World Journal of Economics and Business Research
Print ISSN: 2960-0073
Online ISSN: 2960-0081
DOI: https://doi.org/10.61784/wjebr3082

GREEN FINANCE POLICY AND TECHNOLOGICAL INNOVATION: EVIDENCE FROM 35 CHINESE AUTOMOTIVE FIRMS (2013–2023)

Jean Jacques Yves Leslie Bottine Junior
Business College, Southwest Minzu University, Chengdu 610093, Sichuan, China.

Abstract: This study examines how China's green finance development relates to corporate technological innovation in the automotive industry. Using firm–year observations from 2013–2023 for leading Chinese automotive firms, technological innovation is measured through patent applications and patent grants, expressed as logarithmic outcomes. Green finance is proxied by a national annual index, reflecting the macro policy-finance environment faced by firms each year.

To address missing values in firm-level covariates, the analysis employs multiple imputation (m = 5) and reports pooled estimates. Across baseline models with standard controls, green finance is associated with lower patent applications, while the relationship with patent grants is weaker and generally statistically insignificant. Policy-timing analysis around the 2016 green finance policy shift provides limited evidence of differential effects, and additional robustness checks including alternative cutoffs (lead/placebo timing) and pre/post subsample regressions support the overall pattern. Lag models indicate that the negative association is more pronounced for patent applications with one- to two-year delays, whereas patent grants remain comparatively insensitive.

Collectively, the findings suggest that macro green finance expansion does not translate mechanically into short-run increases in firm innovation outputs, and that firm fundamentals such as R&D, subsidies, and profitability remain central correlates of innovation performance. The results provide practical implications for policy design and corporate strategy in green transition contexts.

Keywords: Green finance; Technological innovation; Patents; Automotive industry; China; Policy timing

1 INTRODUCTION

This Green finance has become a central policy instrument for aligning financial resource allocation with environmental objectives, particularly in economies where industrial upgrading and emission reduction are pursued simultaneously. In China, the expansion of green credit, green bonds, and other sustainable finance mechanisms has been accompanied by policy guidance intended to steer capital toward cleaner production and strategic emerging industries. At the same time, technological innovation remains a key channel through which firms can improve energy efficiency, reduce carbon intensity, and develop competitive advantages in low-carbon transitions. These parallel policy and market dynamics make it important to examine how green finance is associated with firm-level innovation outcomes in practice.

The automotive industry provides a suitable setting for investigating this relationship. The sector is both innovation-intensive and environmentally consequential, involving long product cycles, substantial R&D investment, and complex supply chains. It is also closely linked to China's broader industrial strategy and energy transition agenda, including the diffusion of new energy vehicles and related technologies. Financial conditions and policy-oriented credit allocation can shape innovation incentives in this context, but the direction and timing of effects are not necessarily uniform. In particular, green finance may support innovation by easing financing constraints for R&D and cleaner technologies, while it may also generate short-term adjustment costs through compliance requirements, reporting burdens, or capital reallocation away from certain innovation activities.

This study examines the association between green finance development and corporate technological innovation using a panel of leading Chinese automotive firms over the period 2013–2023. Technological innovation is measured using two complementary patent-based indicators: patent applications (capturing innovation input and inventive activity) and patents granted (capturing realized and recognized outputs). This dual measurement helps distinguish between changes in innovation effort and changes in innovation realization, which may respond differently to financial and policy conditions. The empirical specification includes core firm fundamentals commonly linked to innovation capacity, including R&D intensity, government subsidies, profitability, leverage, employment scale, and revenue growth.

Beyond contemporaneous associations, the analysis evaluates whether effects materialize with delays by incorporating lag structures of green finance. This is particularly relevant in the automotive sector where innovation processes are cumulative and patent outcomes can reflect long lags between research effort, filing, examination, and grant. In addition, given the institutional emphasis on green finance after the mid-2010s, the study also considers whether relationships differ across the pre- and post-policy periods, and implements timing-based checks to assess whether the estimated patterns are consistent with a policy-related shift rather than an artefact of general time trends.

The findings from the empirical results section indicate that green finance is consistently associated with a reduction in patent applications, including in lagged specifications, whereas the relationship with patents granted is generally not statistically distinguishable from zero across comparable models. Moreover, policy-interaction estimates do not yield stable evidence of a discrete post-2016 amplification effect in the main specification. Taken together, these patterns suggest that green finance development may coincide with changes in firms' innovation behavior that are more visible in application-stage activity than in granted outcomes, with firm fundamentals especially R&D expenditure, government support, and profitability remaining the most stable correlates of technological innovation performance in the sample.

This paper contributes to the green finance and innovation literature by providing evidence from an industry that is strategically important for both decarbonization and industrial upgrading, while separating innovation activity into application and grant stages and explicitly testing lag structures and timing-based robustness checks. The results are framed as an assessment of the direction, timing, and heterogeneity of associations rather than as a claim that green finance uniformly increases innovation outputs. The remainder of the paper proceeds as follows: Section 2 reviews related literature and develops testable expectations; Section 3 describes data, variables, and empirical methods; Section 4 presents empirical findings; Section 5 discusses implications and interpretation; and Section 6 concludes with recommendations.

2 LITERATURE REVIEW

2.1 Green Finance and Innovation Outcomes

Green finance is commonly framed as a set of financial instruments and allocation practices intended to steer capital toward environmentally aligned activities while altering firms' investment incentives. In principle, the expansion of sustainable finance mechanisms can support innovation by easing financing frictions, improving risk pricing, and encouraging longer-horizon investment planning [1-4]. However, the same transition can also tighten screening standards, increase disclosure burdens, and reshape credit access, which may generate short-run adjustment pressures and heterogeneous innovation responses across firms and sectors [3,4].

China-focused evidence similarly suggests that the relationship between green finance policy and innovation outcomes is context-dependent rather than uniformly positive. Several studies report that green finance policy frameworks are associated with higher levels of green technology innovation, indicating that capital reallocation and policy signals may foster technology upgrading under certain conditions [5,6]. At the same time, evidence from environmentally intensive firms highlights that green finance-related constraints can coincide with weaker innovation performance in some settings, consistent with tighter financing conditions or compliance costs crowding out innovation activity [7,9]. These mixed findings imply that the net association between green finance development and observable innovation output depends on the dominant channel and the measurement choice used to capture innovation [5-7,9].

2.2 Mechanisms: Enabling and Constraining Channels

The literature typically explains green finance–innovation linkages through two competing channel families.

Enabling channels emphasize resource support and strategic upgrading. When sustainable finance expands and green-oriented funding becomes more accessible, firms may increase innovation investment, accelerate cleaner technology adoption, and strengthen innovation capability to align with evolving capital allocation criteria [1,3,6]. Related research also indicates that sustainability-linked finance and broader ESG/CSR considerations can influence firm value and investment behavior, providing a pathway through which financial conditions may reinforce innovation-oriented strategies [1,2].

Constraining channels emphasize compliance costs, reallocation pressures, and short-term financial tightening. Green finance implementation can involve stricter risk assessments and conditional access to capital, which may reduce discretionary resources available for innovation—particularly for firms facing higher uncertainty and longer payback periods [4,7,9]. Evidence from green lending and portfolio management similarly suggests that risk–return tradeoffs and screening practices shape how financial institutions allocate capital, implying that innovation responses may differ depending on how "green" criteria are operationalized in credit decisions [4]. Reviews of the green finance literature also highlight that outcomes vary with policy instrument design, implementation intensity, and firms' absorptive capacity, which can lead to divergent empirical results even within similar institutional contexts [11,12].

Two moderating pathways receive repeated attention. One is CSR-related positioning, which can strengthen innovation incentives by improving legitimacy and reducing perceived risk among capital providers [8]. Another is digital capability, which can enhance information processing, monitoring, and resource allocation efficiency, potentially increasing the effectiveness with which firms convert external green finance signals into innovation outcomes [10]. Together, these perspectives suggest that green finance can either facilitate or constrain innovation depending on firm capability and the cost of adjustment [8,10].

2.3 Measurement Differences: Patent Applications Versus Patent Grants

Differences in how innovation is measured provide an additional reason for inconsistent conclusions across studies. Patent-based indicators are widely used, yet patent applications and patent grants represent distinct stages of the innovation process. Applications are closer to near-term inventive activity and disclosure decisions, whereas grants reflect a longer-cycle outcome influenced by examination timing and additional filtering mechanisms. As a result, changes in financing conditions may affect application behavior without producing a proportional immediate response in granted outcomes.

This distinction is consistent with process-oriented views of green technology innovation that emphasize learning, exploration, and cumulative capability development [13]. It also aligns with measurement-oriented contributions that encourage using complementary metrics to capture different dimensions and stages of environmental innovation rather than relying on a single proxy [14]. Accordingly, separating applications from grants can improve interpretation when empirical results differ across innovation measures.

2.4 Timing and Dynamic Responses

Innovation responses to financing and policy conditions often unfold over time. Because R&D accumulation and patent production are dynamic, immediate associations may differ from delayed effects observable with lag structures. In policy-oriented environments, firms may initially prioritize compliance and financial restructuring before innovation effects become visible, implying that short-run and medium-run estimates can diverge [6,7,9]. This dynamic logic is compatible with broader sustainable development discussions that treat innovation as a core adjustment mechanism, but one that typically operates with time lags rather than instant effects [15].

International perspectives also emphasize that the design of green finance instruments and the surrounding regulatory–financial architecture can shape adjustment trajectories and investment incentives [2,4]. Systematic reviews likewise conclude that observed outcomes depend on instrument mix and implementation, reinforcing the need to evaluate timing and to interpret results as potentially heterogeneous across periods and innovation stages [11,12].

2.5 Synthesis and Research Expectations

Overall, the literature supports three expectations guiding the empirical analysis. First, the direction of the green finance–innovation association is not predetermined: enabling resource channels and constraining adjustment channels can coexist, leading to mixed net effects depending on context and measurement [5-7,9,11,12]. Second, firm capabilities and positioning such as CSR engagement and digital capability may condition the relationship by affecting how efficiently firms translate external financial signals into innovation output [8,10]. Third, innovation outcomes are sensitive to both timing and the stage of the innovation pipeline, motivating separate innovation measures and lag-based specifications to capture dynamic responses [13,14].

3 DATA, VARIABLES, AND EMPIRICAL STRATEGY

3.1 Data and Sample

This study employs a firm–year panel covering the period 2013–2023. The unit of analysis is the firm–year observation. Firm-level financial and operating variables are compiled from publicly available corporate reports and disclosed financial statements, while the green finance indicator is constructed at the national level and varies by year. Given the presence of missing values in several firm-level covariates, the study adopts multiple imputation to retain sample information and reduce potential bias associated with listwise deletion.

3.2 Variable Construction

Technological innovation (TI) is measured using two complementary outcomes: patent applications and patent grants. To stabilize variance and reduce the influence of extreme values, the dependent variables are expressed in logarithmic form: ln(TI1) for patent applications and ln(TI2) for patent grants.

Green finance (GF) is proxied by a national-level annual green finance index and expressed as ln(GF). For interaction-based specifications, ln(GF) is mean-centered to improve interpretability and limit nonessential collinearity in interaction terms.

Control variables capture core firm fundamentals commonly linked to innovation outcomes, including R&D expenditure (ln(RD)), government subsidies (ln(GovSub)), firm size/employment (ln(Emp)), profitability (ROA), leverage, and revenue growth (RevGrow).

3.3 Baseline Empirical Model

The main empirical specification estimates the association between green finance and technological innovation while controlling for firm characteristics:

$$TI \quad = \alpha + \beta GF_t + \gamma^{'} X \quad + \varepsilon \quad , \tag{1}$$

where TI denotes ln(TI_1) or ln(TI_2) for firm i in year t, GF_t is the national green finance measure, and X is the vector of firm-level controls. Standard errors are reported in parentheses.

3.4 Policy-Timing and Heterogeneity Specifications

To examine whether the relationship differs across the policy environment surrounding the 2016 green finance policy shift, the study estimates an interaction specification:

$$TI \quad = \alpha + \beta_1 cGF_t + \beta_2 Post2016_t + \beta_3 (cGF_t \times Post2016_t) + \gamma' X \quad + \varepsilon \quad , \tag{2}$$

where $Post2016_t$ is an indicator equal to 1 for years from 2016 onward and cGF_t is mean-centered ln(GF). In addition, subsample regressions are estimated separately for Pre-2016 and Post-2016 periods to assess whether coefficients are stable across policy regimes.

To evaluate timing validity, two auxiliary checks are implemented: a lead test shifting the policy cutoff earlier (Post2015) and a placebo test shifting it later (Post2017). These tests assess whether the estimated relationship is specific to the intended policy window rather than reflecting arbitrary breakpoints.

3.5 Dynamic Effects: Lag Specifications

Innovation responses may occur with delay; therefore, the study estimates models using lagged green finance terms:

- Lag-1: TI on GF_{t-1} and controls
- Lag-2: TI on GF_{t-2} and controls

Given that adjacent lags can be highly correlated, specifications that include both GF_{t-1} and GF_{t-2} jointly are treated cautiously and assessed using multicollinearity diagnostics.

3.6 Missing Data Treatment and Estimation

Missing values are addressed using multiple imputation (m = 5). After imputation, all derived variables (log transforms, centered terms, interactions, and lags) are re-generated to ensure internal consistency. Regression coefficients are pooled across imputations using standard MI combining rules, and model fit statistics are reported as averages across imputations (with ranges where relevant).

3.7 Diagnostics

Multicollinearity is evaluated using variance inflation factors (VIFs). In lag models, VIF checks are performed both for single-lag specifications and for joint-lag specifications to identify inflation arising from correlated lag terms.

4 EMPIRICAL RESULTS

4.1 Descriptive Statistics and Correlations

Table 1 summarizes the main variables across firm–year observations. The two innovation measures show similar central tendencies (mean ln(TI_1)=5.48; mean ln(TI_2)=5.27), while green finance varies moderately over time (mean ln(GF)=11.66, SD=0.46). Post2016 has a mean of 0.64, indicating that a larger share of the sample falls in the post-policy period. Overall, the descriptive profile suggests meaningful variation in firm innovation and financial fundamentals (ROA, leverage, revenue growth), supporting multivariate modelling.

Table 1 Descriptive Statistics

Variables	N	Min	Max	Mean	SD
ln(TI_1)	371	.00	9.58	5.4812	1.71661
ln(TI_2)	372	.00	9.11	5.2741	1.62808
ROA	372	-.609	1.471	.07329	.183904
ln(RD)	374	17.57	25.03	20.8050	1.43063
ln(GovSub)	370	14.82	22.47	18.7080	1.62781
ln(Emp)	372	5.76	13.46	9.6542	1.34505
Post2016	383	.00	1.00	.6397	.48072
ln(GF)	383	10.93	12.47	11.6620	.46362
GFxPost	383	-.19	.80	.1810	.28458
RevGrow	380	-.612	3.109	.19495	.349446
Leverage	372	.15	1.04	.6073	.16333

Note 1: Valid N (listwise) = 350

Table 2 reports pairwise Pearson correlations. ln(TI1) and ln(TI2) are strongly correlated (0.934), confirming that applications and grants move closely but are not identical outcomes. Size- and resource-related controls (lnRD, lnGovSub, lnEmp) are also highly correlated with each other, which is expected in firm-level settings; therefore, multicollinearity is later checked using VIF diagnostics. Importantly, ln(GF) shows weak simple correlations with innovation, implying that the GF–TI relationship is better evaluated in controlled regressions.

Table 2 Correlation Matrix (Simple pairwise relationships)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(TI_1)	--								
ln(TI_2)	.934**	--							
ROA	.356**	.311**	--						
ln(RD)	.536**	.591**	.177**	--					
ln(GovSub)	.526**	.570**	.177**	.874**	--				
ln(Emp)	.483**	.511**	.226**	.828**	.762**	--			
ln(GF)	.034	.133*	-.075	.379**	.341**	.120*	--		
RevGrow	-.137**	-.123*	.086	-.019	-.094	.027	-.073	--	
Leverage	.042	.080	-.078	.027	.022	-.202**	.192**	-.085	--

Note 2: N = 371–383 (pairwise). Pearson correlations reported. * p < .10, ** p < .05, *** p < .01 (two-tailed).

4.2 Regression Analyses

Table 3 provides the baseline regression evidence. Firm fundamentals behave consistently across specifications: ln(RD), ln(GovSub), and ROA show positive and statistically significant associations with innovation, while RevGrow is negative and significant. When ln(GF) is added, it is negative and significant for ln(TI1) (Model 2a) but not significant for ln(TI2) (Model 2b), indicating that green finance is linked more clearly to patent applications than to patent grants in the baseline framework.

Table 3 Baseline Regressions Models

Variables	Model 1a ln(TI_1) (Controls + YearTrend)	Model 1b ln(TI_2) (Controls + YearTrend)	Model 2a ln(TI_1) (GF/-YearTrend)	Model 2b ln(TI_2) (GF/- YearTrend)
Constant	-8.231*** (1.330)	-9.040*** (1.242)	-2.549 (1.835)	-6.580*** (1.722)
ln(GF)	--	--	-.527*** (.168)	-.225 (.157)
ln(RD)	.470*** (.113)	.502*** (.107)	0.476*** (.113)	.503*** (.107)
ln(GovSub)	.189** (.081)	.168** (.074)	.190** (.081)	.168** (.074)
ln(Emp)	.027 (.108)	.028 (.100)	.022 (.108)	.028 (.100)
Leverage	.685 (.464)	.865** (.433)	.685 (.463)	.864** (.433)
ROA	2.370*** (.389)	1.800*** (.360)	2.362*** (.388)	1.800*** (.360)
RevGrow	-.592*** (.201)	-.454** (.188)	-.593*** (.200)	-.455** (.188)
YearTrend	-.073*** (.025)	-.033 (.023)	--	--
R^2	.415 (.407–.423)	.441 (.438–.446)	.417 (.409–.425)	.442 (.439–.446)
Adj. R^2	.404 (.396–.412)	.4310 (.428–.435)	.406 (.398–.414)	.431 (.428–.435)

Note 3: N = 383 firms-years (pooled across imputations).Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. Results are pooled from 5 multiple imputations; R^2 and Adj. R^2 are reported as the average across imputations (range in parentheses).

4.3 Robustness Checks

Table 4 tests whether the GF–innovation relationship differs after the 2016 policy shift using centered ln(GF), Post2016, and GF×Post. None of these policy terms are statistically significant for either ln(TI1) or ln(TI2), suggesting limited evidence that the 2016 policy timing moderates the GF–TI link in this interaction setup. In contrast, the control variables remain stable, reinforcing that firm fundamentals are the most consistent correlates of innovation in the sample.

Table 4 Policy Interaction Model

Variables	Model 3a ln(TI_1)	Model 3b ln(TI_2)
Constant	-8.365*** (1.415)	-9.060*** (1.318)
ln(GF) Cent	0.063 (0.687)	0.059 (0.668)
Post2016	-0.060 (0.378)	-0.151 (0.364)
GFxPost	-1.002 (0.737)	-0.297 (0.710)
ln(RD)	0.475*** (0.113)	0.504*** (0.107)
ln(GovSub)	0.189** (0.081)	0.168** (0.074)
ln(Emp)	0.019 (0.107)	0.026 (0.100)
Leverage	0.609 (0.464)	0.854** (0.435)
ROA	2.355*** (0.387)	1.797*** (0.361)
RevGrow	-0.576*** (0.2)	-0.458** (0.189)
R^2	.423 (.415-.431)	.442 (.439-.446)
Adjusted R^2	.409 (.401–.417)	.428 (.425 – .433)

Note 4: N = 383 firms-years (pooled across imputations). Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. Results are pooled from 5 multiple imputations; R^2 and Adj. R^2 are reported as the average across imputations (range in parentheses).

Table 5 below presents lagged models using national green finance in the previous year ln . Lagged green finance is negative and significant for $ln\ (TI_1)$ (applications) ($\beta =- 0.589$, SE=0.202, $p < 0.01$), but not significant for $ln\ (TI_2)$(grants) ($\beta =- 0.253$, SE=0.187). R&D intensity and government subsidies are positive and significant across both specifications, while profitability (ROA) is consistently positive. Revenue growth is negative and significant in both models, suggesting a short-run tradeoff between rapid sales expansion and patent-based innovation. Model fit is stable across imputations ($R^2 \approx 0.40$–0.42).

Table 5 Lagged Green Finance (t−1) and Technological Innovation

Variables	ln(TI_1) Lag	ln(TI_2) Lag
Constant	-1.907 (2.162)	-6.222*** (1.981)
ln(GF) Lag	-.589*** (.202)	-.253 (.187)
ln(RD)	.483*** (.124)	.511*** (.117)
ln(GovSub)	.186** (.086)	.162** (.080)
ln(Emp)	.014 (.117)	.018 (.108)
Leverage	.691 (.501)	.790* (.465)
ROA	2.398*** (.405)	1.845*** (.376)
RevGrow	-.600*** (.210)	-.468** (.194)
R^2	.402 (.395–.409)	.422 (.419–.424)

Adj. R^2	.390 (.383–.397)	.410 (.407–.412)

Note 5: N = 383 firms-years (pooled across imputations). Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Results are pooled from 5 multiple imputations; R^2 and Adj. R^2 are reported as the average across imputations (range in parentheses).

Table 6 reports timing falsification tests by shifting the policy breakpoint away from 2016 in two directions: an early lead cutoff (Post2015) and a later placebo cutoff (Post2017), estimated for both innovation outcomes (ln(TI1) and ln(TI2)). Overall, the results provide little evidence of anticipatory effects or mechanically generated "policy effects" when the breakpoint is moved. Under the lead timing (Post2015), the centered green finance level (ln(GF) cent.), the Post2015 dummy, and the interaction GF×Post2015 are all statistically insignificant for both ln(TI1) and ln(TI2), indicating no detectable pre-2016 structural shift. ln(TI1).

Table 6 Lead timing: Post2015 and Placebo test: Post 2017

Variables	$\ln(TI_1)$ (Post2015)	$\ln(TI_2)$ (Post2015)	$\ln(TI_1)$ (Post2017)	$\ln(TI_2)$ (Post2017)
Constant	-8.558*** (1.911)	-9.123*** (1.778)	-8.328*** (1.395)	-9.106*** (1.305)
ln(GF) Cent.	-.130 (2.101)	-.032 (2.004)	.135 (.529)	-.031 (.506)
Post2015	-.057 (1.380)	-.058 (1.306)	--	--
GF×Post2015	-.565 (2.110)	-.251 (2.016)	--	--
Post2017	--	--	-.053 (.295)	-.115 (.279)
GF×Post2017	--	--	-1.172* (.629)	-.171 (.596)
ln(RD)	.478*** (.113)	.504*** (.107)	.477*** (.113)	.503*** (.107)
ln(GovSub)	.189** (.081)	.168** (.074)	.188** (.081)	.168** (.074)
ln(Emp)	.018 (.108)	.026 (.100)	.018 (.107)	.027 (.100)
Leverage	.649 (.465)	.850** (.434)	.604 (.464)	.856** (.435)
ROA	2.356*** (.388)	1.798*** (.361)	2.355*** (.387)	1.798*** (.361)
RevGrow	-.591*** (.200)	-.454** (.189)	-.568*** (.201)	-.461** (.190)
R^2	.420 (.412–.428)	.442 (.439–.446)	.423 (.415–.431)	.442 (.439–.446)
Adj. R^2	.406 (.398–.414)	.428 (.425–.433)	.409 (.401–.417)	.428 (.425–.433)

Note 6: N = 383 firm-years (pooled across imputations). Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. R^2 and Adj. R^2 are reported as the average across the 5 imputations (range in parentheses).

Under the placebo timing (Post2017), the green finance level and Post2017 dummy remain insignificant for both outcomes; the interaction GF×Post2017 is also insignificant for ln(TI2), while it is only weakly significant for ln(TI1) at the 10% level, suggesting at most a limited and outcome-specific sensitivity to a later cutoff rather than a robust timing pattern. Across all specifications, the controls behave consistently, R&D intensity (lnRD) and government subsidies (lnGovSub) are positive and significant, ROA is strongly positive, and revenue growth (RevGrow) is negative, while model fit is stable across imputations (R^2 and adjusted R^2 ranges are narrow). Taken together, these timing checks support the interpretation that the main results are not driven by spurious breakpoints or pre-trend dynamics, although the weak Post2017 interaction for ln(TI1) suggests the timing evidence is stronger for ln(TI2) than for ln(TI1).

Table 7 separates the sample into pre-2016 and post-2016 periods. Before 2016, ln(GF) is not statistically significant for either innovation measure; after 2016, ln(GF) becomes strongly negative and significant for ln(TI1) while still not significant for ln(TI2). This split-sample evidence indicates that the detectable GF–TI association is concentrated in the post-policy environment and is more visible for patent applications than for grants.

Table 7 Pre/Post subsample regressions around the 2016 policy

Variables	$\ln(TI_1)$ Pre-2016	$\ln(TI_2)$ Pre-2016	$\ln(TI_1)$ Post-2016	$\ln(TI_2)$ Post-2016
Constant	-8.036 (7.332)	-9.003 7.070)	2.665 (3.440)	-6.029* (3.235)
ln(GF)	-.096 (.660)	-.125 (.625)	-.965*** (.292)	-.222 (.275)
ln(RD)	.513*** (.174)	.560*** (.161)	.487*** (.150)	.482*** (.144)
ln(GovSub)	.080 (.125)	.116 (.115)	.289*** (.105)	.222** (.105)
ln(Emp)	.159 (.150)	.086 (.140)	-.136 (.147)	-.048 (.139)
Leverage	1.456** (.696)	1.686*** (.646)	-.129 (.620)	.164 (.584)
ROA	2.039*** (.742)	1.383** (.673)	2.480*** (.460)	1.935*** (.434)
RevGrow	-.012 (.396)	.013 (.397)	-.768*** (.238)	-.616*** (.225)
R^2	.476 (.455–.495)	.514 (.495–.527)	.405 (.400–.408)	.398 (.395–.402)
Adj. R^2	.448 (.426–.467)	.488 (.468–.502)	.388 (.383–.390)	.380 (.377–.384)

Note 7: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. R^2 and Adj. R^2 are reported as the average across the 5 imputations (range in parentheses).

In Table 8, we further test robustness by allowing green finance to affect innovation with time lags, replacing the contemporaneous green finance measure with its one-year (L1) and two-year (L2) lagged mean-centered values. The results show a consistent pattern for ln(TI1) (patent applications): the lagged green finance coefficient is negative and statistically significant in both specifications (L1 and L2), indicating that the association is not driven by immediate-year co-movements and remains when green finance is shifted backward in time. In contrast, the lagged green finance terms for ln(TI2) (patent grants) are not statistically significant under either lag length, which is consistent with the idea that granted patents adjust more slowly due to examination and approval delays. Across all models, the core controls behave as expected—R&D intensity and ROA are strongly positive, while revenue growth is negative—supporting the stability of the specification. Overall, the lag analysis suggests that the main inference is not sensitive to timing assumptions, and that the green finance–innovation relationship is more pronounced for innovation activity measured by applications than by grants.

Table 8 Lagged Green Finance regressions (L1–L2)

Variables	(1) ln(TI1) Lag 1	(2) ln(TI2) Lag 1	(3) ln(TI1) Lag 2	(4) ln(TI2) Lag 2
Constant	-8.920*** (1.496)	-9.213*** (1.393)	-8.868*** (1.597)	-9.174*** (1.486)
ln(GF) Cent. (Lag 1)	-.608*** (.193)	-.243 (.179)	--	--
ln(GF) Cent. (Lag 2)	--	--	-.670*** (.233)	-.270 (.216)
ln(RD)	.500*** (.124)	.519*** (.118)	.489*** (.132)	.519*** (.123)
ln(GovSub)	.183** (.086)	.159* (.081)	.208** (.093)	.184** (.085)
ln(Emp)	.005 (.117)	.015 (.108)	-.019 (.125)	-.027 (.116)
Leverage	.690 (.499)	.795* (.465)	.540 (.536)	.590 (.499)
ROA	2.389*** (.404)	1.848*** (.376)	2.448*** (.424)	1.885*** (.394)
RevGrow	-.618*** (.209)	-.485** (.195)	-.639*** (.218)	-.508** (.204)
R^2	.406 (.400–.412)	.423 (.422–.425)	.402 (.396–.407)	.411 (.410–.413)
Adj. R^2	.394 (0.388–.400)	.411 (.410–.413)	.388 (.382–.393)	.397 (.396–.399)

Note 8: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. R^2 and Adj. R^2 are reported as the average across the 5 imputations (range in parentheses).

5 DISCUSSION, IMPLICATIONS, AND CONCLUSION

This study examined how green finance development is associated with technological innovation among Chinese listed automotive/NEV-related firms over 2013–2023, using patent applications and patent grants as two complementary innovation outputs. The results show that the estimated relationship is not uniformly positive and differs across innovation measures and time specifications. Across the main regressions, green finance is more closely linked to patent applications than to patent grants, and the direction is predominantly negative for applications. In contrast, for patent grants, the coefficients on green finance are generally small and statistically indistinguishable from zero. These patterns remain after addressing missingness via multiple imputation and after a set of robustness checks focusing on timing and dynamics.

5.1 Interpreting the Main Patterns

A consistent feature of the findings is the divergence between patent applications and patent grants. The negative association between green finance and patent applications suggests that, within this sample and period, greener financial expansion may coincide with short-run constraints on firms' propensity to file patents. One plausible explanation is an adjustment-cost mechanism: when financial screening and environmental criteria become more prominent, firms may face stricter external financing conditions, higher reporting burdens, or reallocation pressures that compete with discretionary innovation activity. In such a setting, some firms may prioritize compliance investments, balance-sheet resilience, or operational upgrading over the incremental cost of generating and filing patent applications.

The absence of a robust relationship for patent grants is also interpretable. Granted patents reflect downstream outcomes that are influenced by examination timing and additional filtering, which can delay observed responses. Even if firms adjust innovation inputs, the translation into granted patents may occur later or may be obscured by the grant process itself. As a result, the empirical contrast stronger effects for applications and weaker effects for grants fits a pipeline interpretation in which financing and policy conditions first affect near-term inventive activity and disclosure decisions, while the effect on granted outcomes is slower and less detectable within the same window.

Control variables behave in an economically intuitive way and help anchor the interpretation. Innovation inputs and firm fundamentals (such as R&D expenditure and fiscal/public subsidies) are positively related to innovation outcomes, while some financial structure controls (leverage) and growth indicators show weaker or mixed associations depending on the specification. This reinforces that, in the data, firm-level innovation capacity is strongly tied to internal resources and investment fundamentals, and the green finance indicator operates as a macro-level condition that may amplify or constrain those firm-level drivers rather than acting as a universal innovation booster.

5.2 Policy Timing and What It Implies

The policy-timing models centered on the 2016 guidelines do not provide strong evidence that the post-2016 period systematically flips the green finance–innovation relationship into a positive one. In the interaction framework, the post-period dummy and the interaction term do not consistently produce statistically strong effects across both innovation measures. This does not imply "no policy relevance"; instead, it suggests that the macro green finance series captures broad system-wide shifts that may generate uneven, transitional, or sector-specific responses. In other words, even if the financial system becomes greener after major guidelines, innovation responses can be dominated by adjustment frictions and firm-specific capacity rather than by a uniform post-policy surge in patenting.

The placebo and lead timing checks further support a cautious interpretation: shifting the policy cut-off forward (placebo) or backward (lead) does not yield a stable pattern indicating that the estimated effects are mechanically driven by one arbitrary break year. Together with the pre/post subsample regressions, the evidence points to heterogeneity across periods rather than a single clear structural break. This is consistent with the idea that policy implementation and firm adaptation are gradual, and that measurable innovation effects may appear with delays or only in subsets of firms.

5.3 Dynamics and Lag-based Robustness

Lag-based robustness checks add an important nuance. When green finance is lagged, the association with patent applications becomes more evident in some specifications (one-year or two-year lag models), but the results weaken when multiple lags are entered jointly due to strong correlation between adjacent yearly macro values. This is expected: national-level annual indicators tend to move smoothly over time, so consecutive lags can be highly collinear. Substantively, the lag evidence is still useful because it suggests that the relationship is not purely contemporaneous and may reflect delayed adjustment. At the same time, the joint-lag instability indicates that the data support a limited dynamic interpretation (focusing on a single lag at a time) rather than precise claims about the separate marginal contribution of multiple lag lengths.

Overall, the robustness checks support two practical conclusions: (i) the core empirical signal is concentrated in patent applications rather than patent grants, and (ii) timing matters, but the evidence favors gradual or delayed adjustment rather than a sharp post-2016 discontinuity.

5.4 Implications for Practice and Policy Design

These findings carry implications that are aligned with the paper's goal of evaluating effects rather than proving uniformly positive impacts.

First, green finance expansion may coincide with transitional constraints on near-term inventive activity in the automotive/NEV sector. If adjustment costs and compliance burdens are part of the mechanism, then policy design can improve innovation compatibility by lowering administrative friction, improving clarity of eligibility criteria, and supporting the innovation pipeline during transition phases. Targeted support that complements green financial screening such as mechanisms that protect R&D continuity when financing conditions tighten may help reduce unintended short-run crowding-out of patenting activity.

Second, the divergence between applications and grants highlights the value of using multiple innovation indicators in evaluation. Stakeholders assessing policy effectiveness should avoid relying on a single patent metric, because different stages of innovation respond differently to financial conditions and time lags. Monitoring both early-stage outputs (applications) and downstream outcomes (grants) provides a more accurate picture of whether observed changes reflect reduced inventive activity, delayed translation, or shifting disclosure strategies.

Third, for firms, the results emphasize that internal innovation capacity remains central. Firms facing tighter external screening can reduce vulnerability by strengthening long-horizon R&D planning, improving project selection discipline, and diversifying financing channels consistent with green criteria. In the automotive/NEV context, building stronger documentation and measurement systems for innovation and environmental performance may also lower the effective cost of meeting green-oriented financing requirements, reducing the trade-off between compliance and innovation activity.

5.5 Conclusion

Using a 2013–2023 panel of Chinese listed automotive/NEV-related firms and a national annual green finance indicator, this study finds that green finance development is not associated with uniformly higher innovation output. The estimated relationship is concentrated in patent applications and is predominantly negative, while patent grants show limited and statistically weak associations in most specifications. Timing and lag analyses suggest that effects may operate with delays and through transitional adjustment, but the evidence does not support a simple "post-2016 boost" narrative.

These results support a balanced interpretation: green finance can reshape firms' innovation environment through enabling and constraining channels, and the net effect depends on innovation stage, timing, and firms' capacity to adapt. Future work could strengthen identification and interpretation by incorporating firm-level green finance exposure, richer instrument-level measures, and heterogeneity analyses (by financing constraints or technology segments) to clarify which firms are most likely to experience enabling versus constraining effects.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Chang X, Fu K, Jin Y, et al. Sustainable Finance: ESG/CSR, firm value, and investment returns. Asia-Pacific Journal of Financial Studies, 2022, 51(3): 325-371.

[2] Breitenfellner A, Pointner W. Green finance in Europe: Strategy, regulation, and instruments. Intereconomics, 2020, 55(1): 29-35. DOI: 10.1007/s10272-020-0856-y.

[3] Desalegn G, Tangl A. Enhancing green finance policy for inclusive growth: A systematic approach. Sustainability, 2022, 14(12): 7416. DOI: 10.3390/su14127416.

[4] Mirza N, Afzal A, Umar M, et, al. The impact of green lending on banking performance: Evidence from SME credit portfolios in the BRIC. Economic Analysis and Policy, 2023, 77, 843-850. DOI: 10.1016/j.eap.2022.12.024.

[5] Jiang S, Liu X, Liu Z, et al. Does green finance policy promote enterprises' green technology innovation in China? Frontiers in Environmental Science, 2022, 10, 981013. DOI: 10 3389 fenvs 2022 981013.

[6] Wang Y, Liu J, Yang X, et al. The mechanism of green finance policy's impact on enterprises' sustainable green innovation. Green Finance, 2023, 5(3): 452-478. DOI: 10.3934/GF.2023018.

[7] Wang B, Wang C. Green finance policy and technological innovation in heavily polluting enterprises: Evidence from China. International Journal of Environmental Research and Public Health, 2023, 20(4): 3333. DOI: 10.3390/ijerph20043333.

[8] Li X, Yang Y. Does green finance contribute to corporate technological innovation? The moderating role of corporate social responsibility. Sustainability, 2022, 14(9): 5648. DOI: 10.3390/su14095648.

[9] Du M, Zhang R, Chai S, et al. Can green finance policy stimulate technological innovation and financial performance? Evidence from Chinese listed green enterprises. Sustainability, 2022, 14(15): 9287. DOI: 10.3390/su14159287.

[10] Ren Y, Li B. Digital transformation, green technology innovation and enterprise financial performance: Empirical evidence from the textual analysis of the annual reports of listed renewable energy enterprises in China. Sustainability, 2023, 15(1): 712. DOI: 10.3390/su15010712.

[11] Mudalige H M N K. Emerging new themes in green finance policy: A systematic literature review. Future Business Journal, 2023, 9: 108. DOI: 10.1186/s43093-023-00287-0.

[12] Yameen J, Kijkasiwat P, Hussain, A, et al. Green finance policy in the banking industry: A systematic literature review. SN Business & Economics, 2024, 4(8): 1-28. DOI: 10.1007/s43546-024-00683-w.
[13] Wicki S, Hansen E G. Green technology innovation: Anatomy of exploration processes from a learning perspective. Business Strategy and the Environment, 2019, 28(5): 970-988. DOI: 10.1002/bse.2295.
[14] Dussaux D, Agnelli A, Es-Sadki N. Exploring new metrics to measure environmental innovation. OECD Working Paper, 2023. DOI: 10.1787/e57a8a13-en.
[15] Emas R. The concept of sustainable development: Definition and defining principles. Brief for GSDR 2015. United Nations Secretariat, 2015.