy, over formal ones (Arundel, 2001; Cohen et al., 2000; Hall et al., 2014). In some industries, such as medical instruments, pharmaceuticals, machinery parts, and chemicals, patents are a common protection mechanism, whereas in other, less technological industries such as services, retail, or the creative sector, firms tend to rely more on trademarks, design rights, copyrights or informal mechanisms (Arundel, 2001; Hall et al., 2014; Hall and Sena, 2017; Mendonça et al., 2004).

Firms use trademarks to protect their brands with the goal to distinguish their (innovative) products and services from those of others and to help them create a loyal customer base. While trademarks are a common IPR used by firms of all industries (WIPO, 2013) and sizes (Rogers et al., 2007), the literature on trademarks as a proxy for innovation is still less developed compared to the one on patents. It has been shown that there is a positive correlation between trademark registrations and innovation activity (Block et al., 2014; Flikkema et al., 2014; Gotsch and Hipp, 2012). Trademarks can also be used to identify service and/or business model innovations (Flikkema et al., 2019) or any type of innovations that occur in non-technological industries such as services, retail or the creative sector (Castaldi, 2018; Gotsch and Hipp, 2012; Mendonça et al., 2004). Flikkema et al. (2014) show that trademark counts are a valid indicator of innovation for SMEs and that they are in many cases not combined with other IPRs. Block et al. (2015) show that SMEs use trademarks for a combination of protection, marketing, and exchange motives. Morales et al. (2024b) show that combining trademark and patent measures significantly increases the number of identified innovations by SMEs. Trademarks are particularly important for identifying innovations in scale-intensive, supplier-dominated industries, as well as in certain service sectors. Flikkema et al. (2019) and Castaldi (2020) offer comprehensive overviews of the trademarking literature, highlighting how trademarks can be utilized as a metric in innovation research and related fields.

2.3. Identification of green innovations through patents and trademarks

Empirical research on green innovation mostly relies on surveys and survey data (e.g., Antonioli et al., 2013; Cainelli et al., 2012; Chang, 2011). Survey items referring to different aspects of the innovation process such as R&D spending, inventions, innovation and environmental outcomes and impact, and sales figures are combined to identify green innovations. Cheng and Shiu (2012), for example, provide a validated survey instrument for green innovation in the form of a 17-item scale.

However, due to the time-consuming, costly nature of surveys, and their susceptibility to response biases and difficulties in gathering large datasets, the literature has increasingly turned to information from intellectual property rights (IPRs), particularly patents, to identify green innovations. Organizations such as the OECD and WIPO have developed patent-based indicators to track environment-related innovations. Haščič and Migotto (2015) outline two main approaches for using patent data to identify green innovations. The first approach relies on keyword searches to identify green patents, while the second utilizes patent classification systems, such as the IPC or CPC. For example, Wagner (2007) applies the first approach by searching patent abstracts for ecological terms to identify green innovations within patent data. The thereby identified green patents are matched to the respective firms. Wagner (2007) then surveys the firms on their green innovation activity. He concludes that green innovation can be meaningfully identified using patent data and that green innovation defined this way is less ubiquitous than self-reported green innovation. The second approach using patent classification systems to identify green patents was greatly fostered by the efforts of the WIPO, EPO and OECD. By collaborating with industry, patent, and technology experts, each institution developed lists of IPC or CPC codes corresponding to green technologies. Using this approach, a patent is classified as green if its classification codes align with those on green technology lists, such as WIPO's Green Inventory, EPO's Y02 list, or OECD's ENV-TECH list. This approach combines the benefits of easy, fast, and unlimited access to patent data with expert knowledge. As a result, the use of IPC and CPC codes to identify green patents has become increasingly popular, with a growing number of studies adopting this method. The advantages include the wide availability of patent data, as well as its quantitative, objective, transparent, and invention-focused nature. Additionally, patent data can be disaggregated, a significant advantage when analyzing environmental technologies. The detailed technological information in patent descriptions makes them a comprehensive source for studying green innovation. As a result, numerous studies have utilized patent data to identify green innovations, both at inventor or firm levels and in aggregated analyses across regions, countries, or industry sectors (e.g., Aiello et al., 2021; Bermúdez-Edo et al., 2017; León et al., 2018). Oltra et al. (2010) examine the use of patents as an indicator of green innovation. They argue that, similar to general innovation, patents for green inventions can be used to track research and invention activities and to study the direction of research within a specific technological field. However, they note that new business methods and organizational innovations are rarely patented, as they often lack a clear underlying invention. Service innovations are also infrequently patented. Consequently, they conclude that green patents primarily represent inventions that drive green product innovations and end-of-pipe technologies, where environmental impact is a specific goal and motivation of the invention.

Regarding trademarks as an IPR-based indicator of green innovation, Castaldi (2021) argues that companies pursuing green innovation are inherently adopting a differentiation strategy, which requires significant investment in brand development and protection. Due to significant information asymmetries in the market for sustainable products, trademarks play a crucial role in helping firms signal their commitment to sustainability and establish trust with consumers. In summary, trademarks are suggested as a measure to identify green innovations and green innovative firms, offering a market and commercialization perspective that complements the technological insights provided by patents. Trademarks are especially suited at identifying innovative green products, services, and business models, while they may be less effective for measuring green process innovations. Additionally, their market and commercialization perspective makes trademarks particularly useful for assessing the actual adoption and diffusion of green innovations in the marketplace. To identify green trademarks and designs, Ghisetti et al. (2021) began with the OECD's ENV-TECH green patent classification (Haščič and Migotto, 2015) and extracted environmental keywords from this list. These keywords were then applied to trademark and design descriptions to identify green trademarks and designs. The study used a dataset of about 2000 top R&D investors worldwide containing bundles of IPRs (i.e., patents, designs, and trademarks). Neuhäusler et al. (2021) and Abbasiharofteh et al. (2022) have developed alternative approaches to better capture the actual content of trademarks. Both studies created a sophisticated classification scheme that surpasses the broad and simplistic Nice class trademark classification system commonly used. By employing natural language processing techniques, they were able to develop more detailed subclasses within each Nice class. Abbasiharofteh et al. (2022) analyzed keyword descriptions from the EUIPO harmonized database (HDM) for each Nice class, resulting in the creation of 616 subclasses. They then mapped these subclasses to 650 CPC patent classes, producing a concordance map that facilitates the identification of green trademarks and green patent-trademark bundles. The authors conducted an initial validation of their classification approach by applying their concordance map to a sample of cleantech patents. Using also the HDM as a starting point, the EUIPO (2021) itself has developed an own classification approach to identify green trademarks (for details, see Section 4.2 below). The EUIPO approach differs from those of Abbasiharofteh et al. (2022) and Neuhäusler et al. (2021) in that it relies on expert judgment rather than machine learning for classification. To date, the EUIPO's expert-based method for measuring green trademarks has not been utilized in empirical research, which is one of the gaps our study aims to address.

3. Samples and data sources

To investigate the relationships between green IPRs and survey-based measures of green innovation, we employ two characteristically different data sets and samples from Germany and Italy. The two samples underlying the data sets differ in their industry coverage but also in their firm characteristics. While the German sample concerns established mid-sized and mid-cap firms from the manufacturing industry, the Italian sample is much broader (and larger) and comprises SMEs and mid-cap firms from all industries, sizes and ages. Neither the German nor the Italian data set targeted large firms (see also Tables A3 to A7 in the Appendix for further information about the structural characteristics of the two samples) See Table 1 for a comparison of the two samples and data sets.

The two data sets, however, not only differ in their structural characteristics but also regarding contextual elements. While Germany is known for its strong engineering and manufacturing sectors, Italy is known for its strong luxury, fashion and food sectors. Consequently, the IPR cultures in Germany and Italy may also differ. Patents might be more important as an IPR in Germany, while trademarks (and design rights) might matter more in Italy. Finally, Germany is also known for stricter environmental regulations and higher subsidies for green energy compared to Italy. In summary, the use of two characteristically different data sets allows for a richer and more nuanced understanding of the role of IPRs as indicators of green innovation and puts our findings on a more robust and generalizable perspective.

The two data sets include next to IPRs and archival data about firm size and age also information about green innovation activities that were gathered in surveys in projects unrelated to this study (see Block et al. (2024a, 2024b), for German survey; see Cucculelli et al. (2024), for Italian survey). We now describe in more detail the respective samples, data sources (Sections 3.1 and 3.2), and measures (Sections 4.1 and 4.2) of the two data sets.

3.1. German sample and data set

The German sample and data set was constructed in four steps. In the *first step*, we used the German part of the Orbis database to identify a population of 10,765 German based medium-sized firms active in the manufacturing sector (NACE code between 20 and 30). The firms were at least ten years old (as of September 2020), had a turnover of less than five billion Euros and between 50 and 2999 employees. We excluded subsidiaries of larger corporations, foreign and non-profit firms, as well as public institutions. In the *second step*, we employed a professional company specialized in conducting empirical social research. We randomly selected 1959 firms out of our population, which were contacted via telephone to take part in our survey on green innovation. The survey was conducted via computer-assisted telephone interviews (CATI); 444 of the contacted firms completed the survey (response rate: 22.66 %). The survey period was from the 18th of January to the 14th of April 2022 and the respondent was either the sustainability manager or the CEO of the firm. In the *third step*, we collected patent information for the 444 firms using the European Patent Office's (EPO) patent database PASTAT (De Rassenfosse et al., 2014). For identifying and retrieving the patent applications, we applied the approach by Willeke et al. (2023) using a broad search strategy based on firm names. The matching between the patent applications and the respective firms was realized using name and address similarities. To account for the timeframe of the survey conducted, which asks for changes in the last three years, and in line with the trademark dataset and the work of Seip et al. (2018), we restricted our analysis to patent applications filed between 2017 and 2022.

In the *fourth step*, we enriched our data set with trademark information. The trademark applications were retrieved from the EUIPO using the web interface TMview[1] and a broad search strategy. The trademark platform includes all national trademark applications from all participating patent and trademark offices including EU and

[1] The platform can be accessed via https://www.tmdn.org/tmview (June 10, 2024).

Table 1
Comparison of German and Italian samples and data sets.

	German sample and data set	Italian sample and data set
Target population (Sample)	A sample of 10,765 firms that met the following criteria: (1) the firm was active in September 2020; (2) it was based in Germany; (3) its NACE2 primary code was between 20 and 30; (4) the number of employees was between 50 and 2999; (5) it was at least ten years old; and (6) it was neither a subsidiary/ foreign firm/ non-profit firm/ public institution; from those firms 2832 were randomly selected and contacted.	A sample of 64,872 firms that met the following criteria: (1) the firm was active in 2019; (2) it was based in Italy; (3) the number of employees was between 1 and 3000; (4) it was neither a subsidiary/ foreign firm/ a non-profit firm/ public institution; (5) a telephone number or email address was available; all of these firms were contacted.
Data collection team	A professional company specialized in conducting empirical social research	A team of graduate students with professional experience supervised by a team of experienced researchers
Contact mode	The initial contact was initiated via email, and a suitable contact from either the first or second management level was requested for a CATI (Computer Assisted Telephone Interview).	Firms with 50 or more employees in 2019 were contacted by telephone. Firms with fewer than 50 employees in 2019 were contacted via email with information about the research project and the link to the online survey.
Time period	Between January and April 2022	Between October 2019 and February 2020
Response rate	444 interviews out of the contacted sample of 2832 firms were collected (response rate of 15.68 %).	5400 usable questionnaires out of the contacted sample of 64,872 were collected (response rate of 8.32 %).
Respondent position	The interview was performed with the first or second management level (=sustainability manager).	The questionnaire was addressed to the "person in charge of major company decisions" (CEO, chairman/ president, or highest-ranking executives)"
Breakdown by firm location (NUTS 1 or 2)	NUTS1: Baden-Wuerttemberg (16.22 %); Lower Saxony (9.46 %); Bavaria (13.74 %); Hesse (6.31 %); North Rhine-Westphalia (29.5 %); Saxony (6.08 %); Saxony-Anhalt (3.15 %); Brandenburg (1.8 %); Thuringia (2.7 %); Rhineland-Palatinate (4.5 %); Berlin (1.13 %); Schleswig-Holstein (3.38 %); Saarland (0.68 %); Hamburg (0.68 %); Mecklenburg-Western Pomerania (0.45 %); Bremen (0.23 %)	NUTS2: Marche (7.89 %); Toscana (6.37 %); Molise (0.35 %); Emilia-Romagna (11,17 %); Campania (3,78 %); Lombardia (22.3 %); Veneto (12.85 %); Friuli-Venezia Giulia (3.13 %); Basilicata (0.7 %); Piemonte (7.04 %); Abruzzo (2.31 %); Sicilia (2.46 %); Valle d'Aosta (0.22 %); Sardegna (1.33 %); Umbria (1.39 %); Trentino-Alto Adige (3.41 %); Puglia (3.61 %); Lazio (7.35 %); Liguria (1.37 %); Calabria (0.96 %)
Breakdown by Industry (NACE code)	NACE group code: 20 (6.98 %); 21 (2.25 %); 22 (12.61 %); 23 (6.76 %); 24 (4.96 %); 25 (21.85 %); 26 (7.66 %); 27 (8.11 %); 28 (24.55 %); 29 (3.15 %); 30 (1.13 %);	NACE section code: A (0.56 %); B (0.17 %); C (36.37 %); D (0.39 %); E (1.30 %); F (7.57 %); G (12.76 %); H (3.04 %); I (2.33 %); J (13.76 %); K (1.17 %); L (1.04 %); M (12.09 %); N (3.39 %); P (0.54 %); Q (1.74 %); R (0.91 %); S (0.89 %);
Source of firm data	German part of Bureau van Dijk - Orbis firm database	Italian part of Bureau van Dijk - Orbis firm database (also known as AIDA database)
Source of patent data	The patent applications were retrieved from the PATSTAT patent database (Version Autumn 2022) using a broad search strategy, followed by refinement steps involving location and name similarity checks.	The patent applications were retrieved from the PATSTAT patent database (Version Autumn 2022) using a broad search strategy, followed by refinement steps involving location and name similarity checks.
Source of trademark data	The trademark data was retrieved from EUIPOs trademarks database TMview applying a broad search strategy. The sample of trademark applications was refined using name and location similarities.	The trademark data was retrieved from EUIPOs trademarks database TMview applying a broad search strategy. The sample of trademark applications was refined using name and location similarities.

international trademarks. We applied a filtering process to retrieve all trademarks that are valid in Germany. This comprises national German trademarks as well as international and EU registrations. To ensure a clean trademark data set, we implemented various cleaning procedures, addressing name and address similarities. Additionally, we conducted manual reviews for cases where firm names were ambiguous. In line with the work of Seip et al. (2018) and our survey, we restricted our analysis to trademarks filed between 2017 and 2022. We employed various methods to investigate potential sample and survey biases. We investigated potential *CEO bias* in response behavior by creating a control group of CEO respondents and comparing their survey responses with those of other respondents. Using a Mann-Whitney U test, we found no significant differences in response behavior, except for the variable related to green product innovation ($z = 2.127$, $p = .034$). With this variable, CEOs reported fewer instances of their firms making small changes to green products and more frequently reported no changes in green products. To identify the extent of the *non-response bias*, we compared the 1959 firms in our target sample with the 444 responding firms. The 1515 non-respondents were found to have a larger employee count. Both groups were similar regarding their industry and geographical location (federal state). We further investigated whether the Russian invasion into Ukraine that occurred on February 24, 2022, influenced the response behavior of our survey participants. To test this and to simultaneously address a potential *late-response bias*, we divided our sample into two groups: early respondents (188 firms surveyed from January 18 to February 23, 2022) and late respondents (256 firms surveyed from February 24 to April 14, 2022). A comparison of the distribution of the dependent variables (see Table 2) between the two groups showed no significant differences except for the variable green product innovation (X^2 (2, $N = 439$) $= 7.525$, $p < .023$). We also analyzed the existence of a *social desirability bias*. Even though the questionnaire does not contain individual level questions, it may still be that the respondent responds to some of the questions in a socially desirable way. Such a behavior should be more likely when the respondent is strongly committed to the organization and its goals. To account for such strong commitment and to test whether it influences the answer behavior, we include an organizational commitment measure based on established scales (Allen and Meyer, 1990; Mowday et al., 1979) into the questionnaire. We then ran a linear regression analysis with the measure as dependent variable and the green innovation survey measures as independent variables. No significant relationships were found, alleviating concerns related to individual commitment and social desirability. Finally, it should be noted that we employed mean imputation for the control variable number of employees to preserve eight observations from being deleted in the regressions.

3.2. Italian sample and data set

The Italian sample and data set was also constructed in several steps. In the *first step*, we used the Italian part of the Orbis database (also referred to as AIDA database) to identify a population and target sample

Table 2
Descriptions of the variables in the German data set.

Variable	Description
Overall Green Innovation (ordinal)	Ordinal variable that indicates the level of green innovation, regardless of the innovation type. For each firm, we assigned a value of one when all of the four questions asked were answered with *no changes*. Each firm answering at least one question with *small changes* were labeled with a value of two, and all firms with at least one answer that corresponds to *major changes* received a value of three.
Green Product Innovation (ordinal)	Ordinal variable that indicates the level of green product innovation. Firms that answered *no changes* were labeled with a value of one; those with *small changes* received a value of two, and those with *major changes* received a value of three.
Green Process Innovation (ordinal)	Ordinal variable that indicates the level of green process innovation. Firms that answered *no changes* were labeled with a value of one; those with *small changes* received a value of two, and those with *major changes* received a value of three.
Green Business Model Innovation (ordinal)	Ordinal variable that indicates the level of green business model innovation. Firms that answered *no changes* were labeled with a value of one; those with *small changes* received a value of two, and those with *major changes* received a value of three.
Green Service Innovation (ordinal)	Ordinal variable that indicates the level of green service innovation. Firms that answered *no changes* were labeled with a value of one; those with *small changes* received a value of two, and those with *major changes* received a value of three.
Trademarks (count)	Number of trademark applications of the firm in the years 2017 to 2022. Source: TMview.
Trademark (dummy)	Equals one if firm has at least one trademark application in the years 2017 to 2022, otherwise zero. Source: TMview.
Green Trademarks (count)	Number of green trademarks applications by the firm in the years 2017 to 2022. Green trademarks were identified using the approach provided by the EUIPO (2021).
Green Trademark (dummy)	Equals one if firm has at least one green trademark application in the years 2017 to 2022, otherwise zero.
Patents (count)	Number of patent applications filed by the firm. Source: PATSTAT.
Patent (dummy)	Equals one if firm has filed at least one patent application in the years 2017 to 2022, otherwise zero. Source: PATSTAT.
Green Patents (count)	Number of green patent applications filed by the firm in the years 2017 to 2022. Green patent applications were identified using the three different approaches described in the text above.
Green Patent (dummy)	Equals one if firm has filed at least one green patent application in the years 2017 to 2022, otherwise zero.
Firm Age (log.)	Number of years since the founding of the firm (logarithmized). Source: Orbis.
Employees (log.)	Number of employees of the firm (logarithmized). Source: Orbis.
Industry (dummies)	Equals one if the firm operates within the respective NACE primary code, otherwise zero.

of 64,872 micro, small and medium sized firms active in the manufacturing, service, and utilities (e.g., gas and electricity) sectors. As with the German sample and data set, we excluded subsidiaries of larger corporations, foreign and non-profit firms, as well as public institutions. In the *second step*, we conducted an online survey in which the firms were asked about their green innovation activities. The survey period was from May 2019 to February 2020, and it was conducted by a team of graduate students with professional experience supervised by a team of experienced researchers. Firms with 50 or more employees were contacted by telephone asking for the "person in charge of major company decisions"; firms with <50 employees were contacted by email. The contacted firms were provided with information about the research project and the link to the online survey. 5400 of the target sample of 64,872 firms left a completed and fully usable questionnaire (response rate: 8.32 %). In the *third step,* we retrieved patent data for the 5400 firms from PATSTAT and applied the approach by Willeke et al. (2023) to match patent applications and the filing firms. In line with the German data set, we limited our data set to patent applications filed between 2015 and 2020. In the *fourth step*, we proceeded as with the German data set and enriched the data set with trademark information retrieved from the EUIPO (European Union Intellectual Property Office) using its TMview web platform. In line with the German data set, we included trademarks that were applied between 2015 and 2020.

To investigate potential sample and survey biases, various methods were employed. Regarding the *non-response* and *self-selection bias*, we compared the firm size and firm age distributions of the 5400 firms in our final sample with those of the target sample. No significant differences were found. We performed a similar comparison regarding the 3-digit NACE industry distribution. Again, no significant differences were identified. As for the innovation profile in our final sample, we checked the survey data against the most recent external data on the innovation profile available for Italy (Community innovation survey 2018) and found very similar shares of innovating firms.[2] Regarding potential *confounding events* in the survey period, it should be noted that the survey was conducted in the eight month period from end of May 2019 to late January 2020, i.e., before the insurgence of the COVID-19 crisis. Finally, as with the German sample and data set, it should be noted that we employed mean imputation for the control variable number of employees to preserve 424 observations from being deleted in the regressions.

4. Measures

The measures for green innovation are based on patent, trademark, and survey data. The identification of green trademarks and patents is completely identical in the German and Italian data set, while the survey questions differ to some extent between the two data sets. It should be noted that all measures are on the firm level. Hence, we do not have an exact one-to-one matching of a specific green innovation with a specific green IPR.

4.1. Green patents

We applied three different approaches to identify green patents and green innovative firms. The *first approach* was provided by the WIPO in 2010. The Green Inventory is based on a list of IPC codes for environmental technologies provided by the WIPO. The *second approach* was provided by the EPO in 2012. The Y02 classification is a subclass in the CPC coding system and encompasses climate change mitigation technologies. As *third approach,* we relied on Haščič and Migotto (2015). This approach uses the ENV-TECH list developed by the OECD encompassing different IPCs and CPCs classes referring to environmental technologies. The result of the three approaches are dummy variables indicating firms that filed at least one patent application corresponding to the Green Inventory, Y02 classification, or the ENV-TECH list in the respective time periods (German data set: 2017 to 2022; Italian data set: 2015 to 2020). A detailed comparison of the three different approaches to identify green innovative firms through patent applications is provided in Table A9 in the Appendix.

4.2. Green trademarks

We applied the approach by the EUIPO (2021) to identify green

[2] The share of firms in our sample that have introduced product and process innovation are 49.9 % and 39.3 %, respectively. According to Community innovation survey 2018, the share of firms that have introduced at least one new or significantly improved product or process innovation are 46.1 % and 36.4 %, respectively.

trademarks and green innovative firms. In this approach, a combination of Nice classes and description terms is used to determine whether a trademark can be considered green. The approach relies on over 85,000 description terms from the EUIPO harmonized database (HDM), which are applicable for trademark applications in all European Union trademark offices. The authors of the EUIPO study collaborated with experts from the EUIPO to classify each of these description terms into two categories: green and non-green. As a result, a total of 904 combinations of Nice classes and their corresponding description terms were identified as green. Before applying this approach, it was necessary to harmonize the data, especially due to the different languages (German, English and Italian) of the Nice classification terms. The harmonization was achieved by using the HDM via the EUIPO's platform TMclass. This platform provided harmonized translations of the terms in German, Italian and English. We carefully inspected each trademark application that we identified and assessed whether it is a green trademark or not. We considered thereby English, German, and Italian description terms. As with green patents, a dummy variable green trademark was constructed to indicate firms that applied for at least one green trademark in the period from 2017 to 2022 (German data set) or 2015 to 2020 (Italian data set).

4.3. Survey-based measures of green innovation

4.3.1. Measures in the German survey

To identify green innovative firms via survey-based measures, the firms in the German survey were asked: "To what extent have you implemented changes in the following areas over the past three years with the aim of advancing environmental protection?" The respective areas were (1) Product, (2) Production- and Logistic Processes, (3) Business Model, and (4) Service. The answer options in each of the areas were (1) No changes, (2) Small changes or (3) Major changes. Based on these questions, five ordinal variables were created to indicate different types of green innovation. Table 2 shows the variables of the German data set and how they are constructed.

4.3.2. Measures in the Italian survey

To identify green innovative firms via survey-based measures, the firms in the Italian survey were asked: "With reference to the Circular Economy and the Green Economy, your company has: (1) Already developed a new green product, (2) Already developed green production processes, (3) Improved green features of pre-existing products or processes, (4) Initiated projects aimed at the Circular/Green Economy, (5) None of the above". The respondents were asked to cross the statements that applied. Based on this question, several overlapping dummy variables were created to indicate various types of green innovation. Table 3 shows the variables of the Italian data set and how they are constructed.

5. Descriptive statistics and regression analyses

5.1. Descriptive statistics

5.1.1. German data set

The descriptive statistics of the 444 firms in the German data set are provided in Table 4. According to the survey, the large majority of firms produced some kind of green innovation, whether small (52.05 %) or major (43.18 %). Only 4.77 % of all German firms made no green innovation at all. The most prominent form of green innovation was green process innovation (small = 59.41 %, major = 26.76 %).

34.68 % of the firms in the German data set have at least one patent. Acknowledging the different approaches to identify green patents, 5.86 % (Green Inventory), 4.05 % (Y02) or 3.83 % (ENV-TECH) of the firms have green patents. 29.73 % of firms hold at least one trademark, while 6.31 % have at least one green trademark. Thus, among firms that use trademarks, 21.22 % possess at least one green trademark. The percentage of green trademarks is higher than with the EUIPO (2021), which states that around 10 to 12 % of all trademarks can be considered green. An explanation for this higher percentage could be that the German data set focuses on established manufacturing firms with a minimum of 50 employees and ten years of existence. Further descriptive statistics on patents and trademarks for the German sample can be

Table 3
Descriptions of the variables in the Italian data set.

Variable	Description
Overall Green Innovation (dummy)	Dummy variable that indicates green innovation, regardless of the type. For each firm, we assigned a value of one if they answered "yes" to having either developed green products or production processes, improved green features of pre-existing products or processes or initiated projects aimed at the Circular/Green Economy. They were labeled with zero if they checked having done nothing.
Green Product Innovation (dummy)	Equals one if firm has answered "yes" to having developed green products, otherwise zero.
Green Process Innovation (dummy)	Equals one if firm has answered "yes" to having developed green production processes, otherwise zero.
Circular/Green Economy Projects (dummy)	Equals one if firm has answered "yes" to having initiated projects aimed at the Circular/Green Economy, otherwise zero.
Trademarks (count)	Number of trademark applications of the firm in the years 2015 to 2020. Source: TMview.
Trademark (dummy)	Equals one if firm has at least one trademark application in the years 2015 to 2020, otherwise zero. Source: TMview.
Green Trademarks (count)	Number of green trademark applications of the firm in the years 2015 to 2020. Green trademarks were identified using the approach provided by the EUIPO (2021).
Green Trademark (dummy)	Equals one if firm has at least one green trademark application in the years 2015 to 2020, otherwise zero.
Patents (count)	Number of patent applications of the firm in the years 2015 to 2020. Source: PATSTAT.
Patent (dummy)	Equals one if firm has at least one patent application in the years 2015 to 2020, otherwise zero. Source: PATSTAT.
Green Patents (count)	Number of green patent applications filed by the firm in the years 2015 to 2020. Green patent applications were identified using the three different approaches described in the text above.
Green Patent (dummy)	Equals one if firm has filed at least one green patent application in the years 2015 to 2020, otherwise zero.
Firm Age (log.)	Number of years since the founding of the firm (logarithmized). Source: AIDA.
Employees (log.)	Number of employees of the firm (logarithmized). Source: AIDA.
Industry (dummies)	Equals one if the firm operates within the respective NACE primary code, otherwise zero.

Table 4
Descriptive statistics for the German data set.

Data Source	Variable	Small changes (%)	Major Changes (%)
Survey	Overall Green Innovation	52.05	43.18
	Green Product Innovation	48.29	19.59
	Green Process Innovation	59.41	26.76
	Green Business Model Innovation	40.97	10.42
	Green Service Innovation	40.00	7.14
		Yes (%)	
Patent data	Patent	34.68	
	Green Patent (Green Inventory)	5.86	
	Green Patent (Y02)	4.05	
	Green Patent (ENV-TECH)	3.83	
Trademark data	Trademark	29.73	
	Green Trademark	6.31	

N firms = 444

viewed in Table A4 in the Appendix. The distribution of firms considering firm age and number of employees is skewed. German firms were at the median 36 years (SD = 36.67) old and had 164 employees (SD = 463.17) (Table A3 in the Appendix).

The cross-tabulation of the survey-based measures on green innovation with green patents and green trademarks reveals an overall positive relationship (see Table 5). Firms with green patents and green trademarks show higher percentages with survey-based measures of green innovation. Yet, there are some differences in the strength of the relationship across different types of green innovation. The relationship between IPR-based indicators of green innovation and survey-based measures of green innovation is stronger for product than for process, business model, and service innovation. In addition, the relationship between IPR-based indicators of green innovation and green survey-based measures of innovation seems to be slightly stronger for trademarks than for patents. Comparing the different identification approaches for green patents, no apparent and systematic differences are visible.

5.1.2. *Italian data set*

The descriptive statistics of the 5400 firms in the Italian data set are provided in Table 6. According to the survey, only 31.06 % of the firms made some kind of green innovation. The most prominent form of green innovation according to the survey was the improvement of preexisting products and processes through green features, which is an incremental green innovation (Yes = 20.22 %); 9.28 % of the firms made a green product innovation and 11.41 % developed a green process innovation. 12.72 % of the firms were involved in circular/green economy projects.

Focusing on patents, only 6.22 % of the firms have a patent application. Acknowledging the different approaches to identify green patents, only 0.69 % (Green Inventory), 1.06 % (Y02) or 1.00 % (ENV-TECH) of the firms have a green patent application.

Table 6
Descriptive statistics for the Italian data set.

Data source	Variable	Yes (%)
Survey	Overall Green Innovation	31.06
	Green Product Innovation	9.28
	Green Process Innovation	11.41
	Improvement of Products and Processes through Green Features	20.22
	Circular/Green Economy Projects	12.72
Patent Data	Patent	6.22
	Green Patent (Green Inventory)	0.69
	Green Patent (Y02)	1.06
	Green Patent (ENV-TECH)	1.00
Trademark Data	Trademark	24.33
	Green Trademark	1.65

N firms = 5400

A similar picture emerges with trademarks. 24.33 % of the firms have at least one trademark application and 1.65 % of the firms have a green trademark application. As 6.78 % of all trademarking firms can be considered green trademarking firms, this result is in line with the results of the EUIPO (2021), which found that the number of green trademarks is on a strong rise (from 1600 in their dataset to almost 16,000 in 2020) and accounts in recent years for 10 to 12 % of all trademarks. Further statistics on patents and trademarks for the Italian sample can be viewed in Appendix A5. Italian firms were at the median 18 years old (SD = 14.49) and had 10 employees (SD = 249.58) (Table A3).

As with the German data set, also the Italian data set shows an overall positive relationship between survey-based measures of green innovation and green patents or green trademarks (see Table 7). The relationship is visible throughout all cross-tabulations. Firms with green trademarks and patents are more likely to have any kind of green

Table 5
Cross tabulations (German data set).

		Survey-based Measures										
		Overall Green Innovation			Green Product Innovation		Green Process Innovation		Green Business Model Innovation		Green Service Innovation	
IPR-based Measures		No Changes	Small Changes	Major Changes	Small Changes	Major Changes	Small Changes	Major Changes	Small Changes	Major Changes	Small Changes	Major Changes
Green Patent (Green Inventory)	No (row %)	4.83	51.93	43.24	47.94	19.13	59.28	27.23	40.93	10.78	40.40	7.07
	Yes (row %)	3.85	53.85	42.31	53.85	26.92	61.54	19.23	41.67	4.17	33.33	8.33
Difference		−0.98	1.92	−0.93	5.91	7.79	2.26	−8	0.74	−6.61	−7.07	1.26
Green Patent (Y02)	No (row %)	4.98	51.66	43.36	47.98	19.24	59.57	27.19	40.96	10.60	39.21	7.20
	Yes (row %)	0.00	61.11	38.89	55.56	27.78	55.56	16.67	41.18	5.88	58.82	5.88
Difference		−4.98	9.45	−4.47	7.58	8.54	−4.01	−10.52	0.22	−4.72	19.61	−1.32
Green Patent (ENV-TECH)	No (row %)	4.96	52.25	42.79	48.10	18.96	59.67	26.65	41.35	10.34	39.75	7.16
	Yes (row %)	0.00	47.06	52.94	52.94	35.29	52.94	29.41	31.25	12.50	46.67	6.67
Difference		−4.96	−5.19	10.15	4.84	16.33	−6.73	2.76	−10.1	2.16	6.92	−0.49
Green Trademark	No (row %)	5.10	52.18	42.72	48.06	18.69	58.84	26.63	40.99	9.88	40.61	6.60
	Yes (row %)	0.00	50.00	50.00	51.85	33.33	67.86	28.57	40.74	18.52	30.77	15.38
Difference		−5.1	−2.18	7.28	3.79	14.64	9.02	1.94	−0.25	8.64	−9.84	8.78

N firms = 444

Table 7
Cross tabulations (Italian data set.

IPR-based Measures		Survey-based measures: Overall green innovation No	Overall green innovation Yes	Green product innovation Yes	Green process innovation Yes	Circular/green economy projects Yes
Green Patent (Green Inventory)	No (row %)	69.07	30.93	9.18	11.32	12.68
	Yes (row %)	51.35	48.65	24.32	24.32	18.92
Difference		−17.72	17.72	15.14	13.00	6.24
Green Patent (Y02)	No (row %)	69.14	30.86	9.10	11.29	12.63
	Yes (row %)	50.88	49.12	26.32	22.81	21.05
Difference		−18.26	18.26	17.22	11.52	8.42
Green Patent (ENV-TECH)	No (row %)	69.10	30.90	9.13	11.30	12.63
	Yes (row %)	53.70	46.30	24.07	22.22	22.22
Difference		−15.40	15.40	14.94	10.92	9.59
Green Trademark	No (row %)	69.20	30.80	9.04	11.22	12.65
	Yes (row %)	53.93	46.07	23.60	22.47	16.85
Difference		−15.27	15.27	14.56	11.25	4.20

N firms = 5400.

innovation than firms without green trademarks. The proportion of firms having any kind of green innovation jumps from 30.80 % for firms without a green trademark to 46.07 % for firms with a green trademark. As with the German data set, the relationship between green trademarks and a survey-based measure of green innovation is stronger for product than for process innovation. The proportion of firms with green product innovations according to survey data (more than) doubles when looking at those with green patents or green trademarks. As with the German sample, there are no apparent differences between the three approaches to identify green patents.

5.2. Baseline regressions

5.2.1. German data set

We ran five ordered logistic regressions. The dependent variables were the five survey-based ordinal measures of green innovation: overall green innovation, green product innovation, green process innovation, green business model innovation, and green service innovation. As independent variables, we entered the two IPR-based indicators *green trademark* and *green patent* (either defined by the Green Inventory, Y02, or the ENV-TECH list). Firm age, number of employees and industry dummies were included as control variables. Table 8 shows the results with green patents measured by the Green Inventory.

None of the five models showed a significant coefficient of green patents or green trademarks.[3]

When using the other two approaches to identify green patents, the results were similar (see Table 9).[4] Green patents do not show a significant relationship with green innovation.

5.2.2. Italian data set

We ran several logistic regressions with the Italian data set. The dependent variables were the four survey-based dummy measures of green innovation: overall green innovation, green product innovation, green process innovation, and circular/green economy projects. As independent variables, we entered the two IPR-based indicators *green trademark* and *green patent* (either defined by the Green Inventory, Y02, or the ENV-TECH list). Firm age, number of employees and industry dummies were included as control variables. Table 10 shows the results of the regressions and displays the relationships of the IPR-based measures.[5] The indicator variable green trademark is in three out of four cases significantly positively associated with the survey-based measure of green innovation (the coefficient is insignificant with circular/green economy projects). The relationship is strongest for green product innovation, where the odds to have a green product innovation increase by a factor of >2.4 when a firm has filed a green trademark. As with the German dataset, green patent indicators are not significantly associated with any of the four survey-based measures of green innovation. Yet, we find a significant relation of the overall number of patents of a firm and green product innovation. Hence, it seems that the significant relationship between green patents and green product innovation that can be observed in the cross tabulations (see Table 7) is taken away by the overall number of patents of a firm. This does not happen with green trademarks and the overall number of trademarks of a firm.

5.3. Subsample regressions by firm size

To assess whether firm size influences the predictive power of green trademarks and green patents, we used the Italian data set and created subsamples of large versus small firms via a median split using the number of employees. Keep in mind, however, that the large firms in our datasets are still relatively small given that our samples include only small and mid-cap firms. We chose the Italian sample because of the larger sample size and the wider firm size distribution. The number of employees in the firms ranged from 1 to 2.252 and the median was 10. For the two subsamples, we then ran the same set of regressions as with the baseline regressions in Section 5.2. Table 11 shows the results.[6] The relationship between green trademarks and green product innovation can be found for both small and large firms. Yet, the size of the coefficient is twice as large for small versus large firms. Contrary, the relationship between green trademarks and green process innovation can only be observed for large firms.

5.4. Subsample regressions by firm age

To assess whether firm age influences the predictive power of green trademarks and green patents, we used the Italian data set and created subsamples of young versus established firms. The sample of young (established) firms contains firms with an age of <10 years (>10 years). Again, we chose the Italian sample because of the larger sample size and the wider firm age distribution. For the two subsamples, we then ran the same set of regressions as with the baseline regressions in Section 5.2. Table 12 shows the results.[7] The sample of younger firms revealed neither significant results for green patents nor for green trademarks.

[3] We also tested the models with dichotomized green innovation variables. No or small changes were coded as zero and major changes as one. The results remained consistently non-significant for green patents and green trademarks.
[4] The detailed regressions are shown in Tables A10 and A11 in the Appendix.
[5] The detailed regressions are shown in Tables A12-A14 in the Appendix.
[6] The detailed regressions are shown in Tables A15-A20 in the Appendix.
[7] The detailed regressions are shown in Tables A21-A26 in the Appendix.

Table 8
Ordered logistic regressions with green patents via Green Inventory (German data set).

Independent Variables	(1) Overall Green Innovation (ordinal)	(2) Green Product Innovation (ordinal)	(3) Green Process Innovation (ordinal)	(4) Green Business Model Innovation (ordinal)	(5) Green Service Innovation (ordinal)
Green Trademark (dummy)	0.674 (0.308)	1.215 (0.536)	0.708 (0.32)	1.494 (0.673)	0.769 (0.363)
Green Patent (dummy)	0.838 (0.391)	1.107 (0.479)	0.935 (0.43)	0.667 (0.304)	0.576 (0.276)
Number of TMs (log.)	1.477*** (0.215)	1.199 (0.161)	1.601*** (0.227)	0.981 (0.137)	1.279* (0.18)
Number of Patents (log.)	0.923 (0.096)	1.064 (0.104)	0.839 (0.088)	0.977 (0.098)	1.121 (0.115)
Firm age (log.)	1.025 (0.164)	1.011 (0.153)	0.986 (0.156)	1.184 (0.183)	0.896 (0.145)
Employees (log.)	1.424*** (0.193)	1.154 (0.145)	1.503*** (0.203)	1.22 (0.158)	0.943 (0.126)
Industry (dummies)	Yes	Yes***	Yes***	Yes**	Yes**
N firms	440	439	441	432	420
Chi square	28.462**	51.932***	58.468***	18.108	15.737
McFadden's Pseudo R square	0.038	0.057	0.071	0.022	0.021

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for NACE classes 20–30; differences in N attributed to missing values in the dependent variable.

Table 9
Overview of ordered logistic regressions with green patents via Green Inventory, Y02 and ENV-TECH (German data set).

	Independent Variables	(1) Overall Green Innovation (ordinal)	(2) Green Product Innovation (ordinal)	(3) Green Process Innovation (ordinal)	(4) Green Business Model Innovation (ordinal)	(5) Green Service Innovation (ordinal)
Green Inventory Models	Green TM (dummy)	0.674 (0.308)	1.215 (0.536)	0.708 (0.32)	1.494 (0.673)	0.769 (0.363)
	Green Patent (dummy)	0.838 (0.391)	1.107 (0.479)	0.935 (0.43)	0.667 (0.304)	0.576 (0.276)
Y02 Models	Green TM (dummy)	0.664 (0.303)	1.229 (0.540)	0.702 (0.318)	1.467 (0.658)	0.727 (0.343)
	Green Patent (dummy)	0.810 (0.438)	1.352 (0.693)	0.510 (0.280)	0.724 (0.390)	1.500 (0.801)
ENV-TECH Models	Green TM (dummy)	0.651 (0.297)	1.165 (0.515)	0.709 (0.322)	1.489 (0.672)	0.742 (0.351)
	Green Patent (dummy)	1.367 (0.752)	1.707 (0.902)	0.981 (0.548)	0.718 (0.401)	0.905 (0.512)
N firms		440	439	441	432	420

Notes: included for NACE classes 20–30, firm age and number of employees included in each model; standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; differences in N attributed to missing values in the dependent variable.

Table 10
Overview of logistic regressions with green patents via Green Inventory, Y02 and ENV-TECH (Italian data set).

	Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Inventory Models	Green Trademark (dummy)	1.625** (0.372)	2.440*** (0.679)	1.983** (0.556)	1.140 (0.347)
	Green Patent (dummy)	1.163 (0.437)	1.200 (0.538)	1.219 (0.542)	0.901 (0.428)
Y02 Models	Green Trademark (dummy)	1.635** (0.374)	2.465*** (0.686)	1.991** (0.559)	1.142 (0.347)
	Green Patent (dummy)	1.558 (0.508)	1.671 (0.653)	1.262 (0.503)	1.132 (0.456)
ENV-TECH Models	Green Trademark (dummy)	1.636*** (0.375)	2.460*** (0.685)	1.989*** (0.559)	1.146 (0.349)
	Green Patent (dummy)	1.258 (0.432)	1.258 (0.528)	1.097 (0.465)	1.183 (0.494)
N firms		5400	5350	5399	5400

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; firm age, number of employees and industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table 11
Overview of logistic regressions for small versus large firms (Italian data set).

	Independent Variables	(1) Overall Green Innovation (dummy)		(2) Green Product Innovation (dummy)		(3) Green Process Innovation (dummy)		(4) Circular/Green Economy Projects (dummy)	
		Small Firms	Large Firms	Small Firms	Large Firms	Small Firms	Large Firms	Small Firms	Large Firms
Green Inventory Models	Green Trademark	1.525	1.573	3.767***	1.884*	1.445	2.286**	1.749	0.865
	(dummy)	(0.585)	(0.459)	(1.712)	(0.671)	(0.760)	(0.771)	(0.842)	(0.344)
	Green Patent	0.521	1.465	0.554	1.339	1.371	1.280	(omitted)	1.143
	(dummy)	(0.484)	(0.630)	(0.661)	(0.664)	(1.322)	(0.646)		(0.575)
Y02 Models	Green Trademark	1.478	1.591	3.706***	1.953*	1.476	2.297**	1.684	0.878
	(dummy)	(0.565)	(0.465)	(1.680)	(0.694)	(0.770)	(0.775)	(0.808)	(0.349)
	Green Patent	1.267	1.771	0.823	2.360*	0.909	1.357	0.476	1.496
	(dummy)	(0.732)	(0.716)	(0.661)	(1.074)	(0.665)	(0.651)	(0.421)	(0.693)
ENV-TECH Models	Green Trademark	1.484	1.591	3.727***	1.961*	1.480	2.287**	1.675	0.889
	(dummy)	(0.567)	(0.466)	(1.687)	(0.699)	(0.771)	(0.773)	(0.804)	(0.354)
	Green Patent	1.071	1.454	0.368	2.095	0.774	1.145	0.446	1.647
	(dummy)	(0.667)	(0.611)	(0.350)	(1.006)	(0.610)	(0.585)	(0.415)	(0.785)
N firms		2988	2402	2960	2351	2988	2385	2988	2402

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; firm age, number of employees and industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table 12
Overview of logistic regressions for young versus established firms (Italian data set).

	Independent Variables	(1) Overall Green Innovation (dummy)		(2) Green Product Innovation (dummy)		(3) Green Process Innovation (dummy)		(4) Circular/Green Economy Projects (dummy)	
		Young Firms	Estab. Firms	Young Firms	Estab. Firms	Young Firms	Estab. Firms	Young Firms	Estab. Firms
Green Inventory Models	Green Trademark	0.796	1.858**	1.734	2.629***	1.255	2.169**	1.059	1.091
	(dummy)	(0.451)	(0.475)	(1.184)	(0.810)	(1.025)	(0.658)	(0.842)	(0.365)
	Green Patent	(omitted)	1.257	(omitted)	1.189	(omitted)	1.198	(omitted)	0.894
	(dummy)		(0.490)		(0.544)		(0.542)		(0.432)
Y02 Models	Green Trademark	0.824	1.882**	1.806	2.678***	1.263	2.183**	1.071	1.096
	(dummy)	(0.466)	(0.482)	(1.227)	(0.824)	(1.030)	(0.662)	(0.851)	(0.366)
	Green Patent	0.690	1.704	(omitted)	1.871	(omitted)	1.287	(omitted)	1.199
	(dummy)	(0.909)	(0.580)		(0.746)		(0.523)		(0.493)
ENV-TECH Models	Green Trademark	0.826	1.886***	1.792	2.676***	1.259	2.182**	1.067	1.105
	(dummy)	(0.467)	(0.483)	(1.218)	(0.824)	(1.027)	(0.662)	(0.847)	(0.370)
	Green Patent	0.463	1.430	(omitted)	1.470	(omitted)	1.143	(omitted)	1.338
	(dummy)	(0.594)	(0.518)		(0.633)		(0.497)		(0.574)
N firms		1193	4205	1144	4111	1159	4170	1168	4205

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; firm age, number of employees and industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable; the variable green patent is omitted in the logistic regression for perfectly predicting the failure outcome.

The green patent dummy variable was even omitted in some regressions for perfectly predicting the failure outcome. The results for the subsample of established firms revealed significant coefficients for green trademarks but not for green patents. To summarize, it seems that the predictive power of IPR-based measures of green innovation is higher for established versus young firms.

5.5. Subsample regressions by industry

To assess whether IPR-based measures of green innovation work better in manufacturing versus other industries, we created two subsamples based on the Italian data set. We used NACE classes 10 to 33 to identify firms active in manufacturing. Since the manufacturing industry is a major source for CO_2-emissions, it has the potential to make a large contribution to the reduction of CO_2-emissions by developing green innovations. It is also a large sector in our Italian data set. For the two subsamples, we then ran the same set of regressions as with the baseline regressions in Section 5.2. Table 13 shows the results.[8] We find significant results of the green trademark measures for both subsamples. Interestingly, green trademarks seem to be a valid indicator of green process innovation in non-manufacturing industries. Another interesting finding is that green trademarks seem to be able to predict circular/green economy projects in the manufacturing industry.

6. Discussion and conclusion

6.1. Summary and interpretation of main results

Green patents and green trademarks were evaluated as indicators of green innovation through regression analyses, using two distinct samples of SMEs and mid-cap firms from Germany and Italy. These samples differ significantly in terms of firm size, age, and industry. Table 14 summarizes the main results, which we will now discuss in detail.

Our first finding reveals that many green innovative firms may be

[8] The detailed regressions are shown in Tables A27-A32 in the Appendix.

Table 13
Overview of logistic regressions for firms from manufacturing (NACE 10–33) versus other industries (Italian data set).

	Independent Variables	(1) Overall Green Innovation (dummy)		(2) Green Product Innovation (dummy)		(3) Green Process Innovation (dummy)		(4) Circular/Green Economy Projects (dummy)	
		Manuf.	Other	Manuf.	Other	Manuf.	Other	Manuf.	Other
Green Inventory Models	Green Trademark (dummy)	1.292	2.155**	2.502**	2.494**	1.579	2.664**	1.950*	0.657
		(0.427)	(0.685)	(0.950)	(1.024)	(0.651)	(1.024)	(0.777)	(0.327)
	Green Patent (Dummy)	2.134	0.360	1.430	0.751	1.842	0.312	1.484	0.280
		(1.060)	(0.263)	(0.762)	(0.649)	(0.948)	(0.350)	(0.818)	(0.314)
Y02 Models	Green Trademark (dummy)	1.295	2.086**	2.567**	2.468**	1.555	2.597**	1.940*	0.644
		(0.428)	(0.659)	(0.975)	(1.012)	(0.641)	(0.995)	(0.773)	(0.320)
	Green Patent (dummy)	2.144	1.185	2.343*	1.075	1.109	1.744	1.172	1.250
		(1.000)	(0.587)	(1.168)	(0.710)	(0.587)	(1.095)	(0.654)	(0.758)
ENV-TECH Models	Green Trademark (dummy)	1.290	2.072**	2.554**	2.384**	1.557	2.618**	1.943*	0.649
		(0.426)	(0.655)	(0.969)	(0.983)	(0.641)	(1.005)	(0.774)	(0.322)
	Green Patent (dummy)	2.075	0.770	2.545*	0.347	1.204	1.210	1.314	1.209
		(0.994)	(0.425)	(1.309)	(0.281)	(0.651)	(0.866)	(0.745)	(0.79)
N firms		1964	3436	1963	3387	1963	3436	1964	3436

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; firm age, number of employees and industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table 14
Overview of main results.

			Outcome variable					
Analysis	Sample	Independent Variable	Overall Green Innovation	Green Product Innovation	Green Process Innovation	Green Business Model Innovation	Green Service Innovation	Circular/Green Economy Projects
Types of green innovation	German data set	Green Trademark	n.s.	n.s.	n.s.	n.s.	n.s.	
		Green Patent	n.s.	n.s.	n.s.	n.s.	n.s.	
	Italian data set	Green Trademark	+	+	+			n.s.
		Green Patent	n.s.	n.s.	n.s.			n.s.
Sample splits	Italian data set (small firms)	Green Trademark	n.s.	+	n.s.			n.s.
		Green Patent	n.s.	n.s.	n.s.			n.s.
	Italian data set (large firms)	Green Trademark	n.s.	+	+			n.s.
		Green Patent	n.s.	n.s.	n.s.			n.s.
	Italian data set (young firms)	Green Trademark	n.s.	n.s.	n.s.			n.s.
		Green Patent	n.s.	n.s.	n.s.			n.s.
	Italian data set (established firms)	Green Trademark	+	+	+			n.s.
		Green Patent	n.s.	n.s.	n.s.			n.s.
	Italian data set (manufacturing)	Green Trademark	n.s.	+	n.s.			+
		Green Patent	n.s.	+	n.s.			n.s.
	Italian data set (other industries)	Green Trademark	+	+	+			n.s.
		Green Patent	n.s.	n.s.	n.s.			n.s.

Notes: + = significant with odds ratio > 1, in case of green patents at least significant odds ratios by one approach, − = significant with odds ratio < 1, n.s. = not significant; N firms (German data set) = 444, N firms (Italian data set) = 5400.

overlooked when relying solely on patent- and trademark-based measures of green innovation. This is likely because many green innovations involve operational and supply chain modifications aimed at improving resource and energy efficiency, rather than new products. Such changes are often not sufficiently novel or visible to end consumers, leading firms to forego IPRs. This explanation also accounts for why the relationships are stronger for green product innovations compared to green process, service, and business model innovations.

Our second finding is that, while green trademarks are a useful indicator for various types of green innovation, green patents are less effective in this role. Furthermore, the predictive power and statistical significance of green patents are diminished when considering the overall number of patents held by a firm. This raises the question: why do green trademarks yield stronger and more consistent results compared to green patents? Several factors could explain this finding. First, patent data are closely associated with technological innovations, while many green product, process, service, and business model innovations are non-technological or involve softer forms of innovation. Our results might have been different if we had specifically targeted technological innovations, highlighting a limitation of our study. Second, as discussed by Morales et al. (2022) and Morales et al. (2024a), firms might choose not to patent their green innovations to enhance their accessibility and diffusion, thereby amplifying the firm's positive environmental impact. Another argument is that patents are ineffective as a protection mechanism and informal protection mechanisms such as lead time or secrecy are used instead (Cohen et al., 2000; Hall et al., 2014). We know from prior research that only a small percentage of all innovations are actually patented (Arundel and Kabla, 1998). Patents are in many industries and contexts not the most important mechanism of IP protection. Previous research indicates that environmental innovations are often difficult to protect effectively with patents. Alternative protection mechanisms and appropriation strategies may be more suitable for value capture (Corrocher and Solito, 2017; Morales et al., 2024a). Finally, the finding that the predictive power of green patents is taken away from the overall number of patents of a firm may be due to the multiple objectives associated with technological innovation, making it challenging to link a specific technology to a particular goal. Additionally, the development of green innovations might stem from a firm's general technological capabilities and absorptive capacity, with the total number of patents serving as a useful proxy for these broader capabilities.

Even though our sample contains only small and mid-cap firms, we could observe differences related to firm size regarding the power of green IPRs to predict green innovation. Our third finding is that the power of green trademarks to predict green product innovation is particularly high for small (but established) firms. What are possible explanations? One reason could be that small and established firms view green product innovations as a means to differentiate themselves from larger competitors in the marketplace. These firms may excel in a green niche and have successfully built a green brand, which they protect through green trademarks. Conversely, green trademarks might be less effective as a measure for younger firms, as they may not yet have the experience or resources to apply for and enforce IPRs. Despite trademarks generally having lower fees and costs compared to patents and being easier to obtain, the insignificant relationship observed may be due to a knowledge gap regarding the requirements and benefits of trademarking, particularly among young firms. This gap is more pronounced for firms operating primarily in B2B markets or in upstream value chain activities, where they are farther from end customers and market dynamics. Consequently, these firms may perceive less value in investing in trademarks.

A fourth finding is that the power of green trademarks to predict green innovation is higher for product than for process innovation. This can be explained by the fact that it is often possible to protect process innovations through secrecy and hence green IPRs might not be a good way to identify them.

The findings with regard to the ability of green IPRs to detect green business model innovation are mixed. In the German data set, we could not find any significant relationships for both patents and trademarks. This could be due to the focus on the manufacturing sector, where product and process innovations may (still) account for the majority of innovations. In the Italian data set, which is much broader in industry coverage, there is some tentative evidence that green trademarks can predict green business model innovation. Here, we find (at least for manufacturing firms) that green trademarks show a positive relation with circular/green economy projects. The circular economy has the goal to minimize waste and make the most out of resources. It often leads to changes in business models that increase the lifespan and re-use of products through sharing initiatives and platforms (Bocken et al., 2016; Bocken and Konietzko, 2022) but also by providing additional (repair) services (Saari et al., 2023). Both business model and service innovations can (to some extent) be protected through trademarks (Flikkema et al., 2019; Gotsch and Hipp, 2012). Even though we did not find a significant relation for green patents, we could observe in some regressions a significant relation for the overall number of patents as a measure. This relationship is to be expected as often technological innovations are required to close loops in material flows in the circular economy. Technology allows firms, among others, to sort and (chemically) recycle used materials and resources, convert waste into energy, print spare parts, and capture and store (carbon) emissions. Such technological innovations can be protected through patents. However, the technologies underlying these patents appear to serve broader purposes beyond just green applications.

Our sixth finding indicates that green trademarks are less effective as a measure of green innovation in the manufacturing sector compared to other sectors. This may reflect a broader tendency to rely on hard and technological innovation in manufacturing. Outside the manufacturing industry such as retail or services, product differentiation may be achieved based on "soft" factors and "soft" forms of non-technological innovation, which can be protected through trademarks (Flikkema et al., 2019). Despite the overall lower predictive power of green trademarks in manufacturing, we could still find a positive relationship between green trademarks and green product innovation in manufacturing. This finding is of high practical relevance given that the manufacturing sector is a major source of environmental pollution and CO_2-emissions. Hence, a cost-effective, transparent and fast way to identify green innovations in this sector is of high relevance.

Our final finding is that the different approaches to identify green patents (the Green Inventory developed by the WIPO, the Y02 classification introduced by the EPO, and the ENV-TECH classification from the OECD) show no apparent differences in their relationships with the survey-based measures. This is not surprising given that all approaches rely on IPC and/or CPC classes and that substantial overlaps exists between the IPC and CPC technology classification system.

6.2. Research implications

Our study shows that patents and trademarks can help to identify green innovation and green innovative firms not only in an objective, fast, and cost-effective way but also that this approach has some validity. This finding carries implications for the literature on the identification of green innovation (Cheng and Shiu, 2012; Haščič and Migotto, 2015). Previous studies have mostly relied on surveys to identify green innovation and green innovative firms (Antonioli et al., 2013; Cainelli et al., 2012; Chang, 2011). Our study shows that IPR-based measures can be a valuable addition but should also be used with caution as a substantial share of green innovative firms are overlooked. For the larger and more representative Italian sample, we find that (only) about 1 % (1.65 %) percent of firms have filed a green patent (green trademark) in the 5 years preceding the survey. Still, especially for small (but established) firms, green trademarks are a valuable predictor to identify green innovative firms, particularly regarding green product innovation.

Some prior studies have already utilized patent data to identify green innovative firms (Aiello et al., 2021; Bermúdez-Edo et al., 2017; León et al., 2018). Our study helps to understand the validity of the measurement choices in these studies. While Wagner (2007) stated that green innovation can be meaningfully identified using patent data and that green innovation identified this way is less ubiquitous than self-reported green innovation, our results show a different picture: they indicate that green innovations can be meaningfully identified using patent data only in very specific contexts and that generally an overall patent measure comprising green and non-green patents seems to be a better predictor. Therefore, researchers should be careful when using only patent data to identify green innovative firms because many firms may be overlooked with this approach. Extending on Wagner's (2007) methodology, our study also utilized trademarks to capture green innovations, which seem to work in a broader context than patents focusing not only on technological innovation. Building on our findings, we call for a simultaneous use of both patents and trademarks to capture both the technological and non-technological aspects of green innovation. The results also imply that the approaches to identify green innovations in patent and trademark data developed by the OECD (Haščič and Migotto, 2015), WIPO, EPO and EUIPO (2021) should be explored further. The utilization of trademark data in this context is novel and has only previously been discussed by Castaldi (2021). The results of our study confirm the transferability of trademarks to identify innovation in the field of green innovation and its various types. Thereby, the results extend the applicability of trademarks as an indicator of innovation beyond (venture capital-backed) start-up firms (Block et al., 2014), the creative and cultural sector (Castaldi, 2018), the pharmaceuticals industry (Nasirov, 2020), and SMEs (Block et al., 2015) to the sustainability context. The high odds ratios for green trademarks in the models for green product innovation demonstrate the significance of the connection between trademarks and this type of green innovation. Overall, our results highlight the important role of green trademarks in the identification of green innovative firms, which has implications not only for research but also for practice.

6.3. Practical implications

The results of our study have practical implications for different groups of practitioners. IPR-based measures of green innovation can help policymakers to identify green innovative firms and to get a first overview of firms that may be suitable targets for dedicated environmental R&D (support) policies. Managers trying to identify acquisition targets and cooperation partners active in green innovation can also benefit from our study. Next to this, IPR-based measures of green innovation are also a useful first screening device for entrepreneurial finance or institutional investors searching for investment targets in clean and/or climate tech. Finally, IPR-based measures of green innovation also constitute an additional measure for financial analysts and rating agencies focusing on environmental, social, and governance (ESG) criteria.

To summarize, we believe that the results of our study justify the development and implementation of IPR-based measures of green innovation as an additional screening tool for policymakers, managers, investors, and analysts to identify innovative firms contributing to the achievement of environmental sustainability goals. Yet, some caution is also advised. Particularly green patents seem for small and mid-cap firms not to be a good predictor of green innovation, which should be kept in mind when implementing such a screening tool. Whether green patents are a good predictor of green innovation for large firms is beyond the scope of our study and should be analyzed in further research. Such a validation is clearly needed given that policy reports are already combining green patents and trademarks to measure green innovation by large firms (e.g., Amoroso et al., 2021).

6.4. Limitations and future research

Our study has limitations that provide guidance for further research.

While we criticize the use of surveys for identifying green innovation, we still use them to validate the use of patent and trademark data for the measurement of green innovation. Hence, one could argue that our study does not validate IPR-based measures but rather tests the covariation of self-reported measures of green innovation and IPR-based measures of green innovation. This can be problematic as survey-based measures suffer from social desirability bias and consequently our finding of a positive relationship between green trademarks and green product innovation could be a consequence of the relatedness between greenwashing, branding efforts and trademark application (Schmuck et al., 2018).

Future studies should therefore do more to address the (complex) issue of potential greenwashing in the use of green trademarks and patents. While with patent applications the claims related to the inventions that shall be protected are scrutinized intensively in the application process, trademark descriptions are checked to a lesser extent on truth or completeness. However, we would argue that firms have little incentives to engage in greenwashing in the trademark description as the description itself is not the mark that is communicated to (potential) customers. For the actual marks the WIPO magazine writes that "trademark applications for marks that specifically include direct environmental claims, such as calling a product green, sustainable or eco-friendly, however, are likely to face a refusal" (Park, 2022). The likely reasons for such a refusal are that such trademarks would be too descriptive and loose its function as trademarks, and/or would be deceptive. Dedicated surveys, interviews or validations are necessary to understand better whether the greenness contained in trademark descriptions stands up to critical scrutiny. In a quantitative way, such validations could be undertaken by cross-checking whether a firm with a green trademark is also certified by a certification mark, which is owned by an independent entity and where certain standards need to be fulfilled. Another alternative would be to combine trademark data with data about the firms' actual environmental impacts.

Such research would move beyond the identification of green innovation towards measuring its actual (environmental) impact. Connecting green patents and trademarks with firm-level concrete environmental outcome measures such as CO_2-emissions or plastic usage would add valuable insights to the field and help to better assess the impact of technological and non-technological forms of green innovation and the role of IPRs in this relationship. It would also help to shed new light on the issue of greenwashing and social desirability bias as discussed above.

Another measure against this limitation would be to change the nature of questions in the survey. While we have undertaken some measures against social desirability bias (see Sections 3.1 and 3.2 above), we cannot completely rule out this possibility. Future research could try to ask more concrete questions about the nature of the underlying green innovations and check whether the claims made by the respondents hold up to critical scrutiny. Finally, another way would be to move away from self-reported measures completely and evaluate the "greenness" of the innovation in a more objective way. Future research could, for example, use submissions of a sustainable innovation contest with clear submission criteria and an expert panel and establish the correlation of the expert panel judgment with green IPR measures. This way, one could create an exact one-to-one matching between IPR and a specific green innovation similar to the study by Vimalnath et al. (2022) matching a sample of green innovations recognized by the European Inventor Award with the corresponding IPRs.

Another limitation regarding the specification of survey questions is that we did not distinguish explicitly between technological and non-technological forms of green innovation. This would be an important area for future research that would allow a more fine-grained assessment of the validity of green patents as an indicator of green innovation. Another direction would be to ask more specific questions about specific technologies related to carbon capture and storage, hydrogen, recycling, materials or waste management. Such questions would also allow a more precise disentanglement of the relationships between IPRs and the circular economy which encompasses both technological and non-technological forms of innovation.

A further limitation concerns the nature of our two samples. As our focus is on SMEs and mid-caps, we cannot make a statement how the use of green IPR-based measures for the identification of green innovations works with large firms. Future research should investigate the identification potential of green patents and trademarks in samples of large firms. Such a validation is clearly needed given that policy reports are already combining green patents and trademarks to measure green innovation by large firms (e.g., Amoroso et al., 2021). Because of more substantial resources and oftentimes more experience with IPRs, large firms are more likely to apply for IPRs, which could influence the validity of IPR-based measures of green innovation.

Being beyond the scope of our research, we did not classify the patents in our dataset based on information contained in the abstracts. Building on Wagner (2007), who used patent abstracts to identify green innovations in patent data, future research could compare the results of keyword-based classifications based on abstract data with the classification systems of the EPO, WIPO and OECD. A similar comparison can be done between the EUIPO (2021) classification (that we used) and the approach by Ghisetti et al. (2021), who rely on a keyword search in the descriptions contained in trademark documents. The EUIPO (2021) measurement of green trademarks can also be compared to the classifications developed by Neuhäusler et al. (2021) and Abbasiharofteh et al. (2022) described in Section 2.3 above, which were able to breakdown the relatively simple and broad 45 Nice classes into more fine-grained categories or subclasses. More generally, recent developments in the area of natural language processing and its application in patent/trademark data would allow researchers to produce more fine-grained measures and classifications (Abbasiharofteh et al., 2022; Arts et al., 2021; Erhardt et al., 2022). For example, similarity measures between text in environmental non-patent (academic) publications and text in patent documents can be calculated and used to construct measures of green innovation. Research by von Graevenitz et al. (2022) already uses a similar approach for trademarks to capture innovations via new tokens (words) in trademark descriptions. Another very interesting line of research would be to link patent and trademark data and investigate patent-trademark bundles instead of treating green patents and green trademarks as independent measures (Abbasiharofteh et al., 2022).

Another limitation is that we are not using information from patent and trademark data to identify the exact object of innovation that is protected. Future research could try to identify green process innovations based on patent claims as recent studies by Ganglmair et al. (2022) and Toh and Ahuja (2022) suggest. Similarly, research by Flikkema et al. (2019) suggests that it is possible to distinguish between product and service innovation based on trademark data.

6.5. Conclusion

In this study, we asked whether IPR-based measures of innovation can be used to identify green innovation. The answer is (a tentative) yes. Yet, the answer is more complex when we distinguish between patents and trademarks and between different types of green innovations and firms. Our study is therefore only a first step, and it is our hope that it follows the call by Castaldi et al. (2024) and spurs a vibrant new line of inquiry and insights into the complex relationships between IPRs, innovation and (environmental) sustainability.

Use of generative AI

During the preparation of this work the authors used ChatGPT 4.0 in the late stage of the submission process to improve the language of the article. After using the tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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CRediT authorship contribution statement

Jörn Block: Writing – review & editing, Writing – original draft, Supervision, Project administration, Data curation, Conceptualization. **Darius Lambrecht:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation. **Tom Willeke:** Writing – original draft, Software, Methodology, Data curation. **Marco Cucculelli:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization. **Damiano Meloni:** Writing – original draft, Methodology, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Correlation matrix (German data set).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Overall Green Innovation (ordinal)	–											
(2) Green Product Innovation (ordinal)	0.528*	–										
(3) Green Process Innovation (ordinal)	0.672*	0.254*	–									
(4) Green BM Inno. (ordinal)	0.432*	0.343*	0.232*	–								
(5) Green Service Innovation (ordinal)	0.310*	0.229*	0.197*	0.246*	–							
(6) Green Trademark (dummy)	0.052	0.112*	0.050	0.062	0.030	–						
(7) Green Patent Green Inv. (dummy)	0.000	0.072	−0.052	−0.043	−0.017	0.093*	–					
(8) Green Patent Y02 (dummy)	0.002	0.069	−0.079*	−0.027	0.054	0.041	0.289*	–				
(9) Green Patent ENV-TECH (dummy)	0.051	0.102*	−0.004	−0.016	0.018	0.190*	0.300*	0.554*	–			
(10) Number of TMs (log.)	0.084*	0.065	0.112*	−0.011	0.074	0.349*	0.057	0.111*	0.160*	–		
(11) Number of Patents (log.)	0.022	0.067	0.017	0.001	0.045	0.133*	0.309*	0.411*	0.358*	0.428*	–	
(12) Firm age (log.)	0.036	0.024	0.047	0.065	−0.021	0.076	0.018	0.081*	0.051	0.069	0.125*	–

(*continued on next page*)

Table A1 (*continued*)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(13) Employees (log.)	0.150*	0.086*	0.146*	0.069	−0.007	0.181*	0.178*	0.197*	0.212*	0.195*	0.395*	0.230*

Notes: N firms = 444;
* indicates a 10 % significance level.

Table A2
Correlation matrix (Italian data set).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Overall Green Innovation (dummy)	–										
(2) Green Product Innovation (dummy)	0.477*	–									
(3) Green Process Innovation (dummy)	0.535*	0.265*	–								
(4) Circ./Green economy projects (dummy)	0.117*	0.167*	0.187*	–							
(5) Green Trademark (dummy)	0.042*	0.064*	0.045*	0.016	–						
(6) Green patent Green Inv. (dummy)	0.032*	0.043*	0.034*	0.015	0.060*	–					
(7) Green Patent Y02 (dummy)	0.040*	0.061*	0.037*	0.026*	0.044*	0.299*	–				
(8) Green Patent ENV-TECH (dummy)	0.033*	0.051*	0.034*	0.029*	0.031*	0.330*	0.864*	–			
(9) Number of TMs (log.)	−0.006	0.010	−0.001	−0.011	0.191*	0.044*	0.051*	0.061*	–		
(10) Number of Patents (log.)	0.014	0.013	0.032*	0.028*	0.029*	0.316*	0.312*	0.338*	0.021	–	
(11) Firm age (log.)	0.053*	0.004	0.047*	0.006	0.034*	0.062*	0.046*	0.044*	0.001	0.041*	–
(12) Employees (log.)	0.092*	0.029*	0.078*	0.067*	0.061*	0.068*	0.049*	0.045*	0.008	0.039*	0.392*

Notes: N firms = 5400;
* indicates a 10 % significance level.

Table A3
Descriptive statistics on firm age and number of employees.

Variables	Country	Mean	Median	SD	Min.	Max.	Skew.	Kurt.
Firm age	Germany	49.03	36	36.67	12	208	1.95	7.05
	Italy	21.60	18	14.28	3	121	1.26	5.72
Employees	Germany	298.25	164	463.17	50	2722	7.37	87.15
	Italy	28.95	10	282.71	1	1931	45.71	2257.28

Notes: N firms (German data set) = 444, N firms (Italian data set) = 5400; SD = Standard deviation, Min. =Minimum, Max. = Maximum, Skew = Skewness, Kurt. = Kurtosis.

Table A4
Further descriptive statistics for the German data set.

Variable	Mean	Median	SD	Min.	Max.
Patents	6.91	0	24.49	0	256
Green Patents (Green Inventory)	0.38	0	3.07	0	55
Green Patents (Y02)	0.21	0	1.51	0	20
Green Patents (ENV-TECH)	0.19	0	1.35	0	15
Trademarks	1.94	0	6.61	0	80
Green Trademarks	0.24	0	1.56	0	26

Notes: N firms = 444; SD = Standard deviation, Min. =Minimum, Max. = Maximum.

Table A5
Further descriptive statistics for the Italian data set.

Variable	Mean	Median	SD	Min.	Max.
Patents	1.45	0	26.93	0	1445
Green Patents (Green Inventory)	0.08	0	3.85	0	281
Green Patents (Y02)	0.24	0	10.82	0	754
Green Patents (ENV-TECH)	0.14	0	6.72	0	478
Trademarks	9.26	0	53.72	0	1244
Green Trademarks	0.03	0	0.29	0	9

Notes: N firms = 5400; SD = Standard deviation, Min. =Minimum, Max. = Maximum.

Table A6
NACE industry distribution for the German data set.

NACE class	NACE class description	Percent
20	Manufacture of chemicals and chemical products	6.98
21	Manufacture of pharmaceutical products and pharmaceutical preparations	2.25
22	Manufacture of rubber and plastic products	12.61
23	Manufacture of other non-metallic mineral products	6.76
24	Manufacture of basic metals	4.96
25	Manufacture of fabricated metal products, except machinery and equipment	21.85
26	Manufacture of computer, electronic and optical products	7.66
27	Manufacture of electrical equipment	8.11
28	Manufacture of machinery and equipment n.e.c.	24.55
29	Manufacture of motor vehicles, trailers and semi trailers	3.15
30	Manufacture of other transport equipment	1.13

Notes: N firms = 444.

Table A7
NACE industry distribution for the Italian data set.

NACE class	NACE class description	Percent
1	Crop and animal production, hunting and related service activities	0.52
2	Forestry and logging	0.04
8	Other mining and quarrying	0.17
10	Manufacture of food products	1.69
11	Manufacture of beverages	0.41
13	Manufacture of textiles	0.91
14	Manufacture of wearing apparel	1.02
15	Manufacture of leather and related products	1.26
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	1.22
17	Manufacture of paper and paper products	0.67
18	Printing and reproduction of recorded media	1.41
19	Manufacture of coke and refined petroleum products	0.04
20	Manufacture of chemicals and chemical products	1.02
21	Manufacture of pharmaceutical products and pharmaceutical preparations	0.13
22	Manufacture of rubber and plastic products	2.15
23	Manufacture of other non-metallic mineral products	1.15
24	Manufacture of basic metals	0.30
25	Manufacture of fabricated metal products, except machinery and equipment	8.02
26	Manufacture of computer, electronic and optical products	2.15
27	Manufacture of electrical equipment	1.85
28	Manufacture of machinery and equipment n.e.c.	5.44
29	Manufacture of motor vehicles, trailers and semi trailers	0.43
30	Manufacture of other transport equipment	0.35
31	Manufacture of furniture	1.91
32	Other manufacturing	1.07
33	Repair and installation of machinery and equipment	1.80
35	Electricity, gas, steam and air conditioning supply	0.39
36	Water collection, treatment and supply	0.07
37	Sewerage	0.09
38	Waste collection, treatment and disposal activities; materials recovery	1.02
39	Remediation activities and other waste management services	0.11
41	Construction of buildings	2.04
42	Civil engineering	0.57
43	Specialized construction activities	4.96
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	1.28
46	Wholesale trade, except of motor vehicles and motorcycles	8.83
47	Retail trade, except of motor vehicles and motorcycles	2.65
49	Land transport and transport via pipelines	1.85
50	Water transport	0.04
52	Warehousing and support activities for transportation	1.07
53	Postal and courier activities	0.07
55	Accommodation	1.22
56	Food and beverage service activities	1.11
58	Publishing activities	0.94
59	Motion picture, video and television program production, sound recording and music publishing activities	0.41
60	Programming and broadcasting activities	0.09
61	Telecommunications	0.43
62	Computer programming, consultancy and related activities	10.15
63	Information service activities	1.74
64	Financial service activities, except insurance and pension funding	0.48
65	Insurance, reinsurance and pension funding, except compulsory social security	0.02
66	Activities auxiliary to financial services and insurance activities	0.67
68	Real estate activities	1.04

(*continued on next page*)

Table A7 (*continued*)

NACE class	NACE class description	Percent
69	Legal and accounting activities	0.54
70	Activities of head offices; management consultancy activities	3.13
71	Architectural and engineering activities; technical testing and analysis	2.54
72	Scientific research and development	1.37
73	Advertising and market research	1.46
74	Other professional, scientific and technical activities	3.06
77	Rental and leasing activities	0.48
78	Employment activities	0.19
79	Travel agency, tour operator and other reservation service and related activities	0.44
80	Security and investigation activities	0.24
81	Services to buildings and landscape activities	1.43
82	Office administrative, office support and other business support activities	0.61
85	Education	0.54
86	Human health activities	0.69
87	Residential care activities	0.33
88	Social work activities without accommodation	0.72
90	Creative, arts and entertainment activities	0.37
91	Libraries, archives, museums and other cultural activities	0.13
92	Gambling and betting activities	0.02
93	Sports activities and amusement and recreation activities	0.39
95	Repair of computers and personal and household goods	0.39
96	Other personal service activities	0.50

NACE section	NACE section description	Percent
A	Agriculture, forestry and fishing	0.56
B	Mining and quarrying	0.17
C	Manufacturing	36.37
D	Electricity, gas, steam, and air conditioning supply	0.39
E	Water supply, sewerage, waste management, and remediation activities	1.30
F	Construction	7.57
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	12.76
H	Transportation and storage	3.04
I	Accommodation and food service activities	2.33
J	Information and communication	13.76
K	Financial and insurance activities	1.17
L	Real estate activities	1.04
M	Professional, scientific, and technical activities	12.09
N	Administrative and support service activities	3.39
P	Education	0.54
Q	Human health and social work activities	1.74
R	Arts, entertainment, and recreation	0.91
S	Other service activities	0.89

Notes: N firms = 5400.

Table A8
Crosstabulations for firms indicating any type of green innovation in survey with green patents and green trademarks (German data set).

		Overall green innovation in survey	
		No green innovation in survey	Yes green innovation in survey
Green patent (Green Inventory)	No green patent	20	394
	Yes green patent	1	25
Green Patent (Y02)	No green patent	21	401
	Yes green patent	0	18
Green Patent (ENV-TECH)	No green patent	21	402
	Yes green patent	0	17
Green trademark	No green TM	21	391
	Yes green TM	0	28

Notes: N firms = 444.

Table A9
Green patent and green trademark measurement approaches.

IPR	Approach	Developed by	System	Description
Patent	Green Inventory (first 2010)	• WIPO • IPC Committee of Experts	IPC	• Environmentally Sound Technologies (EST) • Catchword index • Many Type 1 and 2 errors possible
	Y02 classification (first 2012	• EPO	CPC	• Climate Change Mitigation Technologies (CCMTs)

(*continued on next page*)

Table A9 (*continued*)

IPR	Approach	Developed by	System	Description
				• Developed to facilitate the identification of mitigation technologies in the energy sector (Veefkind et al., 2012) • Later extended to the transport and building sectors • The entire Y02 scheme has now been integrated into the CPC system
	ENV-TECH list (first 2016, revised 2020)	• OECD Working Party on Integrating Environmental and Economic Policies (WPIEEP) • OECD Working Party on Climate, Investment and Development (WPCID)	Both IPC and CPC	• Environment-Related Technologies (ENV-TECH) • Codes rely on the CPC-Y02 classes to the extent possible • Also complimented by IPC codes
Trademark	"Green" TMs approach (first 2021)	• EUIPO European Observatory on Infringements of Intellectual Property rights	Nice classes and description terms	• List of combinations of description terms and Nice classifications of trademarks that can be considered green • Trademark had to have at least one specific combination to be classified as green trademark

Table A10
Ordered logistic regressions with green patents via Y02 (German data set).

Independent Variables	(1) Overall Green Innovation (ordinal)	(2) Green Product Innovation (ordinal)	(3) Green Process Innovation (ordinal)	(4) Green Business Model Innovation (ordinal)	(5) Green Service Innovation (ordinal)
Green Trademark (dummy)	0.664 (0.303)	1.229 (0.540)	0.702 (0.318)	1.467 (0.658)	0.727 (0.343)
Green Patent (dummy)	0.810 (0.438)	1.352 (0.693)	0.510 (0.280)	0.724 (0.390)	1.500 (0.801)
Number of TMs (log.)	1.479*** (0.215)	1.198 (0.160)	1.592*** (0.225)	0.986 (0.138)	1.307* (0.185)
Number of Patents (log.)	0.923 (0.096)	1.050 (0.104)	0.873 (0.091)	0.969 (0.098)	1.036 (0.109)
Firm age (log.)	1.029 (0.165)	1.009 (0.153)	0.990 (0.157)	1.196 (0.185)	0.902 (0.146)
Employees (log.)	1.423*** (0.193)	1.158 (0.145)	1.503*** (0.204)	1.218 (0.157)	0.951 (0.126)
Industry (dummies)	Yes	Yes***	Yes***	Yes**	Yes**
N firms	440	439	441	432	420
Chi square	28.471**	52.224	59.948***	17.671	14.965
McFadden's Pseudo R square	0.038	0.057	0.073	0.022	0.020

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for NACE classes 20–30; differences in N attributed to missing values in the dependent variable.

Table A11
Ordered logistic regressions with green patents via ENV-TECH (German data set).

Independent Variables	(1) Overall Green Innovation (ordinal)	(2) Green Product Innovation (ordinal)	(3) Green Process Innovation (ordinal)	(4) Green Business Model Innovation (ordinal)	(5) Green Service Innovation (ordinal)
Green Trademark (dummy)	0.651 (0.297)	1.165 (0.515)	0.709 (0.322)	1.489 (0.672)	0.742 (0.351)
Green Patent (dummy)	1.367 (0.752)	1.707 (0.902)	0.981 (0.548)	0.718 (0.401)	0.905 (0.512)
Number of TMs (log.)	1.485*** (0.215)	1.189 (0.159)	1.604*** (0.227)	0.993 (0.139)	1.295* (0.182)
Number of Patents (log.)	0.893 (0.09)	1.043 (0.099)	0.835* (0.085)	0.963 (0.094)	1.077 (0.108)
Firm age (log.)	1.029 (0.165)	1.018 (0.154)	0.986 (0.156)	1.191 (0.184)	0.909 (0.147)
Employees (log.)	1.423*** (0.193)	1.154 (0.145)	1.503*** (0.204)	1.221 (0.158)	0.944 (0.125)
Industry (dummies)	Yes	Yes***	Yes***	Yes**	Yes**
N firms	440	439	441	432	420
Chi square	28.644**	52.901***	58.448***	17.663	14.421
McFadden's Pseudo R square	0.038	0.058	0.071	0.022	0.019

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for NACE classes 20–30; differences in N attributed to missing values in the dependent variable.

Table A12
Logistic regressions with green patents via Green Inventory (Italian data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.625**	2.440***	1.983**	1.140
(dummy)	(0.372)	(0.679)	(0.556)	(0.347)
Green Patent	1.163	1.200	1.219	0.901
(dummy)	(0.437)	(0.538)	(0.542)	(0.428)
Number of TMs (log.)	0.986	1.005	0.949	0.996
	(0.026)	(0.04)	(0.037)	(0.035)
Number of Patents (log.)	1.119*	1.285***	1.186**	1.157**
	(0.064)	(0.09)	(0.083)	(0.081)
Firm age	0.970	0.861*	1.019	0.876**
(log.)	(0.046)	(0.065)	(0.071)	(0.057)
Employees	1.110***	1.054	1.167***	1.223***
(log.)	(0.031)	(0.047)	(0.047)	(0.047)
Industry (dummies)	Yes***	Yes**	Yes***	Yes**
N firms	5400	5350	5399	5400
Chi square	210.958***	95.113***	113.952***	67.479***
McFadden's Pseudo R square	0.032	0.029	0.030	0.016

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A13
Logistic regressions with green patents via Y02 (Italian data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.635**	2.465***	1.991**	1.142
(dummy)	(0.374)	(0.686)	(0.559)	(0.347)
Green Patent	1.558	1.671	1.262	1.132
(dummy)	(0.508)	(0.653)	(0.503)	(0.456)
Number of TMs (log.)	0.986	1.004	0.949	0.996
	(0.026)	(0.04)	(0.037)	(0.035)
Number of Patents (log.)	1.081	1.231***	1.174**	1.135*
	(0.066)	(0.095)	(0.088)	(0.086)
Firm age	0.970	0.861**	1.020	0.876**
(log.)	(0.046)	(0.065)	(0.071)	(0.057)
Employees	1.111***	1.056	1.168***	1.223***
(log.)	(0.031)	(0.047)	(0.047)	(0.047)
Industry (dummies)	Yes***	Yes**	Yes***	Yes**
N firms	5400	5350	5399	5400
Chi square	212.638***	96.617***	114.091***	67.523***
McFadden's Pseudo R square	0.032	0.029	0.030	0.016

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A14
Logistic regressions with green patents via ENV-TECH (Italian data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.636***	2.460***	1.989***	1.146
(dummy)	(0.375)	(0.685)	(0.559)	(0.349)
Green Patent	1.258	1.258	1.097	1.183
(dummy)	(0.432)	(0.528)	(0.465)	(0.494)
Number of TMs (log.)	0.986	1.005	0.949	0.995
	(0.026)	(0.04)	(0.037)	(0.035)
Number of Patents (log.)	1.104	1.269***	1.191**	1.129
	(0.069)	(0.099)	(0.092)	(0.088)
Firm age	0.970	0.862**	1.020	0.876**
(log.)	(0.046)	(0.065)	(0.071)	(0.057)
Employees	1.110***	1.055	1.167***	1.224***
(log.)	(0.031)	(0.047)	(0.047)	(0.047)
Industry (dummies)	Yes***	Yes**	Yes***	Yes**
N firms	5400	5350	5399	5400
Chi square	211.241***	95.244***	113.805***	67.590***
McFadden's Pseudo R square	0.032	0.029	0.030	0.016

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A15
Logistic regressions with green patents via Green Inventory (Italian small firm data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.525	3.767***	1.445	1.749
(dummy)	(0.585)	(1.712)	(0.760)	(0.842)
Green Patent	0.521	0.554	1.371	(omitted)
(dummy)	(0.484)	(0.661)	(1.322)	
Number of TMs (log.)	0.967	0.929	1.013	0.986
	(0.037)	(0.059)	(0.055)	(0.051)
Number of Patents (log.)	1.183*	1.269*	1.297**	1.166
	(0.117)	(0.164)	(0.157)	(0.151)
Firm age	0.900*	0.802**	0.923	0.825**
(log.)	(0.056)	(0.079)	(0.088)	(0.072)
Employees	1.027	1.024	1.102	1.179**
(log.)	(0.058)	(0.091)	(0.096)	(0.093)
Industry (dummies)	Yes***	Yes	Yes***	Yes**
N firms	2988	2960	2988	2981
Chi square	74.537***	37.239**	46.677***	30.077*
McFadden's Pseudo R square	0.021	0.021	0.025	0.014

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A16
Logistic regressions with green patents via Y02 (Italian small firm data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.478	3.706***	1.476	1.684
(dummy)	(0.565)	(1.680)	(0.770)	(0.808)
Green Patent	1.267	0.823	0.909	0.476
(dummy)	(0.732)	(0.661)	(0.665)	(0.421)
Number of TMs (log.)	0.967	0.929	1.013	0.986
	(0.037)	(0.059)	(0.055)	(0.051)
Number of Patents (log.)	1.120	1.261	1.333*	1.179
	(0.127)	(0.185)	(0.183)	(0.172)
Firm age	0.900*	0.801**	0.923	0.823**
(log.)	(0.056)	(0.079)	(0.088)	(0.072)
Employees	1.028	1.025	1.101	1.180**
(log.)	(0.058)	(0.091)	(0.096)	(0.093)
Industry (dummies)	Yes**	Yes	Yes***	Yes**
N firms	2988	2960	2988	2988
Chi square	74.180***	37.030**	46.590***	29.844
McFadden's Pseudo R square	0.021	0.021	0.025	0.014

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A17
Logistic regressions with green patents via ENV-TECH (Italian small firm data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.484	3.727***	1.480	1.675
(dummy)	(0.567)	(1.687)	(0.771)	(0.804)
Green Patent	1.071	0.368	0.774	0.446
(dummy)	(0.667)	(0.350)	(0.610)	(0.415)
Number of TMs (log.)	0.967	0.932	1.013	0.988
	(0.037)	(0.059)	(0.056)	(0.051)
Number of Patents (log.)	1.142	1.370**	1.360**	1.193
	(0.132)	(0.202)	(0.193)	(0.181)
Firm age	0.900*	0.800**	0.923	0.823**
(log.)	(0.056)	(0.079)	(0.088)	(0.072)
Employees	1.028	1.025	1.101	1.181**
(log.)	(0.058)	(0.091)	(0.096)	(0.093)
Industry (dummies)	Yes***	Yes	Yes***	Yes**
N firms	2988	2960	2988	2988
Chi square	74.025***	38.188***	46.681***	29.889
McFadden's Pseudo R square	0.021	0.022	0.025	0.014

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A18
Logistic regressions with green patents via Green Inventory (Italian large firm data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.573	1.884*	2.286**	0.865
(dummy)	(0.459)	(0.671)	(0.771)	(0.344)
Green Patent	1.465	1.339	1.280	1.143
(dummy)	(0.630)	(0.664)	(0.646)	(0.575)
Number of TMs (log.)	1.002	1.065	0.890**	0.995
	(0.037)	(0.056)	(0.050)	(0.049)
Number of Patents (log.)	1.055	1.261***	1.128	1.137
	(0.075)	(0.109)	(0.097)	(0.096)
Firm age	1.074	0.966	1.141	0.962
(log.)	(0.082)	(0.115)	(0.121)	(0.099)
Employees	1.202***	1.117	1.205***	1.360***
(log.)	(0.064)	(0.089)	(0.082)	(0.089)
Industry (dummies)	Yes***	Yes*	Yes***	Yes
N firms	2402	2351	2385	2402
Chi square	147.724***	71.914***	63.112***	45.222***
McFadden's Pseudo R square	0.048	0.047	0.033	0.023

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A19
Logistic regressions with green patents via Y02 (Italian large firm data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.591	1.953*	2.297**	0.878
(dummy)	(0.465)	(0.694)	(0.775)	(0.349)
Green Patent	1.771	2.360*	1.357	1.496
(dummy)	(0.716)	(1.074)	(0.651)	(0.693)
Number of TMs (log.)	1.002	1.064	0.890**	0.994
	(0.037)	(0.056)	(0.050)	(0.049)
Number of Patents (log.)	1.030	1.180*	1.115	1.103
	(0.076)	(0.108)	(0.101)	(0.099)
Firm age	1.073	0.962	1.141	0.960
(log.)	(0.081)	(0.115)	(0.121)	(0.099)
Employees	1.204***	1.122	1.206***	1.362***
(log.)	(0.064)	(0.090)	(0.082)	(0.089)
Industry (dummies)	Yes***	Yes*	Yes***	Yes
N firms	2402	2351	2385	2402
Chi square	148.936***	74.973***	63.275***	45.886***
McFadden's Pseudo R square	0.048	0.049	0.033	0.024

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A20
Logistic regressions with green patents via ENV-TECH (Italian large firm data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.591	1.961*	2.287**	0.889
(dummy)	(0.466)	(0.699)	(0.773)	(0.354)
Green Patent	1.454	2.095	1.145	1.647
(dummy)	(0.611)	(1.006)	(0.585)	(0.785)
Number of TMs (log.)	1.003	1.066	0.890**	0.995
	(0.037)	(0.056)	(0.050)	(0.049)
Number of Patents (log.)	1.047	1.190*	1.133	1.089
	(0.080)	(0.112)	(0.105)	(0.100)
Firm age	1.075	0.964	1.142	0.960
(log.)	(0.082)	(0.115)	(0.121)	(0.099)
Employees	1.204***	1.127	1.206***	1.366***
(log.)	(0.064)	(0.090)	(0.082)	(0.090)
Industry (dummies)	Yes***	Yes*	Yes***	Yes
N firms	2402	2351	2385	2402
Chi square	147.724***	73.867***	62.949***	46.219***
McFadden's Pseudo R square	0.048	0.048	0.033	0.024

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A21
Logistic regressions with green patents via Green Inventory (Italian young firm data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark (dummy)	0.796 (0.451)	1.734 (1.184)	1.255 (1.025)	1.059 (0.842)
Green Patent (dummy)	(omitted)	(omitted)	(omitted)	(omitted)
Number of TMs (log.)	1.017 (0.054)	1.031 (0.082)	0.968 (0.082)	0.909 (0.074)
Number of Patents (log.)	1.170 (0.233)	0.921 (0.304)	0.617 (0.324)	0.680 (0.270)
Firm age (log.)	0.836 (0.186)	0.803 (0.263)	0.825 (0.284)	1.315 (0.397)
Employees (log.)	1.059 (0.070)	0.950 (0.096)	1.190* (0.116)	0.920 (0.081)
Industry (dummies)	Yes**	Yes**	Yes**	Yes***
N firms	1193	1144	1159	1168
Chi square	41.952***	14.017	25.306	25.748
McFadden's Pseudo R square	0.029	0.019	0.033	0.028

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A22
Logistic regressions with green patents via Y02 (Italian young firm data set).

Independent Variables	(1) Overall green innovation (dummy)	(2) Green product innovation (dummy)	(3) Green process innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark (dummy)	0.824 (0.466)	1.806 (1.227)	1.263 (1.030)	1.071 (0.851)
Green Patent (dummy)	0.690 (0.909)	(omitted)	(omitted)	(omitted)
Number of TMs (log.)	1.015 (0.054)	1.033 (0.082)	0.967 (0.082)	0.909 (0.074)
Number of Patents (log.)	1.148 (0.253)	1.018 (0.354)	0.638 (0.340)	0.707 (0.289)
Firm age (log.)	0.837 (0.186)	0.801 (0.263)	0.826 (0.284)	1.317 (0.398)
Employees (log.)	1.057 (0.070)	0.948 (0.095)	1.190* (0.116)	0.920 (0.081)
Industry (dummies)	Yes**	Yes**	Yes**	Yes***
N firms	1195	1142	1157	1166
Chi square	42.021***	14.232	24.990	25.311
McFadden's Pseudo R square	0.029	0.019	0.033	0.027

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A23
Logistic regressions with green patents via ENV-TECH (Italian young firm data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark (dummy)	0.826 (0.467)	1.792 (1.218)	1.259 (1.027)	1.067 (0.847)
Green Patent (dummy)	0.463 (0.594)	(omitted)	(omitted)	(omitted)
Number of TMs (log.)	1.016 (0.055)	1.033 (0.082)	0.968 (0.082)	0.910 (0.074)
Number of Patents (log.)	1.196 (0.269)	1.046 (0.366)	0.649 (0.348)	0.722 (0.297)
Firm age (log.)	0.836 (0.186)	0.800 (0.263)	0.826 (0.284)	1.316 (0.398)
Employees (log.)	1.057 (0.070)	0.949 (0.096)	1.190* (0.116)	0.920 (0.081)
Industry (dummies)	Yes**	Yes**	Yes**	Yes***
N firms	1195	1141	1156	1165
Chi square	42.329***	14.219	24.828	25.129
McFadden's Pseudo R square	0.029	0.019	0.033	0.027

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A24
Logistic regressions with green patents via Green Inventory (Italian established firm data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.858**	2.629***	2.169**	1.091
(dummy)	(0.475)	(0.810)	(0.658)	(0.365)
Green Patent	1.257	1.189	1.198	0.894
(dummy)	(0.490)	(0.544)	(0.542)	(0.432)
Number of TMs (log.)	0.973	1.000	0.941	1.024
	(0.030)	(0.046)	(0.042)	(0.041)
Number of Patents (log.)	1.110	1.298***	1.210***	1.156**
	(0.067)	(0.095)	(0.086)	(0.083)
Firm age	1.081	0.915	1.084	0.892
(log.)	(0.081)	(0.110)	(0.115)	(0.093)
Employees	1.118***	1.071	1.157***	1.310***
(log.)	(0.035)	(0.054)	(0.051)	(0.056)
Industry (dummies)	Yes***	Yes	Yes***	Yes*
N firms	4205	4111	4170	4205
Chi square	195.676***	88.146***	97.699***	77.775***
McFadden's Pseudo R square	0.037	0.035	0.032	0.025

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A25
Logistic regressions with green patents via Y02 (Italian established firm data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.882**	2.678***	2.183**	1.096
(dummy)	(0.482)	(0.824)	(0.662)	(0.366)
Green Patent	1.704	1.871	1.287	1.199
(dummy)	(0.580)	(0.746)	(0.523)	(0.493)
Number of TMs (log.)	0.973	1.000	0.941	1.024
	(0.029)	(0.046)	(0.042)	(0.041)
Number of Patents (log.)	1.069	1.228***	1.194**	1.126
	(0.068)	(0.098)	(0.091)	(0.087)
Firm age	1.082	0.916	1.085	0.891
(log.)	(0.081)	(0.109)	(0.115)	(0.092)
Employees	1.119***	1.074	1.158***	1.311***
(log.)	(0.035)	(0.054)	(0.051)	(0.056)
Industry (dummies)	Yes***	Yes	Yes***	Yes*
N firms	4205	4111	4170	4205
Chi square	197.776***	90.385***	97.919***	77.913***
McFadden's Pseudo R square	0.038	0.035	0.032	0.025

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A26
Logistic regressions with green patents via ENV-TECH (Italian established firm data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.886***	2.676***	2.182**	1.105
(dummy)	(0.483)	(0.824)	(0.662)	(0.370)
Green Patent	1.430	1.470	1.143	1.338
(dummy)	(0.518)	(0.633)	(0.497)	(0.574)
Number of TMs (log.)	0.973	1.001	0.941	1.023
	(0.029)	(0.046)	(0.042)	(0.041)
Number of Patents (log.)	1.087	1.260***	1.209**	1.112
	(0.071)	(0.102)	(0.095)	(0.089)
Firm age	1.081	0.915	1.085	0.890
(log.)	(0.081)	(0.109)	(0.115)	(0.092)
Employees	1.119***	1.073	1.158***	1.312***
(log.)	(0.035)	(0.054)	(0.051)	(0.056)
Industry (dummies)	Yes***	Yes	Yes***	Yes*
N firms	4205	4111	4170	4205
Chi square	196.305***	88.790***	97.636***	78.171***
McFadden's Pseudo R square	0.038	0.035	0.032	0.025

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 18 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A27
Logistic regressions with green patents via Green Inventory
(Italian manufacturing firms data set)

Independent Variables	(1) Overall Green Innovation (Dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.292	2.502**	1.579	1.950*
(dummy)	(0.427)	(0.950)	(0.651)	(0.777)
Green Patent	2.134	1.430	1.842	1.484
(dummy)	(1.060)	(0.762)	(0.948)	(0.818)
Number of TMs (log.)	1.017	0.991	0.949	0.945
	(0.042)	(0.060)	(0.058)	(0.058)
Number of Patents (log.)	1.017	1.253**	1.145	1.088
	(0.075)	(0.110)	(0.101)	(0.100)
Firm age	1.067	0.997	1.078	0.861
(log.)	(0.079)	(0.111)	(0.119)	(0.094)
Employees	1.248***	1.101	1.276***	1.382***
(log.)	(0.057)	(0.072)	(0.081)	(0.089)
N firms	1964	1963	1963	1964
Chi square	43.421***	23.623***	34.319***	35.471***
McFadden's Pseudo R square	0.017	0.016	0.022	0.023

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; differences in N attributed to missing values in the dependent variable.

Table A28
Logistic regressions with green patents via Y02
(Italian manufacturing firms data set)

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green process innovation (Dummy)	(4) Circular/Green Economy Projects (Dummy)
Green Trademark	1.295	2.567**	1.555	1.940*
(dummy)	(0.428)	(0.975)	(0.641)	(0.773)
Green Patent	2.144	2.343*	1.109	1.172
(dummy)	(1.000)	(1.168)	(0.587)	(0.654)
Number of TMs (log.)	1.017	0.991	0.949	0.945
	(0.042)	(0.060)	(0.058)	(0.058)
Number of Patents (log.)	1.006	1.186*	1.189*	1.104
	(0.076)	(0.111)	(0.107)	(0.105)
Firm age	1.069	0.996	1.085	0.864
(log.)	(0.080)	(0.111)	(0.119)	(0.094)
Employees	1.251***	1.106	1.274***	1.381***
(log.)	(0.058)	(0.073)	(0.081)	(0.089)
N firms	1964	1963	1963	1964
Chi square	43.749***	25.985***	33.000***	35.055***
McFadden's Pseudo R square	0.017	0.018	0.021	0.023

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; differences in N attributed to missing values in the dependent variable.

Table A29
Logistic regressions with green patents via ENV-TECH
(Italian manufacturing firms data set)

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	1.290	2.554**	1.557	1.943*
(dummy)	(0.426)	(0.969)	(0.641)	(0.774)
Green Patent	2.075	2.545*	1.204	1.314
(dummy)	(0.994)	(1.309)	(0.651)	(0.745)
Number of TMs (log.)	1.018	0.995	0.950	0.946
	(0.042)	(0.060)	(0.058)	(0.058)
Number of Patents (log.)	1.006	1.172*	1.180*	1.093
	(0.078)	(0.113)	(0.109)	(0.106)
Firm age	1.069	0.994	1.084	0.863
(log.)	(0.08)	(0.110)	(0.119)	(0.094)
Employees	1.252***	1.110	1.275***	1.383***
(log.)	(0.058)	(0.073)	(0.081)	(0.089)
N firms	1964	1963	1963	1964
Chi square	43.370***	26.369***	33.079***	35.201***
McFadden's Pseudo R square	0.017	0.018	0.021	0.023

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; differences in N attributed to missing values in the dependent variable.

Table A30
Logistic regressions with green patents via Green Inventory
(Italian other industries data set)

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green trademark	2.155**	2.494**	2.664**	0.657
(dummy)	(0.685)	(1.024)	(1.024)	(0.327)
Green patent	0.360	0.751	0.312	0.280
(dummy)	(0.263)	(0.649)	(0.350)	(0.314)
Number of TMs (log.)	0.955	1.010	0.942	1.018
	(0.033)	(0.054)	(0.049)	(0.044)
Number of Patents (log.)	1.232**	1.305**	1.219*	1.212*
	(0.115)	(0.156)	(0.144)	(0.135)
Firm age	0.891*	0.750***	0.972	0.877
(log.)	(0.056)	(0.078)	(0.088)	(0.073)
Employees	1.025	1.009	1.093*	1.146***
(log.)	(0.038)	(0.062)	(0.057)	(0.055)
Industry (dummies)	Yes***	Yes**	Yes***	Yes**
N firms	3436	3387	3436	3436
Chi square	96.541***	46.533***	77.232***	43.426***
McFadden's Pseudo R square	0.024	0.026	0.034	0.017

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 17 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A31
Logistic regressions with green patents via Y02 (Italian other industries data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	2.086**	2.468**	2.597**	0.644
(dummy)	(0.659)	(1.012)	(0.995)	(0.320)
Green Patent	1.185	1.075	1.744	1.250
(dummy)	(0.587)	(0.710)	(1.095)	(0.758)
Number of TMs (log.)	0.954	1.009	0.941	1.018
	(0.033)	(0.054)	(0.048)	(0.044)
Number of Patents (log.)	1.136	1.271*	1.067	1.107
	(0.122)	(0.177)	(0.152)	(0.146)
Firm age	0.890*	0.749***	0.971	0.876
(log.)	(0.056)	(0.078)	(0.088)	(0.073)
Employees	1.025	1.010	1.092*	1.145***
(log.)	(0.037)	(0.062)	(0.057)	(0.055)
Industry (dummies)	Yes***	Yes**	Yes***	Yes**
N firms	3436	3387	3436	3436
Chi square	94.450***	46.431***	76.621***	41.876***
McFadden's Pseudo R square	0.024	0.025	0.034	0.016

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 17 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Table A32
Logistic regressions with green patents via ENV-TECH
(Italian other industries data set).

Independent Variables	(1) Overall Green Innovation (dummy)	(2) Green Product Innovation (dummy)	(3) Green Process Innovation (dummy)	(4) Circular/Green Economy Projects (dummy)
Green Trademark	2.072**	2.384**	2.618**	0.649
(dummy)	(0.655)	(0.983)	(1.005)	(0.322)
Green Patent	0.770	0.347	1.210	1.209
(dummy)	(0.425)	(0.281)	(0.866)	(0.79)
Number of TMs (log.)	0.955	1.014	0.941	1.018
	(0.033)	(0.054)	(0.048)	(0.044)
Number of Patents (log.)	1.203*	1.461***	1.121	1.110
	(0.135)	(0.205)	(0.167)	(0.155)
Firm age	0.890*	0.748***	0.971	0.876
(log.)	(0.056)	(0.078)	(0.088)	(0.073)
Employees	1.025	1.009	1.093*	1.145***
(log.)	(0.037)	(0.062)	(0.057)	(0.055)
Industry (dummies)	Yes***	Yes**	Yes***	Yes**
N firms	3436	3387	3436	3436
Chi square	94.561***	48.292***	75.932***	41.826***
McFadden's Pseudo R square	0.024	0.027	0.033	0.016

Notes: Standard errors in brackets; odds ratios are reported; ***, **, * indicate 1 %, 5 % and 10 % significance levels; industry dummies included for 17 NACE sections A-S; differences in N attributed to missing values in the dependent variable.

Data availability

Data will be made available on request.

References

Abbasiharofteh, M., Castaldi, C., Petralia, S., 2022. From patents to trademarks: towards a concordance map. (EPO ARP Project). Utrecht University. https://documents.epo.org/projects/babylon/eponet.nsf/0/C1DA39F16C29E8F3C125887E004CF8A7/$File/ARP2019_Castaldi_en.pdf.

Acs, Z.J., Anselin, L., Varga, A., 2002. Patents and innovation counts as measures of regional production of new knowledge. Research Policy 31 (7), 1069–1085.

Aiello, F., Cardamone, P., Mannarino, L., Pupo, V., 2021. Green patenting and corporate social responsibility: Does family involvement in business matter? Corp. Soc. Respon. Environ. Manag. 28 (4), 1386–1396.

Allen, N.J., Meyer, J.P., 1990. The measurement and antecedents of affective, continuance and normative commitment to the organization. J. Occup. Psychol. 63 (1), 1–18.

Amoroso S., Aristodemou L., Criscuolo C., Dechezleprêtre A., Dernis H., Grassano N., Moussiegt L., Napolitano L., Nawa D., Squicciarini M., & Tübke A. (2021). World Corporate Top R&D investors: Paving the way for climate neutrality. A joint JRC and OECD report. EUR 30884 EN, Publications Office of the European Union, Luxembourg. doi:https://doi.org/10.2760/49552.

Antonioli, D., Mancinelli, S., Mazzanti, M., 2013. Is environmental innovation embedded within high-performance organisational changes? The role of human resource management and complementarity in green business strategies. Research Policy 42 (4), 975–988.

Archibugi, D., 1992. Patenting as an indicator of technological innovation: a review. Science and Public Policy 19 (6), 357–368.

Arts, S., Hou, J., Gomez, J.C., 2021. Natural language processing to identify the creation and impact of new technologies in patent text: Code, data, and new measures. Research Policy 50 (2), 104144.

Arundel, A., 2001. The relative effectiveness of patents and secrecy for appropriation. Research Policy 30 (4), 611–624.

Arundel, A., Kabla, I., 1998. What percentage of innovations are patented? Empirical estimates for European firms. Research Policy 27 (2), 127–141.

Bermúdez-Edo, M., Hurtado-Torres, N.E., Ortiz-de-Mandojana, N., 2017. The influence of international scope on the relationship between patented environmental innovations and firm performance. Bus. Soc. 56 (2), 357–387.

Blind, K., Edler, J., Frietsch, R., Schmoch, U., 2006. Motives to patent: Empirical evidence from Germany. Res. Policy 35 (5), 655–672.

Block, J., Lorenzen, S., Steinmetz, H., 2024b. Decarbonization types of medium-sized and mid-cap firms in the manufacturing sector. Bus. Strateg. Environ. https://doi.org/10.1002/bse.3947.

Block, J.H., De Vries, G., Schumann, J.H., Sandner, P., 2014. Trademarks and venture capital valuation. J. Bus. Ventur. 29 (4), 525–542.

Block, J.H., Fisch, C.O., Hahn, A., Sandner, P.G., 2015. Why do SMEs file trademarks? Insights from firms in innovative industries. Research Policy 44 (10), 1915–1930.

Block, J.H., Sharma, P., Benz, L., 2024a. Stakeholder pressures and decarbonization strategies in Mittelstand Firms. Journal of Business Ethics 193, 511–533.

Bocken, N., Konietzko, J., 2022. Circular business model innovation in consumer-facing corporations. Technological Forecasting and Social Change 185, 122076.

Bocken, N.M., De Pauw, I., Bakker, C., Van Der Grinten, B., 2016. Product design and business model strategies for a circular economy. J. Ind. Prod. Eng. 33 (5), 308–320.

Burhan, M., Singh, A.K., Jain, S.K., 2017. Patents as proxy for measuring innovations: A case of changing patent filing behavior in Indian public funded research organizations. Technol. Forecast. Soc. Chang. 123, 181–190.

Cainelli, G., Mazzanti, M., Montresor, S., 2012. Environmental innovations, local networks and internationalization. Ind. Innov. 19 (8), 697–734.

Carrillo-Hermosilla, J., González, P.R.D., Könnölä, T., 2009. What is eco-innovation? In *Eco-innovation*. Palgrave Macmillan, London, pp. 6–27.

Carrillo-Hermosilla, J., Del Río, P., Könnölä, T., 2010. Diversity of eco-innovations: Reflections from selected case studies. J. Clean. Prod. 18 (10–11), 1073–1083.

Castaldi, C., 2018. To trademark or not to trademark: The case of the creative and cultural industries. Research Policy 47 (3), 606–616.

Castaldi, C., 2020. All the great things you can do with trademark data: Taking stock and looking ahead. Strateg. Organ. 18 (3), 472–484.

Castaldi, C., 2021. Sustainable innovation and intellectual property rights: friends, foes or perfect strangers?, vol. No. 2021/11 LEM Working Paper Series.

Castaldi, C., Giuliani, E., Kyle, M., Nuvolari, A., 2024. Are intellectual property rights working for society? Research Policy 53 (2), 104936.

Chang, C.H., 2011. The influence of corporate environmental ethics on competitive advantage: The mediation role of green innovation. J. Bus. Ethics 104 (3), 361–370.

Chang, S.B., 2012. Using patent analysis to establish technological position: Two different strategic approaches. Technological Forecasting and Social Change 79 (1), 3–15.

Cheng, C.C., Shiu, E.C., 2012. Validation of a proposed instrument for measuring eco-innovation: An implementation perspective. Technovation 32 (6), 329–344.

Cohen, W.M., Nelson, R., Walsh, J.P., 2000. Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not). National Bureau of Economic Research, Working Paper 7552.

Corrocher, N., Solito, I., 2017. How do firms capture value from environmental innovations? An empirical analysis on European SMEs. Ind. Innov. 24 (5), 569–585.

Cucculelli, M., Cappelli, R., Mondolo, J., 2024. Does market power drive business model innovation? Evidence from Italian family manufacturing firms. Small Bus. Econ. 63 (1), 447–475.

De Rassenfosse, G., Dernis, H., Boedt, G., 2014. An introduction to the Patstat database with example queries. Australian Economic Review 47 (3), 395–408.

Erhardt, S., Ghosh, M., Buunk, E., Rose, M. E., & Harhoff, D. (2022). Logic Mill–A Knowledge Navigation System. arXiv preprint arXiv:2301.00200.

European Commission, 2007. Guideline Document for the Competitiveness and Innovation Framework Programme. Available online at: https://ec.europa.eu/cip/files/docs/factsheets_en.pdf [Last accessed on 8th June 2023].

European Union Intellectual Property Office (EUIPO), 2021. Green EUtrade marks Analysis of goods and services specifications, 1996–2020 (EUIPO).

Flikkema, M., De Man, A.P., Castaldi, C., 2014. Are trademark counts a valid indicator of innovation? Results of an in-depth study of new benelux trademarks filed by SMEs. Ind. Innov. 21 (4), 310–331.

Flikkema, M., Castaldi, C., de Man, A.P., Seip, M., 2019. Trademarks' relatedness to product and service innovation: A branding strategy approach. Research Policy 48 (6), 1340–1353.

Ganglmair, B., Robinson, W.K., Seeligson, M., 2022. The rise of process claims: Evidence from a century of US patents. Available at SSRN 4069994.

Ghisetti, C., Montresor, S., Vezzani, A., 2021. Design and environmental technologies: Does 'green-matching' actually help? Research Policy 50 (5), 104208.

Gotsch, M., Hipp, C., 2012. Measurement of innovation activities in the knowledge-intensive services industry: a trademark approach. Serv. Ind. J. 32 (13), 2167–2184.

Hall, B., H., C., Rogers, M., Sena, V., 2014. The choice between formal and informal intellectual property: a review. J. Econ. Lit. 52 (2), 375–423.

Hall, B.H., Sena, V., 2017. Appropriability mechanisms, innovation, and productivity: evidence from the UK. Econ. Innov. New Technol. 26 (1–2), 42–62.

Haščič, I., & Migotto, M. (2015). Measuring environmental innovation using patent data. Organisation for Economic Co-operation and Development (OECD), Working Paper 89.

Hazarika, N., Zhang, X., 2019. Factors that drive and sustain eco-innovation in the construction industry: The case of Hong Kong. J. Clean. Prod. 238, 117816.

Kemp, R., Pearson, P., 2007. Final report MEI project about measuring eco-innovation. UM Merit, Maastricht 10 (2), 1–120.

Lee, Y.N., Walsh, J.P., 2016. Inventing while you work: knowledge, non-R&D learning and innovation. Research Policy 45 (1), 345–359.

Leiponen, A., Byma, J., 2009. If you cannot block, you better run: Small firms, cooperative innovation, and appropriation strategies. Research Policy 38 (9), 1478–1488.

León, L.R., Bergquist, K., Wunsch-Vincent, S., Xu, N., Fushimi, K., 2018. Measuring innovation in energy technologies: green patents as captured by WIPO's IPC green inventory, vol. 44. WIPO.

Marin, G., Marzucchi, A., Zoboli, R., 2015. SMEs and barriers to Eco-innovation in the EU: exploring different firm profiles. J. Evol. Econ. 25 (3), 671–705.

Mendonça, S., Pereira, T.S., Godinho, M.M., 2004. Trademarks as an indicator of innovation and industrial change. Research Policy 33 (9), 1385–1404.

Morales, P., Flikkema, M., Castaldi, C., de Man, A.P., 2022. The effectiveness of appropriation mechanisms for sustainable innovations from small and medium-sized enterprises. J. Clean. Prod. 374, 133921.

Morales, P., Flikkema, M., Castaldi, C., de Man, A.P., 2024a. Why use or forgo formal and informal appropriation mechanisms? A qualitative study of sustainable innovations from small-and medium-sized enterprises. Bus. Strateg. Environ. 33 (3), 1937–1961.

Morales, P., Flikkema, M., Castaldi, C., de Man, A.P., 2024b. When do trademarks improve the measurement of innovation? An analysis of innovations from Dutch SMEs. Sci. Public Policy 00, 1–16.

Mowday, R.T., Steers, R.M., Porter, L.W., 1979. The measurement of organizational commitment. J. Vocat. Behav. 14 (2), 224–247.

Nasirov, S., 2020. Trademark value indicators: Evidence from the trademark protection lifecycle in the US pharmaceutical industry. Research Policy 49 (4), 103929.

Neuhäusler, P., Feidenheimer, A., Frietsch, R., Kroll, H., 2021. Generating a classification for EUIPO trademark filings: A string matching approach. Fraunhofer ISI.

Oltra, V., Saint Jean, M., 2009. Sectoral systems of environmental innovation: an application to the French automotive industry. Technological Forecasting and Social Change 76 (4), 567–583.

Oltra, V., Kemp, R., De Vries, F.P., 2010. Patents as a measure for eco-innovation. Int. J. Environ. Technol. Manag. 13 (2), 130–148.

Park, K., 2022. Green trademarks and the risk of greenwashing, *WIPO Magazine* 4/2022.

Peeters, C., Pottelsberghe de la Potterie, B.V., 2007. Innovation strategy and the patenting behavior of firms. In: Innovation, Industrial Dynamics and Structural Transformation. Springer, Berlin, Heidelberg, pp. 345–371.

Rammer, C., Czarnitzki, D., Spielkamp, A., 2009. Innovation Success of non-R&D-Performers: Substituting Technology by Management in SMEs. Small Bus. Econ. 33 (1), 35–58.

Rennings, K., 2000. Redefining innovation—eco-innovation research and the contribution from ecological economics. Ecol. Econ. 32 (2), 319–332.

Rogers, M., Greenhalgh, C., Helmers, C., 2007. An Analysis of the Association Between the Use of Intellectual Property by UK SMEs and Subsequent Performance. UK Intellectual Property Office, UK.
Saari, U.A., Damberg, S., Schneider, M., Aarikka-Stenroos, L., Herstatt, C., Lanz, M., Ringle, C.M., 2023. Capabilities for circular economy innovation: Factors leading to product/service innovations in the construction and manufacturing industries. J. Clean. Prod. 140295.
Schmuck, D., Matthes, J., Naderer, B., 2018. Misleading consumers with green advertising? An affect-reason-involvement account of greenwashing effects in environmental advertising. J. Advert. 47 (2), 127–145.
Seip, M., Castaldi, C., Flikkema, M., De Man, A.P., 2018. The timing of trademark application in innovation processes. Technovation 72, 34–45.
Thomä, J., Bizer, K., 2013. To protect or not to protect? Modes of appropriability in the small enterprise sector. Research Policy 42 (1), 35–49.
Toh, P.K., Ahuja, G., 2022. Integration and appropriability: A study of process and product components within a firm's innovation portfolio. Strateg. Manag. J. 43 (6), 1075–1109.
Veefkind, V., Hurtado-Albir, J., Angelucci, S., Karachalios, K., Thumm, N., 2012. A new EPO classification scheme for climate change mitigation technologies. World Patent Inf. 34 (2), 106–111.
Vimalnath, P., Tietze, F., Jain, A., Gurtoo, A., Eppinger, E., Elsen, M., 2022. Intellectual property strategies for green innovations-An analysis of the European Inventor Awards. J. Clean. Prod. 377, 134325.
von Graevenitz, G., Graham, S.J., Myers, A.F., 2022. Distance (still) hampers diffusion of innovations. Reg. Stud. 56 (2), 227–241.
Wagner, M., 2007. On the relationship between environmental management, environmental innovation and patenting: Evidence from German manufacturing firms. Research Policy 36 (10), 1587–1602.
Willeke, T., Block, J., Johann, M., Lambrecht, D., Steinmetz, H., Wunnam, I., 2023. Patent data and how it can be matched to (family) firm data: an example and a guideline. In: Research Handbook on Entrepreneurship and Innovation in Family Firms. Edward Elgar Publishing, pp. 370–390.
World Intellectual Property Organization, 2013. World Intellectual Property Report 2013: Brand-Reputation and Image in the Global Marketplace. World Intellectual Property Organization.