Public Environmental Concern, CEO Turnover, and Green Investment: Evidence from a Quasi-Natural Experiment in China

We investigate the impact of public environmental concern (PEC) on corporate green investments from the perspective of CEO turnover using the extreme event of PM 2.5 surge at the end of 2011 in China as a quasi-natural experiment. Compared with non-heavily polluting companies, the probability of CEO turnover in heavily polluting ones has significantly increased amid the surge of PEC. Heavily polluting companies ease the pressure by increasing green investment. In addition to the hard regulative measures such as environmental regulations, the PEC as a form of soft regulation also makes corporate management more focused on environmental responsibility.

Keywords: Public Environmental Concern, Green Investment, CEO Turnover, PM 2.5 surge, Extreme Event

JEL classifications: G11, G32, N72

1. Introduction

Extreme environmental incidents often bring continued and significant impacts on society and the economy. Around 2011, heavy smog occurred in several places in China, attracting global attention to the problem of air pollution in the country (Zheng et al., 2014; Shi et al., 2016; Chang et al., 2018; Dong et al., 2021). For a long time, the Chinese government and the public did not pay much attention to environmental issues as economic growth has always been the top priority. However, the heavy smog in 2011 prompted the Chinese to realize that the clean air that they had taken for granted did not come easily. The outcome of focusing only on short-term economic growth while ignoring the environment will be very serious. Moreover, air pollution has led to a substantial increase in the costs of environmental governance, largely hindering economic growth (Chen et al., 2013；Arora et al., 2016；Sun et al., 2016；Miao et al., 2019；Zhou et al., 2020；Liao et al., 2021). As a result, the heavy smog was selected as one of the "Top 10 Weather and Climate Events in China and the World in 2011" announced by the China Meteorological Administration.

Extreme smog events have led to a significant increase in public environmental concern, and enterprises are also under tremendous pressure as a result. Business production and operation activities are the main source of environmental pollution (Alam et al., 2019). However, it is not an easy job for companies to address pollution. On the one hand, addressing pollution requires companies to make an additional environmental investment, which will affect the short-term business performance. Therefore, as far as business operations and shareholder value maximization are concerned, it is not advisable for companies to invest in large-scale pollution control projects. On the other hand, pollution has a strong externality. If one company reduces pollution while the surrounding ones do nothing at all, there will be the limited effect of environmental governance and the pressure from the public cannot be mitigated either. Therefore, in the face of market failures caused by the externality, pollution control often requires external intervention from the government, which is also called environmental regulation.

For businesses, environmental regulation is a typical hard regulation which means that non-compliance will increase economic costs (Wilms, 1982). However, businesses do not invest in environmental protection merely to satisfy environmental regulations and reduce supervision costs from them (Chuah et al., 2020). Therefore, environmental regulations make a difference in their production and operating costs, which in turn affects corporate decisions. A considerable literature has focused on examining the effects of environmental regulations on company decision making and been based on theories aimed at three aspects of environmental economics: Costly regulation hypothesis (Boyd & McClelland, 1999), pollution haven hypothesis (Shadbegian & Gray, 2005), Porter hypothesis (Porter & Linde, 1995).

At the same time, in addition to hard environmental regulations, companies will also face some soft regulations among which PEC is an important one. Unlike the hard regulations, soft regulations do not increase the economic costs of non-compliance, but increases the benefits of compliance (Thaler & Sunstein, 2003). Obviously, PEC will not directly impose economic costs of polluting operations on companies. But studies report that following increased public environmental concern (PEC), the environmental investment can help businesses attain numerous social benefits and economic benefits including a favorable social reputation enabling sustainable operations (Aksak et al., 2016), and increased purchasing intention from environmentally concerned consumers (Sueyoshi & Wang, 2014).

In recent years, environmental issues have attracted more and more attention globally, making the ESG (i.e., Environment, Social and Governance) investment increasingly popular across the world. According to MSCI's latest "2021 Global Institutional Investor Survey", 73% of institutional investors plan to increase ESG investment by the end of 2021. Such a widespread and large-scale increase of ESG investment by enterprises is obviously not just to meet the basic requirements of environmental regulations. Obtaining benefits by responding to the PEC may be the key consideration. Therefore, PEC is weighing increasingly heavier on corporate decision-making.

Meanwhile, and a good legal environment is helpful for enterprises to increase environmental investment (Zhang et al., 2019). However, As a developing country, China's performance of rule of law lags far behind other mature economies. According to the Rule of Law Index released by the World Justice Project, China ranked 82nd with a score of just 0.49 in 2019. Therefore, the significance of soft regulations such as PEC cannot be ignored in the development of Chinese businesses (Allen et al., 2005).

Many theoretical studies indicate that PEC significantly affects corporate operations and management (Ji et al., 2018; Wu et al., 2020). However, few empirical studies use microeconomic data to directly inspect the effects of PEC on corporate behavior (Tian et al., 2020). Two types of reasons cause this research gap: First, studies on business behavior require panel data as their basis. PEC indicators that are constructed based on face-to-face survey data are generally available with the cross-sectional data of individual years (Liu & Mu, 2016) and are unsuitable for direct matchups with business panel data for analysis. Second, even if panel data regarding PEC are constructed, differences in PEC continue to exist among populations (Aasen, 2017). Using such panel data for analysis may result in severe challenges from endogenous problems such as missing variables and self-selection bias in empirical research.

In this regard, the massive smog pollution in China in 2011 provides an important opportunity to solve the above-mentioned problems. Over the years, the Chinese have not paid enough attention to environmental issues (especially air pollution) as they were preoccupied with economic growth. However, the extreme smog weather in 2011 greatly increased people's concern about air pollution in China. As a result of the wide media coverage, there was a spike in the search query PM2.5 (which is a rather professional term) on the Internet in China, and the Commercial Press also added the entry PM2.5 to the sixth edition of the *Modern Chinese Dictionary* published in 2012. Obviously, the extreme smog weather in 2011 boosted public awareness of environmental protection, and changed the situation where the environmental awareness only grew in some population groups rather than developing chronologically.

Against the backdrop of the rising PEC triggered by the extreme smog weather in China, this article constructs a quasi-natural experiment to complete an empirical study on the impact of PEC on corporate environmental investment from the perspective of CEO turnover. The quasi-natural experiment is an important research method of social sciences that has been popular in recent years. The method draws on the idea in the bio-medicine experiment that looks at the different effects of exogenous emergencies on the experimental group and the control group, so as to better identify the causal relation in this process. In the face of the surge in PEC in China after the serious smog pollution in 2011, heavily polluting companies had to deal with much more pressure than non-heavily polluting ones. This study takes the heavily polluting companies as the experimental group and the non-heavily polluting ones as the control group to construct a double difference model for the empirical test. The results reveal that following reports of excessive PM2.5 concentration as measured by the Embassy of the United States, in Beijing, China, the sharply increased PEC pressure significantly raises the CEO turnover of heavily polluting companies to 25% higher than that of non-highly-polluting companies. To relieve pressure from public concern, heavily polluting businesses increase their green investments and expenditures greatly, which effectively reduces the CEO turnover of heavily polluting companies from increased PEC pressure. In addition, although the significant effects of increased PEC on increased CEO turnover in heavily polluting companies and their green investments are only observed in areas with aggravated pollution, PEC significantly affects increases in green investment among heavily polluting companies in all areas.

We make several contributions to the literature. First, unlike the existing empirical studies which inspect the effect of hard regulations such as environmental regulations on business decision-making, we focus on the effects of the soft regulations of PEC on corporate environmental investment behavior. Hence, we advance the empirical microeconomic studies on the effects of environmental concerns on business decision-making (Tian et al., 2020).

Moreover, we provide a new perspective for better understanding of the increasingly popular ESG investment, which may be due to increasing PEC (especially during extreme events such as the 2011 smog event in China). As companies attach greater importance to ESG investment including green initiatives in recent years, the world is seeing a rise in ESG investment, which cannot be explained solely by environmental regulations that only increase the costs of non-compliance. Therefore, by using the extreme smog weather in China in 2011 as a quasi-natural experiment, this research empirically examines the impacts of soft regulations such as PEC on corporate decision-making.

In addition, we contribute to the small but growing strand of literature on the role of PEC, as the existing studies mainly only focus on the effect of PEC on consumer behavior and public policy (Wang & Wheeler, 2005; Tong et al., 2020). It is not easy to construct panel data to measure the PEC, given that differences in PEC mainly exist among different groups. Even if panel data regarding PEC are constructed, differences in PEC continue to exist among populations (Aasen, 2017). Hence, it is difficult to solve endogenous problems such as missing variables and self-selection. To solve this problem, this study constructs a quasi-natural experiment to investigate how the rise of PEC over extreme smog weather in China in 2011 impacts heavily polluting and non-heavily polluting companies. It not only provides reliable empirical evidence for the influence of PEC on companies' environmental investment through CEO turnover but also stands as an example for studies that look at how the PEC affects other corporate decisions in the future.

Finally, we provide fresh insights and evidence from the largest emerging market in the world for enterprises to understand and strengthen environmental governance. To the best of our knowledge, we are not aware of any existing study which has investigated the relationship between PEC and corporate decisions (such as CEO turnover and green investments) in China using the 2011 smog as the quasi-natual experient. From the enterprises' perspective, the pressure brought by PEC is more obvious in places with weak environmental regulations. This means that soft regulations such as PEC are actually an important complement to hard environmental regulations. In short, in addition to the hard environmental regulations, the impact of PEC on corporate environmental governance and other related decisions should also be taken seriously.

The remainder of this article is organized as follows. Section 2 describes the system background and 2011 PM 2.5 surge extreme event in China and presents the research hypotheses. Section 3 presents the study's empirical design. Section 4 provides the empirical analysis: including testing of the basic hypothesis, parallel trends, robustness, and other hypotheses; and further analysis. Finally, Section 5 concludes the study.

2. Background and hypothesis

2.1 The Extreme Event of 2011 smog in China and Public Environmental Concerns

Over a long period, the government has focused on growing the gross domestic product (Li & Zhou, 2005). Public concern for environmental problems is generally absent in China. The government did not pay serious attention to environmental problems until 2006, when the State Council of the People's Republic of China launched the Eleventh National Five-Year Plan, which stipulates the 2006–2010 total quantity control goals of chemical oxygen demand and SO_2 for each province (or district or city).

Chinese society is relatively late in expressing concerns over smog. In September 2010, the National Aeronautics and Space Administration of the United States declared a global air pollution map that is averaged over 2001–2006. The map shows that the greatest concentrations of $PM_{2.5}$ (in red) occurred in North Africa and North, East, and Central China. The World Health Organization suggests that a concentration of $PM_{2.5}$ that is lower than 10 μg/m^3 is within a safe range. However, the $PM_{2.5}$ concentrations in the mentioned areas in China were all higher than 50 μg/m^3, with some approaching 80 μg/m^3, which was considerably higher than that in the Sahara Desert.

[Insert Figure 1 around here]

What really prompted the public to take the smog problem seriously was the extreme event of the surge of "PM2.5" around 2011, which assembles the image of the Great Smog in London in December 1952. In both these severe air-pollution events, cold weather, combined with windless conditions, collected airborne pollutants to form a thick layer of smog. In October 2011, extreme heavy smog emerges in many cities in China, seriously affecting residents' daily lives and triggering the public to consider the health impacts of the air quality problem. On December 4, 2011, the PM2.5 reading of the air quality test equipment in the US Embassy in China exceeded the equipment's maximum limit of 500. (A qualitatively similar but less influential incident of smog occurred on November 21, 2010, which unfortunately did not attract as much attention as the one in 2011.) The Chinese started to be increasingly concerned about the smog problem as severe smog weather caused them much discomfort and there had been a burst of media publications especially after the incident of the "PM 2.5" surge. The academic term "PM2.5" also entered the public narrative in China.

In November 2011, the Ministry of Ecology and Environment of China announces an exposure draft of Ambient Air Quality Standards, in which PM2.5 and ozone (8-hour concentration) are included as part of the regular air quality evaluation, while standard limits of emissions such as PM10 and nitrogen oxides are tightened along with increased requirements regarding the validity of air quality index (AQI) statistics. On January 21, 2012, statistics of the hourly PM2.5 concentration for research monitoring is published on the website of the Beijing Municipal Environmental Monitoring Center for the first time. In February 2012, PM2.5 is officially included in the latest *Ambient* Air Quality Standards as part of the regular air quality evaluation. On March 5, 2012, the term "PM2.5," of broad concern to society, first appears in a government work report. In the report, Prime Minister Wen Jiabao indicates that this year, monitoring of items such as fine particles (PM2.5) is to be launched in key areas including the Beijing–Tianjin–Hebei, the Yangtze River Delta, and the Pearl River Delta, as well as municipalities and capital cities, before being generally applied to all cities at the prefectural level or above in 2015. On May 25, 2012, the Ministry of Ecology and Environment stipulates in its Plan for the First-Stage Implementation of Monitoring on *Ambient* Air Quality Standards that a pilot run of monitoring PM2.5 at national control posts is to be conducted in 74 cities throughout the country before the end of October, and the monitoring results are to be published before the end of December.

In summary, following the two representatives' "PM 2.5 surge" extreme events in 2010 and 2011 and reports by the media that cover smog problems and the government's constant concerns for these problems, the PEC over smog pollution in China enhanced substantially. To clearly display the changes in public concerns for smog before and after the "PM 2.5 surge" extreme events in China, Fig. 2 presents the search queries of $PM_{2.5}$ on Google trends between January 2004 and April 2020. The result shows that before November 2011, the number of searches for $PM_{2.5}$ in China was nearly zero. After November 2011, the number of searches for $PM_{2.5}$ in China was significantly higher than zero. This result sufficiently indicates that the public concerns for smog after the "PM 2.5 surge" extreme events increased significantly. In addition, the heavy smog was selected as one of the "Top 10 Weather and Climate Events in China and the World in 2011" published by the China Meteorological Administration, and PM2.5 was also added to the sixth edition of the *Modern Chinese Dictionary* published by the Commercial Press in 2012, indicating that extreme weather events in 2011 greatly increased the PEC in China.

[Insert Figure 2 around here]

2.2 Hypothesis development

Because of the strong externality of pollution governance, the optimal pollution discharge level for maximizing stakeholder interest is necessarily higher than the optimal pollution discharge level of the entire society (Hardin, 1968). Therefore, the environmental regulations stipulated by the government can convert the social costs of pollution into the internal operating costs of businesses, thereby forcing businesses to reduce pollution behavior. A considerable literature has focused on examining the effects of environmental regulations on company decision making and been based on theories aimed at three aspects of environmental economics: costly regulation hypothesis (Boyd & McClelland, 1999), pollution haven hypothesis (Shadbegian & Gray, 2005), and porter hypothesis (Porter & Linde, 1995). Additionally, abundant theoretical and empirical studies are conducted (Gray & Shadbegian, 1998, 2003; Hamamoto, 2006).

Satisfying governmental supervision requirements do not account for the massive investment that an increasing number of companies make for environmental governance. To explore this phenomenon, many scholars adopt the perspective of corporate social responsibility based on stakeholder theory. According to stakeholder theory, although ownership of companies belongs to shareholders, the development of companies cannot be independent from the participation of stakeholders. Companies must consider the rights and interests of stakeholders, including employees, customers, suppliers, and creditors. By assuming social responsibility, companies balance the interest appeals of different stakeholders, increase organizational efficiency, and improve business performance (Barnett, 2007). Following increased PEC, the environmental performance of companies often relates to their social reputation (Aksak et al., 2016) and affects the purchasing intention of environmentally concerned consumers, which has a direct effect on company performance (Sueyoshi & Wang, 2014).

According to the principal-agent theory, shareholders assess CEOs based on company performance. Previously, maximizing shareholder interest was considered, and company operation performance was one of the most crucial factors that affected CEO turnover. Most empirical research has supported sales performance being negatively correlated with the probability of CEO turnover (Engel et al., 2003; Bhagat and Bolton, 2008; Jenter and Kanaan, 2015; Ghosh and Wang, 2018). In addition, company sales performance significantly improves following CEO turnover (Huson et al., 2004). After stakeholders are considered, CEOs are confronted with appraisals that are adjusted accordingly. When PEC increases, the environmental performance of companies attracts increasing attention, and CEOs face increasing environmental performance pressure to which heavily polluting companies are more sensitive. CEOs of these companies face greater pressure during environmental assessments and thereby have greater turnover rates. Therefore, Hypothesis 1 is proposed as follows:

H1: Following increased PEC, the probability of CEO turnover in highly-polluting companies increases compared with that in non-highly-polluting companies.

After the public's environmental concern increases, CEOs confront greater stress from environmental assessment. The pollution haven and Porter hypotheses serve as two paths of thinking; that is, in facing rigorous local environmental regulations, companies can either relocate their operating and investment activities to regions with less strict environmental regulations or upgrade their corporate company techniques for reducing pollutant emissions through research and development. For these companies, the difficulty of changing their main business direction is far greater than that of relocating operation and production activities to other regions. Thus, in the face of greater pressure from the PEC, alleviating pressure through improving environmental performance basically becomes the only possible direction, and increasing green investment expenditure represents a primary approach. This leads to this study's second hypothesis:

H2: After the public's environmental concern increases, the green investment expenditure of highly-polluting companies increases compared with that of non-highly-polluting companies.

Once highly-polluting companies increase their green investment expenditure, the public will deem the attention of such companies to their effects on the environment to have increased; thus, the public will reduce their attention to these companies, and the possibility of the CEO resigning due to the stress of environmental assessment will decrease. Moreover, green investment expenditure substantially improves corporate environmental performance, which includes increased energy efficiency and reduced pollutant emissions, whereas the improvement of environmental performance decreases the probability of CEO turnover in companies. This leads to the third hypothesis of this study:

H3: After the public's environmental concern increases, compared with non-highly-polluting CEOs, increased green investment weakens the positive effect on the probability of CEO turnover in highly-polluting.

3. Empirical design

3.1 Sample

This study uses A-share listed companies in China 4 years before (2007–2010) and after (2012–2015) the "PM 2.5 surge" incident as the initial sample. Because Chinese smog mainly occurs during fall and winter, the 2011 PM 2.5 surge and the public attention it triggers both occur in the fourth quarter. It is difficult to determine the influence of the incident on business decisions in 2011. Thus, data of 2011 are excluded (Chen et al., 2018) and later employed as post-incident data for analysis in a robustness test. Simultaneously, considering the industry distribution characteristics of polluting businesses, this study limits the sample to mining, manufacturing, and the production and supply of electricity, gas, and water to enhance the industry comparability of the experimental and control groups. In the robustness test, sample companies of all industries are used for analysis. We exclude those with debt greater than their total assets, those whose primary business revenue is in the negative, and those with fewer than 10 industry-year observations. Finally, 11,202 annual observation values of businesses over 8 years are obtained. For the classification of industries, the *Guidelines for the Industry Classification of Listed Companies* published by the China Securities Regulatory Commission (CSRC) in 2001 are adopted. The manufacturing businesses are classified into two-digit categories, and nonmanufacturing businesses are classified into one-digit categories.

All business' finance and corporate governance data in this study come from the GTA China Stock Market & Accounting Research (CSMAR) database. The provincial-level, state-level, and municipalities-level smog data are collected from comprehensive evaluation data from NASA satellites and ground observation posts published by the Atmospheric Composition Analysis Group of Dalhousie University in the United States (Van Donkelaar et al., 2015, 2019). To exclude the influence of extreme values, all the continual variables are winsorized at the 1% and 99% levels.

3.2 Variables

To examine Hypothesis 1 of this study, the DID model below is constructed for empirical analysis:

$$Turnover_{it} = \beta_0 + \beta_1 Treat_i * Post_t + \beta_2 Treat_i + \beta_3 Post_t + \sum Controls_{it} + \sum Year + \sum Ind + \varepsilon_{it} \qquad (1)$$

The dependent variable *Turnover* is a dummy variable. It is 1 if there is CEO turnover that year, otherwise it is 0. *Treat* is the classification indicator variable. According to the *Guidelines on Environmental Information Disclosure of Listed Companies* (exposure draft) published by the Ministry of Ecology and Environment on September 14, 2010, the 16 industries (i.e., thermal power, steel, cement, aluminum electrolysis, coal, metallurgy, chemical, petrochemical, construction material, papermaking, brewing, pharmaceutical, fermentation, textile, tanning, and mining industries) are defined as heavy polluting industries. They are also the experimental group of this study, and therefore the *Treat* value is 1. The rest are in the control group, and the *Treat* value is 0.

Post is the event indicator variable; it is 1 before 2011 and 0 after 2011. *Treat*Post* is the key explanatory variable. According to the theoretical analysis of Hypothesis 1, the regression coefficient of this variable in model (1) is expected to be significantly positive. For control variables, this study followed previous research including Cao et al. (2017) and Jarva et al. (2019), and incorporated basic company characteristics as the controlled variables into the model, such as company size, financial leverage, tangible asset ratio, and profit margin. The corporate governance variables are also added to the model as the controlled variables: compensation for the top management, whether the board director and general manager roles are taken by the same person, board size, independent director ratio, whether the company is state-owned or not, and the shareholding ratio of the largest shareholder as well as the year and industry dummy variables.

To examine Hypotheses 2 and 3 of this study, the following models are constructed:

$$GI_{it} = \beta_0 + \beta_1 Treat_i * Post_t + \beta_2 Treat_i + \beta_3 Post_t + \sum Controls_{it} + \sum Year + \sum Ind + \varepsilon_{it} \tag{2}$$

$$\begin{aligned} Turnover_{it} = {} & \beta_0 + \beta_1 Treat_i * Post_t * GI_{it} + \beta_2 Treat_i * GI_{it} + \beta_3 Post_t * GI_{it} + \beta_4 GI_{it} \\ & + \beta_5 Treat_i * Post_t + \beta_6 Treat_i + \beta_7 Post_t + \sum Controls_{it} \\ & + \sum Year + \sum Ind + \varepsilon_{it} \end{aligned} \tag{3}$$

where *GI* is a green investment; alternative measure of *GI* the value of green investment expenditure divided by the total asset *GI_1* and the natural logarithm of green investment expenditure *GI_2*. Regarding GI expenditure, the management cost is found from the notes of financial statements in the CSMAR database. Then, the expenditure entries related to "environment" and "environmental protection" are found hand-collected. They are summed in relation to the year, and the annual green investment expenditures of the businesses are obtained. Because the numerical values of this variable are relatively small, to explain the coefficients, this study adopts the processing method for calculating average firm-specific weekly return during the fiscal year used by Kim et al. (2011, 2016) and multiplies *GI* by 1000. According to the theoretical analysis of Hypotheses 2 and 3, this study expects the regression coefficient for the key explanatory variable *Treat*Post* in the model (2) to be significantly positive and that for the key explanatory variable *Treat*Post*GI* in the model (3) to be significantly negative. Table 1 describes the main variables used in our study.

[Insert Table 1 around here]

3.3 Descriptive statistics

Table 2 presents the descriptive statistical results of the major variables of this study. The average probability of CEO turnover in the sample is 24.4%, which is basically identical to that in the study by Cao et al. (2017). The proportion of polluting businesses in the sample is 39.8%. The average green investment expenditure of the businesses is 1,921,623 CNY, which is close to the statistical results of Stucki's (2019) investigation on businesses in Australia, Germany, and Switzerland. In addition, in the sample businesses, the proportion of state-owned businesses is 22.7%, and the proportion of businesses having one person take both roles of the general manager and the board director is 24.1%.

[Insert Table 2 around here]

4. Empirical results

4.1 Baseline regression

Table 3 presents the standard regression results based on model (1). In the first row, no controlled firm-level variable is added, and the regression coefficient of *Treat*Post* is 0.064 with a 1% significance level. In the second row, the company financial indicators are added, and the regression coefficient of *Treat*Post* is 0.059 and significant. In the third row, the corporate governance indicators are added, and the regression coefficient of *Treat*Post* is 0.061. Overall, no matter which controlled variables are added, the regression coefficient of the key explanatory variable *Treat*Post* remains positive. In addition, the significance level is at least 5%, and the coefficient is approximately 0.06. This result shows that after the PM 2.5 surge extreme event, compared with non-highly-polluting businesses, the highly polluting businesses have a significantly higher probability of CEO turnover, which completely agrees with the expectation of Hypothesis 1. Economically, after the PM 2.5 surge extreme event, the magnitude of increase in the probability of CEO turnover in polluting businesses was 25% higher than that in non-polluting businesses on average.

[Insert Table 3 around here]

4.2 The pre-treatment trends

Whether DID models are effective depends on the parallel trend assumption (Parallel trend assumption): Absent the treatment, the treated firm's CEO turnover would have evolved in the same way as the control firms. The pre-trend between the experimental and control groups is examined. The year of the extreme event, 2011, is used as the benchmark year. The years relative to the PM 2.5 surge extreme event are defined as year−3, year−2, year−1, year+1, year+2, year+3, and year+4. The original interaction term between *Post* and *Treat* is replaced with the interaction terms of the year dummy variables and *Treat* variable, and regression is conducted for the model (1).

The coefficients of the interaction variables of *Treat* with year−3, year−2, and year−1 are critical because the values and significance levels of these coefficients represent the significant presence of a significant difference between the experimental and control group in terms of CEO turnover before the extreme event. The results in Fig. 3 show that the coefficients of these variables are all close to 0 and are insignificant, conforming to the parallel trend assumption of the DID model.

The coefficient of the interaction term between year+1 and *Treat* is insignificant either. Then, the influence of the PM 2.5 surge extreme event starts to show. The coefficients of the interaction terms between *Treat* and year+1, year+2, and year+3 are all positive at a significance level of at least 5%. From year+1 to year+4, the coefficients of them with *Treat* basically exhibit an increasing trend.

In conclusion, Table 4 here shows that before the extreme event, the trends of CEO turnover in the experimental and control groups are similar, which supports the parallel trend assumption of DID models. In addition, the results of Fig. 3 show that the influence of the PM2.5 surgeon CEO turnover starts to appear after 2 years, which supports the causality effect.

[Insert Table 4 around here]

4.3 Placebo test

We use the samples before the PM2.5 surge event, assuming that the event occurred one year (2010), two years (2009), and three years (2008) before the actual occurrence time. Given that the PM2.5 surge event did not actually occur at this time, the expected interaction item has no effect on CEO turnover. Table 5 shows the results of the placebo test. Whether it is assumed that the event is one year, two years, or three years earlier, the coefficient of the interaction term is insignificant. The placebo test results guarantee the validity of the DID regression results.

[Insert Table 5 around here]

4.4 Robustness test

On the basis of the standard regression results, a robustness test was conducted with respect to the following aspects.

First, other regression models are used. First, considering that the explained variable CEO turnover is a dummy variable, the Logit and Probit models are used for examination (Cao et al., 2017). The first and second rows of Table 6 present the results, and the regression coefficient of *Treat*Post* is significantly positive. Second, to eliminate the influence of individual effects that do not change with time, the individual fixed effects are controlled for further examination. The third row of Table 6 presents the results, and the regression coefficient of *Treat*Post* is significantly positive.

[Insert Table 6 around here]

Second, the DID model settings are adjusted. First, the event year, 2011, is added to the sample and defined as a year influenced by the event, namely *Post* = 1, for reexamination. The first row of Table 7 presents the results, and the regression coefficient of *Treat*Post* is significantly positive. Second, the PM 2.5 surge is an air pollution event; consequently, the water-polluting businesses in the sample are adjusted from the experimental group (*Treat* = 1) to the control group (*Treat* = 0) for reexamination. The second row of Table 7 presents the results, and the regression coefficient of *Treat*Post* is significantly positive. Third, the sample is expanded from industrial businesses to all businesses to run the regression again. The third row of Table 7 presents the results, and the regression coefficient of *Treat*Post* is significantly positive. Fourth, in 2013, the Ministry of Ecology and Environment, China, published the *Interpretation of the Announcement on the Implementation of Special Emission Limits of Air Pollutants*, with emission limitation being requested in 19 provinces and municipalities including Beijing and Shanghai. To eliminate potential interference of this policy, the businesses in these 19 provinces and municipalities are selected as a sample for reexamination. The fourth row of Table 7 presents the results, and the regression coefficient of *Treat*Post* is significantly positive. Finally, considering that systematic errors may exist in highly polluting businesses and non-highly-polluting businesses, PSM is used to match the experimental and control groups according to the characteristics of companies and industries before the event. The fifth row of Table 7 presents the results based on the matched sample, and the regression coefficient of *Treat*Post* is significantly positive.

[Insert Table 7 around here]

Third, other factors that influence CEO turnover are controlled. First, Bricky (2003) indicates that the age of CEOs is a crucial factor that influences CEO turnover. In addition, compared with male CEOs, female CEOs have lower risk preferences (Levi et al., 2014). Risk is also a crucial factor that influences CEO turnover (Bushman et al., 2010). Consequently, CEO age and sex are added as controlled variables. The first row of Table 8 presents the results, and the regression coefficient of *Treat*Post* is significantly positive. Second, regular CEO turnovers that result from retirement are excluded. Hence, we exclude female CEOs aged over 60 years, and male CEOs aged over 65 years. The second row of Table 8 presents the results, and the regression coefficient of *Treat*Post* is significantly positive. Finally, CEO turnovers caused by violations are excluded, and the samples with violations in that year are excluded. The third row of Table 8 presents the results, and the regression coefficient of *Treat*Post* is significantly positive.

[Insert Table 8 around here]

Forth, other macroeconomic and industrial factors that may affect the result are also controlled. (1) We add possible macroeconomic factors including the per capita GDP of the city where the company is located, the scale of credit divided by GDP, the proportion of the secondary industry and the tertiary industry. The results are shown in column (1) of Table 9 and the coefficient of *Treat * Post is s*till positive and significant. (2) We add the dummy variables of *City * Year* to control for the possible macroeconomic factors in all cities. The results are shown in column (2) of Table 9 and the coefficient of *Treat * Post is s*till positive and significant. (3) Considering whether our explanatory variables are categorized as the heavily polluting companies is based on the 5-digit industry standard, the industrial fixed effects are adjusted to the corresponding 5-digit industry. Results shown in column (3) of Table 9 suggest that the coefficient of *Treat * Post is s*till positive and significant. (4) We add all the macro-control variables and the industry fixed effects of the 5-digit industry, and the coefficient of *Treat * Post* is still positive and significant as shown in column (4) of Table 9. To conclude, after we control for the macroeconomic and industrial factors as much as possible, the regression results are still robust.

[Insert Table 9 around here]

Fifth, we mainly focus on the impact of informal public concern about the environment on corporate CEO turnover. Allen et al. (2005) point out that informal mechanisms are often complemented to formal ones, and that the impact of informal mechanisms on companies is likely to differ in regions with different formal mechanisms. Therefore, based on the regional differences in formal mechanisms, a triple difference model (DDD) is constructed for testing. First, we refer to the intensity of municipal environmental regulations proposed by Du et al. (2021) and the intensity of environmental regulations before the PM2.5 surge event to set the median value of the intensity of environmental regulations as the dummy variable (ER). Considering the complementary role of the informal mechanism to formal mechanisms, we set the value of the sample with weak environmental regulations as 1, meaning that the intensity of environmental regulations is lower than the median, otherwise the value is 0. Then we use the DDD model to test how the impact of the significant PEC increase caused by the PM2.5 surge event on corporate CEO turnover differs in regions with weak and strong environmental regulations. The results are shown in column (1) of Table 10, the regression coefficient of the three-way interaction term *Treat * Post * ER* is positive and significant, indicating that the effect of PEC on the increase of CEO turnover in heavily polluting companies is more significant in places with weak environmental regulations, which is consistent with our expectations. Finally, given the fact that the Interpretation of the Announcement on the Implementation of Special Emission Limits of Air Pollutants was published following the smog incident in 2013, we only retain the 19 province samples that implemented this policy and re-ran the DDD test. The results in column (2) of table 10 show that the regression coefficient of the three-way interaction term *Treat* * *Post* * *ER* is still positive and significant, which remains robust.

[Insert Table 10 around here]

4.5 The effect of smog on green investment expenditures of enterprises

Table 11 presents the examination results for Hypothesis 2. The regression coefficients of the key explanatory variable *Treat*Post* are all significantly positive at the 1% level. This indicates that after the PM 2.5 surge, compared with non-highly-polluting businesses, highly polluting businesses significantly increase their green investment expenditures, which agrees with the theoretical expectation of Hypothesis 2 in this study. Economically, compared with non-highly-polluting businesses, the proportion of green investment expenditures in total assets increases by 90% in highly polluting businesses, whose green investment expenditures increase by 116%.

[Insert Table 11 around here]

4.6 Smog, green investment, and corporate CEO changes

Table 12 presents the examination results for Hypothesis 3. The regression coefficients of the third-degree interaction term *Treat*Post*GI* are all significantly negative at the 5% level. The regression coefficients of the second-degree interaction term *Treat*Post* are still significantly positive. This indicates that after the PM 2.5 surge, green investment reduces the increase in highly polluting businesses' CEO turnovers caused by the public's attention to the environment. This agrees with the theoretical expectation of Hypothesis 3 in this study. Economically, every standard deviation increase in the green investment expenditure reduces 13% of the increase in polluting businesses' CEO turnover caused by environmental governance pressure.

[Insert Table 12 around here]

4.7 Further research

The theoretical and empirical analyses indicate that after the PM 2.5 surge, the rapid increase in the pressure from the public's environmental concern results in a significantly higher probability of CEO turnover in heavy-polluting businesses. Businesses relieve such pressure by increasing green investment expenditure, which indeed reduces the CEO turnover in heavy-polluting businesses caused by the increasing PEC. Here, this study considers the possible influence of regional difference and infers that if the pollution problem in the region where a business is located becomes more serious, the local people's attention to the environmental problems is also greater. This, theoretically, can contribute to a more significant increase in the probability of CEO turnover. Hence, we divide the sample into the two groups, those in areas with increasing smog intensity and decreasing smog intensity, according to the smog intensities of the provinces and municipalities where the businesses are located for grouped examination.

Table 13 presents the examination results for model (1). For businesses in the areas of increasing smog intensity, the regression coefficient of *Treat*Post* reaches 0.092 at the 1% significance level. This value is higher than 0.061 in the standard regression. For businesses in the areas of decreasing smog intensity, the regression coefficient of *Treat*Post* is only 0.003 and is insignificant. The grouped examination results are completely consistent with the expectations.

Table 14 presents the grouped examination results for model (2). Regardless of being in the areas of increasing or decreasing smog intensity, the regression coefficients of *Treat*Post* are all significantly positive. This indicates that the PM 2.5 surge generally increases green investment in polluting businesses.

Table 15 presents the grouped regression results for model (3). For businesses in the areas of increasing smog intensity, the regression coefficient of *Treat*Post*GI* is significantly negative, and the coefficient values are all greater than the results for the entire sample. For businesses in the areas of decreasing smog intensity, the regression coefficient of *Treat*Post*GI* is insignificant. This indicates that green investments reduce the increase in polluting businesses' CEO turnover caused by smog to a larger degree in areas of increasing smog intensity.

[Insert Table 13-15 around here]

5. Conclusions and policy implications

In recent years, as the public's concern with environmental issues has continued to grow, the environment has become a major factor in company decision-making. Different from the existing empirical research, which mainly examines the influence of hard system constraints such as environmental regulations on business decision making, the focus of this study is on investigating the influence of soft system constraints, namely PEC, on businesses' environmental investment behaviors. This study aims to overcome the serious endogenous problems that possibly occur when studying the influence of PECs on businesses' decision-making behaviors. In view of this, this study constructed a quasi-natural experiment on the PM 2.5 surge extreme event in China in 2011, which increase public concerns for smog significantly, and the effect of the environment on CEO turnover was investigated using DID. Chinese listed companies 4 years before and after the incident are used as the sample for empirical research on the influence of this incident on CEO turnover in heavy-polluting businesses and their green-investment decision making.

The major empirical conclusions of this study are as follows: First, the rapid increase in the pressure from the public's environmental concern significantly increases the CEO turnover probability in heavy-polluting businesses. After the PM 2.5 surge, compared with non-heavy-polluting businesses, the CEO turnover probability of heavy-polluting businesses significantly increases by 25% on average. Second, to relieve the rapidly increasing pressure from the public's environmental concern, businesses increase their green investment. After the PM 2.5 surge, heavy-polluting businesses significantly increase their green investment expenditure. In addition, the increase in green investment significantly attenuates the positive influence of PEC on the CEO turnover probability of heavy-polluting businesses. Third, the rapidly increasing pressure from the public's environmental concern causes significant increases in the CEO turnover probability of heavy-polluting businesses. Additionally, a higher increase CEO turnover in heavy-polluting businesses is observed when these businesses reduce their green investment expenditure as the PEC increases. The two types of CEO turnover increase are significant only in regions with increasing PM2.5 concentration. However, the effect of soaring pressure from the public's environmental concern on the increase of businesses' green investment is significant in all regions.

The abovementioned conclusions have critical policy implications. First, different from businesses' passive increase of environmental investment under the hard system constraints of environmental regulations, when PEC increases, social attention, and pressure make businesses actively increase their environmental investment. Consequently, to improve businesses' environmental performance in the future, in addition, to compel businesses to incur related economic costs through environmental regulations, the promotion of environmental issues to the public should be strengthened. Such promotion improves PEC, the social pressure from which on businesses thus makes them actively increase their environmental investment. Second, with increasing public attention on environmental problems, businesses will actively increase their green investment in consideration of the massive social benefits of environmental investment. Therefore, in addition to increasing punishments for businesses with poor environmental performance, the government should increase positive promotion for businesses with excellent environmental performance. The promotion enhances the social benefits of good environmental performance and thus encourages businesses to actively improve their performance. Finally, corporate governance plays a critical role in the effect of PEC on businesses' environmental decision-making. The rapidly increasing environmental awareness of the public improves the environmental assessment pressure on CEOs, which can be relieved by increasing environmental investment. Accordingly, corporate governance on environmental improvement can facilitate the active response of businesses to external attention to their environmental governance performance and is conducive to their active increase of environmental investment.

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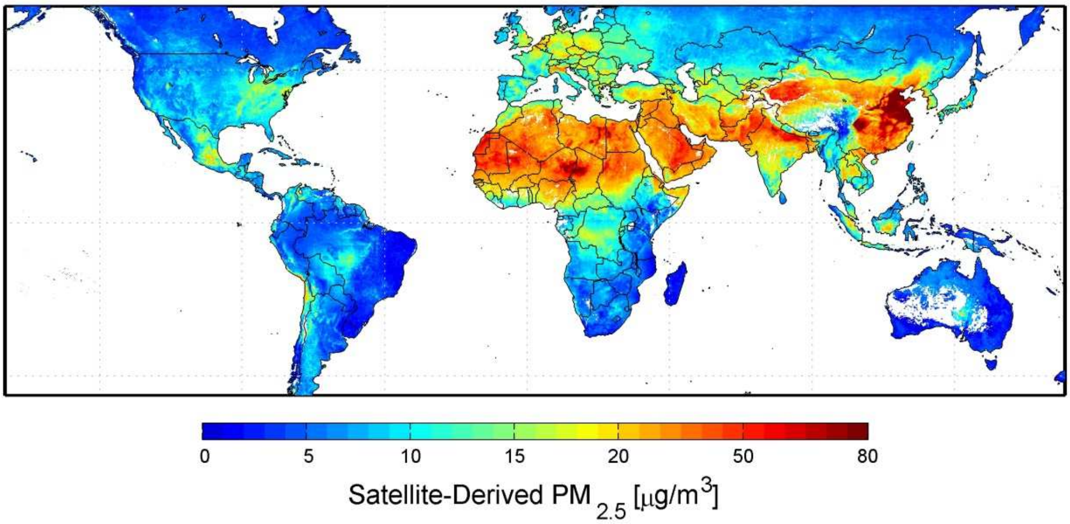

Figure 1. Global satellite-derived map of PM2.5 averaged over 2001-2006

Source: https://www.nasa.gov/topics/earth/features/health-sapping.html

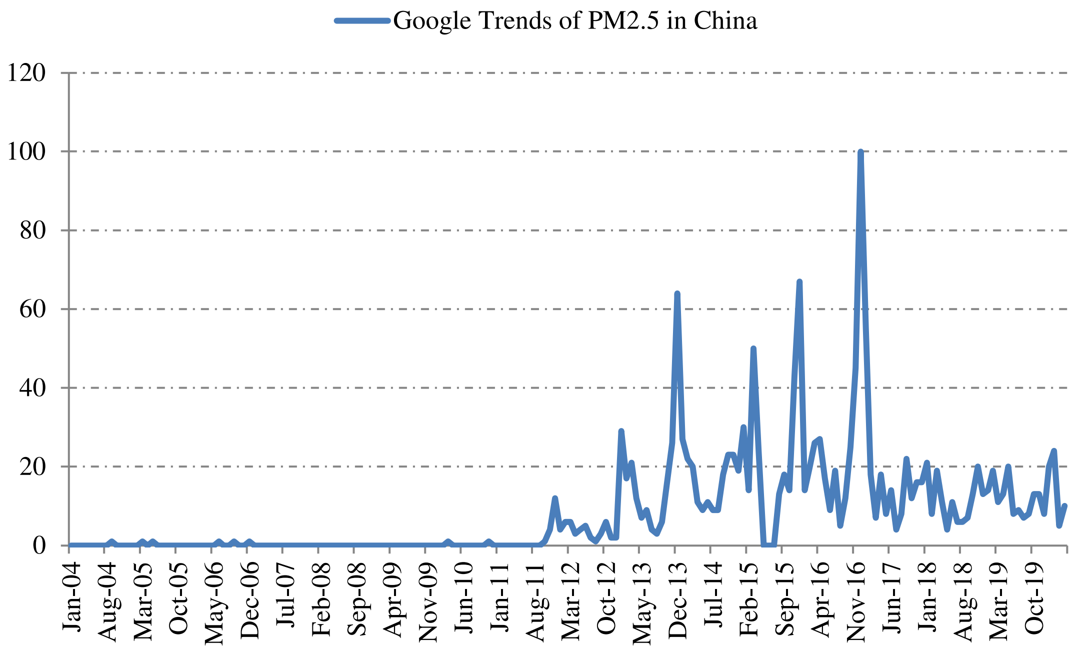

Figure 2. 2004.1-2020.4 Chinese "PM2.5" Google Trends

Source: https://trends.google.com.tw/trends/?geo=TW

Table 1 Variables definition

Variables	Definition
Turnover	A dummy variable that equals 1 if a CEO change in the current year, and 0 otherwise.
Treat	A dummy variable that equals 1 if a heavy pollution industry, and 0 otherwise.
Post	A dummy variable that is equal to 1 before 2011, and 0 otherwise.
GI_1	The value of green investment expenditure divided by the total asset.
GI_2	The natural logarithm of green investment expenditure.
Size	Firm size, Natural log of Market capitalization.
Leverage	The total long-term debt divided by total assets.
Tang	The proportion of fixed assets to total assets.
Margin	The ratio of earnings before extraordinary items to book value of total sales.
Com	The executive salary that the natural logarithm of sum of the salary of the top three executives.
Dual	CEO duality: a dummy variable, with 0 for a company having separate CEO and chairman, and 1 otherwise.
Board	The total number of directors.
Independent	The proportion of independent directors to the total number of directors.
SOE	A dummy variable that equals 1 if the ultimate controlling shareholder of a listed firm is the state and 0 otherwise.
Top1Hold	Top management shareholding ratio.

Table 2. Descriptive statistics

Variables	Obs.	Mean	Median	Min	Max	STD
Turnover	11,202	0.244	0	0	1	0.430
Treat	11,202	0.398	0	0	1	0.490
Post	11,202	0.619	1	0	1	0.486
GI_1	11,202	0.178	0	0	3.214	0.609
GI_2	11,202	1.953	0	0	16.90	5.087
Size	11,202	21.75	21.60	19.03	25.32	1.225
Leverage	11,202	0.437	0.434	0.050	0.908	0.209
Tang	11,202	0.265	0.235	0.001	0.750	0.164
Margin	11,202	0.260	0.228	0	1	0.167
Com	11,202	13.90	13.92	11.16	15.80	0.744
Dual	11,202	0.241	0	0	1	0.428
Board	11,202	8.879	9	3	18	1.788
Independent	11,202	0.369	0.333	0.091	0.714	0.053
SOE	11,202	0.227	0	0	1	0.419
Top1Hold	11,202	0.366	0.350	0.034	0.900	0.152

Table 3. Benchmark regression

Dependent Variable: *Turnover*	(1)	(2)	(3)
*Treat * Post*	0.064***	0.059***	0.061***
	(0.021)	(0.020)	(0.019)
Treat	-0.037*	-0.011	-0.023
	(0.022)	(0.028)	(0.025)
Size		-0.025***	-0.023***
		(0.005)	(0.006)
Leverage		0.012	0.008
		(0.024)	(0.024)
Tang		-0.158***	-0.163***
		(0.029)	(0.029)
Margin		0.040	0.060**
		(0.029)	(0.028)
Com			-0.024***
			(0.007)
Dual			-0.022**
			(0.010)
Board			0.000
			(0.003)
Independent			-0.031
			(0.083)
SOE			0.004
			(0.014)
Top1Hold			0.138***
			(0.034)
Year and Industry FE	*Yes*	*Yes*	*Yes*
Adj R^2	0.025	0.033	0.037
Obs.	11,202	11,202	11,202

Noted: The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 4. Test for parallel trends

Dependent Variable: *Turnover*	(1)	
*Treat * Year-3*	0.068	(0.051)
*Treat * Year-2*	0.054	(0.049)
*Treat * Year-1*	0.022	(0.054)
*Treat * Year+1*	0.055	(0.041)
*Treat * Year+2*	0.123**	(0.049)
*Treat * Year+3*	0.079*	(0.044)
*Treat * Year+4*	0.127***	(0.041)
Treat	-0.058	(0.038)
Size	-0.023***	(0.005)
Leverage	0.008	(0.024)
Tang	-0.162***	(0.028)
Margin	0.059**	(0.028)
Com	-0.024***	(0.007)
Dual	-0.022**	(0.010)
Board	0.000	(0.003)
Independent	-0.033	(0.083)
SOE	0.004	(0.013)
Top1Hold	0.137***	(0.034)
Year and Industry FE	*Yes*	
Adj R^2	0.025	
Obs.	11,202	

Noted: The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 5. Placebo test

Dependent Variable: *Turnover*	(1)	(2)	(3)
*Treat * Post08*	0.047		
	(0.045)		
*Treat * Post09*		0.004	
		(0.036)	
*Treat * Post10*			-0.016
			(0.038)
Treat	-0.028	0.006	0.013
	(0.041)	(0.035)	(0.033)
Control Variables	*Yes*	*Yes*	*Yes*
Year and Industry FE	*Yes*	*Yes*	*Yes*
Adj R^2	0.057	0.056	0.056
Obs.	4,292	4,292	4,292

Noted: The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 6. Robustness tests with alternative regression models

Dependent Variable: *Turnover*	(1)	(2)	(3)
	Logit	Probit	Firm FE
*Treat * Post*	0.335***	0.194***	0.049**
	(0.105)	(0.060)	(0.019)
Treat	-0.108	-0.064	
	(0.142)	(0.081)	
Control Variables	*Yes*	*Yes*	*Yes*
Year and Industry FE	*Yes*	*Yes*	*Yes*
Adj R^2/Pseudo R^2	0.032	0.032	0.030
Obs.	11,202	11,202	11,202

Noted: The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 7. Robustness test: DID model

Dependent Variable: *Turnover*	(1)	(2)	(3)	(4)	(5)
	Include t=0	Air Pollution	All Industries	Restrict Places	PSM
*Treat * Post*	0.048***	0.033*	0.035**	0.065	0.112***
	(0.017)	(0.017)	(0.015)	(0.019)	(0.033)
Treat	-0.020	0.006	-0.021	-0.012	-0.008
	(0.025)	(0.034)	(0.025)	(0.026)	(0.030)
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year and Industry FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adj R^2	0.036	0.036	0.034	0.043	0.013
Obs.	12,738	11,202	18,476	8897	5807

Noted: (1) Including the 2011 (post) sample. (2) It only lists air pollution industries as heavy polluting industries. (3) Including all industries. (4) It only lists 19 provinces and municipalities subject to emission restrictions such as Beijing and Shanghai. (5) PSM matching sample. The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 8. Robustness test: controlling other factors affecting CEO change

Dependent Variable: *Turnover*	(1)	(2)	(3)
	Include Age/Gender	Drop Retirement Sample	Drop Irregularity Sample
*Treat * Post*	0.026**	0.028**	0.034**
	(0.013)	(0.014)	(0.015)
Treat	-0.012	-0.013	-0.017
	(0.021)	(0.021)	(0.023)
Age	-0.232***	-0.246***	-0.248***
	(0.032)	(0.033)	(0.037)
Female	-0.017	-0.016	-0.018
	(0.011)	(0.011)	(0.013)
Control Variables	*Yes*	*Yes*	*Yes*
Year and Industry FE	*Yes*	*Yes*	*Yes*
Adj R^2	0.048	0.048	0.047
Obs.	9,381	9,287	8,231

Noted: The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 9. Robust test: Consider macroeconomic factors industry effect

Dependent Variable: *Turnover*	(1)	(2)	(3)	(4)
*Treat * Post*	0.067***	0.050***	0.047***	0.034**
	(0.019)	(0.019)	(0.016)	(0.016)
Treat	-0.029	-0.009		
	(0.024)	(0.024)		
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*
Macro Control Variables	*Yes*	*Yes*	*No*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
*Year*City FE*	*No*	*Yes*	*No*	*Yes*
Industry (2 digits)FE	*Yes*	*Yes*	*No*	*Yes*
Industry (5 digits)FE	*No*	*No*	*Yes*	*Yes*
Adj R^2	0.036	0.154	0.060	0.176
Obs.	10,118	9,599	11,199	9,596

Noted: The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 10. Robustness test: DDD model

Dependent Variable: *Turnover*	(1)	(4)
	Full Sample	Restrict Places
*Treat * Post * ER*	0.0612*	0.059*
	(0.032)	(0.034)
*Post * ER*	0.028	0.028
	(0.021)	(0.022)
*Treat * ER*	-0.043*	-0.035
	(0.025)	(0.030)
ER	-0.014	-0.012
	(0.017)	(0.022)
*Treat * Post*	0.013	0.015
	(0.025)	(0.026)
Treat	0.014	0.018
	(0.026)	(0.030)
Control Variables	*Yes*	*Yes*
Year and Industry FE	*Yes*	*Yes*
Adj R^2	0.028	0.033
Obs.	9,215	7,282

Noted: The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 11. The effect of smog on green investment expenditures of enterprises

Dependent Variable:	(1) *GI_1*	(2) *GI_2*
*Treat * Post*	0.161***	1.158**
	(0.060)	(0.476)
Treat	-0.045	-0.670
	(0.063)	(0.534)
Control Variables	*Yes*	*Yes*
Year and Industry FE	*Yes*	*Yes*
Adj R^2	0.100	0.133
Obs.	11,202	11,202

Noted: The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 12. Smog, green investment, and corporate CEO changes

Dependent Variable: *Turnover*	(1)	(2)
	GI_1	*GI_2*
*Treat * Post * GI*	-0.073**	-0.008**
	(0.034)	(0.003)
*Post * GI*	0.081***	0.011***
	(0.020)	(0.002)
*Treat * GI*	0.058*	0.007**
	(0.032)	(0.003)
GI	-0.066***	-0.009***
	(0.018)	(0.002)
*Treat * Post*	0.066***	0.064***
	(0.020)	(0.021)
Treat	-0.025	-0.027
	(0.025)	(0.025)
Control Variables	*Yes*	*Yes*
Year and Industry FE	*Yes*	*Yes*
Adj R^2	0.038	0.038
Obs.	11,202	11,202

Noted: The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 13. The effect of smog on CEO changes: regional smog intensity grouping

Dependent Variable: *Turnover*	(1)	(2)
	Local PM 2.5 Inc	Local PM 2.5 Dec
*Treat * Post*	0.092***	0.003
	(0.029)	(0.020)
Treat	-0.066**	0.042
	(0.033)	(0.026)
Control Variables	*Yes*	*Yes*
Year and Industry FE	*Yes*	*Yes*
Adj R^2	0.111	0.024
Obs.	5,526	5,676
Chi^2	7.12***	

Noted: (1) Sample of local PM2.5 increase compared to the previous year. (2) Sample of local PM2.5 decrease compared to the previous year. The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 14. Effect of smog on corporate green investment expenditure: regional smog intensity grouping

Dependent Variable:	(1) *GI_1*	(2) *GI_1*	(3) *GI_2*	(4) *GI_2*
	Local PM 2.5 Inc	Local PM 2.5 Dec	Local PM 2.5 Inc	Local PM 2.5 Dec
*Treat * Post*	0.167***	0.164**	1.059**	1.278**
	(0.054)	(0.072)	(0.446)	(0.574)
Treat	-0.019	-0.075	-0.524	-0.826
	(0.066)	(0.066)	(0.483)	(0.610)
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*
Year and Industry FE	*Yes*	*Yes*	*Yes*	*Yes*
Adj R^2	0.099	0.106	0.133	0.136
Obs.	5,526	5,676	5,526	5,676
Chi^2	0.00		0.35	

Noted: (1) & (3) Sample of local PM2.5 increase compared to the previous year. (2) & (4) Sample of local PM2.5 decrease compared to the previous year. The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.

Table 15. Smog, green investment, and corporate CEO changes: Regional smog intensity grouping

Dependent Variable: *Turnover*	(1)	(2)	(3)	(4)
	Local PM 2.5 Inc	Local PM 2.5 Dec	Local PM 2.5 Inc	Local PM 2.5 Dec
*Treat * Post * GI*	-0.119**	0.007	-0.011**	0.000
	(0.056)	(0.033)	(0.005)	(0.004)
*Post * GI*	0.139***	0.005	0.015***	0.003
	(0.039)	(0.027)	(0.004)	(0.004)
*Treat * GI*	0.072	0.006	0.009*	0.001
	(0.046)	(0.031)	(0.005)	(0.004)
GI	-0.084***	-0.027	-0.010***	-0.004
	(0.030)	(0.023)	(0.003)	(0.003)
*Treat * Post*	0.099***	0.003	0.096***	0.001
	(0.030)	(0.021)	(0.032)	(0.020)
Treat	-0.065**	0.041	-0.068**	0.042
	(0.032)	(0.025)	(0.033)	(0.026)
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*
Year and Industry FE	*Yes*	*Yes*	*Yes*	*Yes*
Adj R^2	0.113	0.025	0.113	0.025
Obs.	5,526	5,676	5,526	5,676
Chi^2	3.73*		2.31	

Noted: (1) & (3) Sample of local PM2.5 increase compared to the previous year. (2) & (4) Sample of local PM2.5 decrease compared to the previous year. The robust standard errors clustered by the industry are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on year and industry fixed effects, respectively.