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The environmental-financial nexus: Centralized environmental monitoring, eco-consciousness, and green revenues

June Cao [a,b,*], Zijie Huang [a], Millie Liew [a]

[a] School of Accounting, Economics and Finance, Curtin Business School. GPO Box U1987, Perth, Western Australia, 6845, Australia
[b] Department of Accounting, Southampton Business School, University of Southampton, UK

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ABSTRACT

Amid tightening environmental governance, we examine whether and how firms' eco-consciousness leads to a harmonious balance between environmental and economic performance in the form of green revenues. We utilize China's centralization of environmental monitoring in 2015 as the basis for a difference-in-differences methodology, using highly and less eco-conscious firms as the treatment and control groups. We find that relative to less eco-conscious firms, highly eco-conscious firms derive greater green revenues post-centralization. This finding is robust to underlying firm characteristics and unobservable industry- and time-specific heterogeneity. Regional internet infrastructure development and corporate greenwashing mitigation facilitate the effect on highly eco-conscious firms' green revenues, suggesting that effective centralized monitoring relies on an integrated information transmission network and an improvement in firms' genuine environmental accountability. Overall, eco-consciousness facilitates a win-win scenario between environmental and economic performance under an increasingly strict environmental regulatory landscape.

1. Introduction

Emerging markets face a critical challenge in reconciling economic development and environmental protection. We explore this issue by investigating how the centralization of environmental monitoring interacts with firms' eco-consciousness to affect corporate green revenues in China. Since 1978, China's socialist market economic reforms have involved the decentralization of power from the central government, which conferred local governments substantial flexibility in pursuing local economic goals (MacFarquhar, 1997). This flexibility fuelled the rapid growth of the Chinese economy until the early 2010s (Harrison and Palumbo, 2019) but also led to severe environmental issues (Kahn and Yardley, 2007). While local governments possessed significant discretionary authority in implementing environmental monitoring policies (Kostka and Nahm, 2017), local officials neglected environmental protection because their performance evaluation prioritized local economic growth (Qi and Zhang, 2014).

With local employment and economic growth in mind, local governments were reluctant to impose environmental compliance costs on firms within their respective jurisdictions due to the negative impact on local products' competitiveness (Wang et al., 2008). Such protectionism arose due to regulatory fragmentation (Chan et al., 1995). The lack of centralized oversight facilitated the execution of clandestine agreements between local governments and polluting firms (Long and Yang, 2016). Local governments often resort to falsifying environmental data to purport an image of environmental compliance.

* Corresponding author.
E-mail addresses: june.cao@curtin.edu.au (J. Cao), zijie.huang@postgrad.curtin.edu.au (Z. Huang), zi.liew@postgrad.curtin.edu.au (M. Liew).

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A decentralized environmental monitoring system led to weak environmental governance and contributed to the tripling of China's carbon emissions over the past three decades (OWID, 2024). The Centralized Environmental Monitoring Scheme ("the Scheme") was implemented in 2015 to strengthen local environmental accountability and governance.[1] The distribution of environmental monitoring authority to the central government comprises an oversight mechanism that mitigates local governments' protectionism (Zhang, 2023a). The national unification of monitoring standards reduces local government protectionism. A centralized environmental monitoring system improves local governments' environmental protection efforts to subsequently affect firms' environmental commitments (Zhang et al., 2023).

Drawing on an integrative view, we consider an intriguing question: Do firms' initial level of eco-consciousness affect their derivation of green revenues following the centralization of environmental monitoring? As centralization improves the balance of environmental and economic regulatory interests in the institutional environment, firms can leverage their eco-consciousness to simultaneously derive environmental and economic benefits in the form of green revenues. Green revenues are derived from business activities and industries related to environmental sustainability (FTSE Russell, 2018), including revenues from products and services that benefit the environment (Bassen et al., 2023). As such, they simultaneously embody environmental and economic benefits.

Firms characterized by a higher level of eco-consciousness (hereafter, highly eco-conscious firms) possess greater environmental interests and an increased awareness of environmental regulations, policies, technologies, and infrastructure (Ojo and Fauzi, 2020). Intuitively, eco-consciousness constitutes a dynamic green capability that assists firms in capturing emerging commercial opportunities in dynamic business environments. We thus conjecture that firms with a higher initial level of eco-consciousness derive greater green revenues following the centralization of environmental monitoring.

Based on data from Chinese listed firms between 2011 and 2019, we utilize a difference-in-differences (DiD) approach to provide causal evidence. We find that, relative to less eco-conscious firms, highly eco-conscious firms increase their likelihood and extent of green revenue derivation post-centralization of environmental monitoring. This effect is economically substantial. The centralization of environmental monitoring increases treated highly eco-conscious firms' likelihood (extent) of green revenue derivation by 23.88 % (16.33 %) of the standard deviation of the treatment group.

We delve into mechanisms through which the impact of the Scheme unfolds. First, because effective centralized monitoring requires the central government to understand local environmental conditions adequately, we posit that the active transmission of environmental information to the central government is crucial to improving local environmental accountability (Nahm, 2017). Second, if central oversight effectively decreases clandestine links between local governments and firms, we expect firms to transition from a facade of environmental compliance to genuine compliance (Zhang, 2023a). Consistent with these expectations, we find that the effect of the Scheme on highly eco-conscious firms' green revenues is contingent upon (1) the level of technical internet infrastructure development within localities and (2) the decline in corporate greenwashing.

We perform an array of robustness tests to rule out further endogeneity concerns. First, as the validity of a DiD estimation relies on the parallel trend assumption, we examine the pretreatment trends between the treatment and control groups using a dynamic model. We observe that there is no difference in green revenues between the treatment and control groups before the implementation of the Scheme. Second, we corroborate results from the propensity score-matched sample using entropy balancing, which allows us to obtain a higher degree of covariate balance while retaining sample observations (Hainmueller, 2012). Third, we perform placebo tests based on fictitious treatment groups and implementation periods to alleviate concerns that unobservable, spurious, or confounding factors drive our results. Fourth, we use an alternative eco-consciousness specification to test our results' sensitivity. Fifth, we follow Oster (2019) to rule out remaining omitted variable concerns. Sixth, we address potential concerns arising from reverse causality and unobserved heterogeneity using a two-stage least-squares instrumental variable (2SLS-IV) method. Seventh, we employ a Heckman selection model to address potential self-selection bias arising from non-random factors affecting firms' eco-consciousness. Eighth, we incorporate alternative fixed effects to ensure our results are not sensitive to different fixed effect specifications. Our results remain consistent across all endogeneity tests.

We advance prior research and practical applications in three ways. First, the vast CSR literature focuses on the trade-off between environmental interests and economic outcomes, with divergent views on the nature of their relationship. Studies document a positive relationship (e.g., Tang et al., 2012; Torugsa et al., 2012), a neutral relationship (e.g., Downar et al., 2021; Zhao and Murrell, 2022), and a curvilinear U-shaped relationship (Barnett and Salomon, 2006, 2012; Nollet et al., 2016). These inconsistencies arise due to (1) an array of contextual factors influencing the financial implications of environmental pursuit and (2) persisting endogeneity issues complicating the establishment of causality (Tang et al., 2012; Awaysheh et al., 2020; Zhao and Murrell, 2022). We undertake an integrative view asserting that environmental and economic interests can be simultaneously achieved in the form of green revenues. This focus emphasizes the environmental-financial nexus and facilitates a win-win direction for firms to progress towards a net zero economy.

We extend to two studies conceptualizing the integrative view of sustainability. Gao and Bansal (2013) document that firms' economic, environmental, and social performance are simultaneously determined using a sample of US-listed firms from 1991 to 2003.

[1] For details on the Notice of the General Office of the State Council on the Centralized Environmental Monitoring Network Construction Plan, please see https://www.gov.cn/zhengce/content/2015-08/12/content_10078.htm.

Despite methodological concerns,[2] they provide empirical support for the integrative view of sustainability. Hahn et al. (2015) propose a theoretical systematic framework for managing sustainability-related tensions using an integrative view. We advance these studies by conceptualizing green revenues as an empirical construct that reflects both environmental and economic benefits. Thus, green revenues are relevant for future empirical investigations concerning the integrative view of sustainability.

Second, we add to the literature on the strengths and shortcomings of the centralized enforcement of environmental regulations in China. Prior studies find that environmental governance can be improved by reducing state-local blame politics (Ran, 2017), increasing local governments' fiscal access (Wong and Karplus, 2017), and enhancing central state-owned enterprises' environmental accountability (Eaton and Kostka, 2017). These studies highlight that a lack of mutual benefit between (1) local and central governments and (2) environmental and economic interests hinder environmental improvements. We document that local-central mutual benefits under centralized monitoring interact with firms' eco-consciousness for a win-win scenario between environmental and economic interests.

Third, we build on the literature on dynamic capabilities by documenting that eco-consciousness is a source of dynamic capability to support firms in navigating environmental regulatory complexities. Prior studies identify intra- and inter-organizational structures (Schilke and Goerzen, 2010; Felin and Powell, 2016), corporate culture (Anand et al., 2009; Bock et al., 2012), and technological information capabilities (Pavlou and El Sawy, 2010; Gupta et al., 2020) as sources of dynamic capability. As environmental regulations worldwide are increasing in stringency (Yan et al., 2023), we emphasize that it is important for firms to cultivate dynamic green capabilities to adapt to and benefit from an increasingly regulated business environment. We add to the literature documenting the positive impact of eco-consciousness on firm profitability (Arocena et al., 2021), environmental performance (Riva et al., 2021), and new product development performance (Tang et al., 2023a).

2. Institutional background and hypothesis development

2.1. Institutional background

Prior to the implementation of the Scheme, the environmental monitoring authority in China primarily resided with local governments under a decentralized system, which suffered from information asymmetry and principal-agent problems (Shen and Jiang, 2020). Decentralized coordination and a lack of centralized oversight resulted in inconsistencies, inadequate enforcement, and data quality issues (Zhang, 2023a). While local government officials were responsible for monitoring and penalizing polluters, enforcing these activities was politically challenging (Wang et al., 2008). As the promotion of local officials primarily depended on local economic performance (Li and Zhou, 2005), they were incentivized to sacrifice the local environment in exchange for better economic growth (Fan et al., 2023). Consequently, the emphasis on protecting local economic growth counteracts the central government's environmental protection goals, gives rise to local governments' protectionism, and renders environmental governance ineffective (Kostka and Hobbs, 2013).

In July 2015, the Centralized Environmental Monitoring Scheme ("the Scheme") was implemented by the Central Leading Group for Deepening Reform to address mounting environmental issues contributed by the decentralized environmental monitoring system (State Council, 2015b). The Scheme increases the balance of power between the central and local governments in environmental monitoring and requires local governments to report their operations to the central government annually (State Council, 2015a).

Centralized environmental monitoring enhances environmental governance and accountability across local jurisdictions in various aspects. First, it mitigates local governments' protectionism by restricting their access to and control over environmental data. Specifically, it enhances the objectivity and impartiality of local environmental data by requiring the implementation of a national environmental monitoring network, which features an integrated data-sharing system for the unified release of data (State Council, 2015a). It details the use of advanced monitoring technologies, such as atmospheric monitoring satellites and uncrewed aerial vehicle remote sensing, thus enabling the central government to assess and monitor environmental compliance across different regions remotely. It also mandates the central government to operate state-controlled facilities to administer national environmental monitoring standards and oversee local government operations.

The combination of an integrated information transmission network, objective sources of environmental data, and centrally managed environmental facilities resolves data availability and quality issues necessary to assess local governments' adherence to environmental standards and requirements (Zhang, 2023a). The Scheme also empowers environmental protection authorities to penalize data tampering and other intentional violations of standardized environmental monitoring standards, thereby facilitating environmental enforcement (State Council, 2015a).

Second, a centralized environmental monitoring system increases the use of central government financing relative to local financing. As the central government must fully finance state-controlled sites to supplement locally controlled sites to carry out monitoring duties (State Council, 2015a), it alleviates financial and operational burdens on local governments to comply with the newly introduced national standards under the Scheme. Thus, a centralised system results in a win-win scenario between the central government's environmental and local governments' economic interests.

[2] Gao and Bansal (2013) use the Generalized Estimating Equations (GEEs) technique followed by a correlation test of simultaneity. Despite that GEEs possess an advantage in modelling multivariate correlated random variables, they do not specify the full likelihood function and lack likelihood-based methods for testing model fit, comparing models, and conducting inferences about parameter estimates. Further, despite that GEEs parameter estimates are sensitive to outliers, this concern is unaddressed (Ballinger, 2004).

Third, the Scheme establishes a national environmental monitoring framework, detailing monitoring techniques and evaluation standards (State Council, 2015a). Mandated adherence to national standards mitigates local governments' concerns that effective environmental monitoring compromises the competitiveness of their local products and business environment relative to those of other provinces. Taken together, centralized environmental monitoring addresses local governments' protectionism, financial constraints, and a lack of motivation to conform associated with prioritising local economic growth. By refining the local balance of economic and environmental interests and establishing central oversight mechanisms, the Scheme enhances the nation's environmental governance and accountability.

2.2. Hypothesis development

We conjecture that the improvements in local environmental governance and accountability resulting from the centralization of environmental monitoring subsequently affect firms' behaviour. As the central government has greater access to higher-quality environmental data under a centralized monitoring system, local governments are compelled to enforce environmental requirements within their respective local jurisdictions. A centralized system mitigates clandestine links between firms and local governments aimed to portray a façade of environmental compliance (Fredriksson et al., 2006). Jining Chen, the former minister of ecology and environment in China, stated that environmental protection commitment diminishes along the top-down administrative hierarchy.[3] Environmental responsibilities are less enforced at lower local administrative levels.[4] Therefore, the centralization of environmental monitoring strengthens the enforcement of environmental regulations.

Improving environmental performance to comply with environmental policies while simultaneously attaining economic benefits is vital for firms. An increase in the stringency of national environmental regulations motivates Chinese firms' environmental engagement, with subsequent effects on economic performance (e.g., Ren et al., 2022; Chu et al., 2024; Tang et al., 2024). These studies focus on an instrumental "business case" view of sustainability (Hahn and Figge, 2011). This instrumental view asserts that environmental and economic interests are independent of one another and that firms commit to environmental objectives based on their expected impact on economic benefits (Gao and Bansal, 2013). The segregation of basic business principles from CSR leads to bounded instrumentality (Shrivastava, 1995), which undermines the stability of CSR by tacitly encouraging firms to prioritize economic interests and harm the environment when necessary (Gladwin et al., 1995; Hahn and Figge, 2011). We deviate from the legion CSR literature and adopt an integrative view of sustainability, which contends that regulators and firms should balance seemingly conflicting environmental and economic interests to attain sustainable development (Hahn et al., 2015). As green revenues embody corporate environmental *or* economic interests (Bassen et al., 2023; Huang et al., 2024), we conceptualize green revenues to embody both environmental *and* economic interests. We extend from the profit maximization rationale to conjecture that an increase in the stringency of environmental regulation motivates firms to simultaneously achieve environmental and economic interests in the form of green revenues.

The ability of firms to derive green revenues following the centralization of environmental monitoring is contingent on their dynamic green capability. Maksimov et al. (2022) define dynamic green capability as the ability to develop complementary green competencies and reconfigure organizational resources to obtain competitive advantage. Eco-consciousness forms a dynamic green capability as it reflects heightened environmental interests and increased awareness of environmental regulations, technologies, and infrastructure in business environments (Ojo and Fauzi, 2020). Highly eco-conscious firms are more adept at capitalizing on emerging market opportunities stemming from shifts in environmental regulations (Teece, 2000). In contrast, less eco-conscious firms are bounded by their limited awareness of environmental issues and information in their business environment (Kogut and Zander, 1996). Therefore, the effect of centralized environmental monitoring on less eco-conscious firms' green revenues is likely less salient due to a lower ability to adapt to and leverage a changing environmental regulatory landscape. Our first hypothesis is formulated as follows:

Hypothesis 1. *Firms with a higher eco-conscious level derive greater green revenues following the centralization of environmental monitoring reform.*

Based on information economics (Giroud, 2013) and the attention-based view (Hoffman and Ocasio, 2001), heightened physical regulatory distance reduces monitoring effectiveness through information asymmetry and the central leaders' inattention (Yang et al., 2023). Geographic distance induces challenges for central leaders to closely monitor local events and gather accurate environmental information (Ghanem and Zhang, 2014). The central government's limited involvement in the local context leads to inattention and a reduced perception of the impact of local environmental issues (Whiteman and Cooper, 2011). If the central government lacks detailed information on the ground realities of local environmental conditions, its ability to effectively administer environmental monitoring is compromised (Nahm, 2017; Ran, 2017). Consequently, oversight failures and a misallocation of resources may arise, leading to undesirable environmental outcomes.

Anticipating the impacts of an information gap, the Scheme underscores the development of technical infrastructure and the implementation of advanced technologies to create a nationwide integrated environmental information transmission network (State Council, 2015a). This network features a big data platform that facilitates interconnected data sharing and the unified real-time release of environmental monitoring data (State Council, 2015a). The Internet is an important technical infrastructure component, as it facilitates the collection, storage, and management of environmental monitoring data (Mollah et al., 2017). Internet infrastructure

[3] Source: http://politics.people.com.cn/n/2015/0308/c70731-26655294.html (accessed 27th June 2024).
[4] Source: http://www.china.com.cn/lianghui/news/2016-03/11/content_37996953.htm (accessed 30th May 2024).

allows data collected to be transmitted in real-time to central governments, including data created from monitoring sensors and devices. This allows the central government to oversee environmental compliance efficiently and effectively (He et al., 2024).

Internet infrastructure development is fundamental for the application of advanced technologies (Abdelwahab et al., 2014), including atmospheric monitoring satellites and uncrewed aerial vehicle remote sensing. These technologies enhance the remote oversight of local governments' environmental compliance (Qi and Zhang, 2014). Internet infrastructure development facilitates the scalability and flexibility needed to manage increasing volumes and diverse environmental data from emerging monitoring technologies. Under Sabatier's policy environment framework (Sabatier, 1986), technical infrastructure development is vital for top-down policy implementation from central to local governments. The effective implementation of pollution control relies on reliable and applicable technology (Wei et al., 2012; Guo et al., 2022). Effective centralized environmental monitoring requires a well-developed technical infrastructure network. Our second hypothesis is formulated as follows:

Hypothesis 2. *Technical infrastructure development facilitates highly eco-conscious firms' greater derivation of green revenues under centralized environmental monitoring.*

The former minister of ecology and environment, Jining Chen, highlighted that local governments' protectionism resulted in firms' rampant violations of environmental protection responsibilities.[5] Centralized environmental monitoring mitigates collusion between local governments and firms to create a façade of environmental compliance. This creation of a green public image is referred to as greenwashing, which occurs when a firm uses an environmentally friendly appearance to cover environmentally unfriendly substances (Du, 2015). While highly eco-conscious firms possess strong "green" attitudes and communicate this to stakeholders, an implementation gap may exist where environmental policies are misaligned with performance outcomes (Gadenne et al., 2009). By preventing clandestine agreements associated with greenwashing, the Scheme reduces the implementation gap and strengthens firms' execution of environmental practices (Zhang, 2023a). Zhang (2023a) suggests that centralized environmental monitoring strengthens local environmental regulation enforcement to reduce firms' greenwashing. Because greenwashing is driven by profit maximization motives (Wu et al., 2020), we conjecture that a reduction in greenwashing incentivizes highly eco-conscious firms to engage in green business activities to genuinely attain environmental objectives while sustaining economic returns. Our third hypothesis is developed as follows:

Hypothesis 3. *The centralization of environmental monitoring decreases highly eco-conscious firms' level of greenwashing to increase their derivation of green revenues.*

3. Sample, data, and research design

3.1. Sample selection

We collect data on all A-share listed firms in China from 2011 to 2019, which comprise four years before and after the implementation of the Scheme. Data for constructing our dependent variables of corporate green revenues are sourced from the WIND database. We obtain other firm-level and financial data from the China Stock Market and Accounting Research (CSMAR) database. Following prior literature (e.g., Ball and Nikolaev, 2022; Shao et al., 2024), we process our sample as follows: (1) excluding firms in the financial industry ;[6] (2) excluding ST, ST*, PT firms ;[7] and (3) winsorizing all continuous variables at the 1st and 99th percentiles to mitigate the influence of outliers.[8] Our final sample period consists of 20,135 observations from 2011 to 2019.

3.2. Variable measures

3.2.1. Green revenues

Green revenues refer to revenues generated from business activities and industries related to environmental sustainability (FTSE Russell, 2018). We identify green business activities and industries using the *2019 Green Industry Guiding Catalogue* (GIGC) issued by China's National Development and Reform Commission.[9] This catalogue, GIGC, identifies six primary categories of green business activities and industries with 30 first-tier subcategories and 211 s-tier subcategories.[10] The six primary categories include "Energy

[5] Source: http://www.china.com.cn/lianghui/news/2016-03/11/content_37996953.htm (accessed 30th May 2024).

[6] Compared to non-financial firms, financial firms have distinct business models, regulatory environments, risk profiles, and accounting standards (Messner, 2016). The exclusion of financial firms improves sample homogeneity and mitigates confounding influences (Fiechter *et al.*, 2024).

[7] ST refers to special treatment firms that have suffered losses for two consecutive years, ST* firms possess financial problems or violations of greater severity, and PT is applied to ST firms that fail to improve their financial situation within a year and which face risks of being delisted. These firms with financial distress are excluded because they strategically manage accounting numbers to reduce delisting risk (Chu *et al.*, 2011).

[8] To ensure our results are not sensitive to winsorizing methods, we follow prior studies (e.g., Liu *et al.*, 2017; Shao *et al.*, 2024) to rerun our baseline analysis after winsorizing all continuous variables at (1) the 2.5% and 97.5% levels, and (2) the 5% and 95% levels. Further, we rerun our analysis using continuous variables that are not winsorized. Across all specifications, the results remain consistent.

[9] Whilst the GIGC was issued after the Scheme, the primary objective in using the defined green industries is to identify green revenues objectively. The industries pre-existed prior to the GIGC, thus serving as a relevant benchmark for the identification of green revenues.

[10] https://www.shanghai.gov.cn/cmsres/32/32688250a2a04d0199748a1cd1387fc0/dc4d0ae4b8416dd07607a68791ba8936.pdf (accessed 02 June 2023).

conservation and environmental protection industries", "Clean production industries", "Clean energy industries", "Eco-industries, green infrastructure industries", and "Green service industries" (NDRC, 2019).

We classify revenues from business activities relating to green industries identified in the GIGC as green revenues. For example, China Dongfang Electric Group Co., Ltd, a power equipment manufacturer, derived revenues from five business activities and industries in 2016. The five sources are: "High-efficiency clean power generation equipment" (59.11 %), "New energy" (23.84 %), "Engineering and services" (11.7 %), "Hydropower and environmental protection equipment" (4.82 %), and "Other businesses" (0.53 %). The sources "High-efficiency clean power generation equipment," "New energy," and "Hydropower and environmental protection equipment" are classified as green industries according to the GIGC. 87.77 % of the firm's revenues in 2016 are classified as green revenues, representing a ratio of 0.88. Table 1 illustrates this example.

We examine the likelihood (*Green Rev Dummy*) and ratio (*Green Rev Ratio*) of green revenues that a firm derives in each given year. (i) *Green Rev Dummy* is coded one for firms that have derived green revenues in a given year and zero for those that did not, and (ii) for *Green Rev Ratio,* we use the ratio of total green revenues to total revenues earned, leaving those cases with no green revenues as zero.

3.2.2. Eco-consciousness

We define our treatment and control groups based on the level of eco-consciousness. The reliability and pertinency of textual analysis in constructing firm-level measures are well-demonstrated (Tang et al., 2021, 2023b). We conduct textual analysis based on a glossary of key terms related to eco-consciousness to develop a firm-level eco-consciousness measure (*EC*). We extract the frequency of the key terms from the annual reports to compile a firm-year index. Categorized into four dimensions, the key terms are derived from *the Guidelines for Environmental Performance Assessment Techniques in Enterprises* issued by China's Ministry of Ecology and Environment, the *White Paper on Green Manufacturing Standardization*, and *The Environmental Protection Law* issued by the central government. The four dimensions are: *Consciousness to environmental policy, Consciousness to environmental protection and governance, Consciousness to environmental stewardship*, and *Consciousness to employee environmental awareness*.

Consciousness to environmental policy pertains to a firm's consciousness and adherence to environmental regulations issued by governments. It encompasses terms related to compliance, regulatory frameworks, and policy guidelines. This dimension reflects the extent to which a firm integrates environmental policies into its operations. *Consciousness to environmental protection and governance* pertains to a firm's consciousness, commitment, and engagement in proactive environmental protection efforts and governance. It incorporates terms related to pollution control and environmental management systems. *Consciousness to environmental stewardship* pertains to a firm's environmental stewardship and encompasses terms related to environmental management agencies, technological advancements, departments, and protection initiatives. *Consciousness to employee environmental awareness* pertains to a firm's consciousness of promoting environmental awareness and responsibility among employees. It evaluates the effort of the firm to cultivate an eco-conscious culture in its workforce.

The firm-level index of eco-consciousness (*EC*) is constructed based on the frequency of key terms across the four dimensions, which are detailed in Table 2. A higher value of *EC* indicates a higher level of eco-consciousness. We categorize firm-year observations in the top tercile of *EC* as the treatment group, which is defined as the group of highly eco-conscious firms. The control group comprises less eco-conscious firms in the bottom and middle terciles of *EC*.

3.2.3. Mechanism variable: technical infrastructure development

We rely on two measures of regional internet infrastructure development to proxy for the level of technical infrastructure development. First, we follow Zhang *et al.* (2022) to use the region's log-transformed number of Internet broadband access ports (*Internet Dev*), which directly captures the level of infrastructure development. Second, we use the region's Internet infrastructure development index (*Internet Dev2*), which comprises six ratios associated with the quality and reliability of Internet infrastructure:

$$\begin{aligned} Internet\ Dev2 = {} & \frac{Long-Distance\ Optical\ Cable\ Line}{Administrative\ Area} + \frac{Internet\ Broadband\ Access\ Ports}{Total\ Population} \\ & + \frac{Employees\ in\ the\ Information\ Transmission,\ Computer\ Services,\ and\ Software\ Industry}{Total\ Employees} \\ & + \frac{Total\ Telecommunications\ Revenue}{Total\ Population} + \frac{Mobile\ Phone\ Users}{Total\ Population} + \frac{Internet\ Broadband\ Access\ Users}{Total\ Population} \end{aligned} \tag{1}$$

The first ratio measures the density of optical cable infrastructure within each administrative area, with a higher ratio signifying better connectivity and availability of high-speed internet connection. The second ratio measures the availability of Internet broadband access points relative to the total population, which reflects the capacity of each region to provide Internet access to its residents. The third ratio measures the share of the workforce employed in key information technology sectors, with a higher proportion reflecting a stronger capacity for technological development and service provision within the region. The fourth ratio measures the average per capita revenue generated by telecommunication service providers and is an indicator of the economic impact and market penetration of telecommunication services in each region. The fifth ratio measures the prevalence of mobile phone usage in each region, with a higher ratio signifying higher mobile technology adoption for internet access and communication. The sixth ratio measures the number of Internet users as a proportion of the population, with a higher ratio indicating higher Internet service coverage and accessibility within the region. This second measure captures the quality and reliability of local internet infrastructure and access.

Table 1
The construction of green revenue measures – an example.

Firm: China Dongfang Electric Group Co. Ltd (Stock code: SH600875) Year: 2016					
Category of Business Activity and Industry	High-efficiency clean power generation equipment	New energy	Engineering and services	Hydropower and environmental protection equipment	Other businesses
Revenue ratio	59.11 %	23.84 %	11.70 %	4.82 %	0.53 %
Meets the classification of GIGC Green Industry classification	Yes	Yes	No	Yes	No
Green revenue ratio	59.11 %	23.84 %	0.00 %	4.82 %	0.00 %
Green Rev Dummy	1				
Green Rev Ratio	59.11 % + 23.84 % + 0.00 % + 4.82 % + 0.00 % = 87.77 %				

Note: This table illustrates an example of how green revenues are calculated from the WIND database, based on the 2019 Green Industry Guiding Catalogue (CIGC) classification of green business activities and industries. *Green Rev Dummy* is an indicator equal to one if the firm earns green revenue during the year, and zero otherwise. *Green Rev Ratio* is the ratio of total green revenues earned to total revenues of the firm during the year.

Table 2
Eco-consciousness glossary.

Classification	Key Terms
Consciousness to environmental policy	Environmental protection strategy, Environmental protection concept, Environmental protection policy, Environmental audit, Environmental protection law, Environmental protection regulation
Consciousness to environmental protection and governance	Emission reduction, Environmental protection, Energy conservation, Low carbon, Environmental governance, Environmental protection governance, Pollution governance
Consciousness to environmental stewardship and infrastructure	Environmental management agency, Environmental technology development, Environmental department, Environmental protection work
Consciousness to employee environmental awareness	Environmental education; Environmental training; Environmental supervision; Environmental inspection

Note: This table identifies the key terms upon which the measure of eco-consciousness is constructed. The key terms are grouped into four dimensions based on the *Guidelines for Environmental Performance Assessment Techniques in Enterprises* issued by China's Ministry of Ecology and Environment, the *White Paper on Green Manufacturing Standardization*, and the *Environmental Protection Law* issued by the central government.

3.2.4. Mechanism variable: greenwashing

Following Zhang (2023b), we construct two measures of firm-level greenwashing behaviour (*Greenwash* and *Greenwash2*) based on the difference between a normalized measure representing a firm's ESG disclosure score and a normalized measure representing the firm's ESG performance score. We obtain ESG disclosure scores from Bloomberg and ESG performance scores from the Sino-Securities Index. The measures are constructed as follows:

$$Greenwash_{i,t} = \left(\frac{Bloomberg\ ESG_{i,t} - \overline{Bloomberg\ ESG}}{SD(Bloomberg\ ESG)}\right) -- \left(\frac{Sino\ ESG_{i,t} - \overline{Sino\ ESG}}{SD(Sino\ ESG)}\right) \tag{2}$$

$$Greenwash2_{i,t} = \left(\frac{Bloomberg\ ESG_{i,t} - Min(Bloomberg\ ESG)}{Max(Bloomberg\ ESG) - Min(Bloomberg\ ESG)}\right) -- \left(\frac{Sino\ ESG_{i,t} - Min(Sino\ ESG)}{Max(Sino\ ESG) - Min(Sino\ ESG)}\right) \tag{3}$$

$Greenwash_{i,t}$ denotes firms' greenwashing intensity calculated using Z-score normalization. $Greenwash2_{i,t}$ denotes firms' greenwashing intensity calculated using Min-Max normalization. $Bloomberg\ ESG_{i,t}$ refers to firms' disclosure ESG scores retrieved from the Bloomberg ESG database. $Sino\ ESG_{i,t}$ represents firms' actual ESG performance scores retrieved from the Sino-Securities Index Information Service. Higher values of $Greenwash_{i,t}$ and $Greenwash2_{i,t}$ indicates a greater intensity of greenwashing.

3.2.5. Control variables

We follow prior studies (e.g., Chen et al., 2022; Zhang et al., 2023) investigating the impact of environmental regulations on corporate environmental practices to include a set of control variables. We control firm age (*Age*) since younger firms are more likely to invest in more novel and thus riskier green business activities (Coad et al., 2016). Older firms depend less on green revenues for competitiveness due to higher scale efficiencies and process expertise (Agarwal et al., 2002). We control book-to-market ratio (*BTM*), as firms with fewer growth opportunities (higher *BTM*) likely prioritize shorter-term traditional profits over environmental investment returns (Attig, 2024). Larger firms may engage in more CSR initiatives due to their greater resource availability (Udayasankar, 2008). Conversely, smaller firms may find green revenues attractive to environmental and economic interests. Therefore, we control firm size (*Size*). We control whether the firm is a state-owned entity (*SOE*) because state ownership influences corporate environmental and financial interests (Hsu et al., 2021). We control firm-level green innovation (*Green Patent*), because innovative firms more effectively compete in green product markets (Chen et al., 2006).

Further, we control firm leverage (*Leverage*) because higher leverage is associated with disseminating private information to financial markets to finance green investments (Lins et al., 2017). We control net working capital (*Working Capital*) as environmentally oriented firms are associated with lower working capital requirements (Barros et al., 2022). We control cash holding (*Cash Holding*) as firms with a higher level of CSR commitment hold less cash under tightened environmental regulations (Chen et al., 2024). We control liquidity (*Quick Ratio*) as the ability of firms to meet short-term liabilities will affect their investment in green business activities in response to environmental regulations. Prior studies suggest that stronger financial performance and higher market valuation are associated with better CSR performance (Awaysheh et al., 2020). Therefore, we control return-on-assets (*ROA*) and Tobin's Q (*Tobin's Q*). We control the level of tangible assets (*Tangible Assets*) as firms require fixed assets as collateral to finance green business investments (Xiang et al., 2022). As prior studies document the influence of market competition on environmental pursuits (Duanmu et al., 2018), we control industry competition (*HHI*). Lastly, we control financial constraints (*SA Index*), as financially constrained firms tend to leverage on the market growth potential for economic returns (Hann et al., 2013).

3.3. Empirical model

We examine the impact of centralized environmental monitoring on the green revenues of highly eco-conscious firms relative to their counterparts using the following model:

$$\begin{aligned} Green\ Revenue_{i,t} \ = \ & \alpha + \beta EC_{i,t} \times EnvScheme_t + \delta Z_{i,t} \\ & + Industry_j + Region_r + Year_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

GreenRevenue represents the two measures of green revenues (*Green Rev Dummy* and *Green Rev Ratio*) of firm *i* in year *t. EC* is an indicator variable that equals one if the firm possesses a high level of eco-consciousness, and zero otherwise. The Scheme for centralized environmental monitoring was implemented in 2015. Thus, *EnvScheme* is an indicator variable that equals one for observations from 2015 to 2019 and zero for those from 2011 to 2014. Z_{it} is a set of control variables. $Industry_j$ and $Region_r$ are the vectors of industry and region dummy variables that account for industry-level and region-level fixed effects, respectively. $Year_t$ represents year dummy variables that account for year-level fixed effects. ε_{it} is the error term. Our model does not include *EC* and *EnvScheme* as the effects of these two variables are absorbed after controlling for industry, region, and year-fixed effects. Detailed definitions of all variables are presented in the Appendix. We implement cluster robust standard errors at the firm level to account for heteroskedasticity and correlation within firms (Petersen, 2009). Cluster robust standard errors do not address the influence of outliers or endogeneity arising from functional form issues, omitted variables, or reverse causality. Therefore, we address these concerns using a suite of robustness tests and sensitivity checks.

The centralization of environmental monitoring under the Scheme represents a plausibly exogenous shock because it is an outcome of the central government's decision-making and is not influenced by firms' derivation of green revenues. We thus use a DiD estimation to obtain more reliable causal inferences as it implicitly controls for time-invariant unobserved factors that affect both treatment and control groups similarly over time (Angrist and Pischke, 2009). Our primary variable of interest is $EC_{i,t} \times EnvScheme_t$, with its coefficient β reflecting the differential impact of the Scheme on the green revenues of highly eco-conscious firms relative to their counterparts. δ captures the impact of a firm's observed characteristics on its green revenues.

To ensure the validity of our DiD model, we perform several checks to ensure it complies with the underlying assumptions of DiD estimation (Angrist and Pischke, 2009). First, the number of pre- and post-implementation periods should be balanced. We select our sample period to include four years before and after 2015, which is the implementation year of the Scheme. Second, the parallel trends assumption requires that the dependent variables of the treatment and control groups exhibit parallel trends prior to the implementation of the Scheme. We conduct a dynamic analysis in Section 4.3 to ensure this is complied with. Third, confounding factors and events should not drive our findings. We test this assumption using a placebo test in Section 5.2. Fourth, an overlap must exist among the covariates of the treatment and control observations. We incorporate a set of control variables and utilize propensity score matching, as detailed in the following Section 3.4, to achieve this requirement.

3.4. Propensity score matching

To alleviate the concern that the differences in green revenue derivation are driven by firm characteristics rather than the centralization of environmental monitoring and firms' eco-conscious level, we employ PSM following Kahn-Lang and Lang (2020). PSM mitigates selection bias due to non-random mutual selection and other functional misspecification (Rosenbaum and Rubin, 1983). PSM matches highly eco-conscious firm-year observations with less eco-conscious firm-year observations so that they are more comparable in terms of observable firm characteristics. Consistent with prior studies (e.g, Rosenbaum and Rubin, 1985; Wu and Wang, 2022), we use the nearest neighbours (1:5) and 0.25 standard error of the propensity score as the matching ratio and caliper width.[11] The differences are significant before matching and become insignificant after matching. The mean (median) standardized bias reduces from 26 % (26.80 %) to 1 % (0.80 %) from the matching process. Fig. 1 illustrates that the standardized bias across covariates after matching is significantly lower than before matching. This suggests that differences in green revenues can plausibly be attributed to the centralization of environmental monitoring and the eco-conscious level of firms.

[11] Table OA.3 in the Online Appendix presents the diagnostic test results for the differences in covariates between highly and less eco-conscious firm-year observations.

4. Empirical results

4.1. Descriptive statistics

Table 3 reports the descriptive statistics. The mean value of *Green Rev Dummy* is 0.113, indicating that only 11.30 % of our sample observations derive green revenues. The mean of the *Green Rev Ratio* when the *Green Rev Dummy* equals one is 0.325. Among firms that derive green revenues, their green revenues account for an average of 32.50 % of total revenues, which is equivalent to approximately 1.04 billion Chinese RMB. These statistics are consistent with prior studies (e.g., Kruse et al., 2020; Klausmann et al., 2024, 2024). The mean value for eco-consciousness (*EC*) is 0.262, indicating that 26.20 % of the sample observations are classified as highly eco-conscious firm-years. The average leverage ratio is 41.70 %, indicating that most firms are heavily leveraged. 33.38 % of our sample observations are from state-owned enterprises. Since our sample comprises listed firms that are sizable, the level of tangible assets exhibits limited variation across our sample. The descriptive statistics are comparable to those of prior literature using a sample of Chinese-listed firms (e.g., Hu et al., 2023; Zhang, 2023a).[12] The highest represented industry in our sample is the metal, nonmetal, machinery, and electronics industry at 38.58 %, while the least represented industry is the education industry at 0.21 %. Among the treatment group, the electronics and gas industries have the highest mean for *Green Revenue Dummy* (0.469), implying that firms in this industry have the highest likelihood of generating green revenues among highly eco-conscious firms.

4.2. Baseline results

4.2.1. Test of hypothesis 1: baseline analysis

Hypothesis 1 predicts that the centralization of environmental monitoring incentivizes highly eco-conscious firms to derive greater green revenues. Columns (1) to (6) of Table 4 present the results based on a DiD identification and Columns (7) to (10) report the results based on a PSM-DiD method. We find that centralized environmental monitoring increases (1) the likelihood of a highly eco-conscious firm's derivation of green revenues and (2) a highly eco-conscious firm's ratio of green revenues to its total revenues relative to a less eco-conscious counterpart. These effects are predominantly significant at the 1 % level. We show the effect sizes. The estimated coefficient of *EC x Env Scheme* is 0.091 in Column (8), which indicates that highly eco-conscious firms are 9.10 % (0.091 × 100 %) more likely to derive any form of green revenues than less eco-conscious firms following the centralization of environmental monitoring. The estimated coefficient of *EC x Env Scheme* is 0.032 in Column (10), which indicates that highly eco-conscious firms report an increase in their green revenues that is 3.20 % (0.032 × 100 %) greater than that of less eco-conscious firms following the centralization of environmental monitoring.

These effects are also economically significant. The centralization of environmental monitoring increases treated highly eco-conscious firms' likelihood (extent) of green revenue derivation by 23.88 %[13] (16.33 %[14]) of the standard deviation of the treatment group. In sum, the empirical results are consistent with Hypothesis 1. The higher the eco-consciousness of a firm, the greater its ability to derive green revenues from tightening environmental regulations. An increase in the stringency of environmental regulations not only motivates CSR engagement to subsequently attain economic returns (Chu et al., 2024). Rather, highly eco-conscious firms leverage their dynamic green capabilities to simultaneously derive environmental and economic benefits when market opportunities emerge from introducing environmental regulations (Maksimov et al., 2022). Eco-consciousness thus forms an important conduit for firms to simultaneously meet environmental and economic objectives under an integrative view in dynamic regulatory business environments.

We discuss the results of the control variables based on Column (10). Firms with a higher level of green innovation are able to compete effectively in green markets to derive green revenues (Chen et al., 2006). Younger firms are more likely to invest in green business activities, while older firms are less dependent on green revenues to comply with environmental regulations (Agarwal et al., 2002; Coad et al., 2016). Firms with fewer growth opportunities (higher *BTM*) have a shorter horizon and thus prioritize traditional profits over green investment returns. A higher return on assets and market valuation is associated with lower green revenue derivation, which suggests that less profitable firms target green revenues due to their embodiment of economic benefits in addition to environmental benefits. For the few major players in concentrated industries, green revenues form a viable source of additional revenues but will not constitute a large proportion of their local revenues. Financially constrained firms tend to leverage the growth potential of green markets to improve financial performance (Hann et al., 2013).

4.2.2. Test of hypothesis 2: mechanism of technical infrastructure development

Hypothesis 2 predicts that technical infrastructure development is crucial for the Scheme to increase highly eco-conscious firms' derivation of green revenues. We test Hypothesis 2 by partitioning our sample based on the sample median of regional internet infrastructure development level (*Internet Dev* and *Internet Dev2*). Panel A of Table 5 reports the results. We find that the effect of the centralization of environmental monitoring on highly eco-conscious firms' likelihood and extent of green revenue derivation is more pronounced in regions with a higher level of internet infrastructure development. Specifically, the positive coefficient of *EC x Env*

[12] The sample distribution by year, presented in Table OA.1 in the Online Appendix, indicates that the distribution of observations exhibits a stable increasing trend over the sample period. Table OA.2 in the Online Appendix reports the observations and mean of green revenues by industry.

[13] The coefficient on *EC x Env Scheme* (0.091) / the standard deviation of *Green Rev Dummy* for the treatment group (0.381) *x* 100%.

[14] The coefficient on *EC x Env Scheme* (0.032) / the standard deviation of *Green Rev Ratio* for the treatment group (0.196) *x* 100%.

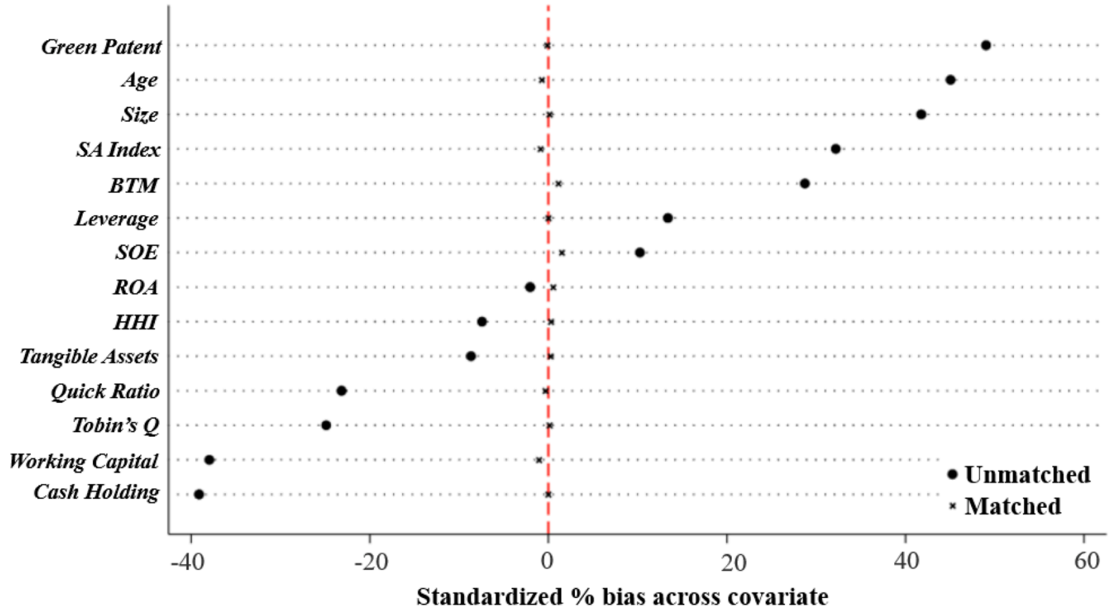

Fig. 1. Standardized percent bias across covariates.
Note: This figure plots the change in the standard deviation of each variable before and after propensity score matching.

Scheme in the subsamples with higher internet infrastructure development levels is more significant than those with a lower internet infrastructure development level. The differences in the coefficients between the subsamples are statistically significant at the 1 % and 5 % levels.

These results highlight that the effectiveness of centralized environmental monitoring in influencing firms' behaviour and outcomes is reliant on the central government's access to accurate and timely local environmental information (Ruof, 2023). In addition to remote data collection and transmission (Mollah et al., 2017), internet infrastructure development is crucial for the application of advanced environmental monitoring technologies (Guo et al., 2022). Therefore, internet infrastructure development allows the central government to effectively administer and oversee local governments' environmental enforcement.

4.2.3. Test of hypothesis 3: mechanism of greenwashing diminishing

Hypothesis 3 conjectures that the centralization of environmental monitoring reduces corporate greenwashing to affect highly eco-conscious firms' green revenue derivation. We test this by partitioning our sample based on the sample median of firm-level greenwashing measures (*Greenwash* and *Greenwash2*). Panel B of Table 5 reports the results. We find that the effect of the centralization of environmental monitoring on highly eco-conscious firms' likelihood and extent of green revenue derivation is more pronounced when the level of corporate greenwashing is low. Specifically, the positive coefficient of the *EC x Env Scheme* is only significant in the subsamples with lower greenwashing and is insignificant in the subsamples with higher greenwashing. The differences in the coefficients between the subsamples are statistically significant at the 1 % level. These results highlight that, by reducing corporate greenwashing, an increase in the central government's oversight of local environmental accountability interacts with eco-consciousness to affect their derivation of green revenues.

4.3. Parallel trend

The underlying assumption required for a DiD estimation to be valid is that the trends in green revenues of highly eco-conscious firms and their counterparts should be parallel prior to the centralization of environmental monitoring. While both observable and unobservable factors may cause the level of green revenues to differ between highly eco-conscious and less eco-conscious firms, this difference must be constant over time in the absence of the Scheme. If differences in green revenues pre-exist between highly eco-conscious (treatment group) and less eco-conscious firms (control group), the parallel trend assumption is violated, and the baseline causal estimate will be invalid because the differential impact on green revenue derivation is unattributed to the Scheme. We test the compliance of our model to the parallel trend assumption using a dynamic analysis framework (Beck et al., 2010). We incorporate interactions of the eco-consciousness measure (*EC*) with dummy variables indicating each of the years relative to the implementation year using the following model:

$$\begin{aligned} Green\ Revenue_{i,t} &= \alpha + \sum_{k=-4}^{k=+4} \beta EC_{i,t} \times EnvScheme_{k_{i,t}} \\ &+ \delta Z_{i,t} + Industry_j + Region_r + Year_t + \varepsilon_{i,t} \end{aligned} \tag{5}$$

Table 3
Descriptive statistics.

Panel A: Full Sample

Variable	Obs.	Mean	SD	Min	Q1	Median	Q3	Max
Green Rev Dummy	20,139	0.113	0.316	0.000	0.000	0.000	0.000	1.000
Green Rev Ratio	20,139	0.037	0.153	0.000	0.000	0.000	0.000	1.000
EC	20,139	0.262	0.440	0.000	0.000	0.000	1.000	1.000
Size	20,139	22.103	1.261	19.617	21.195	21.909	22.781	26.395
SOE	20,139	0.328	0.470	0.000	0.000	0.000	1.000	1.000
Green Patent	20,139	0.789	1.123	0.000	0.000	0.000	1.386	4.970
Age	20,139	2.815	0.337	1.386	2.639	2.833	3.045	3.555
Leverage	20,139	0.417	0.201	0.078	0.251	0.403	0.565	0.908
Working Capital	20,139	0.239	0.243	−0.399	0.070	0.240	0.415	0.786
Cash Holding	20,139	0.161	0.124	0.007	0.072	0.125	0.213	0.667
Quick Ratio	20,139	1.833	1.661	0.127	0.774	1.267	2.220	9.149
BTM	20,139	0.625	0.234	0.137	0.442	0.627	0.803	1.225
ROA	20,139	0.038	0.066	−0.551	0.015	0.039	0.068	0.201
Tobin's Q	20,139	1.933	1.025	0.816	1.246	1.596	2.260	7.322
Tangible Assets	20,139	0.922	0.093	0.450	0.908	0.954	0.977	1.000
HHI	20,135	0.220	0.214	0.023	0.087	0.145	0.259	1.000
SA Index	20,139	3.747	0.254	2.113	3.595	3.750	3.907	5.543

Panel B: Treatment and Control Groups

	Treatment group				Control group			
Variable	Obs.	Mean	Median	SD	Obs.	Mean	Median	SD
Green Rev Dummy	5268	0.177	0.000	0.381	14,871	0.090	0.000	0.286
Green Rev Ratio	5268	0.064	0.000	0.196	14,871	0.027	0.000	0.133
Size	5268	22.451	22.229	1.360	14,871	21.979	21.806	1.200
SOE	5268	0.396	0.000	0.489	14,871	0.304	0.000	0.460
Green Patent	5268	1.151	0.693	1.269	14,871	0.660	0.000	1.037
Age	5268	2.848	2.890	0.328	14,871	2.803	2.833	0.339
Leverage	5268	0.445	0.439	0.195	14,871	0.407	0.388	0.202
Working Capital	5268	0.164	0.162	0.244	14,871	0.266	0.267	0.237
Cash Holding	5268	0.133	0.103	0.105	14,871	0.171	0.134	0.128
Quick Ratio	5268	1.547	1.063	1.460	14,871	1.935	1.346	1.716
BTM	5268	0.688	0.695	0.230	14,871	0.603	0.602	0.232
ROA	5268	0.036	0.036	0.061	14,871	0.038	0.040	0.068
Tobin's Q	5268	1.694	1.438	0.826	14,871	2.017	1.660	1.075
Tangible Assets	5268	0.922	0.952	0.084	14,871	0.921	0.954	0.096
HHI	5268	0.201	0.142	0.196	14,867	0.226	0.145	0.220
SA Index	5268	3.759	3.774	0.266	14,871	3.743	3.742	0.249

Note: This table presents the descriptive statistics of variables, including the number of observations (Obs.), mean, median, standard deviation (SD), quartile (25 % and 75 %), and minimum and maximum values. Panel A presents the descriptive statistics for the full sample. Panel B presents the summary statistics for the treatment and control groups. The treatment group includes firm-year observations with a level of eco-consciousness within the top tercile ($EC = 1$), whereas the control group includes observations with a level of eco-consciousness below the top tercile ($EC = 0$). Details on all variable definitions are provided in the Appendix.

The dummy variables $EnvScheme_k$ for the years relative to the implementation year and the year of implementation equal zero, except as follows: $EnvScheme_{-k}$ equals one for observations in the kth year before implementation, $EnvScheme_0$ equals one for observations in the implementation year, and $EnvScheme_{+k}$ equals one for observations in the kth year after implementation. Other variables are as defined for model (4). The coefficients on *EC* x $EnvScheme_{-k}$ are of interest because the values and significance of these coefficients identify the presence of a significant difference between the treatment and control groups in terms of green revenues before the Scheme.

The results in Table 6 show that the coefficients on $EnvScheme_{-k}$ ($k = -4, -3, -2$, and -1) are all insignificant and indistinguishable from zero. In addition, the coefficients on *EC x* $EnvScheme_0$ and *EC x* $EnvScheme_{+k}$ ($k = 1, 2, 3$, and 4) are all positive and significant at the 1 % and 5 % levels. These results conform to the parallel trend assumption and suggest that the effect of the Scheme on the green revenues of highly eco-conscious firms takes place immediately. The Scheme has a positive and causal effect on the green revenues of highly eco-conscious firms compared to less eco-conscious firms. Further, this effect is of a long-term nature as the green revenues of highly eco-conscious firms remain positively impacted over the subsequent years. These findings indicate that our baseline result is valid.

We perform an F-test on the joint significance of the coefficients of *EC x* $EnvScheme^k$ before and after the implementation year. We find that the joint significance for pre-implementation years is insignificant, while it is significant for post-implementation years at the 1 % level. This provides additional evidence for compliance with the parallel trend assumption. We visualize the results of the parallel trend test in Fig. 2, which plots the coefficients over the observed period. The differences in the green revenues of the treatment and control groups are only significantly different from zero after the Scheme is implemented, which indicates that the treatment effect is

Table 4
Environmental monitoring and green revenues of high eco-conscious firms.

	Difference-in-Differences						PSM + DiD			
	Green Rev Dummy			*Green Rev Ratio*			*Green Rev Dummy*		*Green Rev Ratio*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EC x Env Scheme	0.078***	0.062***	0.062***	0.031***	0.024***	0.024***	0.050***	0.091***	0.023**	0.032***
	(6.611)	(5.609)	(5.633)	(5.131)	(4.110)	(4.221)	(2.879)	(6.022)	(2.346)	(3.779)
Size		−0.018***	−0.017***		−0.010***	−0.010***		−0.010		−0.005
		(−3.169)	(−2.899)		(−3.333)	(−3.298)		(−0.816)		(−0.702)
SOE		−0.023*	−0.018		−0.014**	−0.014**		0.020		0.000
		(−1.835)	(−1.406)		(−2.539)	(−2.504)		(0.701)		(0.004)
Green Patent		0.061***	0.061***		0.026***	0.026***		0.075***		0.026***
		(9.806)	(9.810)		(6.632)	(6.624)		(7.809)		(4.433)
Age		−0.105***	−0.101***		−0.068***	−0.067***		−0.194***		−0.098***
		(−3.812)	(−3.744)		(−4.220)	(−4.268)		(−3.235)		(−3.255)
Leverage		0.091**	0.087**		0.047***	0.044**		−0.104*		−0.001
		(2.524)	(2.410)		(2.667)	(2.546)		(−1.682)		(−0.035)
Working Capital		0.059*	0.066*		0.011	0.012		0.011		0.011
		(1.731)	(1.948)		(0.671)	(0.753)		(0.152)		(0.331)
Cash Holding		−0.060*	−0.058*		−0.018	−0.019		−0.192**		−0.099*
		(−1.776)	(−1.732)		(−1.094)	(−1.175)		(−2.013)		(−1.859)
Quick Ratio		−0.004	−0.005		−0.000	−0.001		−0.009		−0.001
		(−1.380)	(−1.596)		(−0.137)	(−0.336)		(−1.026)		(−0.207)
BTM		−0.007	−0.010		−0.011	−0.013		−0.117		−0.068**
		(−0.209)	(−0.300)		(−0.728)	(−0.867)		(−1.495)		(−2.127)
ROA		−0.119**	−0.131***		−0.016	−0.013		−0.222**		−0.058
		(−2.389)	(−2.661)		(−0.731)	(−0.599)		(−2.121)		(−1.359)
Tobin's Q		−0.001	−0.002		−0.006***	−0.006***		−0.007		−0.010**
		(−0.201)	(−0.279)		(−2.691)	(−2.911)		(−0.501)		(−1.964)
Tangible Assets		−0.086*	−0.086*		0.003	0.006		−0.048		0.006
		(−1.691)	(−1.681)		(0.140)	(0.303)		(−0.560)		(0.139)
HHI		0.046**	0.045**		0.016	0.015		0.222***		0.056
		(2.015)	(1.964)		(1.235)	(1.130)		(2.698)		(1.585)
SA Index		0.184***	0.171***		0.080***	0.077***		0.303***		0.102***
		(5.394)	(5.016)		(4.133)	(4.036)		(4.426)		(3.054)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	No	No	Yes	No	Yes	No	Yes
Observations	20,139	20,135	20,135	20,139	20,135	20,135	12,509	12,509	12,509	12,509
Adjusted R^2	0.157	0.193	0.200	0.149	0.179	0.184	0.174	0.226	0.247	0.186

Note: This table presents the analyses of the causal effect of centralized environmental monitoring on the green revenues of firms with a higher level of eco-consciousness. The dependent variable of green revenues is measured by *Green Rev Dummy and Green Rev Ratio. Green Rev Dummy* is an indicator equal to one if the firm earns green revenue during the year, and zero otherwise. *Green Rev Ratio* is the ratio of total green revenues earned to total revenues of the firm during the year. Columns (1) to (6) report the results based on a difference-in-differences (DiD) specification. Columns (7) to (10) report the results based on propensity score matching (PSM) in combination with DiD. Details on variable definitions are in the Appendix. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Robust t-statistics clustered by the firm are reported in parentheses.

Table 5
Mechanism analyses.

Panel A: Technical Infrastructure Development Effect								
	Green Rev Dummy		*Green Rev Ratio*		*Green Rev Dummy*		*Green Rev Ratio*	
	(1) Higher *Internet Dev*	(2) Lower *Internet Dev*	(3) Higher *Internet Dev*	(4) Lower *Internet Dev*	(5) Higher *Internet Dev2*	(6) Lower *Internet Dev2*	(7) Higher *Internet Dev2*	(8) Lower *Internet Dev2*
EC x Env Scheme	0.077***	0.034**	0.030***	0.017**	0.098***	0.035**	0.037***	0.018**
	(5.312)	(2.046)	(3.905)	(2.058)	(5.319)	(2.431)	(3.701)	(2.514)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_1 - β_2 (*p*-value)	0.001***		0.047**		0.000***		0.000***	
Observations	10,066	10,069	10,066	10,069	8936	9006	8936	9006
Adjusted R^2	0.208	0.204	0.186	0.197	0.221	0.191	0.178	0.219
Panel B: Greenwashing Diminishing Effect								
	Green Rev Dummy		*Green Rev Ratio*		*Green Rev Dummy*		*Green Rev Ratio*	
	(1) Higher *Greenwash*	(2) Lower *Greenwash*	(3) Higher *Greenwash*	(4) Lower *Greenwash*	(5) Higher *Greenwash2*	(6) Lower *Greenwash2*	(7) Higher *Greenwash2*	(8) Lower *Greenwash2*
EC x Env Scheme	0.014	0.070**	−0.001	0.030**	0.012	0.074***	−0.003	0.032**
	(0.772)	(2.484)	(−0.161)	(2.152)	(0.659)	(2.614)	(−0.295)	(2.306)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_1 - β_2 (*p*-value)	0.006***		0.001***		0.000***		0.000***	
Observations	3463	3463	3463	3463	3463	3463	3463	3463
Adjusted R^2	0.256	0.238	0.255	0.221	0.256	0.237	0.255	0.221

Note: This table presents the results of the mechanism analysis. We measure technical infrastructure development using the log-transformed number of Internet broadband access ports in the region (*Internet Dev* and *Internet Dev2*). We measure greenwashing using the difference between normalized ESG disclosure and performance (*Greenwash* and *Greenwash2*). For each mechanism, we partition our sample based on the sample median of the mechanism variable. The statistical significance of the difference in coefficients is obtained using Fisher's permutation tests with 1000 rounds of bootstrapping. This test relies on random permutations and requires that the order of observations is exchangeable. It provides estimates robust to outliers because it is non-parametric and does not rely on specific assumptions about the underlying data distribution (Zhao and Ding, 2021). Details on variable definitions are in the Appendix. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Robust t-statistics clustered by the firm are reported in parentheses.

attributed to the Scheme and that our DiD estimates are valid.

5. Robustness tests

5.1. *Entropy balancing*

Although PSM is an effective method to address endogeneity related to self-selection on observables, it can be sensitive to design choices, including caliper width and the number of control firms matched to treatment firms (Wilde, 2017). Therefore, we use entropy balancing to match control and treatment observations to achieve covariate balance across the two groups. Entropy balancing can be more effective than other matching estimators because it achieves a higher degree of covariate balance and requires less restrictive assumptions (Hainmueller, 2012). Making the treatment and control groups balanced on the high-order moments of covariates through reweighting ensuresthe treatment and control groups more comparable.

We report the covariate balance for the pre- and post-entropy balanced samples in Panels A and B of Table 7, respectively. The differences in standard deviation and variance between treatment and control groups are significant prior to entropy balancing. However, the differences in standard deviation are equal to zero, and the variance ratio is equal to one after entropy balancing, which indicates the effectiveness of entropy balancing in making the treatment and control groups comparable across observable characteristics. Using post-entropy balanced samples, we rerun our baseline analysis and report the results in Panel C of Table 7. The results are consistent with our baseline findings.

5.2. *Placebo tests*

Unobserved factors that influence the treatment and control groups in a manner similar to the Scheme or firms' eco-consciousness can undermine the validity of our results. It is important to ensure that observed causal effects are not attributable to other

Table 6
Parallel trend tests.

	Green Rev Dummy (1)	*Green Rev Ratio* (2)
$EC \times Env\ Scheme_{-4}$	0.031	0.003
	(0.826)	(0.177)
$EC \times Env\ Scheme_{-3}$	−0.015	−0.011
	(−0.481)	(−0.872)
$EC \times Env\ Scheme_{-2}$	0.011	−0.012
	(0.329)	(−0.895)
$EC \times Env\ Scheme_{-1}$	0.004	−0.000
	(0.142)	(−0.004)
$EC \times Env\ Scheme_{0}$	0.095***	0.036***
	(3.612)	(2.656)
$EC \times Env\ Scheme_{+1}$	0.116***	0.043***
	(4.846)	(3.305)
$EC \times Env\ Scheme_{+2}$	0.107***	0.031***
	(5.184)	(2.820)
$EC \times Env\ Scheme_{+3}$	0.074***	0.026**
	(3.644)	(2.551)
$EC \times Env\ Scheme_{+4}$	0.076***	0.028***
	(3.910)	(2.778)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Region FE	Yes	Yes
F: $\sum_{-4}^{-1} Interaction = 0$ (p-value)	0.712	0.575
F: $\sum_{0}^{+4} Interaction = 0$ (p-value)	0.000***	0.000***
Observations	12,509	12,509
Adjusted R^2	0.247	0.235

Note: This table presents the tests of parallel trends. We examine the pre-trend between the treatment and control group by interacting with a series of dummy variables in the standard DiD regression. We estimate model (2), where the years relative to the implementation year are defined as *Env* Scheme$_{-4}$, *Env* Scheme$_{-3}$, *Env* Scheme$_{-2}$, *Env* Scheme$_{-1}$, *Env* Scheme$_{+1}$, *Env* Scheme$_{+2}$, *Env* Scheme$_{+3}$, and *Env Scheme*$_{+4}$. *Env Scheme*$_{-k}$ equals one for observations in the *k*th year before the Scheme, while *Env Scheme*$_{+k}$ equals one for observations in the *k*th year after the Scheme. We include all control variables and fixed effects in our baseline analysis. We report the p-values for the joint significance of the relative years' interaction coefficients before and after the implementation year of 2015. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Robust t-statistics clustered by the firm are reported in parentheses.

confounding regulations. Following prior studies (Xiao et al., 2023; Sun et al., 2024), we select fictitious implementation years and assign random treatment groups to conduct a placebo test.

We re-estimate our baseline model based on a fictitious sample. We repeat this process 1000 times to obtain 1000 pseudo coefficients. For our baseline findings to remain valid, the pseudo coefficients are to be statistically insignificant from zero. We plot the kernel density of the pseudo coefficients in Fig. 3, which illustrates that the pseudo coefficients fluctuate around zero, follow a normal distribution, and are significantly smaller than the true coefficients (0.091 and 0.032). These findings confirm that our results are not driven by confounding factors.

5.3. Alternative specification

To ensure our findings are not sensitive to measurement bias or errors associated with our variable of eco-consciousness, we use alternative specifications of eco-consciousness. We alternatively specify treatment and control groups based on the sample median of *EC* (*EC Med*). *EC Med* is an indicator variable equal to one if the observation has an above sample-median level of eco-consciousness, and zero otherwise. We rerun our baseline analysis using *EC Med* and report the results in Table 8. The results are consistent with our baseline findings.

5.4. Omitted variable bias

Potential omitted variable bias may impact our estimates. If a characteristic of a firm is simultaneously correlated with its level of eco-consciousness and derivation of green revenues, an omission of this characteristic may render eco-consciousness correlated with

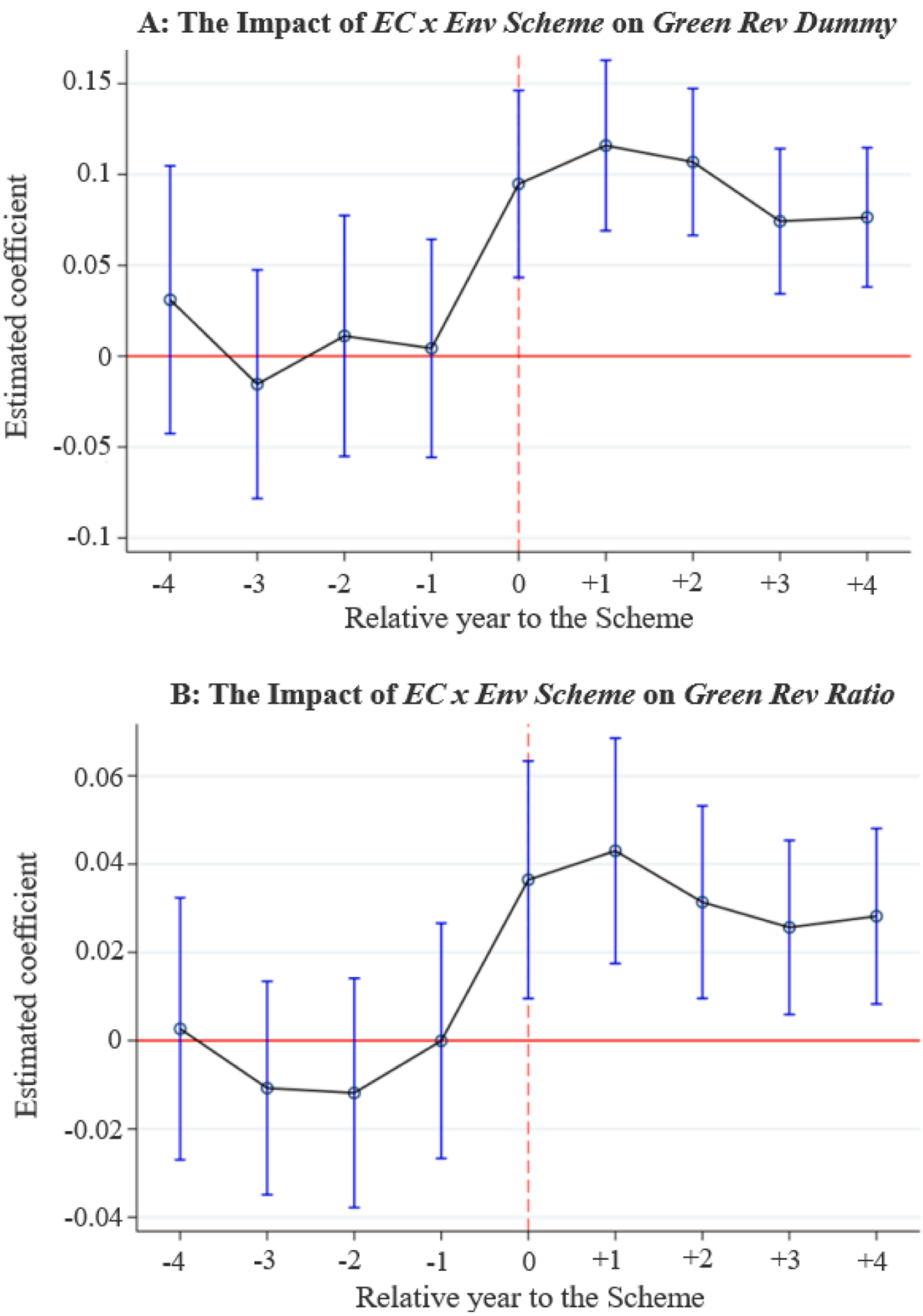

Fig. 2. Pre-treatment trend visualization.

Note: This figure visualizes the coefficients of the interactions as reported in Table 3. Variable definitions are in the Appendix. Panels A-B show that the interaction coefficients for years after the Scheme in 2015 are significantly greater than those before the Scheme prior to 2015. We consider an eight-year window, spanning from four years before implementation until four years after implementation. Panel A shows the effect on green revenues as indicated by *Green Rev Dummy*, capturing the effect on the derivation of green revenues by the treatment group. Panel B illustrates the effect on green revenues as indicated by the *Green Rev Ratio*, capturing the effect on the treatment group's extent of green revenue derivation. 95 % confidence intervals adjusted for firm-level clustering are presented.

Table 7
Entropy balancing approach.

Panel A: Pre-Entropy Balancing Covariate Balance

	Treatment group			Control group			SD	Variance
	Mean	*Variance*	*Skewness*	*Mean*	*Variance*	*Skewness*	*Diff.*	*Ratio*
Size	22.540	1.788	0.683	22.000	1.492	0.909	0.115	1.198
SOE	0.368	0.233	0.547	0.319	0.217	0.774	0.016	1.070
Green Patent	1.263	1.717	0.824	0.681	1.096	1.615	0.264	1.567
Age	2.929	0.075	−0.556	2.789	0.118	−0.791	−0.071	0.629
Leverage	0.438	0.036	0.136	0.412	0.041	0.342	−0.015	0.857
Working Capital	0.166	0.054	0.030	0.256	0.059	−0.133	−0.011	0.914
Cash Holding	0.125	0.009	1.591	0.169	0.016	1.304	−0.034	0.537
Quick Ratio	1.538	1.957	2.511	1.900	2.918	1.923	−0.309	0.671
BTM	0.680	0.056	−0.007	0.613	0.054	0.050	0.006	1.051
ROA	0.037	0.004	−3.080	0.038	0.004	−3.062	0.000	1.000
Tobin's Q	1.736	0.780	2.298	1.978	1.102	1.933	−0.167	0.707
Tangible Assets	0.915	0.008	−2.164	0.923	0.009	−2.450	−0.003	0.939
HHI	0.207	0.038	2.439	0.222	0.048	2.105	−0.024	0.791
SA Index	3.813	0.064	−0.775	3.732	0.063	−0.317	0.000	1.004

Panel B: Post-Entropy Balancing Covariate Balance

	Treatment group			Control group			SD	Variance
	Mean	*Variance*	*Skewness*	*Mean*	*Variance*	*Skewness*	*Diff.*	*Ratio*
Size	22.540	1.788	0.683	22.540	1.788	0.683	0.000	1.000
SOE	0.368	0.233	0.547	0.368	0.233	0.547	0.000	1.000
Green Patent	1.263	1.717	0.824	1.263	1.717	0.824	0.000	1.000
Age	2.929	0.075	−0.556	2.929	0.075	−0.558	0.000	1.000
Leverage	0.438	0.036	0.136	0.438	0.036	0.136	0.000	1.000
Working Capital	0.166	0.054	0.030	0.166	0.054	0.030	0.000	1.000
Cash Holding	0.125	0.009	1.591	0.125	0.009	1.591	0.000	1.000
Quick Ratio	1.538	1.957	2.511	1.539	1.957	2.511	0.000	1.000
BTM	0.680	0.056	−0.007	0.680	0.056	−0.007	0.000	1.000
ROA	0.037	0.004	−3.080	0.037	0.004	−3.080	0.000	1.000
Tobin's Q	1.736	0.780	2.298	1.736	0.780	2.298	0.000	1.000
Tangible Assets	0.915	0.008	−2.164	0.915	0.008	−2.164	0.000	1.000
HHI	0.207	0.038	2.439	0.207	0.038	2.439	0.000	1.000
SA Index	3.813	0.064	−0.775	3.813	0.064	−0.776	0.000	1.000

Panel C: Environmental Monitoring and Green Revenues on Entropy-Balanced Sample

	Green Rev Dummy			*Green Rev Ratio*		
	(1)	(2)	(3)	(4)	(5)	(6)
EC x Env Scheme	0.065***	0.073***	0.073***	0.026***	0.027***	0.028***
	(4.701)	(5.555)	(5.545)	(3.710)	(4.024)	(4.056)
Controls	No	Yes	Yes	No	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	No	No	Yes
Observations	20,135	20,135	20,135	20,135	20,135	20,135
Adjusted R^2	0.185	0.230	0.238	0.189	0.220	0.226

Note: This table presents the covariate balance pre- (Panel A) and post-entropy balancing (Panel B). The difference in standard deviations (SD) between the treatment and control groups are presented in the columns labelled "*Diff.*" The "*Ratio*" column displays the ratio of treatment group variance to control group variance, with a ratio of 1 signifying the attainment of variance balance. We rerun our baseline analysis based on a DiD specification using the entropy balanced sample and report the results in Panel C. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Robust t-statistics clustered by the firm are reported in parentheses.

the error term, thus resulting in endogeneity and bias in our findings. To address this concern, we follow Oster (2019) to ascertain the sensitivity of our results to omitted variables.[15]

We focus on β, the coefficient of interest, which is the coefficient on the *EC x Env Scheme*. This method employs observable controls that are correlated with unobservables to examine how β and the regression R^2 change when these observable controls are included (Oster, 2019). If a coefficient remains stable after including observed controls, it provides confidence that omitted variable bias is limited. To establish a confidence level, a parameter δ is calculated to represent how strong the selection on unobservables would have

[15] This method is used in recent studies in the economics, finance, and accounting literature (e.g., Heimer *et al.*, 2019; Argyle *et al.*, 2021; Bao *et al.*, 2022; Li *et al.*, 2022; Fox and Wilson, 2023).

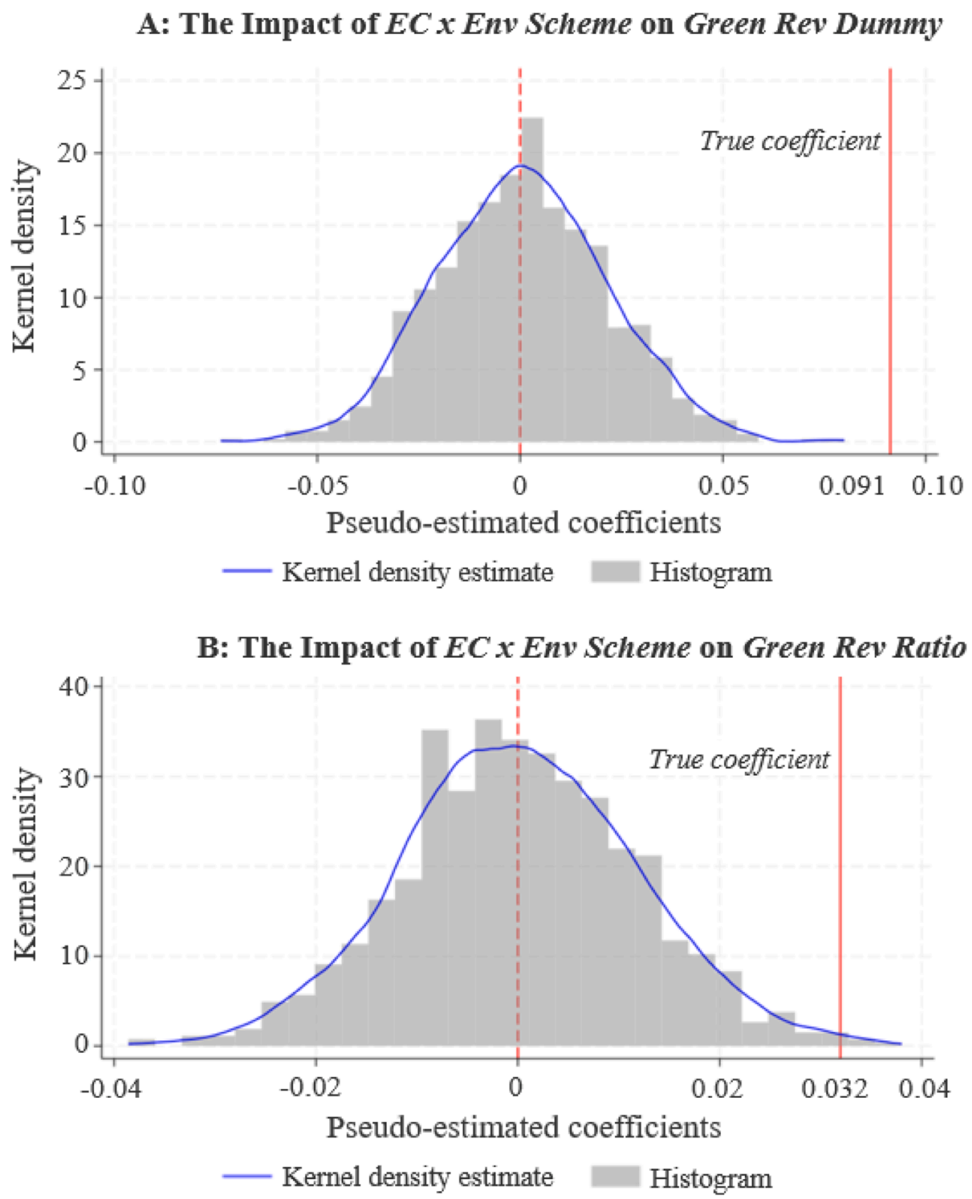

Fig. 3. Placebo tests.
Note: The figures present the kernel density plots and histogram of the estimated pseudo coefficients from random permutation tests. Panel A plots the pseudo coefficients for the dependent variable of *Green Rev Dummy*, while Panel B plots the pseudo coefficients for the dependent variable of *Green Rev Ratio*.

to be, relative to the selection on observables, to reduce β to zero. An absolute value of one for δ indicates that unobservable controls need to be as important as the observable controls to overturn our findings. The higher the absolute value of δ, the less likely it is that omitted variables significantly impact our results. The two tests under the method are the coefficient stability test and the unobservable selection test. The test results are reported in Table 9.

For the first test, we follow Oster (2019) to set the parameters such that $R^2_{max} = 1.3$ times R^2 of the baseline results with controls and $\delta = 1$. We obtain the bias-adjusted coefficient estimate β*, which is reported in the table's top row of each panel. Since the bias-adjusted coefficient β* is within the 95 % confidence interval of the original estimates, that is, the coefficient stability is high, then our baseline results are robust and are unlikely to be subject to an omitted variable bias.

For the second test, we set the parameters $\beta^* = 0$, and R^2_{max} remains the same as the previous test. We obtain the value of δ, which is reported in the bottom row of each panel. If δ is below −1 or above 1, our baseline results are unlikely to be affected by omitted variables. The absolute values of δ estimated are 4.987 and 7.277 for *Green Rev Dummy* and *Green Rev Ratio*, respectively, which suggest that an omitted variable would have to be approximately 500 % and 700 % as important as the observable and included

Table 8
Alternative specification.

	Difference-in-Differences						PSM + DiD			
	Green Rev Dummy			*Green Rev Ratio*			*Green Rev Dummy*		*Green Rev Ratio*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EC Med x Env Scheme	0.067***	0.053***	0.053***	0.025***	0.019***	0.019***	0.061***	0.091***	0.026***	0.033***
	(6.991)	(5.846)	(5.921)	(5.107)	(4.156)	(4.235)	(3.342)	(5.585)	(2.658)	(3.644)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	No	No	Yes	No	Yes	No	Yes
Observations	20,139	20,135	20,135	20,139	20,135	20,135	12,508	12,508	12,508	12,508
Adjusted R^2	0.157	0.193	0.200	0.148	0.178	0.183	0.170	0.239	0.178	0.228

Note: This table reports the results from an alternative specification of treatment and control groups. Columns (1) to (6) report the results based on a difference-in-differences (DiD) specification. Columns (7) to (10) report the results based on propensity score matching (PSM) in combination with DiD. We alternatively classify firm-year observations into treatment and control groups based on the sample median of *EC* (*EC Med*). Details on variable definitions are in the Appendix. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Robust t-statistics clustered by the firm are reported in parentheses.

Table 9
Omitted variable tests.

Panel A: *Green Rev Dummy*		
	(1)	(2)
Judgment standard	Estimated value	Test fulfilled?
$\beta*(R_{\max}, \delta) \epsilon [0.057, 0.119]$	$\beta* (R_{\max}, \delta) = 0.105$	Yes
$\delta > 1$ or $\delta < -1$	$\delta = -4.987$	Yes
Panel B: *Green Rev Ratio*		
	(1)	(2)
Judgment standard	Estimated value	Test fulfilled?
$\beta*(R_{\max}, \delta) \epsilon [0.016, 0.050]$	$\beta* (R_{\max}, \delta) = 0.038$	Yes
$\delta > 1$ or $\delta < -1$	$\delta = -7.277$	Yes

Note: This table reports the results of unobservable selection and coefficient stability tests following Oster (2019). Oster (2019) proposes a coefficient of proportionality, δ, which uses information from the movement in the coefficient of interest (*EC x Env Scheme*) and explanatory power (R^2). First, we use the model $\beta^*(R_{max}, \delta)$ to obtain bias-adjusted coefficients β*. δ takes the value of 1, and R_{max} takes the value of 1.3 times the R^2 of the controlled baseline regressions, and we obtain the value of coefficient estimate β*. Second, β* takes the value of 0, and R_{max} remains the same as the first test, and we obtain the value of δ. If β* is within the 95 % confidence interval of our original estimates in the first test and $\delta > 1$ or $\delta < -1$ in the second test, the baseline results are unlikely to be subject to an omitted variable bias.

controls to render the coefficient of interest β insignificant, which is highly unlikely. Omitted variable bias is not a concern in our study.

5.5. 2SLS-IV approach

Endogeneity concerns may arise from reverse causality, simultaneity, and omitted variables. First, there may be a bidirectional causal relationship between green revenues and eco-consciousness as a firm's higher participation in green industries can induce a market-driven incentive to be more eco-conscious. Second, a firm's eco-consciousness or its tendency towards environmental protection or green revenue derivation may be correlated with or driven by unobservable factors unaccounted for. We adopt a 2SLS-IV method to address these concerns. The relevance assumption under this method requires an instrument that correlates with eco-consciousness, while the exclusion restriction requires this instrument to not directly affect green revenues (Angrist and Pischke, 2009).

The level of Confucianism influence (*Confucianism*) can be a valid instrument. Confucianism has been a dominant cultural framework shaping China's social beliefs and institutional values for over 2000 years. Confucianism prioritizes the achievement of equilibrium and harmony among people, society, and the Earth (Allen et al., 2005). Confucianism instigates firms' environmental protection behaviours (e.g., Cho et al., 2013; Chen et al., 2021; Dong and Li, 2023), which positively affects its eco-consciousness. Following Chen et al. (2021), we use the number of Confucius temples and academies within a 300-kilometre radius of a firm's registered location (*Confucianism*) to proxy for the level of firms' Confucianism.

Table 10 reports the results. In the first stage, we regress *EC x Env Scheme* on *Confucianism x Env Scheme* and report the results in Column (1). The coefficient on *Confucianism x Env Scheme* is positive and significant at the 1 % level. It is unlikely that Confucianism

Table 10
Instrumental variable approach and heckman selection model.

	2SLS-IV			Heckman Selection Model		
	EC x Env Scheme (1) 1st stage	*Green Rev Dummy* (2) 2nd stage	*Green Rev Ratio* (3) 2nd stage	*EC x Env Scheme* (4) 1st stage	*Green Rev Dummy* (5) 2nd stage	*Green Rev Ratio* (6) 2nd stage
Confucianism x Env Scheme	0.001***			0.003**		
	(3.049)			(2.211)		
EC x Env Scheme (Instrumented)		0.369**	0.153**			
		(2.325)	(2.040)			
EC x Env Scheme					0.063***	0.025***
					(5.340)	(3.909)
Inverse Mills Ratio					−0.190**	−0.070
					(−2.202)	(−1.620)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,135	20,135	20,135	12,603	12,603	12,603
Pseudo/Adjusted R^2	0.270	0.180	0.158	0.212	0.207	0.200
Instrumental validity tests						
(i) F-test of excluded instrument in the first stage						
Sanderson-Windmeijer F-test statistic (p-value)		28.550 (0.000)				
(ii) Under-identification test						
Kleibergen-Paap rk LM statistic (p-value)		28.150 (0.000)				
(iii) Weak identification test						
Kleibergen-Paap Wald rk F statistic		28.550				
Stock-Yogo weak ID test						
10 % maximal IV size	16.380					
15 % maximal IV size	8.960					
20 % maximal IV size	6.660					
25 % maximal IV size	5.530					
Weak-instrument-robust inference						
Anderson-Rubin Wald test – F statistic (p-value)		6.290 (0.012)				
Anderson-Rubin Wald test – Chi^2 (p-value)		6.330 (0.012)				

Note: This table reports the results of the 2SLS-IV and Heckman selection models. Columns (1) to (3) present the results from the 2SLS-IV method, while Columns (4) to (6) present the results from the Heckman selection model. Column (1) presents the first stage regression of the 2SLS-IV with the baseline DiD interaction variable as the dependent variable. The instrumental variable is *Confucianism*, defined as the number of Confucius temples and academies within a 300-kilometere radius of the firm. Columns (2) and (3) report the second stage of the 2SLS-IV for the dependent variable of green revenue derivation. We repeat our baseline analysis but replace the interaction variable of interest, *EC x Env Scheme*, with instrumented *EC x Env Scheme* from the first stage. Column (4) presents the first stage of the Heckman selection model. We use a Probit model to estimate the likelihood of a firm possessing a higher level of eco-consciousness. We regress *Confucianism x Env Scheme* on *EC x Env Scheme* to account for the presence of the Scheme. Columns (5) and (6) show the results of the second stage of the Heckman selection model. We incorporate the inverse Mills ratio generated from the first stage into the second-stage regression to control for self-selection bias. Details on variable definitions are in the Appendix. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Robust t-statistics clustered by the firm are reported in parentheses.

influences a firm's green revenue derivation except through its eco-consciousness. We do not observe a direct link between the geographic distance of Confucius institutions and the derivation of green revenues; thus, *Confucianism* also satisfies the exclusion criterion.

Following Giannetti et al. (2015), we employ several instrumental validity tests that indicate our instrumental variable is correctly identified, strong, and valid.[16] First, the Sanderson-Windmeijer *F*-test of the first stage regression is significant at the 1 % level, which allows us to reject the null that *Confucianism* is a weak instrument (Larcker and Rusticus, 2010). Accordingly, the coefficient estimates and the t-statistics in the second stage are likely unbiased and thus provide reasonably valid results. Second, the result from the under-identification test (Kleibergen-Paap rk LM test) is significant (28.150), which rejects the null of under-identification. Similarly, in identifying the strengths of the instrument, the value of the Kleibergen-Paap Wald rk *F*-statistic (28.550) is higher than stock-Yogo critical values (max 16.380 at 10 %), which confirms that *Confucianism* is a strong instrument. Finally, the significant p-value of the Anderson-Rubin Wald test rejects the null that the instrument is weak and thus provides additional evidence that *Confucianism* has strong explanatory power for firms' eco-consciousness. These tests indicate that the instrument is valid.

In the second stage, we repeat our baseline analysis but replace the interaction variable of interest, *EC x Env Scheme*, with instrumented *EC x Env Scheme* from the first stage. Columns (2) and (3) report that the coefficient on instrumented *EC x Env Scheme* continues to be positive and significant at the 1 % and 5 % levels across both dependent variables. This confirms that our baseline results are robust.

[16] The values of Weak-instrument-robust inference (6.290 for F statistics and 6.330 for Chi^2) provide evidence that the instrument is correctly identified, strong, and valid.

Table 11
Baseline results after incorporating other fixed effects.

	Difference-in-Differences						PSM + DiD			
	Green Rev Dummy			*Green Rev Ratio*			*Green Rev Dummy*		*Green Rev Ratio*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EC x Env Scheme	0.018**	0.018***	0.018**	0.011***	0.011***	0.011***	0.010*	0.013**	0.009***	0.010***
	(2.547)	(2.613)	(2.559)	(3.242)	(3.274)	(3.207)	(1.820)	(2.258)	(2.701)	(2.884)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE *x* Region FE	No	No	Yes	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,962	19,960	19,960	19,962	19,960	19,960	12,098	12,098	12,098	12,098
Adjusted R^2	0.764	0.767	0.756	0.831	0.833	0.824	0.794	0.797	0.830	0.817

Note: This table presents the results based on different combinations of fixed effects. In addition to the industry, year, and region fixed effects included in the baseline analysis, firm fixed effects, and the interaction term of industry and region fixed effects are included. Columns (1) to (6) report the results based on a difference-in-differences (DiD) specification. Columns (7) to (10) report the results based on propensity score matching (PSM) in combination with DiD. Details on variable definitions are in the Appendix. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Robust t-statistics clustered by the firm are reported in parentheses.

5.6. Heckman selection model

Firms with a higher level of green revenues may more likely possess a higher level of eco-consciousness following the implementation of the Scheme. Eco-consciousness may not be a random choice for firms under the presence of the Scheme, which can cause self-selection bias. We employ a Heckman selection model to mitigate this concern. As Heckman's model requires an exogenous variable, *Confucianism* meets this requirement. In the first-stage selection equation, we utilize a Probit model to estimate the likelihood of a firm possessing a higher level of eco-consciousness. We regress *Confucianism x Env Scheme* on *EC x Env Scheme* to account for the presence of the Scheme. Column (4) of Table 10 reports that *Confucianism x Env Scheme* is positively significant at the 5 % level, suggesting that the exogenous variable is valid. We incorporate the inverse Mills ratio (IMR) generated from the first stage into the second-stage outcome equation to control for self-selection bias and obtain adjusted estimated coefficients. Columns (5) and (6) report that the coefficients on *EC x Env Scheme* are positive and significant at the 1 % level, which suggests that our findings are unlikely to be driven by potential self-selection bias.

5.7. Alternative fixed effects

In our baseline analysis, we incorporate industry, year, and region-fixed effects to account for the influence of industry, time, and region-specific unobservable heterogeneity on our findings. We alternatively incorporate firm fixed effects and the interaction term of industry and region fixed effects to rerun our analysis. This allows us to control unobserved time-invariant firm-specific characteristics and unobservable industry heterogeneity specific to different regions. Table 11 presents the results based on different combinations of fixed effects. As the coefficients of the *EC x Env Scheme* are positively significant, our baseline findings are reliable.

6. Heterogeneity analysis

We further examine whether highly eco-conscious firms' derivation of green revenues from the Scheme relative to their counterparts is affected by their level of green innovation, financial constraints, and competitive environment.

6.1. Heterogeneity of green innovation level

Firms with a higher level of green innovation are able to obtain competitive advantages in environmental offerings, which differentiates them from competitors in environmental markets (Chen et al., 2006). Further, these innovative firms possess enhanced adaptability to evolving stakeholders' demands arising from environmental regulatory changes (Chang, 2011) and thus are likely associated with higher green revenues. To test this heterogeneous effect, we partition our sample based on the median level of green innovation (*Green Patent*), measured using the log-transformed number of green patent applications eventually granted (Amore and Bennedsen, 2016). We rerun our baseline analysis and the results in Panel A of Table 12 indicate that the effect of centralized

Table 12
Heterogeneity analysis.

Panel A: Green Innovation				
	Green Rev Dummy		*Green Rev Ratio*	
	(1) Higher *Green Patent*	(2) Lower *Green Patent*	(3) Higher *Green Patent*	(4) Lower *Green Patent*
EC x Env Scheme	0.111***	0.025**	0.042***	0.013**
	(6.343)	(2.409)	(4.568)	(2.421)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
β_1 - β_2 (p-value)	0.000***		0.000***	
Observations	8826	11,309	8826	11,309
Adjusted R^2	0.181	0.133	0.175	0.131
Panel B: Financial Constraint				
	Green Rev Dummy		*Green Rev Ratio*	
	(1) Higher *SA Index*	(2) Lower *SA Index*	(3) Higher *SA Index*	(4) Lower *SA Index*
EC x Env Scheme	0.071***	0.086***	0.024***	0.042***
	(4.957)	(4.806)	(3.905)	(3.958)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
β_1 - β_2 (p-value)	0.240		0.001***	
Observations	10,068	10,067	10,068	10,067
Adjusted R^2	0.205	0.160	0.201	0.154
Panel C: Competitive Environment				
	Green Rev Dummy		*Green Rev Ratio*	
	(1) Higher *Lerner*	(2) Lower *Lerner*	(3) Higher *Lerner*	(4) Lower *Lerner*
EC x Env Scheme	0.036**	0.100***	0.020***	0.038***
	(2.446)	(6.676)	(2.587)	(4.984)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
β_1 - β_2 (p-value)	0.000***		0.001***	
Observations	6689	13,446	6689	13,446
Adjusted R^2	0.261	0.142	0.272	0.128

Note: This table presents the results of heterogeneity analysis. We measure green innovation using the log-transformed number of green patent applications eventually granted (*Green Patent*). We measure financial constraints using Hadlock and Pierce (2010)'s SA index (*SA Index*). We measure the level of competition a firm faces using Lerner (1934)'s index of monopoly power, with a lower index indicating a higher level of competition (*Lerner*). The statistical significance of the difference in coefficients is reported in each panel. The statistical significance of the difference in coefficients is obtained using Fisher's permutation tests with 1000 rounds of bootstrapping. This test relies on random permutations and requires that the order of observations is exchangeable. It provides estimates that are robust to outliers because they are non-parametric and do not rely on specific assumptions about the underlying data distribution (Zhao and Ding, 2021). Details on variable definitions are in the Appendix. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Robust t-statistics clustered by the firm are reported in parentheses.

environmental monitoring on highly eco-conscious firms' green revenues is more significant for those with a higher level of green innovation. This difference is significant at the 1 % level. This supports the notion that green innovation supports firms' competitiveness in green industries, thus enabling them to derive greater green revenues.[17]

[17] For example, Sungrow is a prominent provider of renewable energy solutions including solar inverters, energy storage systems, and floating solar power plants (Sungrow, 2023). In 2011, the firm engaged in three types of business activities. By 2022, it derives green revenues from six types of green business activities. This is attributable to Sungrow's continuous investment in green innovation as part of its strategic shift to providing energy storage solutions (Sungrow, 2021).

6.2. Heterogeneity of financial constraints

The centralization of environmental monitoring represents a shift in the regulatory landscape, and firms seeking to redirect investments to green business activities require adequate financial resources to do so effectively (Dang et al., 2022). Firms face higher financing costs during periods of policy uncertainty (Pástor and Veronesi, 2013); thus, financially constrained firms tend to be risk-averse when faced with regulatory changes (Wen et al., 2021). We expect that less financially constrained firms can derive a higher level of green revenues under policy changes. We partition our sample based on the sample median level of financial constraints (*SA Index*), which is measured following Hadlock and Pierce (2010)'s SA index of financial constraints of a firm based on its size and age.[18] For ease of interpretation, we take the absolute value of the SA index, wherein a higher index indicates a higher level of financial constraints. We rerun our analysis and report the results in Panel B of Table 12. While we do not observe results for *Green Rev Dummy*, the effect of centralized environmental monitoring on highly eco-conscious firms' extent (rather than the initiation) of green revenues is more significant when these firms are less financially constrained. This difference is significant at the 1 % level. This result suggests that financial resources play a vital role in supporting firms' extent of investment in green business activities and thus their derivation of green revenues.[19]

6.3. Heterogeneity of competitive environment

In highly competitive environments, firms seek to utilize green practices as a source of differentiation and meet consumer preferences to gain access to new markets (Becerra et al., 2020). For these firms, engagement in green business activities is incentivized by the notion that it provides a unique selling proposition for stakeholders beyond mere compliance with tightened environmental regulations (Ljubownikow and Ang, 2020). Thus, we expect firms in a competitive environment to derive greater green revenues as they seek to differentiate themselves following the Scheme.

To test this heterogeneous effect, we partition our sample based on Lerner (1934)'s index of monopoly power, a proxy for a firm's competitive environment (*Lerner*). The Lerner index is the difference between total price and marginal cost divided by total price. Given a firm's output level, it reflects the relative markup of the output price over marginal cost. *Lerner* has values between 0 and 1; the lower it is, the closer it is to perfect competition; the higher it is, the higher the firm's market power and, hence, closer to a monopoly. As such, we identify observations at the top tercile of *Lerner* as those operating in a less competitive environment.

We rerun our analysis and the results in Panel C of Table 12 show that the positive effect of centralized environmental monitoring on highly eco-conscious firms' green revenues is more pronounced for firms operating in more competitive environments (lower *Lerner*). This difference is significant at the 1 % level, which suggests that firms facing higher competition view environmental stewardship as an important source of competitive advantage under tightened environmental regulations.[20]

7. Outcome analyses

In this section, we examine whether the centralization of environmental monitoring leads to positive outcomes for eco-conscious firms.

7.1. CSR performance

As the Scheme enhances environmental governance and accountability of local governments, we expect that firms subject to tightened environmental monitoring to improve their CSR performance in meeting environmental standards. We investigate this effect by employing two measures of CSR performance: (1) the average disclosure frequency of CSR information from twelve categories[21] and (2) the average disclosure frequency of CSR information from eight categories.[22] We regress the CSR performance measures (*CSR 1* and

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[18] $SA = -0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age$.

[19] Future research can investigate the role of financial instruments and other government policies in addressing financial constraints for green revenue derivation. We thank an anonymous reviewer for highlighting this.

[20] For example, LONGi Green Energy Technology proactively leverage on the dynamic demands of the green industries. The firm maintains its position as a global leader in solar solutions by (1) continuously and heavily investing in research and development, (2) scaling up production capabilities to meet increasing global demand, (3) expanding its presence in international markets through cost efficiencies. These strategies has enhanced LONGi's brand value and reinforced its position in increasingly competitive green markets (Sina Finance, 2023).

[21] The twelve dimensions comprise of third-party organization verification, adherence to the sustainable development reporting guidelines, protection of shareholder rights; protection of creditor rights, safeguarding employee rights, ensuring supplier rights; preserving customer and consumer rights, commitment to environmental sustainability, engagement in public relations and social welfare initiatives, establishment and improvement measures for social responsibility systems, occupational safety content, and identification of company shortcomings.

[22] The eight dimensions comprise of environmental protection, shareholders protection, staff protection, supplier protection, customer protection, creditor protection, system construction, and work safety.

Table 13
Outcome analysis.

Panel A: CSR Performance				
	CSR 1		*CSR 2*	
	(1)	(2)	(3)	(4)
EC x Env Scheme	0.058***	0.034***	0.527***	0.307***
	(8.901)	(5.542)	(7.890)	(4.769)
Controls	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	Yes
Observations	20,111	20,107	20,111	20,107
Adjusted R^2	0.126	0.232	0.131	0.219

Panel B: Carbon Disclosure Quality			
	CD Quality		
	(1)	(2)	(3)
EC x Env Scheme	0.058***	0.031***	0.032***
	(5.282)	(3.154)	(3.408)
Controls	No	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	No	Yes
Observations	20,139	20,135	20,135
Adjusted R^2	0.063	0.152	0.159

Note: This table presents the results of the outcome analysis. We measure CSR performance using the average disclosure frequency of CSR information from twelve categories (*CSR 1*) and the average disclosure frequency of CSR information from eight categories (*CSR 2*). We measure carbon disclosure quality based on whether the firm discloses qualitative, quantitative, or no information regarding its carbon footprint (*CD Quality*). Control variables in our baseline analysis are included. Details on variable definitions are in the Appendix. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively. Robust t-statistics clustered by the firm are reported in parentheses.

CSR 2) individually on the *EC x Env Scheme*. Panel A of Table 13 reports that centralized environmental monitoring leads to highly eco-conscious firms' positive CSR performance outcomes. This suggests that the centralization of environmental monitoring has positive implications for the well-being of the environment and community.[23]

7.2. *Carbon disclosure quality*

Tightened environmental monitoring and the development of an integrated monitoring network can drive improvements in carbon disclosure quality by providing standardized environmental data, which assists firms in reporting their carbon footprint. The pressure exerted by governments in relation to corporate environmental accountability prompts enhanced information accuracy, transparency, and stakeholder engagement, which leads to more meaningful and relevant carbon disclosures (Liu and Cheng, 2023). We investigate the potential effect of centralized environmental monitoring on highly eco-conscious firms' carbon disclosure quality by regressing the carbon disclosure quality (*CD Quality*) measure on the *EC x Env Scheme* and include the set of control variables in our baseline analyses. *CD Quality* equals one if a firm discloses qualitative information about its carbon footprint, two if it discloses quantitative carbon information, and zero otherwise.[24] As reported in Panel B of Table 13, centralized environmental monitoring enhances highly eco-conscious firms' carbon disclosure quality, which suggests that a centralized monitoring network positively affects corporate carbon disclosure outcomes.[25]

8. Conclusions

Corporate eco-consciousness enables a firm to simultaneously achieve environmental and economic benefits under the centralization of environmental monitoring. We find that highly eco-conscious firms derive a greater extent of green revenues relative to their counterparts. As the central government relies on the effective transmission of local environmental information to oversee local

[23] The manufacturer of electric vehicles (EVs) and rechargeable batteries BYD Co. utilizes its knowledge of the two products to implement initiatives for battery recycling. In addition to reducing local pollution through the replacement of fuel-powered cars (BYD, 2022), BYD addresses local governments' environmental concerns regarding battery waste by transforming old EV batteries into power storage for renewable energy and factories (Ando and Kawakami, 2020).

[24] The data are obtained directly from CSMAR.

[25] Future research can investigate the barriers faced by firms in improving carbon disclosure quality, which will provide valuable insights for policymakers and practitioners under evolving carbon disclosure regulations. We thank an anonymous reviewer for highlighting this.

environmental accountability, the effect on green revenues is reliant on the level of local internet infrastructure development. Centralized environmental monitoring reduces corporate greenwashing to motivate firms' achievement of environmental objectives in the form of green revenues. We reveal that corporate eco-consciousness represents a dynamic capability that enables a firm to adjust to shifts in environmental regulations and capitalize on the resulting market opportunities.

The findings of this study have important practical implications for various stakeholders. First, for firms, elevating the level of eco-consciousness becomes vital to obtaining competitive advantages from increasingly stringent environmental regulations. Through continuous engagement with environmental regulations, technologies, and markets, firms can obtain a first-mover advantage to differentiate themselves and obtain simultaneous outcomes in environmental and economic performance. Further, by assisting firms to comply with emerging environmental regulations, eco-consciousness minimizes potential penalties and legal risks. This, in turn, allows firms to divert their resources to further generate green revenues.

Second, we highlight that it is important for investors and shareholders to consider a firm's level of eco-consciousness as part of their investment decision-making process. Specifically, highly eco-conscious firms possess an advantage in adapting to emerging environmental regulations and can take advantage of the resulting market opportunities.

Third, for regulators across the globe, an increase in the stringency of environmental regulations will incentivize firms to engage and invest in green business activities. Given that firms with a heightened level of eco-consciousness derive a greater extent of green revenues, these regulations directly reward environmentally conscious firms in alignment with their intended purpose. We highlight that the vibrancy of green industries and business activities should be areas of focus for regulators in their decision-making, as they embody environmental and economic benefits simultaneously.

Fourth, green finance providers can leverage the findings of this study to tailor financial products and services that incentivize and support firms' green business investments. The incorporation of metrics related to firms' eco-consciousness into the investment criteria can enhance the effectiveness of green finance initiatives and ensure that capital is allocated to projects that yield both environmental and economic outcomes.

Fifth, enhancements in environmental data quality under tightened environmental governance benefit consumers, supply chain partners, and governments in ascertaining the environmental accountability of firms. This allows consumers to make informed choices to support green businesses. Moreover, it increases the ability of environmental advocacy groups and auditors to hold firms accountable for their environmental impact, particularly given the emergence of environmental accounting and auditing. Overall, we highlight to stakeholders across the globe that an integrative view facilitates win-win scenarios amid conflicts between economic and environmental interests. Global firms need to sufficiently develop dynamic green capabilities to understand evolving environmental regulations and green business opportunities across different regions where they operate.

Future research can utilize qualitative research to investigate factors influencing firms' derivation of green revenues in dynamic business environments, including the role of green innovation and policy-based financial instruments. Interviews with industry experts will assist the transition towards integrated sustainability by uncovering strategies and processes different industries implement to compete in green markets. Future research can also delve into the underlying mechanisms and barriers influencing the impact of centralized environmental monitoring on carbon disclosure quality and other dimensions of CSR performance.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

June Cao reports financial support was provided by Curtin University. June Cao reports a relationship with Curtin University that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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All authors have contributed equally to this study and are listed alphabetically.

Appendix

Variable Definitions

Independent Variables	
EC	An indicator variable equal to one if firm *i*'s level of eco-consciousness in year *t* is within the top tercile, and zero otherwise.
Env Scheme	An indicator variable equal to one if the observation is between the years of 2015 and 2019, as the Scheme was implemented in 2015. This variable takes the value of zero for years 2011 to 2014.
Dependent Variables	
Green Rev Dummy	An indicator variable equal to one if firm *i* earns green revenue in year *t*, and zero otherwise.
Green Rev Ratio	The ratio of total green revenues to total revenues of firm *i* in year *t*.
Control Variables	
Size	The natural logarithm of one plus total assets value.
SOE	An indicator variable that equals one if an enterprise is a state-owned enterprise, and zero otherwise.
Green Patent	The natural logarithm of one plus the number of green patent applications eventually granted.
Age	The natural logarithm of one plus the number of years since the firm's listing.
Leverage	The ratio of total liabilities to total assets.
Working Capital	Net working capital scaled by total assets.
Cash Holding	Total cash and cash equivalents scaled by total assets.
Quick Ratio	Quick ratio is the ratio of quick assets to total current liabilities. Quick assets are the sum of cash and cash equivalents, marketable securities, and net accounts receivable.
BTM	The book-to-market ratio is defined as the book value of equity divided by market capitalization.
ROA	Return on assets, defined as the ratio of net profit to total assets.
Tobin's Q	Tobin's Q ratio is defined as the ratio of the firm's market value to the replacement value of its capital.
Tangible Assets	Total tangible assets scaled by total assets.
HHI	Herfindahl-Hirschman index (HHI) is a measure of market concentration and competitiveness. A low HHI indicates high industry competition, whereas a high HHI indicates high industry concentration.
SA Index	Hadlock and Pierce (2010)'s SA index measures the financial constraints of a firm based on its size and age. The index is calculated as the absolute value of $SA = -0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age$. The absolute value of the SA index is used, where a higher index indicates a higher level of financial constraints.
Mechanism Variables	
Internet Dev	The natural logarithm of one plus the number of internet broadband access ports in the region.
Internet Dev2	The quality and reliability of local internet infrastructure and access are evaluated across six dimensions: high-speed Internet connectivity, internet availability for residents, capacity for information technology-related development, market importance and penetration of telecommunication services, mobile technology adoption, and internet usage. A higher value indicates better quality and reliability.
Greenwash	The difference between ESG disclosure and ESG performance score is calculated using Z-score normalization.
Greenwash2	The difference between ESG disclosure and ESG performance score is calculated using Min-Max normalization.
Additional Variables	
EC Med	The indicator variable equals one if the firm's eco-consciousness is above the median, and zero otherwise.
Confucianism	The number of Confucius temples and academies within a 300-kilometre radius of a firm's registered location.
Lerner	The monopoly power index of Lerner (1934) is based on the relative markup of the output price over marginal cost. A higher value indicates a higher monopoly power and a less competitive environment.
CSR 1	Average disclosure frequency of CSR information from twelve categories.
CSR 2	Average disclosure frequency of CSR information from eight categories.
CD Quality	An indicator variable equals two if the firm discloses quantitative carbon information and equals one if the firm discloses qualitative carbon information. If the firm reports neither, this indicator equals zero.

Data availability

Data will be made available on request.

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