The Power of Local Grassroot: The Impact of Local Public Attention on Corporate Green Innovation

ABSTRACT

Firms proactively maintain social legitimacy by demonstrating accountability to external audiences, especially those in close geographic proximity. However, existing literature provides limited insights into how local audience's attention reshapes corporate green innovation activities. Using an internal dataset, we find that local public attention significantly promotes green innovation, suggesting that geographic proximity enhances corporate oversight and accountability. We identify risk perception and reputation enhancement as the primary channels. To establish the causality, we leverage the first-time inclusion of a firm's ultimate controller in the Hurun Rich List as an exogenous shock. Additionally, we employ the cumulative number of cities included in the "Broadband China" initiative as an instrumental variable, confirming the robustness of our results. Further analysis reveals that firms strategically focus on green innovation projects that deliver quicker and more tangible environmental benefits, allowing local residents to perceive improvements more immediately. Our findings highlight that local communities, as direct beneficiaries of firms' energy-saving and emission-reduction efforts, can act as a catalyst for corporate green innovation, thereby offering new policy insights for fostering green innovation.

1. INTRODUCTION

Over the past two decades, China has made substantial progress in environmental governance, yet the country continues to grapple with severe ecological challenges. According to Yale University's 2022 Environmental Performance Index Report, more than 50% of China's population breathes air containing hazardous particulate matter, and air pollution causes over 1.4 million deaths annually -- accounting for 20% of total deaths and ranking as the third most significant public health risk factor[1]. These alarming statistics underscore the urgent need for more effective environmental policies that not only enforce compliance but also incentivize firms to engage in sustainable innovation. To understand what drives corporate engagement in green innovation, extant research has explored the influence of various external and internal stakeholders (Acemoglu et al., 2012; Calel & Dechezleprêtre, 2016; Wang et al., 2021; Luo et al., 2023; Gugler et al., 2024). However, evidence on the role of local residents -- whose life are directly impacted by firms' sustainable practices -- remains largely absent. Our study addresses this research gap by providing the first empirical evidence on the impact of local public attention on corporate green innovation.

Firms often lack intrinsic motivation to engage in green innovation due to two primary economic constraints. First, technological spillover effects prevent firms from fully capturing the benefits of their innovation, reducing the incentive for private investment in green R&D (Stojčić, 2021). Second, environmental quality improvements function as public goods, making it difficult for firms to internalize the financial returns of their green innovation efforts (Borghesi et al., 2015; Caravella & Crespi, 2020).

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[1] The Environmental Performance Index Report could be found via https://epi.yale.edu/faq/epi-faq

Without adequate economic compensation, firms may prioritize cost-saving, less sustainable production methods over long-term investment in green technologies (Holmstrom, 1989).

In response to these challenges, top-down regulatory approaches have been widely implemented to compel firms to undertake green innovation (Iqbal et al., 2021). Porter and Linde (1995) argue that well-designed environmental regulations can drive firms toward sustainability-oriented technological advancements. However, the effectiveness of this approach remains highly contested. On the one hand, multi-tiered governance structures introduce policy enforcement challenges, as local governments may deviate from central policies to protect local businesses. This regulatory inconsistency reduces firms' incentives to proactively invest in green technologies (Zhang et al., 2018). On the other hand, government mandates may induce opportunistic corporate behavior, where firms pursue symbolic green innovation solely for compliance rather than as a genuine effort to improve environmental outcomes (Farza et al., 2021; Hao et al., 2022).

Given these limitations of government-driven environmental policies, alternative bottom-up mechanisms have gained attention as potential solutions to bridge regulatory gaps. Public attention, in particular, serves as a grassroots enforcement mechanism by placing firms under continuous public scrutiny (Wu & Ye, 2020). Historical evidence from the United States illustrates how public awareness and activism can drive environmental policy reforms. In 1970, despite widespread industrial pollution, neither legal frameworks nor the media held corporations accountable for their environmental impact. However, on April 22 of that year, over 20 million Americans participated in

large-scale environmental protests, demanding more stringent regulations. This public outcry led to the creation of the U.S. Environmental Protection Agency (EPA) and the passage of landmark legislation such as the Clean Air Act and Clean Water Act. This event, now recognized as Earth Day, marked the beginning of the modern environmental movement, demonstrating how public mobilization can catalyze corporate accountability and policy reform.

Unlike Western countries, China's environmental governance has historically been government-led. However, public participation has increasingly played a role in shaping corporate and policy responses to environmental concerns. Over the past two decades, the government has introduced legal frameworks to strengthen public involvement in environmental governance. Notably, in 2003, China enacted the Environmental Impact Assessment (EIA) Law, which mandates public hearings for projects with potential environmental risks. This marked the first legal recognition of public environmental rights, granting citizens the authority to access, oversee, and challenge public decisions that affect their living environment. Public activism in China has also influenced corporate and policy decisions in tangible ways. In 2012, large-scale protests erupted in Shifang City, Sichuan Province, over a proposed molybdenum-copper processing plant. Despite passing formal environmental assessments, local residents feared severe water contamination and health risks, leading to sustained protests that ultimately forced the government to halt the project. Similarly, in Qidong, Jiangsu Province, residents opposed a wastewater discharge pipeline planned by the Japanese firm Oji Paper, arguing that it would devastate the local fishery industry. The intensity of public protests led the municipal government to cancel the project permanently.

These cases illustrate that local public attention may be more effective than non-local oversight in influencing corporate environmental behavior. While external stakeholders, such as national regulators or distant investors, may be less directly affected by pollution, local residents -- who experience firsthand the consequences of environmental degradation -- are more motivated to take actions. Following this logic, it is reasonable to expect that firms operating under greater local public scrutiny may face stronger incentives to adopt green technologies to mitigate public pressure and maintain social legitimacy. However, the actual impact of local public attention on corporate green innovation remains theoretically ambiguous.

On the one hand, public scrutiny can enhance firms' risk perception and reputational concerns, encouraging them to invest in sustainable innovation. Local residents actively monitor corporate environmental performance, file complaints, and engage in grassroots activism, which, in turn, intensifies regulatory oversight. To mitigate potential fines and public backlash, firms may adopt green innovation as a proactive risk management strategy (Li et al., 2022). Additionally, green innovation can serve as a tool to strengthen corporate reputation, enhancing stakeholder trust, brand loyalty, and competitive positioning (Berrone & Gomez-Mejia, 2009; Hao et al., 2022; Ren et al., 2022).

On the other hand, local public attention may also impose constraints on corporate innovation efforts. Firms under intense public scrutiny may experience heightened short-term performance pressure, compelling them to prioritize immediate financial performance over long-term R&D investments. Similar to the impact of analyst coverage and media scrutiny, excessive public pressure may discourage firms from undertaking high-risk, long-term innovation projects (He & Tian, 2013). Therefore, while local public

attention may incentivize compliance-driven sustainability efforts, it may simultaneously deter risk-taking in cutting-edge green technologies.

Given these competing theoretical perspectives, an empirical investigation is necessary to determine the net effect of local public attention on corporate green innovation. This study examines non-financial A-share listed firms in Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) from 2011 to 2016, employing a novel firm-level measure of public attention by using an internal database in China. Unlike previous studies that assess public concern using aggregate regional data (Xie et al., 2020; Jiang et al., 2022), we construct a firm-specific public attention index by aggregating search volumes of multiple firm-related keywords, including company names, stock abbreviations, and commonly searched terms.

Our findings indicate that local public attention significantly influences corporate green innovation, primarily through risk perception and reputational enhancement mechanisms. To mitigate potential endogeneity concerns, we employ instrumental variable regression and difference-in-differences (DID) approaches. Specifically, we use the cumulative number of cities included in the "Broadband China" demonstration initiative as an instrumental variable. Additionally, we exploit the exogenous shock of a firm's controlling shareholder being listed in the Hurun Rich List for the first time, allowing us to isolate the effect of public visibility on corporate green innovation.

Further analysis classifies green patents into two categories: pollution control technologies and clean energy innovations. We find that firms under high public scrutiny tend to focus on pollution control technologies, likely because they yield more immediate and visible environmental improvements. Additionally, firms exposed to stronger public

oversight favor independent R&D strategies, as these enable faster implementation of green technologies compared to collaborative research efforts.

This study makes several important theoretical contributions to the literature on public attention, corporate green innovation, and external governance mechanisms. First, we provide a novel refined measurement for public attention in the context of corporate environmental engagement. While existing studies primarily assess public attention at a regional level using aggregate search volumes of pollution-related terms such as "air pollution" or "haze" (Zhang et al., 2018; Li et al., 2022), this approach does not capture the extent to which individual firms are subject to public scrutiny. Our study is among the first to introduce a local firm-level public attention index, which is constructed by aggregating the total local search volume of multiple firm-specific keywords, including the company's full name, common name, frequently searched name, stock abbreviation, and stock code. This method provides a far more granular and precise measurement of how local residents monitor and interact with specific firms, rather than relying on generalized public environmental concerns. By shifting the measurement of public attention from a broad regional level to a focused local firm-level perspective, this study provides a foundation for future empirical research on the micro-level effects of public scrutiny on corporate behavior, particularly in the domain of environmental innovation.

Second, our study unveils the role of public attention as a bottom-up driver of corporate green innovation. Existing research on external influences on green innovation has largely focused on top-down mechanisms, particularly government environmental regulations as a key force in compelling firms to engage in environmentally friendly technological advancements (Gans, 2012; Berrone et al., 2013). The logic of these studies

follows the Porter Hypothesis, which suggests that well-designed environmental regulations can create incentives for firms to improve their resource efficiency and innovate in ways that enhance their long-term competitiveness. However, the effectiveness of this approach is often constrained by regulatory enforcement challenges and local government-business collusion, where local authorities may weaken enforcement to protect firms operating in their jurisdiction (Zhang et al., 2018). Our study shifts the focus from government-imposed environmental regulations to public-driven environmental pressure, offering a complementary bottom-up perspective on corporate green innovation.

Finally, our study highlights the difference between local public attention and non-local external monitoring mechanisms, providing new insights into how different forms of oversight impact corporate innovation strategies. Previous studies have extensively examined how analyst coverage, media exposure, and online discussions shape corporate decision-making. However, these studies typically view external monitoring as a homogeneous force, without distinguishing between local and non-local sources of attention (He & Tian, 2013; Kim et al., 2019). Our study challenges this assumption by highlighting the unique role of local public attention, which differs from traditional external oversight mechanisms. Existing research suggests that local media outlets can be co-opted by powerful businesses or influenced by local governments, leading to biased reporting that favors corporate interests over environmental concerns (Gurun & Butler, 2012; Hope et al., 2021). In contrast, organic public attention, as captured by search trends and grassroots activism, may be harder for firms to control, making it a more independent and reliable source of pressure. Unlike external analysts or

national media outlets, local communities experience firsthand exposure to pollution, environmental degradation, and industrial hazards. As a result, local public attention is often more persistent, issue-specific, and action-driven. By making this distinction, our research advances the understanding of external monitoring mechanisms and offers a new perspective on how different types of attention influence corporate innovation incentives. These findings open new avenues for future research on regional variations in corporate responses to public scrutiny, as well as the interplay between local activism, regulatory enforcement, and firm-level strategic decision-making. In addition, our findings provide practical implications for regulators, corporate management and other stakeholders who concerns the impact of corporate decisions on local environment.

The rest of the study is organized as follows. Section 2 presents the literature review and hypotheses development. Section 3 describes the research methodology and the samples. Sections 4 and 5 present the empirical results and discussion. Section 6 concludes.

2. LITERATURE REVIEW AND HYPOTHESES

2.1 Local public attention

Utilizing the high public exposure events such as the inclusion of a firm's ultimate controller in the Hurun Rich List, existing research has revealed that public attention increases audit fees and prompts auditors to issue more negative audit reports (Wu and Ye, 2020), attracts analysts to conduct on-site visits (Zhang et al., 2023), and reduces managers' perquisite consumption (Zhang et al., 2022). While the literature on public attention does not explicitly differentiate between local and non-local scrutiny,

research on media coverage provides insights into how geographic proximity affects reporting and oversight, and how local media and national media play distinct roles in corporate and governmental monitoring.

Three key factors contribute to these differences. First, local media are more susceptible to corporate influence. Local media outlets rely on advertising revenue from nearby businesses and may avoid publishing negative coverage to maintain relationships with key advertisers. Consequently, local media tend to use fewer negative words when reporting on local firms (Gurun & Butler, 2012). Second, local media are more vulnerable to government intervention. Hope et al. (2021) analyze differences in how local and national media reported on corporate tunneling scandals in China. They find that national media outlets are more likely to report on corporate misconduct, whereas local media engage in selective reporting, downplaying negative news to protect local businesses. Notably, investors respond more strongly to national media coverage, suggesting that external scrutiny provides a more objective source of information. Third, local media cater to local readers' biases. Research by Lu et al. (2018) on U.S. newspapers find that local economic interests influence news coverage. Specifically, newspapers in regions affected by Chinese import competition are more likely to publish anti-China articles, driving up readership. This highlights how local media narratives are shaped by audience preferences, reinforcing regional biases. Despite these limitations, local investors still rely more on local media for investment decisions. Engelberg & Parsons (2011) find that individual investors are more likely to trade stocks based on earnings reports published in local newspapers. This suggests that while local media may be biased, they remain a crucial information source for regional investors.

By distinguishing between local and non-local public attention, our study contributes to the literature by providing a more nuanced understanding of how geographic proximity affects corporate oversight and accountability.

2.2 Green innovation

Research on the drivers of green innovation highlights the importance of both external regulatory forces and internal firm characteristics. A dominant perspective in the literature examines government regulations as a key motivator, particularly in testing the Porter Hypothesis, which posits that well-designed environmental policies can simultaneously drive innovation and enhance firm competitiveness (Porter & Linde, 1995). Empirical studies show that stringent command-and-control policies (e.g., emissions reduction mandates and environmental legislation) and market-based incentives (e.g., carbon pricing, green subsidies, and emissions trading) significantly influence firms' innovation activities (Acemoglu et al.，2012; Calel & Dechezleprêtre, 2016; Ren et al, 2021; Zhang, 2022; Gugler et al., 2024).

Beyond regulatory influences, capital markets also play a crucial role, as investors increasingly integrate environmental, social, and governance (ESG) factors into investment decisions (Wang & Zhao, 2018). Firms seeking to attract investment are thus incentivized to engage in green innovation as part of their long-term strategy (Ren et al., 2021). At the firm level, factors such as executive backgrounds, board diversity, and R&D capabilities also influence the extent to which firms pursue sustainable innovation (Zhang et al., 2022; Lu & Jiang, 2022).

Corporate governance mechanisms shape firms' commitment to environmental innovation. Firms with independent boards, gender-diverse leadership, and long-term oriented CEOs are more likely to invest in sustainability-driven innovation (Nadeem, 2017; Wang et al., 2021). Strong corporate governance also reduces managerial short-termism, ensuring continued investment in R&D-intensive green technologies (Amore & Bennedsen, 2016). Additionally, linking executive compensation to environmental performance has been shown to enhance firms' green innovation efforts (Moreno-Ureba et al., 2022).

Green innovation offers both financial and environmental benefits. Previous studies show that sustainability-driven firms experience higher market valuation, improved profitability, and enhanced brand reputation (Farza et al., 2021; Truong & Berrone, 2022; Hao et al., 2022). Green technologies also contribute to carbon emission reductions, pollution mitigation, and overall environmental sustainability (Töbelmann & Wendler, 2020; Khan et al., 2020). However, challenges remain, including high R&D costs, uncertain returns, and potential regulatory inconsistencies. Some research suggests that green subsidies may incentivize opportunistic behavior, leading to symbolic compliance rather than genuine technological advancement (Li & Xiao, 2020).

Existing literature underscores the multifaceted drivers and consequences of corporate green innovation, shaped by regulatory frameworks, market forces, and corporate governance structures. However, few research examines the role of local residents, the direct beneficiaries of greener corporate practice. This study extends the literature by introducing local public attention as an external force influencing green

innovation, providing new insights into the role of public scrutiny in corporate sustainability efforts.

2.3 Hypotheses development

When firms operate under low levels of local public scrutiny, they may exploit information asymmetry between themselves and local residents by exceeding legally permissible pollution levels. As long as these violations do not visibly impact the daily lives of the local population, firms may evade external detection and continue unsustainable production practices. However, when local public attention intensifies, firms face a higher probability of detection and regulatory penalties, increasing their perceived risk of environmental non-compliance. The rationale behind this mechanism is that local residents, as the primary victims of environmental pollution, have strong incentives to monitor and report corporate misconduct. Public complaints and whistleblower reports play a crucial role in exposing environmental violations. In severe pollution cases, local residents actively collect evidence and submit complaints to regulatory authorities, prompting stricter environmental enforcement (Zheng et al., 2013). Given that government agencies have limited resources for regulatory inspections, public complaints significantly influence the allocation of enforcement efforts (Wheeler & Dasgupta, 1997).

In practice, government agencies adjust their enforcement intensity based on public complaints and environmental petitions. For instance, China's 2015 environmental policy reform mandated randomized inspections of firms based on local complaint frequencies, ensuring that companies with higher public scrutiny were subject to more

frequent regulatory checks. In 2015 alone, over 1.64 million environmental complaints were lodged nationwide, highlighting the high level of civic engagement in environmental monitoring.

Beyond regulatory concerns, local public attention can drive green innovation through reputational incentives. Firms that are frequently scrutinized by local communities are effectively placed under a public spotlight, creating pressure to enhance their corporate image. A strong reputation for environmental responsibility can yield multiple strategic benefits, including greater customer loyalty, improved employee retention, lower financing costs, and enhanced firm valuation (Turban & Greening, 1997; Caruana & Ewing, 2010; Cao et al., 2015). Empirical studies on media exposure and corporate social responsibility support this argument. For example, Xu et al. (2011) found that firms with higher media coverage tend to engage in greater philanthropic giving to cultivate a positive public image. Similarly, Borghesi et al. (2014) demonstrated that media scrutiny enhances corporate social responsibility (CSR) initiatives, prompting firms to adopt sustainability measures beyond regulatory compliance.

In the context of environmental sustainability, firms exposed to high levels of local public attention may engage in green innovation as a strategic tool to signal their commitment to sustainability. Since green innovation contributes to public goods -- such as cleaner air, reduced emissions, and improved ecological balance -- firms that invest in such initiatives enhance their reputation among stakeholders (Berrone & Gomez-Mejia, 2009). Thus, we hypothesize that local public attention strengthens the reputational incentives for firms to engage in green innovation:

Hypothesis 1a: Local public attention enhances corporate green innovation.

Despite the positive mechanisms outlined above, local public attention may also hinder green innovation under certain conditions. Studies on external monitoring mechanisms suggest that increased public scrutiny can impose significant short-term performance pressure on firms, leading to a reduction in long-term innovation investment. For example, He & Tian (2013) found that analyst coverage creates performance pressures on firms, compelling managers to meet short-term earnings targets at the expense of long-term R&D investment. Similarly, Yang et al. (2017) reported that negative media coverage exerts short-term market pressure on corporate managers, potentially discouraging firms from engaging in riskier, long-term innovation projects. Jiang et al. (2021) extended this analysis to online investor sentiment, showing that negative public discussions in financial forums lead to managerial conservatism, reducing corporate innovation efforts.

Local public attention shares similar characteristics with these external monitoring mechanisms, potentially leading to two forms of adverse effects on green innovation. First, green innovation involves high uncertainty and a high probability of failure (Holmstrom, 1989). When firms receive extensive local public scrutiny, private stakeholders -- such as employees, customers, and suppliers -- may amplify information about unsuccessful innovation projects, spreading negative perceptions of corporate performance. This heightened risk of public backlash may discourage firms from investing in long-term, uncertain innovation projects. Second, firms under intense local public scrutiny may face higher expectations for immediate financial performance. If a firm's profitability declines or fails to meet market expectations, local governments may reduce subsidies or policy support, further constraining innovation resources.

Consequently, firms facing persistent local public pressure may prioritize short-term financial stability over long-term green R&D investments. Given these concerns, local public attention may not always foster green innovation. Instead, it could create adverse managerial pressures, leading firms to scale back innovation efforts to minimize performance volatility. Given these dynamics, we propose the following hypothesis:

Hypothesis 1b: Local public attention impedes corporate green innovation.

3. SAMPLE AND METHODOLOGY

3.1. Data and sample

To analyze the impact of the local public attention on corporate green innovation, we utilize a sample of Chinese listed companies from 2011 to 2016. We obtained local public attention index from China Research Data Services. This unique internal dataset provides a significant advantage, as it enables us to capture of the level of local public attention directed toward a publicly traded firm based on Baidu search engine. The dataset is not available from the public channel. The green patent data are sourced from the CNRDS (China Research Data Services) database, which provides detailed firm-level innovation data. Additionally, financial and governance-related control variables are obtained from the CSMAR (China Stock Market & Accounting Research) database, which is widely used in Chinese financial and economic research. The choice of 2011 as the starting year is based on the following consideration: Prior to 2011, Chinese internet users could search for corporate information using both Baidu and Google. However, after Google withdrew its search services from mainland China in 2010, Baidu became the dominant search engine. As a result, using Baidu internal search data from 2011

onward provides a more comprehensive and consistent measure of local public attention, reducing potential measurement errors in the variable construction. The sample period ends in 2016, as the local search index data is only available up to 2016 in the database.

Consistent with prior research, the following criteria are applied in sample construction: (1) financial firms (e.g., banks, insurance companies, and securities firms) are excluded due to their distinct regulatory environment and financial reporting structures.; (2) firms that were delisted, classified as *ST (Special Treatment) or ST (Delisting Risk Warning) during the sample period are removed; and (3) observations with missing values for control variables are removed. Additionally, to mitigate the impact of outliers, continuous variables are winsorized at the 1% and 99% levels. The final sample consists of 8,782 firm-year observations.

3.2 Research methodology

We employ the following model to assess the effect of local public attention on corporate green innovation:

$$Green_{i,t+1} = \alpha + \beta_1 SVI\_Local_{i,t} + \beta_2 Controls_{i,t} + \varepsilon_{i,t} \qquad （1）$$

where our test variable is *SVI_Local*, representing the total volume of local online searches of the company *i*. In the studies on investor attention, stock ticker symbol is commonly used to capture investors' searches of a firm's information (Huang et al., 2016; Chi & Shanthikumar, 2017). However, local residents—who are the primary source of local public attention—are generally less familiar with stock ticker symbols. Therefore, to construct a more comprehensive measure of local public attention, we include a broader set of firm-related keywords, including full company names, company used

names, frequently searched names, stock abbreviation and stock ticker symbol[2]. By aggregating local search volumes across all these keywords, we construct a firm-level public attention index, which better captures the search volume of local residents and provides a more granular measure of the public attention on a firm within local communities.

To measure corporate green innovation, we adopt the International Patent Classification (IPC) Green List, which categorizes green patents into seven broad domains: waste management, nuclear power, transportation, energy conservation, agriculture and forestry, alternative energy production, and administrative management and design[3]. Given that a listed firm consists of a parent company and multiple subsidiaries, and the subsidiaries may be registered in different provinces, we focus on the green patent applications filed by the parent company to mitigate potential biases arising from subsidiary operations across different locations. *Green* is defined as the natural log of one plus the number of green patent applications for the firm to normalize the distribution and reduce skewness in the data.

Following prior literature (Chen et al., 2018; Xiang et al., 2022; Hao, 2023), we incorporate a series of control variables related to firm financial characteristics and corporate governance to ensure robustness, including firm size (*SIZE*), return on assets (*ROA*), leverage (*LEV*), revenue growth (*GROW*), operating cash flow (*OCF*), R&D

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[2] For example, in the case of Yonyou Network Technology Co., Ltd. (Stock Code: 600588), the search keywords include: (1) Stock ticker: "600588"; (2) Stock abbreviation: "用友网络" (Yonyou Network); (3) the company's current official name: "用友网络科技股份有限公司" (Yonyou Network Technology Co., Ltd.); (4) Previous names: "北京用友软件股份有限公司" (Beijing Yonyou Software Co., Ltd.) and "用友软件股份有限公司" (Yonyou Software Co., Ltd.); and (5) Commonly searched names: "用友软件" (Yonyou Software) and "北京用友软件" (Beijing Yonyou Software).
[3] The details of International Patent Classification (IPC) Green List can be found via https://www.wipo.int/classifications/ipc/green-inventory/home

intensity (*R&D*), board size (*Board*), independent director ratio (*INDEP*), ownership concentration (*TOP*), CEO duality (*DUAL*), and state ownership (*SOE*). To account for other external monitoring mechanisms, we also control for institutional shareholding (*INST*), audit quality (*BIG4*), analyst coverage (*Analyst*), and media coverage (*Media*). Finally, to control for unobserved time, industry, and regional effects, we include year, industry and province fixed effects. These controls help isolate the specific impact of local public attention on corporate green innovation, reducing potential omitted variable bias. Variable definitions are provided in Appendix A.

3.3 Summary statistics

Table 1 presents the descriptive statistics of the key variables used in this study. The average value of *Green* is 0.4044, indicating that, on average, each listed firm applies for approximately 1.50 ($e^{0.4044}$) green patents per year. For comparison, Amore and Bennedsen (2016), using data from U.S. publicly listed firms between 1976 and 1995, report an average of 8.5 patent applications per firm per year. This contrast suggests that Chinese firms lag behind the U.S. firms in developing technologies aimed at pollution reduction and waste utilization, highlighting the need for greater investment in sustainability-driven R&D in China. The local public attention variable (*SVI_Local*) has a mean of 3.4548 and a standard deviation of 6.2441, indicating substantial variation across firms in terms of the level of attention they receive from local residents. Some firms experience high levels of local public scrutiny, while others remain largely unnoticed, suggesting heterogeneous public engagement in corporate environmental affairs.

[Table 1 about here]

We then divide the sample into two groups based on the intensity of local public attention. Given that the median value of *SVI_Local* is 0, firms are classified into two categories: (1) firms with zero local public attention (*SVI_Local* = 0) and; (2) firms with positive local public attention (*SVI_Local* > 0). Table 2 reports the univariate test results, comparing green patent applications between these two groups. The findings reveal that firms receiving local public attention exhibit an average of 0.4753 green patents per year, whereas firms without local public attention report a lower average of 0.3579 green patents per year. A statistically significant difference is observed between these two groups, providing preliminary empirical support for the association between higher local public attention and greater green innovation efforts.

[Table 2 about here]

4. RESULTS AND DISCUSSION

4.1. Baseline results

Table 3 presents the baseline regression results, examining the relationship between local public attention (*SVI_Local*) and corporate green innovation (*Green*). Column (1) reports the results from a univariate regression, where *SVI_Local* is the sole independent variable. Column (2) introduces a set of control variables to account for firm-specific financial and governance characteristics. Column (3) further incorporates year fixed effects, industry fixed effects, and province fixed effects to control for time-specific trends, industry-wide dynamics, and regional variations. The coefficients on *SVI_Local* are positive and statistically significant across all columns, indicating a strong association between local public attention and firms' engagement in green innovation.

From an economic significance perspective, a one-standard-deviation increase in local public attention (*SVI_Local*) leads to a 13.43%[4] increase in green patent applications (*Green*) relative to the sample mean. These findings provide primary supports for the notion that local public engagement serves as a key driver of corporate sustainability-driven technological advancements.

[Table 3 about here]

4.2. Robustness tests

4.2.1. Difference-in-difference (DID) analysis

While the baseline regression results provide strong evidence of a positive association between local public attention (*SVI_Local*) and corporate green innovation (*Green*), concerns regarding reverse causality may still arise. Specifically, firms that engage more actively in green innovation may naturally attract greater local public attention, rather than the other way around.

To mitigate endogeneity concerns and establish a causal relationship, we leverage an exogenous shock, the first-time inclusion of a firm's ultimate controller in the Hurun Rich List, for a difference-in-difference (DID) analysis. This event serves as an ideal exogenous variation in local public attention, as the public visibility of a firm's controlling shareholder directly influences the firm's level of public scrutiny but is not directly related to the firm's green innovation activities. To further ensure robustness, we examine three different thresholds: (1) the Top 200 of the Hurun Rich List (*Hurun200*); (2) the Top 300 of the Hurun Rich List (*Hurun300*), and; (3) the Top 400 of the Hurun

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[4] The estimated coefficient on *SVI_Local* is 0.0087 in Table 3, and the standard deviation of *SVI_Local* and the mean value of *Green* are 6.2441 and 0.4044, respectively, as presented in Table 1. Therefore, we calculate the economic significance change as 0.0087*6.2441/0.4044*100% = 13.43%.

Rich List (*Hurun400*). The treatment group consists of firms whose ultimate controller was included in the Hurun Rich List for the first time during the sample period. Since only a limited number of firms experience this shock, we employ propensity score matching (PSM) to ensure comparability. Each treated firm is matched with three control firms that exhibit similar characteristics but whose controlling shareholders were not listed. For each firm, the sample includes observations from one year before, the year of, and one year after the Hurun Rich List inclusion event. The variable *Treated* is coded as follows: for firms in the treatment group, the variable equals 1 in the year of listing and the following year, and 0 in the year prior. While for firms in the control group, the variable is set to 0 for all years. Our interested variables are *Hurun200*, *Hurun300*, and *Hurun400*, which are the interaction terms of *Post* and *Treated*.

Table 4 reports the difference-in-differences (DID) regression results, with Columns (1), (2), and (3) presenting findings for the *Hurun200*, *Hurun300*, and *Hurun400* thresholds, respectively. Across all specifications, the coefficients on *Hurun200*, *Hurun300*, and *Hurun400* are positive and statistically significant, confirming that an exogenous increase in local public attention significantly enhances corporate green innovation.

[Table 4 about here]

4.2.2. Instrumental variable (IV) analysis

We then employ an instrumental variable approach to further address potential endogeneity issues. The chosen instrument is the number of cities within a province

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designated as "Broadband China" pilot cities (*Net*)[5]. In August 2013, China's State Council launched the Broadband China Strategy and Implementation Plan, which aimed to accelerate the development of broadband infrastructure. The plan set ambitious targets to be achieved by 2015, expanding fiber-optic broadband coverage to both urban households and rural areas. Following this initiative, broadband accessibility and internet penetration improved significantly. Starting in 2014, the Ministry of Industry and Information Technology (MIIT) and the National Development and Reform Commission (NDRC) began annually announcing a list of "Broadband China" pilot cities. These cities were recognized for substantial improvements in broadband penetration, accessibility, and internet speed following the strategy's implementation.

The instrumental variable (*Net*) is highly relevant to our interested variable (*SVI_Local*). A greater number of "Broadband China" pilot cities within a province implies higher broadband penetration and faster internet speeds, which in turn reduces the cost of searching for corporate information online. As a result, regions with better broadband infrastructure are expected to exhibit higher levels of local public attention toward firms. This satisfies the relevance condition for a valid instrumental variable. At the same time, the designation of "Broadband China" pilot cities is not directly related to firms' green innovation activities, satisfying the exogeneity condition. The expansion of broadband infrastructure affects public information access and search behavior, but it does not directly influence firms' green patent applications, making it an ideal exogenous shock for identifying causal effects.

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[5] Before 2013, China's broadband infrastructure lagged significantly behind its economic development. According to the International Telecommunication Union (ITU), in 2013, China's household broadband penetration rate was only 13.57%, ranking 80th globally. Moreover, broadband services in China were not only limited in coverage but also suffered from slow connection speeds. The high cost and slow speed of internet access were widely recognized as major public concerns.

Table 5 presents the instrumental variable regression results. In Column (1), the coefficient on *Net* is positive and statistically significant at the 1% level, with a first-stage F-statistics of 184.55, mitigating the concerns of weak instrument. In Column (2), the coefficient on *SVI_Local* remains positive and statistically significant, suggesting the robust impact of local public attention on corporate green innovation.

[Table 5 about here]

4.2.3. Alternative measurements

To further validate the robustness of our findings, we conduct three additional tests using alternative measurements of local public attention and green innovation quality. These tests assess whether the observed relationship between public scrutiny and corporate green innovation remains consistent under different methodological approaches.

Our first analysis aims to examine whether the observed effect of local public attention on green innovation is driven primarily by a subset of the public or by the collective influence of all local stakeholders. Local public attention can be classified into two distinct groups: attention from local stock investors and attention from local non-investment-driven residents. The first group track firm performance not only from an environmental perspective but also from an investment return standpoint. Since green innovation requires significant financial investment, which may reduce short-term profitability, local investors might be less inclined to support aggressive sustainability initiatives. In contrast, the second group are primarily concerned with environmental quality and community well-being. These individuals have strong incentives to monitor corporate environmental behavior and push for sustainability-driven innovation.

Therefore, we decompose local public attention into two components: (1) variable *SVI_Investor* measures local investor attention, proxied by total local search volume for stock ticker symbols of the firm; (2) variable *SVI_Noninvestor* captures non-investor public attention, calculated as total local search volume (*SVI_Local*) minus investor-related searches (*SVI_Investor*). Columns (1) and (2) of Table 6 report the regression results. The coefficients on both *SVI_Investor* and *SVI_Noninvestor* are positive and statistically significant at the 1% level, indicating that both local investors and non-investors contribute to increased green innovation. These findings suggest that corporate sustainability efforts are driven by broad public engagement rather than by any single subset of stakeholders.

Our second analysis aims to address the concerns about Baidu search data. While Baidu search data provides a strong measure of local public attention, it does not capture public discourse and activism expressed on social media platforms. To address this limitation, we construct an alternative province-level public attention index using the data from Weibo, a top 3 popular social media in China. Since 2022, China's provincial environmental protection bureaus have been mandated by the central government to operate official Weibo accounts to enhance public engagement. This platform provides a space for local residents to voice concerns about environmental issues, making them a valuable source of public attention data[6]. We define the following Weibo-based variables: (1) *Weibo*: The total number of comments on official environmental bureau Weibo posts from local users; (2) *Weibo_robust*: A refined measurement of Weibo, where duplicate

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[6] Due to data limitations, Weibo comments did not display user locations prior to 2022, preventing us from distinguishing between local and non-local commenters. However, since 2022, Weibo has included user province-level information, enabling us to construct a location-specific public attention measure. Therefore, our sample size reduces to 4,023 in the tests of analyzing Weibo data.

usernames are removed to reduce potential bias from repeated comments by the same users. Both variables are log-transformed for empirical analysis. Columns (3) and (4) of Table 6 report the regression results using these Weibo-based measures. The results remain statistically significant and consistent with our primary findings, confirming that local public attention—whether measured through search engine data or social media interactions—positively influences corporate green innovation.

These findings further strengthen the study's empirical validity, demonstrating that the relationship between public attention and corporate green innovation remains robust under different methodological approaches.

[Table 6 about here]

4.2.4. PSM and entropy balance analyses

Since Table 2 indicates significant differences in control variables between the high and low public attention groups, to ensure that these differences do not introduce biases in the regression analysis, we employ propensity score matching (PSM) and entropy balancing as robustness tests to mitigate the risk of selection bias affecting the reliability of the results.

First, we divide our sample into treatment and control groups based on the median value of the total province-based search volume in each year. We apply PSM to minimize significant differences in firm characteristics between these groups, using propensity scores calculated from all control variables listed in Table 2. Second, we employ entropy balancing, a technique designed to achieve covariate balance in binary treatment studies (Wilde, 2017). Unlike PSM, entropy balancing retains all observations while ensuring

that covariate distributions between treatment and control groups are balanced. By preserving the full sample, this method minimizes information loss and reduces the risk of bias due to ex-ante inefficiency (Wilde, 2017). To implement this, we apply entropy weights to balance the first, second, and third moments of all control variables used in our main analysis, aligning the mean, variance, and skewness of covariates between the treated and control groups. The definition of the treated group remains consistent throughout.

Table 7 presents the results from both PSM and entropy balancing tests. The coefficient on *SVI_Local* remains significant and positive, indicating that our conclusions hold even after accounting for potential sample selection bias. This reinforces the robustness of our findings.

[Table 7 about here]

4.2.5. Other robustness tests

While our baseline analysis uses green patent counts as a measure of corporate green innovation, it does not capture the quality or impact of these innovations. To address this limitation, we adopt an alternative measure based on patent citations, following the methodology of Chu et al. (2019). We introduce *Citation*, which represents the number of non-self-citations received by a firm's green patents, as a proxy for the technological significance and influence of green innovation. Column (1) of Table 8 presents the regression results using *Citation* as the dependent variable. The coefficient on *SVI_Local* remains positive and statistically significant, indicating that higher local

public attention is not only associated with a greater number of green patents but also with higher-quality, more widely recognized green innovations.

One potential limitation of our baseline analysis is that unobserved time-invariant firm characteristics may bias the results. To account for this possibility, we include firm fixed effects in addition to year fixed effects. Column (2) of Table 8 reports the regression results after controlling for both year and firm fixed effects. The coefficient on *SVI_Local* remains positive and statistically significant, indicating that the relationship between local public scrutiny and green innovation persists even after accounting for firm-specific heterogeneity.

Another potential concern is that the results may be influenced by time-varying industry- and region-specific factors. For example, differences in industry growth opportunities and regional economic development could serve as potential confounding variables. To address this, we follow the approach of Flammer and Kacperczyk (2019) and introduce two additional interaction fixed effects: Year × Industry and Year × Region fixed effects to control for industry-wide trends that evolve over time, and differences in regional economic conditions across years. Column (3) of Table 8 presents the regression results after incorporating these higher-dimensional fixed effects. The coefficient on *SVI_Local* remains robustly positive and significant, confirming that the observed relationship is not driven by unobserved industry or regional shocks. These results provide strong empirical support for the validity of the findings.

[Table 8 about here]

Although the results suggest a robust link between local public attention and corporate green innovation, an alternative explanation could be that local public attention

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is influenced by external information spillover from national media coverage. Existing research suggests that non-local media outlets are more likely to report on corporate scandals and environmental controversies than local media (Hope et al., 2021). While our baseline regressions control for media attention, it is possible that negative national media coverage of a firm may lead to increased external public scrutiny, triggering both non-local and local public attention simultaneously. If external public attention also promotes corporate green innovation, then the observed relationship between local public attention and green innovation may be confounded by unobservable omitted variables.

To rule out this alternative explanation, we conduct a placebo test using an alternative measure of non-local public attention (*SVI_Nonlocal*). This variable is constructed as the average level of firm-specific public attention from all provinces except the firm's home province. If the positive relationship between local public attention and green innovation were merely driven by external media spillover, then the coefficient on *SVI_Nonlocal* should also be significantly positive.

Column (4) of Table 8 presents the placebo test results. The coefficient on *SVI_Nonlocal* fails to reach statistical significance, indicating that non-local public attention does not have a measurable impact on corporate green innovation. This finding rejects the alternative hypothesis that the relationship between local public attention and green innovation is driven by external information spillover effects.

5. FURTHER ANALYSES

5.1. Mechanism test

5.1.1. Risk perception mechanism

To further explore the mechanisms through which local public attention influences corporate green innovation, we examine two potential channels: risk perception and reputation enhancement.

The first proposed mechanism is the risk perception mechanism, which suggests that firms facing greater public scrutiny perceive a higher risk of regulatory penalties (Wu & Ye, 2020), leading them to proactively invest in green innovation as a risk mitigation strategy. The effectiveness of public monitoring depends on the cost of public supervision on corporate environmental performance. Lower public supervision costs enable more active monitoring, increasing firms' perceived regulatory risks and penalty pressures.

To measure public supervision costs, we use the environmental complaint resolution rate, which reflects the time and communication costs incurred by local residents when reporting environmental violations. Public environmental complaints serve as a critical mechanism for holding firms accountable. In severe pollution incidents, local residents—who experience environmental degradation firsthand—often provide key evidence to environmental enforcement agencies. However, if complaints remain unresolved for extended periods, residents may resort to repeated complaints, public demonstrations, or protests, increasing the supervisory burden on the public. Thus, a higher complaint resolution rate indicates lower public supervision costs.

We rely on two proxies for environmental complaint resolution rates: (1) phone and online complaints resolution rate, calculated as the number of resolved complaints filed via phone or online platforms divided by the total number of such complaints, and (2) letter and in-person complaints resolution rate, measured as the number of resolved complaints submitted via letters or in-person visits divided by the total number of such complaints. Using these two proxies, we then introduce two variables for our analyses: (1) *Cost_Pub1*, a dummy variable equal to 1 if the region's phone and online complaint resolution rate is below the national median, and 0 otherwise; (2) *Cost_Pub2*, a dummy variable equal to 1 if the region's letter and in-person complaint resolution rate is below the national median, and 0 otherwise.

[Table 9 about here]

Columns (1) and (2) of Table 9 present the regression results for *Cost_Pub1*. The coefficient on *SVI_Local* is 0.0068 and significant at the 10% level in the high supervision cost group, while it is 0.0120 and significant at the 1% level in the low supervision cost group. A formal coefficient difference test confirms that the effect of local public attention is stronger when public supervision costs are lower. Columns (3) and (4) of Table 9 report the results for *Cost_Pub2* (letter and in-person complaints). documenting similar more pronounced impact of local public attention on green innovation when public monitoring costs are lower.

Beyond public supervision costs, the effectiveness of regulatory enforcement also depends on government monitoring capacity (Xiao & Shao, 2020). When government monitoring costs are high, enforcement tends to be delayed or ineffective, reducing firms' perceived regulatory risks and penalties. To measure government supervision costs, we

use the number of key polluting enterprises in a province that have installed automatic pollution monitoring systems. According to the Water Pollution Prevention and Control Law and the Air Pollution Prevention and Control Law of China, major polluting firms are required by law to install real-time monitoring systems connected to environmental authorities. A higher number of enterprises with automated monitoring indicates lower government monitoring costs, as officials can oversee compliance without increasing enforcement personnel. We construct a new variable *Cost_Gov*, a dummy variable equals to 1 if the number of monitored polluting firms in a province is below the national median, and 0 otherwise, for additional analysis.

Columns (5) and (6) of Table 9 present the results for government monitoring costs. In the high government supervision cost group, the coefficient on *SVI_Local* is not significant, while in the low government supervision cost group, it is significantly positive. The coefficient difference test confirms that local public attention has a stronger impact on green innovation when government monitoring costs are lower. These findings provide strong support for the risk perception mechanism, demonstrating that local public scrutiny is most effective in promoting green innovation when public and governmental supervision costs are low.

5.1.2. Reputation mechanism

The second proposed mechanism is the reputation mechanism, which suggests that local public attention incentivizes firms to engage in green innovation to maintain a positive corporate image. Legitimacy theory suggests that firms will be proactive in maintaining legitimacy by satisfying the external audiences (Jeong & Kim, 2019).

Therefore, we expect that the positive relationship between local public attention and green innovation should be stronger for firms with better reputations.

Following Dyck and Zingales (2002), we use the number of positive online news articles about a firm as the first proxy for corporate reputation. Specifically, we introduce a dummy variable *Media_d*, which is equal to 1 if the number of positive media reports is above the sample median, and 0 otherwise. Columns (1) and (2) of Table 10 present the results based on positive media coverage. In firms with higher positive media exposure, the coefficient on *SVI_Local* is significantly positive, whereas in firms with lower positive media coverage, the coefficient is not significant. The coefficient difference test confirms that the influence of local public attention on green innovation is stronger in firms with higher reputational capital.

Our second measurement for corporate reputation is whether a firm has been penalized by regulators. We introduce a new dummy variable *Punish*, which is equal to 1 if the firm has received regulatory penalties, and 0 otherwise. Columns (3) and (4) of Table 10 report the regression results based on regulatory penalties. In firms that have not been penalized, the coefficient on *SVI_Local* is significantly positive at the 1% level, whereas in firms that have received penalties, the coefficient is not significant. These results suggest that local public attention has a stronger impact on green innovation for firms that maintain a clean regulatory record, further validating the reputation mechanism.

These findings confirm that local public attention drives corporate green innovation partly through reputational incentives. Firms with stronger reputational capital are more likely to respond to public scrutiny by engaging in sustainability-driven

innovations, whereas firms with a history of regulatory penalties do not exhibit the same responsiveness.

[Table 10 about here]

5.2. Types of green innovation

Given that local public attention drives corporate green innovation, a key question arises: Do firms adjust their R&D focus to align with public expectations? To explore this, we categorize green patents from the International Patent Classification Green List into three distinct types based on their primary environmental functions: (1) Pollution control patents (*Green_PC*): These patents are designed to reduce pollutant emissions, including waste management technologies and transportation-related innovations; (2) Clean energy development patents (*Green_CEDP*): These patents focus on renewable energy and energy efficiency, encompassing alternative energy production, energy conservation, and nuclear power technologies; (3) Other green patents (*Green_OGP*): This category includes agriculture, forestry, and administrative management & design patents, which are environmentally relevant but not directly tied to pollution reduction or energy efficiency. Since pollution control patents offer the most immediate and visible environmental improvements, we expect them to be the most perceptible to local residents. In contrast, clean energy development represents a long-term investment with delayed environmental benefits, making it less tangible to the public in the short run. Under high levels of public scrutiny, firms may prioritize pollution control innovations, which demonstrate immediate environmental improvements and help alleviate public concerns about corporate pollution.

Columns (1), (2), and (3) of Table 11 present the impact of local public attention (*SVI_Local*) on different types of green innovation. The results indicate that *SVI_Local* has a significantly positive effect on pollution control patents (*Green_PC*), suggesting that firms prioritize tangible, immediate environmental improvements in response to public pressure. In contrast, the impact on clean energy patents (*Green_CEDP*) and other green patents (*Green_OGP*) is weaker, supporting the argument that firms adjust their green innovation strategy to align with public concerns about pollution. These findings indicate that corporate environmental R&D efforts are not only shaped by regulatory mandates but also strategically tailored to public perceptions and expectations.

[Table 11 about here]

Beyond shaping the direction of green innovation, local public attention may also influence firms' choices between independent and collaborative R&D. Research by Cuijpers et al. (2011) suggests that collaborative innovation requires longer development cycles due to higher coordination and resource integration costs. If firms seek to demonstrate environmental improvements quickly in response to public scrutiny, they may favor independent R&D strategies, which allow for faster patent filings and shorter innovation lead times. To test this hypothesis, we classify patents into: (1) Independently developed green patents (*Green_ID*): Patents filed solely by the firm, reflecting in-house innovation efforts; and (2) Collaboratively developed green patents (*Green_CP*): Patents co-filed with external research partners, representing joint R&D initiatives. Columns (4) and (5) of Table 11 present the findings. The coefficient on *SVI_Local* is significantly positive in the independent R&D model (Column 4), indicating that firms exposed to higher public attention tend to rely more on independent innovation strategies. In contrast,

the coefficient on *SVI_Local* in the collaborative R&D model (Column 5) is positive but not statistically significant, suggesting that local public attention does not significantly influence collaborative green innovation efforts. These findings imply that firms under greater public scrutiny prioritize independent innovation to expedite the green innovation process. Since collaborative projects often require extended negotiations, resource-sharing agreements, and cross-organizational coordination, firms facing strong public pressure may prefer internal R&D efforts to deliver visible environmental improvements more quickly.

6. CONCLUSION

Existing research on corporate green innovation has primarily followed the logic of the Porter Hypothesis, emphasizing the role of government environmental regulations in driving sustainability efforts. However, evidence from developed economies suggests that public engagement also plays a crucial role in advancing environmental initiatives and incentivizing firms to adopt green innovation strategies. This study examines non-financial A-share listed firms in Shanghai and Shenzhen from 2011 to 2016, constructing a novel measure of local public attention by aggregating province-level search volumes for various firm-related keywords from an internal database. Using this unique public attention index, we investigate the impact of local public scrutiny on corporate green innovation. We find that local public attention significantly promotes corporate green innovation. Mechanism analyses confirm that local public attention influences green innovation through both risk perception and reputation effects. Further analyses reveal

that local public attention shapes both the direction and types of corporate green innovation. Our results are robust to a battery of robustness tests.

This study contributes to the literature by shifting the focus from top-down government regulation to bottom-up public scrutiny as a driver of corporate green innovation. By developing a novel firm-level measure of public attention, we provide empirical evidence that local public scrutiny effectively incentivizes firms to engage in sustainable technological advancements. Our findings underscore the importance of public participation in environmental governance, demonstrating that a combination of government regulation and grassroots monitoring can significantly enhance corporate sustainability efforts. Moving forward, policymakers should prioritize institutionalizing public participation, strengthening environmental credit transparency, and leveraging reputation mechanisms to drive corporate green innovation.

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Appendix A Variable definition

Variable	Definition
Green	Natural log of one plus numbers of green patent.
SVI_Local	The total province-based search volume of the firm, including full company name, company used names, frequently searched names, stock abbreviation and stock ticker symbol.
SIZE	Natural log of total assets.
ROA	Net profit divided by total assets.
LEV	Total liabilities divided by total assets.
GROW	The annual growth rate of total sales.
OCF	Operating cash flow divided by total assets
R&D	Research and development expenses divided by total sales.
Board	Natural log of board members.
INDEP	Number of independent directors divided by total number of board members.
TOP	The percentage of shares held by the largest shareholder.
DUAL	Dummy variable, equal to 1 if CEO is also the chairman, 0 otherwise.
INST	The percentage of shares held by institutional investors.
SOE	Dummy variable, equal to 1 if the firm is state-owned, 0 otherwise.
BIG4	Dummy variable, equal to 1 if the auditor is Big 4.
Analyst	The number of analyst reports about the firm of the year.
Media	The number of financial news reports about the firm of the year.
Hurun200	Dummy variable, equal to 1 if the firm is on the Top 200 of the Hurun Rich List, 0 otherwise.
Hurun300	Dummy variable, equal to 1 if the firm is on the Top 300 of the Hurun Rich List, 0 otherwise.
Hurun400	Dummy variable, equal to 1 if the firm is on the Top 400 of the Hurun Rich List, 0 otherwise.
Net	The number of cities within a province designated as "Broadband China" pilot cities.
SVI_Investor	The total local online search volume for stock ticker symbols of the firm.
SVI_Noninvestor	The total local online search volume minus investor-related searches.
SVI_Nonlocal	The average firm-specific search volume from all provinces except the firm's home province.
Citation	The total number of non-self-citations received by a firm's green patents.
Weibo	The total number of comments on official environmental bureau Weibo posts from local users
Weibo_robust	A refined measurement of Weibo, where duplicate usernames are removed to reduce potential bias from repeated comments by the same users.
Cost_Pub1	Dummy variable, equal to 1 if the number of resolved complaints filed via phone or online platforms divided by the total number of such complaints is below the national median, and 0 otherwise.
Cost_Pub2	Dummy variable, equal to 1 if the number of resolved complaints filed via letters or in-person visits divided by the total number of such complaints is below the national median, and 0 otherwise.
Cost_Gov	Dummy variable, equal to 1 if the number of the number of monitored polluting firms in a province is below the national median, and 0 otherwise.
Media_d	Dummy variable, equal to 1 if the number of positive media reports is above the sample median, and 0 otherwise.
Punish	Dummy variable, equal to 1 if the firm has received regulatory penalties, and 0 otherwise.
Green_PC	The total number of pollution control patents.
Green_CEDP	The total number of clean energy development patents.
Green_OGP	The total number of other green patents.
Green_ID	The total number of independently development green patents.

Green_CP	The total number of patents co-filed with external research partners.

Table 1 Summary statistics

This table presents descriptive statistics. Variables are defined in Appendix A.

Variable	Obs	Mean	Std	25%	50%	75%
Green	8,782	0.4044	0.8163	0.0000	0.0000	0.0000
SVI_Local	8,782	3.4548	6.2441	0.0000	0.0000	4.5898
SIZE	8,782	22.3295	1.2493	21.4224	22.1250	23.0534
ROA	8,782	0.0419	0.0456	0.0153	0.0359	0.0637
LEV	8,782	0.4400	0.2000	0.2806	0.4399	0.5989
GROW	8,782	0.3399	0.8955	-0.0349	0.1233	0.3844
OCF	8,782	0.0493	0.0670	0.0103	0.0475	0.0895
R&D	8,782	0.0258	0.0274	0.0009	0.0209	0.0382
Board	8,782	2.2777	0.1736	2.1972	2.3026	2.3026
INDEP	8,782	0.3698	0.0487	0.3333	0.3333	0.4000
TOP	8,782	0.3630	0.1519	0.2410	0.3470	0.4710
DUAL	8,782	0.2148	0.4107	0.0000	0.0000	0.0000
INST	8,782	0.4289	0.2295	0.2530	0.4493	0.6102
SOE	8,782	0.4629	0.4986	0.0000	0.0000	1.0000
BIG4	8,782	0.0733	0.2607	0.0000	0.0000	0.0000
Analyst	8,782	16.3121	20.0957	1.0000	8.0000	24.0000
Media	8,782	10.2288	12.8103	2.0000	5.0000	12.0000

Table 2 Univariate test results

This table presents the univariate test results. Variables are defined in Appendix A. *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

Variable	SVI_Local = 0		SVI_Local > 0		Difference	t-value
	Obs	Mean	Obs	Mean		
Green	5,308	0.3579	3,474	0.4753	-0.1174	-6.6051***
SIZE	5,308	22.1500	3,474	22.6038	-0.4538	-16.9120***
ROA	5,308	0.0395	3,474	0.0455	-0.0060	-6.0256***
LEV	5,308	0.4302	3,474	0.4549	-0.0248	-5.6842***
GROW	5,308	0.3474	3,474	0.3285	0.0189	0.9689
OCF	5,308	0.0448	3,474	0.0561	-0.0113	-7.7692***
R&D	5,308	0.0269	3,474	0.0242	0.0027	4.5582***
Board	5,308	2.2747	3,474	2.2824	-0.0077	-2.0421**
INDEP	5,308	0.3691	3,474	0.3709	-0.0019	-1.7768*
TOP	5,308	0.3605	3,474	0.3670	-0.0065	-1.9638**
DUAL	5,308	0.2255	3,474	0.1983	0.0272	3.0339***
INST	5,308	0.4178	3,474	0.4458	-0.0280	-5.5985***
SOE	5,308	0.4456	3,474	0.4893	-0.0438	-4.0281***
BIG4	5,308	0.0571	3,474	0.0982	-0.0411	-7.2408***
Analyst	5,308	13.9593	3,474	19.9070	-5.9477	-13.7057***
Media	5,308	8.0902	3,474	13.4963	-5.4060	-19.7618***

Table 3 Main results: Local public attention and corporate green innovation

This table presents the baseline results. *Green* is measured as the natural log of one plus number of green patents. *SVI_Local* is measured as the total local online search volume of the firm. Control variables are defined in Appendix A. The standard errors are reported in parentheses and are clustered at firm levels. *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

Variable	$Green_{t+1}$	$Green_{t+1}$	$Green_{t+1}$
	(1)	(2)	(3)
SVI_Local_t	0.0200***	0.0076**	0.0087***
	(0.0040)	(0.0032)	(0.0029)
$SIZE_t$		0.1296***	0.1261***
		(0.0205)	(0.0211)
ROA_t		0.2842	0.6591**
		(0.3492)	(0.3036)
LEV_t		0.3634***	0.2147**
		(0.0985)	(0.0975)
$GROW_t$		-0.0378***	0.0064
		(0.0110)	(0.0107)
OCF_t		0.0482	0.1263
		(0.1729)	(0.1574)
$R\&D_t$		9.0932***	4.4162***
		(0.6771)	(0.7713)
$Board_t$		0.1467	0.1995*
		(0.1252)	(0.1147)
$INDEP_t$		-0.2072	-0.0067
		(0.3406)	(0.3093)
TOP_t		0.0998	-0.0420
		(0.1163)	(0.1053)
$DUAL_t$		0.0491	0.0388
		(0.0359)	(0.0329)
$INST_t$		0.0094	0.1133*
		(0.0678)	(0.0638)
SOE_t		0.0376	0.1033***
		(0.0376)	(0.0397)
$BIG4_t$		0.2050**	0.1974**
		(0.0982)	(0.0903)
$Analyst_t$		0.0034***	0.0027***
		(0.0010)	(0.0009)
$Media_t$		0.0007	0.0022
		(0.0015)	(0.0013)
Year FE	NO	NO	YES
Industry FE	NO	NO	YES
Province FE	NO	NO	YES
Observations	8,782	8,782	8,782
Adj R^2	0.0264	0.1673	0.2848

Table 4 Robustness test: Difference-in-difference (DID) analysis

This table presents the results of difference-in-difference (DID) analysis. *Hurun200(300, or 400)* is a dummy variable, equal to 1 if the firm is on the Top 200 (300, or 400) of the Hurun Rich List, and 0 otherwise. *Green* is measured as the natural log of one plus number of green patents. *SVI_Local* is measured as the total local online search volume of the firm. Control variables are defined in Appendix A. The standard errors are reported in parentheses and are clustered at firm levels. *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

Variable	$Green_{t+1}$	$Green_{t+1}$	$Green_{t+1}$
	(1)	(2)	(3)
$Hurun200_t$	0.2238***		
	(0.0853)		
$Hurun300_t$		0.2225**	
		(0.0958)	
$Hurun400_t$			0.1550*
			(0.0830)
$SIZE_t$	0.2673	0.0692	-0.0606
	(0.1676)	(0.1041)	(0.0817)
ROA_t	-0.5287	0.8826	1.4319*
	(1.5099)	(1.0484)	(0.8022)
LEV_t	0.2418	0.3377	0.7904**
	(0.6208)	(0.4056)	(0.3352)
$GROW_t$	-0.0023	-0.0109	-0.0211
	(0.0358)	(0.0318)	(0.0259)
OCF_t	0.7727	0.0971	-0.7415**
	(0.7808)	(0.4766)	(0.3761)
$R\&D_t$	0.4030	-1.1375	1.6943
	(2.3647)	(2.4015)	(1.5739)
$Board_t$	0.3300	0.8657**	0.3931
	(0.5727)	(0.4082)	(0.4999)
$INDEP_t$	-0.5617	0.7018	1.4356
	(1.5258)	(0.8503)	(1.0591)
TOP_t	0.8329	-0.0687	0.2860
	(1.1989)	(0.7464)	(0.3226)
$DUAL_t$	0.0680	0.2334*	0.0187
	(0.3362)	(0.1351)	(0.1654)
$INST_t$	-0.1655	-0.1235	-0.1864
	(0.3055)	(0.2625)	(0.1714)
SOE_t	1.4154***	-0.2135	0.1409
	(0.4541)	(0.1376)	(0.1079)
$BIG4_t$	-0.2236	-0.5291***	-0.4221
	(0.1534)	(0.0847)	(0.3162)
$Analyst_t$	0.0045	0.0031	0.0016
	(0.0042)	(0.0030)	(0.0019)
$Media_t$	0.0028	-0.0126***	0.0002
	(0.0080)	(0.0040)	(0.0030)
Year FE	NO	NO	NO
Industry FE	NO	NO	NO
Province FE	YES	YES	YES
Observations	539	826	981
Adj R^2	0.6776	0.7019	0.7266

Table 5 Robustness test: Instrumental variable (IV) estimates

This table presents the results of instrumental variable (IV) estimates. Column (1) shows the first stage result and column (2) shows the second stage results. *Net* is the number of cities within a province designated as "Broadband China" pilot cities. *Green* is measured as the natural log of one plus number of green patents. *SVI_Local* is measured as the total local online search volume of the firm. Control variables are defined in Appendix A. The standard errors are reported in parentheses and are clustered at firm levels. *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

	SVI_Local_t	$Green_{t+1}$
	(1)	(2)
Net_t	2.8118***	
	(0.2084)	
SVI_Local_t		0.0186**
		(0.0093)
$SIZEe_t$	0.8424***	0.1176***
	(0.0867)	(0.0136)
ROA_t	4.7362***	0.6137***
	(1.8230)	(0.2339)
LEV_t	0.0051	0.2147***
	(0.4624)	(0.0583)
$GROW_t$	-0.1593**	0.0078
	(0.0769)	(0.0098)
OCF_t	1.9962*	0.1042
	(1.0563)	(0.1348)
$R\&D_t$	-5.5598*	4.4715***
	(3.1510)	(0.4008)
$Board_t$	-0.2387	0.2017***
	(0.4468)	(0.0564)
$INDEP_t$	-0.2962	-0.0053
	(1.4877)	(0.1876)
TOP_t	0.7859*	-0.0494
	(0.4680)	(0.0594)
$DUAL_t$	0.1822	0.0372*
	(0.1581)	(0.0200)
$INST_t$	-2.0673***	0.1341***
	(0.3298)	(0.0460)
SOE_t	0.9639***	0.0934***
	(0.1574)	(0.0219)
$BIG4_t$	0.4421	0.1922***
	(0.2695)	(0.0343)
$Analyst_t$	0.0326***	0.0023***
	(0.0040)	(0.0006)
$Media_t$	0.1115***	0.0011
	(0.0052)	(0.0012)
Year FE	YES	YES
Industry FE	YES	YES
Province FE	YES	YES
F-value	182.0400	-
Observations	8,782	8,782
Adj R^2	0.3203	0.1141

Table 6 Robustness test: Alternative measurements

This table presents the baseline results with alternative measurements of local public attention. *SVI_Investor* is measured as the total local online search volume for stock ticker symbols of the firm. *SVI_Noninvestor* is measured as the total local online search volume minus investor-related searches. *Weibo* is the total number of comments on official environmental bureau Weibo posts from local users. *Weibo_robust* is a refined measurement of *Weibo*, where duplicate usernames are removed to reduce potential bias from repeated comments by the same users. *Green* is measured as the natural log of one plus number of green patents. Control variables are defined in Appendix A. The standard errors are reported in parentheses and are clustered at firm levels. *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

	$Green_{t+1}$	$Green_{t+1}$	$Green_{t+1}$	$Green_{t+1}$
	(1)	(2)	(3)	(4)
$SVI\_Investor_t$	0.0042***			
	(0.0014)			
$SVI\_Noninvestor_t$		0.0223***		
		(0.0069)		
$Weibo$			0.0165***	
			(0.0059)	
$Weibo\_robust$				0.0227**
				(0.0107)
$SIZE_t$	0.1238***	0.1268***	0.0909***	0.0906***
	(0.0202)	(0.0210)	(0.0132)	(0.0132)
ROA_t	0.6356**	0.6449**	0.4707**	0.4708**
	(0.2934)	(0.3040)	(0.1870)	(0.1871)
LEV_t	0.2196**	0.2144**	0.4306***	0.4333***
	(0.0950)	(0.0976)	(0.0686)	(0.0686)
$GROW_t$	0.0055	0.0063	-0.0571*	-0.0577*
	(0.0104)	(0.0107)	(0.0342)	(0.0342)
OCF_t	0.1452	0.1397	-0.0512	-0.0515
	(0.1520)	(0.1576)	(0.1686)	(0.1689)
$R\&D_t$	4.7584***	4.4166***	0.6523***	0.6365***
	(0.7730)	(0.7709)	(0.1728)	(0.1729)
$Board_t$	0.1941*	0.1974*	0.0342	0.0348
	(0.1094)	(0.1144)	(0.0753)	(0.0754)
$INDEP_t$	0.0182	-0.0123	0.2976	0.2979
	(0.3013)	(0.3092)	(0.2711)	(0.2713)
TOP_t	-0.0392	-0.0401	0.1173	0.1140
	(0.1022)	(0.1052)	(0.0790)	(0.0791)
$DUAL_t$	0.0374	0.0388	-0.0156	-0.0171
	(0.0319)	(0.0329)	(0.0223)	(0.0223)
$INST_t$	0.1137*	0.1163*	-0.0550	-0.0532
	(0.0624)	(0.0640)	(0.0561)	(0.0561)
SOE_t	0.1035***	0.1051***	0.0494	0.0502
	(0.0383)	(0.0396)	(0.0312)	(0.0312)
$BIG4_t$	0.1830**	0.1959**	-0.0489	-0.0477
	(0.0855)	(0.0903)	(0.0552)	(0.0553)
$Analyst_t$	0.0026***	0.0027***	0.0166	0.0163
	(0.0008)	(0.0009)	(0.0123)	(0.0124)
$Media_t$	0.0023*	0.0022*	0.0002***	0.0002***
	(0.0014)	(0.0013)	(0.0000)	(0.0000)
Year FE	YES	YES	NO	NO
Industry FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Observations	8,782	8,782	4,023	4,023
Adj R^2	0.2819	0.2850	0.1319	0.1311

Table 7 Robustness test: PSM and entropy balance analyses

This table reports the results of propensity score matching (PSM) and entropy balancing methods. *Green* is measured as the natural log of one plus number of green patents. *SVI_Local* is measured as the total local online search volume of the firm. Variables are defined in Appendix A. The standard errors are reported in parentheses and are clustered at firm levels. *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

Variable	Match type	Mean Treated	Mean Control	t	P-value	$Green_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
SVI_Local_t	-	-	-	-	-	0.0064**
	-	-	-	-	-	(0.0032)
$SIZE_t$	U	22.6800	22.3230	3.4900	0.0000	0.1349***
	M	22.6800	22.7970	-0.8500	0.3960	(0.0237)
ROA_t	U	0.0836	0.0412	11.4500	0.0000	0.5182
	M	0.0836	0.0768	1.0200	0.3090	(0.3459)
LEV_t	U	0.3966	0.4407	-2.7000	0.0070	0.1240
	M	0.3966	0.4321	-1.5400	0.1250	(0.1143)
$GROW_t$	U	0.3634	0.3395	0.3300	0.7450	0.0023
	M	0.3634	0.4394	-0.6000	0.5470	(0.0128)
OCF_t	U	0.0761	0.0488	4.9800	0.0000	0.4373**
	M	0.0761	0.0708	0.5900	0.5530	(0.1905)
$R\&D_t$	U	0.0339	0.0257	3.6500	0.0000	4.7798***
	M	0.0339	0.0294	1.3800	0.1680	(0.9033)
$Board_t$	U	2.2150	2.2788	-4.5000	0.0000	0.2256*
	M	2.2150	2.2130	0.1000	0.9170	(0.1289)
$INDEP_t$	U	0.3850	0.3695	3.8700	0.0000	0.0317
	M	0.3850	0.3877	-0.4200	0.6730	(0.3814)
TOP_t	U	0.4477	0.3616	6.9500	0.0000	-0.0852
	M	0.4477	0.4782	-1.6300	0.1050	(0.1165)
$DUAL_t$	U	0.3290	0.2128	3.4600	0.0010	0.0697*
	M	0.3290	0.3026	0.4900	0.6230	(0.0386)
$INST_t$	U	0.5104	0.4275	4.4200	0.0000	0.0898
	M	0.5104	0.5204	-0.3600	0.7200	(0.0755)
SOE_t	U	0.0921	0.4694	-9.2900	0.0000	0.1313***
	M	0.0921	0.1184	-0.7500	0.4560	(0.0426)
$BIG4_t$	U	0.0592	0.0736	-0.6700	0.5010	0.1935*
	M	0.0592	0.0658	-0.2400	0.8130	(0.1006)
$Analyst_t$	U	32.8620	16.0210	10.3000	0.0000	0.0025**
	M	32.8620	31.7830	0.3600	0.7200	(0.0010)
$Media_t$	U	15.5070	10.1360	5.1300	0.0000	0.0034**
	M	15.5070	16.6250	-0.5800	0.5610	(0.0016)
Year FE	-	-	-	-	-	YES
Industry FE	-	-	-	-	-	YES
Province FE	-	-	-	-	-	YES
Observations	-	2199	2141	-	-	4,340
Adj R^2	-	-	-	-	-	0.3039

Table 8 Robustness test: Additional analyses

This table reports the results of additional robustness tests. *Citation* is measured as total number of non-self-citations received by a firm's green patents. *SVI_Nonlocal* is measured as the average firm-specific search volume from all provinces except the firm's home province. *Green* is measured as the natural log of one plus number of green patents. *SVI_Local* is measured as the total local online search volume of the firm. Variables are defined in Appendix A. The standard errors are reported in parentheses and are clustered at firm levels. *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

Variable	$Citation_{t+1}$	$Green_{t+1}$	$Green_{t+1}$	$Green_{t+1}$
	(1)	(2)	(3)	(4)
SVI_Local_t	0.0082**	0.0074**	0.0069**	
	(0.0040)	(0.0030)	(0.0030)	
$SVI\_Nonlocal_t$				0.0083
				(0.0061)
$SIZE_t$	0.4115***	-0.0028	-0.0080	0.1326***
	(0.0306)	(0.0215)	(0.0224)	(0.0211)
ROA_t	0.3063	0.4447**	0.4796**	0.6917**
	(0.4401)	(0.1855)	(0.1981)	(0.3078)
LEV_t	0.3812***	0.1597**	0.1818**	0.2132**
	(0.1420)	(0.0755)	(0.0826)	(0.0976)
$GROW_t$	0.0196	-0.0074	-0.0106	0.0059
	(0.0184)	(0.0065)	(0.0069)	(0.0106)
OCF_t	0.1486	0.0170	-0.0255	0.1503
	(0.2353)	(0.0961)	(0.1036)	(0.1580)
$R\&D_t$	10.5112***	0.6650	0.4224	4.3773***
	(1.1234)	(0.5610)	(0.6154)	(0.7726)
$Board_t$	0.1463	0.0853	0.1330*	0.1936*
	(0.1602)	(0.0770)	(0.0782)	(0.1149)
$INDEP_t$	-0.1921	0.0236	0.0482	-0.0082
	(0.4756)	(0.2210)	(0.2343)	(0.3098)
TOP_t	-0.1997	-0.0707	-0.0157	-0.0408
	(0.1646)	(0.1373)	(0.1431)	(0.1056)
$DUAL_t$	-0.0012	0.0294	0.0317	0.0387
	(0.0476)	(0.0245)	(0.0259)	(0.0329)
$INST_t$	0.0205	-0.0064	0.0042	0.1090*
	(0.0969)	(0.0457)	(0.0476)	(0.0640)
SOE_t	0.1900***	0.0426	0.0287	0.1117***
	(0.0579)	(0.0617)	(0.0638)	(0.0398)
$BIG4_t$	0.2829**	-0.0135	-0.0258	0.1985**
	(0.1099)	(0.0942)	(0.0990)	(0.0909)
$Analyst_t$	0.0009	0.0007	0.0009	0.0030***
	(0.0012)	(0.0006)	(0.0007)	(0.0009)
$Media_t$	0.0047**	-0.0001	-0.0003	0.0030**
	(0.0020)	(0.0009)	(0.0010)	(0.0014)
Year FE	YES	YES	NO	YES
Industry FE	YES	NO	NO	YES
Province FE	YES	NO	NO	YES
Firm FE	NO	YES	YES	NO
Year FE*Industry FE	NO	NO	YES	NO
Year FE*Province FE	NO	NO	YES	NO
Observations	8,782	8,782	8,782	8,782
Adj R^2	0.4344	0.7390	0.7344	0.2819

Table 9 Mechanism test: Risk perception

This table presents the results of risk perception mechanism analysis. *Cost_Pub1* is a dummy variable, equal to 1 if the number of resolved complaints filed via phone or online platforms divided by the total number of such complaints is below the national median, and 0 otherwise. *Cost_Pub2* is a dummy variable, equal to 1 if the number of resolved complaints filed via letters or in-person visits divided by the total number of such complaints is below the national median, and 0 otherwise. *Cost_Gov* is a dummy variable, equal to 1 if the number of the number of monitored polluting firms in a province is below the national median, and 0 otherwise. *Green* is measured as the natural log of one plus number of green patents. *SVI_Local* is measured as the total local online search volume of the firm. Control variables are defined in Appendix A. The standard errors are reported in parentheses and are clustered at firm levels. *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

	$Green_{t+1}$	$Green_{t+1}$	$Green_{t+1}$	$Green_{t+1}$	$Green_{t+1}$	$Green_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
	Cost_Pub1=1	Cost_Pub1=0	Cost_Pub2=1	Cost_Pub2=0	Cost_Gov=1	Cost_Gov=0
SVI_Local_t	0.0068*	0.0120***	0.0062	0.0098***	-0.0008	0.0142***
	(0.0035)	(0.0043)	(0.0041)	(0.0030)	(0.0046)	(0.0035)
Difference	P-value=0.007		P-value=0.001		P-value<0.001	
$SIZE_t$	0.1228***	0.1269***	0.1555***	0.1017***	0.1459***	0.1126***
	(0.0219)	(0.0313)	(0.0250)	(0.0220)	(0.0348)	(0.0249)
ROA_t	0.4108	0.9061*	0.8094**	0.5375	-0.0606	0.9428**
	(0.3322)	(0.4781)	(0.3584)	(0.3671)	(0.5217)	(0.3694)
LEV_t	0.2124**	0.2286	0.1419	0.2827***	-0.3370**	0.4016***
	(0.1065)	(0.1446)	(0.1172)	(0.1088)	(0.1674)	(0.1182)
$GROW_t$	0.0039	0.0064	0.0033	0.0085	0.0203	-0.0018
	(0.0122)	(0.0150)	(0.0136)	(0.0130)	(0.0143)	(0.0152)
OCF_t	0.0663	0.2888	-0.0477	0.2651	0.1552	0.1333
	(0.1736)	(0.2606)	(0.1970)	(0.1912)	(0.2652)	(0.1926)
$R\&D_t$	5.0281***	4.3948***	4.6705***	4.8435***	3.9848***	4.5438***
	(0.9710)	(1.0983)	(1.0013)	(0.8772)	(1.5053)	(0.8996)
$Board_t$	0.1650	0.2081	0.1931	0.2041	0.1559	0.1635
	(0.1274)	(0.1581)	(0.1228)	(0.1273)	(0.1905)	(0.1391)
$INDEP_t$	0.1218	-0.1028	-0.4663	0.3111	-1.2171**	0.3800
	(0.3585)	(0.4500)	(0.3895)	(0.3437)	(0.5235)	(0.3751)
TOP_t	-0.0086	-0.0657	-0.1192	0.0328	0.1339	-0.1239
	(0.1159)	(0.1621)	(0.1235)	(0.1165)	(0.1805)	(0.1297)
$DUAL_t$	0.0134	0.0878*	0.0505	0.0294	0.0085	0.0408
	(0.0362)	(0.0529)	(0.0416)	(0.0359)	(0.0533)	(0.0389)
$INST_t$	0.1700**	0.0349	0.0805	0.1346*	-0.0312	0.1977***
	(0.0723)	(0.0982)	(0.0793)	(0.0738)	(0.1139)	(0.0759)
SOE_t	0.0642	0.1427**	0.0661	0.1244***	0.0331	0.1275***
	(0.0450)	(0.0572)	(0.0478)	(0.0427)	(0.0674)	(0.0491)
$BIG4_t$	0.1886**	0.1848	0.1725*	0.1951**	0.2447*	0.2255*
	(0.0950)	(0.1262)	(0.0955)	(0.0921)	(0.1279)	(0.1220)
$Analyst_t$	0.0020**	0.0034***	0.0025**	0.0026***	0.0054***	0.0015
	(0.0009)	(0.0013)	(0.0011)	(0.0010)	(0.0017)	(0.0009)
$Media_t$	0.0033*	0.0010	0.0016	0.0028*	0.0029	0.0015
	(0.0017)	(0.0020)	(0.0017)	(0.0016)	(0.0022)	(0.0017)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Observations	5,376	3,406	3,514	5,268	2,612	6,170
Adj R^2	0.2721	0.2924	0.3005	0.2661	0.3826	0.2757

Table 10 Mechanism test: Reputation mechanism

This table presents the results of reputation mechanism analysis. *Media_d* is a dummy variable, equal to 1 if the number of positive media reports is above the sample median, and 0 otherwise. *Punish* is a dummy variable, equal to 1 if the firm has received regulatory penalties, and 0 otherwise. *Green* is measured as the natural log of one plus number of green patents. *SVI_Local* is measured as the total local online search volume of the firm. Control variables are defined in Appendix A. The standard errors are reported in parentheses and are clustered at firm levels. *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

	$Green_{t+1}$	$Green_{t+1}$	$Green_{t+1}$	$Green_{t+1}$
	(1)	(2)	(3)	(4)
	Media_d=1	*Media_d*=0	*Punish*=1	*Punish*=0
SVI_Local_t	0.0109***	0.0007	-0.0013	0.0084***
	(0.0035)	(0.0026)	(0.0140)	(0.0030)
Difference	P-value<0.001		P-value=0.089	
$SIZE_t$	0.1759***	0.0380*	0.0754	0.1230***
	(0.0299)	(0.0220)	(0.1016)	(0.0205)
ROA_t	1.0273**	0.6203**	-0.5409	0.6619**
	(0.4779)	(0.3028)	(1.5172)	(0.2972)
LEV_t	0.1742	0.2558**	-0.0339	0.2218**
	(0.1470)	(0.1065)	(0.3828)	(0.0963)
$GROW_t$	0.0106	0.0111	0.0629	0.0037
	(0.0160)	(0.0124)	(0.0475)	(0.0106)
OCF_t	0.0556	0.0981	-0.8491	0.1559
	(0.2526)	(0.1651)	(0.8235)	(0.1527)
$R\&D_t$	4.8000***	4.2657***	7.6587**	4.7174***
	(1.1733)	(0.8264)	(3.5200)	(0.7858)
$Board_t$	0.1804	0.1837	-0.0448	0.1871*
	(0.1419)	(0.1383)	(0.4208)	(0.1109)
$INDEP_t$	-0.3113	0.0848	-0.2068	0.0294
	(0.4283)	(0.3927)	(1.1425)	(0.3048)
TOP_t	-0.0565	-0.0285	0.3088	-0.0463
	(0.1501)	(0.1188)	(0.4294)	(0.1034)
$DUAL_t$	0.0747	-0.0014	-0.1204	0.0392
	(0.0477)	(0.0347)	(0.1358)	(0.0326)
$INST_t$	0.0194	0.2323***	0.0140	0.1064*
	(0.0926)	(0.0724)	(0.3189)	(0.0630)
SOE_t	0.1094**	0.0330	-0.0401	0.1057***
	(0.0549)	(0.0458)	(0.1345)	(0.0388)
$BIG4_t$	0.2474**	0.0090	0.4467	0.1798**
	(0.1032)	(0.1198)	(0.3759)	(0.0855)
$Analyst_t$	0.0020*	0.0029**	0.0117**	0.0024***
	(0.0011)	(0.0012)	(0.0052)	(0.0008)
$Media_t$	0.0009	-0.0007	-0.0001	0.0026*
	(0.0014)	(0.0031)	(0.0047)	(0.0015)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Observations	4,256	4,526	266	8,516
Adj R^2	0.3743	0.1704	0.2165	0.2824

Table 11 Further analysis: Local public attention and different types of green innovation

This table presents the results of further analyses for the impact of local public attention on different types of green innovation. *Green_PC* is the total number of pollution control patents. *Green_CEDP* is the total number of clean energy development patents. *Green_OGP* is the total number of other green patents. *Green_ID* is the total number of independently development green patents. *Green_CP* is the total number of patents co-filed with external research partners. *SVI_Local* is measured as the total local online search volume of the firm. Control variables are defined in Appendix A. The standard errors are reported in parentheses and are clustered at firm levels. *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

	$Green\_PC_{t+1}$	$Green\_CEDP_{t+1}$	$Green\_OGP_{t+1}$	$Green\_ID_{t+1}$	$Green\_CP_{t+1}$
	(1)	(2)	(3)	(4)	(5)
SVI_Local_t	0.0038**	0.0035	0.0012	0.0092***	0.0005
	(0.0019)	(0.0023)	(0.0011)	(0.0027)	(0.0015)
$SIZE_t$	0.0553***	0.1007***	0.0510***	0.0761***	0.0638***
	(0.0126)	(0.0163)	(0.0083)	(0.0195)	(0.0093)
ROA_t	0.1460	0.4613*	0.2572**	0.6680**	0.0205
	(0.1837)	(0.2400)	(0.1267)	(0.2829)	(0.1258)
LEV_t	0.1591***	0.2578***	0.1535***	0.2399***	-0.0329
	(0.0601)	(0.0756)	(0.0394)	(0.0899)	(0.0394)
$GROW_t$	0.0013	-0.0035	-0.0023	0.0017	0.0066
	(0.0071)	(0.0083)	(0.0044)	(0.0093)	(0.0053)
OCF_t	0.0830	0.0805	0.0567	0.0314	0.0836
	(0.0991)	(0.1293)	(0.0669)	(0.1427)	(0.0781)
$R\&D_t$	1.4723***	3.7503***	2.0911***	3.4076***	1.4720***
	(0.4129)	(0.6243)	(0.3209)	(0.7036)	(0.3679)
$Board_t$	0.1862***	0.1434	0.0827*	0.2029**	0.0383
	(0.0721)	(0.0874)	(0.0439)	(0.1025)	(0.0546)
$INDEP_t$	0.0197	-0.1020	-0.0482	0.0163	-0.0292
	(0.1900)	(0.2398)	(0.1257)	(0.2826)	(0.1363)
$TOPop_t$	0.0345	0.0247	0.0089	0.0345	-0.0783
	(0.0635)	(0.0827)	(0.0428)	(0.0950)	(0.0500)
$DUAL_t$	0.0160	0.0305	0.0143	0.0289	0.0191
	(0.0195)	(0.0262)	(0.0136)	(0.0305)	(0.0154)
$INST_t$	-0.0018	0.0096	0.0020	0.1063*	0.0402
	(0.0404)	(0.0513)	(0.0269)	(0.0574)	(0.0305)
SOE_t	0.0519**	0.0548*	0.0326**	0.0793**	0.0367**
	(0.0253)	(0.0300)	(0.0155)	(0.0361)	(0.0182)
$BIG4_t$	0.1370**	0.1398**	0.0598*	0.0815	0.1175**
	(0.0559)	(0.0699)	(0.0339)	(0.0784)	(0.0486)
$Analyst_t$	0.0014**	0.0017**	0.0010***	0.0014*	0.0015***
	(0.0005)	(0.0007)	(0.0004)	(0.0008)	(0.0005)
$Media_t$	0.0021**	0.0012	0.0004	0.0031**	-0.0003
	(0.0009)	(0.0011)	(0.0005)	(0.0013)	(0.0007)
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
Observations	8,782	8,782	8,782	8,782	8,782
Adj R^2	0.2309	0.2646	0.2657	0.2396	0.1798