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ESG Ratings and Corporate Sustainable Growth Under Financing Constraints: A Dual-Route Mechanism of Green Technological Innovation and Resource Improvement

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Abstract

Under China's dual-carbon and high-quality development goals, this study examines whether and how third-party ESG ratings are associated with corporate sustainable growth, defined as the internally financeable growth rate of Higgins. Using 25,683 firm-year observations of Shanghai and Shenzhen A-share listed firms from 2011 to 2022 and Huazheng ESG ratings, of which only seven of the nine levels (C to A) are observed, we estimate a moderated mediation model (Hayes Model 21). A one-level rating upgrade is associated with a 1.42 percentage-point-higher sustainable growth rate (1.69 points when profitability controls mechanically linked to the dependent variable are excluded), and a one-standard-deviation increase corresponds to 10.5% of the standard deviation of the growth rate. The association holds under instrumental-variable estimation, propensity-score matching, firm fixed effects and alternative measures. Green technological innovation, measured by green patent applications, partially mediates the relationship, but the indirect effect (0.0020) accounts for only 14.2% of the total effect; supplementary tests suggest that lower financing costs and reduced operating and crash risks are potential complementary channels behind the direct effect. Financing constraints weaken the first stage of the green technological innovation route, whereas a stronger market competitive position strengthens the second stage; the conditional indirect effect under low constraints and a strong position (0.0029) is 2.25 times that under the opposite conditions. The associations are stronger for non-state-owned, growth-stage and heavily polluting firms. The findings are consistent with a dual-route view in which ESG ratings relate to sustainable growth through both an innovation route and a resource-improvement route, each with distinct boundary conditions.

Keywords: ESG rating; corporate sustainable growth; green technological innovation; ability; financing constraints; market competitive position; moderated mediation

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1. Introduction

Sustainable growth capacity, in the sense of Higgins, is the rate at which a firm can expand without issuing new equity or changing its financial policy, that is, growth financed by endogenous accumulation rather than by external debt or equity dilution; it reflects the quality rather than the speed of development [1]. Throughout this paper, "sustainable growth" refers to this financially sustainable growth capacity, which is related to but distinct from the broader notion of corporate sustainability in environmental and social terms. As China's economy shifts from high-speed growth to high-quality development, corporate growth logic is moving from scale-driven to quality-driven, and rapid expansion financed by

external capital no longer fits tightening resource constraints or the capital market's renewed emphasis on long-term value. Identifying the drivers of sustainable growth therefore matters both for firm resilience and for whether macro-level structural transformation can take root at the micro level.

ESG ratings, which condense environmental, social and governance information into a single third-party assessment, have evolved from a marginal disclosure concept into a key reference for capital allocation. The 2024 sustainability reporting guidelines issued by the Shanghai, Shenzhen and Beijing stock exchanges under the guidance of the China Securities Regulatory Commission (CSRC) marked a shift in ESG reporting from voluntary practice towards a semi-mandatory norm, and institutional investors increasingly embed ESG information in stock selection and risk pricing [2,3]. Yet whether and how ESG ratings translate into real growth remains unsettled: some studies report positive value effects through signalling and stakeholder channels [4,5], whereas others argue that ESG investment can crowd out productive resources or that ratings are too noisy to carry reliable information [6–8].

Closely related studies have examined parts of this chain. Wang et al. show that receiving a SynTao Green Finance rating increases green patenting, and Zhang et al. find that ESG performance promotes green technological innovation partly by relaxing financing constraints [9,10]. Deng et al. and Zhang et al. (2025) link ESG to total factor productivity, while Teng et al. and Gong et al. relate ESG risk or ratings to sustainable growth and corporate sustainability [11–14]. International evidence likewise shows that better ESG or CSR profiles ease access to finance and reduce firm risk [15]. Three questions nevertheless remain open. First, studies of the ESG–innovation link stop at innovation output and rarely ask how much of the downstream growth consequence actually travels through innovation. Second, studies of the ESG–growth link usually treat transmission as a single path and do not ask whether its stages are governed by different conditions. Third, financing constraints are typically examined either as a mediator or as a sample split, rather than as a boundary condition that governs whether a rating can be converted into green investment. Chinese evidence is particularly informative on these questions, because listed firms face pronounced ownership-based differences in access to finance and a rapidly tightening environmental regulatory regime.

Drawing on signalling theory and the natural-resource-based view, we treat the ESG rating as a third-party signal rather than as a direct measure of underlying ESG performance, and argue that it can relate to sustainable growth through two routes. In the innovation route, a better rating raises stakeholder expectations and improves access to funding, which encourages green R&D whose outputs can later be commercialised. In the resource-improvement route, the same signal lowers financing costs and perceived risk and thereby directly relaxes the financial limits on internally financed growth. The strength of the innovation route is expected to depend on two distinct conditions: financing constraints determine whether a rating's latent funding advantage can be converted into green investment (the first stage), whereas market competitive position determines whether green technological innovation can be converted into profitable growth (the second stage). We test this framework with a moderated mediation model on 25,683 firm-year observations of Chinese A-share listed firms from 2011 to 2022.

This study makes three contributions. First, it develops and tests a dual-route account of how ESG ratings relate to financially sustainable growth. By decomposing the total association, it shows that green technological innovation is a statistically reliable but quantitatively secondary route, which qualifies the tendency in the ESG–innovation literature to treat innovation as the main transmission mechanism. Second, it identifies stage-specific boundary conditions: a resource-side condition (financing constraints) that governs the

conversion of rating signals into green technological innovation, and a market-side condition (competitive position) that governs the conversion of green technological innovation into growth. This shifts the question from whether ESG ratings matter to the resource and market conditions under which their innovation route operates. Third, it clarifies the conceptual status of the key constructs by separating the signalling effect of ESG ratings from underlying ESG performance, and Higgins-type financial sustainability from broader corporate sustainability, which helps reconcile mixed findings in prior research.

The remainder of the paper is organised as follows. The next part reviews the literature and develops the hypotheses. The Section 3 describes the research design; the Section 4 reports the empirical results, including heterogeneity and channel tests; the Section 5 discusses the findings; and the Section 6 concludes with implications and limitations.

2. Theoretical Framework, Literature Review and Hypotheses

2.1. Theoretical Framework

The analysis rests on two complementary perspectives. Signalling theory holds that when insiders know more than outsiders, credible third-party information can reduce information asymmetry and change how resource providers price a firm [16]. An ESG rating is such a signal: it is an external agency's assessment of disclosed and collected non-financial information, and it may differ from a firm's true ESG performance because of methodological choices and noise [7,17]. We therefore study the informational and signalling effect of ESG ratings and interpret a rating as an imperfect, publicly observed proxy for underlying performance rather than as performance itself. The resource-based view [18] and its natural-resource-based extension [19] complement this perspective by explaining how resources obtained through a favourable signal, such as cheaper capital and stakeholder support, are converted into capabilities that yield durable advantages, including green technologies. Stakeholder considerations enter through both lenses, since ratings shape stakeholders' expectations and the terms on which they supply resources [20]. Combining these perspectives yields a two-stage logic: the signal first affects resource access, which can either be invested in green technological innovation or directly relax the financial limits on growth, and green technological innovation then creates value only if the firm can appropriate its returns in the product market.

The outcome studied is the sustainable growth rate of Higgins, which captures the growth a firm can finance through retained profits while keeping its financial policy unchanged. It is a financial notion of sustainability, and it is used here because it summarises the joint outcome of profitability and earnings retention, the two margins through which better resource access and green technological innovation should ultimately appear. It does not measure environmental or social performance, and the results should not be read as evidence about corporate sustainability in that broader sense.

2.2. Literature Review

2.2.1. ESG Ratings and Firm Outcomes: Conflicting Evidence

A large literature finds that better ESG profiles are associated with easier access to finance, lower costs of debt and equity, and lower risk [4,21–24], and meta-analytic evidence suggests that the relationship between ESG and financial performance is positive on average [5]. Chinese studies link ESG ratings to higher total factor productivity and corporate sustainability [11,12,14] and to lower stock price crash risk [25,26]. Other work is more sceptical: ESG activities may reflect agency problems and be penalised by investors [6], and several widely held beliefs about ESG are not supported by evidence [8]. These conflicting findings appear to stem from three sources, namely differences in outcome horizons (market

reactions versus real outcomes), differences in institutional settings, and differences in the rating sources used to measure ESG.

2.2.2. ESG Ratings and Green Technological Innovation

A second strand examines whether ESG ratings stimulate green technological innovation. Using the staggered coverage of SynTao Green Finance ratings as a quasi-natural experiment, Wang et al. [9] find that rated firms increase green patenting, and Zhang et al. [10] show that ESG performance promotes green technological innovation partly by easing financing constraints. Governance quality and reduced managerial short-termism are further mechanisms [27,28]. At the same time, rating disagreement can distort innovation incentives: Geng et al. [29] find that divergent ratings are associated with green technological innovation bubbles driven by managerial myopia, and external shocks such as geopolitical risk and economic policy uncertainty also condition firms' green production practices [30]. This strand typically stops at innovation output and does not assess how much of the downstream growth effect passes through innovation.

2.2.3. Measurement Limitations of ESG Ratings

Ratings from different providers correlate only moderately because agencies differ in scope, indicators and weights [7,17]. Rating disagreement affects stock returns and investor demand [3,31] and creates uncertainty about what a rating actually signals [32,33]. Two implications follow for this study. First, any single rating is a noisy proxy, which tends to attenuate estimated coefficients. Second, because the coarse categories of Chinese ratings concentrate firms in the middle of the scale, estimated effects mainly describe movements within the lower and middle range. We address these issues with an alternative rating source, rating-category dummies and instrumental variables, and interpret the results accordingly.

Relative to these studies, this paper differs in three respects. Unlike Wang et al. [9] and Zhang et al. [10], which end at green technological innovation, it follows the chain to financially sustainable growth and quantifies the share transmitted through innovation. Unlike Teng et al. [13] and Gong et al. [14], which examine the ESG–growth or ESG–sustainability relationship as a single path, it separates an innovation route from a direct resource route. Unlike studies that treat financing constraints as a mediator or a sample split, it models financing constraints and market position as stage-specific moderators of the innovation route.

2.3. ESG Ratings and Corporate Sustainable Growth

Within the Higgins framework, sustainable growth rises when a firm earns a higher return on equity or retains a larger share of its earnings. A favourable rating can affect both margins. As a credible signal, it reduces information asymmetry and lowers the cost of debt and equity [21,34], which raises net profitability for a given investment programme and reduces the need to distribute cash to reassure outside investors. It also strengthens legitimacy and stakeholder relationships, improving access to trade credit and reducing transaction costs and operating risk [15,23], which stabilises the earnings that feed internal accumulation. Accordingly:

H1. *Higher ESG ratings are positively associated with corporate sustainable growth.*

2.4. Two Routes: Green Technological Innovation and Direct Resource Improvement

ESG ratings are expected to promote green technological innovation through incentive and resource mechanisms. On the incentive side, a rating makes environmental performance visible to investors, regulators and customers, so improving or defending the rating

raises the payoff to green R&D; external scrutiny also discourages the managerial short-termism that would otherwise cut long-horizon projects [9,28]. On the resource side, the funding advantages associated with a better rating can be channelled into green R&D, which is otherwise hard to finance externally [10]. Green technological innovation, in turn, can raise Higgins-type sustainable growth through the profitability margin: process innovations lower energy, material and compliance costs, and product innovations allow for price premiums in markets that increasingly value low-carbon attributes [19,35]. Higher and more stable margins raise the return on equity and the retained earnings available for reinvestment.

The innovation route is unlikely to be the only one. Green technological innovation takes years to mature and its returns are uncertain, whereas lower financing costs and lower risk affect profitability and retention immediately. A substantial part of the rating–growth association is therefore expected to operate through a direct resource-improvement route, in which cheaper capital and lower operating and tail risk relax the financial limits on growth without requiring an innovation outcome. Accordingly:

H2a. *Green technological innovation partially mediates the positive association between ESG ratings and corporate sustainable growth.*

H2b. *ESG ratings remain positively associated with corporate sustainable growth after accounting for green technological innovation, consistent with a direct resource-improvement route operating through lower financing costs and lower risk.*

2.5. First-Stage Moderating Role of Financing Constraints

Green technological innovation requires substantial, long-term and stable funding because of its high investment, long development cycle, uncertain returns and low collateral value [36,37]. Financing constraints are expected to act primarily on the first stage, because this is where external funds are needed: converting a rating signal into green R&D requires the firm to raise or reallocate capital. When constraints are severe, the funding advantage implied by a better rating is absorbed by short-term operating needs or debt service, and green projects are postponed [10,38]. By contrast, the second stage, in which existing innovations are commercialised, depends mainly on product-market conditions rather than on new external financing, so the theoretical case for financing constraints moderating that stage is weaker; we nevertheless test cross-stage moderation empirically. Accordingly:

H3. *Financing constraints negatively moderate the indirect effect of ESG ratings on sustainable growth through green technological innovation; stronger constraints weaken the first-stage relationship and thereby the overall indirect effect.*

2.6. Second-Stage Moderating Role of Market Competitive Position

The conversion of green technological innovation into sustainable growth depends on a firm's ability to appropriate innovation returns. Firms with stronger competitive positions can commercialise green technological innovations more rapidly and use their market share, brand influence, pricing power, scale and distribution channels to raise innovation returns [39,40], whereas firms with weaker positions face greater imitation and commercialisation barriers. Market position is expected to act primarily on the second stage, because pricing power matters once an innovation exists and must be turned into margins; it is less directly related to whether a rating signal leads the firm to start green R&D, which is mainly a funding and incentive decision. A strong position could also supply internal funds for R&D, but this effect is largely captured by financing constraints, so we treat the

second stage as the theoretically primary locus of market-side moderation and test the alternative empirically. Accordingly:

H4. *Market competitive position positively moderates the indirect effect of ESG ratings on sustainable growth through green technological innovation; a stronger position strengthens the second-stage relationship and thereby the overall indirect effect.*

Overall, the study proposes a dual-route moderated mediation framework (Figure 1). ESG ratings relate to sustainable growth through an indirect green technological innovation route, whose first stage is moderated by financing constraints and whose second stage is moderated by market competitive position, and through a direct resource-improvement route.

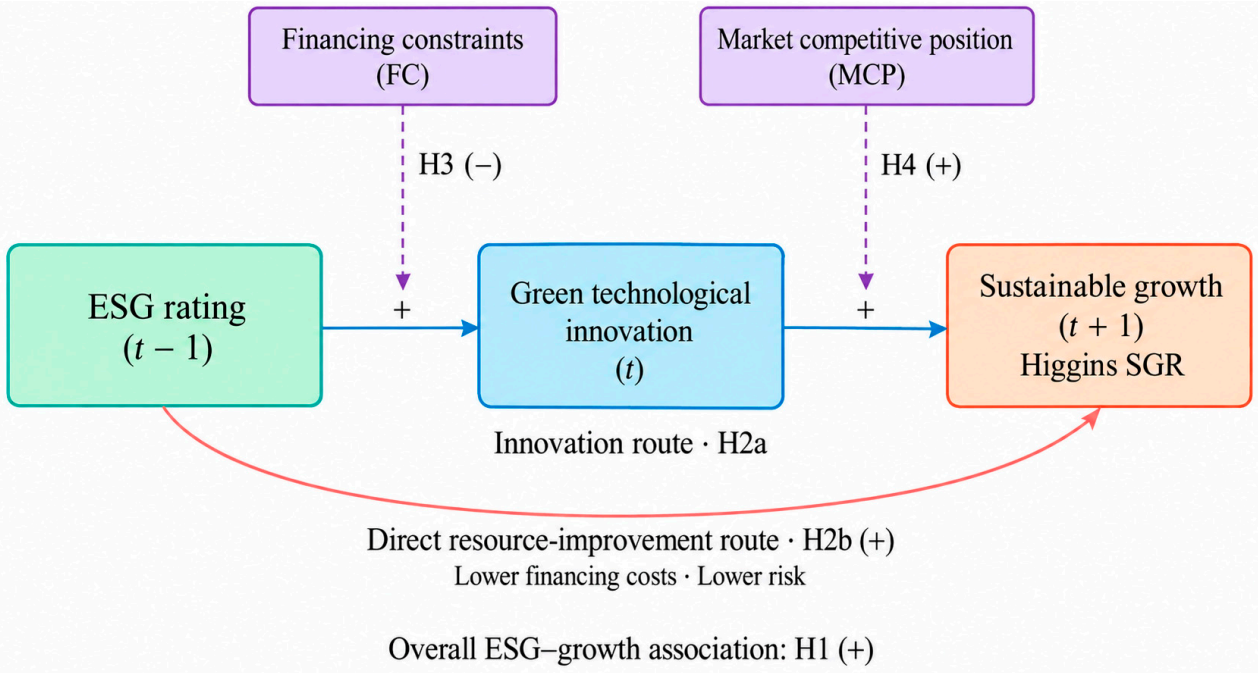


Figure 1. Theoretical framework diagram of research.

3. Research Design

3.1. Sample Selection and Data Sources

The initial sample comprises Shanghai and Shenzhen A-share listed firms from 2011 to 2022. The sample starts in 2011 because Huazheng ESG ratings, which have covered A-share firms since 2009, achieved substantially better industry coverage and data completeness from that year onwards. The sample ends in 2022 because green patent data are the binding constraint. Chinese invention patent applications are normally published only 18 months after filing, and green patents are then identified by matching IPC codes to the WIPO IPC Green Inventory, so application counts for recent years remain incomplete for some time. When the data were assembled, 2022 was the latest year for which green patent applications and all other required variables were consistently available; extending the sample is left for future work once later patent records are complete. The initial sample contains 38,127 firm-year observations. We sequentially exclude 1463 observations from financial and insurance firms, whose capital structures and business models differ fundamentally from those of non-financial firms; 1832 observations of ST, *ST and PT firms; 2514 IPO-year observations; and 6635 observations with missing core variables (ESG rating, sustainable growth rate, green patents, SA index or Lerner index). The final unbalanced panel contains

25,683 firm-year observations from 2847 firms, with an average of 9.02 years per firm. All continuous variables are winsorised at the 1st and 99th percentiles.

We use Huazheng ESG ratings for three reasons. First, they cover essentially all A-share listed firms over the whole sample period, whereas SynTao Green Finance ratings cover mainly constituents of major indices (yielding 9317 observations in our robustness test), Wind ESG ratings have a considerably shorter history, and Bloomberg scores cover a limited subset of large Chinese firms and mainly reflect disclosure. Second, Huazheng ratings are updated quarterly and incorporate China-specific indicators such as regulatory penalties and negative events. Third, they are widely used in Chinese ESG research, which facilitates comparison with prior studies. On the 9317 overlapping observations, the Spearman correlation between Huazheng and SynTao ratings is 0.56, in line with the moderate cross-provider correlations reported in the literature [7], and the main result holds with SynTao ratings.

3.2. Definition and Measurement of Variables

(1) Dependent variable: corporate sustainable growth (SGR). Following Higgins [1], SGR = (ROE × b)/(1 − ROE × b), where ROE is net profit divided by beginning-of-year shareholder equity, so the denominator is not affected by current retained earnings, and b is the earnings retention ratio, equal to one minus the dividend payout ratio (cash dividends/net profit). Two adjustments follow common practice and have a clear economic rationale. For loss-making firm-years the payout ratio is undefined; because a firm with a loss cannot retain positive earnings, b is set to 1, so SGR takes the sign of ROE and correctly indicates negative internally financed growth. When cash dividends exceed net profit, the firm distributes more than it earns and retains nothing from current profit, so b is set to 0, which yields SGR = 0 instead of a negative retention ratio with no economic meaning. Because the formula diverges as ROE × b approaches 1, winsorisation removes such extreme values; the winsorised SGR ranges from −0.428 to 0.563. To show that these conventions do not drive the results, we re-estimate the baseline model excluding the observations affected by either adjustment, and we use sales growth and total asset growth as alternative growth measures.

$$SGR = (ROE \times b)/(1 - ROE \times b) \quad (1)$$

Equation (1) shows that sustainable growth is jointly determined by profitability and retention policy; their product is the rate at which equity grows endogenously, and the higher this rate, the more room the firm has for steady growth without external financing. We use SGR rather than realised sales or asset growth as the main measure because it captures the growth a firm can finance without external capital, which matches our interest in the quality rather than the speed of growth, whereas realised growth may be driven by debt-financed expansion or acquisitions.

(2) Explanatory variable: ESG rating (ESG). Huazheng's nine grades from C to AAA are assigned values from 1 to 9, and the fourth-quarter rating is used as the annual value. In our sample, the highest observed grade is A (value 7), and no AA or AAA ratings occur. The numerical coding implicitly treats adjacent grades as equally spaced, and the estimates mainly reflect variation within the lower and middle grades, so they should not be extrapolated to the two highest grades. We therefore also estimate a specification with a separate dummy for each observed rating category. An ordered logit model is designed for an ordinal dependent variable; because the rating is the explanatory variable here, the category-dummy specification is the appropriate way to relax the linearity assumption. SynTao Green Finance ratings serve as an alternative measure.

(3) Mediating variable: green technological innovation (GTI). GTI is the natural logarithm of one plus the number of green invention and green utility-model patent applications filed by the firm in the year, identified with the WIPO IPC Green Inventory. This indicator measures observable green technological innovation output and activity rather than the broader organisational capability to innovate, and we label the construct accordingly. Applications are used rather than grants because filing is closer in time to the innovation decision and is not affected by the length of the examination process [41]. The median GTI is 0: more than half of the firm-years record no green patent application, so the variable is strongly left-censored. We therefore report PPML and Tobit estimates alongside OLS in the main mediation analysis [42] and use green patent grants as an alternative measure.

(4) Moderating variables. Financing constraints (FCs) are measured by the absolute value of the SA index [38], $|-0.737 \times \text{Size} + 0.043 \times \text{Size}^2 - 0.040 \times \text{Age}|$, where Size is the natural logarithm of total assets (RMB millions) and Age is firm age in years. Because the index relies only on firm size and age, which are largely exogenous in the short run, it avoids the endogeneity that financial variables introduce into the KZ and WW indices; higher values indicate more severe constraints. Because the SA index is structurally related to size and age, we use the KZ index [43] in robustness tests and add ESG × Size and ESG × Age interaction terms to rule out the possibility that the moderating effect merely reflects size or age effects. Market competitive position (MCP) is measured by the industry-adjusted Lerner index, (operating revenue − operating costs − selling expenses − administrative expenses)/operating revenue, minus the annual industry mean; higher values indicate a more favourable product-market position. Because the Lerner index is related to profitability and SGR is built from ROE, the interaction GTI × MCP could partly capture mechanical profitability effects. We address this in two ways: all second-stage models control for ROA, which absorbs the common profitability component, and we replace the Lerner index with market share (firm revenue/industry revenue), which reflects market position without being a margin measure; the second-stage moderation remains significant.

(5) Control variables. Following prior research, we control for firm size (Size), leverage (Lev), return on assets (ROA), revenue growth (Growth), firm age (Age), board size (Board), ownership concentration (Top1), CEO duality (Dual), Tobin's Q (TobinQ) and operating cash flow (Cashflow), together with year and industry fixed effects. Because ROE equals ROA multiplied by the equity multiplier, ROA and Lev are partly mechanically related to SGR, and Growth is the realised counterpart of sustainable growth. Including them may over-control and bias the ESG coefficient towards zero, whereas excluding them risks omitting genuine determinants of growth. We therefore report both specifications, treating the full-control estimate as a conservative lower bound and the specification excluding ROA and Growth as an upper benchmark, and we further decompose SGR into its ROE and retention components in the robustness tests.

(6) Grouping variables. Ownership is classified as state-owned or non-state-owned according to the type of ultimate controller in the CSMAR database. Life-cycle stages (growth, maturity and decline) are identified with the cash-flow pattern method of Dickinson (2011) [44], based on the signs of operating, investing and financing cash flows. Heavy-polluting industries are the 16 categories listed by the former Ministry of Environmental Protection (Circular No. 373, 2008), matched to the CSRC 2012 industry classification (Table 1).

Table 1. Variable definitions and measurements.

Type	Variable	Symbol	Measurement
Dependent	Sustainable growth rate	SGR	Higgins model: (ROE × b)/(1 − ROE × b); ROE = net profit/beginning-of-year equity; b = 1 − dividend payout ratio; b = 1 for loss-making firm-years and b = 0 when the payout ratio exceeds 1
Independent	ESG rating	ESG	Huazheng ESG rating (fourth-quarter value), C to AAA assigned 1 to 9
Mediator	Green technological innovation	GTI	ln(1 + green invention and green utility-model patent applications), identified with the WIPO IPC Green Inventory
Moderator (first stage)	Financing constraint	FC	Absolute value of the SA index: $\lvert -0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age \rvert$; Size = ln(total assets, RMB millions); Age = firm age in years
Moderator (second stage)	Market competitive position	MCP	Industry-adjusted Lerner index: (Revenue − COGS − Selling expenses − Administrative expenses)/Revenue, minus the annual industry mean
Control	Firm size	Size	Natural logarithm of total assets (RMB)
Control	Leverage	Lev	Total liabilities/total assets
Control	Return on assets	ROA	Net profit/total assets
Control	Revenue growth	Growth	Year-on-year growth rate of operating revenue
Control	Firm age	Age	ln(1 + years since establishment)
Control	Board size	Board	Natural logarithm of the number of directors
Control	Ownership concentration	Top1	Shareholding ratio of the largest shareholder
Control	CEO duality	Dual	1 if the chairman and the CEO are the same person, 0 otherwise
Control	Tobin's Q	TobinQ	Market value/replacement cost of assets
Control	Cash flow	Cashflow	Net operating cash flow/total assets
Grouping	State ownership	SOE	1 if the ultimate controller is the state, 0 otherwise
Grouping	Life-cycle stage	LC	Growth/mature/decline stage, cash-flow pattern method (Dickinson, 2011, [44])
Grouping	Heavy-polluting industry	HPI	1 if the firm belongs to one of the 16 heavy-polluting industries listed by the Ministry of Environmental Protection (2008), 0 otherwise

Note: Data sources: ESG ratings from Huazheng (Sino-Securities Index); green patent applications and grants from the China National Intellectual Property Administration (CNIPA); ownership, financial and governance data from **CSMAR**. Ratios are expressed as decimals; all continuous variables are winsorised at the 1st and 99th percentiles.

3.3. Model Setting

Temporal structure. Because ESG ratings need time to stimulate green technological innovation, and innovation needs further time to affect growth, we use a lead–lag structure in which ESG, the first-stage moderator FC and the controls are measured in year t − 1, GTI and the second-stage moderator MCP in year t, and SGR in year t + 1; this also mitigates contemporaneous reverse causality. Each moderator is therefore measured in the same year as the predictor of the stage it moderates, so the interaction terms are ESG(t − 1) × FC(t − 1) in the first stage and GTI(t) × MCP(t) in the second stage. Each observation is a firm-level triple matched on the firm identifier, indexed by year t. Accordingly, ESG, FC and the controls cover 2011–2020; GTI and MCP cover 2012–2021; and SGR covers 2013–2022, so every variable lies within the 2011–2022 data window. All main models are estimated on a common sample of 25,683 observations with non-missing values for every variable in the full moderated mediation system. This keeps the samples identical across equations, ensures that the decomposition c = c′ + a × b holds exactly, and explains why the sample size is unchanged across the main analyses. All models include year and industry fixed effects, and standard errors are clustered at the firm level. The baseline model tests the total effect of ESG ratings on sustainable growth (H1):

$$SGR_{i,t+1} = \alpha_0 + \alpha_1 ESG_{i,t-1} + \alpha_2 Controls_{i,t-1} + Year + Industry + \varepsilon_{i,t+1} \quad (2)$$

The mediating effect models are set as follows:

$$GTI_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 Controls_{i,t-1} + Year + Industry + \varepsilon_{i,t} \quad (3)$$

$$SGR_{i,t+1} = \gamma_0 + \gamma_1 ESG_{i,t-1} + \gamma_2 \mathrm{GTI}_{i,t} + \gamma_3 Controls_{i,t-1} + Year + Industry + \varepsilon_{i,t+1} \quad (4)$$

where α_1 represents the total effect (c), β_1 the first-stage path (a), γ_2 the second-stage path (b) and γ_1 the direct effect (c′). Because Equations (2)–(4) are estimated on the same sample, the mediating effect satisfies the identity

$$c = c' + a \times b \quad (5)$$

which we use as an internal consistency check. In addition to the stepwise test, we estimate the confidence interval of the indirect effect a × b with a bias-corrected bootstrap (5000 replications). Because the data contain repeated observations of the same firms, resampling is conducted at the firm level: in each replication, firms are drawn with replacement and all of their years are retained, which preserves the within-firm correlation of the panel [45]. The indirect effect is considered significant when the 95% confidence interval excludes zero.

H3 and H4 posit that one moderator acts on the first stage and another on the second stage of the same indirect path. Among the conditional process models of Hayes [46,47], Model 21 is the specification with exactly this structure, a first-stage moderator W and a distinct second-stage moderator Z, and it corresponds to the first- and second-stage moderation model of Edwards and Lambert [48]. We therefore set FC as the first-stage moderator and MCP as the second-stage moderator:

$$GTI_{i,t} = \alpha_0 + a_1 ESG_{i,t-1} + a_2 FC_{i,t-1} + a_3 (ESG_{i,t-1} \times FC_{i,t-1}) + \alpha_4 Controls_{i,t-1} + Year + Industry + \varepsilon_{i,t} \quad (6)$$

$$SGR_{i,t+1} = b_0 + c_1{}' ESG_{i,t-1} + b_1 GTI_{i,t} + b_2 (MCP_{i,t}) + b_3 (GTI_{i,t} \times MCP_{i,t} + b_4 Controls_{i,t-1} + Year + Industry + \varepsilon_{i,t+1} \quad (7)$$

In Equation (7), $c_1{}'$ is the direct effect of ESG ratings conditional on GTI, MCP and their interaction, which is why its estimate differs from c′ in Equation (4). All the continuous variables involved in the interaction term construction are mean-centred to reduce the

influence of multicollinearity. Under the above model framework, the conditional indirect effect can be expressed as:

$$\theta(W,Z) = (a_1 + a_3W)(b_1 + b_3Z) \quad (8)$$

where W and Z denote FC and MCP. With Z at its mean, the change in θ for a one-unit increase in W is a_3b_1, the index of moderated mediation for financing constraints; with W at its mean, the change for a one-unit increase in Z is a_1b_3, the index for market position. Intuitively, a_3b_1 shows how much the indirect effect shrinks as financing constraints tighten, and a_1b_3 how much it grows as market position improves. An index is significant when its bootstrap confidence interval excludes zero. Equations (6) and (7) are estimated jointly as a system, so both moderators enter simultaneously and coefficients are not combined across separately estimated models. As a consistency check, the difference between the conditional indirect effects at +1 SD and −1 SD of a moderator must equal the corresponding index multiplied by two standard deviations of that moderator.

4. Empirical Results and Analysis

4.1. Descriptive Statistics and Correlation Analysis

Table 2 reports descriptive statistics for the 25,683 observations. The mean SGR is 0.082 with a standard deviation of 0.147. The mean ESG rating is 4.183, close to grade B, and observed ratings range from C (1) to A (7). The median GTI is 0, confirming that most firm-years record no green patent application.

Table 2. Descriptive statistics.

Variable	N	Mean	SD	Min	Median	Max
SGR	25,683	0.082	0.147	−0.428	0.071	0.563
ESG	25,683	4.183	1.092	1.000	4.000	7.000
GTI	25,683	0.736	1.084	0.000	0.000	5.347
FC	25,683	3.821	0.258	3.106	3.815	4.612
MCP	25,683	0.094	0.142	−0.486	0.087	0.521
Size	25,683	22.314	1.286	19.627	22.158	26.183
Lev	25,683	0.428	0.205	0.052	0.421	0.918
ROA	25,683	0.041	0.063	−0.252	0.039	0.227
Growth	25,683	0.168	0.392	−0.573	0.108	2.413
Age	25,683	2.916	0.327	1.792	2.944	3.611
Board	25,683	2.118	0.197	1.609	2.197	2.708
Top1	25,683	0.347	0.149	0.084	0.327	0.751
Dual	25,683	0.273	0.446	0.000	0.000	1.000
TobinQ	25,683	2.043	1.287	0.842	1.628	8.176
Cashflow	25,683	0.048	0.067	−0.169	0.046	0.243

Note: Variables are defined in Table 1. SGR, Lev, ROA, Growth, Top1 and Cashflow are ratios; ESG is the rating level (1–9); GTI is in logarithms. Continuous variables are winsorised at the 1st and 99th percentiles.

Table 3 reports the correlations. The correlation between ESG and SGR is 0.118 and significant at the 1% level, consistent with H1. ESG is positively correlated with GTI, and GTI is positively correlated with SGR, providing preliminary evidence for the mediating role of green technological innovation. Correlations among the explanatory variables are generally low, and all variance inflation factors are below 5, indicating no serious multicollinearity.

Table 3. Correlation matrix of key variables.

	SGR	ESG	GTI	FC	MCP	Size	Lev	ROA
SGR	1.000							
ESG	0.118 ***	1.000						
GTI	0.094 ***	0.213 ***	1.000					
FC	−0.087 ***	−0.142 ***	−0.196 ***	1.000				
MCP	0.156 ***	0.098 ***	0.067 ***	−0.073 ***	1.000			
Size	0.063 ***	0.276 ***	0.341 ***	−0.518 ***	0.082 ***	1.000		
Lev	−0.142 ***	−0.064 ***	0.108 ***	0.087 ***	−0.213 ***	0.412 ***	1.000	
ROA	0.487 ***	0.152 ***	0.046 ***	−0.118 ***	0.394 ***	0.018 **	−0.367 ***	1.000

Note: ***and ** indicate significance at the 1% and 5% levels, respectively.

4.2. Benchmark Regression Results

Table 4, Panel A, reports the baseline results. Column (1) includes only year and industry fixed effects, column (2) adds all controls, and column (3) excludes ROA and Growth. In column (2), the ESG coefficient is 0.0142 (t = 6.83) and significant at the 1% level: a one-grade-higher rating is associated with a 1.42 percentage-point-higher sustainable growth rate, and a one-standard-deviation increase in ESG (1.092 grades) with an increase of 0.0155, about 10.5% of the standard deviation of SGR. H1 is supported. In economic terms, the 1.42-point difference is about 17% of the sample mean SGR (8.2%). For the median firm, with total assets of about RMB 4.2 billion and leverage of 0.42, implying equity of about RMB 2.4 billion, it corresponds to roughly RMB 35 million of additional equity growth per year that can be financed without new external capital (about RMB 41 million based on column (3)). A one-grade upgrade is therefore associated with a meaningful reduction in the external financing a firm would need to sustain a given growth plan.

The ROA coefficient (1.0237) largely reflects its mechanical link with SGR. When ROA and Growth are excluded, the ESG coefficient rises to 0.0169 (t = 7.42), between the estimate without controls (0.0186) and the full-control estimate (0.0142), and the adjusted R^2 falls from 0.412 to 0.183, confirming that much of the explanatory power of ROA is mechanical. Because ROA and Growth may absorb part of the profitability channel through which ratings operate, the full-control coefficient should be interpreted as a conservative lower bound and the column (3) coefficient as an upper benchmark, so the association plausibly lies between 1.42 and 1.69 percentage points.

Within-firm evidence is particularly informative. When industry fixed effects are replaced with firm fixed effects (row 15), the ESG coefficient is 0.0106 (t = 4.89), about 75% of the baseline estimate. The association therefore does not merely reflect permanent differences between firms, such as management quality or business models; it also holds when the same firm's rating changes over time. Because these are observational estimates, we interpret them as evidence consistent with H1 rather than as precise causal effects.

Among the controls, leverage is negatively associated with SGR, firm size positively and Tobin's Q negatively, suggesting that high leverage limits steady growth and that highly valued firms rely more on external financing. Panel B reports the sub-dimensions. Entered separately, the environmental, social and governance scores have coefficients of 0.0118, 0.0047 and 0.0126. Entered jointly, the environmental and governance coefficients (0.0089 and 0.0097) remain significant at the 1% level, whereas the social coefficient falls to 0.0031 and becomes insignificant, suggesting that the environmental and governance components of the rating carry most of the information relevant to sustainable growth (Figure 2).

Table 4. Baseline regression: ESG rating and sustainable growth.

Variable	(1) SGR (t + 1)	(2) SGR (t + 1)	(3) SGR (t + 1), Excl. ROA and Growth
Panel A: Composite ESG rating	-	-	-
ESG (t − 1)	0.0186 *** (8.27)	0.0142 *** (6.83)	0.0169 *** (7.42)
Size	-	0.0093 *** (5.14)	0.0121 *** (6.35)
Lev	-	−0.1124 *** (−14.62)	−0.1873 *** (−21.07)
ROA	-	1.0237 *** (52.18)	-
Growth	-	0.0418 *** (16.73)	-
Age	-	−0.0156 *** (−4.27)	−0.0198 *** (−5.06)
Board	-	0.0061 * (1.82)	0.0074 ** (2.14)
Top1	-	0.0214 *** (4.36)	0.0287 *** (5.42)
Dual	-	0.0017 (1.04)	0.0021 (1.19)
TobinQ	-	−0.0029 *** (−4.91)	−0.0013 ** (−2.08)
Cashflow	-	0.0683 *** (8.27)	0.2418 *** (18.94)
Constant	0.0438 *** (6.18)	−0.0517 (−1.43)	−0.0846 ** (−2.24)
Year/Industry FE	Yes	Yes	Yes
N	25,683	25,683	25,683
Adj. R^2	0.087	0.412	0.183
Panel B: ESG sub-dimensions	**(4)**	**(5)**	**(6)**	**(7)**
E score (t − 1)	0.0118 *** (6.24)	-	-	0.0089 *** (4.52)
S score (t − 1)	-	0.0047 ** (2.38)	-	0.0031 (1.54)
G score (t − 1)	-	-	0.0126 *** (6.71)	0.0097 *** (5.03)
Controls	Yes	Yes	Yes	Yes
Year/Industry FE	Yes	Yes	Yes	Yes
N	25,683	25,683	25,683	25,683
Adj. R^2	0.409	0.403	0.410	0.415

Note: The dependent variable is SGR (t + 1). *t*-statistics based on firm-clustered standard errors are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels. In Panel B, all controls of column (2) are included.

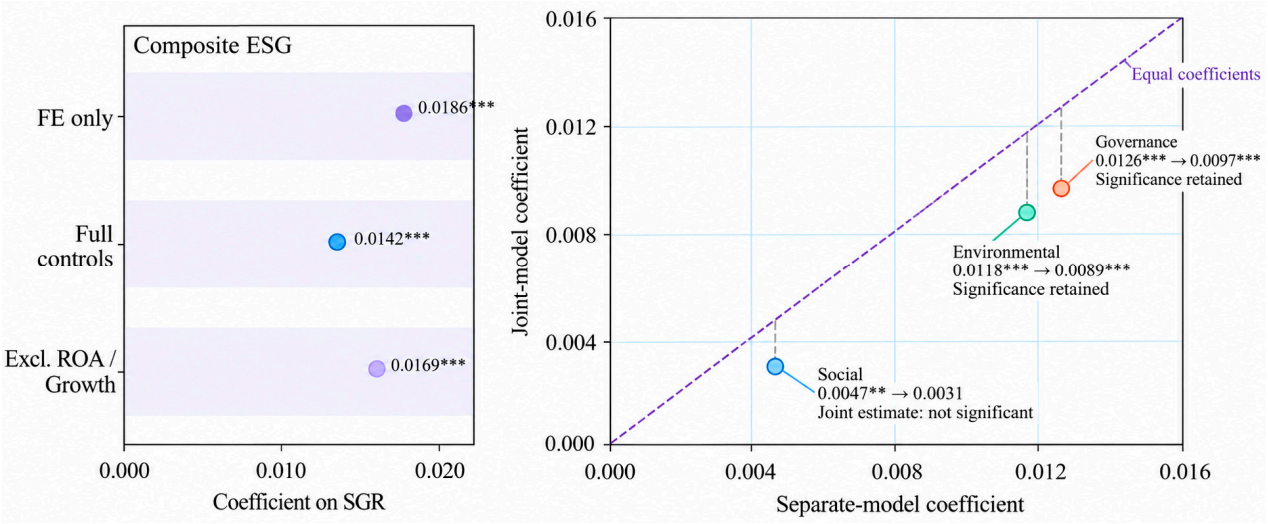


Figure 2. Associations of the composite ESG rating and its sub-dimensions with sustainable growth. The left panel shows the composite ESG coefficient under the three specifications of Table 4; the right panel compares separate- and joint-model coefficients of the environmental, social and governance scores, and the dashed line marks equal coefficients. Colours only distinguish the specifications and sub-dimensions. *** and ** indicate significance at the 1% and 5% levels.

4.3. Mediation Effect Test

To test the mediating role of green technological innovation, we estimate Equations (3) and (4); the results are reported in Table 5. The total effect of ESG ratings on sustainable growth is 0.0142. The coefficient of ESG (t − 1) on GTI(t) is 0.0876 and significant at the 1% level. When ESG and GTI enter Equation (4) together, the coefficient of GTI(t) on SGR (t + 1) is 0.0231 and the direct effect of ESG (t − 1) falls to 0.0122, both significant at the 1% level. The indirect effect is 0.0020 (0.0876 × 0.0231), and the decomposition identity holds (0.0142 = 0.0122 + 0.0020), indicating that green technological innovation partially mediates the association between ESG ratings and corporate sustainable growth.

Table 5. Mediation test: green technological innovation.

Variable	(1) SGR (t + 1)	(2) GTI (t)	(3) SGR (t + 1)
ESG (t − 1)	0.0142 *** (6.83)	0.0876 *** (11.24)	0.0122 *** (5.91)
GTI (t)			0.0231 *** (9.86)
Size	0.0093 *** (5.14)	0.2143 *** (18.62)	0.0044 ** (2.38)
Lev	−0.1124 *** (−14.62)	−0.0847 *** (−3.21)	−0.1104 *** (−14.35)
ROA	1.0237 *** (52.18)	0.2847 *** (3.86)	1.0171 *** (51.84)
Growth	0.0418 *** (16.73)	0.0214 *** (2.63)	0.0413 *** (16.52)
Age	−0.0156 *** (−4.27)	−0.0392 ** (−2.14)	−0.0147 *** (−4.03)
Board	0.0061 * (1.82)	0.0873 *** (2.94)	0.0041 (1.23)
Top1	0.0214 *** (4.36)	−0.0684 ** (−2.19)	0.0230 *** (4.69)
Dual	0.0017 (1.04)	0.0102 (0.87)	0.0015 (0.92)
TobinQ	−0.0029 *** (−4.91)	0.0136 *** (3.42)	−0.0032 *** (−5.36)
Cashflow	0.0683 *** (8.27)	0.3241 *** (4.76)	0.0608 *** (7.41)
Constant	−0.0517 (−1.43)	−4.4926 *** (−17.38)	0.0521 (1.42)
Year/Industry FE	Yes	Yes	Yes
N	25,683	25,683	25,683
Adj. R^2	0.412	0.387	0.418
Effect decomposition			
Total effect (c)	0.0142		
First-stage path (a)		0.0876	
Second-stage path (b)			0.0231
Direct effect (c′)			0.0122
Indirect effect (a × b)			0.0020
Proportion mediated			14.2%

Note: *t*-statistics based on firm-clustered standard errors are in parentheses; ***, ** and * indicate significance at the 1%, 5% and 10% levels. In the effect decomposition, c is the total effect, a the first-stage path, b the second-stage path and c′ the direct effect, as defined in Equations (2)–(5).

The firm-level cluster bootstrap with 5000 replications yields an indirect effect of 0.00202 with a 95% confidence interval of [0.00148, 0.00261] (Table 6, Panel A). The direct effect is 0.01218, and its confidence interval also excludes zero, supporting H2a and H2b. The indirect effect accounts for 14.2% of the total effect and the direct effect for 85.8%. Green technological innovation is therefore a reliable but secondary route, and most of the association operates through the direct route examined in the channel analysis below (Figure 3).

Because more than half of the GTI observations are zero, OLS may misstate the first-stage path. We therefore re-estimate Equation (3) with PPML, which is consistent for count outcomes with many zeros [42], and with a Tobit model, and recompute the indirect effect with the firm-cluster bootstrap (Table 6, Panel B). The PPML coefficient of ESG on green patent applications is 0.1352 (t = 9.74), implying that a one-grade upgrade is associated with about 14.5% more applications (exp(0.1352) − 1). To make these first stages comparable with the second stage, we convert them into average marginal effects on GTI

before multiplying by b. The resulting indirect effects are 0.0031 (PPML) and 0.0046 (Tobit), accounting for 22.0% and 32.1% of the total effect, with bootstrap confidence intervals that exclude zero. These shares are larger than the OLS-based 14.2%, so the OLS figure is best viewed as a conservative estimate, but the qualitative conclusion is unchanged: green technological innovation remains a secondary route.

Table 6. Bootstrap decomposition of the mediation effect (firm-cluster bootstrap, 5000 replications).

Effect	Path	Coefficient	Boot SE	95% CI Lower	95% CI Upper	Share of Total Effect
Panel A: OLS						
Indirect	ESG → GTI → SGR	0.00202	0.00029	0.00148	0.00261	14.2%
Direct	ESG → SGR	0.01218	0.00206	0.00814	0.01622	85.8%
Total	ESG → SGR	0.01420	0.00208	0.01012	0.01828	100.0%
Panel B: Censored Mediator	**First-Stage Coefficient**	**AME on GTI**	**Indirect Effect**	**Boot SE**	**95% CI**	**Share of Total Effect**
OLS (baseline)	0.0876 ***	0.0876	0.00202	0.00029	[0.00148, 0.00261]	14.2%
PPML first stage	0.1352 ***	0.1352	0.00312	0.00045	[0.00224, 0.00400]	22.0%
Tobit first stage	0.1974 ***	0.1974	0.00456	0.00059	[0.00339, 0.00573]	32.1%

Note: Bootstrap resampling is conducted at the firm level (all years of a sampled firm are retained). In Panel B, the first-stage PPML and Tobit coefficients are converted into average marginal effects (AME) on GTI and multiplied by the second-stage coefficient b = 0.0231. *** indicates significance at the 1% level.

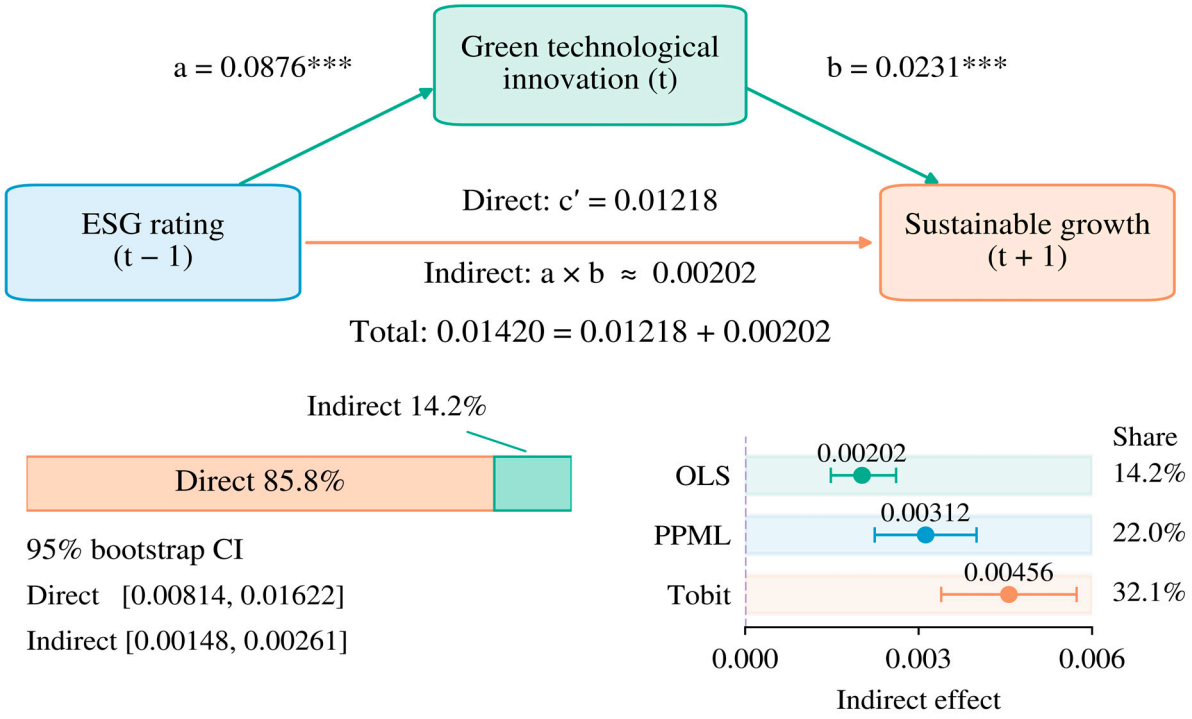


Figure 3. Mediation path of green technological innovation and decomposition of the total effect. Green denotes the indirect route through green technological innovation and orange the direct route; in the lower right panel, colours distinguish the OLS, PPML and Tobit estimates. *** indicates significance at the 1% level.

The firm-level cluster bootstrap with 5000 replications yields an indirect effect of 0.00202 with a 95% confidence interval of [0.00148, 0.00261] (Table 6, Panel A). The direct effect is 0.01218, and its confidence interval also excludes zero, supporting H2a and H2b. The indirect effect accounts for 14.2% of the total effect and the direct effect for 85.8%. Green technological innovation is therefore a reliable but secondary route, and most of

the association remains in the direct path, for which the channel analysis below identifies potential complementary channels (Figure 3).

4.4. Moderating Effect Tests

4.4.1. First-Stage Moderation by Financing Constraints

Table 7 reports the first-stage moderation. The coefficient of ESG × FC is −0.0524 and significant at the 1% level: the positive association between ESG ratings and green technological innovation weakens as financing constraints tighten. In practical terms, the simple slope of ESG on GTI is 0.1048 at low constraints (mean − 1 SD) and 0.0778 at high constraints (mean + 1 SD), a reduction of about 26%. This is consistent with the argument that severely constrained firms cannot provide sustained funding for green technological innovation, so a favourable rating is less readily converted into R&D investment. H3 is supported at the first stage (Figure 4).

Table 7. First-stage moderation: financing constraint.

Variable	(1) GTI(t)
ESG (t − 1)	0.0913 *** (11.78)
FC (t − 1)	−0.3286 *** (−7.41)
ESG (t − 1) × FC (t − 1)	−0.0524 *** (−4.86)
Controls	Yes
Year/Industry FE	Yes
N	25,683
Adj. R^2	0.392

Note: Interaction variables are mean-centred; *t*-statistics based on firm-clustered standard errors are in parentheses; *** indicates significance at the 1% level.

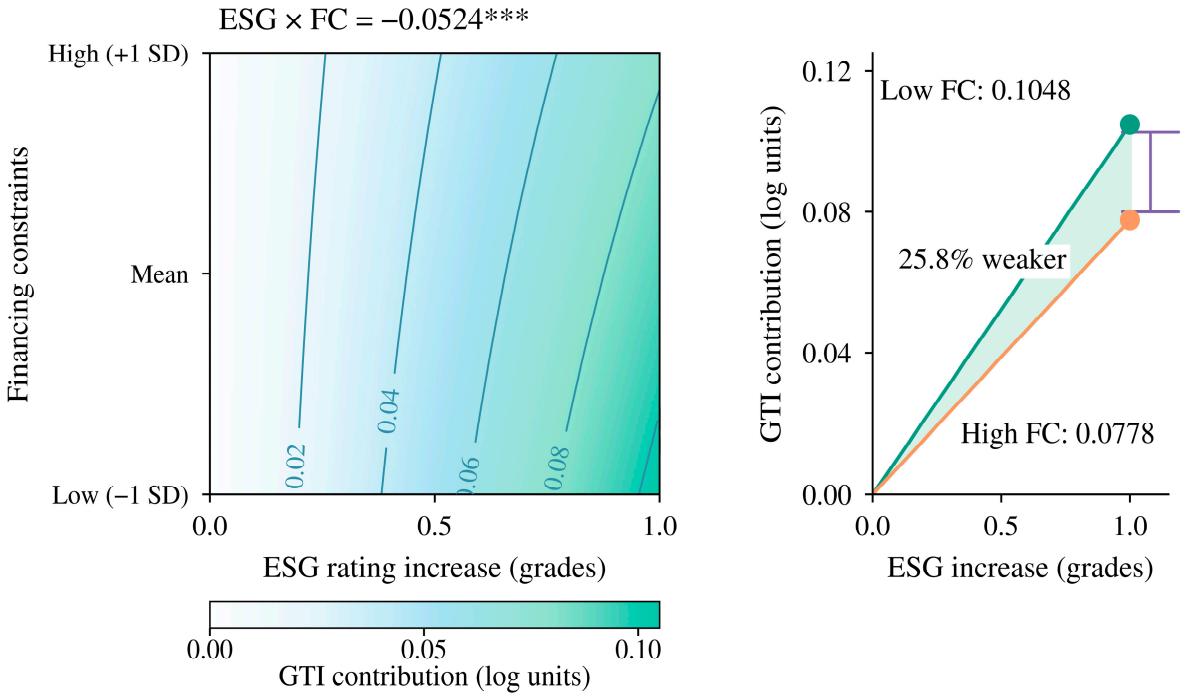


Figure 4. Simple slopes of ESG on green technological innovation at low and high financing constraints. In the left panel, colour shading shows the predicted contribution of ESG to GTI (see the colour bar); in the right panel, green and orange denote low and high financing constraints (mean ± 1 SD). *** indicates significance at the 1% level.

4.4.2. Second-Stage Moderation by Market Competitive Position

Table 8 reports the second-stage moderation. The coefficient of GTI × MCP is 0.0387 and significant at the 1% level: green technological innovation is more strongly associated with sustainable growth when the firm's market position is more favourable. The simple slope of GTI on SGR rises from 0.0163 at low MCP to 0.0273 at high MCP, an increase of about 67%. Firms with stronger positions appear better able to capture the value created by green technological innovation through pricing power and market reach. H4 is supported at the second stage (Figure 5).

Table 8. Second-stage moderation: market competitive position.

Variable	(1) SGR (t + 1)
GTI ** (t)	0.0218 *** (9.31)
MCP(t)	0.1573 *** (12.46)
GTI (t) ** × MCP ** (t)	0.0387 *** (5.62)
ESG (t − 1) **	0.0089 *** (4.33)
Controls	Yes
Year/Industry FE	Yes
N	25,683
Adj. R^2	0.431

Note: Interaction variables are mean-centred; *t*-statistics based on firm-clustered standard errors are in parentheses; *** and ** indicate significance at the 1% and 5% level.

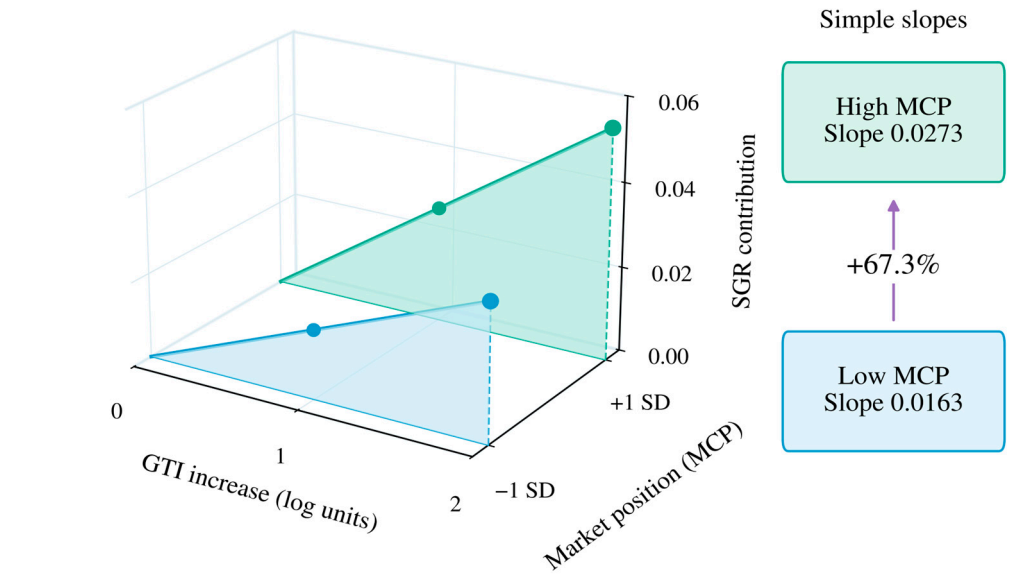


Figure 5. Simple slopes of green technological innovation on sustainable growth at low and high market competitive position. Green and blue denote high and low market competitive position (mean ± 1 SD), respectively. *** indicates significance at the 1% level.

4.4.3. Test of the Moderated Mediation Effect

Table 9 reports the moderated mediation results from the joint estimation of Equations (6) and (7), in which both moderators enter simultaneously. The index of moderated mediation for financing constraints is $a_3 \times b_1 = (-0.0524) \times 0.0218 = -0.00114$, with a bootstrap 95% confidence interval of [−0.00166, −0.00062] that excludes zero. The conditional indirect effect is 0.00229 at low constraints (mean − 1 SD) and 0.00170 at high constraints (mean + 1 SD); the difference (−0.00059) equals the index multiplied by two standard

deviations of FC (-0.00114×0.516), satisfying the consistency check. H3 is supported. The index for market position is $a_1 \times b_3 = 0.0913 \times 0.0387 = 0.00353$, with a confidence interval of [0.00216, 0.00490]. The conditional indirect effect rises from 0.00149 at low MCP to 0.00249 at high MCP, and the difference (0.00100) equals 0.00353×0.284. H4 is supported. Figure 6 plots the conditional indirect effect continuously over the range of each moderator, together with the joint surface over both moderators, showing how the two boundary conditions reshape the ESG–growth pathway.

Table 9. Index of moderated mediation and conditional indirect effects.

Moderator	Stage	Level	Conditional Indirect Effect	Boot SE	95% CI	Index of Moderated Mediation	Boot SE	95% CI
Financing constraint (FC)	First stage (ESG → GTI)	Low (mean − 1 SD)	0.00229 ***	0.00038	[0.00155, 0.00303]			
		Mean	0.00199 ***	0.00029	[0.00142, 0.00256]	−0.00114 ***	0.00027	[−0.00166, −0.00062]
		High (mean + 1 SD)	0.00170 ***	0.00027	[0.00117, 0.00223]			
Market competitive position (MCP)	Second stage (GTI → SGR)	Low (mean − 1 SD)	0.00149 ***	0.00031	[0.00088, 0.00210]			
		Mean	0.00199 ***	0.00029	[0.00142, 0.00256]	0.00353 ***	0.00070	[0.00216, 0.00490]
		High (mean + 1 SD)	0.00249 ***	0.00036	[0.00179, 0.00320]			

Note: Estimates from the joint estimation of Equations (6) and (7); each index is evaluated with the other moderator at its mean. Confidence intervals are from the firm-cluster bootstrap with 5000 replications. *** indicates significance at the 1% level.

Conditional indirect effect of ESG on sustainable growth through green technological innovation across financing constraints (A), market competitive position (B) and their combination (C). The lines and surface are computed from $(a_1 + a_3W)(b_1 + b_3Z)$ using the estimates in Tables 7–9; markers show bootstrap 95% confidence intervals at −1 SD, the mean and +1 SD.

Because each index is evaluated with the other moderator at its mean, Table 10 reports conditional indirect effects for the four combinations of high and low FC and MCP, calculated as $(a_1 + a_3W)(b_1 + b_3Z)$. The indirect effect is largest for firms with low constraints and a strong position (0.00286) and smallest for firms with high constraints and a weak position (0.00127); the former is 2.25 times the latter, and the difference (0.00159) is significant (Figure 7). The innovation route therefore operates most fully when firms can both fund green technological innovation and sell its results; if either condition is missing, the indirect association is markedly smaller.

Because both moderators could in principle affect both stages, we also estimate a fully moderated model that adds ESG × MCP to Equation (6) and GTI × FC to Equation (7). The cross-stage interaction coefficients are 0.0048 ($t = 0.72$) and −0.0056 ($t = -0.91$) and are statistically insignificant, whereas the hypothesised interactions remain significant, with similar magnitudes. This supports the stage-specific moderation structure of Model 21.

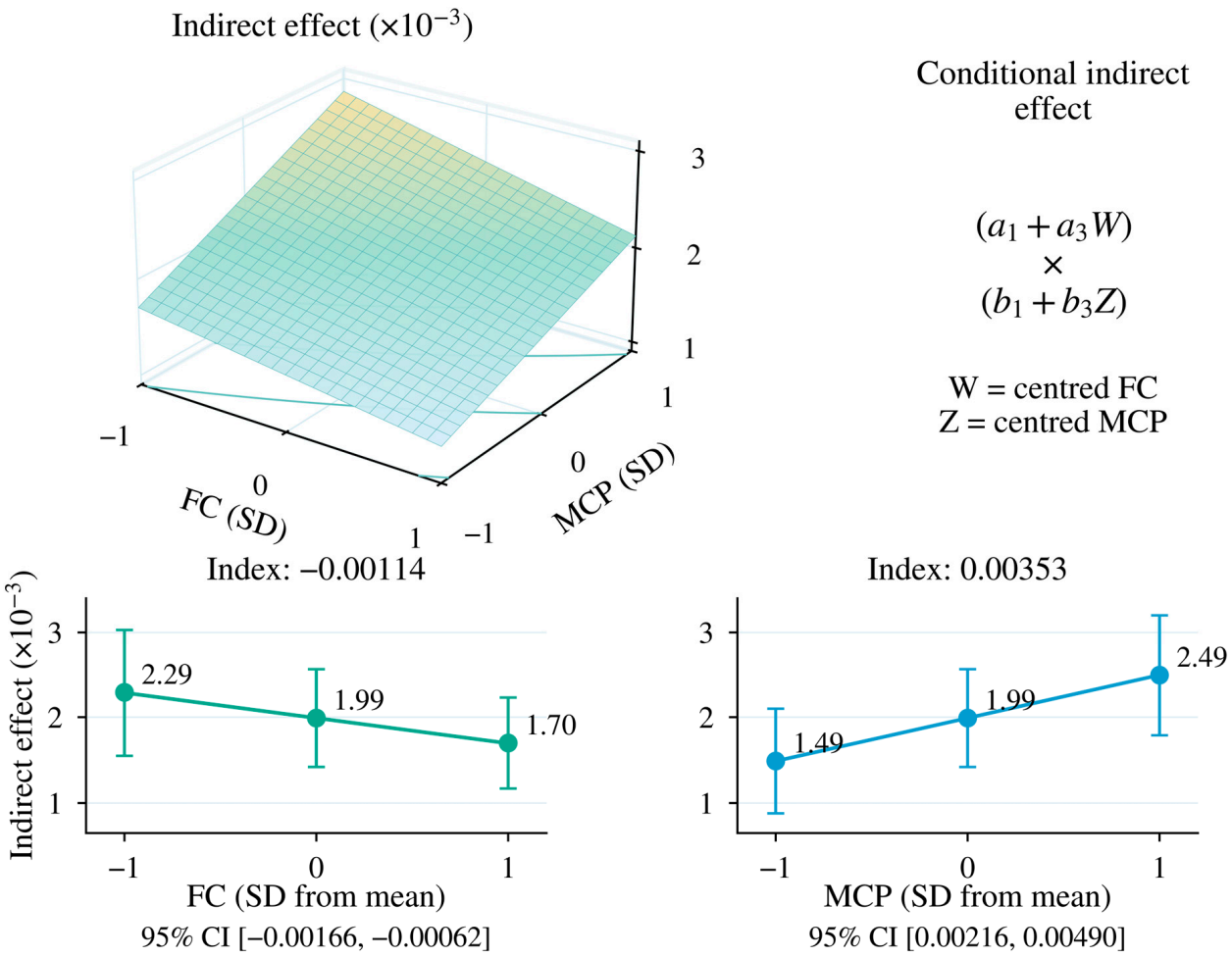


Figure 6. Marginal-effect plots. Marginal-effect plots showing conditional indirect effects across FC and MCP levels. The yellow-to-cyan gradient on the 3D surface indicates decreasing indirect-effect values. The green line represents conditional indirect effects across FC levels, while the blue line represents conditional indirect effects across MCP levels. Error bars indicate 95% confidence intervals.

Table 10. Conditional indirect effects across combinations of financing constraint and market competitive position.

Financing Constraint	Market Competitive Position	Conditional Indirect Effect	Boot SE	95% CI
Low (−1 SD)	High (+1 SD)	0.00286 ***	0.00051	[0.00186, 0.00386]
High (+1 SD)	High (+1 SD)	0.00212 ***	0.00042	[0.00130, 0.00294]
Low (−1 SD)	Low (−1 SD)	0.00171 ***	0.00036	[0.00100, 0.00242]
High (+1 SD)	Low (−1 SD)	0.00127 ***	0.00031	[0.00066, 0.00188]
Difference (best vs. worst scenario)		0.00159 ***	0.00043	[0.00075, 0.00243]

Note: Confidence intervals are from the firm-cluster bootstrap with 5000 replications. *** indicates significance at the 1% level.

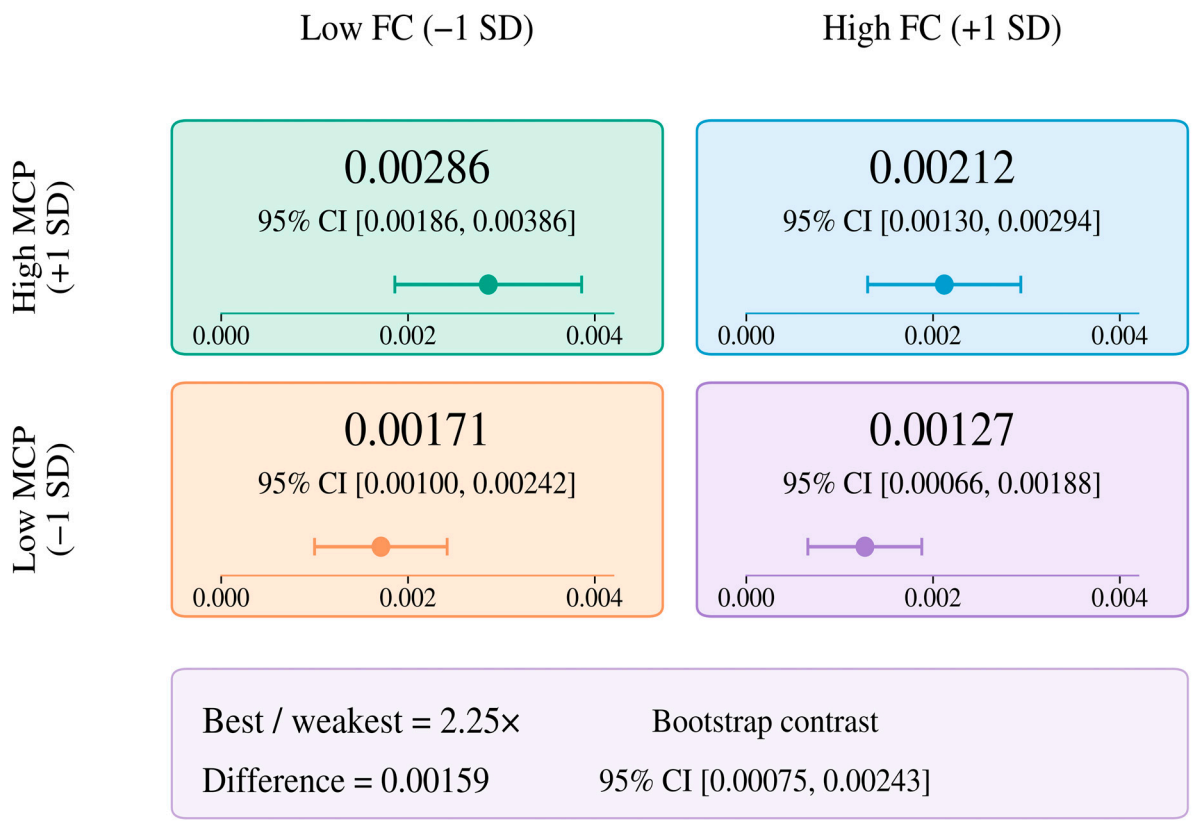


Figure 7. Conditional indirect effects in the four scenarios of Table 10 with bootstrap 95% confidence intervals.

4.5. Endogeneity

Reverse causality and omitted variables may affect the relationship between ESG ratings and sustainable growth: firms with strong growth may be better able to invest in ESG and obtain higher ratings, and unobserved management quality may drive both. The lead–lag design, in which ESG is measured two years before SGR, mitigates contemporaneous reverse causality but cannot rule out persistent growth trends, and firm fixed effects remove only time-invariant confounders. We therefore use instrumental variables (Table 11).

The first instrument, IV_Industry, is the average ESG rating of other firms in the same industry and year; peer practice affects a focal firm's ESG decisions through imitation and the diffusion of industry norms. The second, IV_Region, is the average rating of other listed firms registered in the same city and year, reflecting regional institutional and regulatory pressure. The exclusion restriction requires that, conditional on the controls and fixed effects, peer ratings affect a firm's growth only through its own rating. Two threats are relevant. First, peer ratings could capture industry booms or regional economic conditions; we therefore control in both stages for industry–year mean revenue growth and regional GDP growth, so the remaining variation in the instruments comes from differences in ESG practice that are not explained by contemporaneous demand. Second, peer ratings could reflect competition—for example, when greener rivals gain market share; because competition operates mainly within industries, we recompute IV_Region using only firms in other industries in the same city, which removes direct competitors, and the second-stage ESG coefficient is 0.0209 (t = 5.51; Table 12, row 22).

Table 11. Endogeneity test: instrumental variable estimation (2SLS).

Variable	(1) First Stage: ESG (t − 1)	(2) Second Stage: SGR (t + 1)
IV_Industry	0.6142 *** (38.27)	
IV_Region	0.4318 *** (24.61)	
ESG (t − 1) (fitted)		0.0218 *** (5.94)
Size	0.3184 *** (24.63)	0.0072 *** (3.68)
Lev	−0.2847 *** (−6.18)	−0.1096 *** (−13.84)
ROA	1.4726 *** (12.84)	1.0184 *** (49.72)
Growth	0.0384 *** (3.21)	0.0412 *** (16.24)
Age	−0.1263 *** (−4.52)	−0.0142 *** (−3.86)
Board	0.2417 *** (4.86)	0.0048 (1.42)
Top1	0.3892 *** (6.74)	0.0187 *** (3.72)
Dual	−0.0287 ** (−2.13)	0.0021 (1.26)
TobinQ	0.0216 *** (3.94)	−0.0033 *** (−5.42)
Cashflow	0.6318 *** (7.26)	0.0621 *** (7.31)
Ind_Growth (industry-year mean)	0.0642 ** (2.27)	0.0234 *** (2.86)
GDP_Growth (regional)	0.5183 *** (3.08)	0.1847 ** (2.31)
Constant	−3.8412 *** (−12.47)	−0.0684 * (−1.78)
Year/Industry FE	Yes	Yes
Identification tests		
Kleibergen–Paap rk LM statistic	794.2 [0.000]	
Kleibergen–Paap rk Wald F	412.6	
Stock–Yogo 10% critical value	19.93	
Partial R^2 of excluded instruments	0.031	
Hansen J statistic		1.362 [0.243]
Durbin–Wu–Hausman test		6.32 [0.012]
N	25,683	25,683
Adj. R^2/Centred R^2	0.418	0.409

Note: *t*-statistics based on firm-clustered standard errors are in parentheses; *p*-values are in brackets; ***, ** and * indicate significance at the 1%, 5% and 10% levels.

In the first stage, both instruments are positive and significant at the 1% level. The Kleibergen–Paap rk Wald F statistic is 412.6, far above the Stock–Yogo 10% critical value of 19.93, so weak instruments are not a concern. The Hansen J statistic ($p = 0.243$) does not reject the overidentifying restrictions; this provides supporting evidence rather than definitive proof of instrument validity, since the test has power only if at least one instrument is valid. In the second stage, the ESG coefficient is 0.0218 and significant at the 1% level, consistent with the baseline result.

The 2SLS estimate (0.0218) exceeds the OLS estimate (0.0142). If reverse causality, whereby better-growing firms improve their ESG performance, were the main source of bias, OLS would overstate the effect and the IV estimate would be smaller. The opposite pattern is more consistent with attenuation bias from measurement error: as a third-party assessment of non-financial performance with coarse categories (nine grades, of which seven are observed), the rating contains considerable noise, which biases the OLS coefficient towards zero; this interpretation agrees with the literature on rating disagreement and noise. Because the IV estimate is a local estimate for firms whose ratings respond to peer ratings, we treat the OLS coefficient as a conservative benchmark rather than a precise lower bound. Regarding sample selection, Huazheng ratings cover all A-share listed firms, so there is no selection into being rated and a Heckman correction is not required; differences in ESG ratings are a treatment-selection issue, which we address with propensity-score matching.

4.6. Robustness Tests

Table 12 summarises the robustness tests and Figure 8 compares the main coefficients. First, alternative measures: with SynTao ratings (9317 observations), the ESG coefficient is 0.0128; with the four-quarter average Huazheng rating, it is 0.0149; and when green technological innovation, market position and financing constraints are measured by green patent grants, market share and the KZ index, the mediating effect and both moderating effects remain significant. Second, rating-category dummies: replacing the linear ESG term

with dummies for each observed grade (C and CC as the base category), the coefficients for CCC, B, BB, BBB and A are 0.0091, 0.0218, 0.0345, 0.0472 and 0.0599, increasing broadly monotonically, so the linear specification is a reasonable approximation within the observed range (row 16). Third, alternative growth measures: the ESG coefficient is 0.0068 for sales growth and 0.0054 for total asset growth (rows 17 and 18), and 0.0146 when loss-making firm-years and firm-years with a payout ratio above one are excluded (row 19).

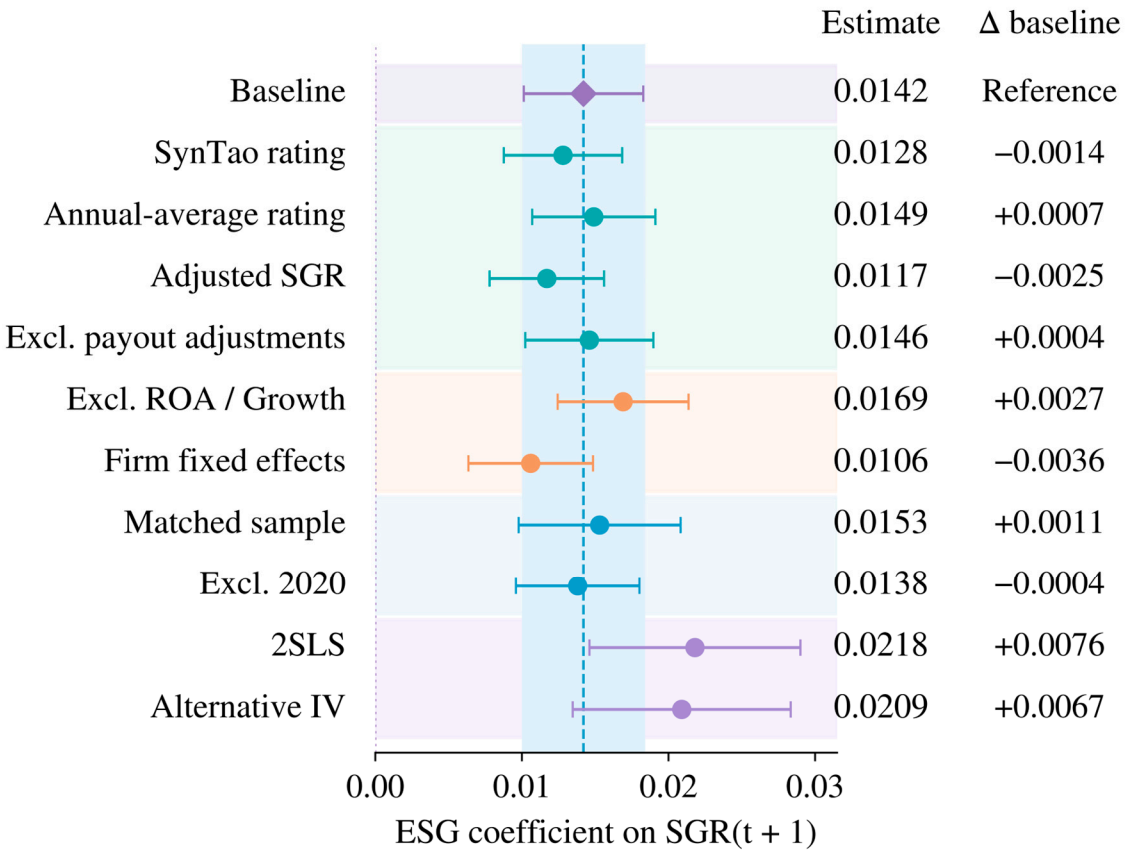


Figure 8. Comparison of ESG coefficients on SGR (t + 1) across robustness tests (95% confidence intervals). The dashed line and the blue band mark the baseline estimate and its 95% confidence interval; background colours group the tests into alternative measures, control and fixed-effect specifications, sample checks and instrumental-variable estimates.

Fourth, the PPML and Tobit first-stage estimates (rows 7 and 8), discussed with the mediation results, exceed the OLS estimate, so the OLS-based mediation share is conservative. Fifth, excluding ROA and Growth gives 0.0169 (row 9); decomposing SGR, the ESG coefficients for ROE and the retention ratio are 0.0148 and 0.0217, and the implied profit and retention contributions (0.0107 and 0.0018) together account for about 88% of the total effect. Sixth, adding ESG × Size and ESG × Age leaves the ESG × FC coefficient at −0.0498, within 5% of the baseline value of −0.0524, so the moderating effect of financing constraints is not a disguised size or age effect.

Seventh, propensity-score matching. Because ESG is ordinal, treated firms are those with a rating at or above BB (ESG ≥ 5), that is, above the sample median grade of B, and control firms are the remaining firms. The propensity score is estimated with a logit model of treatment status on all control variables (Size, Lev, ROA, Growth, Age, Board, Top1, Dual, TobinQ and Cashflow) and year and industry dummies. One-to-one nearest-neighbour matching with a caliper of 0.01 yields 11,246 matched pairs (22,492 observations); after matching, all standardised differences are below 10%, and the ESG coefficient on the matched sample is 0.0153 (row 13). Finally, excluding 2020 (COVID-19 shock) gives 0.0138

on 22,969 observations (row 14), and firm fixed effects give 0.0106 (row 15), as discussed above. Across all tests, the ESG–growth association remains positive and significant, and the estimates based on the four-quarter average rating, PPML, Tobit, 2SLS and the reduced control set exceed the baseline coefficient, reinforcing the view that 0.0142 is conservative.

Table 12. Robustness checks.

#	Category	Method	Coefficient	t-Value	N	Conclusion
1	Alternative explanatory variable	SynTao Green ESG rating replaces Huazheng	0.0128 ***	6.21	9317	H1 supported
2	Alternative explanatory variable	Four-quarter average Huazheng rating	0.0149 ***	6.95	25,683	H1 supported
3	Alternative mediator	Green patent grants replace applications	0.0641 ***	6.83	25,683	H2a supported
4	Alternative dependent variable	Adjusted SGR allowing external financing	0.0117 ***	5.87	25,683	H1 supported
5	Alternative moderator (first stage)	KZ index replaces SA index	−0.0087 ***	−3.94	25,683	H3 supported
6	Alternative moderator (second stage)	Market share replaces industry-adjusted Lerner index	0.0846 ***	4.21	25,683	H4 supported
7	Censored mediator	Tobit estimation of Equation (3)	0.1974 ***	12.83	25,683	H2a supported
8	Censored mediator	PPML estimation of Equation (3)	0.1352 ***	9.74	25,683	H2a supported
9	Avoiding over-control	Excluding ROA and Growth	0.0169 ***	7.42	25,683	H1 supported
10	Decomposing the dependent variable	ROE as the dependent variable	0.0148 ***	7.32	25,683	H1 supported
11	Decomposing the dependent variable	Retention ratio (b) as the dependent variable	0.0217 ***	4.65	25,683	H1 supported
12	Ruling out size/age effects	Adding ESG × Size and ESG × Age to Equation (6)	−0.0498 ***	−4.31	25,683	H3 supported
13	Propensity score matching	Regression on the 1:1 nearest-neighbour matched sample	0.0153 ***	5.43	22,492	H1 supported
14	Alternative sample period	Excluding 2020 (COVID-19 shock)	0.0138 ***	6.42	22,969	H1 supported
15	Alternative fixed effects	Firm fixed effects replace industry fixed effects	0.0106 ***	4.89	25,683	H1 supported
16	Ordinal rating	Rating-category dummies (coefficient on grade A; base C/CC)	0.0599 ***	5.20	25,683	H1 supported
17	Alternative growth measure	Sales growth (t + 1) as the dependent variable	0.0068 ***	3.12	25,683	H1 supported
18	Alternative growth measure	Total asset growth (t + 1) as the dependent variable	0.0054 ***	2.76	25,683	H1 supported
19	SGR adjustments	Excluding loss-making and payout > 1 observations 0.0146	0.0146 ***	6.55	25,683	H1 supported
20	Cross-stage moderation	ESG × MCP added to Equation (6)	0.0048	0.72	25,683	Not significant
21	Cross-stage moderation	GTI × FC added to Equation (7)	−0.0056	−0.91	25,683	Not significant
22	Alternative instrument	IV_Region computed from firms in other industries (2SLS)	0.0209 ***	5.51	25,683	H1 supported

Note: The coefficient reported is that of the key variable in each test (ESG, the interaction term, or the mediator path). *** indicates significance at the 1% level.

4.7. Heterogeneity Analysis

We examine heterogeneity by ownership, life-cycle stage and industry pollution attributes, defined as in Section 3.2; heavy-polluting industries account for 28.9% of observations. Because differences in subsample coefficients are not by themselves evidence of

differences in effects, we test them with seemingly unrelated estimation (SUEST) and a Fisher permutation test with 1000 draws (Table 13). The association is significantly stronger for non-state-owned than for state-owned firms (0.0179 vs. 0.0086; difference 0.0093, empirical $p = 0.008$). Across life-cycle stages, it is strongest in the growth stage (0.0204), weaker in the mature stage (0.0098) and weakest and only marginally significant in the decline stage (0.0061); the growth–mature difference (0.0106) is significant ($p = 0.004$). It is also stronger in heavy-polluting than in clean industries (0.0193 vs. 0.0116; difference 0.0077, $p = 0.026$) (Figure 9). The interpretation of these patterns is developed in the Discussion section.

Table 13. Heterogeneity of the association between ESG ratings and sustainable growth by ownership, life-cycle stage and industry pollution.

Dimension	Subsample	ESG Coefficient	t-Value	N	Empirical *p*-Value of Between-Group Difference
Ownership	State-owned	0.0086 ***	3.21	9842	0.008
	Non-state-owned	0.0179 ***	6.48	15,841	
Life cycle	Growth stage	0.0204 ***	5.92	8267	0.004 (growth vs. mature)
	Mature stage	0.0098 ***	3.84	11,436	
	Decline stage	0.0061 *	1.87	5980	
Industry pollution	Heavy-polluting	0.0193 ***	5.67	7415	0.026
	Clean	0.0116 ***	4.93	18,268	

Note: *** and * indicate significance at the 1% and 10% levels. Between-group differences are tested with SUEST and a Fisher permutation test (1000 draws).

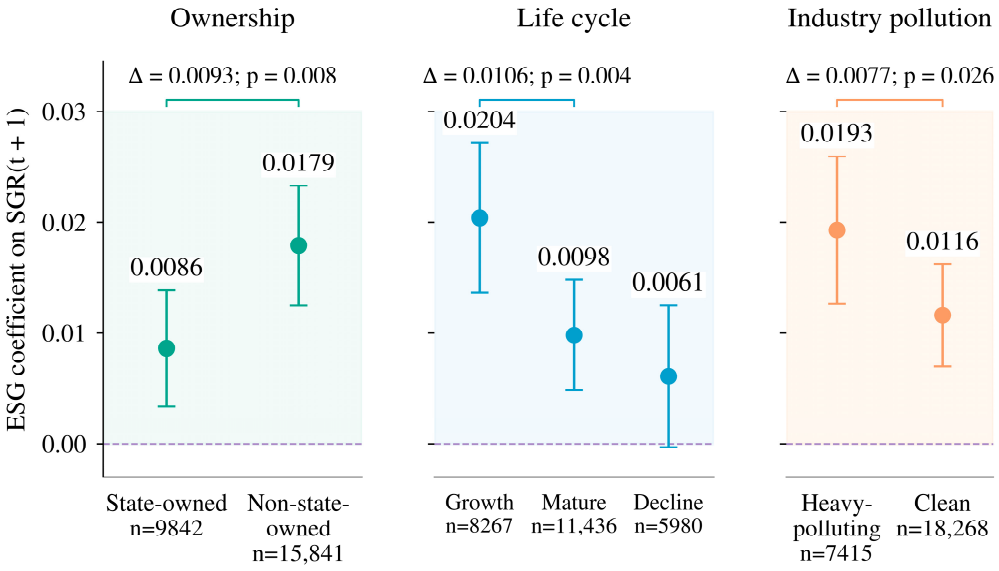


Figure 9. Heterogeneity in the ESG–SGR association with 95% confidence intervals. Colours only distinguish the three grouping dimensions; Δ is the between-group difference in coefficients and p is the empirical *p*-value of the Fisher permutation test.

4.8. Channel Analysis of the Direct Route

To explore the direct route anticipated in H2b, we regress four resource and risk indicators on ESG (Table 14). The cost of debt is interest expense divided by average interest-bearing liabilities, the cost of equity is estimated with the PEG model, operating risk is the rolling three-year standard deviation of ROA, and crash risk is the negative coefficient

of skewness of firm-specific returns (NCSKEW). A one-grade upgrade is associated with a 0.21 percentage-point lower cost of debt and a 0.34 percentage-point lower cost of equity, and with significantly lower operating and crash risk, all at the 1% level. These results are consistent with H2b and with prior evidence on ESG, financing and risk [26,49,50]: higher-rated firms face cheaper capital and lower volatility, which can loosen the financial limits on internally financed growth and stabilise the earnings that feed retention. Because each indicator is examined in a separate regression rather than in a formal multiple-mediation model, the results identify plausible complementary channels; they do not show that these channels fully account for the remaining 85.8% of the total association (Figure 10).

Table 14. Channel analysis: potential complementary channels of the direct association.

Variable	(1) Cost of Debt	(2) Cost of Equity	(3) Operating Risk	(4) Crash Risk (NCSKEW)
ESG (t − 1)	−0.0021 *** (−4.73)	−0.0034 *** (−5.28)	−0.0018 *** (−4.06)	−0.0163 *** (−3.71)
Controls	Yes	Yes	Yes	Yes
Year/Industry FE	Yes	Yes	Yes	Yes
N	24,106	16,428	23,517	24,892
Adj. R^2	0.216	0.183	0.264	0.078

Note: *t*-statistics based on firm-clustered standard errors in parentheses; *** indicates significance at the 1% level. Sample sizes differ because of data availability for each indicator.

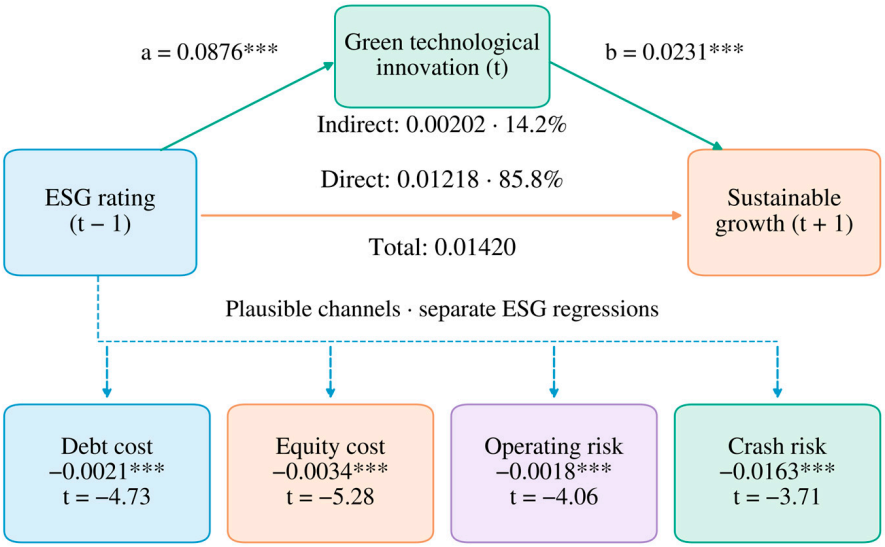


Figure 10. Dual-route mechanism linking ESG ratings and sustainable growth (summary of main estimates). Green and orange arrows denote the indirect route through green technological innovation and the direct route; dashed blue arrows lead to the channel regressions of Table 14, whose box colours only distinguish the four channels. *** indicates significance at the 1% level.

The financing channel may also link the two routes. Better financing conditions can lower the cost of capital needed to sustain existing growth, and part of the funds they release may be allocated to green R&D, feeding the first stage of the green technological innovation route. This potential overlap may help explain why both a significant direct association and a significant indirect association are observed [10,24]. Because each indicator is examined in a separate regression rather than in a formal multiple-mediation model, the results point to potential complementary channels; they do not establish that these channels account for the remaining 85.8% of the total association (Figure 10).

5. Discussion

5.1. Why Green Technological Innovation Explains Only a Limited Share

The finding that green technological innovation accounts for about 14% of the total association, or somewhat more under count-data estimators, admits three complementary explanations. First, timing: the innovation route requires a rating to stimulate R&D, R&D to produce patents and patents to be commercialised, whereas any effects operating through lower financing costs and reduced risks would reach profitability and retention more quickly, so within a two-year window the innovation route can capture only part of its eventual effect. Second, measurement: patent applications record codified, patentable output and miss process improvements, organisational green practices and non-patented know-how, so the measured indirect effect understates the role of green technological innovation broadly understood. Third, uneven innovation propensity: more than half of the firm-years have no green patent applications, so for many firms the innovation route is inactive and any rating–growth association must arise outside it—for example, through the potential financing and risk channels suggested by Table 14. Together, these explanations suggest that the large direct association partly reflects horizon and measurement, and they caution against interpreting a significant mediator as evidence that it is the main mechanism.

5.2. Interpreting the Heterogeneous Effects

The heterogeneity results are consistent with the signalling and resource arguments. The stronger association for non-state-owned firms is consistent with their greater dependence on market-based financing: state-owned firms obtain credit largely on the basis of ownership and implicit guarantees [51,52], which dilutes the incremental information of a rating, whereas for private firms facing financing discrimination a good rating is a scarce credential that may lower financing costs, in line with the potential financing channel suggested by Table 14. The stronger association for growth-stage firms follows the same logic: these firms have abundant investment opportunities but limited internal funds [44], so any relaxation of financing constraints is more likely to translate into growth, while mature firms with ample cash flow gain less at the margin. The stronger association in heavy-polluting industries is consistent with the greater regulatory and reputational value of ESG improvements in sectors exposed to environmental enforcement; for these firms a better rating may signal a lower risk of penalties, production restrictions and reputational damage, which lenders price [53], and their larger scope for green transformation may strengthen both routes.

5.3. Comparison with Prior Research

The positive baseline association agrees with evidence that better ESG profiles ease financing and lower risk [4,15,21] and with Chinese evidence linking ESG to productivity and sustainable growth [11–13]. In line with Wang et al. and Zhang et al. [9,10], higher ratings are associated with more green patenting, and like Zhang et al., we find that financing conditions matter, although we identify them as a boundary condition of the first stage rather than only as a mediator. Our results differ from studies that implicitly treat green technological innovation as the principal channel: by decomposing the total association, we show that the innovation route is real but secondary. Finally, the IV estimate exceeding OLS is consistent with the rating-noise argument of Berg et al. [7] and suggests that measurement error in ratings, rather than an absence of real effects, may account for some of the weaker results reported in the literature.

6. Conclusions

6.1. Main Conclusions and Theoretical Implications

Using 25,683 firm-year observations of Chinese A-share firms from 2011 to 2022, this study finds that a one-grade-higher Huazheng ESG rating is associated with a 1.42 to 1.69 percentage-point-higher Higgins sustainable growth rate. Green technological innovation partially mediates this association but accounts for only about 14% of the total, and supplementary tests point to lower financing costs and reduced risks as potential complementary channels rather than formally identified mediators.

Green technological innovation partially mediates this association but accounts for only about 14% of the total, and supplementary tests point to lower financing costs and lower risk as plausible complementary channels. Financing constraints weaken the first stage of the innovation route, and a stronger competitive position strengthens its second stage. The associations are stronger for non-state-owned, growth-stage and heavily polluting firms. Theoretically, the results support a dual-route view in which a rating signal relates to financial sustainability both by mobilising resources for green technological innovation and by directly improving resource conditions, and they show that the two stages of the innovation route are governed by distinct resource-side and market-side conditions. Research on the consequences of ESG should therefore model both routes and should not equate the existence of a mediator with its dominance.

6.2. Practical Implications

First, because the association is driven mainly by the financing and risk route and is concentrated among non-state-owned and growth-stage firms, regulators can increase the value of ratings by improving their transparency and comparability—for example, by requiring rating agencies to disclose methodologies and the indicators behind rating changes, so that lenders and investors can price the signal more reliably. Second, because financing constraints weaken the conversion of ratings into green technological innovation (the indirect effect is about 26% smaller for highly constrained firms), green credit, green bond and guarantee programmes should target constrained firms with good ratings, for which funding rather than incentives is the binding constraint. Third, because market position strengthens the second stage (the indirect effect is about two-thirds larger for firms with strong positions), managers of firms with weak positions should pair green R&D with investment in commercialisation, such as certification, branding and channel development, rather than expecting patents alone to deliver growth. Fourth, because the association is strongest in heavy-polluting industries, where ESG improvements carry high regulatory and reputational value, investors and lenders should pay particular attention to rating upgrades in these sectors.

6.3. Limitations and Future Research

This study has several limitations. First, it relies on a single primary rating source; although the results hold with SynTao ratings on a smaller sample, ratings from different providers diverge, and future work could use multiple ratings or treat rating disagreement itself as a variable. Second, the evidence comes from Chinese A-share firms, whose ownership structures and regulatory environment differ from those of other markets, so generalisation should be cautious. Third, green technological innovation is measured by patent applications, which capture observable, patentable output but not organisational capability, process improvements or innovation quality; future studies could use patent citations, green R&D expenditure or survey-based capability measures. Fourth, observed ratings range only from C to A, so the results do not speak to the highest grades. Fifth, although lagged variables, instrumental variables, matching and firm fixed effects improve

credibility, the analysis relies on observational data, and the estimates should be interpreted as evidence consistent with the proposed mechanisms rather than as definitive causal effects; the channel tests of the direct route are association-based and could be extended with formal multiple-mediation or quasi-experimental designs, such as rating initiations or methodology changes. Finally, extending the sample beyond 2022 once complete patent data become available would allow for longer horizons for the innovation route.

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