Policy Uncertainty Discourages Green Investment: Evidence from China[*]

Mengyu Wang **Jeffrey Wurgler** **Hong Zhang**

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Abstract

Government subsidies are widely used to stimulate investment in green technology. We find that uncertainty about the consistency of subsidies inhibits the desired policy outcome in the setting of Chinese corporate environmental research and development. We identify this effect using transient weather changes that cause exogenous variation in the official air quality readings used to allocate subsidies: Firms in cities with increasing weather-driven subsidy volatility reduce their green R&D investment, patent applications, and research staff. Major emitting sectors such as mining and manufacturing, as well as green tech and environmental industries, are most responsive to this policy uncertainty. The results underscore the importance of policy stability in encouraging long-term investment and the pursuit of environmental goals.

Keywords: R&D, Environmental Investment, Policy Uncertainty, Subsidies.

[*] Wang: PBC School of Finance, Tsinghua University, Email: wangmy@pbcsf.tsinghua.edu.cn; Wurgler: Stern School of Business, New York University, Email: jwurgler@stern.nyu.edu. Zhang: PBC School of Finance, Tsinghua University, Email: zhangh@pbcsf.tsinghua.edu.cn. We are grateful to Yakov Amihud, Sabrina Howell, Holger Mueller, and seminar participants at NYU Stern and the University of Miami for helpful comments.

I. Introduction

Industrial pollution is an ongoing challenge for both developed and developing economies. Air pollution, in particular, has well-documented health and economic impacts on billions of individuals and, consequently, on aggregate health and economic performance.[1] In fighting against pollution through the allocation of investments and subsidies, policymakers often rely on observed pollution indices. In particular, the AQI (the Air Quality Index) that is reported in the media and on the weather app on your mobile phone is used by policymakers in the U.S., E.U., and China. They use AQI to set up targets, allocate subsidies to local governments and firms, and evaluate success and failure.[2] For example, in November 2010, the AQI index at the U.S. Embassy in Beijing reached 562. The programmer who set up the Embassy's automatic Twitter reporting algorithm apparently never contemplated the pollution level of a forest fire, so the air quality was famously broadcast as "crazy bad." A silver lining of this episode was renewed attention to the problem, the method of measurement, and the relevant governmental policies and incentives.

It is intuitive and reasonable that subsidy policies respond to measured pollution indices. High AQI readings are salient and informative indicators of heavy air pollution. However, decisions that take this relationship too far may not be optimal, particularly when they are heavily shaped by the most accessible features of the underlying problem—a fallacy referred to as narrow framing (e.g., Kahneman and Lovallo 1993; Kahneman 2003).[3] Although AQI and similar indices provide the most accessible information, their usefulness and accuracy in assessing the severity of local pollution could be strongly influenced by some less-salient conditions, noticeably weather

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[1] For an overview of health effects, see Fonken et al., 2011; Mohai et al., 2011; Weuve et al., 2012. With respect to economic effects, see human capital measures related to education (e.g., Currie et al., 2009; Mohai et al., 2011), labor supply (Hanna and Oliva, 2015), productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016a,b; Isen, Rossin-Slater, Walker, 2017; He, Wang, and Zhang, 2020), investor behavior (Li, Massa, Zhang, and Zhang 2019), and financial markets (e.g., Levy and Yagil, 2011; Lepori, 2016; Heyes, Neidell, and Saberian, 2016; Huang, Xu, and Yu, 2017).

[2] For detail about U.S. and E.U. air quality measurement practices, see https://www.epa.gov/criteria-air-pollutants/naaqs-designations-process and https://www.eea.europa.eu/themes/air/air-quality-management, respectively.

[3] Of course, as pointed out in Kahneman (2003), narrow framing is quite general as agents typically do not and cannot know all relevant details of the situation.

fluctuations. A failure to endogenize these conditions may give rise to policy uncertainty and unintended consequences.

Figure 1 gives a remarkable visual demonstration of the effect of wind on AQI and offers a starting point for our study. Panel A shows pictures taken on different days of 2014 of the same building in Beijing. A bluer sky corresponds directly to better air quality. What differentiates these pictures is not the underlying local emissions, since the pictures are taken within a few months of each other, but simply modest differences in the prevailing wind speed. The graph below the pictures connects the clarity of the skies to the average daily AQI and then to wind speed. There is a strong negative effect of wind on AQI. Panel B shows a similar relationship between AQI and rain, which reduces air pollution by pushing particulate matter to the ground and washing it away.

Would it be optimal to design a policy that allocates environmental subsidies in proportion to AQI? Not here. A subsidy policy that ignored wind, for example, might be affected by transitory wind fluctuations, adding exogenous uncertainty to managers that rely on such subsidies to complement their firms' own green investments. While this motivating picture and thought experiment draw from daily fluctuations in AQI in a given city, the same principles and concerns apply under lower-frequency, cross-city variation in plans, budgets, subsidies, investments, and weather that we consider here.

In this paper, we examine the effect of policy uncertainty on investment undertaken by firms. The policy setting is Chinese environmental R&D subsidies and how they are allocated across cities; the policy uncertainty is driven by the interaction of the weather and a narrowly-framed allocation rule; and, the primary notion of investment—the dependent variable of policy interest, although not our sole focus—is green R&D efforts by firms. The results support the notion that policy uncertainty, idenfied using the exogenous variation in the weather, blunts the effectiveness of the policy's ability to spur the hoped-for corporate investments.

This environmental policy setting is an excellent one for our analysis for several reasons. First, China is the most populous country and sits at or near the top of the list facing severe air pollution challenges. Second, the literature views environmental regulation as a necessary response to the market's failure to price pollution externalities. As a result, subsidies have become one of the most important policy tools. Since its goal to encourage the development and adoption of clean technologies is well defined, subsidy policy also provides a natural benchmark to assess the real impact of policymaking shortcomings. Finally, uncertainty is a standard feature of certain Chinese policy domains, ranging from the sudden shift in support for the Didi IPO to the reversal of the "coal-to-gas" policy.[4] Policy uncertainty is, of course, hardly limited to China.[5]

Our analysis proceeds in three steps. First, we show that the cross-section of city-level environmental subsidies is driven, in part, by recent AQI. This is expected. China's environmental policymaking process resembles a top-down resource allocation across regions, and policymakers in China articulate pollution targets in terms of AQI, even if the underlying target—the broader "frame"—is to address actual polluting resources.[6] Over the sample from 2003 to 2018, a one-standard-deviation increase in realized pollution (AQI and wastewater emissions) of a city is associated with a 28.9% increase in its log-value of environmental subsidy in the next year (scaled by the standard deviation).[7]

Second, we show that annual AQI depends on annual wind and rain patterns, as suggested

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[4] Two days after Didi's listing in the US on July 30, 2021 (the biggest IPO of a Chinese firm since Alibaba in 2014), China's cyber regulator launched an investigation into the company and banned Didi's app from new customers. This regulatory shock sank Didi's stock price and discouraged various corporate activities (https://www.ft.com/content/809b31e2-6b1e-42b6-8009-3ea78969d870). The "Coal-to-Gas" policy detailed in the Internet appendix provides another relevant example. China intended to replace coal with natural gas. The policy was initiated in 2013 but largely reversed in 2019 due to various unintended consequences. Both the adoption and suspension of the policy created substantial uncertainty in the real economy, and illustrated to economic actors that a delayed reaction to new policy dictates may be in their best interest.

[5] It should also be noted that policy uncertainty is not necessarily suboptimal. It might be a consequence of rational learning, for example. In our case, though, the effect of wind and rain on air pollution is straightforward.

[6] As detailed in the Internet appendix, China implements its environmental policies in a three-layer top-down system, from central government to provinces and finally to city-level governments. China often specifies three types of environmental targets related to the number of days with good/poor air quality, the density of air pollutants (e.g., PM 10 or PM 2.5), and emissions. The first two directly build on observed AQI and its components (e.g., a day with "good" air quality is defined as one with an AQI value below 100). The third, emissions, is often difficult to measure in China, adding to the reliance on AQI in environmental policymaking. Indeed, China does not generally require disclosure of emissions. Even regulated firms face a moral hazard in reporting emissions. For instance, it is a widespread practice for firms to "run during the night and close during the daytime" to distort emission measurements (see Wang et al. 2018).

[7] The economic magnitude in later periods after 2007 is even larger (33%). To assess the robustness of this inference, we also examine another important government-guided environmental program, city-level Investment in Treatment of Industrial Pollution Sources on waste gas (hereafter, ITIPSWG). We find a similar influence of AQI: a one-standard-deviation increase in AQI gives rise to a 16.67% increase in the log-value of ITIPSWG.

by the higher-frequency pictures in Figure 1. Due to the importance of the heating season to air pollution in Northern cities (Almond et al., 2009; Chen et al., 2013), we separately estimate wind influence in heating and non-heating seasons for all cities and Northern cities and establish a highly robust negative impact of seasonal wind on seasonal AQI.[8]

Third, we pursue the implication of these observations to the firm-level real investment that the subsidy policy attempts to inspire. When the environmental policy relies on AQI while ignoring less salient or accessible weather conditions that affect the proper interpretation of AQI, the policy may unintendedly respond to short-term weather fluctuations. Although those fluctuations may average out in a suitably long run and hence not affect the long-term level of environmental subsidies, the year-by-year policy can nonetheless exhibit variation, or policy uncertainty, due to weather fluctuations. A burgeoning literature shows that economic policy uncertainty diminishes firm investment (e.g., Baker, Bloom, and Davis 2016; Gulen and Ion 2016; Hassan et al., 2019). Applying this intuition to our setting, we hypothesize that weather-induced policy uncertainty may reduce firm incentives for investing in environmental R&D, the goal in the first place, and find support for this hypothesis.

We adopt a two-stage framework to demonstrate this effect. In the first stage, we link policy uncertainty (measured as the standard deviation of yearly city-characteristics-adjusted environmental subsidy over the prior six years' rolling window) to lagged weather fluctuations (measured as the standard deviation of the yearly number of windy and rainy days in a once-lagged rolling window). This allows us to measure weather-induced policy uncertainty as policy uncertainty attributable to weather fluctuations. In the second stage, we examine how firm environmental incentives, proxied by the firm environmental R&D investments aggregated at the city level, are shaped by this component of policy uncertainty. Since yearly weather fluctuations are exogenous to policymakers and firms, we can also view weather fluctuations as an instrument,

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[8] For instance, an increase of the average wind speed by 1 meter/second is associated with a decline of heating-season AQI of northern cities by 5.0. This is consistent with both Figure 1 and scientific studies (e.g., Cai et al., 2017; Zhang et al., 2018) that document a linearly declining relationship between AQI and meteorological conditions in which wind plays a leading, and causal, role. The scientific literature typically interprets the AQI-pollution relationship as causal—e.g., a strong wind blows away air pollutants or prevents them from accumulating near to the ground.

and can interpret the two-stage analysis as an instrumental variable approach.

Our main finding is that policy uncertainty can substantially reduce firm environmental R&D and undermine the intention of the policy. In particular, a one-standard-deviation increase in both wind and rain fluctuations transfers into a 12.8% reduction in R&D in our two-stage analysis. A variety of robustness tests reinforce this conclusion.

While our main analysis is conducted at the city-year level, reflecting the source of policy variation, we also extend the analysis to the firm level to understand which firms are particularly affected. We find that environmental R&D-intensive firms—i.e., green-tech suppliers and high-tech firms—suffer more from this policy uncertainty. Hence, policy uncertainty not only goes against the general goal of promoting green technologies among all firms, it hurts exactly the type of firms that the policy wants to incentivize the most.

Finally, we explore how weather-induced policy uncertainty affects several related firm green activities, including the R&D "team size" of green-R&D firms and green patent applications as an innovation output. The literature has previously recognized reduced investment and employment as the two main detrimental consequences of uncertainty (e.g., Bernanke 1983; Baker, Bloom, and Davis 2016; Hassan et al., 2019); to relate this intuition more tightly to our previous analysis, we focus on R&D-related employment. The second variable, patent applications, also sheds light on the efficiency of R&D investment. Of course, the development and application of patents often takes more than one year, so we use a rolling-window-based average annualized regression (e.g., Minton and Schrand 1999; Bates, Kahle, and Stulz 2009) to capture the long-term impact of policy uncertainty on innovation. We find that weather-induced policy uncertainty hurts both R&D-related employment and, to a modest degree, green patenting.

The results contribute to several literatures. The climate finance literature examines how climate risk affects firm values due to investor preference or the information content of issuing green securities.[9] Several recent studies show that climate policy uncertainty is priced in the

[9] The literature of climate finance is booming quickly. Alok, Kumar, and Wermers (2020) and Krueger, Sautner, and Starks (2020) provide evidence on institutional investors' preference for climate risk. Shive and Forster (2020) compare private and public firms. Karpf and Mandel (2018), Baker, Bergstresser, Serafeim, and Wurgler (2021), and

market (e.g., Barnett 2019; Ilhan, Sautner, Vilkov 2020; Ramelli et al., 2020; Delis et al. 2020). We obviously also contribute to the economic analysis of air pollution, one of the most important environmental challenges (e.g., World Health Organization 2016). The results also suggest the importance of behavioral economics to policy uncertainty. It is well-documented that individuals often resort to shortcuts, or heuristics (e.g., Simon 1956; Kahneman, Slovic, and Tversky 1982), in making decisions. Although it is widely believed that heuristics are the resorts of those limited cognitive or information resources and that policymaking should be more rational and considered, the reliance on AQI and similar pollution indices is suggestive of such limitations affecting policy as well (e.g., Kahneman and Lovallo 1993; Kahneman 2003). The notion that policymakers' heuristics give rise to policy uncertainty extends the list of known sources of policy uncertainty.[10]

Finally, the results also suggest that we can potentially improve policy efficiency based on broad framing and the precautionary principle of environmental policymaking (i.e., Arrow and Fisher 1974).[11] "Framing" the policy target in terms of reducing point-source *emissions*, rather than air pollution levels, helps avoid the cognitive trap of basing subsidy allocations on AQI. A simple modification of the subsidy allocation rule to account for the "noise" added by wind and rain would be to base allocations on an AQI that is measured on low-wind days only. On such days, observed air quality closely reflects local emissions.

The remainder of the paper proceeds as follows. Section II describes our data. Section III

Zerbib (2019) examine the pricing of green municipal bonds. Chava (2014), Hong, Li, and Xu (2019), Bolton and Kacperczyk (2021), Engle, Giglio, Kelly, Lee, and Stroebel (2020), Choi, Gao, and Jiang (2020), and Flammer (2020) examine the pricing of climate risk on securities issued by firms, such as stocks, corporate bonds, and bank loans. Murfin and Spiegel (2020) and Baldauf, Garlappi, and Yannelis (2020) examine the influence of climate risk on the real estate market. Barnett, Brock, and Hansen (2019), Pedersen, Fitzgibbons, and Pomorski (2020), and Pastor, Stambaugh, and Taylor (2020) provide recent theoretical analyses on the influence of carbon risk, information, and investor preference.

[10] Baker et al. (2014) suggest that the increasing trend in the Economic Policy Uncertainty index (Baker, Bloom, and Davis 2016) could reflect enhanced government activities and heated political polarization in the US. In Pastor and Veronesi (2012, 2013), policy uncertainty arises due to the stochastic political costs of different potential policies, for which both the government and companies need to learn. In the literature on environmental policies, policy uncertainty is often directly linked to the uncertainty nature of environmental damages and the real resource costs of mitigating such damages.

[11] The precautionary principle of policymaking of Arrow and Fisher (1974) suggests that environmental policy uncertainty is undesirable. Arrow and Fisher (1974) further argue that a typical issue with environmental policies is to treat a stochastic problem as static. In a broad sense, this intuition is consistent with the issue of narrow framing when important but less salient stochastic factors are ignored.

examines the economic source of narrow framing in environmental policy. The resulting unintended consequence is examined in Section IV. Section V conducts additional analysis, followed by a short conclusion.

II. Data and Sample

We collected data from multiple sources. Most firm-level data, such as stock prices and firm characteristics, come from CSMAR and WIND, the two leading databases of the capital market in China. In addition, we also collect information about the classification of firms (e.g., whether a firm is a green tech supplier) from the Chinese Research Data Services Platform (CNRDS). Appendix A provides a detailed list of firm-level variables, their definitions, and the sources of data. In particular, we obtain firm-level R&D expenditure and granted government subsidies from the footnotes of the financial statement of firms as reported in the CSMAR database. We identify the environmental component of each variable by the list of environment-related keywords shown in the item description.[12] Later tests will show that the results are also robust based on the subsets of more frequently used keywords.

We then use firm headquarter locations to aggregate firm environmental R&D and granted government subsidies at the city level each year. Following the literature on R&D expenditure (e.g., Jaffe et al., 1988; Adams et al., 1993; Bloom et al., 2002; Adams et al., 2003), we use the logarithm of the RMB value of city-level environmental R&D as our main proxy for firm incentives for that type of investment. We refer to this variable as *Environmental R&D*—or simply *R&D* when there is no confusion. Accordingly, we use the logarithm of the RMB value of government environmental subsidy in each city as our main proxy for environmental policy,

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[12] The list of environment-related keywords include the following, listed by frequency of usage: energy conservation, environmental protection, environment, waste, furnace, pollution, emission reduction, energy, cyclic utilization, cleansing, sewage, electricity consumption, waste water, recycle, green, desulfuration, resource conservation, water saving, ecologic, solar power, waste heat, smoke, dedusting, pollution discharge, denitration, emission, natural gas, coal mine, nitrogen, diesel oil, fuel oil, wind electricity, garbage, tailings, harmless, tail gas, purify, energy efficiency, low carbon, renewable, afforest, air, electricity saving, fresh water capacity, clean, high-efficiency motors, sintering machine, blue sky, nitric acid, lithium iron phosphate, gasoline, mineral waste residue, energy dissipation, electric bus, changing fuel, exhaust gas emissions, carbonic oxide. These English words are translated from an original list of keywords in Chinese; Internet appendix IN2 tabulates these Chinese words.

which we label *Environmental Subsidy* or *Subsidy* unless otherwise specified.

We collect the daily Air Quality Index (AQI) from the Ministry of Environmental Protection of China (MEPC) for major cities in China. China adopts the AQI standard since 2013, which synchronizes the concentrations of six air pollutants. Before that, China has used a similarly constructed Air Pollution Index (API) that covers fewer pollutants. As detailed in the Internet appendix IN1, the two indices are highly correlated and provide comparable reference points for policymakers. For instance, both API and AQI values less than 50 or between 50 and 100 are classified as “superior” or “good” air quality.[13] In this regard, the reported magnitudes of the two indices are likely to have similar policy implications. Hence, we use *API-augmented* AQI in our main analysis and refer to it as AQI when there is no confusion. We calculate the annual AQI as the average daily AQI of a city in a given year.

The China Meteorological Administration provides information on daily city-level weather conditions. We build our main instruments of weather fluctuations on two yearly meteorological measures: i.e., *Windy Days* and *Rainy Days*. The first variable refers to the number of days in a year in which wind speed exceeds 5.5 m/s (equivalent to a wind speed of level 4 or above in the Beaufort Scale).[14] The second refers to the number of days having level 3 (out of 6) or above rain conditions according to China Meteorological Administration (i.e., more than 25mm/day). Based on these two variables, we will construct our main instruments, *SD (Windy Days)* and *SD (Rainy Days)*, as detailed in later sections.

We use both variables because they crucially affect the two most important policy goals of China’s environmental regulation: 1) the number of clean-air days in a given year; 2) the yearly AQI and density of pollutants. The Internet appendix (IN1) provides more details about China’s

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[13] Each city has monitoring stations to observe the concentrations of a list of air pollutants (e.g., Sulfur Dioxide, Nitrogen Dioxide, Particulate Matter 10, PM 2.5, Carbonic Oxide, and Ozone), based on which the composite index of AQI is then calculated. API covers the first three pollutants.

[14] The Beaufort Scale, adopted in China, classify wind speed into ten levels (https://en.wikipedia.org/wiki/Beaufort_scale; a higher level means stronger wind). We include the days in which the wind speed belongs to level 4 and above. Daily rain volume is classified into 6 levels (http://www.cma.gov.cn/2011xzt/2018zt/20100728/2010072804/201807/t20180706_472586.html) according to China Meteorological Administration. Again, a higher level means heavier rain. We include the days in which the rain volume belongs to level 3 and above.

environmental policy goals. Since both meteorological conditions can create weather-induced clear-air days, they may become important missing variables in a narrowly framed policy. Our robustness checks will show that using wind or rain alone leads to similar conclusions.

Finally, our main analysis controls for both city and firm characteristics. Our main city-level control variables come from CNRDS (which digitalizes the data from China City Statistical Yearbook), including GDP per capita, GDP Growth, Population Growth, and Consumption per capita. The last control variable is available only at the province level. But this coarser information will not affect our main analysis because we control for city fixed effects in most of our analysis. In addition, we also obtain industrial pollution data, such as the log-value of industrial SO2 emission, from CNRDS for robustness checks.

Our main firm-level characteristics come from WIND and CSMAR, including total assets, turnover ratio, return on assets, leverage ratio, firm size, cash holdings, capital expenditures, profit margin, and annual stock return. Appendix A provides detailed definitions of these variables. These characteristics describe the capital structure, profitability, and growth of firms, which could affect firm investment decisions (e.g., Jaffe et al., 1988; Adams et al., 1993; Minton and Schrand 1999; Bloom et al., 2002; Adams et al., 2003; Baker, Stein, and Wurgler 2003; Howell et al., 2019). For city-level analysis, we value-weight these variables based on firm assets to obtain city-level control variables. It is worth noting that, since our main two-stage specification controls for city or firm-fixed effects in city-level and firm-level analysis, the inclusion of more or fewer firm characteristics does not affect our main results.

Our sample covers 3,168 listed firms in 345 cities in China from 2003 to 2019. As described in Internet appendix IN3, most cities have granted subsidies to firms in this period, and firms in most cities have made environmental R&D investments.

Table 1 presents summary statistics. The mean value of AQI is 78, whereas that of Low-wind AQI is 97.84. Hence, air quality is in general worse with unfavorable wind conditions. Meanwhile, Wind Speed has an average value of 4.65 m/s. All variables appear to have reasonable distributions.

III. Environmental R&D Subsidy, AQI, and the Rise of Narrow Framing

A. The determinants of the allocation of environmental R&D subsidies

We first provide a cross-sectional analysis of the determinants of environmental R&D subsidy. To achieve this goal, we examine the cross-sectional determinants of Environmental R&D Subsidy in the following Fama-MacBeth specification:

$$Subsidy_{j,t} = \alpha + \beta \times Polution_{j,t-1} + C \times X_{j,t-1} + \varepsilon_{j,t}, \tag{1}$$

where $Subsidy_{j,t}$ denotes the log-value of environmental R&D subsidy provided by city j in year t, $Polution_{j,t-1}$ are leading pollution indices of the previous year, including AQI and wastewater emission, and $X_{j,t-1}$ stacks a list of control variables, including city characteristics and firm characteristics aggregated at the city level (value-weighted according to the value of firm assets).[15] City characteristics include consumption per capita, population growth rate, GDP per capita, and GDP growth rate. Firm characteristics aggregated at the city level include total asset turnover ratio, return on assets, leverage ratio, firm size, cash holdings, capital expenditures, profit margin, and annual stock return. The main sample period for this test spans from 2003 to 2018. Since early data are not as complete as later periods, we will also conduct robust checks in the more recent period (e.g., 2013-2018).

The results are in Table 2. We find that the annual policy is significantly related to lagged AQI. Since water pollution is also a major environmental problem in China (second only to air pollution), we also include wastewater emission to proxy for its influence. In a Fama-Macbeth specification, when we control for city characteristics such as GDP and population, a one-standard-deviation increase in both AQI and wastewater can generate a 29% increase in the log-

[15] We include both AQI and wastewater emission because both air and water pollutions have been important to China's environmental policies. China had initially started a series of policies in fighting against air pollution, as discussed in Internet appendix IN1. In later periods, China had also expanded its effort to reduce water pollutions (see, e.g., He, Wang, and Zhang 2020). Our current analysis focuses on AQI and related policymaking issues while controlling the potential influence of water pollution in subsidy allocation. We leave the direct analysis on water pollution-related policy issues to future research.

value of environmental subsidy (scaled by the standard deviation of its distribution). The results are also robust in the more recent period of 2013-2018 and when we replace AQI with AQI ranks. We report these robustness checks in the Internet appendix (Tables IN1 and IN2).

To assess the robustness of this policy-AQI relationship, we further assess another important government-guided environmental program, *Investment in Treatment of Industrial Pollution Sources* on waste gas (ITIPSWG). We obtain city-level data of ITIPSWG from EPSnet, which collects the city-level data from China Statistical Yearbooks.[16] We replace $Subsidy_{j,t}$ with ITIPSWG and find similar results. For instance, a one-standard-deviation increase in AQI typically gives rise to a 13% increase in the log-value of ITIPSWG (scaled by the standard deviation of its distribution) in a Fama-Macbeth specification when we control for city characteristics such as GDP and population. In the interest of space, we tabulate the results in the Internet appendix (Table IN3).

B. The relationship between AQI and wind speed

We now revisit the relationship between AQI and wind on a broad scale and yearly frequency. To achieve this goal, we start with a graphic demonstration by sorting all cities into AQI groups according to their average AQI in the entire sample period (e.g., AQI∈(25, 50], AQI∈(50, 75], etc.). This way, we can interpret each city group as a representative city with a certain pollution level. We then plot the relationship between yearly AQI and wind speed for these representative cities. Due to the importance of heating season in enhancing air pollution in

[16] ESPnet (www.espnet.com.cn) collects city-level ITIPS data from China Statistical Yearbook on Environment, National Environmental Statistics Bulletin, and China Environment Yearbook. A snapshot of the province-level investment for 2014 in China can be found at http://www.stats.gov.cn/ztjc/ztsj/hjtjzl/2014/201609/t20160913_1399660.html. The Chinese government provides policy guidance and direct funding for ITIPS from State Budgetary Funds, Environmental Protection Subsidy Funds, Environmental Protection Loans. In the last two decades, the government also encourages more funding from other resources (e.g., firms). See, for instance, http://tjj.hubei.gov.cn/tjsj/sjkscx/tjnj/qstjnj/ for the detailed funding information from the Hubei province of China. The pollution sources are categorized as waste gas, wastewater, waste solid, and others. We focus on waste gas in this robustness check. This sample consists of 119 cities in the period from 2003 to 2017.

northern cities (e.g., Almond et al., 2009; Chen et al., 2013), Figure 2 separately plots the AQI-wind relationship in heating and non-heating seasons for all cities in Panel A over the main sample period (2003-2018).[17] In Panel B, we demonstrate the robustness of Panel A by providing the same plots for northern cities in later periods (2013-2018).

Consistent with the Beijing plot, Figure 2 demonstrates a clear and negative relationship between AQI and wind speed. The slope is more negative in the heating season, particularly for northern cities, confirming a more critical role of wind in dissipating air pollution in the winter. All cities in later periods and northern cities in the entire sample period exhibit very similar patterns (see Internet appendix Figure IN2).

Next, we more formally examine the city-level AQI-wind relationship in the following specification:

$$AQI_{j,t,s} = a + b_1 \times Wind\ \ Speed_{j,t,s} + b_2 \times X_{j,t} + \eta_{j,t,s}, \tag{2}$$

where $AQI_{j,t,s}$ denotes the average daily AQI of city j in the heating (or the non-heating season—the subscript s denotes the seasons) of year t, and $Wind\ \ Speed_{j,t,s}$ is the average daily wind speed of the city measured in the same period. Finally, $X_{j,t}$ stacks the same city characteristics. In addition, we control for city and year fixed effects with double-clustered standard errors.

Table 3 presents the influence of yearly wind speed (averaged over daily speed) on yearly AQI. Models 1 and 2 tabulate the influence of wind speed on AQI in both heating and non-heating season in the full sample of all cities, whereas Models 3 and 4 apply the same analysis to the subsample of northern cities. We find a significantly negative relationship between annual AQI and its contemporaneous wind speed. The economic magnitude is sizable. For instance, in the sample of all cities (northern cities), every increase of the wind speed by 1 meter/second is associated with a decline of heating-season AQI of representative cities by 3.2 (5.0). The effect

[17] The heating season of a given year is defined as January, February, March, November and December. The remaining months are classified as non-heating season. Although the real starting and ending dates of the heating season vary across cities and years, our classification suffices to capture the potential influence of coal-based heating activities on air pollution.

reduces in the non-heating season.

To further demonstrate that the impact of wind on AQI is robust to the time horizon, we also apply the test to later periods and examine the impact of the number of windy/rainy days on yearly AQI, as well as that of daily wind speed on daily AQI. The Internet appendix (Table IN4) tabulates the results. We can see that both wind and rain variables reduce AQI significantly. For instance, every increase of the daily wind speed by 1 meter/second is associated with a decline of daily AQI by 2.205.

Overall, the results show a significant negative relationship between AQI and wind speed. Note that we also observe similar influences of *Windy Days*, *Rainy Days*, and rain volume on AQI (Table IN4 provides more results). But since meteorological studies have extensively examined the weather impact on air pollution (e.g., Cai et al., 2017; Zhang et al., 2018 and their cited references), we only tabulate the influence of wind speed on AQI in our sample. The meteorological literature also typically explains this effect as strong wind blowing away air pollutants or preventing them from accumulating in the near-ground—i.e., weather conditions can causally affect air pollution.

IV. The Unintended Consequence of a Narrowly-Framed Policy

This section empirically explores the intuition that failing to endogenize weather-caused pollution variations in environmental policies may give rise to weather-induced policy uncertainty, which subsequently influences firm incentives for adopting green technology.

A. Weather-induced policy uncertainty and unintended consequences

We first adopt the following two-stage framework to examine weather-induced policy uncertainty and its impact on firm environmental R&D.

$$PU_{j,t} = a + b_1 \times SD(Windy\ \ Days)_{j,t-1} + b_2 \times SD(Rainy\ \ Days)_{j,t-1} + b_3 \times X_{j,t} + \varepsilon_{j,t}, \qquad (3A)$$

$$R\&D_{j,t+1} = \alpha + \beta_1 \times PU(Weather)_{j,t} + \beta_2 \times PU(Other)_{j,t} + C \times X_{j,t} + \eta_{j,t}. \quad (3B)$$

In the first stage, as described in Equation (3A), $PU_{j,t}$ denotes the policy uncertainty of city j estimated as the standard deviation of characteristics-adjusted subsidy policy in the rolling period from year $t-5$ to t, where the characteristics-adjusted subsidy policy of a city in any given year is estimated as the residual of the cross-sectional regression in Model 1 of Table 2.

The above calculation of policy uncertainty involves two assumptions. First, we essentially measure policy uncertainty as time-series volatility in a six-year rolling window. This particular time convention follows the literature on cash flow uncertainty (e.g., Minton and Schrand 1999)—later tests will show that the results are robust to the choice of rolling window.[18] Secondly, we want to adjust for city characteristics because they can influence the routine resource allocation made by the central planner. For instance, if all cities adopt similar production technologies and consumption patterns, then larger GDP or more population could indicate more pollution and require more routing environmental resource allocation. Hence, we calculate the characteristics-adjusted subsidy policy of a city in any given year as the residual (i.e., $\varepsilon_{j,t}$) of the cross-sectional regression, $Policy_{j,t} = \alpha + C \times X_{j,t-1} + \varepsilon_{j,t}$, when city characteristics are controlled for. The results are again robust to this assumption.

The two variables $\sigma(Windy\ Days)_{j,t-1}$ and $\sigma(Rainy\ Days)_{j,t-1}$ refer to the standard deviation of the number of windy days and rainy days per year in the same rolling period from year $t-6$ to $t-1$. The one-year lag between policy uncertainty and weather fluctuation follows the time convention of Equations (1) and (2), in which weather conditions of a given year affect the same-year AQI and thus the next-year policy. Our later tests will also provide some additional analyses on this time convention.

The first stage analysis allows us to decompose $PU_{j,t}$ into two components: $PU(Weather)_{j,t} = b_1 \times \sigma(Windy\_Days)_{j,t-1} + b_2 \times \sigma(Rainy\_Days)_{j,t-1}$ denotes weather-

[18] It is a long literature convention to measure policy uncertainty based on time-series volatility (see, among others, Segal, Shaliastovich, and Yaron 2015; Kang and Pflueger 2015; and Fernandez-Villaverde at al. 2015). Moreover, within the six-year rolling window, we require at least two valid obervations to calculate uncertainty. The results are robust to this threshold.

induced policy uncertainty, and $PU(Others)_{j,t}$ synchronizes the remaining policy uncertainty. In the second stage described in equation (3B), these two components are then linked to $R\&D_{j,t+1}$, the logarithm of the aggregate environmental R&D investments that firms of the city make in the following year. In both stages, $X_{j,t}$ stacks the control variables including city and aggregated firm characteristics. We also control for city and year fixed effects with standard errors clustered at the city and year level.

Note that we calculate weather-induced policy uncertainty based on a six-year rolling window and characteristics-adjusted subsidy policy. The six-year rolling window simply follows some literature (e.g., Minton and Schrand 1999); an alternative of five years leads to similar results.[19] The adjustment for city characteristics is for economic reasons. Since larger cities are likely to have more resources to distribute as environmental subsidies, the adjusted subsidy better captures how weather conditions induce the local government to deviate from its capacity in regulating pollution. It is worth noting that the results are robust to alternative lengths or the rolling window or adjustment of city characteristics.

The results are reported in Table 4. Model 1 reports the results of the first stage. We can see that short-term variation in weather conditions significantly increases policy uncertainty. Figure 3 provides an intuitive view of distribution of policy uncertainty and *Weather-induced Policy Uncertainty*. On the map, a larger pie indicates larger policy uncertainty, and the dark-shaded part indicates the portfolio of policy uncertainty attributable to weather fluctuations. We can see that both variables are reasonably dispersed across different Chinese cities.

Models 2 to 8 tabulate the results of the second stage. Across different specifications, weather-induced policy uncertainty significantly reduces firm environmental R&D. The economic magnitude of the effect is sizable. For instance, Model 6 (and together with Model 1) suggests that a one-standard-deviation increase in both wind and rain fluctuations transfers into a 13.3 % reduction in R&D in this two-stage analysis.[20] In contrast, $PU(Others)_{j,t}$ has insignificant

[19] We require a minimum of two valid yearly observations in the rolling window to calculate uncertainty. The results are robust to the minimum threshold.

[20] From Models 1 and 6, we have $(\mathrm{b}_1 \times \mathrm{SD}_{\mathrm{wind}} + \mathrm{b}_2 \times \mathrm{SD}_{\mathrm{rain}}) \times \beta_1/\mathrm{SD}_{\mathrm{R\&D}} = (0.01 \times 25.66 + 0.12 \times 1.93) \times$

influence, suggesting that the main policy uncertainty that has a real impact is indeed weather-driven policy uncertainty.

The good news is that the policy itself (previous rolling average) translates into high R&D investment as intended. A one-standard-deviation increase in the subsidy increases firm R&D by about 22.2%. This is consistent with the positive influence of government environmental subsidies on the innovation and value of firms in the U.S. (e.g., Howell, 2017). However, policy uncertainty exerts precisely the opposite (and thus unintended) influence. Indeed, a direct comparison between the economic magnitudes of the two effects suggests that the unintended consequence of weather-induced policy uncertainty is quite large, economically speaking, compared to the level effect of the policy.

B. Robustness checks

Many choices must be made to yield an empirical specification.. We report the results of various robustness checks in Table 5. To deal with the concern that some cities do not have green R&D in a given year, Models 1 and 2 include only city-year observations with non-zero R&D. The results are robust in this subsample test. Indeed, the results are robust when we exclude observations with zero government subsidies in general or environmental subsidies in particular or when we exclude city observations before its first non-zero subsidies. These additional robustness checks are reported in the Internet appendix.

Next, policymakers may respond not only to last year's AQI. Our main model (Equation 3) specifies that policymakers allocate resources in year *t* based on *t-1* AQI. But the year *t* allocation may be determined in the late part of year *t-1*, when the year *t-1* AQI is not fully realized; furthermore, different cities may time allocations in slightly different ways. We assess such a

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$(-2.85)/9.51 = -13.30\%$, where $b_1 = 0.01$ and $b_2 = 0.12$ are the regression coefficients of the first stage, $\beta_1 = -2.85$ is the regression coefficient of Model 6 in 2nd stage, $SD_{wind} = 25.66$, $SD_{rain} = 1.93$, and $SD_{R\&D} = 9.51$ are the standard deviations of windy days, rainy days, and the left-side variable $R\&D_{j,t+1}$, respectively.
.

process by assuming that the policy responds to the average of two-year information. Models 3 and 4 suggest that the results are the same in this alternative policymaking specification.

In Models 5 and 6, we control for the standard deviation of non-weather-related AQI and wastewater. To achieve this goal, we regress pollution on weather conditions and treat the residuals as non-weather-related pollution variation. Controlling for the time-series volatility of these residuals has no impact. These observations are consistent with the meteorological literature on the importance of weather on observed pollution and reveal the unique role of weather fluctuations in inducing policy uncertainty.

In our main two-stage specification, we adjust subsidy policies by the cross-sectional influence of city characteristics (such as GDP, population, and consumption) based on the first model of Table 2. We have argued that this adjustment controls the potential importance of cities when the government makes routine environmental allocations. In addition to macro conditions, however, firm characteristics may also exert some influence. Hence, in Models 7 and 8, we adopt an alternative method (i.e., following Model 5 of Table 2) to use both city and firm characteristics to adjust for policy. The results are unchanged.

In addition, we also use an alternative rolling window of five years to calculate policy uncertainty (Models 9-10) and alternative weather information—e.g., wind only—to explore unintended consequences (Models 11-12). Our Internet appendix (Table IN5) provides more alternative timing and weather specifications of a similar spirit, with no noteworthy changes in results.

The Internet appendix provides more analysis and robustness checks. As a placebo test, we show that weather-induced policy uncertainty does not affect non-environmental R&D. Next, we identify environmental subsidies and environmental R&D based on the list of keywords detailed in Footnote 12 and the Internet appendix IN2. Table IN6 further shows that focusing on the top 20 or top 30 most frequently used keywords (in identifying environmental subsidies and R&D) does not change our main results. The magnitude is also comparable (a one-standard-deviation increase in both wind and rain fluctuations transfers into a 13.69% and 12.97% reduction in environmental

R&D, respectively). In addition, the results are also robust to winsorization, the inclusion of emission variables (e.g., SO2 and industrial dust), and the inclusion of controls for the general volatility of AQI and wastewater emissions. All these results are tabulated in Table IN6. Finally, Table IN7 adopts an average annualized regression approach (e.g., Minton and Schrand 1999; Bates, Kahle, and Stulz 2009) instead of a panel specification. Our main conclusions are highly robust in all these tests.

In brief, the weather effect and its impact on firm R&D are highly robust to alternative ways of specifying characteristics-adjusted policy, policy uncertainty, or weather conditions.

V. Additional Analysis

After the baseline results, we examine a few economic questions to shed further light on our baseline findings. They are 1) the type of firms that are more vulnerable to weather-induced policy uncertainty; 2) the influence of the uncertainty on other related firm activities, such as R&D team size and green patents; 3) whether the same analysis applies to the other type of environmental policy: penalty (as it is often argued that both benefits and punishments are needed for environmental policies).

A. Which firms respond most to policy uncertainty?

To draw inferences about firms, we apply the two-stage analysis at that level. While the policy is determined at the city level,[21] in the second stage we introduce an interaction term between policy uncertainty and firm types (with firm and year fixed effects):

[21] In the first stage, we reestimate the city-level policy uncertainty for each firm based on the cross-section of all firms. We get similar results if directly using the 1st-stage estimation of Table 4.

$$R\&D_{i\in j,t+1} = \alpha + \beta_1 \times PU(Weather)_{j,t} + \beta_2 \times PU(Others)_{j,t} + \gamma \times PU(Weather)_{j,t} \times D(Firm\ \ Type)_{i\in j,t} + C \times X_{i\in j,t} + \eta_{i\in j,t}, \qquad \text{(3B')}$$

In the above question, $R\&D_{i\in j,t+1}$ is the environmental R&D investment made by firm i headquartered in city j in year $t+1$, $D(Firm\ \ Type)_{i\in j,t}$ represents dummy variables indicating various firm types, including green-tech suppliers, high tech firms, firms in the metropolitan area, large firms, energy firms, manufacturing firms, mining firms, and chemicals firms. The dummy variable itself is absorbed by firm fixed effects. We report interactions of firm types with weather-induced policy uncertainty and average policy; the remaining part of policy uncertainty is insignificant so we exclude it here.

The results are in Table 6. Weather-induced policy uncertainty retains its significant and negative influence on environmental R&D in firm-level specifications. Models 3 and 4 are of special interest: Policy uncertainty hurts green-tech suppliers and high-tech firms the most. These are industries that subsidy policies often want to incentivize. We can infer the relative PU exposure of green-tech suppliers and high-tech firms from $\gamma + \beta_1$ in these models. Their exposures (-0.78 and -0.98, respectively) are notably higher than the average exposure (i.e., $\beta_1 = -0.46$ in Model 1).

We also explore several characteristics related to the headquarters location of the firm, size (top 10% assets), state ownership, and reliance on environmental subsidies. We find that firms headquartered in metropolitan areas and with more reliance on environmental subsidies are more sensitive to environmental policy uncertainty. The second effect is intuitive, whereas the first could be related to the higher cost of maintaining R&D employment in these cities (our later tests suggest that uncertainty also reduces R&D employment). In contrast, state ownership and size do not enhance the influence of policy uncertainty.

In analyzing the headquarters location of the firm, an issue is that some listed firms have a complex geographic structure, making it difficult to determine which local government policy influences them the most. This complexity works against finding a significant relationship between firm investments and policy uncertainty, however. Nonetheless, we create a dummy variable that equals one if a firm is registered in one city and has its headquarters in another city. Potentially, policy uncertainty in the headquarters area might have a weaker impact. The interaction of this dummy variable with the weather-induced policy uncertainty of the headquarters location, however, is insignificant.

We finally examine the impact of policy uncertainty on industries by interacting weather-induced policy uncertainty with certain industry dummies. The Internet appendix (IN4) provides a detailed matching between China's industry classification provided by China Securities Regulatory Commission (CSRC) and the SIC or Fama-French classifications. Among the industries, manufacturing (CSRC industry code C) and Water conservancy, environment, and public facility management (CSRC industry code N) are most affected. This result is not unexpected since manufacturing includes many important polluters and public facilities includes environmental firms. Within manufacturing firms, chemicals and metals are more influenced.

Table 6 allows firms to have different lengths of years in our sample. Perhaps a firm listed more recently is younger and somehow more vulnerable to policy uncertainty. In our Internet appendix (Table IN8), we apply the same test to the subset of firms that exist in the entire sample period of the second-stage regression from 2009-2019. The results are unaffected.

B. Environmental R&D Employment and Green Patents

Next, we come back to our main specifications and use the two-stage analysis to examine other firm activities that can shed more light on their environmental incentives. We focus on two variables, Environmental R&D Employment and Green Patent Application, both of which are again aggregated (asset value-weighted) at the city level.

Green-tech R&D Employment is the logarithm of the number of green-tech R&D researchers in a city plus one. The number of green-tech R&D researchers is defined as the total number of R&D and technical employees in those firms with environmental R&D investments.

The results are reported in Table 7. Consistent with reduced R&D investment, we also see a reduction in R&D Employment, suggesting that policy uncertainty also negatively influences firm investments in human capital. A one-standard-deviation increase in both wind and rain fluctuations transfers into a 15.1% reduction in R&D Employment in this two-stage analysis, which is on par with the economic magnitude of R&D investment.

Table 8 reports the results for green patent applications as a proxy for the output of firm environmental incentives. Of course, the development of patents often takes longer than a year. Hence, instead of using panel regression, we use the cross-sectional average annualized regression (e.g., Minton and Schrand 1999; Bates, Kahle, and Stulz 2009) to capture the long-term impact of policy uncertainty on innovation.

More specification, we first calculate the average green patents that a firm generates in a rolling window of 6 years and policy uncertain a one-year lagged rolling window. We then estimate the cross-sectional relationship between the two variables for this particular rolling window. Next, we move the rolling window for one year and estimate the relationship. Finally, we report the average relationship between green patents and the corresponding lagged policy uncertain. We find that weather-induced policy uncertainty also reduces green patents. Jointly, environmental policy uncertainty seems to reduce both the human capital inputs as well as the outputs of green technologies.

VI. Conclusion

In this paper, we examine whether environmental policymaking could be subject to the fallacy of *narrow framing* when it relies substantially on the easily-accessible information in the AQI (or closely related indices) in making environmental investment decisions. This decision process is problematic because important but somewhat less salient information, such as the effect of local weather on recent average AQI, reduces the ability of AQI to measure the fundamental sources of pollution. In this regard, a more broadly framed, low-wind AQI index can better capture underlying pollution and help improve the efficiency of environmental policymaking.

Based on the data of environmental subsidy aiming to promote green investments in fighting against the sources of industrial pollution on wasted gas in China, we find compelling evidence supporting the presence and influence of narrow framing in environmental policymaking. In particular, although environmental investment responds to lagged AQI, it fails to respond to the more broadly framed low-wind AQI. The process appears suboptimal and exhibits unintended policy uncertainty introduced by weather fluctuations.

Perhaps most importantly, weather-induced policy uncertainty reduces firm incentives to invest in environmental R&D. Hence, the uncertainty of narrowly framed environmental policy exerts the opposite influence on its goals.

Although our empirical analysis exploits environmental investment in China, its policy implications are general, as the reliance of environmental policies and investments on the AQI-type of accessible information is worldwide. The results, therefore, call for more scrutiny and future research to curtail the issue of narrow framing in environmental policymaking.

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Appendix A. Variables and Databases

Variable	Definition	Source
A. Proxies for Policy Uncertainty		
Policy (Subsidy)	The logarithm of city subsidy (RMB value) plus one.	CSMAR
Char-adj Policy (Subsidy)	The characteristics-adjusted subsidy policy of a city in any given year is estimated as the residual (i.e., $\varepsilon_{j,t}$) of the cross-sectional regression: $\mathrm{Policy}_{j,t} = \alpha + C \times X_{j,t-1} + \varepsilon_{j,t}$, where all city and firm characteristics are controlled for (i.e., the specification used in Model 2 of Table 2).	
PolicyUncer_Subsidy	The subsidy policy uncertainty is estimated as the standard deviation of characteristics-adjusted subsidy policy in the rolling period from year $t-4$ to t.	
PolicyUncer (Weather)	Weather-driven policy uncertainty estimated from: $PU_{j,t-5,t} = a + b_1 \times SD(Windy\ \ Days)_{j,t-6,t-1} + b_2 \times SD(Rainy\ \ Days)_{j,t-6,t-1} + b_3 \times X_{j,t} + \delta_t + \theta_j + \varepsilon_{j,t}$. We then further decompose $\mathrm{PU}_{j,t}$ into two components: $PU(Weather)_{j,t-5:t} = b_1 \times SD(Windy\ \ Days)_{j,t-6:t-1} + b_2 \times SD(Rainy\ \ Days)_{j,t-6:t-1}$ denotes the weather-driven policy uncertainty.	
PolicyUncer (Others)	The remaining policy uncertainty, calculated as the difference between subsidy policy uncertainty and weather-driven policy uncertainty: $\mathrm{PU(Others)}_{j,t-5:t} = \mathrm{PU}_{j,t-5:t} - \mathrm{PU(Weather)}_{j,t-5:t}$.	
Policy (Penalty)	The logarithm of city-level environmental penalties (RMB value) plus one. For penalty, we also construct characteristics-adjusted policy, policy uncertainty, weather-driven policy uncertainty, and the remaining part of policy uncertainty in a similar way.	Institute of Public and Environmental Affairs
B. Environmental R&D and Market Variables (Firm-level and City-level)		
Environmental R&D (City)	The logarithm of the aggregate environmental R&D investments (RMB value) that firms of the city plus one.	CSMAR
Ave Environmental R&D (City)	The 6-year moving average of Environmental R&D (City).	
Environmental *R&D Employment (City)*	Environmental R&D Employment (City) is the logarithm of the number of Environmental R&D employees that firms of the city plus one. The number of Environmental R&D researchers is defined as the total number of R&D and technical employees in those firms with environmental R&D investments.	Resset
Tobin's Q (City)	The value-weighted average of firms' Tobin's Q in a city. Tobin’s Q =(Market Value -Total Liabilities)/ Total Liabilities and Stockholders' Equity, that is the firm’s market value divided by the total asset value.	Factset
Ave Green Patent (City)	The 6-year moving average of Green Patent. Green Patent is the logarithm of the number of green patent applications in a city plus one.	CSMAR
C. Weather and Pollution Variables		
Windy Days	The number of windy days in a year in which the wind speed belongs to level 4 (out of 12) or above according to the Beaufort Scale (i.e., higher than 5.5 m/s).	China Meteorological Administration (CMA)
Rainy Days	The number of rainy days in a year in which the rain volume belongs to level 3 (out of 6) or above according to the China Meteorological Administration (i.e., more than 25mm/day).	
Wind Speed	The daily wind speed in m/s.	
Rain Volume	The volume of rain in mm/day.	
SD (Windy Days)	The standard deviation of the number of windy days per year in a 6-year	

	rolling window	
SD (Rainy Days)	The standard deviation of the number of rainy days per year in a 6-year rolling window	
Daily AQI	The daily AQI in a city.	Ministry of Ecology and Environment of China
Average AQI	The annual average AQI in a city.	
Waste Water	The logarithm of wastewater emissions (in tons) in a city in a given year	Download from CNRDS. The ultimate source is China City Statistical Yearbook
SO2 Emission	The logarithm of SO2 emissions (in tons) plus one in a city in a year.	
Ind Dust Emission	The logarithm of the average level of industrial dust emissions (in tons) of a city plus one in a year.	
SD (adj-AQI)	The 6-year moving standard deviation of the AQI, when the long-term (full period) influence of weather conditions is adjusted	
SD (adj-Waste Water)	The 6-year moving standard deviation of the wastewater emission, when the long term (full period) influence of weather conditions is adjusted	
C. City-level Control Variables		
GDP (Per capita)	GDP is the logarithm of GDP divided by the total population.	Download from CNRDS. The ultimate source is China City Statistical Yearbook
GDP Growth	The growth rate of GDP.	
Population Growth	The growth rate of the population	
Consumption (Per capita)	The logarithm of resident consumption per capita	
D. Firm-level Control Variables (also asset value-weighted at the city-level as control variables)		
Environmental R&D	The logarithm of environmental R&D investments (RMB value) of a firm plus one.	CSMAR
Green-tech Suppliers	This equals one if a firm is a Green-tech Supplier and zero otherwise. Green-tech Supplier is defined as if a firm provides environmental/green products and services.	CNRDS
High-tech	This equals one if a firm is recognized as a high-tech enterprise and zero otherwise.	CSMAR
Metropolitan	This equals one if a firm is located in metropolitans (Beijing, Shanghai, Guangzhou, and Shenzhen), and zero otherwise.	CNRDS
Big Firm	This equals one if a firm size is belong to big top 10% of firms and zero otherwise.	WIND
SOE	SOE is the dummy variable that equals one if a firm is State Owned Enterprise and zero otherwise.	CNRDS
High Reliance on Subsidy	This equals one if a firm's ratio of environmental subsidy to total assets is higher than the median value and zero otherwise.	CSMAR
Office and Registered in Diff City	This equals one if a firm's office address and registered address are in different cities and zero otherwise.	CSMAR
Manufacturing	This equals one if a firm belongs to the manufacturing industry and zero otherwise. The CSRC code for the manufacturing industry is C.	CSMAR
Chemical	This equals one if a firm belongs to the chemical industry and zero otherwise. The CSRC code for the chemical industry is C25, C26, C28, C29, C41, and C43.	CSMAR
Metal	This equals one if a firm belongs to the energy and water supply industry and zero otherwise. The CSRC code for the metal industry is C31, C32, C65, C67, C33.	CSMAR
Public Facility Industry	This equals one if a firm belongs to the public facility industry and zero otherwise. The CSRC code for the public facility industry is N.	CSMAR

Environmental Industry	This equals one if a firm belongs to the environmental industry and zero otherwise. The CSRC code for the environmental industry is N77.	CSMAR
Turnover	Total Assets turnover ratio is calculated by net sales to total assets.	WIND
ROA	ROA is operating income divided by total assets.	WIND
Leverage	Leverage is the book value of total debt divided by total assets.	WIND
Size	Firm size is the logarithm of total assets.	WIND
Cash	Cash is cash holdings divided by total assets.	WIND
CAPEX	Capital Expenditure is capital expenditure divided by total assets.	WIND
Profit Margin	The ratio of net income to revenue.	WIND
Lagged Ret	The total stock return in year t-1.	CSMAR

Table 1. Summary Statistics

This table presents the summary statistics of the main variables during the period from 2003 to 2019, including the mean, median, standard deviation, and various quintile values of each variable. All variables are defined in Appendix A. Panel B presents the Spearman rank correlation coefficients of Subsidy Policy, pollution, and GDP.

Panel A: Summary Statistics of Main Variables

	N	Mean	Std Dev	5%	25%	Median	75%	95%
A1: Environmental Policy-related Variables								
Policy (Subsidy)	1297	12.94	6.35	0.00	12.77	15.44	16.85	18.64
Policy (Penalty)	1297	3.13	5.27	0.00	0.00	0.00	9.21	13.30
Char-adj Policy (Subsidy)	1297	0.08	5.67	-12.44	-0.79	1.87	3.56	6.45
PolicyUncer_Subsidy	1297	3.00	2.40	0.55	1.20	2.03	4.61	7.60
PolicyUncer (Weather)	1297	3.00	2.08	0.65	1.52	2.40	4.02	7.51
PolicyUncer (Others)	1297	0.00	1.19	-2.02	-0.59	0.00	0.58	1.90
A2: Firm Environmental R&D and Market Variables (aggregated at the city level)								
Environmental R&D (City)	1297	11.11	9.51	0.00	0.00	17.04	19.43	21.62
R&D Employment (City)	1297	4.04	3.70	0.00	0.00	5.11	7.32	9.18
Green Patent (City)	1340	0.54	1.05	0.00	0.00	0.00	0.69	2.83
A3: Pollution and Weather Variables								
AQI	1297	77.95	24.42	47.56	62.36	73.58	87.27	122.68
Waste Water	1297	17.74	1.12	15.61	17.12	17.84	18.45	19.37
Windy Days	1297	103.23	75.54	4.00	40.00	92.00	152.00	248.00
Rainy Days	1297	10.89	7.71	1.00	5.00	9.00	16.00	26.00
SD (Windy Days)	1297	24.22	25.66	2.48	8.90	16.33	29.76	73.92
SD (Rainy Days)	1297	3.30	1.93	0.82	2.00	2.94	4.28	7.00
A4: City Characteristics (Control Variables)								
Consumption (Percapita)	1297	9.61	0.47	8.72	9.33	9.63	9.94	10.33
Population Growth	1297	5.47	5.50	-2.61	2.26	5.30	8.48	14.68
GDP (Percapita)	1297	10.64	0.78	9.39	10.17	10.65	11.12	11.94
GDP Growth	1297	9.89	4.86	3.90	7.70	9.40	12.50	16.00
A5: Firm Characteristics Aggregate at the City Level (Control Variables)								
Turnover	1297	0.73	0.33	0.33	0.54	0.69	0.85	1.25
ROA	1297	7.78	11.45	-1.29	4.70	7.59	10.48	15.85
Leverage	1297	0.50	0.28	0.27	0.40	0.47	0.56	0.81
Size	1297	21.79	0.89	20.38	21.22	21.77	22.34	23.22
Cash	1297	0.06	0.07	-0.02	0.03	0.06	0.08	0.14
CAPEX	1297	0.06	0.04	0.02	0.04	0.05	0.07	0.12
Profit Margin	1297	4.55	105.35	-0.26	0.04	0.09	0.13	0.24
Lagged Ret	1297	0.19	0.57	-0.39	-0.17	0.02	0.34	1.35

Panel B. Correlations

	Policy (Subsidy)	Char-adj Policy (Subsidy)	AQI	Waste Water	Windy Days	Rainy Days	GDP (Percapita)	GDP Growth
Policy (Subsidy)	1.00							
Char-adj Policy (Subsidy)	0.90***	1.00						
AQI	0.16***	0.16***	1.00					
Waste Water	0.33***	0.19***	0.22***	1.00				
Windy Days	0.03	-0.02	-0.13***	-0.16***	1.00			
Rainy Days	0.02	0.01	-0.38***	0.09***	-0.02	1.00		
GDP (Percapita)	0.38***	0.01	0.05*	0.33***	0.15***	0.09***	1.00	
GDP Growth	-0.05*	0.02	-0.15***	0.16***	-0.13***	0.03	-0.06**	1.00

Table 2. The Determinants of Environmental R&D Subsidies

This table presents the determinants of environmental R&D subsidy policies. We examine the cross-sectional determinants of Environmental R&D Subsidy in the following Fama-MacBeth specification: $Subsidy_{j,t} = \alpha + \beta \times Polution_{j,t-1} + C \times X_{j,t-1} + \varepsilon_{j,t}$, where $Subsidy_{j,t}$ denotes the environmental R&D subsidy provided by city j in year t, $Pollution_{j,t-1}$ are pollution index values of the previous year, including AQI and wastewater emission, and $X_{j,t-1}$ stacks control variables, including city characteristics and firm characteristics aggregated at the city level (value-weighted according to the value of firm assets). City characteristics include consumption per capita, population growth rate, GDP per capita, and GDP growth rate. Firm characteristics include total asset turnover ratio, return on assets, leverage ratio, firm size, cash holdings, capital expenditures, profit margin, and annual stock return. The sample period is from the year 2003 to 2018. Appendix A provides more detailed variable definitions. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Subsidy							
AQI		0.06***		0.04***		0.05***		0.03**
		(4.98)		(5.91)		(3.68)		(2.93)
Waste Water			1.19***	0.96***			1.34***	1.18***
			(4.76)	(4.10)			(4.38)	(4.11)
Consumption (Percapita)	-0.45	-0.08	-1.93***	-1.36**	0.08	0.42	-1.53**	-1.09*
	(-0.89)	(-0.15)	(-3.42)	(-2.43)	(0.15)	(0.86)	(-2.64)	(-2.01)
Population Growth	0.02	0.05	0.03	0.05	0.05	0.08**	0.08**	0.10**
	(0.47)	(1.66)	(1.03)	(1.70)	(1.40)	(2.43)	(2.39)	(2.50)
GDP (Percapita)	3.20***	3.15***	3.13***	3.14***	2.93***	2.92***	2.91***	2.91***
	(5.93)	(6.04)	(6.02)	(6.19)	(5.81)	(5.92)	(5.83)	(5.95)
GDP Growth	-0.05	-0.05	-0.07	-0.07	-0.04	-0.03	-0.07	-0.06
	(-0.99)	(-0.97)	(-1.30)	(-1.18)	(-0.73)	(-0.56)	(-1.11)	(-0.95)
Turnover					-0.28	-0.44	-0.28	-0.37
					(-0.65)	(-0.93)	(-0.61)	(-0.78)
ROA					-0.02	-0.03	-0.04*	-0.04
					(-1.01)	(-1.00)	(-2.12)	(-1.74)
Leverage					1.78**	1.24	1.44	1.11
					(2.27)	(1.42)	(1.35)	(0.97)
Size					0.93***	0.65***	0.71***	0.55**
					(4.80)	(3.10)	(3.79)	(2.59)
Cash					0.29	0.31	1.05	0.94
					(0.06)	(0.07)	(0.24)	(0.22)
CAPEX					-10.61***	-10.63***	-7.97*	-8.45**
					(-4.05)	(-3.97)	(-2.08)	(-2.41)
Profit Margin					-0.13	-0.11	-0.14	-0.12
					(-0.87)	(-0.85)	(-0.83)	(-0.80)
Lagged Ret					0.23	0.18	0.20	0.16
					(0.42)	(0.30)	(0.32)	(0.24)
Intercept	-19.25***	-26.38***	-25.39***	-29.81***	-41.40***	-41.88***	-44.94***	-44.91***
	(-3.96)	(-4.51)	(-4.19)	(-4.41)	(-5.69)	(-5.69)	(-5.74)	(-5.72)
Adj R^2	0.19	0.22	0.22	0.24	0.26	0.29	0.31	0.32
Number of Observations	1838	1838	1725	1725	1826	1826	1713	1713

Table 3. The Influence of Wind Speed on AQI

This table presents the influence of wind speed on AQI in heating and non-heating seasons. The specification is: $AQI_{j,t,s} = a + b_1 \times Wind\ Speed_{j,t,s} + b_2 \times X_{j,t} + \eta_{j,t,s}$, where $AQI_{j,t,s}$ denotes the average daily AQI of city j in the heating or the non-heating season s of year t, and $Wind\ Speed_{j,t,s}$ is the average daily wind speed measured in the same period. Finally, $X_{j,t}$ stacks the same city characteristics. City characteristics include consumption per capita, population growth rate, GDP per capita, and GDP growth rate. Model 1 and Model 2 compares the influence of wind speed on AQI between heating season and non-heating season in the sample of all cities. Model 3 and Model 4 compares the influence of wind speed on AQI between heating season and non-heating season in the sample of northern cities. The heating season includes November through March. The non-heating season includes April through October. Figure 2 shows the corresponding plots of AQI and wind speed in the heating season and non-heating season. The sample period is from 2013 to 2018. Appendix A provides more detailed variable definitions. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	Model 1	Model 2	Model 3	Model 4
	Average AQI (t)			
	Sample of All cities		Sample of Northern Cities	
	Heating	Non-heating	Heating	Non-heating
Average Wind Speed (t)	-3.18***	-2.63***	-5.02***	-2.34*
	(-3.56)	(-3.49)	(-3.02)	(-1.79)
Average Rain Volume (t)	-2.60***	-1.73***	-2.19	-3.36**
	(-4.72)	(-4.62)	(-0.66)	(-2.42)
Consumption (Percapita) (t)	7.21	-0.52	-27.16***	-19.69**
	(1.56)	(-0.13)	(-2.78)	(-2.32)
Population Growth (t)	0.08	0.08	0.51***	0.19
	(0.67)	(0.80)	(2.75)	(1.01)
GDP (Percapita) (t)	-1.95	-1.81	-1.21	-0.43
	(-1.14)	(-1.46)	(-0.46)	(-0.25)
GDP Growth (t)	-0.10	0.00	0.49**	0.43**
	(-1.28)	(0.05)	(2.47)	(2.40)
Clustering city year	YES	YES	YES	YES
City and Year Fixed	YES	YES	YES	YES
Adj R^2	0.98	0.98	0.98	0.97
Observations	1699	1699	845	845

Table 4. Weather-Induced Policy Uncertainty in R&D Subsidies and Green R&D Investment

This table presents the impact of subsidy policy uncertainty on green-tech R&D investment. It shows the results of the following two-stage specifications:

1st stage: $PU(Subsidy)_{j,t-5:t} = a + b_1 \times SD(Windy\_Days)_{j,t-6:t-1} + b_2 \times SD(Rainy\_Days)_{j,t-6:t-1} + b_3 \times X_{j,t} + \delta_t + \theta_j + \varepsilon_{j,t}$,

2nd stage: $R\&D_{j,t+1} = \alpha + \beta_1 \times PU(Weather)_{j,t-5:t} + \beta_2 \times PU(Others)_{j,t-5:t} + \beta_3 \times AveSubsidy_{j,t-5:t} + \beta_4 \times X_{j,t} + \delta_t + \theta_j + \eta_{j,t}$.

In the first stage, $PU(Subsidy)_{j,t-5:t}$ denotes the policy uncertainty of city j estimated as the standard deviation of characteristics-adjusted subsidy policy in the rolling period from year $t-5$ to t, where characteristics-adjusted subsidy policy of a city in any given year is estimated as the residual (i.e., $\varepsilon_{j,t}$) of the cross-sectional regression, $Policy_{j,t} = \alpha + C \times X_{j,t-1} + \varepsilon_{j,t}$, when city characteristics are controlled for (i.e., the specification used in Model 1 of Table 2). $SD(Windy\_Days)_{j,t-6:t-1}$ and $SD(Rainy\_Days)_{j,t-6:t-1}$ refer to the standard deviation of the number of windy days and rainy days per year in the same rolling period from year $t-6$ to $t-1$. $X_{j,t}$ stacks a list of control variables, including the pollution indices as well as the city and firm characteristics. We then further decompose $PU(Subsidy)_{j,t-5:t}$ into two components according to the first stage: $PU(Weather)_{j,t-5:t} = b_1 \times SD(Windy\_Days)_{j,t-6:t-1} + b_2 \times SD(Rainy\_Days)_{j,t-6:t-1}$, which denotes weather-induced policy uncertainty, and $PU(Others)_{j,t-5:t}$, which synchronizes the remaining policy uncertainty. These two components are then linked to $R\&D_{j,t+1}$, the logarithm of the aggregate environmental R&D investments that firms of the city make in the following year, in the second stage. As an additional control in the second stage, $AveSubsidy_{j,t-5:t}$ refers to the 6-year moving average for the characteristics-adjusted subsidy policy. Model 1 presents the first stage estimation. Models 2 to 9 present the second stage regressions. Models 9 shows the 2nd-stage regression result if we predict Char-adj Subsidy starting from 2007, and the regression starts from 2013 (Internet appendix Table IN2). All specifications include city and year-fixed effects, with standard errors clustered by city and year. Robust t-statistics are reported in parentheses. *, **, and *** refer to 10%, 5%, and 1% levels of statistical significance, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	PU(Char-adj subsidy) (Vol t-5:t)	y = Environmental R&D (City)							Start from 2013
	1st Stage	2nd Stage: Influence of projected policy uncertainty and other policy variables							
PolicyUncer (Weather)		-3.01***		-3.01***		-2.85***		-2.73***	-5.37***
		(-3.08)		(-3.09)		(-2.93)		(-2.76)	(-3.37)
PolicyUncer (Others)			-0.09	-0.09		0.01		0.00	0.11
			(-0.63)	(-0.64)		(0.06)		(0.02)	(0.58)
Char-adj Policy (Subsidy)					0.49***	0.48***			0.20
					(3.78)	(3.70)			(0.93)
Policy (Subsidy)							0.40***	0.37***	
							(3.31)	(3.01)	
SD (Windy Days) _(Vol t-6:t-1)	0.01***								
	(3.30)								
SD (Rainy Days) _(Vol t-6:t-1)	0.12***								
	(2.79)								
AQI	0.00	0.03**	0.03**	0.03**	0.03**	0.03**	0.02*	0.03**	0.04***
	(0.30)	(2.24)	(2.02)	(2.23)	(1.97)	(2.18)	(1.90)	(2.10)	(2.91)
Waste Water	-0.10	0.79	1.03*	0.79	1.05*	0.82	1.13*	0.91	1.76***
	(-0.67)	(1.35)	(1.78)	(1.36)	(1.79)	(1.39)	(1.94)	(1.54)	(2.71)
Consumption (Percapita)	-0.01	-0.95	-0.62	-0.95	-1.01	-1.31	-1.78	-2.00	-3.25
	(-0.01)	(-0.34)	(-0.22)	(-0.34)	(-0.36)	(-0.46)	(-0.63)	(-0.70)	(-0.85)
Population Growth	-0.03**	-0.07	0.02	-0.07	0.02	-0.07	0.02	-0.07	-0.05
	(-2.44)	(-1.10)	(0.39)	(-1.09)	(0.39)	(-1.04)	(0.35)	(-1.02)	(-0.73)
GDP (Percapita)	-0.54**	-0.88	0.96	-0.88	1.01	-0.73	0.80	-0.85	-2.86**
	(-2.51)	(-0.92)	(1.19)	(-0.92)	(1.27)	(-0.76)	(1.01)	(-0.89)	(-2.13)
GDP Growth	0.01	0.04	0.01	0.04	0.00	0.03	0.01	0.04	0.09**
	(1.57)	(0.88)	(0.13)	(0.87)	(0.07)	(0.78)	(0.20)	(0.89)	(2.56)
Turnover	-0.28	-1.38	-0.64	-1.38	-0.38	-1.08	-0.53	-1.21	0.96
	(-0.87)	(-1.39)	(-0.65)	(-1.39)	(-0.38)	(-1.09)	(-0.56)	(-1.25)	(0.83)
ROA	0.00	0.03*	0.02	0.03*	0.02	0.03*	0.02	0.02	-0.06
	(0.34)	(1.67)	(1.18)	(1.68)	(1.22)	(1.69)	(1.13)	(1.59)	(-0.87)
Leverage	-0.19	-2.47**	-1.83	-2.47**	-1.56	-2.17**	-1.50	-2.10*	-2.73
	(-0.72)	(-2.18)	(-1.63)	(-2.19)	(-1.46)	(-2.01)	(-1.38)	(-1.90)	(-0.80)
Size	0.07	1.24	0.95	1.24	0.80	1.08	0.90	1.17	0.31
	(0.30)	(1.61)	(1.24)	(1.61)	(1.05)	(1.40)	(1.18)	(1.52)	(0.29)
Cash	-1.30**	-0.75	2.87	-0.75	2.44	-0.97	2.47	-0.78	-4.42
	(-2.04)	(-0.27)	(1.10)	(-0.27)	(0.94)	(-0.36)	(0.96)	(-0.29)	(-0.69)
CAPEX	-0.09	-1.35	-1.70	-1.35	-0.66	-0.36	-1.33	-1.04	-28.69**
	(-0.03)	(-0.17)	(-0.21)	(-0.17)	(-0.08)	(-0.05)	(-0.17)	(-0.13)	(-2.19)
Profit Margin	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.08
	(1.15)	(1.29)	(0.59)	(1.29)	(0.71)	(1.39)	(0.60)	(1.24)	(-1.33)
Lagged Ret	0.06	0.25	0.06	0.25	0.08	0.26	0.13	0.30	-1.12
	(0.40)	(0.45)	(0.12)	(0.46)	(0.16)	(0.49)	(0.26)	(0.56)	(-1.41)
Year Fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
City Fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clustering city year	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj R^2	0.88	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.88
Observations	1297	1297	1297	1297	1297	1297	1297	1297	1000

Table 5. Robustness Checks

This table presents robustness checks to the baseline results are reported in Models 1 and 6 in Table 4. Models 1 and 2 show the results if we exclude city observations with zero environmental R&D. Models 3 and 4 use 2-year average AQI instead of AQI as the control variable. Models 5 and 6 show the results of adding SD(adj-AQI) and SD (adj-Water) as pollution-related control variables. SD(adj-AQI) and SD (adj-Water) are the 6-year rolling standard deviation of weather-adjusted AQI and Water. To get weather-adjusted AQI and Water, we first estimate the betas of weather in the full-period time series specification: $Pollution_{j,t} = \alpha + b_1 \times WindyDays_{j,t} + b_2 \times RainyDays_{j,t} + b_3 \times X_{j,t} + \varepsilon_{j,t}$, and then we remove the weather components from AQI and Waste Water to calculate the adjusted AQI and adjusted wastewater emissions in this equation: $Adj\_Pollution_{j,t} = Pollution_{j,t} - b_1 \times WindyDays_{j,t} - b_2 \times RainyDays_{j,t}$. Models 7 and 8 show the results of using Model 2 of Table 2 to estimate an alternative Char-adj Policy Uncertainty, i.e., the characteristics-adjusted subsidy policy of a city in any given year is estimated as the residual ($\varepsilon_{j,t}$) of the cross-sectional regression, $Policy_{j,t} = \alpha + C \times X_{j,t-1} + \varepsilon_{j,t}$, where only city characteristics are controlled for (the specification used in Model 1 of Table 2). Models 9 and 10 show the results of defining PU as 5-year moving SD of subsidy. Models 11 and 12 show the results if the first stage only uses Windy Days. All specifications include city and year-fixed effects, and cluster standard errors by city and year. Robust t-statistics are reported in parentheses. *, **, and *** refer to 10%, 5%, and 1% levels of statistical significance, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
	Excluding zero R&D cities		Policy responses to 2-year average AQI		AQI, Water, SD(adj-AQI), SD (adj-Water)		Alternative Char-adj Policy (Table 2 Model 5)		5-year Policy Uncertainty		Only Wind	
	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
PolicyUncer (Weather)		-3.81**		-2.03**		-2.83***		-2.72***		-2.50***		-2.55**
		(-2.40)		(-2.39)		(-2.84)		(-2.98)		(-2.71)		(-2.07)
PolicyUncer (Others)		0.14		0.01		0.01		0.02		-0.02		-0.02
		(0.77)		(0.06)		(0.08)		(0.10)		(-0.16)		(-0.13)
Char-adj Policy (Subsidy)		0.28*		0.48***		0.48***		0.47***		0.45***		0.47***
		(1.71)		(3.68)		(3.73)		(3.73)		(3.99)		(3.61)
SD (Windy Days)	0.01**		0.01***		0.01***		0.01***		0.01***		0.01***	
	(2.28)		(3.52)		(3.17)		(3.79)		(3.28)		(3.15)	
SD (Rainy Days)	0.10**		0.21***		0.12***		0.13***		0.12***			
	(2.08)		(3.72)		(2.76)		(2.93)		(2.98)			
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year and city fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clustering Year City	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj R^2	0.90	0.88	0.90	0.87	0.90	0.87	0.90	0.87	0.88	0.87	0.90	0.87
Observations	1088	1088	1297	1297	1297	1297	1297	1297	1297	1297	1297	1297

Table 6. Firm Differences

This table presents the extrapolation-induced policy uncertainty in R&D subsidy and its impact on firm-level environmental R&D investments. We estimate the following specifications:

1st stage: $PU_{j,t-5,t} = a + b_1 \times \sigma(Windy\_Days)_{j,t-6,t-1} + b_2 \times \sigma(Rainy\_Days)_{j,t-6,t-1} + b_3 \times X_{j,t} + \delta_t + \theta_j + \varepsilon_{j,t}$,
2nd stage: $R\&D_{i\in j,t+1} = \alpha + \beta_1 \times PU(Weather)_{j,t-5,t} + \beta_2 \times PU(Others)_{j,t-5,t} + \gamma \times PU(Weather)_{j,t-5,t} \times D(Firm\_Type)_{i\in j,t} + C \times X_{i\in j,t} + \delta_t + \varphi_i + \eta_{i\in j,t}$.

In the first stage, we estimate the city-level policy uncertainty for each firm based on the cross-section of all firms. In the second stage, the two components of policy uncertainty are linked to $R\&D_{i\in j,t+1}$, the logarithm of the environmental R&D investments made by firm i located in city j (i.e., $i \in j$), with firm and year fixed effects. $D(Firm\_Type)_{i\in j,t}$ represents the dummy variables for firm characteristics, including green-tech suppliers, high tech firms, firms in metropolitan, big firms, State-Owned Enterprises, firms with high reliance on environmental subsidy, and firm's register and office addresses located in different cities, firms in the manufacturing industry, the chemical industry, the metal industry, the public facility industry, and environmental industry. High Reliance on Environmental Subsidy equals one if the ratio of Environmental Subsidy to total assets is higher than median value and otherwise equals zero. The CSRC Industry Classification Code is reported in parentheses. We also control for the 6-year moving average for the characteristics-adjusted subsidy policy. Models 1 to 16 tabulate the results of the second stage regressions. All specifications include firm and year fixed effects. Robust t-statistics are reported in parentheses. *, **, and *** refer to 10%, 5%, and 1% levels of statistical significance, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
	y = Environmental R&D (Firm)														
PolicyUncer (Weather)	-0.46***	-0.46***	-0.22	-0.09	-0.39**	-0.46***	-0.47***	-0.28*	-0.44***	0.00	-0.38**	-0.42***	-0.46***	-0.45***	0.69***
	(-2.81)	(-2.81)	(-1.35)	(-0.52)	(-2.32)	(-2.83)	(-2.82)	(-1.71)	(-2.69)	(0.01)	(-2.35)	(-2.60)	(-2.79)	(-2.77)	(3.74)
Char-adj Policy (Subsidy)	0.06*	0.06*	0.06*	0.06*	0.06*	0.06*	0.06*	0.06*	0.06*	0.06**	0.06*	0.06*	0.06*	0.06*	0.06*
	(1.77)	(1.77)	(1.70)	(1.95)	(1.87)	(1.78)	(1.78)	(1.74)	(1.70)	(1.96)	(1.75)	(1.72)	(1.79)	(1.74)	(1.76)
PolicyUncer (Others)		-0.02													-0.01
		(-0.40)													(-0.33)
PolicyUncer (Weather) * Green Supplier			-0.56***												-0.45***
			(-7.45)												(-5.86)
PolicyUncer (Weather) * High Tech				-0.89***											-0.65***
				(-11.90)											(-7.83)
PolicyUncer (Weather) * Metropolitan					-0.16**										-0.31***
					(-1.97)										(-3.68)
PolicyUncer (Weather) *Big Firm						0.04									-0.25**
						(0.35)									(-2.00)
PolicyUncer (Weather) * SOE							0.02								-0.11
							(0.28)								(-1.31)
PolicyUncer (Weather) * High_Reliance on Env Subsidy								-0.49***							-0.15*
								(-6.28)							(-1.80)
PolicyUncer (Weather) * Office and register in different city									-0.08						-0.16*
									(-0.82)						(-1.76)
PolicyUncer (Weather) * Manufacturing (C)										-0.77***					-0.55***
										(-10.20)					(-6.24)
PolicyUncer (Weather) * Chemical (C25, C26, C28, C29, C41, C43)											-0.72***				-0.40***
											(-4.78)				(-2.55)
PolicyUncer (Weather) * Metal (C31, C32, C65, C67, C33)												-0.81***			-0.40*
												(-3.90)			(-1.89)
PolicyUncer (Weather) * Public Facility Industry (N)													-1.39***		0.63
													(-3.89)		(0.82)
PolicyUncer (Weather) * Environmental Industry (N77)														-2.18***	-2.82***
														(-5.40)	(-3.26)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj R^2	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43
Observations	27202	27202	27202	27202	27202	27202	27202	27202	27202	27202	27202	27202	27202	27202	27202

Table 7. Weather-Induced Policy Uncertainty in R&D Subsidy and R&D Employment

This table presents the impact of subsidy policy uncertainty on green-tech R&D investment. It shows the 2nd stage results of the following two-stage specifications:

1st stage: $PU(Subsidy)_{j,t-5:t} = \alpha + b_1 \times \sigma(Windy\_Days)_{j,t-6:t-1} + b_2 \times \sigma(Rainy\_Days)_{j,t-6:t-1} + b_3 \times X_{j,t} + \delta_t + \theta_j + \varepsilon_{j,t}$,

2nd stage: $Environmental\ R\&D\ Employment_{j,t+1} = \alpha + \beta_1 \times PU(Weather)_{j,t-5:t} + \beta_2 \times PU(Others)_{j,t-5:t} + \beta_3 \times AveSubsidy_{j,t-5:t} + \beta_4 \times X_{j,t} + \delta_t + \theta_j + \eta_{j,t}$.

In the first stage, $PU(Subsidy)_{j,t-5:t}$ denotes the policy uncertainty of city j estimated as the standard deviation of characteristics-adjusted subsidy policy in the rolling period from year $t-5$ to t, where characteristics-adjusted subsidy policy of a city in any given year is estimated as the residual (i.e., $\varepsilon_{j,t}$) of the cross-sectional regression, $Policy_{j,t} = \alpha + C \times X_{j,t-1} + \varepsilon_{j,t}$, when city characteristics are controlled for (i.e., the specification used in Model 1 of Table 2). $\sigma(Windy\_Days)_{j,t-6:t-1}$ and $\sigma(Rainy\_Days)_{j,t-6:t-1}$ refer to the standard deviation of the number of windy days and rainy days per year in the same rolling period from year $t-6$ to $t-1$. $X_{j,t}$ stacks control variables, including the pollution indices as well as the city and firm characteristics. We then further decompose $PU(Subsidy)_{j,t-5:t}$ into two components according to the first stage: $PU(Weather)_{j,t-5:t} = b_1 \times \sigma(Windy\_Days)_{j,t-6:t-1} + b_2 \times \sigma(Rainy\_Days)_{j,t-6:t-1}$ denotes the weather-induced policy uncertainty, and $PU(Others)_{j,t-5:t}$ synchronizes the remaining policy uncertainty. These two components are then linked to $Environmental\ R\&D\ Employment_{j,t+1}$ in the following year, in the second stage. Environmental R&D Employment is the logarithm of the number of environmental R&D researchers in a city plus one. The number of environmental R&D researchers is defined as the total number of R&D and technical employees in those firms with environmental R&D investments. As an additional control in the second stage, $AveSubsidy_{j,t-5:t}$ refers to the 6-year moving average for the characteristics-adjusted subsidy policy. The first stage estimation and all control variables are the same as in Table 3. Models 1 to 7 present the second stage regressions. All specifications include city and year-fixed effects, with standard errors clustered by city and year. Robust t-statistics are reported in parentheses. *, **, and *** refer to 10%, 5%, and 1% levels of statistical significance, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	y = Environmental R&D Employment (City)						
	2nd Stage: Influence of projected policy uncertainty and other policy variables						
PolicyUncer (Weather)	-1.32***		-1.32***		-1.26***		-1.20***
	(-3.72)		(-3.74)		(-3.59)		(-3.36)
PolicyUncer (Others)		-0.09*	-0.09*		-0.04		-0.04
		(-1.65)	(-1.68)		(-0.87)		(-0.82)
Char-adj Policy (Subsidy)				0.21***	0.19***		
				(4.39)	(4.05)		
Policy (Subsidy)						0.18***	0.16***
						(4.26)	(3.66)
Control Variables	YES	YES	YES	YES	YES	YES	YES
City and Year Fixed	YES	YES	YES	YES	YES	YES	YES
Clustering city year	YES	YES	YES	YES	YES	YES	YES
Adj R^2	0.85	0.85	0.85	0.85	0.86	0.85	0.86
Observations	1297	1297	1297	1297	1297	1297	1297

Table 8. Weather-induced Policy Uncertainty in R&D Subsidy and its Impact on Green Patenting

This table presents the effect of subsidy policy uncertainty on green patent applications. Green Patent is the logarithm of the total number of green patent applications in a city plus one. We show the 2nd stage results of the following two-stage specifications:

1st stage: $PU(Subsidy)_{j,t-5:t} = \alpha + b_1 \times \sigma(Windy\_Days)_{j,t-6:t-1} + b_2 \times \sigma(Rainy\_Days)_{j,t-6:t-1} + b_3 \times X_{j,t-5:t} + \delta_t + \theta_j + \varepsilon_{j,t}$,

2nd stage: $Ave\_Green\ \ Patent_{j,t-5:t} = \alpha + \beta_1 \times PU(Weather)_{j,t-5:t} + \beta_2 \times PU(Others)_{j,t-5:t} + \beta_3 \times AveSubsidy_{j,t-5:t} + \beta_4 \times X_{j,t-5:t} + \eta_{j,t}$.

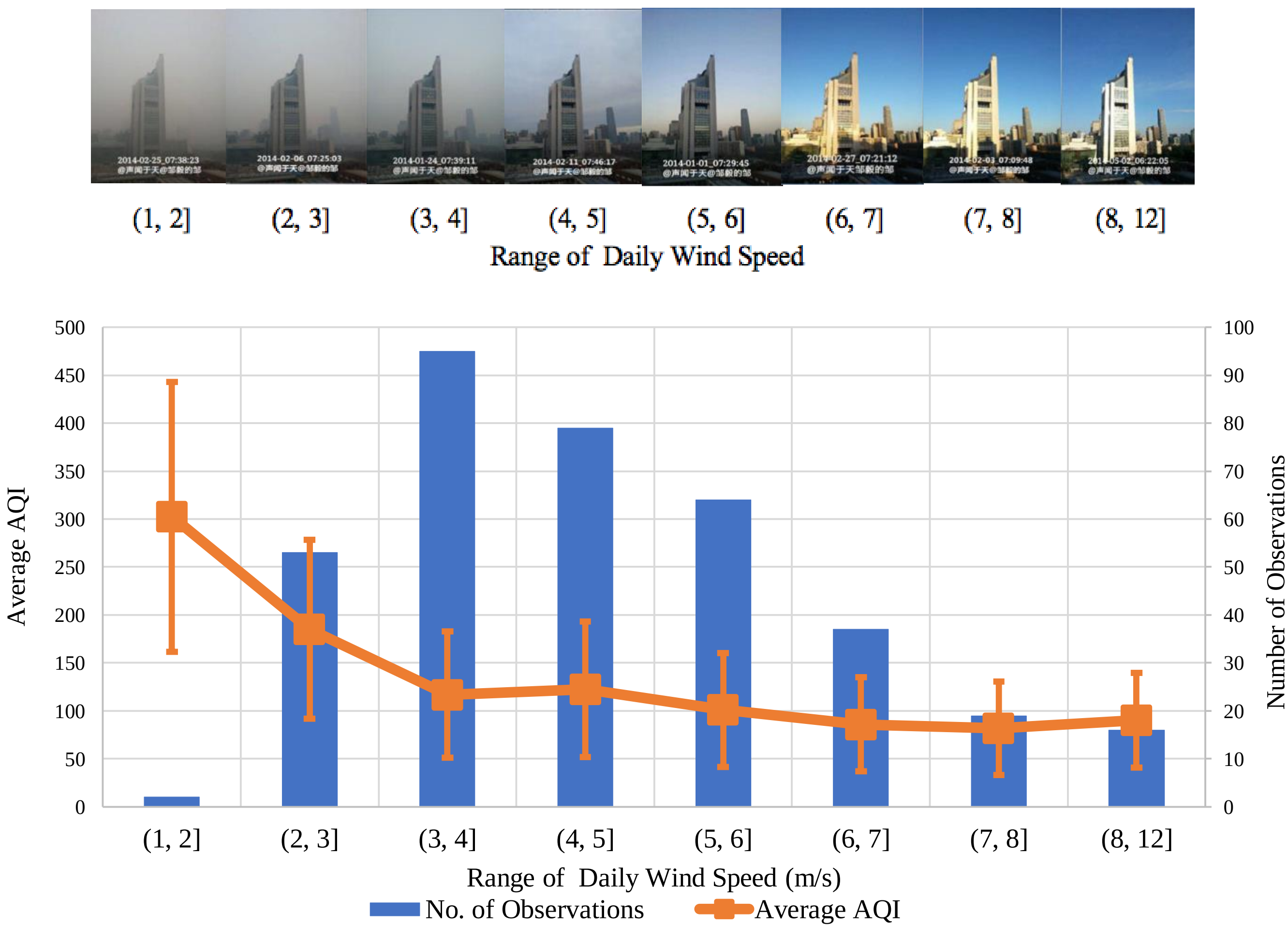
Where, $\sigma(Windy\_Days)_{j,t-6:t-1}$ and $\sigma(Rainy\_Days)_{j,t-6:t-1}$ are the 6-year moving standard deviation of windy days and rainy days. $Ave_Green\ \ Patent_{j,t-5:t}$refers to the 6-year moving average of Green Patent. The $X_{j,t-5:t}$ stacks a list of control variables in a 6-year average value. In the first stage, all specifications include city and year-fixed effects, with standard errors clustered by city and year. The second stage is using Fama-MacBeth regressions, referring to Minton and Schrand (1999 JFE). Robust t-statistics are reported in parentheses. *, **, and *** refer to 10%, 5%, and 1% levels of statistical significance, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	y = Ave Green Patent (City) (Ave t-5:t)						
	2nd Stage: Influence of projected policy uncertainty and other policy variables						
PU (Char-adj subsidy) (Vol t-5:t)	-0.05***		-0.05***		-0.03**		-0.03***
	(-5.26)		(-4.75)		(-2.25)		(-3.24)
Other PU Subsidy (Vol t-5:t)		0.02	0.03		0.03		0.03
		(1.22)	(1.47)		(1.66)		(1.64)
Average Char-adj Subsidy (Ave t-5:t)				0.03***	0.03***		
				(14.15)	(8.81)		
Average Subsidy (Ave t-5:t)						0.03***	0.02***
						(12.38)	(6.51)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Average Adj R^2	0.47	0.47	0.48	0.48	0.49	0.48	0.48
Number of Observations	1374	1374	1374	1374	1374	1374	1374

Figure 1. AQI and Weather in Beijing

This figure illustrates how air quality depends on wind and rain in Beijing. Panel A shows representative pictures of the same building in Beijing taken on different days in 2014. Source: https://tinyurl.com/4d5kcjk4. A bluer sky corresponds to cleaner air and typically a lower AQI. From left to right, the wind speed is 1-2, 2-3, etc. meters per second. Panel B plots the average AQI in Beijing in 2014 as a function of average wind speed. Rain is scarce in Beijing, so Panel C pools 2013-2018 data to show the dependence of AQI on rain. The rain levels are: <=10mm, 10mm-25mm), 25-50mm, and >50mm.

Panel A. Photos of Beijing and Average AQI Versus Wind Speed, 2014.



Panel B. Rain Volume and Average AQI in Beijing, 2013-18.

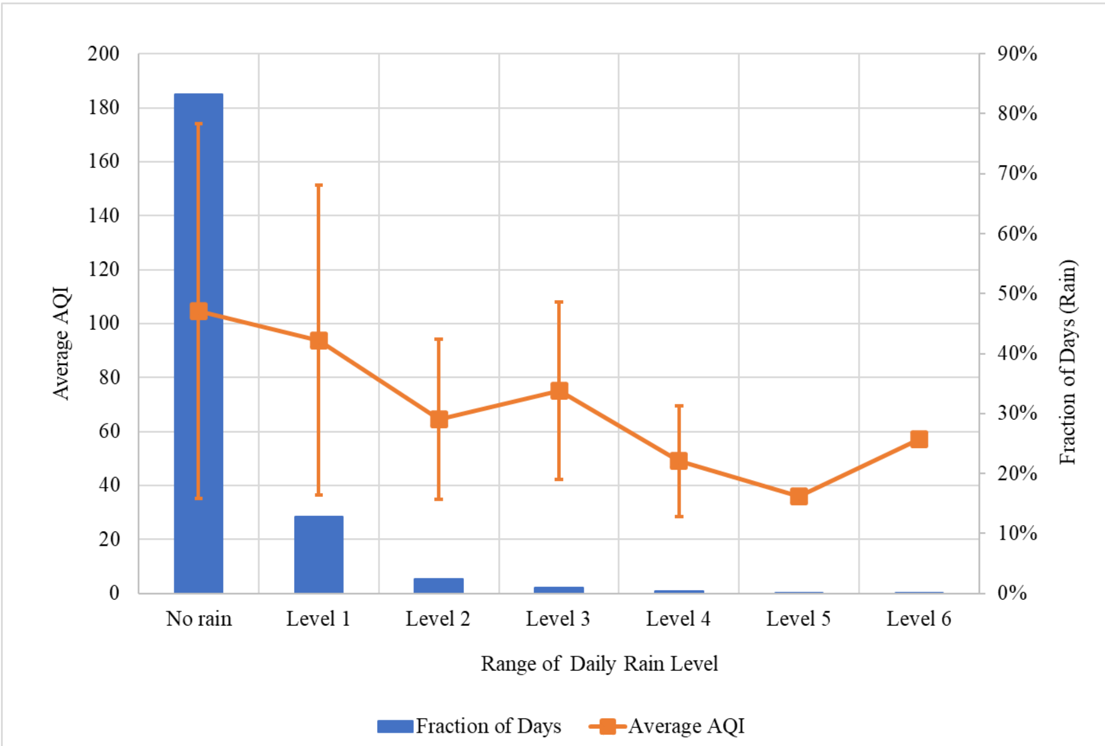
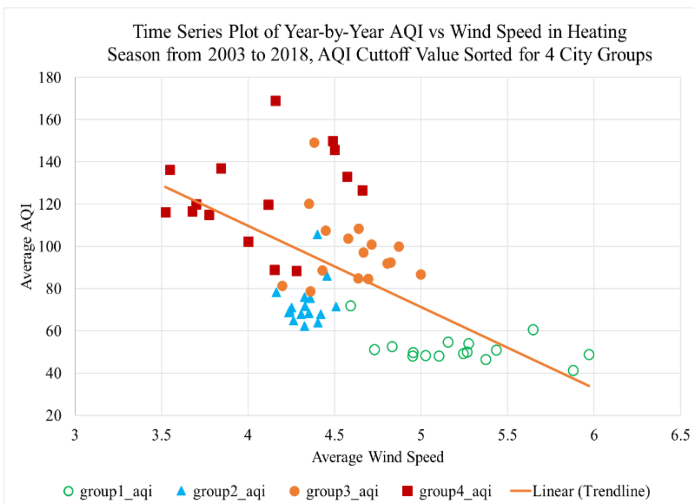


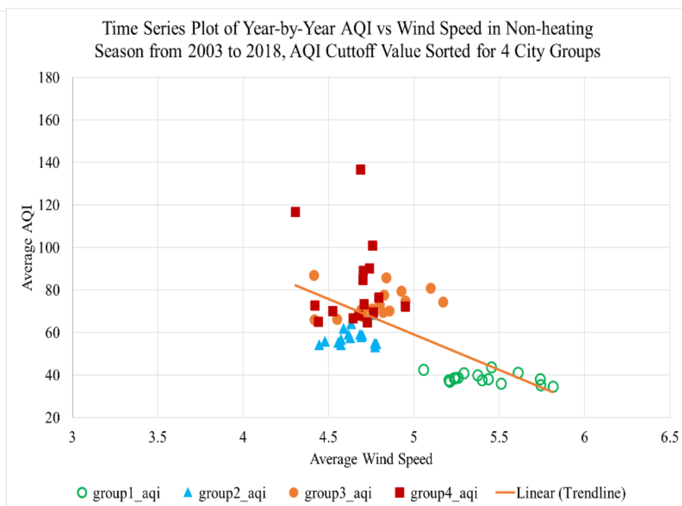
Figure 2. AQI vs Wind in Heating and Non-Heating Seasons

This figure plots the AQI-wind relationship in heating and non-heating seasons for all cities. The heating season of a given year is defined as January, February, March, November, and December. The remaining months are classified as non-heating season. Although the real starting and ending dates of the heating season vary across cities and years, our classification suffices to capture the potential influence of coal-based heating activities on air pollution.

Panel A. AQI Cutoff Value for Four City Groups

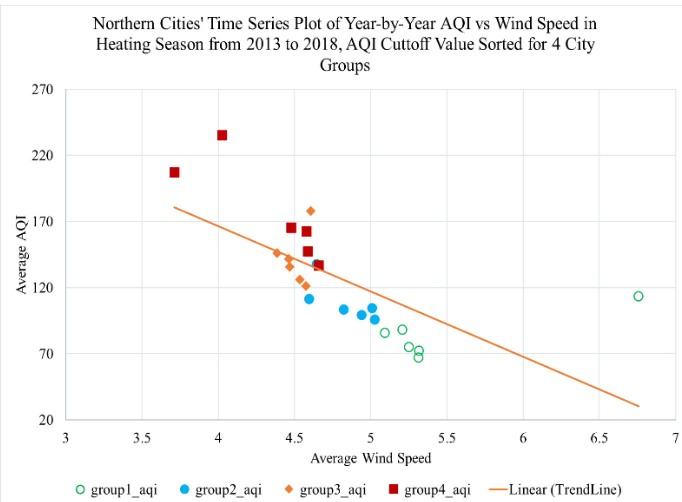
Group	Number of cities
Group 1: AQI [25, 50]	16
Group 2: AQI [50, 75]	97
Group 3: AQI [75, 100]	103
Group 4: AQI [100, 150]	24





Panel B. AQI Cutoff Value for Four Northern City Groups (2013-2018)

Group	Number of cities
Group 1: AQI [50, 75]	27
Group 2: AQI [75, 100]	51
Group 3: AQI [100, 125]	34
Group 4: AQI [125, 150]	5



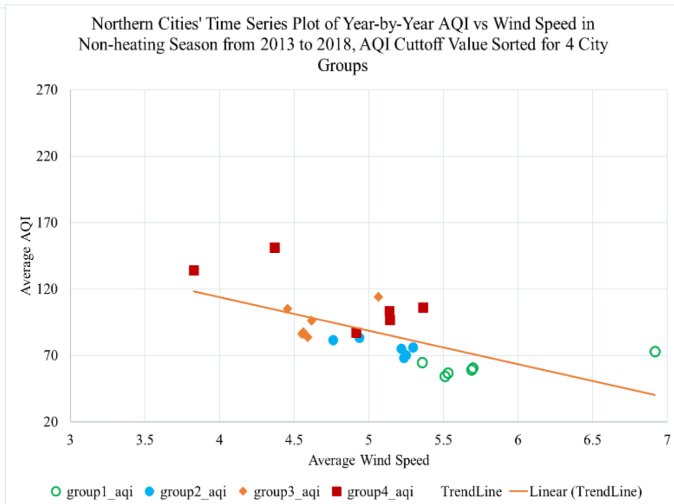


Figure 3. Total Policy Uncertainty and Weather-Induced Policy Uncertainty Across China

This figure illustrates the distribution of (Environmental Subsidy) Policy Uncertainty and Weather-Induced Policy Uncertainty in China. The area of the circle represents the magnitude of Policy Uncertainty in a city. The black portion corresponds to the fraction of policy uncertainty we attribute to the weather and the grey portion is the residual.