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ABSTRACT

Air Pollution and Green Innovation*

With air pollution remaining a significant problem in many regions globally, an increasing number of environmentally conscious entrepreneurs have been taking initiatives to combat this issue, accompanied by a growing environmental awareness among the general public. To test the strength of this relationship, we use individual-level information from an enterprise survey in China in 2018 and conducted instrumental variable analyses to study the impact of air pollution on the green innovation behaviours of non-agricultural entrepreneurs. The results indicate that, on average, a one standard deviation increase in PM2.5 concentration is associated with a 4.3 percentage points increase in green innovation (or a 11.9 percentage points increase in green innovation intensity). Entrepreneurs' gambling preferences could potentially mediate the relationship between air pollution and green innovation, while expected firm income and actual firm income may act as suppressors. Specifically, entrepreneurs who launch their businesses following the implementation of environmental policies are more likely to adopt green innovation practices. This study provides insight into why there is a growing trend of environmentally-conscious entrepreneurs in regions with high levels of air pollution.

JEL Classification: J01, Q53, Q55

Keywords: air pollution, green innovation, China

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1. Introduction

Green innovation is a valuable approach to achieving environmental objectives, and entrepreneurs, as key decision-makers in companies, can play a crucial role in promoting environmental awareness and taking green actions that contribute to improving air quality and addressing environmental challenges[1]. Entrepreneurs may be incentivized to change their behaviours and become agents of environmental improvement due to the presence of air pollution. However, previous studies have not focused on the potential changes in green innovation behaviours of entrepreneurs in response to air pollution. The most relevant study to date has suggested that air pollution may reduce the willingness of middle-aged and elderly adults to start a business[2]. However, the study did not give much attention to entrepreneurs who continue to operate their businesses despite experiencing air pollution.

Furthermore, the existing literature on the impacts of air pollution on individual well-being and behaviours presents mixed findings. While some studies suggest that air pollution could have short-term positive effects on local production and human welfare, this is in contrast to other research findings, leading to conflicting evidence. For example, increased air pollution may be related to the increase in short-term income[3]. However, much of the literature states that air pollution affects physical and mental health[4] and productivity[5] in the short and long term. Our study aims to add fundamental evidence to the possible relationship between air pollution and entrepreneurs' adoption of green innovation behaviours. In doing so, we contribute insights on potential adaptive responses (i.e., "flight or fight" survival mechanisms) and social costs associated with air pollution, as well as underlying factors that drive entrepreneurs' adoption of green innovation practices.

In the face of environmental adversity, such as air pollution, people may have flight or fight responses. On the one hand, air pollution can have detrimental effects on human capital. To avoid these negative effects, individuals may take action, such as relocating to areas with lower pollution levels. Furthermore, studies have suggested that people with higher levels of education are more likely to migrate to such areas[6]. On the other hand, individuals may be motivated by personal or corporate social responsibility to address local environmental problems. Adversity can also build resilience and adaptability to polluted environments[7,8]. At the same time, it is important to acknowledge that when the government enforces environmental policies, individuals who are subject to these regulations, such as entrepreneurs, may become more attentive to environmental concerns and may be compelled to take actions towards environmental protection, such as adopting green innovation.

The negative effects of air pollution on entrepreneurs have been widely acknowledged, but the same attention has not been reserved to potential positive outcomes. Previous studies seem to have overlooked this aspect, for several reasons. Firstly, studies have focused on the general population rather than specific subgroups that are more likely to struggle with air pollution. Secondly, few studies have examined the relationship between air pollution and the increase in environmental awareness and actions. Thirdly, the role of environmental policies in the impact of air pollution has not been fully explored in existing research.

Entrepreneurs who have been operating their businesses in areas with high air pollution for a long time may have developed a high level of resilience and found ways to overcome local air pollution. In addition, since the behaviour of the entrepreneur is closely linked to the image of the company in society, maintaining a positive corporate image may increase the value of the brand and lead to high benefits for the company. Therefore, entrepreneurs who are aware of the potential negative impacts of air pollution on society and the environment may feel a sense of responsibility to contribute to environmental protection. Non-compliance with relevant policies and regulations may pose risks to business success, which may motivate entrepreneurs to adopt eco-friendly behaviours. Finally, entrepreneurs who are directly affected by current or proposed environmental policies may be more attentive to air pollution and more inclined to engage in eco-friendly practices compared to those who are not affected.

Besides addressing the research questions of how entrepreneurs' green innovation behaviours are impacted by air pollution, we also investigate the mechanisms behind this impact and which populations are affected. The current literature on air pollution outcomes has mostly focused on the negative effects and has paid less attention to cleaner air after the implementation of environmental policies, people's adaptation to air pollution, and their actions to address the problem (such as increasing environmental awareness and activism). Therefore, our research provides novel insights into these less-explored areas.

In this paper, we use an enterprise survey that includes respondents' (i.e., entrepreneurs, managers and others) personal information. After linking this dataset with the National Aeronautics and Space Administration (NASA) satellite data of air pollution and climate conditions as well as city-level characteristics from official statistical yearbooks, we assess the impact of air pollution on entrepreneurs' green innovation behaviours at the micro level. We use individual-level characteristics to explore the channels through which air pollution impacts green innovation and conduct heterogeneity tests according to how entrepreneurs are affected by environmental policies. Our study shows that entrepreneurs in highly polluted areas are more likely to adopt green innovations, and this effect is mediated by their increased preferences for risk-taking. Additionally, while air pollution can reduce both expected and actual firm income, the negative effects of low income on green innovation offset this positive impact. We also find that the relationship between air pollution and green innovation is heterogeneous, with firms established after the implementation of environmental policies being more likely to adopt green innovations. Moreover, our results suggest that greater environmental policy stringency can amplify the positive relationship between air pollution and green innovation. Overall, our study contributes to the literature on the consequences of air pollution and sheds light on the role of environmental policy in promoting green innovation.

We examine hypotheses in the Chinese context for several reasons. First of all, China is a developing country suffering from serious air pollution problems, and the air quality has been improving in recent years due to environmental governance decisions. Yet, there are areas where the annual average PM2.5 still far exceeds the standard set by the World Health Organization. Second, China's Clean Air Act (CCAA), promulgated in September 2013, is the most influential environmental policy in recent years. This policy has led to a continuous decline in China's overall air pollution since 2014, and the policy has set various goals for reducing PM2.5 in different places, allowing us to explore the role of the environmental policy in the impact of air pollution and provide a background for a natural experiment. Third, the number of environmentalists in China is constantly increasing. Since Chai Jing's documentary Under the Dome (i.e., a documentary investigation into China's smog) in 2014 has been widely disseminated and discussed on social media, more and more people have begun to pay attention to environmental issues and understand that it is not advisable to pursue economic growth at the expense of environment.

This study aims to fill the literature on the impact of air pollution on people's decision-making and adaptive behaviours. First, our study contributes to the existing literature by shedding light on the positive impact of air pollution on environmental entrepreneurship. We argue that individuals who have experienced prolonged exposure to air pollution may develop resilience to it and become more determined to find solutions to address the issue. Our research also adds to the literature on adversity and resilience by highlighting the notion that adversity can foster resilience and determination. We examine how entrepreneurs can overcome the challenges posed by air pollution, operate in adverse conditions, and take actions to mitigate its impact. Second, we contribute to the analysis of various pathways that may influence the impact of air pollution on green innovation. These pathways include factors such as risk (gambling) preferences, expected firm income, and actual firm income. The specific mechanisms through which air pollution affects green innovation remain unclear, and previous research has produced inconsistent results regarding the relationship between air pollution and risk preferences (i.e., conservative and aggressive) and actual income (i.e., negative and positive) in the short term. We aim to examine these factors as potential mediators to better understand how air pollution impacts green innovation. Third, our focus is on the heterogeneous role of environmental policy in the relationship between air pollution and its impact on people. This can broaden the discussion on the effects of air pollution, as the importance of this particular environmental policy has been largely overlooked in previous studies.

2. Literature review

2.1 Air pollution and green innovation

Chronic exposure to air pollution may cause entrepreneurs to either avoid its negative effects by migrating to areas with lower levels of air pollution or to fight against it by staying in the local area and finding ways to solve the problem. We hypothesize that entrepreneurs who are regularly exposed to air pollution may be motivated to adopt green innovations for two primary reasons.

First, entrepreneurs may be motivated to combat air pollution and mitigate its negative impacts through adaptation and resilience. The literature on climate change adaptation suggests that individuals facing environmental adversity may adapt and build resilience. For example, in response to drought-induced crop failure and income losses, Mali's smallholder farmers may use traditional institutions such as polygyny to improve their resilience and adaptation strategy[9]. Similarly, individuals living under prolonged exposure to air pollution may develop physical or psychological adaptations to mitigate its negative impacts. A relevant study in China also proposed the existence of hedonic adaptation (i.e., the process that will help to attenuate the long-term psychological impact of unfavourable circumstances[10]) and suggested that people may upwardly adjust their neutral reference point for air pollution levels if exposed to long-term air pollution[4].

In addition, the ability to adapt to air pollution is strongly linked to air pollution resilience. Exposure to environmental challenges, such as air pollution, may contribute to the development and reinforcement of an individual's or a group's resilience. Resilience is the ability of individuals or groups to avoid adverse effects and make changes to cope with difficult situations[11]. The resilience of entrepreneurs may be viewed as their ability to bounce back and seek new business opportunities[12] after failure[13] or environmental issues[14,15]. Based on relevant literature, it has been suggested that adversities such as earthquakes and famines can increase people's resilience to future misfortunes[16]. For instance, post-disaster entrepreneurship typically arises when established organizations are unable to fully address the needs arising from the disaster[17–19]. It is important to note that the ability to improve resilience and reduce vulnerability to threats, including the impacts of air pollution, depends on several economic factors. These include the level of human capital, as well as the capacity of the community and social capital[20–22].

Second, entrepreneurs might implement green innovation for the fulfilment of societal goals and the creation of a corporate reputation. Our hypothesis is that individuals exposed to air pollution may be motivated to improve local environmental conditions and air quality. Workers who have a strong sense of environmental activism may even choose to work for environmental organizations or companies in order to combat air pollution in their communities. For individuals with a strong sense of corporate social responsibility and resilient entrepreneurial spirit, exposure to air pollution may increase their willingness to start businesses or restructure existing ones to help community members and mitigate the negative effects of air pollution on local populations[23]. The decision to pursue investment opportunities may be influenced by underlying motivations for seeking additional resources. While victims of air pollution may adopt a resource-preservation posture consistent with the Conservation of Resources motivational theory, individuals with high levels of human capital who do not invest resources may experience regret for their conservative actions. In addition, individuals who have a strong altruistic motivation to help others may be more inclined to pursue investment opportunities that can lead to greater resources and thus greater ability to make a positive impact[24].

From the discussion above, we hypothesize that green innovative behaviours may increase with increasing air pollution levels.

2.2 Mediating roles of gambling preferences, expected income, and income

First, air pollution has the potential to impact people's risk preferences, which could have implications for green innovation. Previous studies investigating this relationship have yielded mixed results. Air pollution might lead to a more conservative or more aggressive risk appetite. On one hand, if air pollution causes people to adopt a more conservative stance (perhaps due to the development of pessimistic attitudes), such as reducing investment in stocks[25], entrepreneurs may become less likely to engage in green innovation. For example, entrepreneurs may be hesitant to engage in radical eco-innovation activities in production unless the potential benefits and risks associated with the innovation can be accurately assessed. Specifically, unless the potential return on investment is clear and the risks are small or unlikely, entrepreneurs may be reluctant to undertake cleaner production eco-innovation (i.e., spontaneous eco-innovation, in contrast to pollution prevention eco-innovation or unspontaneous eco-innovation[1]). This is because they seek to minimize risks and ensure the long-term sustainability of their company's strategies and operations. On the other hand, if air pollution predisposes people to choose risky behaviours (due to aggressivity, impulsivity, irritability and loss of self-control[26]), such as committing violent and other crimes[27], then entrepreneurs may be motivated to engage in green innovation activities due to the potential advantages associated with environmental improvements, such as enhancing work efficiency, building a positive corporate image, and obtaining government policy support. When operating a business, entrepreneurs usually take on higher risks than employees, and it is improbable that they would be risk-averse if the business could continue to function in the presence of air pollution. In fact, air pollution may even increase the risk appetite of these entrepreneurs, leading to riskier behaviours such as gambling. Investing in innovation involves a certain degree of uncertainty and risk, which makes it similar to a lottery, a characteristic that is preferred by individuals who have a preference for gambling. Therefore, risk (gambling) preferences may have a more significant impact on innovative activities and ultimately result in greater innovation output[28,29].

Second, air pollution may impact green innovation behaviours through the firm's financial forecasting. Research indicates that air pollution can have adverse effects on cognition and increase pessimism, which can ultimately lead to a reduction in expected incomes of both individuals and firms. This could hinder green innovation, as firms may have limited financial resources to allocate towards eco-innovation. Innovating in this manner often involves additional financial investments, and in situations where expected income is low, enterprises might be more risk-averse and opt for conventional, less environmentally-friendly production processes instead of engaging in green innovation. Moreover, eco-innovation can be a high-risk endeavour that requires external assistance, such as from experts and additional financial resources, which could further compound financial constraints for firms[30]. This suggests that the impact of air pollution on green innovation may be suppressed by expected income, based on existing empirical evidence.

Third, the influence of air pollution on income could have implications for the adoption of green innovation. The productivity and income of individuals and companies may be negatively impacted by air pollution, which could also create financial constraints that affect the ability of companies to engage in green innovation[31]. The effects of expected income and income on green innovation may be similar since companies may need to allocate additional resources and use them efficiently in order to innovate their production processes and operational management[1].

Based on the reasoning above, we assume 1) air pollution increases green innovation by increasing gambling behaviours, 2) air pollution suppresses the increase in green innovation by reducing expected firm income, and 3) air pollution suppresses the increase in green innovation by reducing firm income.

2.3 The heterogeneous role of environmental policies

Our research identifies a heterogeneous role of environmental policy in the relationship between air pollution and green innovation. We find that entrepreneurial green innovation behaviours can take both passive forms, i.e., pollution prevention eco-innovation, and active forms, i.e., cleaner production eco-innovation. Both types of behaviours, passive and active, can contribute to environmental performance but involve different incentives and approaches. Passive behaviours refer to enterprises' efforts in environmental protection in response to government regulations after environmental problems occur. Active behaviours involve the spontaneous redesign of production processes to meet the needs of the environment in anticipation of future environmental challenges[1]. Hence, our hypothesis suggests that the implementation of environmental policy will lead to an increase in green innovation behaviours among entrepreneurs compared to pre-policy levels. Entrepreneurs who proactively engage in green innovation behaviours may not be affected by environmental policies and will continue to take such actions, regardless of government regulations. However, after policy implementation, the number of entrepreneurs carrying out green innovation behaviours will increase, as it includes both active and passive eco-entrepreneurs. Environmental policy implementation can also enhance societal environmental awareness and encourage more entrepreneurs to initiate independent green innovations.

Therefore, we assume that the implementation of environmental policy amplifies the positive relationship between air pollution and green innovation.

3. Methods

Data

The survey data used in this study is the Enterprise survey for innovation and entrepreneurship in China (ESIEC). It is collected by Peking University through scientific sampling method and field tracking. It provides national representative micro data reflecting Chinese enterprises' information, such as entrepreneurs' personal characteristics (i.e., including employer entrepreneurs and solo entrepreneurs), basic enterprise information and innovation activities. Interview participants include entrepreneurs, managers and other workers in the company. The baseline survey was conducted in 2018 and a follow-up COVID-19-related survey was in 2020. We use the 2018 ESIEC survey due to its rich information on green innovation. Moreover, air pollution and weather conditions data linked with this dataset is obtained from NASA. The satellite-based surface-level air pollution data has a spatial resolution of 0.1° × 0.1°.

The original data is estimated by Washington University in St. Louis (V5.GL.02). The data is calibrated by Geographically Weighted Regression (GWR) after com combining Aerosol Optical Depth (AOD) retrievals from multiple satellite instruments. Thermal inversions and weather data with a 0.1° × 0.1° spatial resolution are sourced from the NASA Goddard Earth Sciences (GES) Data and Information Services Centre (DISC). The data is calculated from Modern-Era Retrospective Analysis for Research and Applications version 2 project (MERRA-2) instantaneous 3-dimensional 6-hourly data with a 0.5° × 0.625° spatial resolution and 42 pressure levels (V5.12.4) and Global Land Data Assimilation System (GLDAS) Noah Land Surface Model L4 3-hourly data with a 0.25° × 0.25° spatial resolution (V2.1), respectively. Additionally, we also link city-level information with the dataset. The data is gathered from China City Statistical Yearbook and China Statistical Yearbook.

Empirical model

We measure green innovation behaviours from two dimensions. Binary green innovation variable $I\_dum_{i,j,t}$ is one if entrepreneur i in city j at time t adopt green innovation (i.e., providing new products or services, having production processes, organizational methods or marketing that is beneficial to the environment, which could occur during the production process or post-sales usage), and 0 otherwise. Green innovation intensity variable is the sum of the aspects of green innovation behaviours. There are eleven aspects of green innovation behaviours: reduce energy consumption per unit of output, reduce the use of materials per unit of output, reduce carbon emissions, reduce air pollution (sulphide, nitride and so on), reduce water or soil pollution, reduce noise pollution, replacing fossil energy with renewable energy (such as using solar energy to replace coal), using less dangerous raw materials instead of raw materials with hazardous substances (such as mercury, lead, and cadmium), recycling wastewater and waste materials for self-sue or sale, reducing radioactive pollution (might for workers in the production process) and other green innovation behaviours. The linear probability models (LPM) of the green innovation dichotomous variable and green innovation intensity variable are as follows:

$$I\_dum_{i,j,t} = \alpha_0 P_{i,j,t} + X_{i,j,t} + \varepsilon_{i,j,t} \,, \tag{1}$$

$$I\_int_{i,j,t} = \alpha_1 P_{i,j,t} + X_{i,j,t} + \varepsilon_{i,j,t} \tag{2}$$

The independent variable of interest, city-level yearly mean PM2.5, is $P_{i,j,t}$. It is a reasonable measure of air pollution since it is more harmful to people's physical health than larger and more extensive air pollutants. Air pollution data from NASA is more accurate and reliable than air quality data from Chinese official monitors due to potential manipulation problems (i.e., Chinese government officers might underreport air pollution data for promotion incentives)[6]. The set of covariates $X_{i,j,t}$ includes individual-level attributes such as age and its square, male (yes = 1), high school or above education (yes = 1), migrant (yes = 1), has non-agricultural hukou (yes = 1), has children (yes = 1), married (yes = 1), han nationality (yes = 1), Chinese Communist Party member (yes = 1), has relevant entrepreneurial experiences (yes = 1), entrepreneurial type (solo entrepreneur = 0, employer entrepreneur = 1) and parents have a high school or above education (yes = 1). We control for firm-level information such as years of firm existence, newly established firm (yes = 1), the company belonging to the second industry (yes = 1) and the industry types of the company. To mitigate the influences from the city's economic and population characteristics, we real gross domestic product per capita (thousand yuan) and population density (per km2). Weather controls include ground-level temperature (°C) and ground-level wind speed (m/s). Considering the possibility of different variances of air pollution in counties within the city and spillover effects of air pollution, we also control for a dichotomous variable to represent a high variance of PM2.5 within the city (yes=1).

Endogeneity of air pollution

The usage of air pollution in Equation (1) and Equation (2) might not be able to show reasonable results due to endogenous issues of air pollution. The endogeneity arises from sorting problems (e.g., wealthy people tend to live in low-polluted areas or communities), avoidance behaviours in response to air pollution and the close correlation between air pollution and unobserved economic activities. We utilize predicted PM2.5 based on the value of thermal inversions, wind speed, wind direction, and the number of occurrences of thermal inversions as an instrumental variable of PM2.5. Thermal inversions occur when the air in lower layers is cooler than the air in higher layers of the atmosphere. PM2.5 tend to be high when thermal inversions occur[32]. The thermal inversion data sourced from NASA is different from National Oceanic and Atmospheric Administration (NOAA) data[33], where the former shows the average temperature in standard pressure points and the latter provides atmospheric temperature in detailed pressure points. We estimate the first step of the two-stage least squares (2SLS) method based on thermal inversions-induced air pollution as follows:

$$P_{i,j,t} = P\_fit_{i,j,t} + X_{i,j,t} + \varepsilon_{i,j,t} \ , \tag{3}$$

$$P\_fit_{i,j,t} = \sum_{0}^{t,j} \gamma_{1_{i,t,j}} InverValue_{i,t,j} + \sum_{0}^{t,j,l} \gamma_{2_{i,j,t,l}} WS_{i,j,t,l} + \sum_{0}^{t,j,l} \gamma_{3_{i,t,j,l}} WD_{i,j,t,l} + \sum_{0}^{t,j,l} \gamma_{4_{i,j,t,l}} InverDay_{i,j,t,l} + \varepsilon_{i,j,t}$$

(4)

In the above equations, where $P\_fit_{i,j,t}$ is the predicted value of PM2.5 for entrepreneur i in city j at time t. In Equation (3), $P_{i,j,t}$ and $X_{i,j,t}$ are the same PM2.5 and the set of control variables in Equation (1) and Equation (2). As for Equation (4), $InverValue_{i,j,t}$ is the value of thermal inversions computed from 1000-975, 975-950, 950-925, 925-900, 900-875 hPa for entrepreneur i at time t in city j; $WS_{i,j,t,l}$, $WD_{i,j,t,l}$, and $InverDay_{i,j,t,l}$ is wind speed, wind direction and the total number of occurrences of temperature inversions at time t in city j at layer l, respectively.

Mediation and heterogeneity

We utilize a three-step approach to investigate the mediation roles of possible channels[34] and used the sub-group analysis according to environmental policy to check heterogeneity. For the former, we regress the dependent variable on the independent variable (i.e., first step), regress the dependent variable on one of the mediators (i.e., second step) and regress the dependent variable, both the independent variable and one of the mediators (i.e., third step). To determine the partial mediation effects of the mediator, we need to find significant results of the independent variable and mediator in both regressions and the relatively lower coefficient of the independent variable in the third regression than in the first regression. There is full mediation effects of the mediator if the coefficient of the independent variable in the third regression is not significant. For the latter, we test the impact of air pollution on green innovation behaviors according to whether the company starts before or after the environmental policy implementation. We conduct a seemingly unrelated test to check whether or not the coefficients for the pre-policy cohort and post-policy cohort are equal. We also perform a further test on the impact of environmental policy on green innovation behaviours by generating a difference-in-differences (DID) estimator to show the stringency level of environmental policy. We generate the DID estimator by using the interaction of whether the firm started the business after the implementation of environmental policy and the level of environmental goals according to Supplementary Table 1 (i.e., since the provinces in ESIEC have 10% or above PM2.5 reduction targets, we assign categorical variables to the goals compared to the reference method[35], the greater the number, the higher the environmental policy stringency).

Sample sizes

The sample in the 2018 ESIEC survey contains 6005 observations. After excluding interviewees who do not provide detailed demographic information such as gender and those who are not entrepreneurs of the company, we obtain a final sample of 3465 observations. There are approximately 25.2% of them started businesses before the implementation of CCAA and about 74.8% of them created a company after the policy. The sample includes individuals from corporations and individual household businesses (both private and foreign-owned companies registered from 2010 to 2017) in 60 cities in Liaoning province, Shanghai city, Zhejiang province, Henan province, Guangdong province, and Gansu province in China.

4. Results

There are around 24.8% of entrepreneurs might take green innovation behaviours and the average number of aspects of green innovation behaviours is approximately 0.545. According to the summary statistics in Supplementary Table 2, there are no significant differences between entrepreneurs in the pre-policy and post-policy cohorts (i.e., start businesses before or after the environmental policy implementation, Welch's t-statistics equals 0.122 for green innovation dichotomous variable and equals to 0.434 for green innovation intensity). We check the distributions of the green innovation according to starting year of the company in Figure 1. The figure indicates the high levels of green innovation between 2012 and 2014 and similar average levels between pre-policy and post-policy cohorts. For the air pollution levels, the yearly average PM2.5 is 37.627. Those entrepreneurs who start businesses after the environmental policy tend to live in places with more severe air pollution than their pre-policy counterparts. Although the summary statistics do not point to a strong causal link between air pollution and green innovation behaviours, we start to use our LPM and 2SLS strategy to check the causal relationship.

We focus on instrumental-variables strategy results since it provides us with more reliable results than the LPM method (LMP models show similar and smaller estimates in Table 1). The 2SLS results of Table 1 show that a standard deviation increase in PM2.5 is associated with a 4.3% increase in the probability of having green innovation behaviours and a 11.9% increase in green innovation intensity scores.

When considering possible mediators, we find that in the relationship between air pollution and green innovation, the gambling preferences of entrepreneurs might play a mediator role after excluding people with the highest risk aversion, and the expected firm income and firm income are suppressor variables (Figure 2 and Supplementary Table 3). The increase in air pollution is positively associated with high-risk behaviours and thus amplifies the possibility of having green innovation and green innovation intensity, and negatively associated with low expected firm income and firm income. This factor might add a suppressive effect in the correlations between air pollution and green innovation.

We find significant impact heterogeneity in green innovation models across policy cohorts (Figure 3 and Supplementary Table 4). Probably due to the increase in pollution prevention eco-innovation or non-spontaneous eco-innovation, the high possibility of green innovation air pollution influenced by high air pollution is significant for the post-policy cohort whereas not significant for the pre-policy cohort. The seemingly unrelated estimation results show that the differences are significant (Prob>chi2=0.086 for green innovation models and Prob>chi2=0.654 for green innovation intensity models). We further test the impact of environmental policy on green innovation by using a DID estimator (i.e., the interaction of whether post-policy cohort and province-level environmental policy stringency) and find that the higher the environmental policy stringency, the higher the green innovation intensity for companies established after environmental policy implementation (Figure 4 and Supplementary Table 5).

When including additional instrumental variable, our findings are consistent with the findings from Table 1 (Supplementary Table 6). The identification is achieved by utilizing a generated instrumental variable based on heteroskedasticity in errors[36]. The results are robust if using an alternative sample by adding survey responses from both entrepreneurs and managers in our sample (Supplementary Table 7). We do not find the mediating role of environmental issues perception (Supplementary Table 8) and do not prove the significant response heterogeneity across entrepreneurial types (i.e., solo entrepreneur and employer entrepreneur) (Prob>chi2=0.565 for green innovation models, Prob>chi2=0.158 for green innovation intensity models, Supplementary Table 9). To test to what extent our estimates suffer from omitted variable bias, we adopt the Oster method to evaluate whether our estimates are robust to it[37]. The estimates meet the robustness standards that the bounds between controlled beta and bias-adjusted beta do not include zero and do not exceed or less than 2.8 standard errors of the controlled estimates. In order to capture the nonlinear effects of air pollution, we also include a quadratic term of air pollution and thermal inversion-induced air pollution; we do not find significant results due to weak instrumental variable issues.

5. Discussion

An expanding body of research has highlighted the adverse effects of air pollution, and individuals have been observed to "flee" to other locations to escape these detrimental impacts[6]. Our findings highlight the potential positive outcomes associated with severe air pollution, as individuals may be motivated to fight against it and contribute to environmental protection through green innovation. Specifically, we find that higher levels of air pollution are associated with higher probabilities and intensities of green innovation, indicating a potential silver lining to the negative impact of pollution on human health and well-being.

The impact of air pollution on green innovation can be influenced by various factors such as behaviours, emotions, and well-being. Air pollution may affect green innovation probability and intensity through channels such as gambling preferences, expected firm income, and firm income. Consistent with the literature showing a close relationship between air pollution and criminal activities[27], our findings suggest that air pollution may increase the risky behaviours of entrepreneurs, leading to a higher likelihood of engaging in green innovation behaviours and increasing the intensity of such activities. Our results also support the previous evidence about the depression[4] and productivity loss[33] caused by air pollution. We find that there may be a positive relationship between expected firm income and firm income with green innovation, and that both variables may be negatively impacted by air pollution.

The implementation of current environmental policies has the potential to promote pollution prevention eco-innovation and non-spontaneous eco-innovation, leading to environmentally-friendly behaviours among entrepreneurs and resulting in environmental benefits. Our heterogeneity tests and quasi-natural experiment identification results suggest that there is significant variation in the impact of environmental policy on the probability of green innovation among entrepreneurs who started their companies before and after the implementation of the policy. Additionally, the stringency of environmental policy is positively associated with the intensity of green innovation among entrepreneurs who start businesses after policy implementation. Gaining a deeper comprehension of the environmental advantages of entrepreneurship, the ways in which positive and negative effects offset each other, and methods for fostering resilience and encouraging green innovation will be vital for shaping environmental policy and obtaining a more comprehensive understanding of how individuals respond to air pollution.

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Table 1

The Impact of Air Pollution on Green Innovation

Dependent variable	(1) Green Innovation		(2) Green Innovation Intensity		(3) Green Innovation		(4) Green Innovation Intensity	
PM2.5 (μg/m^3)	0.004***	(0.001)	0.007**	(0.003)	0.004**	(0.002)	0.011*	(0.006)
Age	0.008*	(0.004)	0.034***	(0.012)	0.008*	(0.004)	0.034***	(0.012)
Age squared	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Male (yes = 1)	0.038**	(0.017)	0.122**	(0.047)	0.038**	(0.016)	0.123***	(0.047)
High school or above (yes = 1)	-0.015	(0.015)	0.006	(0.055)	-0.015	(0.015)	0.007	(0.055)
Migrant (yes = 1)	0.012	(0.016)	0.034	(0.061)	0.012	(0.016)	0.044	(0.062)
Non-agricultural hukou (yes = 1)	0.016	(0.013)	0.006	(0.047)	0.016	(0.013)	0.013	(0.047)
Has children (yes = 1)	0.044	(0.031)	0.131	(0.094)	0.044	(0.031)	0.126	(0.091)
Married (yes = 1)	0.002	(0.041)	-0.028	(0.121)	0.001	(0.040)	-0.037	(0.119)
Han nationality (yes = 1)	0.057**	(0.025)	0.177**	(0.079)	0.057**	(0.024)	0.172**	(0.076)
Chinese Communist Party member (yes = 1)	-0.002	(0.021)	-0.065	(0.073)	-0.002	(0.021)	-0.068	(0.073)
Relevant entrepreneurial experiences (yes = 1)	0.012	(0.013)	0.053	(0.056)	0.012	(0.013)	0.057	(0.057)
Entrepreneurial type (solo entrepreneur = 0, employer entrepreneur = 1)	0.006	(0.004)	0.011	(0.013)	0.006	(0.004)	0.013	(0.013)
Parents have high school or above education (yes = 1)	-0.040**	(0.016)	-0.033	(0.050)	-0.040***	(0.016)	-0.035	(0.050)
Years of firm existence	-0.023	(0.023)	-0.118	(0.089)	-0.023	(0.022)	-0.122	(0.090)
New established firm (yes = 1)	0.017	(0.018)	0.061	(0.059)	0.017	(0.018)	0.057	(0.059)
Second industry (yes = 1)	0.152***	(0.028)	0.394***	(0.087)	0.152***	(0.028)	0.400***	(0.085)
Industry types	-0.006***	(0.002)	-0.011*	(0.006)	-0.006***	(0.002)	-0.011*	(0.006)
Real gross domestic product per capita (thousand yuan)	-0.002	(0.002)	-0.007	(0.008)	-0.002	(0.003)	-0.004	(0.008)
Population density (per km^2)	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)
Ground-level temperature (°C)	0.007***	(0.002)	0.021**	(0.009)	0.007***	(0.002)	0.023**	(0.009)
Ground-level wind speed (m/s)	-0.016***	(0.005)	-0.040***	(0.014)	-0.016***	(0.005)	-0.048**	(0.019)
High variance of PM2.5 within city (yes=1)	-0.041	(0.027)	-0.026	(0.078)	-0.041	(0.031)	-0.070	(0.087)
Constants	-0.102	(0.125)	-0.641*	(0.370)	-0.104	(0.139)	-0.825*	(0.428)
Observations	3321		3321		3321		3321	
Clusters	59		59		59		59	

Methodology	LPM	LPM	2SLS	2SLS
t-statistic (instrument)	n.a.	n.a.	5.90	5.90
Kleibergen-Paap rk Wald F-statistic (instrument)	n.a.	n.a.	34.789	34.789

Notes: Robust standard errors are clustered by city and reported in parentheses.

$*$ p <.10

$**$ p <.05

$***$ p <.01

Figure 1
Correlations between Start Year and Green Innovation in the Survey Year

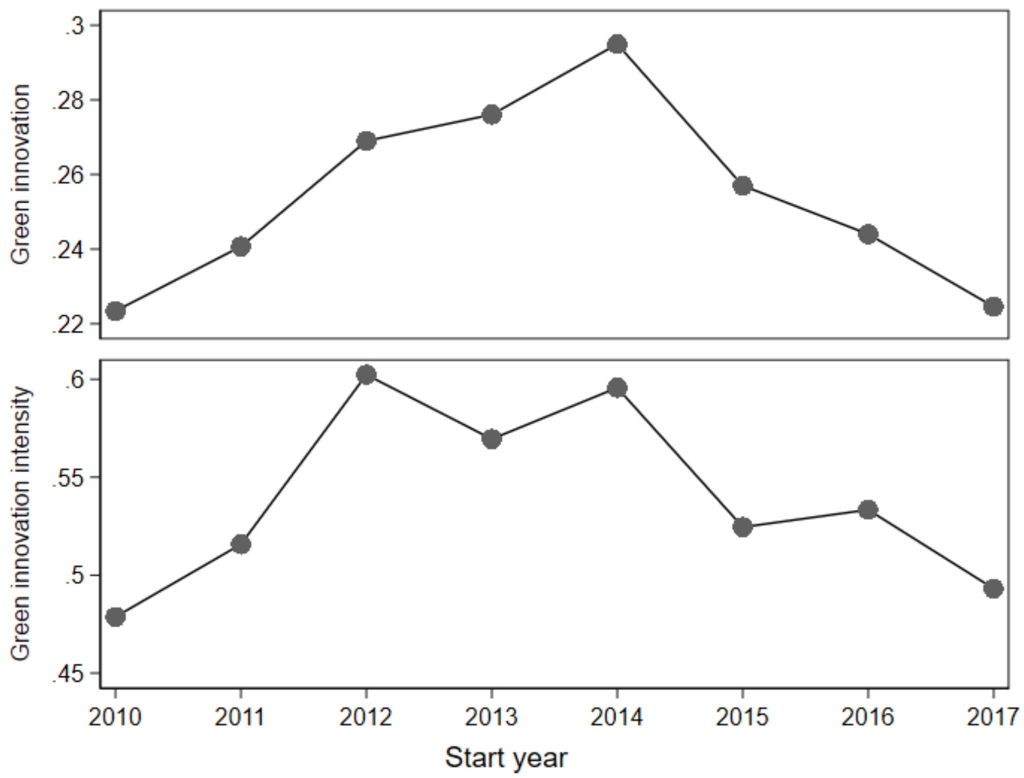
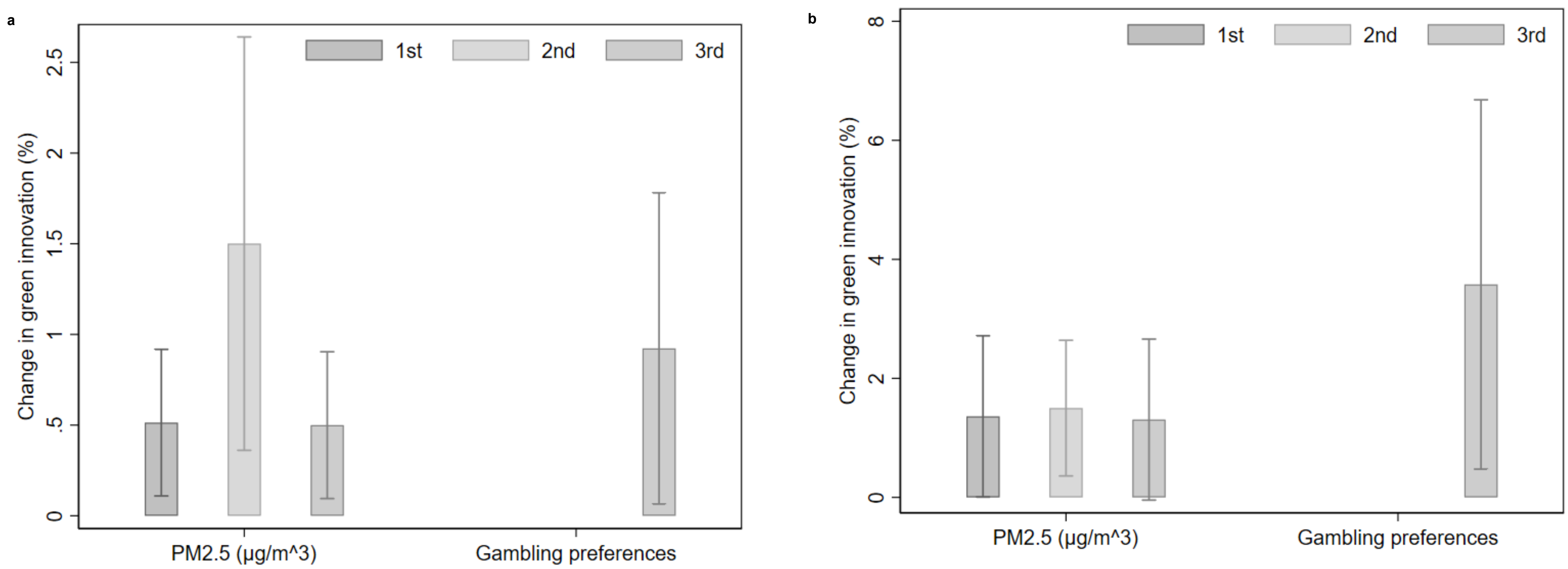
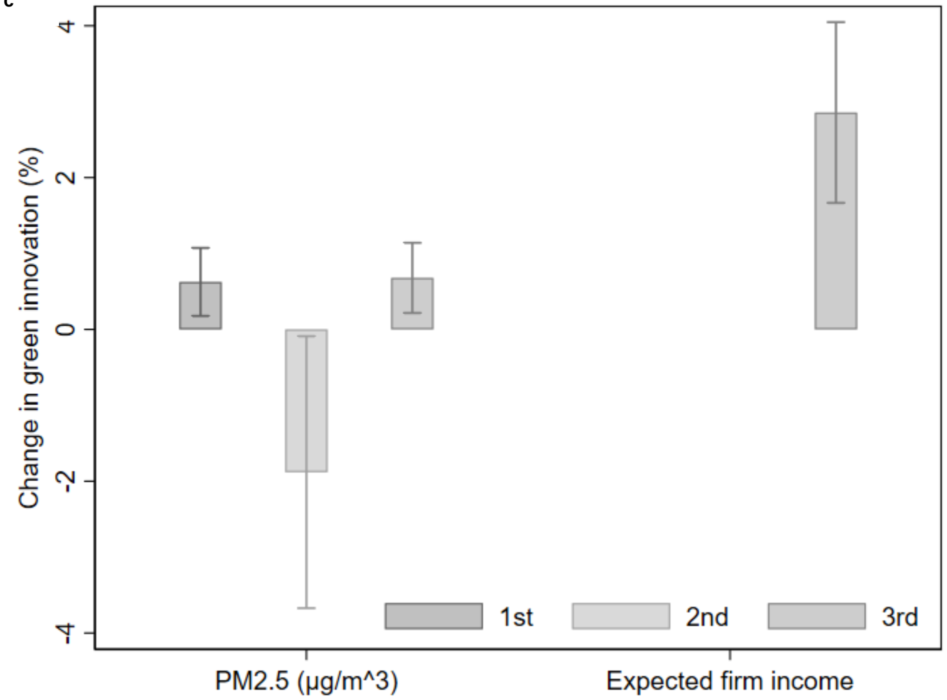


Figure 2

The Impact of Air Pollution on Green Innovation through Gambling Preferences, Expected Firm Income and Firm Income

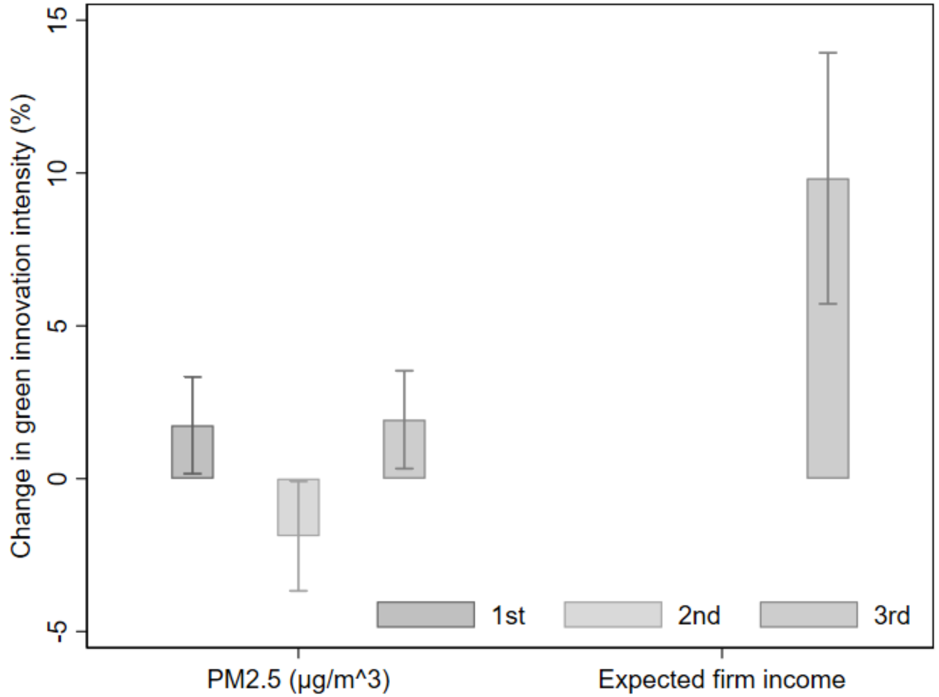


c



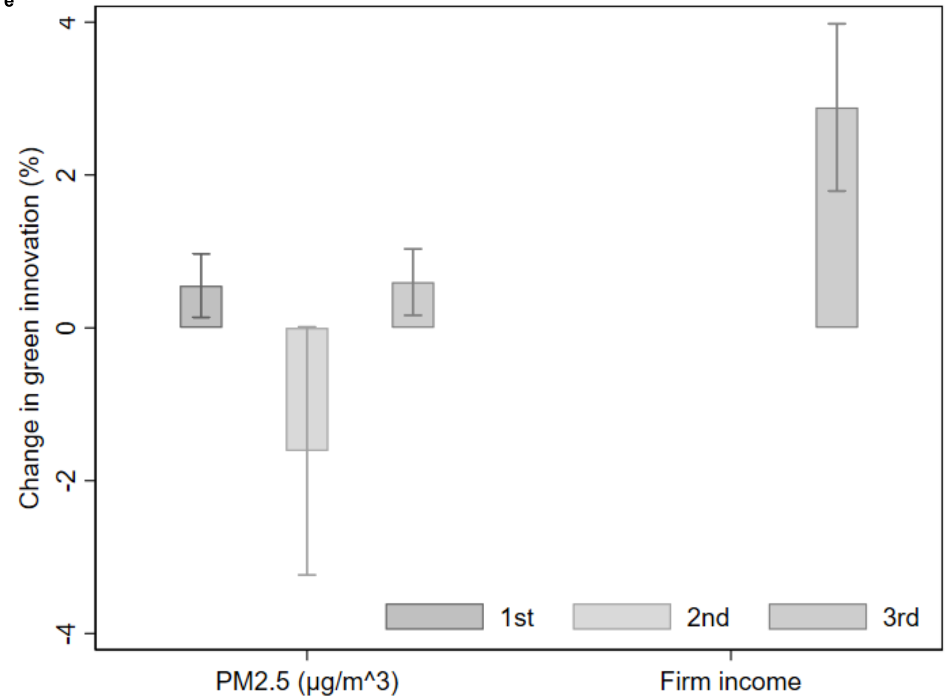
Change in green innovation (%)
4
2
0
-2
-4
1st
2nd
3rd
PM2.5 (μg/m^3)
Expected firm income

d



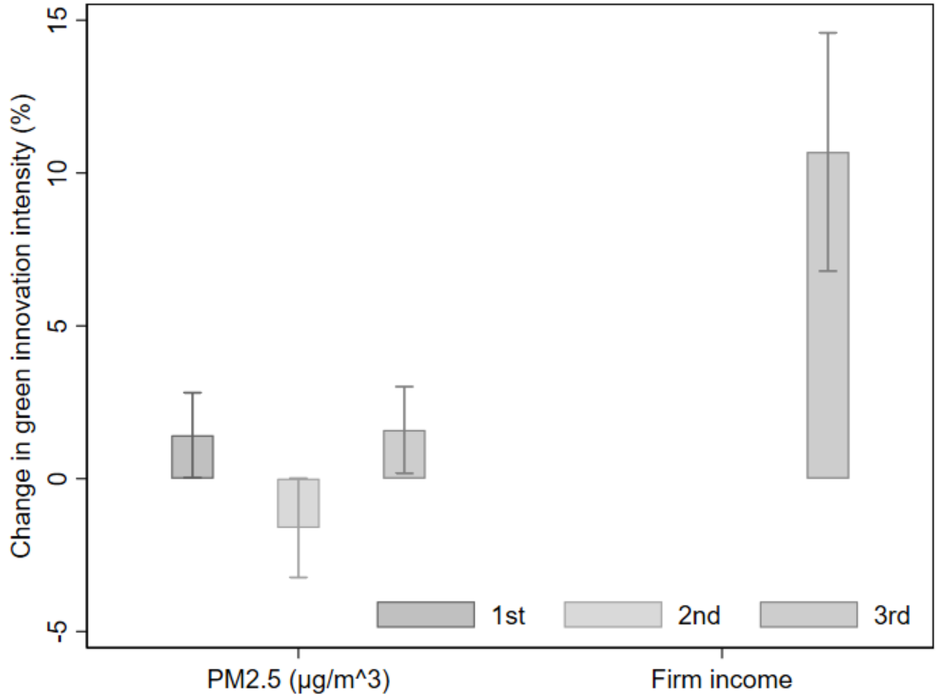
Change in green innovation intensity (%)
15
10
5
0
-5
1st
2nd
3rd
PM2.5 (μg/m^3)
Expected firm income

e



Change in green innovation (%)
4
2
0
-2
-4
1st
2nd
3rd
PM2.5 (μg/m^3)
Firm income

f



Change in green innovation intensity (%)
15
10
5
0
-5
1st
2nd
3rd
PM2.5 (μg/m^3)
Firm income

Figure 3

The Impact of Air Pollution on Green Innovation across Policy Cohort

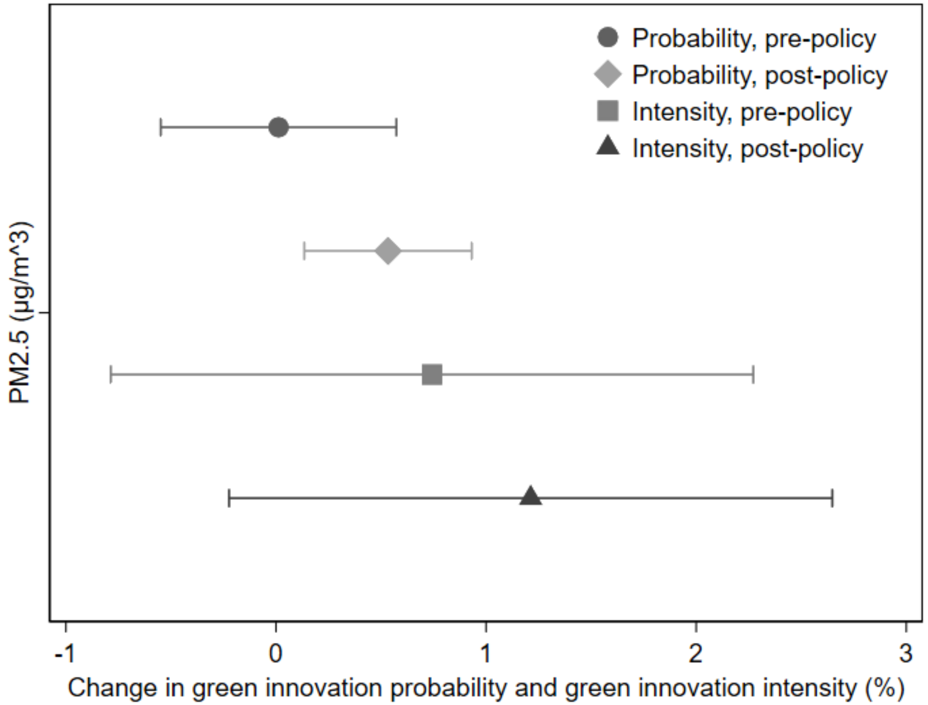
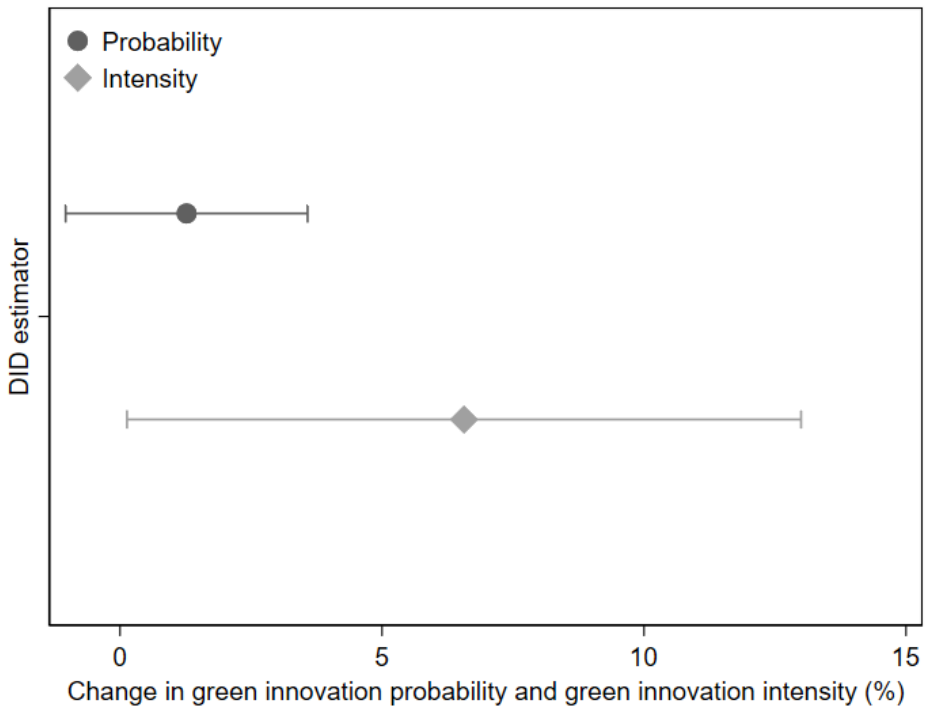


Figure 4

The Impact of Environmental Policy on Green Innovation



Supplementary Tables

Supplementary Table 1

Varying Goals of CCAA for provincial governments in China

Province name	PM 2.5 reduction goals (%)	Included in ESIEC	Area type	Assignment
Liaoning	10	Yes	Other areas	1
Gansu	12	Yes	Other areas	2
Henan	15	Yes	Other areas	3
Guangdong	15	Yes	Has cities in Pearl River Delta	3
Zhejiang	20	Yes	Has cities in Yangtze River Delta	4
Shanghai (city)	20	Yes	Centrally-administered municipality, belongs to Yangtze River Delta	5

Notes: Other areas indicate areas not included in three key regions in CCAA (i.e., Beijing-Tianjin-Hebei, Yangtze River Delta and the Pearl River Delta).

Supplementary Table 2

Descriptive Statistics

	Full Sample		Pre-policy Cohort		Post-policy Cohort		Welch's t-statistic
	Mean	SD	Mean	SD	Mean	SD	
Green innovation (yes = 1)	0.248	0.432	0.250	0.433	0.248	0.432	0.122
Green innovation intensity	0.545	1.353	0.563	1.397	0.539	1.339	0.434
PM2.5 (μg/m^3)	37.627	10.786	36.911	10.096	37.866	10.999	-2.310**
Thermal-inversion-induced fitted PM2.5 (μg/m^3)	37.498	7.555	37.365	7.548	37.542	7.559	-0.586
Gambling preferences	3.468	1.579	3.413	1.589	3.486	1.576	-0.904
Expected firm income (ten million yuan)	10.796	442.389	39.002	874.607	1.116	19.211	0.991
Firm income (ten million yuan)	5.749	171.020	6.083	127.108	5.633	183.936	0.063
Environmental perception	7.275	2.290	7.227	2.352	7.290	2.269	-0.657
Environmental policy stringency	2.972	1.162	2.998	1.235	2.963	1.136	0.705
Age	40.332	9.329	43.577	9.420	39.245	9.043	11.603***
Male (yes = 1)	0.704	0.457	0.715	0.451	0.700	0.458	0.845
High school or above (yes = 1)	0.594	0.491	0.573	0.495	0.601	0.490	-1.430
Migrant (yes = 1)	0.407	0.491	0.385	0.487	0.414	0.493	-1.444
Non-agricultural hukou (yes = 1)	0.347	0.476	0.366	0.482	0.340	0.474	1.359
Has children (yes = 1)	0.947	0.225	0.971	0.167	0.939	0.240	4.335***
Married (yes = 1)	0.970	0.171	0.969	0.174	0.970	0.170	-0.212
Han nationality (yes = 1)	0.953	0.211	0.951	0.216	0.954	0.209	-0.396
Chinese Communist Party member (yes = 1)	0.148	0.355	0.149	0.356	0.147	0.354	0.123
Relevant entrepreneurial experiences (yes = 1)	0.300	0.458	0.239	0.427	0.320	0.467	-4.655***
Years of firm existence	3.174	2.102	6.277	1.116	2.135	1.084	93.373***
Entrepreneurial type (solo entrepreneur = 0, employer entrepreneur = 1)	0.632	0.482	0.622	0.485	0.635	0.481	-0.702
Parents have high school or above education (yes = 1)	0.903	0.296	0.879	0.327	0.912	0.284	-2.591***
New established firm (yes = 1)	0.307	0.462	0.274	0.446	0.319	0.466	-2.493**
Second industry (yes = 1)	0.239	0.426	0.271	0.445	0.228	0.420	2.472**
Industry types	8.460	4.202	7.898	4.248	8.648	4.170	-4.433***
Real gross domestic product per capita (thousand yuan)	11.516	7.045	12.134	7.191	11.308	6.985	2.889***
Population density (per km^2)	844.563	736.353	885.041	758.715	831.011	728.366	1.797*
Ground-level temperature (°C)	16.933	5.116	17.102	5.141	16.877	5.108	1.093
Ground-level wind speed (m/s)	3.925	2.251	4.172	2.146	3.843	2.280	3.770***

High variance of PM2.5 within city (yes=1)	0.101	0.301	0.125	0.331	0.093	0.290	2.490**

Notes: SD = standard deviation. The sample only includes entrepreneurs in the second and third industry. We assume that our unpaired data do not have equal variances, and we present Welch's *t*-statistic (pre-policy cohort−post-policy cohort).

∗ p <.10
∗∗ p <.05
∗∗∗ p <.01

Supplementary Table 3

The Impact of Air Pollution on Green Innovation through Gambling preferences, Expected Firm Income and Firm Income

Panel A. Gambling preferences

	(1)		(2)		(3)	
Dependent variable	**Green Innovation**		**Gambling preferences**		**Green Innovation**	
PM2.5 (μg/m^3)	0.005**	(0.002)	0.015***	(0.006)	0.005**	(0.002)
Gambling preferences					0.009**	(0.004)
Control variables	YES		YES		YES	
Observations	2103		2103		2103	
Clusters	59		59		59	
Methodology	2SLS		2SLS		2SLS	
t-statistic (instrument)	5.58		5.58		5.59	
Kleibergen-Paap rk Wald F-statistic (instrument)	31.177		31.177		31.205	
Sample	Excluding highest risk aversion		Excluding highest risk aversion		Excluding highest risk aversion	

	(4)		(5)		(6)	
Dependent variable	**Green Innovation Intensity**		**Gambling preferences**		**Green Innovation Intensity**	
PM2.5 (μg/m^3)	0.014**	(0.007)	0.015***	(0.006)	0.013*	(0.007)
Gambling preferences					0.036**	(0.016)
Control variables	YES		YES		YES	
Observations	2103		2103		2103	
Clusters	59		59		59	
Methodology	2SLS		2SLS		2SLS	
t-statistic (instrument)	5.58		5.58		5.59	
Kleibergen-Paap rk Wald F-statistic (instrument)	31.177		31.177		31.205	
Sample	Excluding highest risk aversion		Excluding highest risk aversion		Excluding highest risk aversion	

Panel B. Expected Firm Income

Dependent variable	(1) Green Innovation		(2) Expected firm income		(3) Green Innovation	
PM2.5 (μg/m^3)	0.006***	(0.002)	-0.019**	(0.009)	0.007***	(0.002)
Expected firm income					0.029***	(0.006)
Control variables	YES		YES		YES	
Observations	2047		2047		2047	
Clusters	59		59		59	
Methodology	2SLS		2SLS		2SLS	
t-statistic (instrument)	6.00		6.00		6.00	
Kleibergen-Paap rk Wald F-statistic (instrument)	36.021		36.021		36.019	

Dependent variable	(4) Green Innovation Intensity		(5) Expected firm income		(6) Green Innovation Intensity	
PM2.5 (μg/m^3)	0.017**	(0.008)	-0.019**	(0.009)	0.019**	(0.008)
Expected firm income					0.098***	(0.021)
Control variables	YES		YES		YES	
Observations	2047		2047		2047	
Clusters	59		59		59	
Methodology	2SLS		2SLS		2SLS	
t-statistic (instrument)	6.00		6.00		6.00	
Kleibergen-Paap rk Wald F-statistic (instrument)	36.021		36.021		36.019	

Panel C. Firm Income

Dependent variable	(1) Green Innovation		(2) Firm income		(3) Green Innovation	
PM2.5 (μg/m^3)	0.006***	(0.002)	-0.016*	(0.008)	0.006***	(0.002)
Firm income					0.029***	(0.006)
Control variables	YES		YES		YES	
Observations	2152		2152		2152	
Clusters	59		59		59	
Methodology	2SLS		2SLS		2SLS	
t-statistic (instrument)	6.12		6.12		6.12	
Kleibergen-Paap rk Wald F-statistic (instrument)	36.177		36.177		36.101	

Dependent variable	(4) Green Innovation Intensity		(5) Firm income		(6) Green Innovation Intensity	
PM2.5 (μg/m^3)	0.014**	(0.007)	-0.016*	(0.008)	0.016**	(0.007)
Firm income					0.107***	(0.020)
Control variables	YES		YES		YES	
Observations	2152		2152		2152	
Clusters	59		59		59	
Methodology	2SLS		2SLS		2SLS	
t-statistic (instrument)	6.12		6.12		6.12	
Kleibergen-Paap rk Wald F-statistic (instrument)	36.177		36.177		36.101	

Notes: Robust standard errors are clustered by city and reported in parentheses.

* p <.10

** p <.05

*** p <.01

Supplementary Table 4

The Impact of Air Pollution on Green Innovation across Policy Cohort

	(1)		(2)		(3)		(4)	
Dependent variable	**Green Innovation**		**Green Innovation**		**Green Innovation Intensity**		**Green Innovation Intensity**	
PM2.5 (μg/m^3)	0.000	(0.003)	0.005***	(0.002)	0.007	(0.008)	0.012*	(0.007)
Observations	833		2488		833		2488	
Clusters	59		59		59		59	
Methodology	2SLS		2SLS		2SLS		2SLS	
t-statistic (instrument)	5.67		5.88		5.67		5.88	
Kleibergen-Paap rk Wald F-statistic (instrument)	32.114		34.525		32.114		34.525	
p-value of seemingly unrelated estimation tests	0.086				0.654			
Sample	Pre-policy cohort		Post-policy cohort		Pre-policy cohort		Post-policy cohort	

Notes: Robust standard errors are clustered by city and reported in parentheses.

∗ p <.10

∗∗ p <.05

∗∗∗ p <.01

Supplementary Table 5

The Impact of Environmental Policy on Green Innovation

	(1)		(2)	
Dependent variable	**Green Innovation**		**Green Innovation Intensity**	
Post-policy cohort * Environmental policy stringency	0.013	(0.012)	0.066**	(0.032)
Post-policy cohort	-0.005	(0.056)	-0.221	(0.175)
Environmental policy stringency	-0.018	(0.013)	-0.083**	(0.036)
Control variables	YES		YES	
Observations	3321		3321	
Clusters	59		59	
Methodology	LPM		LPM	

Notes: Robust standard errors are clustered by city and reported in parentheses.

∗ p <.10

∗∗ p <.05

∗∗∗ p <.01

Supplementary Table 6

Robustness Checks: Alternative Instrumental Variables

Dependent variable	**(1) Green Innovation**		**(2) Green Innovation Intensity**	
PM2.5 (µg/m^3)	0.004***	(0.001)	0.007**	(0.004)
Control variables	YES		YES	
Observations	3321		3321	
Clusters	59		59	
Methodology	2SLS		2SLS	
Hansen J-statistic (instrument)	0.277		0.537	
Kleibergen-Paap rk Wald F-statistic (instrument)	65.056		65.056	

Notes: Robust standard errors are clustered by city and reported in parentheses.

∗ p <.10

∗∗ p <.05

∗∗∗ p <.01

Supplementary Table 7

Robustness Checks: Alternative Sample

Dependent variable	(1) Green Innovation		(2) Green Innovation Intensity	
PM2.5 (μg/m^3)	0.004**	(0.002)	0.012*	(0.007)
Control variables	YES		YES	
Observations	4195		4195	
Clusters	59		59	
Methodology	2SLS		2SLS	
t-statistic (instrument)	5.82		5.82	
Kleibergen Paap rk wald F-statistic (instrument)	33.862		33.862	
Sample	Entrepreneurs and managers		Entrepreneurs and managers	

Notes: Robust standard errors are clustered by city and reported in parentheses.

$*$ p <.10

$**$ p <.05

$***$ p <.01

Supplementary Table 8

Robustness Checks: Alternative Mediator

Dependent variable	**(1) Green Innovation**		**(2) Environmental Perception**		**(3) Green Innovation**	
PM2.5 ($\mu g/m^3$)	0.004**	(0.002)	-0.015	(0.009)	0.004**	(0.002)
Environmental perception					0.002	(0.003)
Control variables	YES		YES		YES	
Observations	3986		3986		3986	
Clusters	59		59		59	
Methodology	2SLS		2SLS		2SLS	
t-statistic (instrument)	5.82		5.82		5.81	
Kleibergen-Paap rk Wald F-statistic (instrument)	33.870		33.870		33.810	

Dependent variable	**(4) Green Innovation Intensity**		**(5) Environmental Perception**		**(6) Green Innovation Intensity**	
PM2.5 ($\mu g/m^3$)	0.012*	(0.007)	-0.015	(0.009)	0.012*	(0.007)
Environmental perception					0.019**	(0.008)
Control variables	YES		YES		YES	
Observations	3986		3986		3986	
Clusters	59		59		59	
Methodology	2SLS		2SLS		2SLS	
t-statistic (instrument)	5.82		5.82		5.81	
Kleibergen-Paap rk Wald F-statistic (instrument)	33.870		33.870		33.810	

Supplementary Table 9

Robustness Checks: Alternative Heterogeneity Test

Dependent variable	**(1) Green Innovation**		**(2) Green Innovation**		**(3) Green Innovation Intensity**		**(4) Green Innovation Intensity**	
PM2.5 (μg/m^3)	0.005*	(0.003)	0.004**	(0.002)	0.020***	(0.007)	0.008	(0.007)
Observations	1222		2099		1222		2099	
Clusters	59		59		59		59	
Methodology	2SLS		2SLS		2SLS		2SLS	
t-statistic (instrument)	4.94		6.37		4.94		6.37	
Kleibergen-Paap rk Wald F-statistic (instrument)	24.436		40.619		24.436		40.619	
p-value of seemingly unrelated estimation tests	0.565				0.158			
Sample	Solo entrepreneur		Employer entrepreneur		Solo entrepreneur		Employer entrepreneur	

Notes: Robust standard errors are clustered by city and reported in parentheses.

$*$ p <.10

$**$ p <.05

$***$ p <.01

Supplementary Table 10

Robustness Checks: Oster Test

	(1) Baseline effect beta			(2) Controlled effect beta			(3) Bias-adjusted beta R_{max}=1.3R
Green innovation	0.001	(0.002)	[0.002]	0.004**	(0.002)	[0.062]	0.004
Green innovation intensity	0.001	(0.004)	[0.001]	0.011*	(0.006)	[0.041]	0.011

Notes: Robust standard errors are clustered by city and reported in parentheses. R squared are reported in square brackets. All specifications control for variables as in Table 2.

∗ p <.10

∗∗ p <.05

∗∗∗ p <.01

Supplementary Table 11

Robustness Checks: Nonlinear Effects

	(1)		(2)	
Dependent variable	**Green Innovation**		**Green Innovation Intensity**	
PM2.5 ($\mu g/m^3$)	-0.047	(0.033)	-0.079	(0.112)
PM2.5 squared	0.001	(0.000)	0.001	(0.001)
Control variables	YES		YES	
Observations	3321		3321	
Clusters	59		59	
Methodology	2SLS		2SLS	
t-statistic of PM2.5 (instrument)	-1.20		-1.20	
t-statistic of PM2.5 squared (instrument)	1.92		1.92	
Kleibergen-Paap rk Wald F-statistic (instrument)	4.587		4.587	

Notes: Robust standard errors are clustered by city and reported in parentheses.

$* \ p < .10$

$** \ p < .05$

$*** \ p < .01$