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The impact of environmental regulations on innovation in heavy polluting enterprises: a quasi-natural experiment based on environmental tax reform

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This paper uses data from the CSMAR database and listed companies' annual reports to examine the impact of China's 2018 environmental tax reform on the innovation capacity of heavily polluting enterprises. Treating the policy as a quasi-natural experiment, the study finds that the reform significantly enhances innovation in such firms, with results remaining robust across various tests. Heterogeneity analysis reveals that the policy's positive effect is stronger in state-owned, large-scale, and high-tech heavy polluters compared to their counterparts. Furthermore, the mechanism analysis reveals that the reform primarily promotes innovation by increasing R&D investment. Further analysis shows that the environmental tax reform also enhances firms' innovation quality and efficiency, and exerts a significant impact on both green and non-green innovation. These findings offer policy implications for leveraging environmental regulations to foster green innovation in polluting industries.

KEYWORDS

DID, environmental regulation, green innovation, heavily polluting firms, R&D investment

1 Introduction

Environmental regulation plays a crucial role in shaping long-term economic growth. Well-designed policies can improve the allocation of environmental resources while supporting the sustainability of economic activity within ecological limits (Arrow et al., 1995). Achieving environmental goals does not necessarily require sacrificing economic progress or relying on ongoing government intervention. However, in the absence of regulation, market forces alone are unlikely to prevent severe environmental damage (Acemoglu et al., 2012). As such, the relationship between environmental policy and economic development remains a central concern in economic research, especially in light of current global challenges.

This issue is particularly urgent for China and other developing countries, where environmental degradation poses significant risks to public health and economic stability. Air, soil, and water pollution continue to escalate, underscoring the need for prompt and effective policy responses. These countries must not only confront environmental harm but also navigate the delicate balance between fostering growth and promoting sustainability (Unstats, 2024). In China's case, the tension between environmental protection and

economic expansion has become especially evident in recent years, as many cities face persistent air pollution and declining environmental quality.

Improving environmental quality has become a central policy priority for the Chinese government. In recent years, authorities have introduced a range of environmental governance measures, resulting in some notable progress. However, the effect of such regulations on corporate innovation remains a topic of active debate. While environmental policies support energy conservation, emissions reduction, and broader ecological goals, they also influence how economic resources are allocated within firms.

Critics argue that environmental regulations can constrain innovation by raising the costs of compliance and pollution control (Clarkson et al., 2004). Under strict regulatory pressure, firms may scale back production or halt operations altogether (Palmer et al., 1995; Petroni et al., 2019), thereby reducing funds available for research and development. In contrast, supporters of the Porter Hypothesis suggest that regulation can encourage innovation by applying external pressure that pushes firms to overcome internal resistance to change. In this view, regulation acts as a catalyst, strengthening governance structures and motivating firms to invest in new technologies and processes (Ambec and Barla, 2002).

Despite extensive research, no clear consensus has emerged on the economic impact of environmental regulation. This ongoing debate underscores the need to consider both the costs and potential innovation benefits of environmental policy, as their effects are often shaped by industry characteristics, firm size, and regulatory design. Therefore, understanding how environmental regulation shapes enterprise innovation is critical to evaluating the broader relationship between environmental protection and economic development.

Recent studies have examined the impact of China's environmental tax reform on innovation. For example, Zhao et al. (2024), using firm-level data from the manufacturing sector, show that the environmental tax significantly increases the quantity of innovation (Zhao et al., 2024), lending support to the Porter Hypothesis in the Chinese context. Building on this literature, the present study explicitly focuses on high-polluting firms and further investigates how the environmental tax reform reshapes firms' innovation strategies under intensified regulatory pressure. The paper makes several contributions. First, it provides firm-level empirical evidence to inform the debate on whether environmental regulation and business competitiveness are necessarily at odds or can instead be complementary (Rugman et al., 1998). Second, it offers theoretical and practical guidance for policymakers in developing countries on designing effective regulatory frameworks. It also sheds light on how firms can respond strategically to environmental policies in ways that support both innovation and sustainable growth.

2 Literature review

The literature relevant to this study can be divided into two main areas. The first explores the nature and development of environmental regulation, including its definition, classification, and the strategic considerations behind its use (Cai and Guo, 2023; Chen and Duan, 2025; Li Q. et al., 2025; Li X. et al., 2025; Liu X. et al., 2024). The second focuses on how environmental regulation influences corporate innovation, with a particular emphasis on green innovation within enterprises (Liu Z. et al., 2024; Qi et al., 2023; Tan et al., 2025; Tang et al., 2023).

In the first area, scholars generally agree on the substantial negative externalities caused by environmental degradation. However, the understanding of environmental regulation has expanded over time. Initially, it was limited to government-imposed measures—such as bans, standards, and licenses—commonly referred to as command-and-control tools. More recently, the scope has broadened to include market-based instruments like taxes and subsidies, as well as approaches driven by public engagement, such as environmental disclosure and reporting (Testa et al., 2011).

Reflecting this evolution, environmental regulatory tools are commonly grouped into three categories: (1) command-and-control mechanisms based on legal and administrative directives; (2) market-based tools that rely on financial incentives and disincentives; and (3) informal instruments shaped by environmental awareness, public perception, and social norms. Other classification schemes also exist, depending on the research focus (Böcher, 2012). Despite their differences, all types of environmental regulation serve the same essential purpose: to internalize the environmental costs of industrial activity. By doing so, they alter the strategic incentives facing firms and encourage more sustainable production decisions aligned with the public interest.

The second strand of literature focuses on the relationship between environmental regulation and innovation. Porter and van der Linde introduced the influential "Porter Hypothesis," which argues that well-designed environmental regulations can improve firm competitiveness by encouraging innovation that offsets compliance costs (Porter and Linde, 1995). This perspective highlights the potential for regulation to drive technological advancement and enhance firm performance.

Subsequent research has explored whether environmental regulation consistently promotes innovation. However, empirical findings across different national contexts remain inconclusive. Some studies support the Porter Hypothesis. For example, Lee found that environmental regulations stimulated R&D in the U.S. automobile industry (Lee et al., 2011). Lanoie reported similar results in the European Union, where such policies boosted innovation and reduced production costs. Likewise (Lanoie et al., 2008), Johnstone analyzing data from 25 countries, showed that environmental regulation positively influenced innovation in the energy sector (Johnstone et al., 2010).

In contrast, other studies cast doubt on the universal applicability of the Porter effect. Ramanathan observed that, in U.S. industrial firms, regulatory compliance discouraged innovation by increasing costs (Ramanathan et al., 2010). Similarly, Kneller and Manderson found that in the United Kingdom manufacturing sector, environmental regulations raised capital expenditures related to compliance, which diverted resources away from innovation (Kneller and Manderson, 2012).

Additionally, a growing body of literature specifically examines the relationship between environmental regulation and corporate

green innovation outcomes. Guo et al. (2023) utilize data from China's high-polluting enterprises to demonstrate that stricter environmental regulation significantly promotes green innovation by increasing compliance costs and incentivizing clean technology adoption. From a broader sustainability perspective (Guo et al., 2023), He et al. (2023) confirm that the Environmental Protection Tax Law enhances corporate ESG performance, with green innovation serving as a key transmission channel. Recent studies further deepen this topic (He et al., 2023). Chen and Han (2025) focus on green innovators, confirming that environmental tax reforms reshape corporate green innovation structures by redirecting innovation resources toward environmental technologies (Chen and Han, 2025). Zhou and Su (2025) similarly find that environmental taxes significantly enhance firms' green technological innovation capabilities, with management efficiency and government subsidies playing crucial moderating roles (Zhou and Su, 2025).

While these studies convincingly demonstrate that environmental regulation can stimulate green technological change, they primarily concentrate on green patents or green innovation metrics. In contrast, little attention has been paid to how environmental tax reforms influence firms' overall innovation activities—especially in highly polluting industries where firms may respond through dual green and non-green innovation strategies. By examining the broader innovation responses induced by the environmental tax reform and highlighting heterogeneous effects across different types of firms, this study offers new insights to the existing literature.

To address these issues, this paper exploits the implementation of China's Environmental Protection Tax Law as a quasi-natural experiment to examine the impact of environmental regulation on corporate green innovation. Enforced on January 1, 2018, the law replaced the existing pollutant discharge fee system and aims to promote cleaner and more sustainable production practices through tax incentives, thereby reducing industrial emissions. Treating the reform as an exogenous policy shock, the study employs a Difference-in-Differences (DID) approach using micro-level patent data from Chinese firms. Specifically, it compares green innovation performance between high-polluting firms before and after the reform and low-polluting firms over the same period. Since the timing and industry coverage of the reform were determined by central policy rather than firm behavior, its effect on innovation decisions can be regarded as largely exogenous. To further ensure identification validity, the analysis incorporates firm- and year-level fixed effects, conducts parallel trends tests, and implements a series of robustness checks to account for potential confounding factors and contemporaneous shocks. This approach provides evidence on the impact of environmental tax reforms on corporate innovation activities.

3 Data and methods

3.1 Sample and data

This study utilizes panel data from Chinese A-share listed companies for the period 2013–2023. The sample is carefully filtered through several steps to ensure data quality and consistency. First, firms labeled as ST, *ST, or PT are excluded due to potential financial distress or abnormal trading status. Second, companies in the financial sector are removed because of their distinct regulatory environment. Third, firms that shift between treatment and control groups during the sample period are excluded to maintain group stability. Fourth, treatment group firms with fewer than one observation prior to policy implementation are omitted to ensure adequate pre-treatment data. Fifth, firms with only a single observation are excluded. Finally, all continuous variables are winsorized at the 1st and 99th percentiles to reduce the influence of outliers. The data are drawn from the CSMAR database and supplemented with information from the annual reports of listed companies.

3.2 Variable definition

3.2.1 Explained variables

The explanatory variable in this study is enterprise innovation. Following the approach of Kau Tong and related research, innovation is measured by the number of patent applications filed by a firm (Tong et al., 2014). Specifically, the natural logarithm of one plus the total number of patent applications is used to account for skewness and to ensure all values are defined. This transformed variable serves as the primary indicator of a firm's innovation activity.

3.2.2 Explanatory variables

This study aims to assess the effect of China's environmental tax reform on innovation within heavily polluting industries. To capture this relationship, a Difference-in-Differences (DID) model is employed to construct the key explanatory variable. Firms are classified based on the industry codes used for Chinese listed companies. Following the definition by Zhou et al. (2025), industries identified as heavily polluting include B06, B08, B09, C17, C19, C22, C25, C26, C28, C29, C30, C31, C32, and D44. Companies operating in these sectors are assigned to the treatment group (treat = 1), while all others are placed in the control group (treat = 0). The policy reform is considered effective beginning in 2018. Observations from 2018 onward are coded as post = 1, while those before 2018 are coded as post = 0. The interaction term, DID = treat × post, is used to estimate the differential impact of the reform on innovation outcomes in the treatment group compared to the control group over time.

3.2.3 Mediating variables

To capture the mediating effect, this study employs R&D investment intensity, defined as the ratio of a firm's annual research and development expenditure to its operating revenue from the previous year.

3.2.4 Control variables

To control for firm-level characteristics that may influence innovation, this study includes several control variables: firm size, gearing ratio, accounts receivable ratio, inventory ratio, cash flow, equity concentration, equity balance, book-to-market ratio, executive compensation, and executive shareholding. These variables are defined and measured as follows:

TABLE 1 Variable definitions.

Variable type	Variable name	Variable symbol	Variable definition
Explanatory variable	Enterprise innovation	Patent	Total number of patent applications filed by the enterprise in the year +1 followed by logarithmic value
Explanatory variable	Policy effect	DID	×treat post. Where treat is the treatment group division, treat = 1 if the firm is a heavy polluter, 0 otherwise. Post is the policy implementation time variable, 2018 and after = 1,2017 and before = 0
Intermediary variable	R&D investment intensity	LRDinc	Ratio of current year's R&D investment to previous year's revenue
Control variable	Firm size	Size	Total assets of the enterprise +1 rounded to the nearest logarithm
	Gearing ratio	Lev	Total liabilities/total assets
	Accounts receivable ratio	REC	Net accounts receivable/total assets
	Inventory ratio	INV	Net inventory/total assets
	Cash flow	Cashflow	Net cash flow from operations/total assets
	Equity concentration	Top10	Shareholding ratio of top ten shareholders
	Equity balance	Balance	Shareholding of 2nd to 10th largest shareholder/Shareholding of 1st largest shareholder
	Book-to-market ratio	BM	Book value/total market value
	Executive compensation	TMTPay	Logarithmic total compensation of top three executives +1
	Executive shareholding	Mshare	Number of shares held by executives/total shares

Firm Size is a key determinant of innovation capacity, as larger firms typically possess greater financial, technological, and human resources. They are also better equipped to manage innovation-related risks and exercise greater market influence.

Gearing Ratio (Lev) measures a firm's financial leverage. Firms with high debt levels may face tighter financial constraints, limiting their ability to invest in innovation and secure external R&D financing.

Accounts Receivable Ratio (REC) reflects a firm's sales practices and market strategy. While a high ratio may suggest competitiveness, it can also increase credit risk and reduce liquidity available for innovation activities.

Inventory Ratio (INV) indicates operational efficiency and inventory management. Excess inventory may point to inefficiencies, tying up capital that could otherwise support R&D investment.

Cash Flow serves as a direct indicator of financial health. Strong cash flow provides the necessary resources to support sustained innovation efforts.

Equity Concentration (Top 10) represents ownership concentration among the largest shareholders. High concentration may lead to a short-term focus, potentially discouraging long-term innovation investment.

Equity Balance (Balance) captures the degree of equilibrium in the internal ownership structure. A more balanced distribution of shares may improve corporate governance and foster a longer-term orientation toward innovation.

Book-to-Market Ratio (BM) compares a firm's book value to its market value, serving as a proxy for market expectations regarding future growth and innovation potential.

Executive Compensation (TMTPay) reflects incentive structures that can influence managerial decisions, including those related to R&D investment.

Executive Shareholding (Mshare) indicates the extent to which executives are financially invested in the firm. Greater ownership alignment may encourage a stronger commitment to innovation-driven strategies.

All variables are summarized and defined in Table 1. These controls help isolate the effect of environmental tax reform on firm-level innovation outcomes.

3.3 Model construction

To evaluate the proposed hypotheses, we construct quantitative models using the variables and data outlined earlier. As a first step, we assess whether environmental regulation influences firm innovation by applying a difference-in-differences (DID) approach. The empirical model is specified as follows:

Model 1: The Effect of Environmental Tax Reform on Firm Innovation

$$\begin{aligned} Patent_{i,t} = {} & \alpha_0 + \alpha_1 DID_{i,t} + \alpha_2 Size_{i,t} + \alpha_3 Lev_{i,t} + \alpha_4 REC_{i,t} \\ & + \alpha_5 INV_{i,t} + \alpha_6 Cashflow_{i,t} + \alpha_7 Top10_{i,t} + \alpha_8 Balance_{i,t} \\ & + \alpha_9 BM_{i,t} + \alpha_{10} TMTPay_{i,t} + \alpha_{11} Mshare_{i,t} + \lambda_i + year_t \\ & + \varepsilon_{i,t} \end{aligned} \tag{1}$$

Here, the dependent variable Patent represents firm innovation level, with i and t denoting firm and year, respectively, α_0 is the intercept, $\alpha_1 - \alpha_{11}$ is the coefficients of each variable, λ_i is the individual fixed effects, $year_t$ is the year fixed effects, and $\varepsilon_{i,t}$ is the randomized disturbance term.

TABLE 2 Descriptive statistics.

VarName	Obs	Mean	Median	SD	Min	Max
Patent	31257	2.820	2.996	1.735	0.000	6.967
LRDinc	31257	0.053	0.039	0.062	0.000	0.345
Treat	31257	0.195	0.000	0.396	0.000	1.000
Post	31257	0.646	1.000	0.478	0.000	1.000
DID	31257	0.117	0.000	0.322	0.000	1.000
Size	31257	22.304	22.103	1.299	19.941	26.347
Lev	31257	0.424	0.414	0.203	0.058	0.904
REC	31257	0.128	0.107	0.104	0.000	0.466
INV	31257	0.138	0.109	0.125	0.000	0.686
Cashflow	31257	0.047	0.046	0.068	−0.155	0.241
Top10	31257	0.575	0.581	0.151	0.229	0.901
Balance	31257	0.990	0.771	0.807	0.052	4.018
BM	31257	0.617	0.608	0.254	0.118	1.202
TMTPay	31257	14.605	14.574	0.693	12.899	16.558
Mshare	31257	0.077	0.003	0.139	0.000	0.603

TABLE 3 Variance inflation factor test.

Variable	VIF	1/VIF
DID	2.800	0.357
Treat	2.720	0.368
Size	2.580	0.387
BM	1.800	0.556
Lev	1.660	0.602
TMTPay	1.580	0.631
Post	1.500	0.667
LRDinc	1.360	0.736
Mshare	1.220	0.821
REC	1.200	0.834
Cashflow	1.200	0.835
INV	1.160	0.860
Top10	1.120	0.892
Balance	1.070	0.938
Mean VIF	1.640	-

Firms often rely on research and development (R&D) investment to drive innovation. This raises a key question: Does environmental regulation promote innovation in heavily polluting firms by encouraging increased R&D spending? To answer this, it is necessary to identify and test the specific channels through which such regulations influence innovation outcomes. This study addresses the question by constructing a mediation model to examine the potential role of R&D investment in this process.

Model 2: The Mediating Role of R&D Investment in the Effect of Environmental Tax Reform on Firm Innovation

$$\begin{aligned} LRDinc_{i,t} = {} & \alpha_0 + \alpha_1 DID_{i,t} + \alpha_2 Size_{i,t} + \alpha_3 Lev_{i,t} + \alpha_4 REC_{i,t} \\ & + \alpha_5 INV_{i,t} + \alpha_6 Cashflow_{i,t} + \alpha_7 Top10_{i,t} \\ & + \alpha_8 Balance_{i,t} + \alpha_9 BM_{i,t} + \alpha_{10} TMTPay_{i,t} \\ & + \alpha_{11} Mshare_{i,t} + \lambda_i + year_t + \varepsilon_{i,t} \end{aligned} \quad (2)$$

In Equation 2, the dependent variable LRDinc represents firm's R&D investment, the meaning of each symbol is the same as Equation 1.

$$\begin{aligned} Patent_{i,t} = {} & \alpha_0 + \alpha_1 DID_{i,t} + \alpha_2 LRDinc_{i,t} + \alpha_3 Size_{i,t} + \alpha_4 Lev_{i,t} \\ & + \alpha_5 REC_{i,t} + \alpha_6 INV_{i,t} + \alpha_7 Cashflow_{i,t} + \alpha_8 Top10_{i,t} \\ & + \alpha_9 Balance_{i,t} + \alpha_{10} BM_{i,t} + \alpha_{11} TMTPay_{i,t} \\ & + \alpha_{12} Mshare_{i,t} + \lambda_i + year_t + \varepsilon_{i,t} \end{aligned} \quad (3)$$

In Equation 3, $\alpha_1 - \alpha_{12}$ is the coefficient of each variable, and the rest of the symbols have the same meaning as in Equation 1.

4 Empirical results

4.1 Descriptive statistics

Table 2 presents the descriptive statistics for the main variables. The mean value of the enterprise innovation variable (Patent) is 2.820, with a median of 2.996 and a standard deviation of 1.735. The slightly lower mean relative to the median suggests a concentration of firms with lower innovation levels, alongside a subset of firms with notably high patent activity. The values range from 0 to 6.967, indicating that while some firms submitted no patent applications during the year, others recorded substantial innovation output.

The mean R&D investment intensity (LRDinc) is 0.053, with a median of 0.039. The distribution reflects relatively modest R&D spending among most firms, though a few exhibit significantly higher investment levels. The variable ranges from 0 to 0.345, indicating that while some firms allocated no resources to R&D, others invested up to 34.5% of their prior year's operating revenue.

The treatment group indicator (Treat) has a mean value of 0.195, showing that 19.5% of the sample firms are classified as heavily polluting. The average value of the DID interaction term is 0.117, suggesting that 11.7% of the observations correspond to treated firms in the post-policy period.

4.2 VIF test

To ensure the validity of the linear regression model, it is important to confirm that multicollinearity among independent variables is not severe. High multicollinearity can distort

TABLE 4 Benchmarking regression results.

Variable	(1)	(2)
	Patent	Patent
DID	0.252***	0.249***
	(0.029)	(0.028)
Size		0.519***
		(0.019)
Lev		−0.389***
		(0.064)
REC		0.844***
		(0.132)
INV		−0.0729
		(0.117)
Cashflow		−0.165
		(0.103)
Top10		0.364***
		(0.094)
Balance		−0.000810
		(0.017)
BM		−0.129***
		(0.045)
TMTPay		−0.0237
		(0.018)
Mshare		0.250***
		(0.091)
_cons	2.790***	−8.519***
	(0.006)	(0.444)
Firm	Yes	Yes
Year	Yes	Yes
N	31245	31245
F	76.524***	82.987***
r2	0.790	0.800

Robust Standard errors in parentheses $^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$.

coefficient estimates and weaken the reliability of the results. Therefore, before proceeding with the regression analysis, a multicollinearity test is conducted to evaluate the degree of correlation among explanatory variables. Table 3 presents the results, the average variance inflation factor (VIF) is 1.64, with all individual VIF values below the commonly accepted threshold of 5. This suggests that multicollinearity among the explanatory variables is not a concern and does not compromise the reliability of the regression estimates.

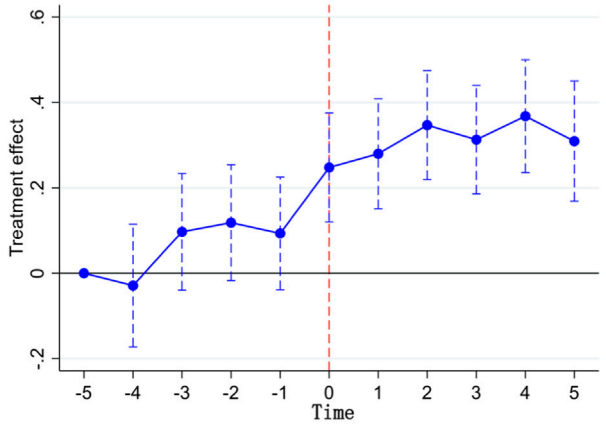

FIGURE 1
Parallel trend test results.

4.3 Benchmarking regression

The benchmark regression results, based on the model specified in this study, are summarized in Table 4. Column (1) presents estimates without control variables, revealing a positive and statistically significant coefficient on the DID term, indicating an initial link between the environmental tax reform and increased firm innovation. After including a comprehensive set of control variables in Column (2), the DID coefficient remains positive and significant at the 1% level, with a magnitude of 0.249. This finding suggests that, controlling for firm-specific factors, the environmental tax reform correlates with a 24.9% increase in innovation activity among heavily polluting firms.

4.4 Parallel trend test

The validity of the Difference-in-Differences (DID) approach rests on the assumption that, in the absence of the policy intervention, the treatment and control groups would have followed similar trends. To assess this assumption, a parallel trends test is performed by comparing the pre-policy evolution of the outcome variable across the two groups. This is implemented using a dynamic DID model, specified as Equation 4:

$$Patent_{it} = \alpha_0 + \sum_{s=-4}^{-1} \beta_s^{pre} [treat_i \times I(t - T_D = s)] + \sum_{s=0}^{5} \beta_s^{las} [treat_i \times I(t - T_D = s)] + \gamma X_{i,t} + \lambda_i + year_t + \varepsilon_{i,t} \quad (4)$$

where β_s^{pre} and β_s^{las} denote the regression coefficients of the dummy variables in each period before and after the policy implementation respectively, $treat_i$ is the identification variable of whether the sample firms deal with the group, which is quantified as 1 if the sample firms are affected by the policy in the data period, and 0 otherwise; $I(\cdot)$ is the schematic function, $t - T_D = s$ denotes the

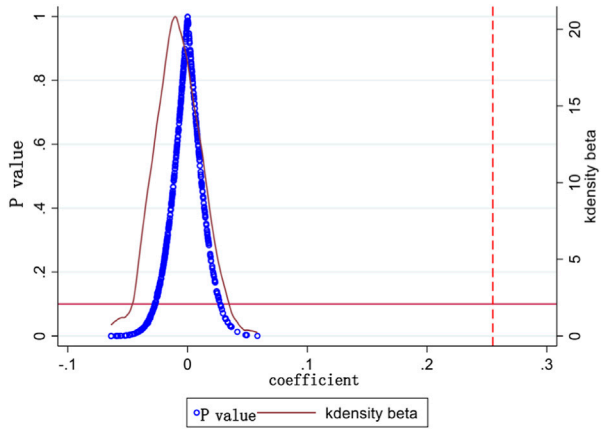

FIGURE 2
Placebo test results.

period before and after the policy implementation, s∈ [-5,5], and the rest of the symbols have the same meaning as that of the baseline regression model. Taking the first period of the data cycle as the base period, the test results are shown in Figure 1.

Figure 1 reports the results of the parallel trends test. During the pre-policy period (years −4 to −1), the confidence intervals of the estimated coefficients include zero and are statistically insignificant, indicating no meaningful difference in innovation levels between the treatment and control groups before the policy was enacted. This confirms that the parallel trends assumption holds.

In contrast, the estimated coefficients for the policy implementation year and the following 5 years are positive and statistically significant, as their confidence intervals exclude zero. This suggests that the environmental tax reform led to a notable increase in innovation among firms in heavily polluting industries relative to those in less polluting sectors. These findings support the existence of a dynamic treatment effect, demonstrating that the policy had a sustained positive impact on innovation performance in the targeted firms.

4.5 Parallel trend test

To verify that the observed effects are driven by the environmental tax reform rather than external factors, this study conducts a placebo test focused on innovation outcomes among heavily polluting firms. Following the methodology of Ferrara, the analysis employs 500 iterations of random sampling to construct a pseudo-treatment variable (Ferrara et al., 2012). The resulting distribution of estimated coefficients, p-values, and kernel density curves from these placebo regressions is illustrated in Figure 2.

Figure 2 presents the results of the placebo test. The distribution of regression coefficients from 500 random samples falls within the range of approximately [−0.1, 0.1], which is notably distant from the baseline estimate of 0.252. Additionally, most of the placebo coefficients are statistically insignificant, with p-values exceeding 0.1. The results follow a normal distribution centered around zero, suggesting no systematic effect in the absence of actual policy intervention. These findings confirm the robustness of the main results and support the conclusion that the observed increase in innovation among heavily polluting firms is attributable to the environmental tax reform, rather than to random external shocks.

4.6 PSM-DID

In this study, heavily polluting firms constitute 19.5% of the sample, while non-heavy polluting firms account for 80.5%. The relatively small size of the treatment group raises concerns about potential sample selection bias, which may lead to endogeneity and bias the regression results. To mitigate this issue, propensity score matching (PSM) is applied before conducting regression analysis.

Three matching approaches are utilized: mixed matching on the full sample, year-by-year matching to control for temporal variations, and individual matching using pre-policy data (2013–2017) transformed into a wide panel format. The individual matching method improves upon the other approaches by addressing discontinuities in the control group sample and enhancing comparability between treated and control firms. This, in turn, increases the reliability of the difference-in-differences estimates. The results from these matched samples are presented in Table 5.

Due to space limitations, the results of the balance tests are reported in the Appendix Table A1. After matching, no statistically significant differences are observed in the covariates between the treatment and control groups, indicating that the balance condition is largely satisfied. This suggests that propensity score matching effectively improves the comparability of the original sample by approximating a randomized assignment, thereby enhancing the credibility and reliability of the estimated results.

The PSM-DID regression results consistently show a significant positive impact of the policy on patenting across all three matching approaches. This confirms that, even after correcting for sample selection bias, the policy's effect on firm innovation remains robust. These findings reinforce the credibility of the study's core conclusions.

4.7 Robustness tests

To ensure the robustness of the results, this study incorporates province-by-year and city-by-year fixed effects, thereby accounting for region-specific policy environments and time-varying local shocks that may affect innovation among heavily polluting firms across the broad sample of A-share listed companies. In addition, to further address concerns regarding industry-level heterogeneous trends and other contemporaneous policy shocks, we include industry-specific linear time trends in the robustness analysis, which helps absorb unobserved industry-wide dynamics such as cyclical fluctuations, structural adjustments, or sector-specific reforms around the policy implementation period.

Furthermore, recognizing the significant disruption caused by the COVID-19 pandemic—particularly widespread production shutdowns in 2020—the analysis excludes observations from that year to avoid confounding effects. Additionally, patents are categorized into invention patents, utility model patents, and design patents. Compared to the latter two, invention patents

TABLE 5 PSM-DID regression results.

Variable	(1) Mix-and-match	(2) Matching year by year	(3) Individual matching
	Patent	Patent	Patent
DID	0.126***	0.163***	0.254***
	(0.040)	(0.040)	(0.042)
Size	0.483***	0.500***	0.451***
	(0.034)	(0.034)	(0.041)
Lev	−0.334***	−0.165	−0.336**
	(0.111)	(0.113)	(0.135)
REC	1.248***	1.262***	1.161***
	(0.292)	(0.309)	(0.335)
INV	0.0214	0.0548	0.364
	(0.241)	(0.245)	(0.313)
Cashflow	−0.331*	−0.349*	−0.289
	(0.185)	(0.190)	(0.228)
Top10	0.667***	0.771***	0.655***
	(0.161)	(0.160)	(0.191)
Balance	−0.0233	−0.0457	0.00247
	(0.030)	(0.030)	(0.035)
BM	−0.188**	−0.205**	−0.0936
	(0.080)	(0.082)	(0.095)
TMTPay	0.0157	0.00466	0.0466
	(0.031)	(0.030)	(0.035)
Mshare	0.403**	0.402**	0.492**
	(0.190)	(0.180)	(0.224)
_cons	−8.742***	−9.062***	−8.482***
	(0.783)	(0.759)	(0.920)
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	11204	11274	7059
F	25.707***	30.284***	20.937***
r2	0.798	0.800	0.794

Robust Standard errors in parentheses $^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$.

involve higher R&D costs and greater technical complexity, with stricter application procedures and protection regulations, thereby better reflecting substantive innovation capabilities. A higher proportion of utility model and design patents may indicate the presence of a "patent bubble," and treating these patent types as homogeneous could introduce measurement bias. To address this issue, we construct a quality-weighted alternative innovation output indicator. Specifically, drawing on scholarly consensus regarding the relative technical content and innovation value of the three patent types, we assign differentiated weights of 3:2:1 to invention patents, utility model patents, and design patents, respectively. We then re-estimate the baseline models using the weighted patent index as the dependent variable. The results from these robustness checks are reported in Table 6.

Table 6 presents robustness tests that incorporate province-by-year and city-by-year fixed effects, excluding data from 2020, replacing core explanatory variables, and including industry-specific trends. The results show that the DID variable maintains a significant positive impact on patent activity, further supporting the robustness and validity of the study's main findings.

TABLE 6 Robustness tests.

Variable	(1)	(2)	(3)	(4)	(5)
	Capturing provincial policies	Capturing urban policies	Excluding the 2020 sample	Alternative dependent variable	Including industry-specific trends
	Patent	Patent	Patent	Patent2	Patent
DID	0.238***	0.232***	0.235***	0.261***	0.136***
	(0.029)	(0.035)	(0.03)	(0.032)	(0.047)
Size	0.528***	0.531***	0.515***	0.586***	0.543***
	(0.02)	(0.022)	(0.02)	(0.021)	(0.018)
Lev	−0.376***	−0.390***	−0.402***	−0.479***	−0.362***
	(0.064)	(0.071)	(0.068)	(0.071)	(0.06)
REC	0.776***	0.727***	0.916***	1.012***	0.741***
	(0.131)	(0.142)	(0.141)	(0.152)	(0.127)
INV	−0.0641	−0.0723	−0.0772	−0.124	0.0384
	(0.117)	(0.125)	(0.124)	(0.128)	(0.108)
Cashflow	−0.122	−0.187*	−0.146	−0.108	−0.103
	(0.103)	(0.113)	(0.111)	(0.117)	(0.098)
Top10	0.336***	0.257**	0.346***	0.337***	0.285***
	(0.094)	(0.103)	(0.099)	(0.1)	(0.085)
Balance	−0.0022	0.00445	0.00061	0.01	0.00445
	(0.017)	(0.018)	(0.018)	(0.019)	(0.016)
BM	−0.147***	−0.134***	−0.123**	−0.0857*	−0.0909**
	(0.045)	(0.049)	(0.048)	(0.05)	(0.043)
TMTPay	−0.0263	−0.0272	−0.0282	−0.0338*	−0.0149
	(0.018)	(0.02)	(0.019)	(0.02)	(0.017)
Mshare	0.200**	0.176*	0.267***	0.303***	0.188**
	(0.091)	(0.097)	(0.096)	(0.101)	(0.086)
_cons	−8.638***	−8.647***	−8.397***	−9.230***	−17.93***
	(0.45)	(0.497)	(0.462)	(0.48)	(3.057)
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Province × year	Yes				
City × year		Yes			
Industry-specific trends					Yes
N	31257	31257	28203	33261	33261
F	80.699***	65.670***	75.026***	89.147***	20.394***
r2	0.804	0.828	0.797	0.789	0.799

Robust Standard errors in parentheses *p < 0.1, **p < 0.05, ***p < 0.01.

TABLE 7 Heterogeneity analysis of the nature of equity.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	State enterprise	Non-state enterprise	Broad scale	Small and medium-sized	high tech	Non-high tech
	Patent	Patent	Patent	Patent	Patent	Patent
DID	0.311***	0.166***	0.303***	0.155***	0.361***	0.183***
	(0.043)	(0.038)	(0.04)	(0.046)	(0.044)	(0.037)
Size	0.487***	0.533***	0.476***	0.622***	0.617***	0.484***
	(0.038)	(0.023)	(0.033)	(0.032)	(0.029)	(0.027)
Lev	0.114	−0.505***	−0.378***	−0.280***	−0.251***	−0.484***
	(0.123)	(0.076)	(0.113)	(0.085)	(0.093)	(0.089)
REC	1.467***	0.610***	0.712***	0.767***	0.414**	1.219***
	(0.259)	(0.156)	(0.213)	(0.179)	(0.189)	(0.188)
INV	−0.618***	0.167	−0.217	0.263	0.499**	−0.0496
	(0.219)	(0.14)	(0.173)	(0.175)	(0.223)	(0.139)
Cashflow	−0.118	−0.250**	−0.125	−0.213	−0.246	−0.0693
	(0.176)	(0.125)	(0.156)	(0.137)	(0.152)	(0.138)
Top10	0.302	0.0309	0.810***	0.1	0.137	0.421***
	(0.196)	(0.115)	(0.149)	(0.14)	(0.14)	(0.134)
Balance	0.0972***	−0.0298	0.0285	−0.0450**	0.00115	−0.00909
	(0.033)	(0.021)	(0.027)	(0.022)	(0.024)	(0.024)
BM	0.108	−0.272***	−0.0164	−0.122*	−0.253***	−0.0468
	(0.082)	(0.054)	(0.065)	(0.068)	(0.066)	(0.06)
TMTPay	0.00881	0.00146	−0.00845	−0.0197	0.0142	−0.0274
	(0.03)	(0.023)	(0.025)	(0.027)	(0.026)	(0.024)
Mshare	1.047*	0.116	0.687***	0.0856	0.0514	0.334**
	(0.567)	(0.096)	(0.203)	(0.107)	(0.124)	(0.134)
_cons	−8.971***	−8.693***	−8.166***	−10.56***	−10.72***	−8.030***
	(0.829)	(0.535)	(0.785)	(0.714)	(0.666)	(0.628)
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	9725	21469	15475	15388	13709	17407
F	40.052***	54.484***	31.152***	38.663***	52.218***	38.842***
r2	0.852	0.776	0.833	0.759	0.787	0.809

Robust Standard errors in parentheses *p < 0.1, **p < 0.05, ***p < 0.01.

5 Additional tests

5.1 Heterogeneity tests

To examine heterogeneity in firms' responses to the environmental tax reform, we conduct subgroup regressions along three dimensions: ownership structure, firm size, and technological intensity. The results are reported in Table 7. First, firms are classified into state-owned enterprises (SOEs) and non–state-owned enterprises (non-SOEs). As shown in Columns (1) and (2) of Table 7, the estimated DID coefficient is 0.311 for SOEs and 0.166 for non-SOEs, both statistically significant at the 1% level, indicating that the innovation-enhancing effect of the environmental tax reform is substantially stronger for SOEs. This difference may reflect the institutional advantages enjoyed by SOEs in China, including preferential access to fiscal support, policy

TABLE 8 Mediated effects test.

Variable	(1)	(2)
	LRDinc	Patent
DID	0.00125*	0.246***
	(0.001)	(0.028)
LRDinc		2.467***
		(0.225)
Size	0.00496***	0.507***
	(0.001)	(0.019)
Lev	−0.00630***	−0.373***
	(0.002)	(0.063)
REC	−0.0228***	0.901***
	(0.005)	(0.131)
INV	−0.00904**	−0.0506
	(0.004)	(0.116)
Cashflow	−0.0121***	−0.135
	(0.003)	(0.102)
Top10	0.0292***	0.291***
	(0.004)	(0.094)
Balance	0.00227***	−0.00640
	(0.001)	(0.017)
BM	−0.0113***	−0.101**
	(0.001)	(0.045)
TMTPay	−0.000449	−0.0226
	(0.001)	(0.018)
Mshare	0.00624**	0.235***
	(0.003)	(0.090)
_cons	−0.0558***	−8.381***
	(0.017)	(0.439)
Firm	Yes	Yes
Year	Yes	Yes
N	31245	31245
F	21.242***	86.709***
r2	0.849	0.801

Robust Standard errors in parentheses *$p < 0.1$,**$p < 0.05$, ***$p < 0.01$.

information, and key production factors. Such advantages allow SOEs to better absorb compliance costs and transform regulatory pressure into incentives for technological upgrading. Moreover, relatively stable resource allocation and organizational structures facilitate long-term investment in research and development.

Second, firms are divided into large and small- and medium-sized enterprises based on the median firm size. Columns (3) and (4) of Table 7 show that the estimated coefficient is 0.303 for large firms and 0.155 for small and medium-sized firms, with both estimates significant at the 1% level. Compared with smaller firms, large firms typically possess stronger financing capacity, more developed R&D infrastructure, and greater risk tolerance. These characteristics enable them to respond to environmental tax constraints by pursuing sustained innovation to achieve both regulatory compliance and competitive advantage. In contrast, smaller firms face tighter financial and market constraints and are therefore more likely to adopt short-term, cost-minimizing strategies.

Finally, firms are grouped by technological intensity into high-tech and non–high-tech enterprises based on industry classification. As reported in Columns (5) and (6) of Table 7, the DID coefficient is 0.361 for high-tech firms and 0.183 for non–high-tech firms, both significant at the 1% level. This disparity reflects the stronger innovation orientation and absorptive capacity of technology-intensive firms, which are more inclined to increase R&D investment in response to environmental tax pressure. By contrast, non–high-tech firms are more constrained by technological path dependence and limited innovation capabilities, resulting in a weaker policy response. Overall, the heterogeneity analysis suggests that the innovation-stimulating effect of the environmental tax reform is more pronounced among firms with stronger resource endowments and institutional advantages, underscoring the critical role of firm characteristics in shaping the transmission of environmental policy.

5.2 Mechanism tests

Using the mediation model developed in this study, we conducted a regression analysis, with the results summarized in Table 8. As shown in column (1), the estimated coefficient of the difference-in-differences (DID) variable on R&D investment intensity is 0.00125 and statistically significant at the 10% level. This suggests that the implementation of the environmental tax reform policy has encouraged heavier polluting firms to increase their R&D spending. Column (2) further shows that both the policy variable (DID) and R&D intensity are positively associated with patent output. According to the standard three-step mediation test (Baron and Kenny, 1986), these findings confirm a mediating effect: the policy boosts innovation partly by encouraging greater investment in R&D.

This relationship supports established views in the innovation literature, which emphasize the central role of R&D in driving technological progress. By investing in research and development, firms are better positioned to introduce new products, improve production processes, and maintain competitiveness in evolving markets. These improvements not only enhance firm-level performance but also contribute to broader industrial transformation and long-term economic growth.

Beyond firm performance, R&D investment also plays a critical role in sustainable development. From this perspective, innovation is not only a path to higher productivity but also a means to address environmental and social challenges. Through targeted R&D, companies can develop cleaner technologies, reduce resource consumption, and minimize environmental impact. In doing so, they align economic objectives with broader societal goals. This approach reflects a growing recognition that business innovation

TABLE 9 Extended analysis.

Variable	(1)	(2)	(3)	(4)	(5)
	LnCit	LnCit2	IE	LnGreen	LnNonGreen
DID	0.0934***	0.0355***	0.0105***	0.124***	0.228***
	(0.022)	(0.006)	(0.002)	(0.021)	(0.027)
Size	0.426***	0.0144***	0.0248***	0.406***	0.516***
	(0.016)	(0.004)	(0.001)	(0.014)	(0.018)
Lev	0.0902*	−0.0538***	−0.0171***	−0.0912**	−0.309***
	(0.053)	(0.015)	(0.004)	(0.045)	(0.062)
REC	0.257**	0.0664**	0.0410***	0.217**	0.614***
	(0.107)	(0.03)	(0.007)	(0.098)	(0.127)
INV	−0.156*	−0.00818	0.00788	−0.0908	−0.143
	(0.095)	(0.03)	(0.007)	(0.077)	(0.112)
Cashflow	−0.0512	0.036	−0.0108*	−0.0158	−0.186*
	(0.087)	(0.026)	(0.006)	(0.07)	(0.099)
Top10	−0.616***	0.157***	0.0107**	0.199***	0.267***
	(0.077)	(0.022)	(0.005)	(0.065)	(0.088)
Balance	0.0337**	0.00455	0.00037	−0.00377	−0.00193
	(0.014)	(0.004)	(0.001)	(0.011)	(0.016)
BM	−0.369***	−0.00303	−0.00394	−0.0744**	−0.0947**
	(0.037)	(0.011)	(0.003)	(0.032)	(0.042)
TMTPay	−0.013	0.0130***	−0.00181*	0.00994	0.00154
	(0.015)	(0.004)	(0.001)	(0.013)	(0.017)
Mshare	−0.237***	0.0705***	0.00744	0.177***	0.203**
	(0.076)	(0.022)	(0.005)	(0.06)	(0.087)
_cons	−6.026***	−0.148	−0.364***	−8.278***	−8.830***
	(0.368)	(0.101)	(0.024)	(0.324)	(0.414)
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	24888	24888	29439	32002	31191
F	87.520***	17.000***	58.290***	94.467***	92.927***
r2	0.893	0.691	0.724	0.777	0.805

Robust Standard errors in parentheses $^{*}p < 0.1$,$^{**}p < 0.05$, $^{***}p < 0.01$.

should contribute to sustainability and that long-term value creation increasingly depends on a company's ability to address both economic and environmental imperatives.

5.3 Extended analysis

The preceding analysis shows that the environmental protection tax promotes firm innovation by increasing R&D investment. This section further examines the quality and efficiency of innovation. Following Bradley et al. (2016), innovation quality is measured using the number of forward citations received by firms' patents (Bradley et al., 2017). Specifically, we construct two measures of innovation quality. Overall innovation quality (LnCit) is defined as the natural logarithm of one plus the total number of forward citations received by patents applied for in the following year. Average innovation quality (LnCit2) is measured as the natural logarithm of one plus the average number of forward citations per patent applied for in the following year. Innovation efficiency (IE) is proxied by the number of patent applications per unit of R&D expenditure, calculated as ln (1 + Patent) divided by ln (1 + RD).

The regression results are reported in Table 9. Column (1) presents the results for overall innovation quality (LnCit), Column (2) for average innovation quality (LnCit2), and Column (3) for innovation efficiency (IE). In Column (1), the coefficient on the core explanatory variable is 0.09 and statistically significant at the 1% level. In Column (2), the corresponding coefficient is 0.035, also significant at the 1% level. These findings indicate that the environmental tax reform significantly improves the quality of firm innovation. In Column (3), the estimated coefficient is 0.01 and significant at the 1% level, suggesting that the reform also enhances innovation efficiency.

Compared with other types of innovation, green innovation exhibits dual externalities related to both knowledge creation and environmental benefits. As a result, firms' green innovation activities are jointly influenced by resource endowments and environmental regulation Song et al. (2020). To further distinguish the effects of the environmental protection tax across different types of innovation, we classify firms' patents into green and non-green patents.

Green patents are identified based on the "Green Inventory" introduced by the World Intellectual Property Organization (WIPO) in 2010, which is constructed in accordance with the classification standards of the United Nations Framework Convention on Climate Change and mapped to International Patent Classification (IPC) codes. The Green Inventory covers seven broad categories: transportation, waste management, energy conservation, alternative energy production, administrative regulatory or design aspects, agriculture or forestry, and nuclear power generation. We aggregate firms' patent applications in these categories, add one, and take the natural logarithm to construct the measure of green innovation (LnGreen), with larger values indicating higher levels of green innovative activity. The corresponding regression results are reported in Columns (4) and (5) of Table 9, where Column (4) presents the results for green innovation and Column (5) for non-green innovation. The estimated coefficients on the core explanatory variable are positive and statistically significant at the 1% level in both regressions, indicating that the environmental protection tax reform not only stimulates firms' green innovation but also promotes non-green innovation.

6 Conclusion

This study uses China's 2018 environmental tax reform as a quasi-natural experiment to assess how environmental regulation affects innovation in heavily polluting firms. Drawing on firm-level data from the CSMAR database and annual reports of listed companies from 2013 to 2023, the analysis finds that the reform significantly boosted the innovation capacity of targeted firms. These results remain consistent across a range of robustness checks, strengthening confidence in the policy's effect.

The analysis also highlights how the impact of the reform varies across different types of firms. Specifically, the positive effect on innovation is more pronounced among state-owned enterprises than among non-state-owned firms. Large firms respond more strongly to the reform than small and medium-sized enterprises, and high-tech firms show greater gains in innovation compared to non-high-tech counterparts. Further investigation reveals that these improvements are primarily driven by increased investment in research and development, suggesting that the policy encourages innovation by enhancing firms' R&D commitment.

Further analysis indicates that, in terms of the underlying mechanisms, the environmental tax reform promotes firm innovation by increasing R&D investment. An examination of the formation process and quality of innovation outputs further shows that the reform also enhances both innovation quality and innovation efficiency, and exerts a significant impact on firms' green as well as non-green innovation activities.

These findings carry important policy implications. They suggest that well-designed environmental regulation can serve as a catalyst for innovation, helping to align environmental goals with economic development. In particular, the observed response among key polluters supports the effectiveness of command-and-control policies in driving technological progress. To amplify this effect, policymakers should refine the design of environmental tax instruments to provide clearer and more consistent signals that encourage firms to innovate in areas such as energy efficiency and emissions reduction.

At the same time, supporting policies that increase R&D investment such as financial incentives, tax credits, or innovation subsidies can reinforce the link between regulation and innovation. Establishing a feedback mechanism that rewards firms for sustainable innovation can create a virtuous cycle, where environmental regulation not only reduces pollution but also drives long-term competitiveness and structural transformation.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YC: Conceptualization, Data curation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review and editing. YP: Formal Analysis, Methodology, Resources, Visualization, Writing – review and editing. JW: Investigation, Software, Writing – review and editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix A

TABLE A1 Balance test results of trend score matching.

Covariate name	Mix-and-Match						Matching year by year					Individual matching				
	Unmatched matched	Mean		Bias (%)	t	P	Mean		Bias (%)	t	P	Mean		Bias (%)	t	P
		Treated	Treated				Treated	Control				Treated	Treated			
Size	U	22.586	22.236	26.5	18.96	0.000	22.565	22.214	26.6	19.74	0.000	22.784	22.662	9.9	1.54	0.125
	M	22.586	22.508	5.9	3.17	0.002	22.565	22.483	6.2	3.47	0.001	22.784	22.563	18	2.22	0.027
Lev	U	0.44417	0.41889	12.6	8.74	0.000	0.44612	0.41865	13.6	9.78	0.000	0.44784	0.43499	6.5	1.01	0.313
	M	0.44417	0.43611	4	2.2	0.028	0.44612	0.43807	4	2.27	0.023	0.44784	0.41863	14.9	1.86	0.063
REC	U	0.08981	0.13682	−48.8	−32.18	0.000	0.0885	0.13576	−49.3	−33.59	0.000	0.08374	0.12565	−45.2	−6.52	0.000
	M	0.08981	0.09215	−2.4	−1.5	0.133	0.0885	0.09149	−3.1	−2.01	0.045	0.08374	0.10097	−18.6	−2.55	0.011
INV	U	0.11255	0.1436	−27.6	−17.41	0.000	0.11366	0.14567	−28.1	−18.29	0.000	0.10964	0.15805	−39.8	−5.46	0.000
	M	0.11255	0.11079	1.6	0.95	0.343	0.11366	0.11358	0.1	0.04	0.965	0.10964	0.1164	−5.6	−6.88	0.378
Cashflow	U	0.05924	0.0446	21.9	15.2	0.000	0.05897	0.04438	21.8	15.65	0.000	0.05589	0.03245	35.3	5.45	0.000
	M	0.05924	0.05752	2.6	1.45	0.147	0.05897	0.05687	3.1	1.84	0.065	0.05589	0.04904	10.3	1.29	0.197
Top10	U	0.56675	0.57709	−6.9	−4.8	0.000	0.56809	0.57799	−6.5	−4.73	0.000	0.55152	0.55154	0.000	0.000	0.998
	M	0.56675	0.56653	0.1	0.08	0.938	0.56809	0.56849	−0.3	−0.15	0.882	0.55152	0.54477	4.7	0.59	0.555
Balance	U	0.89026	1.0144	−15.7	−10.79	0.000	0.87788	1.0034	−15.9	−11.34	0.000	0.8814	0.94461	−8.1	−1.25	0.211
	M	0.89026	0.91181	−2.7	−1.55	0.121	0.87788	0.89139	−1.7	−1.02	0.308	0.8814	0.90291	−2.7	−0.34	0.731
BM	U	0.68926	0.59959	35.3	24.95	0.000	0.69352	0.60559	34.9	25.49	0.000	0.65867	0.60289	25	3.81	0.000
	M	0.68926	0.67973	3.8	2	0.045	0.69352	0.683	4.2	2.34	0.019	0.65867	0.62119	16.8	2.03	0.043
TMTPay	U	14.454	14.642	−27.1	−19.02	0.000	14.423	14.613	−27.3	−19.85	0.000	14.417	14.583	−24.7	−3.84	0.000
	M	14.454	14.461	−0.9	−0.52	0.605	14.423	14.426	−0.5	−0.26	0.793	14.417	14.424	−1.1	−0.14	0.887
Mshare	U	0.05515	0.08229	−20.3	−13.68	0.000	0.05501	0.08175	−20	−13.93	0.000	0.03716	0.04977	−12.3	−1.83	0.068
	M	0.05515	0.05822	−2.3	−1.37	0.171	0.05501	0.05958	−3.4	−2.07	0.038	0.03716	0.03633	0.8	0.11	0.913

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