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Timing Differences in ESG Ratings' Recognition of Quantity and Quality Signals in Green Patents

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Abstract

Whether ESG rating agencies can distinguish the quantity from the quality of green patents, and whether the two are recognized at different points in time, remains an open question. This article decomposes green patents into applications (quantity), authorization (certification quality) and citations (market influence), and uses panel data of China's A-share listed companies from 2010 to 2024 to examine the time series structure of its impact on ESG ratings. We find that the quantitative signal is immediate—patent applications significantly and consistently boost ESG ratings—while the qualitative signal is significantly lagging: patent citations are not positively related during the same period (the common sample estimate is significantly negative), and their impact only turns positive and reaches a peak in the second lag period, conveying significantly more information than the quantitative signal. This "quantity is immediate, quality-lagged" model still holds true under nonlinear settings and a series of robustness tests. The root cause is the delay in the inclusion of citation information by rating agencies. The results show that ESG ratings use the time dimension to distinguish quantitative expansion and quality improvement in green patents, which provides a possible information basis for identifying "greenwashing" behavior and improving rating information processing.

Keywords: green patents; ESG ratings; signaling theory; patent quality; signal lag

1. Introduction

Under the "dual-carbon" agenda and the low-carbon transition, firms' environmental, social, and governance (ESG) performance has become an increasingly important basis for capital-market resource allocation and pricing, with ESG ratings serving as the key information intermediary. Yet the green information on which these ratings rely is largely voluntarily disclosed and only weakly verifiable; how rating agencies separate genuine green attributes from noise is therefore a question of both theoretical and practical concern.

Green patents are considered to be the core signal of a company's green attributes. Compared with the self-proclaimed green vision of enterprises, patents have undergone substantive review by the State Intellectual Property Office and are more objective and verifiable. Therefore, they have become an important basis for external entities to evaluate corporate green innovation. Existing research has generally confirmed that green patents

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can increase the possibility of companies obtaining green credit, government subsidies and investor attention, and improve their ESG performance [1,2]. However, most of these studies regard green patents as a homogeneous whole, implicitly assuming that "how many patents have been filed" and "how good the patents are" convey the same information. This assumption is questionable. Signaling theory [1] emphasizes that only signals with sufficiently different costs possess separating power, and the cost of filing a patent application differs enormously from the cost of producing a patent that is widely cited by peers. If rating agencies can exploit this cost difference, they should exhibit different ways—and different timing—of recognizing the quantity and quality signals.

This paper examines, from the neglected temporal dimension, how ESG ratings differentially recognize the quantity and quality signals of green patents. Specifically, we decompose green patents into three components—applications (quantity expansion), grants (certified quality), and citations (market-recognized influence and quality)—and trace their marginal effects on ESG ratings contemporaneously and over two lags. Our expectations are as follows: quantity information is observable at the moment of filing, so the quantity signal should be immediate; citations, by contrast, require peers to become aware of, evaluate, and cite a patent, a process that depends heavily on the passage of time, so the quality signal should be lagged.

Examining this recognition-timing difference carries both theoretical and practical significance. Theoretically, the signaling literature emphasizes that differences in transmission costs determine a signal's separating power [3,4], yet pays little attention to the timing of signal recognition in information-intermediary settings; we introduce a "recognition timing" perspective to examine how rating agencies differentially process quantity and quality signals, extending the application of signaling theory to the ESG-rating context. Practically, clarifying this temporal structure has multiple implications: for rating agencies and investors, recognizing that quality signals require a longer observation window to fully materialize helps avoid the bias of judging firms by contemporaneous application counts alone—overweighting the quantity signal while underweighting the lagged quality signal; for regulators, if quality signals emerge with a lag, quantity expansion that masks insufficient quality is hard to detect in the short run but hard to conceal in the long run, so improving the disclosure and tracking of quality information can shorten the materialization cycle and improve market screening efficiency; for firms, quality signals built on genuine technological accumulation are the only signals that markets durably recognize, and short-run quantity expansion cannot substitute for long-run quality building. We stress that this paper characterizes how the ESG-rating function varies with the dimensions and timing of green patents—an identification of rating agencies' information-processing behavior—rather than a causal estimate of the green-patent–ESG-rating relationship; the identification boundary is discussed further below.

The rest of this article is organized as follows: Section 2 reviews relevant literature and proposes hypotheses; Section 3 introduces the sample, variables and empirical model; Section 4 presents the empirical results, including benchmark time series structure, coefficient difference test and robustness test; Section 5 discusses the findings based on existing research; Section 6 concludes.

2. Literature Review and Hypotheses

2.1. The Signaling Function of Green Patents

Green patents are a core indicator of corporate green innovation. Prior research generally treats green patents as a proxy for corporate green attributes and examines their economic consequences, finding that green patents help firms obtain green credit, government subsidies, and investor attention, ease financing constraints, and raise market

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value [2–4]. In the field of environmental regulation and innovation, Porter's hypothesis emphasizes that appropriate environmental regulation can induce green technology innovation in enterprises [5–7]. Research in the Chinese context has further identified the differentiated incentive effects of heterogeneous environmental regulation tools on green patents [8]. The implicit premise of these studies is that external entities can effectively identify the information contained in green patents.

Green patents, also known as environmentally friendly technology patents, refer to patented inventions that contribute to environmental protection, resource conservation and low-carbon transformation. They cover technologies in areas such as renewable energy (such as solar, wind and biomass), energy efficiency, pollution control and governance, waste management and recycling, low-emission transport and more. Because green patents are classified by their technical content rather than by firm type, they provide a comparable, objectively verifiable measure of a firm's commitment to green innovation, which is why external stakeholders use them as a signal of a firm's green attributes.

However, green patents are not homogeneous signal carriers. From the perspective of information economics, patents contain at least two layers of heterogeneous information: one is "quantity" information, which reflects the company's investment and activity in green innovation; the other is "quality" information, which reflects the technical influence and market recognition of green innovation results. There are significant differences in the formation costs and observability of the two: the cost of submitting a patent application is relatively limited, but producing a high-impact patent that is continuously cited by peers requires long-term technology accumulation and real innovation capabilities [9,10]. Research on the Chinese context has found that while industrial policies, government subsidies and market mechanisms increase the number of patents, they often fail to simultaneously improve the quality of patents and even induce strategic innovation motivated by "seeking support" [11–15], the constraints of intellectual property supervision on patent quality have also received attention [16], highlighting the realistic constraints that quantity and quality deviate from. Signaling theory holds that only signals whose transmission costs differ sufficiently between high- and low-quality types can achieve a separating equilibrium [1,17–19]. It follows that the quality information of green patents should be more capable than quantity information of distinguishing genuine green attributes.

2.2. Information Sources and Recognition Capacity of ESG Ratings

ESG rating agencies combine firms' voluntary disclosures, regulatory records, media coverage, and third-party data to form their assessments, and the quality and credibility of environmental-information disclosure have long been a focus of both rating and regulation [20–22]. Because self-reported information is only weakly verifiable, rating agencies tend to rely on more objective information to calibrate their judgments; however, the divergence among raters over the same firm indicates that the measurement and integration of ESG information still lack a unified standard, and that firm characteristics such as size systematically affect ratings [23–26]. Green patents, by virtue of their objectivity and verifiability, are an important basis on which raters identify corporate greenness, but evidence from U.S. listed firms finds an "innovation–ESG disconnect" in which patent quality information is not fully captured by environmental scores [27]. Prior research also finds that good ESG performance lowers financing costs and raises market value [28,29], and that investors increasingly incorporate ESG information into investment decisions [30,31].

Over the past decade, China's ESG rating landscape has expanded rapidly. Major domestic suppliers include Huazheng (Sino-Securities Index), China Chengxin and

SynTao Green Finance, while international suppliers include MSCI, Sustainalytics and Refinitiv. These rating agencies differ in data sources, indicator systems, and weighting schemes: domestic rating agencies usually place more emphasis on information disclosure availability and regulatory records, while international rating agencies rely more on media reports and third-party controversy screening, which has led to well-known differences among rating agencies [23–26]. The explained variable in this article comes from the Huazheng ESG rating, which covers the widest range of Chinese A-share companies and is updated every year, making it very suitable for enterprise-annual panel analysis.

Rating agencies' information processing, however, faces cost and time constraints. Quantity information enters public databases at the moment of filing and can be obtained immediately, whereas citation information depends on peers' subsequent citing behavior and must go through an "awareness–evaluation–citation" process, so its full manifestation is naturally delayed relative to the point of patent creation. This means that rating agencies' recognition of green patent quantity signals and quality signals should show systematic differences in timing. If rating agencies are unable to distinguish the timing of the two, companies may use information time lags to implement greenwashing, covering up quality deficiencies with low-cost quantity expansion, and greenwashing may in turn crowd out real green innovation [32–37].

2.3. Marginal Contributions

The marginal contributions of this article are first, it decomposes green patents from a single homogeneous indicator into three dimensions—quantity, certification quality and market influence—and systematically compares the signal strength and timing structure of the three, which provides more refined evidence for understanding the signaling function of green patents; second, it introduces the "recognition timing" perspective to reveal the differentiated treatment of quantity signals and quality signals by ESG rating agencies, complementing the application of signal theory in ESG rating situations; third, it provides inspiration for preventing greenwashing—if the rating mechanism can only identify quality signals with a lag, then the short-term behavior of covering up insufficient quality with quantity expansion will be difficult to hide for a long time, and the market needs to leave an observation window for the emergence of quality signals.

2.4. Hypotheses

Based on the above analysis, we propose the following hypotheses:

Signaling theory emphasizes that observability is a precondition for a signal to transmit and perform its screening function [1,19]. A patent application enters the public database of the national patent office upon filing, so application information is observable at near-zero cost at the moment of submission, and rating agencies can infer a firm's green-innovation activity without waiting for examination or market validation; moreover, ESG rating agencies tend to rely on objective, verifiable public information to calibrate their judgments [23,25]. The quantity signal is therefore recognized immediately.

H1. *green patent applications have a significant positive effect on contemporaneous ESG ratings.*

Citations are the established yardstick of patent value and technological influence [10,38,39], yet their formation requires peers to proceed through an "awareness–evaluation–citation" process, so the full manifestation of citation information is naturally delayed relative to the point of patent creation, and the collection and updating of citation data are themselves subject to a lag; evidence from U.S. listed firms likewise documents an "innovation–ESG disconnect," indicating that patent quality information is not

captured by ratings in a timely manner [27]. The recognition of the quality signal is therefore lagged.

H2. *green patent citations have no significant contemporaneous effect on ESG ratings but a significant positive effect on lagged ratings.*

Signaling theory holds that a signal achieves a separating equilibrium and performs its screening function only when its transmission cost differs sufficiently across types [1,17,18]. Filing an application is relatively cheap, whereas producing a widely cited high-impact patent requires long-run technological accumulation and genuine innovative capacity [9,10], so the two signals differ enormously in transmission cost. Once recognized, the quality signal—whose transmission cost differs more—should carry more information than the quantity signal.

H3. *the lagged citation signal exerts a significantly stronger effect on ESG ratings than the quantity signal.*

There is a systematic differentiation in the timing of signals across three dimensions—quantity, certification quality, and market influence. Signaling theory emphasizes that the observability and transmission cost of a signal jointly determine whether it can perform the screening function, and the three dimensions are different in these two aspects, so the time points at which they are recognized are also different [1,19]. In terms of the three dimensions, once a patent application is submitted, it enters the public database of the State Intellectual Property Office. Quantitative signals can be observed at low cost when submitted and can be recognized and maintained in the current period; authorization is the official certification that the patent has passed substantive examination, and the certification information is released at the time of authorization. However, certification itself does not reflect the market's continued recognition of the value of the patent, so the signal appears in the current period but lacks sustainability; citations rely on peer recognition, evaluation and citations, which naturally lags behind the time when the patent is generated, so the signal does not appear in the current period but lags behind. The information formation process and observability of the three are different, and their signal timing also shows systematic differentiation. Accordingly, the three dimensions together constitute a complete time series structure of "contemporaneous recognition of quantity signals and delayed recognition of quality signals".

Based on the above reasoning, we propose three sub-hypotheses.

H4a. *The quantitative signal (applications) of green patents is identified and sustained in the current period.*

H4b. *Authentication signals (authorization) appear in the current period but lack persistence.*

H4c. *The market influence signal (citation) has no positive signal in the current period, but appears and strengthens with the lag period. Therefore, the signal timing in the three dimensions shows systematic differentiation.*

3. Materials and Methods

3.1. Sample and Data

This article takes the Shanghai and Shenzhen A-share listed companies from 2010 to 2024 as the research sample. It excludes financial companies and ST companies as usual, and winsorizes the continuous variables at the 1% and 99% quantiles. The green patent data (application, authorization and citation information) comes from the patent database of the State Intellectual Property Office, the ESG rating comes from the Huazheng (Sino-Securities) ESG rating system, and the remaining financial and governance data comes from the CSMAR database. Finally, 48,423 company-year observations were obtained, covering 5087 listed companies; due to missing some control variables, the baseline regression sample size was 48,338 observations.

3.2. Variable Definitions

The dependent variable is the ESG rating; Huazheng ESG ratings are converted from low to high into ordered integers from 0 to 9 (no rating is recorded as 0, C is recorded as 1, ..., AAA is recorded as 9). The higher the value, the better the ESG performance. The key explanatory variables are the natural logarithms (ln(1 + x)) of three green-patent dimensions: applications (quantity expansion), grants (examined, certified quality), and citations (market-recognized influence and quality). Following research on the determinants of ESG ratings [23–25], we control for firm characteristics. Firm size (natural log of total assets): larger firms have richer resources and more complete disclosure, so their ESG ratings are systematically higher [24]. Leverage reflects financial risk, as highly leveraged firms may face constrained ESG investment and ratings. ROA captures profitability, the resource base for ESG investment. Sales growth reflects growth opportunities that shape a firm's willingness to invest in ESG and its sustainability prospects. The fixed-asset ratio captures environmental and transition risk faced by asset-heavy firms. Firm age reflects operating maturity and the accumulation of ESG practices. Top-one shareholding, the independent-director ratio, and board size characterize ownership structure and board governance, which affect the quality of ESG disclosure and governance. Tobin's Q reflects the market's overall assessment of a firm's growth prospects and governance quality.

There are three points that need to be emphasized regarding variable construction. First, the time basis of patent variables: applications are counted by application year, authorizations are counted by grant year, and citations are counted by the application year of cited patents. Therefore, the citation variable is the annual flow of new citations rather than the cumulative stock. Second, the citation measure therefore captures the forward citations received by corporate green patents in a given year, and we do not set a fixed citation window because the forward window requires data after the sample period; this construction does not assume that the rating agency has observed citations throughout the year at the rating time point, which is crucial for the explanation of lagged effects. Third, regarding the processing of missing ratings, companies without a Huazheng rating are coded as 0. In our sample, 684 firm-year observations (1.41%) are unrated and are mainly small businesses with limited disclosures. We code it as 0 because in the Chinese context, the lack of ratings itself reflects information on corporate ESG visibility and disclosure capabilities, and separate categories will destroy the ordinal structure of the explained variables. As a robustness check reported in Section 4.4, we reestimate the main model on the valid ratings subsample (esgscore > 0) and the results are unchanged.

3.3. Model

To examine the effects of green patent quantity and quality signals on ESG ratings and their temporal structure, we estimate the following two-way fixed-effects model:

$$esgscore_{it} = \beta_0 + \beta_1 Apply_{it} + \beta_2 Grant_{it} + \beta_3 Cite_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \text{ (contemporaneous)}$$

$$esgscore_{it} = \beta_0 + \beta_1 Apply_{i,t-k} + \beta_2 Grant_{i,t-k} + \beta_3 Cite_{i,t-k} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \text{ (k-period lag, k = 1, 2)}$$

where μ_i is the firm fixed effect, λ_t is the year fixed effect, and X_{it} is the vector of controls. β_1, β_2, and β_3 capture the marginal effects of the application, grant, and citation signals at the corresponding horizon. Comparing the three coefficients across the contemporaneous, first-lag, and second-lag specifications identifies the "quantity-immediate, quality-lagged" temporal structure. Standard errors are clustered at the firm level. In addition, because the dependent variable is an ordered 0–9 outcome, we use a panel random-effects ordered logit (xtologit) as a nonlinear check.

4. Results

4.1. Descriptive Statistics

Table 1 reports descriptive statistics. The ESG rating has a mean of 3.708, a standard deviation of 1.418, and a median of 4, indicating that sample firms' ESG performance is on average moderate with substantial dispersion. The three green-patent measures have means of 0.899 (applications), 0.733 (grants), and 0.767 (citations), with medians of zero, indicating a sparse distribution in which a large fraction of firms hold no green patents. The distributions of the remaining controls are within reasonable ranges.

Table 1. Descriptive statistics.

Variable	Obs.	Mean	SD	Min	Median	Max
esgscore	48,338	3.708	1.418	0	4	9
ln_gpatapply	48,338	0.899	1.213	0	0	5.568
ln_gpatgrant	48,338	0.733	1.065	0	0	5.063
ln_gpatcite	48,338	0.767	1.238	0	0	6.057
size	48,338	22.311	1.489	14.942	22.033	31.519
lev	48,338	0.420	0.214	0.030	0.408	0.938
roa	48,338	0.039	0.066	−0.373	0.038	0.255
salesg	48,338	0.125	0.313	−0.648	0.089	2.486
fixrat	48,338	0.202	0.158	0	0.169	0.971
firmage	48,338	20.722	6.549	1	20	70
top1	48,338	0.338	0.151	0.003	0.314	0.900
tobinq	48,338	2.048	1.907	0.024	1.511	18.862
indep	48,338	0.377	0.056	0	0.364	0.818
boardsize	48,338	8.502	1.785	0	9	21

Note: Descriptive statistics are calculated based on the regression sample (N = 48,338). boardsize and indep contain three extreme observations equal to 0 (≈0.0062%, or 3 out of 48,338), which are records from the original data source and are not winsorized; they appear to be data entry anomalies rather than real board characteristics, and the results remain unchanged after elimination.

4.2. Baseline Results: The Temporal Structure

Table 2 reports the baseline results, with columns (1)–(3) corresponding to the contemporaneous, first-lag, and second-lag specifications.

Table 2. Green patent quantity and quality signals: temporal structure.

Variable	(1) Contemporaneous	(2) Lag 1	(3) Lag 2
ln_gpatapply (applications)	0.054 ***	0.061 ***	0.053 ***
	(0.011)	(0.011)	(0.012)
ln_gpatgrant (grants)	0.059 ***	0.032 **	0.010
	(0.013)	(0.013)	(0.013)
ln_gpatcite (citations)	−0.072 ***	0.033 **	0.092 ***
	(0.011)	(0.013)	(0.014)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	37,523	37,523	37,523
Firms	4793	4793	4793
Within R^2	0.229	0.228	0.230

Note: Columns (1)–(3) are separate regressions of current ESG ratings on contemporaneous, first-lagged, and second-lagged green patent variables, respectively, all estimated on a common sample of 37,523 company-year observations. The robust standard errors for enterprise-level clustering are in parentheses; ** and *** denote significance at the 10%, 5%, and 1% levels, respectively. Control variables include firm size, leverage ratio, ROA, sales growth rate, fixed asset ratio, firm age, largest shareholder's shareholding, Tobin's Q, proportion of independent directors and board size (same throughout the text). The three columns report very similar within R^2 values (0.229, 0.228, and 0.230). This similarity is expected because the three specifications share the same firm and year fixed effects and the same set of controls, differing only in whether the patent variable enters contemporaneously, at the first lag, or at the second lag; since the contemporaneous, first-lagged, and second-lagged patent variables are highly serially correlated, they contribute almost identically to the within (fixed-effects-transformed) variation, so the similarity does not indicate misspecification.

The benchmark results are estimated on a common sample of 37,523 firm-year observations in which the contemporaneous, first-lagged, and second-lagged patent variables are not missing, so that the three columns are directly comparable. Table 2 reveals the timing structure of "quantity-immediate, quality-lagged". In terms of the quantity dimension, green patent applications are positively significant in the same period (0.054), first lag (0.061), and second lag (0.053), with stable amplitude, indicating that the quantity signal is immediately visible and continuously effective, supporting H1. This is consistent with expectations: patent application information is entered into public databases upon submission, rating agencies are able to identify companies' green innovation activities in the current period, and the signal remains stable in subsequent periods.

As far as the quality dimension is concerned, the signal effect of green patent citations shows significant time lag characteristics: the coefficient for the same period is −0.072 and is significantly negative, the first lag turns positive (0.033) and is significant at the 5% level, and the second lag further rises to 0.092, reaching the maximum value in all dimensions and all periods. During the same period, there was no positive correlation—in fact, it was a significant negative correlation—and then there was an enhanced positive effect, which is consistent with H2: citations have long been regarded as a key yardstick for patent value and technological influence [9,38–41]. Its formation requires peers to go through the process of "cognition-evaluation-citation", and the information content is gradually released over time, so the quality signal naturally lags behind the quantity signal.

Since citations are measured by annual new citations—that is, the number of times a company's green patents are cited in the current year—this variable is a flow rather than

a cumulative stock, so there is no mechanical growth of the stock within the observation window. The absence of a positive correlation in the same period and the subsequent enhanced lag effect directly reflects the timing of the inclusion of citation information by rating agencies: there is a lag in the collection and update of citation data, so citations that occur in year t can only be used by rating agencies after the database is updated, and the citation snapshot actually available to rating agencies in year t is an earlier one. As a result, contemporaneous citations have no positive effect on contemporaneous ratings, while first- and second-lagged citations—which are fully documented—increase in their signaling value. The significantly negative contemporaneous coefficient is consistent with this lag: if rating agencies could incorporate current-period citation information immediately, the contemporaneous coefficient should at least be positive rather than negative. We do not over-interpret the negative sign, which may also reflect unobserved characteristics of the citation population; the robust contrast we emphasize is between contemporaneous periods and second lags. We cannot directly observe the data processing process of rating agencies, so this mechanism should be understood as a reasonable inference based on the temporal structure.

The authorization dimension—the "authentication quality" signal—shows the form of "the strongest and rapidly decaying in the current period": its coefficient of 0.059 for the same period is the largest among the three dimensions, but it decays to 0.032 at the first lag, and to 0.010 (not significant) at the second lag. Authorization is an official certification that a patent has passed review, and its information is released at the time of authorization. However, the certification itself does not reflect the market's continued recognition of the value of the patent, so the signal lacks sustainability. The three dimensions together form a differentiated temporal structure of "application is immediate and continuous, authorization is immediate but attenuates, and citations are lagging and enhanced", supporting H4a–H4c.

In terms of economic significance, a one standard deviation increase in green patent applications (1.213) will increase the current ESG rating by about 0.066 units, which is about 4.6% of the ESG rating sample standard deviation (1.418); a one standard deviation increase in citations (1.238) will increase the second-lagged rating by about 0.114 units, which is about 8.0% of the standard deviation—about 1.7 times the application effect in the same period. Admittedly, the absolute magnitudes of both effects are modest; however, given that green patents are highly sparse in the sample (median is zero), a change in one standard deviation represents a substantial shift from "no" to "some" for most firms, so the effect size is not negligible relative to this discrete distribution. More importantly, our core contribution is to reveal the systematic temporal structure difference between quantity and quality signals—the lagged quality signal is about 1.7 times larger than the contemporaneous quantity signal—and it is this relative difference (rather than the absolute size) that constitutes the key finding.

4.3. Wald Tests: Does the Quality Signal Carry More Information?

To test H3—whether lagged quality signals convey significantly more information than quantity signals—we conducted a series of Wald tests on a common sample. Following the reviewer's suggestion, we examine both the coefficient differences across time periods within each signal and the coefficient differences across signals within each time period. Table 3 reports the results in two panels.

Table 3. Coefficient-difference tests between quality and quantity signals.

Test	Null Hypothesis	F-Statistic	*p*-Value
Panel A: Cross-horizon differences within each signal			
Apply L0 = Apply L1 = Apply L2	Application signal is constant across horizons	1.24	0.289
Cite L1 = Cite L2	Citation signal strengthens from the first to the second lag	42.18	<0.001
Panel B: Cross-signal differences at each horizon			
Cite L0 = Apply L0	Citations equal applications when contemporaneous	57.49	<0.001
Cite L0 = Grant L0	Citations equal grants when contemporaneous	54.17	<0.001
Cite L2 = Apply L2	Second-lag citations equal second-lag applications	4.43	0.035
Cite L2 = Grant L2	Second-lag citations equal second-lag grants	15.59	<0.001

Note: Wald test estimated on common sample (N = 37,523). Panel A tests whether the coefficients of each signal are equal across time periods; Panel B tests whether the reference coefficients and application/authorization coefficients of each time period are equal. All tests are based on firm-year fixed effects regressions with full control variables and standard errors clustered at the firm level.

The Wald test confirmed the timing asymmetry. Across time periods (Panel A), application coefficients are statistically indistinguishable across contemporaneous, first-lag, and second-lag specifications (F = 1.24, p = 0.289), consistent with a continuing quantity signal; whereas citation coefficients significantly strengthen from first to second lags (F = 42.18, $p < 0.001$), consistent with a gradually emerging quality signal. Across signals (Panel B), citations are significantly different from applications and grants in both periods: contemporaneous citations are significantly smaller than contemporaneous applications (F = 57.49, $p < 0.001$) and grants (F = 54.17, $p < 0.001$), while second-lagged citations are significantly larger than second-lagged applications (F = 4.43, p = 0.035) and grants (F = 15.59, $p < 0.001$). We interpret these differences as indicating that citation signals have a stronger conditional association with ESG ratings when revealed, rather than as a direct measure of information content (which is not directly observable). This is consistent with signaling theory: due to greater differences in delivery costs, quality signals have stronger separation capabilities and thus have a stronger impact on ESG ratings, supporting H3.

4.4. Robustness Checks

The dependent variable *esgscore* is an ordered 0–9 outcome; although the linear panel model is easier to interpret, its assumptions may be strong. We therefore estimate a panel random-effects ordered logit (xtologit) as a nonlinear check (Table 4). The ordered-logit results are highly consistent with the baseline: citations are insignificant contemporaneously (−0.015), significant at the 1% level at the first lag (0.055), and significant and largest within the citation dimension at the second lag (0.110), while applications are positive and significant at every horizon. The core "quantity-immediate, quality-lagged" structure holds under the nonlinear specification, indicating that the conclusion is not an artifact of the linear functional form.

Table 4. Panel random-effects ordered logit.

Variable	(1) Contemporaneous	(2) Lag 1	(3) Lag 2
ln_gpatapply (applications)	0.097 ***	0.123 ***	0.117 ***
	(0.017)	(0.019)	(0.021)
ln_gpatgrant (grants)	0.112 ***	0.063 ***	0.014
	(0.020)	(0.022)	(0.024)

ln_gpatcite (citations)	−0.015	0.055 ***	0.110 ***
	(0.017)	(0.021)	(0.023)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	48,338	42,901	37,818

Note: Panel random effects ordered logit (xtologit). Columns (1)–(3) are separate regressions of current ESG ratings on the same-period, first-lagged, and second-lagged green patent variables, respectively. Clustered robust standard errors are in parentheses; *** denote significance at the 5%, and 1% levels, respectively. The control variables are the same as in Table 2.

We further examine robustness from three angles: (i) winsorizing the green-patent variables at the 1% and 99% levels; (ii) excluding the COVID years 2020–2022; and (iii) estimating on the manufacturing subsample (CSRC industry code C). Table 5 shows that the "quantity-immediate, quality-lagged" structure is broadly preserved across all three specifications: applications are contemporaneously significant under winsorization and COVID exclusion, and although the contemporaneous application coefficient is insignificant in the manufacturing subsample, the first and second lags remain significantly positive, so the persistence of the quantity signal still holds; grants are strongest contemporaneously and then decay (the second-lagged grant coefficient is insignificant in all three specifications); and citations are insignificant contemporaneously in all specifications, with second-lagged citations significant at the 1% level and largest in every case (0.088, 0.099, and 0.056). The core conclusion is robust.

Two additional robustness checks respond to concerns about missing rating coding and comparability of citations across technology areas. First, we reestimate the main model on the valid ESG rating subsample (esgscore > 0), excluding 684 unrated observations; the time series structure is retained, with the reference period being significantly negative (−0.027), the first lag being positive (0.046), and the second lag being the largest (0.093), while the effects are significant in all periods. Second, because citation counts may differ systematically across technology fields, we add industry-year fixed effects to absorb field-specific trends that change over time; the second-lagged citation coefficient is still 0.075 and significant at the 1% level. The core conclusions are robust to both revisions.

Table 5. Robustness: the temporal structure of green patent signals.

Variable	Baseline	Winsorize 1%/99%	Exclude COVID	Manufacturing
Citations contemporaneous	0.008	0.007	−0.014	−0.007
Citations L1	0.045 ***	0.043 ***	0.053 ***	0.020
Citations L2	0.091 ***	0.088 ***	0.099 ***	0.056 ***
Applications contemporaneous	0.038 ***	0.037 ***	0.036 ***	0.013
Applications L1	0.056 ***	0.053 ***	0.066 ***	0.032 ***
Applications L2	0.052 ***	0.051 ***	0.071 ***	0.035 **
Grants contemporaneous	0.061 ***	0.059 ***	0.103 ***	0.044 ***
Grants L1	0.036 ***	0.034 ***	0.050 ***	0.041 ***
Grants L2	0.010	0.009	0.024	0.022

Note: Each column is a set of separate regressions with the current ESG rating as the explained variable. ** and *** denote significance at the 5%, and 1% levels, respectively. The control variables are the same as Table 2. Sample size (same period/L1/L2): Baseline 48,338/42,901/37,818; Winsored 48,338/42,901/37,818; Excluding COVID 35,547/31,471/27,497; Manufacturing 30,893/27,279/23,862.

4.5. Further Analysis: Subsample Tests

To further examine the robustness and generality of the "lagged quality signal" finding, we conduct subsample tests along two dimensions (Table 6). For ownership type, the second-lagged citation coefficient is 0.108 (t = 5.11) for state-owned enterprises and 0.096 (t = 6.05) for private firms—both significant at the 1% level and close in magnitude—indicating no substantive ownership difference and hence a general mechanism. For board governance, the coefficient is 0.119 (t = 6.46) in the high-independence group and 0.079 (t = 4.43) in the low-independence group, a direction consistent with expectations (better-governed firms have stronger quality signals); however, a further interaction test shows that the interaction between second-lagged citations and the independent-director ratio is insignificant (0.087, p = 0.492). The moderating role of board governance is therefore not yet statistically robust, and we refrain from overinterpreting it.

Table 6. Heterogeneity: ownership and board governance.

Subsample	Citations L2 Coefficient	Std. Err.	t-Statistic	Observations
State-owned enterprises	0.108 ***	0.021	5.11	14,394
Private firms	0.096 ***	0.016	6.05	23,129
High independent-director ratio	0.119 ***	0.018	6.46	19,598
Low independent-director ratio	0.079 ***	0.018	4.43	17,925

Notes: Each row is a firm- and year-fixed-effects regression; the reported coefficient is that of second-lagged green patent citations. *** denote significance at the 5%, and 1% levels, respectively.

5. Discussion

This paper documents a systematic temporal asymmetry in how ESG ratings absorb the information contained in green patents: the quantity signal (applications) is recognized immediately and persistently, whereas the quality signal (citations) is recognized only with a lag, and once recognized, it carries significantly more information. This asymmetry has both a substantive and a practical interpretation.

From a substantive perspective, the findings of this article expand the signaling perspective of green patents from the static "if" to the dynamic "when". Existing research treats green patents as homogeneous signals, examining whether they affect credit, subsidies, or valuations [2–4]; our three-dimensional decomposition shows that applications, authorizations, and citations are not interchangeable indicators because they are different in terms of formation costs and observable time points. This complements the patent valuation literature—which has long established that citations (rather than number of original applications or grants) best characterizes technology value [9,39,40]—suggesting that this qualitative distinction determines not only the strength of ESG rating responses, but also the timing of their responses. The contrast between applications (contemporaneous), grants (contemporaneous but decaying), and citations (lagged and intensifying) is exactly what signaling theory predicts when rating agencies exploit the cost differential between cheap quantity expansion and expensive quality accumulation [1,17,18]. Our results also echo the "innovation-ESG disconnect" that has been documented in US corporations [27]: This disconnect may partly reflect an incomplete observation window, where quality information is present but emerges after the contemporaneous snapshot that ratings typically emphasize. Therefore, the disagreement between our findings and studies reporting a weak association between patent quality and ESG scores is at least partly attributable to differences in the time span examined rather than the absence of a quality signal.

From a practical perspective, the findings of this paper relate to the issue of greenwashing, but with an important reservation. Due to the lag in quality signals, companies can in principle use low-cost scale expansion to imitate green attributes in the short term; however, once the observation window is long enough and citation-based quality signals emerge, this strategy will be unsustainable. We emphasize, however, that this study does not directly measure or test greenwashing; our evidence involves the point at which quality signals are identified by rating agencies, and the association with greenwashing is an interpretive implication rather than an empirical finding. With this reservation, our results suggest that disclosure and tracking mechanisms that shorten the display period of quality information can improve market screening efficiency.

This article has several limitations that need to be interpreted with caution. First, identification relies on firm fixed effects and lagged explanatory variables, which cannot completely exclude time-varying omitted variables (such as changes in corporate green awareness or management ESG preferences) and reverse causation (the response of ESG ratings to subsequent green innovations); therefore, the estimates should be interpreted as evidence of robust correlations in the information processing behavior of rating agencies rather than strictly causal effects. Second, citations are measured as annual new citations (flow rather than stock), so the lagged enhancement pattern is not mechanical; however, we cannot directly observe the data processing processes of rating agencies, so the mechanism is still a reasonable inference. Third, our patent data are aggregated to the enterprise-year level and cannot control patent age, technology field or application queue at the patent level; we use industry-year fixed effects to partially deal with differences in technology fields, but the heterogeneity of citation tendencies at the patent level is still a limitation. Fourth, the moderating effect of board governance is suggestive in direction but not statistically significant. We do not over-interpret it. Future research can use instrumental variables or quasi-natural experimental designs to deal with endogeneity issues, control for patent-level characteristics, and more directly distinguish the channels through which citation information is collected, updated, and included.

6. Conclusions

This article uses China's A-share listed companies from 2010 to 2024 to decompose green patents into applications (quantity), authorization (certification quality) and citations (market influence), and examine the temporal structure of their impact on ESG ratings. We find that the quantitative signal is immediately visible—patent applications have a significant positive contemporaneous effect on ESG ratings that persists over time—while the qualitative signal is significantly lagging: patent citations have no contemporaneous positive correlation, and their effect turns significantly positive at the first lag and reaches a peak at the second lag, and conveys significantly more information than the quantitative signal. These conclusions are robust to nonlinear settings and a series of robustness tests.

These findings bring three implications. First, for rating agencies and investors, the quality information of green patents requires a longer observation window to fully appear. Therefore, the evaluation of corporate green innovation should avoid relying solely on the number of applications in the same period, but should give quality indicators such as citations a longer time dimension. Second, for regulators, "lagging quality signals" means that quantity-based greenwashing is difficult to detect in the short term but difficult to hide in the long term; improving the disclosure and tracking of green patent quality information can shorten the display period of quality signals and improve market screening efficiency. Third, for enterprises, forming high-impact green patents through real technology accumulation is the sustainable path to be effectively recognized by the market. Short-term quantitative expansion cannot replace long-term quality construction.

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