Policy Uncertainty Reduces Green Investment*

Mengyu Wang Jeffrey Wurgler Hong Zhang

June 9, 2023

Abstract

Government subsidies are often used to stimulate environment-friendly investment. We find that Chinese firms reduce green investment as the uncertainty of subsidies rises. This effect is identified from weather-driven fluctuations in air pollution that lead to fluctuations in subsidy allocations: Firms in cities where weather-driven subsidy uncertainty is high engage in less green R&D investment, patent applications, and research staff. Industries that are heavy emitters and those focused on environmental technologies are more affected. The results suggest that policy uncertainty may originate not only from political and macroeconomic shocks but from behavioral mechanisms that link policy to salient recent conditions.

Keywords: Economic Policy Uncertainty, R&D, Environment, Irreversible Investment

---

* Wang: PBC School of Finance, Tsinghua University, wangmy@pbcsf.tsinghua.edu.cn; Wurgler: Stern School of Business, New York University, and NBER, jwurgler@stern.nyu.edu; Zhang: Singapore Management University, hongzhang@smu.edu.sg. We are grateful to Yakov Amihud, Nick Barberis, Sanjiv Das, David Hirshleifer, Mohammed Shehub Bin Hasan, Sabrina Howell, Holger Mueller, Lasse Pedersen, Andrei Shleifer, Meir Statman, and seminar participants at Florida International University, NYU Stern, and the Universities of Edinburgh, Miami, Reading, and Santa Clara for helpful comments.

I. Introduction

On November 19, 2010, the Air Quality Index (AQI) measured at the U.S. Embassy in Beijing reached 562. The cheeky programmer who set up the Embassy's automatic Twitter report apparently never imagined that air pollution would reach the level of a forest fire, and air quality was broadcast as "crazy bad." "An official said there was insufficient research to explain why the pollution haze has been so murky this week. The culprit is likely to be a combination of weather, traffic and coal-burning power stations."[1] Although the cause of the pollution spike could not be isolated, the government increased environment-related subsidies to Beijing firms by 78% the next year.[2]

Air pollution control efforts are so important because airborne particulates have broad health and economic impacts. They shorten human lifespans by an average of two years, and they reduce the healthfulness of the remaining years in many ways.[3] The list of negative economic consequences of particulate matter is also growing rapidly, including reduced productivity, human capital formation, and economic growth, and even altered investor behavior and stock prices.[4]

---

[1] https://www.theguardian.com/environment/blog/2010/nov/19/crazy-bad-beijing-air-pollution.

[2] Data and calculations described herein.

[3] https://aqli.epic.uchicago.edu/pollution-facts/. For methodological underpinnings, see Chen, Ebenstein, Greenstone, and li., 2013 and Ebenstein et al., 2017).

[4] For an overview of health effects, see Fonken et al., 2011; Mohai, Kweon, Lee, and Ard., 2011; Weuve et al., 2012. For 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, Graff Zivin, Gross, Neidell, 2016, 2019; Isen, Rossin-Slater, and Walker, 2017; He, Wang, and Zhang, 2020), growth (Ebenstein et al. 2015), happiness (Zheng et al. 2019), neighborhood sorting (Heblich, Trew, and Zylberberg., 2021), investor

In addition to air pollution being a problem worth attention in its own right, it shares a feature with other policy settings: It can manifest as an immediate, salient problem that requires a response despite an imperfect understanding of its causes. In this sense, combating air pollution has similarities with fiscal and monetary policy decisions that must react to shocks whose nature is not fully clear in the moment; climate policy decisions in the absence of a sharp breakdown between manmade and natural sources of temperature rise; or, financial market regulation in a complex meltdown. Economic policy made under such conditions is at greater risk of having unintended consequences.

In this paper, we study how environmental subsidies to Chinese firms are allocated and how effective they are in terms of the "green" investment that they are intended to stimulate. Our evidence suggests that policymakers who allocate the subsidies may be prone to react to current, salient circumstances, even though the causes may be beyond the reach of policy; these reactions, in turn, create policy uncertainty, which is known to discourage firm investment when investments are costly to reverse (e.g., Bernanke, 1983; McDonald and Siegel, 1986; Dixit and Pindyck, 1994; Julio and Yook, 2012; Gulen and Ion, 2016). Our evidence confirms that policy uncertainty discourages the green investment that the subsidies were intended to stimulate, and we speculate about new and potentially behavioral mechanisms that give rise to the policy uncertainty in the first place.

---

behavior (Li, Massa, Zhang, and Zhang 2021), and financial markets (e.g., Heyes, Neidell, and Saberian, 2016; Huang, Xu, and Yu, 2020).

To illustrate, consider the task facing a central planner who periodically allocates subsidies to firms to encourage environmentally-friendly investment. The starting point is to figure out where the problems are. Since it is infeasible to monitor more than a small fraction of the point sources of emissions in a municipal area, policymakers rely on collection devices like the one at the U.S. Embassy in Beijing. With AQI data from many cities in hand, the central planner can establish targets and allocate subsidies to more polluted areas and eventually down to the firms that can make best use of them.[5]

Figure 1 suggests why this allocation problem is, in practice, far more difficult. Panel A shows the same building in Beijing on different weekdays in 2014. Panel B connects the pictures to wind speed and the associated AQI. What differentiates the pictures is not the prevailing local emissions, which are stable within a year, but modest differences in wind speed, as wind disperses air pollution. Panel C shows a similar relationship between AQI and rainfall. Rain clears the air by pushing particulates to the ground. Given that weather can both improve pollution and make it severe—importantly, an effect that prevails not just day to day, but at lower, policy-relevant frequencies as well—the attribution of pollution becomes difficult, and subsidy allocations are at risk of being influenced by weather "noise."

We assemble a panel of thousands of firms across hundreds of cities in China from 2003 to 2019 (pausing at the Covid onset). For each city-year we observe weather, air pollution,

[5] For more on 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. The WHO uses a closely related index which includes most of the same pollutants as the AQI.

various city characteristics, and—via translations from Chinese keywords—the environmental subsidies received by local firms along with their own green investment. We document that a one-standard-deviation increase in wind and rain variability relative to a city's long-term average translates into a 13% reduction in green R&D investment by firms headquartered in the city, controlling for the long-term average subsidy level. A clear demonstration of the effect of policy uncertainty on *green* investment, a novel type of investment of broad current interest, is our main contribution. Our findings support the concerns of academics, professionals, and regulators that regulatory risk is now the top climate risk facing firms (Stroebel and Wurgler, 2021).

This finding is robust to timing, levels of aggregation (firm and city level), and additional measures of green investment (green R&D employment and patenting). Firms that respond the most to policy uncertainty include green-tech, manufacturing, and chemicals firms; this is notable because from an environmental perspective, one might want to incentivize such firms the most. Importantly, the negative effect of uncertainty is separate from the positive effect of the level of the subsidy. Hence, even if weather fluctuations average out in a long run and do not affect the long-run total environmental subsidy in a given city, the uncertainty itself reduces the cumulative firm response.

What gives rise to this uncertainty? Every Chinese citizen and bureaucrat knows that wind affects air pollution. But when the problem is acute, it is difficult to defend inaction on the basis that the extreme conditions might be due to a spell of weak winds. We speculate that the mechanism connecting weather to subsidy uncertainty is enhanced by a collection of related judgmental biases, known in individual choice contexts, that lead to a policy reaction to recent, salient conditions. Well-studied biases that imply this behavior include salience, extrapolation, projection, recency, and availability. We discuss such “recency biases” and suggest they provide a novel driver of generating policy uncertainty that complements standard political and macroeconomic shocks that also generate policy uncertainty. This is our second, more speculative contribution. The mechanism is itself interesting beyond our context because, as noted at the outset, many policy challenges manifest as immediate, salient problems that need a response despite an imperfect understanding of their causes.

The paper proceeds as follows. Section II gives institutional background and describes our data. Section III documents that policy depends on AQI, which in turn depends on weather, and then combines weather variability and potential behavioral underpinnings to motivate an instrument for policy uncertainty. Section IV shows that policy uncertainty discourages green R&D investment. Section V conducts additional analysis using other measures of investment, and Section VI concludes. An Internet appendix is available.[6]

II. Institutional Setting and Data

A. Environmental Subsidies

Subsidies are an essential economic tool in China, used to incentivize or encourage development in numerous directions. Companies that receive subsidies earmarked for

[6] https://tinyurl.com/3wedr7up.

environmental purposes may also receive other subsidies, such as those to support agriculture, health, manufacturing, insurance, or tax subsidies that cannot be connected to a specific goal. See Branstetter, Li, and Ren (2022), for a broader discussion of economic subsidies, their magnitudes, and associations with firm productivity and employment.

As explained below, we use footnotes to the financial statements, translated from the original Chinese, to identify subsidies with an environmental objective. Here are two examples for concreteness. Shandong Lukang Pharmaceutical Co., Ltd., received 3.8 million RMB of environmental subsidies in 2009 with labels of "ecological compensation fund," "special funds for industrial pollution control," and "environmental protection equipment." This total then varied as follows: 5.1 million RMB in 2010; 1.5 million RMB in 2011; 1.1 million RMB in 2012; 0.2 million RMB or less in 2013-2016; 0.6 million RMB in 2017; and, 2.1 million RMB in 2018. Zijin Mining Group Co., Ltd., received subsidies with a dozen environment-related labels over the same period, with totals of 2.9 million RMB in 2008 and 2009; 8.1 million RMB in 2010; 39.3 million RMB in 2011; 22.0 million RMB in 2012; 13.5 million RMB in 2013; 15.7 million RMB in 2014; and, 9 million RMB or less in 2015-2017. These examples suggest how the considerable variability in environmental subsidies could complicate corporate plans.

B. Top-Down Decisions

To understand the allocation of these subsidies across space and time, one must understand the mechanics of the process. The Chinese government makes and implements environmental policies in a three-layer top-down system: From central government, to provinces, and finally to city-level governments. This system is institutionalized in the Environmental Protection Law.

The general process is as follows. The central government moves first by stating its environmental targets either in its regular five-year plans or interim special-purpose regulations. Crucially, for our purpose, the central government often explicitly specifies air quality targets, be they national or at the province or city level, in terms of Air Quality Index (AQI) metrics. After the central government releases the goals, provincial and lower governments launch their own five-year plans and local policies. The provincial five-year plans implement such targets in part by allocating environmental subsidies. The provincial government assigns the administration of such tasks to its lower-level governments (i.e., cities), completing the three-layer process. (One might consider the allocation to firms within a city as a fourth layer.) Tracking the implementation of this process, Zhang, Chen, and Guo (2018) document the role of central supervision of local enforcement, while Chen, Li, and Lu (2018) show the efficacy of target-based environmental performance evaluation systems for local bureaucrats.

For example, after the State Council released the national 11th five-year plan in 2007 proposing various targets, the Hebei provincial government released its five-year plan in 2008, targeting the number of days with "good" air quality (an AQI below 100) in its main cities to exceed 80% by 2010. The province's 12th five-year plan (covering the period 2011-2015) moved the targeting number to 85% days by 2015. After experiencing the heavy pollution in 2013 that had prevailed in northern China, it reset the target in its 13th five-year plan (2016-2020) to achieve 63% days with good air quality in 2020. Each of these changes had implications for subsidies to firms. And, to be sure, these plans contain no discussion of "controlling for weather" in achieving these goals.

By their very definition, "five-year plans" create uncertainty. The Chinese government is well-known for interim policy shifts as well. The sudden abandonment of the stringent "zero COVID" policy in December 2022 is one example. Or, in another context, two days after Didi's listing in the U.S., China's cyber regulator launched an investigation into the company and banned Didi's app from new customers, punishing the stock price.[7] A further relevant example is the "Coal-to-Gas" policy reviewed in the Internet appendix. China wished to replace coal with cleaner natural gas, but had to reverse policy due to a gas shortage. Both the adoption and suspension of the policy reinforced uncertainty and illustrated to those concerned—such as steel manufacturers, which saw costs under gas double—that it may be privately optimal to delay costly responses to a new policy.

Many other unpredictable dictates could be cited. Suffice to say, China presents an empirically interesting setting for our purpose. It resides at or near the top of the list of countries with air pollution challenges and it offers a rich environment of policy uncertainty.

C. Data

We gather data on firms and their investment, government subsidies, pollution, weather, and city-level characteristics. Appendix A provides a list of variables, their definitions, and

---

[7] https://www.ft.com/content/809b31e2-6b1e-42b6-8009-3ea78969d870.

sources. Table 1 shows summary statistics. From 2020 through the most available data at the time of this writing, economic policies and firm responses in China are highly likely to be influenced by the Covid pandemic, so we end our sample in 2019.

Some essential data come from the China Stock Market & Accounting Research Database (CSMAR). We obtain firm-level R&D expenditure and received government subsidies from the footnotes of the financial statement of firms as reported in CSMAR, which we translated from the original Chinese. We identify the green component of both R&D efforts and government subsidies from environment-related keywords appearing in the item description. We group subsidies into 21 types and choose only subsidies with a clear connection to the environment.[8]

We then use the locations of firms' headquarters to aggregate firm environmental R&D and granted government subsidies at the city-year level. Following the literature on R&D expenditure (e.g., Jaffe., 1988; Adams,1993; Bloom Griffith, and Van Reenen, 2002; Adams Chiang, and Jensen, 2003), we use the logarithm of the RMB value of city-level environment-related R&D, summed across firms, as our main measure of that type of investment. We refer to this variable as

---

[8] The list of environment-related keywords, 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 tabulated in the Internet appendix. As we report, the main results do not depend on this precise list of keywords. See Branstetter et al. (2022) for a neural-network-based classification approach for other categories of subsidies.

Green R&D. We then use the logarithm of the RMB value of the government environmental subsidy in each city-year as our basic measure of environmental policy, which we label *Raw Green Subsidy.* The annual average Green R&D is 486.5 million RMB from 2009 to 2019. The annual average raw subsidy is 51.5 million RMB from 2009 to 2019. We can see that most cities in our sample have granted environmental subsidies in this period, and, as further discussed in our Internet appendix, a majority of city-years in our sample have nonzero green R&D investment.

We collect government expenditures on another government-guided environmental program, industrial *Waste Gas Treatment*, also measured in log RMB, from EPSnet.[9] This variable is distinct from subsidies to firms and does not incentivize firms, but it can be used to independently confirm policymakers' attention to AQI.

Daily AQI readings are from the Ministry of Environmental Protection of China (MEPC) for major cities in China. The AQI incorporates the concentrations of six air pollutants—sulfur dioxide, nitrogen dioxide, particulate matter 10 microns or smaller (PM10), PM2.5, carbonic oxide, and ozone—based on data from local monitoring stations. We calculate the annual AQI as the average daily AQI of a city in a given year.[10] It is worth mentioning that while the subsidies

---

[9] EPSnet collects city-level waste gas treatment data from China Statistical Yearbook on Environment, National Environmental Statistics Bulletin, and China Environment Yearbook. A snapshot of the province-level investment for 2014 is at http://www.stats.gov.cn/zt_18555/ztsj/hjtjzl/2014/202303/t20230303_1924039.html. The funds are provided largely by the state. These data cover 119 cities from 2003 to 2017.

[10] Before 2013, China used an Air Pollution Index (API) that covered the first three of these pollutants. As detailed in the Internet appendix, the two indices are highly correlated and used comparable numerical reference points for policymakers. Hence, we use API data before 2013 but for simplicity refer to the whole series as AQI.

that we study are to encourage green investment by firms, AQI depends not just on industrial production and power plants but also transport, household heating and waste burning, road dust, and other pollution sources that may be influenced only indirectly by these subsidies.

The average annual value of AQI across cities is 78. By U.S. standards, this level is of "Moderate" concern when considered as a daily value; Chinese authorities call it "Good." An AQI above 100, which is one-standard-deviation worse than average, is called "Unhealthy for sensitive groups" in the U.S. and "Lightly polluted" in China. A year with this pollution level as a daily average would have seen multiple periods of unambiguously hazardous levels.

The China Meteorological Administration (CMA) provides daily city-level weather data. We build our instruments for weather fluctuations from two yearly measures. *Windy Days* counts 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). *Rainy Days* counts the number of days having more than 25mm of rain (corresponding to Level 3 or above out of the six rain levels categorized by the CMA). Based on these two variables, we construct our instruments, *SD Windy Days* and *SD Rainy Days*, as the standard deviation of the number of *Windy Days* and *Rainy Days* observed in a given city over the prior six years, with minor adjustments as detailed below. These weather variables vary substantially across cities.

Our main analysis controls for both city and firm characteristics that may affect subsidies and firm behavior for other reasons. Our main city-level control variables come from CNRDS (which digitalizes data from China City Statistical Yearbook), including log consumption, log

GDP, GDP growth, and population growth. Consumption data are available only at the province level, but this does not affect our inferences because of city fixed effects.

More firm-level characteristics come from Wind, CSMAR, and the Chinese Research Data Services Platform (CNRDS). These include industry classifications, state ownership, total assets, turnover ratio, return on assets, leverage ratio, firm size, cash holdings, capital expenditures, profit margin, and stock returns. Appendix A provides definitions. These characteristics describe the capital structure, profitability, and investment opportunities of firms, which could also affect firm decisions (e.g., Jaffe, 1988; Adams, 1993; Minton and Schrand 1999; Bloom et al., 2002; Adams et al., 2003). For our city-level analysis, we weight these variables by firm assets to obtain city-level control variables reported in Table 1. Our main two-stage specifications control for city or firm effects in city-level and firm-level analysis, respectively, so it is not surprising that the inclusion of firm characteristics or the exclusion of financial firms have only minor effects on our main results.

The resulting sample includes an unbalanced panel of 3,168 listed firms, across 345 Chinese cities, from 2003 to 2019. As mentioned above, we exclude the most recent data due to the potential impacts of the Covid pandemic.

III. Determinants of Subsidy Allocations and Origins of Policy Uncertainty

In this section, we establish that the anecdote from our introductory paragraph, in which a brief but extreme AQI reading in the Beijing area led to a large increase in environmental subsidies, is part of a robust pattern. We document the role of weather, form an instrument for policy uncertainty, and suggest some more fundamental mechanisms that may connect subsidy uncertainty to weather variability.

A. The Effect of AQI on Subsidy Policy

We first provide a cross-city analysis of the determinants of green subsidies in a given year. We regress the sum of green subsidies reported by firms in the city in a Fama-MacBeth (1973) specification, a standard methodology in asset pricing in which coefficients are averaged across cross-sections to yield standard errors robust to cross-sectional correlation:

$$Raw\ Green\ Subsidy_{j,t} = a_0 + a_1 \times AQI_{j,t-1} + A \times X_{j,t-1} + \varepsilon_{j,t}, \quad (1)$$

where $Raw\ Green\ Subsidy_{j,t}$ denotes the log of the total environmental subsidy provided to firms in city j in year t, $AQI_{j,t-1}$ is the average Air Quality Index in the previous year, and the vector $X_{j,t-1}$ is a set of control variables including city characteristics and asset-weighted averages of the characteristics of firms in city j. City characteristics are log consumption, log GDP, GDP growth rate, and population growth rate. Firm characteristics averaged at the city level are asset turnover, return on assets, leverage, firm size, cash holdings, capital expenditures, profit margin, and lagged stock return. Annual is the highest frequency at which certain data are available, but in light of the substantial yearly variation in subsidies granted to the firms in the examples above it also seems an appropriate frequency for study.[11]

[11] Chang, Huang, and Wang (2018) show that bad air pollution leads to an almost immediate increase in health insurance demand.

The results are in Table 2. The first model examines the effect of city characteristics only. The takeaway is that wealthier cities receive considerably more environmental subsidies, consistent with the univariate correlation from the summary statistics. As this is a log-log relationship, the coefficient indicates that a 1% increase in GDP per capita is associated with a 3.2% increase in green subsidy. A number of political and economic processes might lead to this intuitive relationship; we treat GDP per capita as a control variable.

Our interest centers on a_1. The next model shows that year *t* environmental subsidies are, on average, higher in cities with worse air pollution in year *t*-1 (higher AQI). When we control for city characteristics in Model (2), a one-standard-deviation greater AQI is associated with a 0.205 standard deviation greater green subsidy in the following year.[12] Other models in Table 2 show that these conclusions are little affected by the inclusion of firm characteristics, which for brevity we do not report. In the Internet appendix, we show that the policy-AQI relationship is robust in the post-2013 sample and to permutations such as using the city's rank of AQI rather than its level.

We have already noted that top-down targets are explicitly based on AQI, so the fact that subsidies correlate with it is not surprising. As further confirmation of the importance of this measure, we study another government-guided environmental program, city-level expenditures on treatment of industrial waste gas. With $Waste\ Gas\ Treatment_{j,t}$ as the dependent variable,

---

[12] $(\hat{a}_1 \times SD\ AQI)/SD\ Subsidy = (0.06\ \times 25.3)/7.4 = 0.205$. (The standard deviations relevant to Table 2 are based on additional observations than those in Table 1, which summarizes the primary regression sample.)

we find qualitatively similar results. In particular, from Model (5), a one-standard-deviation increase in AQI gives rise to a 0.137 standard deviation increase in the log of waste gas treatment.[13] Further specifications are reported in the Internet appendix.

In summary, subsidy expenditures meant to combat air pollution are, intuitively and sensibly, directed toward the most-polluted areas, as measured by the standard AQI and consistent with how air quality targets are communicated. The bureaucratic concern with the air quality figures themselves is also apparent in the slight manipulation that occurs to keep figures just below prominent targets (e.g., Andrews, 2008).

B. The Effect of Weather on AQI

Although AQI measures underlying point sources of pollution, Figure 1 shows that it is also influenced by wind and rain at a daily frequency. We now document the effects of weather on AQI across cities at a lower frequency which is more relevant to policymaking; just as some days are windier and rainier than others, so are some months or years. In addition, due to the impact of the coal-intensive heating season on air pollution in northern cities (e.g., Almond et al., 2009; Chen et al., 2013; Ebenstein et al., 2017), we establish the AQI-weather relationship separately in heating and non-heating seasons. The heating season is defined as November through March.

We document the AQI-weather relationship in a simple specification:

$$AQI_{j,t,s} = b_0 + b_1 \times Wind\ Speed_{j,t,s} + b_2 \times Rain\ Volume_{j,t,s} + B \times X_{j,t} + \delta_j + \delta_t + \varepsilon_{j,t,s} \quad (2)$$

[13] $(\hat{a}_1 \times SD\ AQI)/SD\ Subsidy = (0.04 \times 25.3)/7.4 = 0.137$.

where $AQI_{j,t,s}$ denotes the average daily AQI of city j in the heating or non-heating season s of year t and $Wind\ Speed_{j,t,s}$ and $Rain\ Volume_{j,t,s}$ are the average daily wind speed and rain volume in the same city and period, respectively. $X_{j,t}$ includes city characteristics as before. We also include city and year fixed effects with double-clustered standard errors.

Equation (2) is not a sophisticated physical model. A physical model that would consider humidity, temperature, wind direction relative to nearby cities, cloudiness, humidity, and other known weather effects on air quality is beyond the scope of this paper. See Cai et al. (2017) or Zhang et al. (2018b) for treatments that illustrate that even local geography has important interactions with all of these factors. Fortunately, the first-order effects of simple wind and rain measures are strong enough that that we can form an instrument for policy uncertainty without modeling other physical conditions.

The results in Table 3 confirm expected relationships between the average AQI and the average wind and rain over a season. This is true for both heating and non-heating seasons as well as for northern cities separately. The magnitude is sizable. In the sample of all cities (northern cities), for example, an increase of the average wind speed by one meter per second is associated with a decline of heating-season AQI of 3.2 (5.0) points. The meteorological literature explains this relationship in a straightforward way; wind prevents pollutants from accumulating near ground level and rain pushes down particulates and washes them away.

In summary, weather has a robust, causal effect on AQI that is detectable at annual frequencies, controlling for city and year fixed effects. See the Internet appendix for variations of the specification in Eq. (2).

C. Weather Uncertainty as an Instrument for Policy Uncertainty

Putting the pieces together, we use weather to form an instrumental variable for subsidy policy uncertainty as a first stage toward estimating the effect of policy uncertainty on green investment, our main question of interest. We measure uncertainty based on time-series volatility (e.g., Segal, Shaliastovich, and Yaron, 2015; Fernandez-Villaverde, Guerron-Quintana, Kuester, and Rubio-Ramirez, 2015), which is the natural notion of uncertainty in our context. Specifically, we define policy uncertainty $PU_{j,t-5:t}$ as the standard deviation of the characteristics-adjusted subsidy in city *j* over the prior six-year period. This is computed from the residuals of Model (1) of Table 2.

Two assumptions are worth comment. First, the six-year rolling window follows Minton and Schrand (1999), and is a practical tradeoff between sample size and older, less relevant data. Second, we adjust for city characteristics as they can influence the routine resource allocation made by the "central planner." For instance, wealthier or faster-growing cities may be associated with more pollution and require additional subsidy allocation; or, the authorities may be more concerned with pollution in such cities for political reasons. Based on the results earlier, *Green Subsidy* is largely just the raw subsidy adjusted for income per capita. Robustness tests reported in the Internet appendix indicate that the results are not sensitive to the particular timing window or the characteristics-adjustment approach.

The first-stage regression then isolates the component of this policy uncertainty that is associated with recent weather uncertainty:

$$PU_{j,t-5:t} = c_0 + c_1 \times SD\ Windy\ Days_{j,t-6:t-1} + c_2 \times SD\ Rainy\ Days_{j,t-6:t-1} + C \times X_{j,t} + \delta_j + \delta_t + \varepsilon_{j,t}. \tag{3}$$

The specification again controls for city characteristics and city and year fixed effects.

The weather variability terms refer to the standard deviation of the number of windy days and rainy days per year in the rolling period from year $t-6$ to $t-1$. The one-year lag between policy uncertainty and weather fluctuation follows the timing convention of Equations (1) and (2), in which weather conditions of a given year affect the contemporaneous AQI and the next year's policy. One can imagine slower, faster, or, indeed, heterogeneous responses, so it is reassuring that robustness tests show that this time convention is not crucial for our approach.

The results are in the first column of Table 4. They confirm the expected effect of weather on policy variability: Relative to a city's norm, a period of more variable weather is associated with a period of more variable policy. From Model (1), a one-standard-deviation increase in wind and rain fluctuations versus local norms leads to a 0.196 standard deviation increase in PU.[14]

[14] $(\hat{c}_1 \times SD\ (SD\ Windy\ Days) + \hat{c}_2 \times SD\ (SD\ Rainy\ Days))/SD\ PU = (0.01 \times 25.3 + 0.11 \times 1.95)/2.39 = 0.196$.

The strength of the two weather variables, with an F-statistic of 9.0, allows us to construct a weather-based component of policy uncertainty:

$$\widehat{PU}_{j,t-5:t} = \hat{c}_1 \times SD\ Windy\ Days_{j,t-6:t-1} + \hat{c}_2 \times SD\ Rainy\ Days_{j,t-6:t-1}. \qquad (4)$$

Figure 2 illustrates the strength of weather variability as an instrument. On the map, a larger pie for a city indicates greater policy uncertainty, and a larger dark pie slice indicates the fraction connected to weather fluctuations.

D. Discussion: Recency Biases as an Origin of Policy Uncertainty

Understanding the origin of policy uncertainty is important for understanding how its consequences might be mitigated. The literature often focuses on politics. Pastor and Veronesi (2012, 2013) model and document the effects of political uncertainty on asset prices, while Baker, Bloom, Canes-Wrone, Davis, and Rodden (2014) emphasize trends in the scale of government activity and political polarization. Measures of policy uncertainty, such as Baker, Bloom, and Davis (2016)'s approach, are built around standard government activities including fiscal and monetary policy, regulation, and national security.[15]

Our setting is quite different. The environmental subsidy allocations we observe are the collective outcome of decisions made by hundreds of bureaucrats, guided only loosely by a hypothetical central planner, as opposed to the consequence of an election or a macroeconomic shock. These bureaucrats operate in an institutional context with their own incentives; possess

[15] A smaller, related thread, surveyed by Heal and Millner (2018), highlights scientific uncertainty in climate processes as contributing to climate policy uncertainty.

authority that may exceed their scientific qualifications; and, in light of this discretion, may display their own judgmental biases.

We suggest that our uncertainty instrument, based on the observation that mere weather variability feeds through to policy variability, derives in part from a set of related biases that are well-known in *individual* choice settings. The further down the central government's original lump allocation flows toward individual cities and firms across the country, the fewer bureaucrats are responsible for the next stage of allocations and they respond to more granular conditions. This enhances the likelihood that pervasive personal biases may influence small group decisions as well.

The relevant biases include salience, extrapolation, projection, recency, and availability. We group these together and, taking a considerable liberty of terminology, refer to them as "recency biases" because each one leads to the common prediction of a strong response to unusual recent pollution and AQI readings.

The biases are, by nature, intuitive. Attention and decision making can be guided by *salient* features of the problem, which in our context include recent, relatively high air pollution levels. In contrast, the slightly weaker wind or lower precipitation over the course of several months, which can have large effects on observed pollution, would not be nearly as salient. One might *project* the efficacy of high subsidies from beliefs based on *extrapolating* present conditions, not fully accounting for the subtle role of recent weather patterns. Several studies document a bias toward overweighting *recent* conditions (again, prevailing pollution levels) *per* *se*. These biases are clearly related. For example, salience and recency can both drive an *availability* bias.[16] Representativeness, reinforced by vividness, is yet another related judgmental pattern that could be seen as a foundation for the observed behavior.

Some of these biases have been studied in the context of air pollution by Chang, Huang, and Wang (2018) in their analysis of why demand for health insurance fluctuates with air pollution. The various biases are may be possible to isolate in lab experiments, but, as Chang et al. (2018) and Busse et al. (2015) point out, they generate similar predictions in data such as theirs and ours. We propose they are best viewed as a related group that form one intuitive mechanism that transfers uncertainty in weather into uncertainty in policy.

Finally, we suspect that in a governmental system that prioritizes stability and articulates quantitative targets, Chinese bureaucrats may face political or institutional imperatives to simply "do something" in response to unusual pollution levels. But, if this sort of political pressure is driven by weather and not emissions, it itself derives from recency biases among the population.

IV. Consequences of Policy Uncertainty for Investment

Regardless of its origin, uncertainty tends to discourage investments that are costly to reverse. This option-value mechanism has been articulated in classic theory by Bernanke (1983),

---

[16] See, for example, Taylor and Thompson (1982) and Bordalo, Gennaioli, and Shleifer (2022) (and references therein) on salience; Loewenstein, O'Donoghue, and Rabin (2003), Conlin, O'Donoghue, and Vogelsang (2007), and Busse, Pope, Pope, and Silva-Risso (2015) on projection bias; Greenwood and Shleifer (2014) on extrapolation; Hogarth and Einhorn (1992) on recency; and Tversky and Kahneman (1973) on availability and representativeness.

McDonald and Siegel (1986), and Dixit and Pindyck (1994). Julio and Yook (2012) and Gulen and Ion (2016) find empirical evidence that U.S. corporate investment is discouraged by impending elections and news-based measures of policy uncertainty, respectively. In this section, we explore the relevance of policy uncertainty for a novel dimension of investment which is of special current interest—environmental investment—and based on a source of uncertainty that, we propose, may have novel origins.

A. Green Investment

Table 4 proceeds with the second-stage regression that links green investment to the exogenous component of policy uncertainty. We begin with green R&D spending by firms across city j, a natural unit of aggregation given the city-level variation in weather, as the outcome of interest:

$$Green\ R\&D_{j,t+1} = d_0 + d_1 \times \widehat{PU}_{j,t-5:t} + d_2 \times Avg\ Subsidy_{j,t:t-5} + D \times X_{j,t} + \delta_j + \delta_t + \eta_{j,t+1} \quad (5)$$

where $Green\ R\&D_{j,t+1}$ is the logarithm of the aggregate environmental R&D investments that firms of the city make in the following year.

The average recent subsidy for the city is a natural control variable, as a higher environmental subsidy is presumably associated with more green investment. Hence, we expect its coefficient to be positive. The more interesting hypothesis is that failing to endogenize weather-caused air quality variation may give rise to weather-induced policy uncertainty, which in turn diminishes firms' incentives to invest in green technology. The prediction is a negative coefficient on the instrumented policy uncertainty variable.

The remaining columns of Table 4 tabulate the results of this second stage. The good news is that the subsidy policy itself has the intended stimulative effect on R&D investment. In particular, a one-standard-deviation increase in the subsidy leads to a 0.209 standard deviation increase in firm R&D.[17] This is consistent with the stimulative influence of government environmental subsidies on innovation in the U.S. (e.g., Howell, 2017).

However, policy uncertainty exerts the opposite, and surely unintended, influence. For instance, Model (4), viewed in conjunction with Model (1), suggests that a one-standard-deviation increase in wind and rain fluctuations translates into a 0.137 standard deviation reduction in R&D.[18] In the more recent data in Model (5), the point estimate on the uncertainty effect is even higher (while the point estimate of the average level effect is lower), although the standard errors are such that we cannot reject that these coefficients have been constant. A direct comparison between the magnitudes of the positive level effect and the negative uncertainty effect suggests that the consequences of policy uncertainty may be material, with subsidy uncertainty meaningfully undermining the effect of the subsidy level on green investment. This is our main message.

[17] $(\hat{d}_2 \times SD\ Avg\ Subsidy)/SD\ Green\ R\&D = (0.45 \times 4.43)/9.52 = 0.209.$

[18] $(\hat{c}_1 \times SD\ (SD\ Windy\ Days) + \hat{c}_2 \times SD\ (SD\ Rainy\ Days)) \times \hat{d}_1/SD\ Green\ R\&D = (0.01 \times 25.3 + 0.11 \times 1.95) \times (-2.78)/9.52 = -0.137.$

B. Robustness Checks

These empirical patterns are highly robust. We report the results of further robustness checks in Table 5 and additional specifications in the Internet appendix.

Firms in a minority of cities do not report green subsidies at all in a given year, so Models (1) and (2) include only city-year observations with nonzero R&D. The results are robust in this subsample. In the Internet appendix, we report similar findings when excluding observations with zero subsidies in general or excluding any city's observations before its first year of non-zero subsidy.

We must make an empirical assumption about the lag between observed AQI and the allocation of subsidies. A one-year lag is a reasonable approximation, but, for example, a year *t* allocation may be determined in the late part of year *t-1*, when the year t-1 average AQI is not fully realized; or, cities may allocate subsidies over a multi-year period; or, different cities may time allocations in different ways. Models (3) and (4) indicate that the results are similar when averaging AQI over the prior two years.

In Models (5) and (6), we control for the variation in non-weather related AQI. To achieve this, 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. This suggests a unique role of weather fluctuations on policy uncertainty.

In our main two-stage specification, we adjust raw subsidy policies by the cross-sectional influence of city characteristics such as wealth and population growth. These are natural macrolevel control variables, separate influences from the weather. In Models (7) and (8), we base routine allocations on both city and aggregated firm characteristics. The results are unchanged.

In the remaining specifications, we try a rolling window of five years to calculate policy uncertainty (Models (9)-(10)) and a wind-only instrument (Models (11)-(12)) to explore unintended consequences. The Internet appendix provides additional analysis of timing and weather effects; there are no noteworthy differences in results. Using wind only, as opposed to both wind and rain, slightly weakens the second-stage results, but since both weather dimensions are equally exogenous and known to be relevant to air quality there is no reason to prefer a more limited approach.

The Internet appendix provides further analyses supporting these main results. The results are also robust to a number of methodological choices, e.g., environmental subsidies and environmental R&D based on other lists of keywords, the effects of winsorization, the inclusion of emission variables, the inclusion of controls for the volatility of AQI, and an average annualized regression approach (e.g., Minton and Schrand, 1999; Bates, Kahle, and Stulz, 2009) as opposed to a panel specification. Finally, in a placebo test, we show that weather-induced green subsidy policy uncertainty does *not* affect *non*-green R&D.

C. Heterogeneity in Impact of Policy Uncertainty

We now turn to firm-year data. This level of granularity is the third and final step down the top-down policy chain. There are several natural hypotheses about which firms might be more sensitive to subsidy policy uncertainty. We use firm-level investment in the second stage and an interaction of the instrument for uncertainty and firm types:

$$Green\ R\&D_{i\in j,t+1} = e_0 + e_1 \times \widehat{PU}_{j,t-5:t} + e_2 \times Firm\ Type_{i\in j,t} \times \widehat{PU}_{j,t-1} \\ +e_3 \times Avg\ Subsidy_{j,t-5:t} + E \times X_{i\in j,t} + \delta_i + \delta_t + \eta_{i\in j,t+1}. \tag{6}$$

$Green\ R\&D_{i\in j,t+1}$ is the year t+1 investment made by firm i of city j. $Firm\ Type_{i\in j,t}$ is an indicator for firm types such green-tech suppliers, firms in a metropolitan area, large firms, energy firms, manufacturing firms, mining firms, and chemicals firms. The indicator itself is absorbed by firm fixed effects.

The results are in Table 6, which show that the effect of weather-induced policy uncertainty also appears in firm-level specifications. The first model shows that policy uncertainty hurts green-tech suppliers more than the average firm, an intuitive result. This is concerning, however, if subsidies are intended to incentivize such firms in particular.

The next several models 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 latter effect is intuitive; the former might be related to the higher cost of hiring and maintaining R&D employees in these cities (our tests below suggest that uncertainty also reduces R&D staffing). Size and state ownership status do not mediate the influence of policy uncertainty, on the other hand, in the absence of other interactions. It is possible that the higher government dependence of such firms is offset by an informal insulation from the full variability in subsidies.[19]

Some listed firms have a complex geographic footprint, making it unclear which city's policy affects them the most. We create a dummy variable that equals one if a firm is registered in one city and has its headquarters in another, but we find no detectable differential effect of policy uncertainty on these firms.

We next examine the impact of policy uncertainty on particular industries. The Internet appendix provides a detailed matching between China's industry classification provided by China Securities Regulatory Commission (CSRC) and the SIC or Fama and French (1997). Manufacturing and water conservancy, environment, and public facility management are most affected. Manufacturing includes many important polluting industries, such as chemicals and metals, and the public facilities designation includes environmental firms. The last column shows that these characteristics tend to embody independent sensitivities to policy uncertainty.

V. Consequences of Policy Uncertainty for Employment and Patenting

A. Green R&D Employment

We can also employ the two-stage analysis to examine other inputs and outputs of green investment. We define *Green R&D Employment* as the logarithm of one plus the total number of

[19] Table 6 allows sample firms to have different data lengths in our sample. In the Internet appendix, we apply the same specifications to the subset of firms that exist for the full sample period for the second-stage regression. The results indicate that mature firms, like large firms and SOEs, are also affected by policy uncertainty.

R&D and technical employees in firms in the city that report environmental R&D investments. This is simply a count of the jobs most likely to be supported by the subsidies in question and presumably another basic input into R&D. Bloom (2009) estimates sizeable hiring adjustment costs, which imply the same costly reversibility mechanism and thus optimal inertia that we see in R&D spending. We then repeat the second-stage analysis with this dependent variable.

The results are in Table 7. In addition to reducing green R&D, exogenous shocks to policy uncertainty also reduce associated employment. A one-standard-deviation increase in wind and rain fluctuations leads to a 0.153 standard deviation reduction in *Green R&D Employment* in our estimates. While the production function of R&D output is difficult to know, we note that this effect is of the same order of magnitude as the effect on R&D.

B. Patenting

Next, we examine a specific output of innovation, *Green Patent Applications*, again aggregated to the city level. Since the development of patents can take years, we again use cross-sectional average annualized regressions. We first calculate the average applications that a firm generates in a rolling window of six years and policy uncertainty in 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 patent applications and the corresponding lagged policy uncertainty.

Table 8 reports the results for green patent applications as a proxy for the output of firm environmental incentives. Model (1), viewed in conjunction with the first stage, suggests that an increase in both wind and rain fluctuations is associated with a statistically significant, but economically small, reduction in green patent applications.[20] To summarize, the results suggest that policy uncertainty reduces green research and human capital investment and has a modest negative impact on patenting activity.

VI. Conclusion

This paper makes two contributions. First, and most importantly, the evidence indicates that economic policy uncertainty has real consequences in the domain of green investment. This context is particularly important because air pollution has numerous health and economic impacts and because many of the policies that combat air pollution also combat climate change. Controlling for the average level of subsidies, we find that exogenous variation in the subsidies over time reduces the amount of green research and development expenditure and employment that the subsidies are intended to promote. An obvious implication is that the variability in subsidies, such as those we document to Zijin Mining Group Co., Ltd., in our example, be purged as much from variation in weather as science permits; that is, hard AQI target levels that

[20] $(\hat{c}_1 \times SD\ (SD\ Windy\ Days) + \hat{c}_2 \times SD\ (SD\ Rainy\ Days)) \times \hat{d}_1 / SD\ Green\ Patent\ Apps\ =$ $(0.01 \times 25.3 + 0.11\ \times 1.95) \times (-0.07)/0.84 = -0.039.$

top-down policymakers specify can provide guidance, but it should be recognized that weather alone can cause breaches.

Second, more speculatively, we propose that policy uncertainty can, at times, originate in a set of “recency biases.” Extensively-documented such biases include salience, extrapolation, projection, recency (per se), and availability. When unusual wind and rain patterns in a given location cause unusual air quality readings (including AQI), local bureaucrats responsible for allocating subsidies may be susceptible to making decisions influenced by recent exogenous conditions in addition to the underlying, imperfectly observable level of emissions. Since economic policy often must be made in settings where the problem is salient and immediate, but the causes involve a complex mix of exogenous and endogenous factors, we suggest that this mechanism augments traditional politics and macroeconomic shocks and provides a novel mechanism for policy uncertainty.

References

Adams, J.D., 1993. Science, R&D, and invention potential recharge: US evidence. *American Economic Review* 83:458-462.

Adams, J.D., Chiang, E.P. and Jensen, J.L., 2003. The influence of federal laboratory R&D on industrial research. *Review of Economics and Statistics* 85:1003-1020.

Almond, D., Chen, Y., Greenstone, M., and Li, H., 2009. Winter heating or clean air? Unintended impacts of China's Huai River policy. *American Economic Review* 99:184-190.

Alok, S., Kumar, N. and Wermers, R., 2020. Do fund managers misestimate climatic disaster risk? *The Review of Financial Studies* 33:1146-1183.

Andrews, S., 2008. Inconsistencies in air quality metrics: 'Blue Sky' days and PM10 concentrations in Beijing. *Environmental Research Letters* 3:1-14.

Baker, S.R., Bloom, N., Canes-Wrone, B., Davis, S.J., and Rodden, J., 2014. Why has US policy uncertainty risen since 1960? *American Economic Review* 104:56-60.

Baker, S.R., Bloom, N. and Davis, S.J., 2016. Measuring economic policy uncertainty. *The Quarterly Journal of Economics* 131:1593-1636.

Bates, T.W., Kahle, K.M. and Stulz, R.M., 2009. Why do US firms hold so much more cash than they used to? *Journal of Finance* 64:1985-2021.

Bernanke, B.S., 1983. Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics* 98:85-106.

Bloom, N., 2009. The impact of uncertainty shocks. *Econometrica* 77:623-685.

Bloom, N., Griffith, R. and Van Reenen, J., 2002. Do R&D tax credits work? Evidence from a panel of countries 1979–1997. *Journal of Public Economics* 85:1-31.

Bordalo, P., Gennaioli, N., and Shleifer, A., 2022. Salience. *Annual Review of Economics* 14:521-544.

Branstetter, L., G. Li, and Ren, M., 2022. Picking winners? Government subsidies and firm productivity in China. National Bureau of Economic Research working paper.

Busse, M.R., Pope, D.G., Pope, J.C., Silva-Risso, J., 2015. The psychological effect of weather on car purchases. *Quarterly Journal of Economics* 130:371-414.

Chang, T., Graff Zivin, J., Gross, T., Neidell, M.J., 2016. Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy* 8:141–169.

Chang, T., Graff Zivin, J., Gross, T., Neidell, M.J., 2019. The effect of pollution on worker productivity: Evidence from call-center workers in China. *American Economic Journal: Applied Economics* 11:151-173.

Chang, T.Y., Huang, W. and Wang, Y., 2018. Something in the air: Pollution and the demand for health insurance. *The Review of Economic Studies 85*:1609-1634.

Cai, W., Li, K., Liao, H., Wang, H. and Wu, L., 2017. Weather conditions conducive to Beijing severe haze more frequent under climate change. *Nature Climate Change* 7:257-262.

Chen, Y., Ebenstein, A., Greenstone, M. and Li, H., 2013. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proceedings of the National Academy of Sciences* 110:12936-12941.

Chen, Y., Li, P., and Lu, Y., 2018. Career concerns and multitasking local bureaucrats: Evidence of a target-based performance evaluation system in China. *Journal of Development Economics* 133:84-101.

Conlin, M., O'Donoghue, T., and Vogelsang, T.J., 2007. Projection bias in catalog orders. *American Economic Review* 97:1217-1249.

Currie, J., Hanushek, E.A., Kahn, E.M., Neidell, M., Rivkin, S.G., 2009. Does pollution increase school absences? *Review of Economics and Statistics* 91:682–694.

Dixit, A.K., and Pindyck, R.S., 1994. *Investment Under Uncertainty*. Princeton: Princeton UP.

Ebenstein, A., Fan, M., Greenstone, M., He, G., and Zhou, M. 2015. Growth, pollution, and life expectancy: China from 1991-2012. *American Economic Review Papers and Proceedings* 105:201-204.

Ebenstein, A., Fan, M., Greenstone, M., He, G., and Zhou, M. 2017. New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Hua River policy. *Proceedings of the National Academy of Sciences* 114:10384-10389.

Fama, E.F., and French, K.R. 1997. Industry costs of equity. *Journal of Financial Economics* 43(2):153-193.

Fama, E.F., and MacBeth, J. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81(3):607-636.

Fernandez-Villaverde, J., Guerron-Quintana, P., Kuester, K., and Rubio-Ramirez, J., 2015. Fiscal volatility shocks and economic activity. *American Economic Review* 105:3352-3384.

Fonken, L.K., Xu, X., Weil, Z.M., Chen, G., Sun, Q., Rajagopalan, S., Nelson, R.J., 2011. Air pollution impairs cognition, provokes depressive-like behaviors and alters hippocampal cytokine expression and morphology. *Molecular Psychiatry* 16:987–995.

Gulen, H. and Ion, M., 2016. Policy uncertainty and corporate investment. *The Review of Financial Studies* 29:523-564.

Graff Zivin, J., Neidell, M., 2012. The impact of pollution on worker productivity. *American Economic Review* 102:3652–3673.

Greenwood, R., Shleifer, A., 2014. Expectations of returns and expected returns. *Review of Financial Studies* 27:714-746.

Hanna, R., Oliva, P., 2015. The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City. *Journal of Public Economics* 122:68–79.

He, G., Wang, S. and Zhang, B., 2020. Watering down environmental regulation in China. *The Quarterly Journal of Economics* 135:2135-2185.

Heal, G., and Millner, A., 2018, Uncertainty and ambiguity in environmental economics: Conceptual issues. In: *Handbook of Environmental Economics* 4:439-468.

Heblich, S., A. Trew, and Zylberberg, Y., 2021. East-side story: Historical pollution and persistent neighborhood sorting. *Journal of Political Economy* 129:1508-1552.

Heyes, A., Neidell, M., Saberian, S., 2016. The effect of air pollution on investor behavior: Evidence from the S&P 500. National Bureau of Economic Research working paper.

Hogarth, R.M., Einhorn, H.J., 1992. Order effects in belief updating: The belief-adjustment model. *Cognitive Psychology* 24:1-55.

Howell, S.T., 2017. Financing innovation: Evidence from R&D grants. *American Economic Review* 107:1136-64.

Huang, J., Xu, N., Yu, H., 2020. Pollution and performance: Do investors make worse trades on hazy days? *Management Science* 66:4455-4476.

Isen, A., Rossin-Slater, M., Walker, W.R., 2017. Every breath you take—every dollar you'll make: The long-term consequences of the Clean Air Act of 1970. *Journal of Political Economy* 125:848–902.

Jaffe, A.B., 1988. Demand and supply influences R&D intensity and productivity growth. *The Review of Economics and Statistics* 70:431-437.

Julio, B. and Yook, Y., 2012. Political uncertainty and corporate investment cycles. *The Journal of Finance* 67:45-83.

Kahneman, D., 2003. A perspective on judgment and choice: Mapping bounded rationality. *American Psychologist* 58:697.

Kahneman, D., Slovic, P. and Tversky, A. eds., 1982. *Judgment under uncertainty: Heuristics and biases.* Cambridge: Cambridge UP.

Kang, J. and Pflueger, C.E., 2015. Inflation risk in corporate bonds. *The Journal of Finance* 70:115-162.

Li, J., Massa, M., Zhang, H., and Zhang, J. 2021. Air pollution, behavioral bias, and the disposition effect in China. *Journal of Financial Economics* 142:641-673.

Loewenstein, G., O'Donoghue, T., and Rabin, M., 2003. Projection bias in predicting future utility. *Quarterly Journal of Economics* 118:1209-1248.

McDonald, R., Siegel, D., 1986. The value of waiting to invest. *Quarterly Journal of Economics* 101:707-728.

Minton, B.A. and Schrand, C., 1999. The impact of cash flow volatility on discretionary investment and the costs of debt and equity financing. *Journal of Financial Economics* 54:423-460.

Mohai, P., Kweon, B., Lee, S., Ard, K., 2011. Air pollution around schools is linked to poorer student health and academic performance. *Health Affairs* 30:852–862.

Pastor, L. and Veronesi, P., 2012. Uncertainty about government policy and stock prices. *Journal of Finance* 67:1219-1264.

Pastor, L. and Veronesi, P., 2013. Political uncertainty and risk premia. *Journal of Financial Economics* 110:520-545.

Segal, G., Shaliastovich, I. and Yaron, A., 2015. Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics* 117:369-397.

Sheehan, P., Cheng, E., English, A. and Sun, F., 2014. China's response to the air pollution shock. *Nature Climate Change* 4:306-309.

Shive, S.A. and Forster, M.M., 2020. Corporate governance and pollution externalities of public and private firms. *The Review of Financial Studies* 33:1296-1330.

Stroebel, J. and Wurgler, J., 2021. What do you think about climate finance? *Journal of Financial Economics* 142:487-498.

Taylor, S.E., and Thompson, S.C., 1982. Stalking the elusive "vividness" effect. *Psychological Review* 89:155-181.

Tilt, B., 2019. China's air pollution crisis: Science and policy perspectives. *Environmental Science and Policy* 92:275-280.

Tversky, A., Kahneman, D., 1973. Availability: A heuristic for judging frequency and probability. *Cognitive Psychology* 5:207-232.

Wang, L., Zhang, F., Pilot, E., Yu, J., Nie, C., Holdaway, J., Yang, L., Li, Y., Wang, W., Vardoulakis, S., and Krafft, T., 2018. Taking action on air pollution control in the Beijing-Tianjin-Hebei (BTH) region: Progress, challenges, and opportunities. *International Journal of Environmental Research and Public Health* 15:306.

Weuve, J., Puett, R.C., Schwartz, J., Yanosky, J.D., Laden, F., and Grodstein, F., 2012. Exposure to particulate air pollution and cognitive decline in older women. *Archives of Internal Medicine* 172:219–227.

Yan, Y., Li, Y., Sun, M. and Wu, Z., 2019. Primary pollutants and air quality analysis for urban air in China: Evidence from Shanghai. *Sustainability* 11:2319.

Zhang, B., Chen, X., and Guo, H., 2018. Does central supervision enhance local environmental enforcement? Quasi-experimental evidence from China. *Journal of Public Economics* 164:70-90.

Zhang, X., Zhong, J., Wang, J., Wang, Y., and Liu, Y., 2018b. The interdecadal worsening of weather conditions affecting aerosol pollution in the Beijing area in relation to climate warming. *Atmospheric Chemistry and Physics* 18:5991-5999.

Zheng, S., and Kahn, M.E., 2017. A new era of pollution progress in urban China? *Journal of Economic Perspectives* 31:71-92.

Zheng, S., Wang, J., Sun, C., Zhang, X., and Kahn, M.E., 2019. Air pollution lowers Chinese urbanites' expressed happiness on social media. *Nature Human Behavior* 3:237-243.

Appendix A. Variable Definitions and Sources

Variables in Panels A through D are at the city-year level. In indicated cases, they are aggregates or asset-weighted averages of the firm-year-level variables in Panel E.

Variable	Definition	Source
A. Policy and Policy Uncertainty		
Raw Green Subsidy	The logarithm of one plus city environmental ("Green") subsidy (RMB value).	CSMAR
Green Subsidy	The residual of the cross-sectional regression of *Raw Green Subsidy* controlling for city characteristics, i.e., Model (1) of Table 2: $Raw\ Green\ Subsidy_{j,t} = a_0 + A \times X_{j,t-1} + \varepsilon_{j,t}$, where *X* denotes city characteristics.	(constructed)
PU	Policy uncertainty in a city-year estimated as the standard deviation of *Subsidy* in the six-year window $t-5{:}t$.	(constructed)
$\widehat{PU}$	Weather-driven policy uncertainty estimated in two steps. First, Model (1) of Table 4: $PU_{j,t-5,t} = c_0 + c_1 \times SD\ Windy\ Days_{j,t-6,t-1} + c_2 \times SD\ Rainy\ Days_{j,t-6,t-1} + C \times X_{j,t} + \delta_t + \delta_j + \varepsilon_{j,t}$, where *X* denotes city characteristics. Second, the projection: $\widehat{PU}_{j,t-5:t} = \hat{c}_1 \times SD\ Windy\ Days_{j,t-6:t-1} + \hat{c}_2 \times SD\ Rainy\ Days_{j,t-6:t-1}$.	(constructed)
Waste Gas Treatment	The logarithm of one plus city-level investment in treatment of industrial waste gas.	EPSnet
B. Green Investment		
Green R&D	The logarithm of one plus aggregate environmental R&D investment (RMB value) of firms in the city (the aggregate of the firm-level *Green R&D*).	CSMAR
Green R&D Employment	The logarithm of one plus the aggregate number of R&D and technical employees among firms with nonzero environmental R&D investment in the city.	Resset
Green Patent Applications	The six-year moving average of the logarithm of one plus the aggregate number of green patent applications by firms in the city.	CSMAR
C. Air Pollution and Weather		
AQI	The AQI in a city (annual average of daily values unless otherwise indicated).	Ministry of Ecology and Environment

Wind Speed	The daily wind speed in the city in m/s.	China Meteorological Administration
Windy Days	The number of days in the year in which the city's wind speed is level 4 or above on the Beaufort Scale (i.e., more than 5.5 m/s).	(constructed)
SD Windy Days	The standard deviation of the number of windy days in the city per year in a six-year rolling window.	(constructed)
Rain Volume	The volume of rain in the city in mm.	China Meteorological Administration
Rainy Days	The number of days in the year in which the city's rain volume is level 3 or above (i.e., more than 25mm/day).	(constructed)
SD Rainy Days	The standard deviation of the number of rainy days in the city per year in a six-year rolling window.	(constructed)
D. City Characteristics		
Consumption	The logarithm of consumption (RMB value).	CNRDS
GDP	The logarithm of GDP (RMB value).	CNRDS
GDP Growth	The GDP growth rate.	CNRDS
Population Growth	The population growth rate.	CNRDS
E. Firm Characteristics		
Green R&D	The logarithm of one plus environmental R&D investment (RMB value) of a firm.	CSMAR
Green Tech	One if a firm provides environmental/green products and services else zero.	CNRDS
Metropolitan	One if a firm is located in Beijing, Shanghai, Guangzhou, or Shenzhen, else zero.	CNRDS
Large	One if firm total assets is in the top decile else zero.	WIND
SOE	One if a firm is state owned else zero.	CNRDS
Subsidy Reliant	One if a firm's ratio of environmental subsidy to total assets is higher than the median else zero.	CSMAR
Different Cities	One if a firm's office address and registered address are in different cities else zero.	CSMAR
Manufacturing	One if a firm belongs to the manufacturing industry (CSRC prefix C) else zero.	CSMAR
Chemical	One if a firm belongs to the chemical industry (CSRC C25, C26, C28, C29, C41, and C43) else zero.	CSMAR

Metal	One if a firm belongs to the metals industry (CSRC C31, C32, C33, C65, and C67) else zero.	CSMAR
Public Facility	One if a firm belongs to the public facility industry (CSRC prefix N) else zero.	CSMAR
Environmental	One if a firm belongs to the ecological protection and environmental governance industry (CSRC N77) else zero.	CSMAR
Turnover	Total assets turnover defined as revenue divided by total assets.	WIND
ROA	Operating income divided by total assets.	WIND
Leverage	Book value of total debt divided by total assets.	WIND
Size	The logarithm of total assets (RMB value).	WIND
Cash	Cash holdings divided by total assets.	WIND
Capex	Capital expenditure divided by total assets.	WIND
Profit Margin	Net income divided by revenue.	WIND
Stock Return	Prior-year stock return.	CSMAR

Table 1. Summary Statistics

Variables are defined in Appendix A and are generally at the city-year level in an unbalanced panel of up to 345 cities in the pre-Covid period 2009 to 2019 (the *SD* weather variables, constructing using a six-year rolling window, are defined using weather data back to 2003), which is the sample used in our main analyses of policy uncertainty and green investment.

	N	Mean	SD	5%	25%	50%	75%	95%
Policy								
Raw Green Subsidy	1340	12.98	6.31	0.00	12.82	15.44	16.84	18.64
Green Subsidy	1340	0.14	5.66	-12.37	-0.78	1.92	3.66	6.46
Waste Gas Treatment	1340	13.96	7.93	0.00	13.48	18.07	19.24	20.32
Green Investment								
Green R&D	1340	11.17	9.52	0.00	0.00	17.13	19.47	21.63
Green R&D Employment	1340	4.07	3.70	0.00	0.00	5.17	7.37	9.16
Green Patent Applications	1378	0.51	0.84	0.00	0.00	0.12	0.66	2.29
Weather and Pollution								
AQI	1340	77.79	24.35	47.35	62.18	73.59	87.18	122.41
Wind Speed	1340	4.56	1.10	2.78	3.91	4.50	5.20	6.43
Windy Days	1340	103.27	75.20	4.00	40.00	92.50	152.00	246.50
SD Windy Days	1340	24.02	25.35	2.54	9.02	16.29	29.59	73.17
Rain Volume	1340	2.68	1.59	0.60	1.46	2.29	3.75	5.64
Rainy Days	1340	10.87	7.78	1.00	5.00	9.00	15.63	26.00
SD Rainy Days	1340	3.30	1.95	0.82	2.00	2.94	4.27	7.03
City Characteristics								
Consumption	1340	9.61	0.47	8.72	9.33	9.63	9.94	10.33
GDP	1340	10.63	0.78	9.36	10.15	10.65	11.10	11.94
GDP Growth	1340	9.83	4.82	3.89	7.60	9.30	12.50	16.00
Population Growth	1340	5.47	5.56	-2.77	2.23	5.30	8.49	14.74
City Firm Characteristics (Asset-weighted averages by headquarters city)								
Turnover	1340	0.73	0.33	0.34	0.54	0.69	0.84	1.25
ROA	1340	7.70	11.29	-1.31	4.62	7.52	10.40	15.74
Leverage	1340	0.50	0.27	0.27	0.40	0.47	0.56	0.80
Size	1340	21.80	0.89	20.40	21.23	21.77	22.36	23.22
Cash	1340	0.06	0.07	-0.02	0.03	0.06	0.08	0.14
Capex	1340	0.06	0.04	0.02	0.04	0.05	0.07	0.12
Profit Margin	1340	0.07	0.12	-0.12	0.04	0.09	0.12	0.18
Stock Return	1340	0.18	0.57	-0.39	-0.17	0.01	0.34	1.34

Table 2. AQI as a Determinant of Green Subsidies

This table presents the determinants of two policies related to air pollution treatment. In Models (1) to (4), we examine the cross-city determinants of the environmental subsidy in versions of the Fama-MacBeth (1973) cross-sectional specification:

$$Raw\ Green\ Subsidy_{j,t} = a_0 + a_1 \times AQI_{j,t-1} + A \times X_{j,t-1} + \varepsilon_{j,t},$$

where $Raw\ Green\ Subsidy_{j,t}$ denotes the log RMB level of the total environmental subsidy level for city j in year t, $AQI_{j,t-1}$ is the average Air Quality Index of the previous year, and the vector $X_{j,t-1}$ is a set of control variables, including city characteristics and firm characteristics averaged at the city level (weighted according to the value of firm assets). In Models (5) and (6), the city's log RMB level of $Waste\ Gas\ Treatment_{j,t}$ expenditure is the dependent variable. City characteristics include log consumption, log GDP, GDP growth, and population growth. Firm characteristics include asset-weighted averages of the city's firms' asset turnover ratio, return on assets, leverage ratio, firm size, cash holdings, capital expenditures, profit margin, and stock return. The sample period is t = 2003 to 2019 and includes up to 345 cities. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Raw Green Subsidy				*Waste Gas Treatment*	
AQI		0.06***		0.05***	0.04***	0.04***
		(4.98)		(3.68)	(5.08)	(5.00)
Consumption	-0.45	-0.08	0.08	0.42	-1.40	-1.06
	(-0.89)	(-0.15)	(0.15)	(0.86)	(-1.29)	(-1.06)
GDP	3.20***	3.15***	2.93***	2.92***	2.36**	2.27**
	(5.93)	(6.04)	(5.81)	(5.92)	(2.57)	(2.52)
GDP Growth	-0.05	-0.05	-0.04	-0.03	0.04	0.05
	(-0.99)	(-0.97)	(-0.73)	(-0.56)	(1.09)	(1.28)
Population Growth	0.02	0.05	0.05	0.08**	-0.11***	-0.11***
	(0.47)	(1.66)	(1.40)	(2.43)	(-3.77)	(-3.62)
Average firm characteristics	NO	NO	YES	YES	NO	YES
Avg R^2	0.19	0.22	0.26	0.29	0.22	0.33
Observations	1838	1826	1838	1826	1825	1813

Table 3. Influence of Weather on the Air Quality Index (AQI)

This table estimates the influence of wind and rain on AQI in both heating and non-heating seasons and in northern cities, with colder climates, separately. The specification is:

$$AQI_{j,t,s} = b_0 + b_1 \times Wind\ Speed_{j,t,s} + b_2 \times Rain\ Volume_{j,t,s} + B \times X_{j,t} + \delta_j + \delta_t + \varepsilon_{j,t,s},$$

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, $Wind\ Speed_{j,t,s}$ is the average daily wind speed in that period, and $Rain\ Volume_{j,t,s}$ is the average daily rain volume in that period. The vector $X_{j,t}$ is a set of city characteristics including log consumption, log GDP, GDP growth rate, and population growth rate. Models (1) and (2) compare the influence of wind speed on AQI between heating season and non-heating season in the sample of all cities. Models (3) and (4) compare the influence of wind speed on AQI between the heating season and non-heating season in cities north of the Qinling Mountain-Huai River line. The heating season is November through March. The non-heating season is April through October. The sample period is t = 2003 to 2018 and includes up to 345 cities. Standard errors are clustered by city and year. Robust t-statistics are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

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

Table 4. Policy Uncertainty and Green R&D Investment

This table presents the impact of environmental subsidy policy uncertainty on green R&D investment conducted by firms in a city. In the first stage, Model (1), we estimate:

$$PU_{j,t-5:t} = c_0 + c_1 \times SD\ Windy\ Days_{j,t-6:t-1} + c_2 \times SD\ Rainy\ Days_{j,t-6:t-1} + c_3 \times AQI_{j,t} + C \times X_{j,t} + \delta_j + \delta_t + \varepsilon_{j,t},$$

where the dependent variable $PU_{j,t}$ denotes the policy uncertainty of city j, measured as the standard deviation of the residual of the cross-sectional regression, $Raw\ Green\ Subsidy_{j,t} = a_0 + A \times X_{j,t-1} + \varepsilon_{j,t}$ (the specification in Model (1) of Table 2) in the rolling six-year period ending year t. $SD\ Windy\ Days_{j,t-6:t-1}$ and $SD\ Rainy\ Days_{j,t-6:t-1}$ are the standard deviation of the number of windy days and rainy days per year, respectively, in the rolling six-year period ending year $t-1$. The vector $X_{j,t}$ is a set of control variables, including AQI as well as city and average firm characteristics. We then use the component of policy uncertainty due to weather variability,

$$\widehat{PU}_{j,t-5:t} = \hat{c}_1 \times SD\ Windy\ Days_{j,t-6:t-1} + \hat{c}_2 \times SD\ Rainy\ Days_{j,t-6:t-1},$$

to explain green R&D investment in the second stage:

$$Green\ R\&D_{j,t+1} = d_0 + d_1 \times \widehat{PU}_{j,t-5:t} + d_2 \times Avg\ Green\ Subsidy_{j,t:t-5} + D \times X_{j,t} + \delta_j + \delta_t + \eta_{j,t+1},$$

where *Green R&D* is the log of city aggregate environmental R&D, *Avg Green Subsidy* is the city's average *Green Subsidy* over the prior six years, and other variables are as above. The sample period is generally t = 2009 to 2019. Models (2)-(4) present the second-stage regressions. Model (5) shows the second-stage results if policy uncertainty is based on subsidies starting in 2007 (resulting in the second-stage observations beginning in t = 2013). All specifications include city and year fixed effects. Standard errors are clustered by city and year. Robust t-statistics are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% levels of significance, respectively.

	(1)	(2)	(3)	(4)	(5)
	PU First Stage		*Green R&D* Second Stage		(Since 2013) Second Stage
$\widehat{PU}$		-2.90***		-2.78***	-5.49***
		(-2.89)		(-2.80)	(-3.23)
Avg Green Subsidy			0.46***	0.45***	0.15
			(3.58)	(3.52)	(0.71)
SD Windy Days	0.01***				
	(3.30)				
SD Rainy Days	0.11**				
	(2.55)				
AQI	0.00	0.03**	0.02*	0.03**	0.04***
	(0.45)	(2.22)	(1.87)	(2.17)	(2.69)
Consumption	-0.02	-0.96	-0.79	-1.20	-2.64

	(-0.02)	(-0.34)	(-0.28)	(-0.43)	(-0.71)
GDP	-0.55***	-0.34	1.48*	-0.19	-2.21*
	(-2.80)	(-0.36)	(1.95)	(-0.20)	(-1.65)
GDP Growth	0.01	0.04	0.00	0.03	0.09**
	(1.61)	(0.92)	(0.13)	(0.82)	(2.50)
Population Growth	-0.03**	-0.06	0.03	-0.05	-0.01
	(-2.35)	(-0.89)	(0.60)	(-0.79)	(-0.08)
Average firm characteristics	YES	YES	YES	YES	YES
City and year fixed effects	YES	YES	YES	YES	YES
City and year clustering	YES	YES	YES	YES	YES
Adj R^2	0.88	0.84	0.84	0.85	0.88
Observations	1340	1340	1340	1340	1039

Table 5. Policy Uncertainty and Green R&D Investment: Robustness

This table presents a variety of robustness checks to the baseline results in Table 4. As there, the dependent variable in the first-stage regressions is $PU_{j,t}$, leading to the construction of $\widehat{PU}_{j,t-5:t}$, and the dependent variable in the second-stage regressions is $Green\ R\&D_{j,t+1}$. The variations are as follows. Models (1) and (2) exclude city observations with no reported environmental R&D. Models (3) and (4) use two-year average AQI and Models (5) and (6) add the six-year rolling standard deviation of weather-adjusted AQI as control variables in both stages. Weather-adjusted AQI is obtained by estimating $AQI_{j,t} = \alpha + b_1 \times Windy\ Days_{j,t} + b_2 \times Rainy\ Days_{j,t} + b_3 \times X_{j,t} + \varepsilon_{j,t}$, and then removing the weather components from AQI to yield $Adj\ AQI_{j,t} = AQI_{j,t} - b_1 \times Windy\ Days_{j,t} - b_2 \times Rainy\ Days_{j,t}$. Models (7) and (8) use Model (3) of Table 2 (rather than Model (1) of Table 2) to estimate a subsidy uncertainty variable that controls for both city and average firm characteristics. Models (9) and (10) define policy uncertainty based on the five-year (rather than six-year) rolling standard deviation of the subsidy. Models (11) and (12) exclude rain from the first-stage weather variability calculation. The sample period is t = 2009 to 2019. All specifications include city and year fixed effects, and standard errors are clustered by city and year. Robust t-statistics are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% levels of statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Excluding R&D=0 obs		Two-year Avg AQI		AQI and SD Adj AQI		Subsidy controlling for average firm chars		Five-year PU		Wind only	
	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage
$\widehat{PU}$		-3.98**		-2.03**		-2.73***		-2.65***		-2.68***		-2.55**
		(-2.37)		(-2.40)		(-2.78)		(-2.86)		(-2.65)		(-2.06)
Green Subsidy		0.22		0.47***		0.45***		0.42***		0.43***		0.34***
		(1.42)		(3.63)		(3.55)		(3.42)		(3.97)		(2.93)
SD Windy Days	0.01**		0.01***		0.01***		0.01***		0.01***		0.01***	
	(2.19)		(3.56)		(3.35)		(3.77)		(2.88)		(3.19)	
SD Rainy Days	0.09*		0.21***		0.11***		0.12***		0.11***			
	(1.89)		(3.70)		(2.61)		(2.75)		(2.69)			
City and aggregated firm-level characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
City and year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

City and year clustering	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj R^2	0.88	0.85	0.88	0.84	0.88	0.85	0.88	0.84	0.86	0.84	0.88	0.84
Observations	1129	1129	1340	1340	1340	1340	1340	1340	1412	1412	1340	1340

Table 6. Policy Uncertainty and Green R&D Investment: Firm Differences

This table presents the effect of environmental subsidy policy uncertainty on firm-level green R&D. We estimate

$$Green\ R\&D_{i\in j,t+1} = e_0 + e_1 \times \widehat{PU}_{j,t-5:t} + e_2 \times Firm\ Type_{i\in j,t} \times \widehat{PU}_{j,t-1} + e_3 \times Avg\ Green\ Subsidy_{j,t-5:t}$$
$$+ E \times X_{i\in j,t} + \delta_i + \delta_t + \eta_{i\in j,t+1},$$

where $Green\ R\&D_{i\in j,t+1}$ is the logarithm of the environmental R&D investments made by firm i located in city j. The construction of city-level weather-driven policy uncertainty $\widehat{PU}_{j,t-5:t}$ follows Table 4. $Firm\ Type_{i\in j,t}$ represents indicator variables for firm characteristics: green tech, metropolitan area headquarters, large size (top assets decile), state-owned enterprises, high (above-median) reliance on environmental subsidies, registration and office addresses located in different cities, manufacturing industry, chemical industry, metals industry, public facility industry, and environmental industry. The CSRC Industry Classification Code is in parentheses. $Avg\ Green\ Subsidy_{j,t-5:t}$ is the six-year moving average of the characteristics-adjusted environmental subsidy. The sample period is t = 2009 to 2019. All specifications include city characteristics, firm characteristics, and firm and year fixed effects. Robust t-statistics are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% levels of statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Green R&D (Firm)												
$\widehat{PU}$	-0.44***	-0.19	-0.34**	-0.45***	-0.44***	-0.23	-0.42***	0.06	-0.36**	-0.40***	-0.44***	-0.43***	0.81***
	(-2.93)	(-1.27)	(-2.21)	(-2.98)	(-2.91)	(-1.52)	(-2.80)	(0.40)	(-2.42)	(-2.70)	(-2.92)	(-2.89)	(4.73)
$\widehat{PU}$ * Green Tech		-0.59***											-0.48***
		(-7.62)											(-6.04)
$\widehat{PU}$ * Metropolitan			-0.23***										-0.41***
			(-2.75)										(-4.86)
$\widehat{PU}$ * Large				0.07									-0.22*
				(0.62)									(-1.69)
$\widehat{PU}$ * SOE					0.01								-0.12
					(0.09)								(-1.35)
$\widehat{PU}$ * Subsidy Reliant						-0.56***							-0.21**
						(-6.97)							(-2.42)
$\widehat{PU}$ * Different Cities							-0.07						-0.15

							(-0.73)						(-1.56)
$\widehat{PU}$ * Manufacturing (C)								-0.83***					-0.60***
								(-10.80)					(-6.70)
$\widehat{PU}$ * Chemical (C25, C26, C28, C29, C41, C43)									-0.73***				-0.36**
									(-4.75)				(-2.26)
$\widehat{PU}$ * Metal (C31, C32, C65, C67, C33)										-0.85***			-0.41*
										(-4.08)			(-1.90)
$\widehat{PU}$ * Public Facility (N)											-1.12***		0.92
											(-3.18)		(1.31)
$\widehat{PU}$ * Environmental (N77)												-2.08***	-3.00***
												(-5.11)	(-3.70)
Avg Green 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*
	(1.82)	(1.71)	(1.96)	(1.85)	(1.82)	(1.79)	(1.75)	(2.00)	(1.81)	(1.77)	(1.82)	(1.78)	(1.93)
City and firm characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm and year fixed effects	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
Observations	27644	27644	27644	27644	27644	27644	27644	27644	27644	27644	27644	27644	27644

Table 7. Policy Uncertainty and Green R&D Employment

This table presents the impact of subsidy policy uncertainty on the number of environmental R&D researchers across firms in a city. *Green R&D Employment* is the logarithm of one plus the total number of R&D and technical employees among firms with environmental R&D investment headquartered in the city. The construction of weather-driven policy uncertainty $\widehat{PU}_{j,t-5:t}$ follows Table 4. In addition to city and average firm characteristics as controls, $Avg\ Green\ Subsidy_{j,t-5:t}$ is the six-year moving average of *Green Subsidy*. All specifications include city and year fixed effects, and standard errors are clustered by city and year. The sample period is t = 2009 to 2019. Robust t-statistics are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% levels of statistical significance, respectively.

	(1)	(2)	(3)
	Green R&D Employment		
$\widehat{PU}$	-1.28***		-1.23***
	(-3.50)		(-3.42)
Avg Green Subsidy		0.19***	0.19***
		(4.16)	(4.09)
City and average firm characteristics	YES	YES	YES
City and year fixed effects	YES	YES	YES
City and year clustering	YES	YES	YES
Adj R^2	0.86	0.86	0.86
Observations	1340	1340	1340

Table 8. Policy Uncertainty and Green Patenting

This table presents the effect of subsidy policy uncertainty on green patent activity by firms in a city. *Green Patent Applications* is the six-year moving average of the logarithm of one plus the total number of green patent applications across firms headquartered in a city. The construction of weather-driven policy uncertainty $\widehat{PU}_{j,t-5:t}$ follows Table 4. In addition to six-year average values of city and averaged firm characteristics as controls, $Avg\ Green\ Subsidy_{j,t-5:t}$ is the six-year moving average of the characteristics-adjusted environmental subsidy. We report Fama-MacBeth (1973) coefficients and t-statistics as in Minton and Schrand (1999). The sample period is *t* = 2009 to 2019. The estimation includes 11 years of city cross sections, and we report the average cross-sectional R-squared. *, **, and *** indicate 10%, 5%, and 1% levels of statistical significance, respectively.

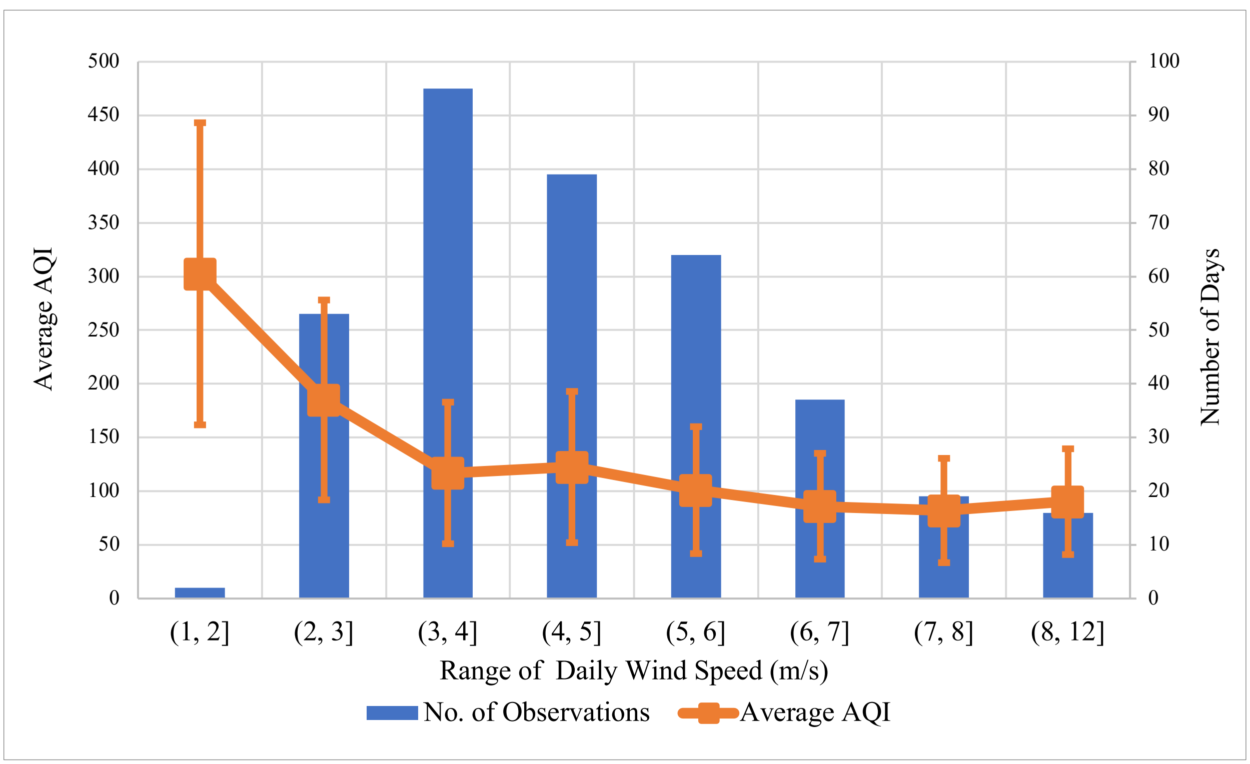
	(1)	(2)	(3)
	Green Patent Applications		
$\widehat{PU}$	-0.07***		-0.03**
	(-5.81)		(-3.04)
Avg Green Subsidy		0.04***	0.03***
		(12.97)	(10.83)
City and average characteristics	YES	YES	YES
Avg R^2	0.45	0.46	0.47
Observations	1378	1378	1378

Figure 1. AQI and Weather

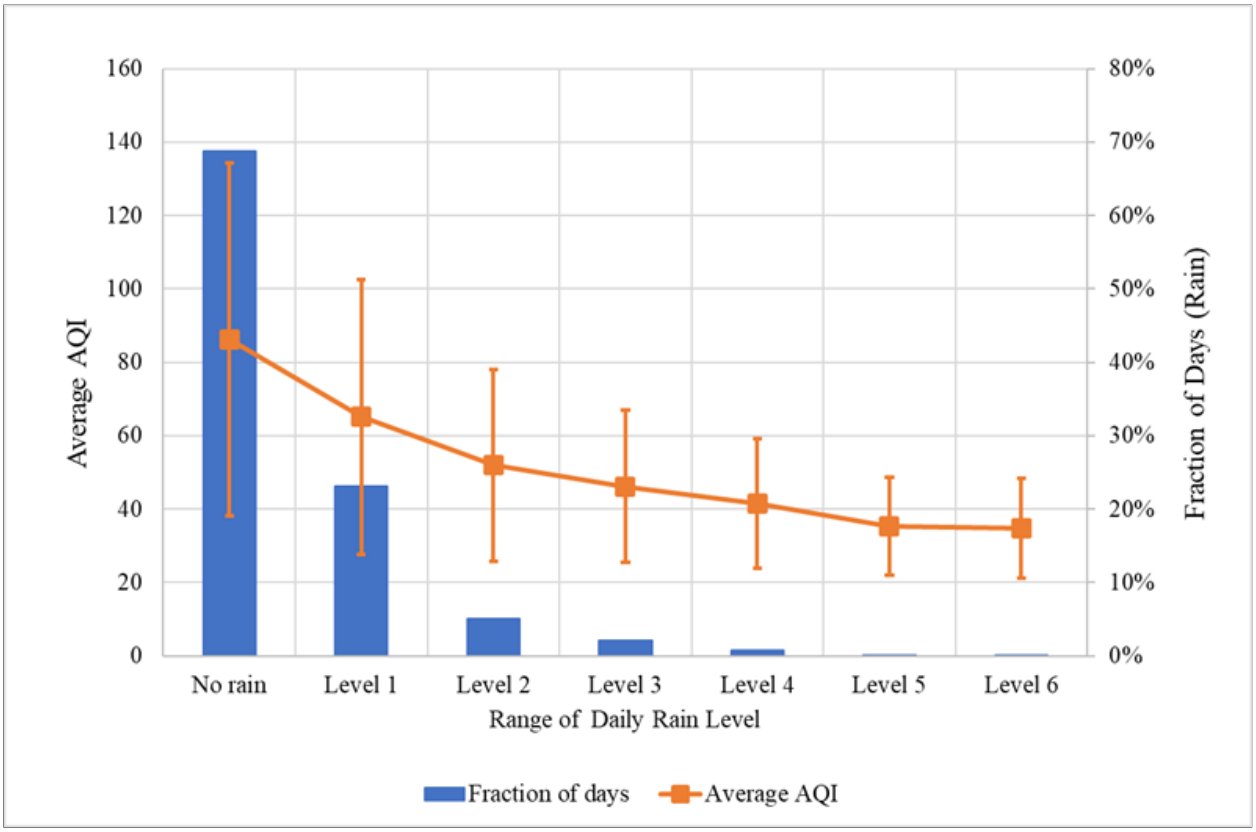
This figure illustrates how air quality depends on wind and rain. Panel A shows representative pictures of the same building in Beijing taken on different days in 2014. Source: https://tinyurl.com/4d5kcjk4. From left to right, the wind speed is 1-2, 2-3, etc. meters per second. Panel B plots the corresponding average AQI in Beijing in 2014 as a function of average wind speed and the number of days in 2014 at each wind speed. Rain is scarce in Beijing, so Panel C pools 2013-2018 data for all cities in the sample to show the effect of rain on AQI. The six nonzero daily rain levels tracked by the China Meteorological Association are: < 10mm, 10-25mm, 25-50mm, 50-100mm, 100-200mm, and > 200mm.

Panel A. Photos from Beijing Versus Wind Speed, 2014

Panel B. AQI and Wind Speed in Beijing, 2014



Panel C. AQI and Rain Volume, all cities, 2013-2018



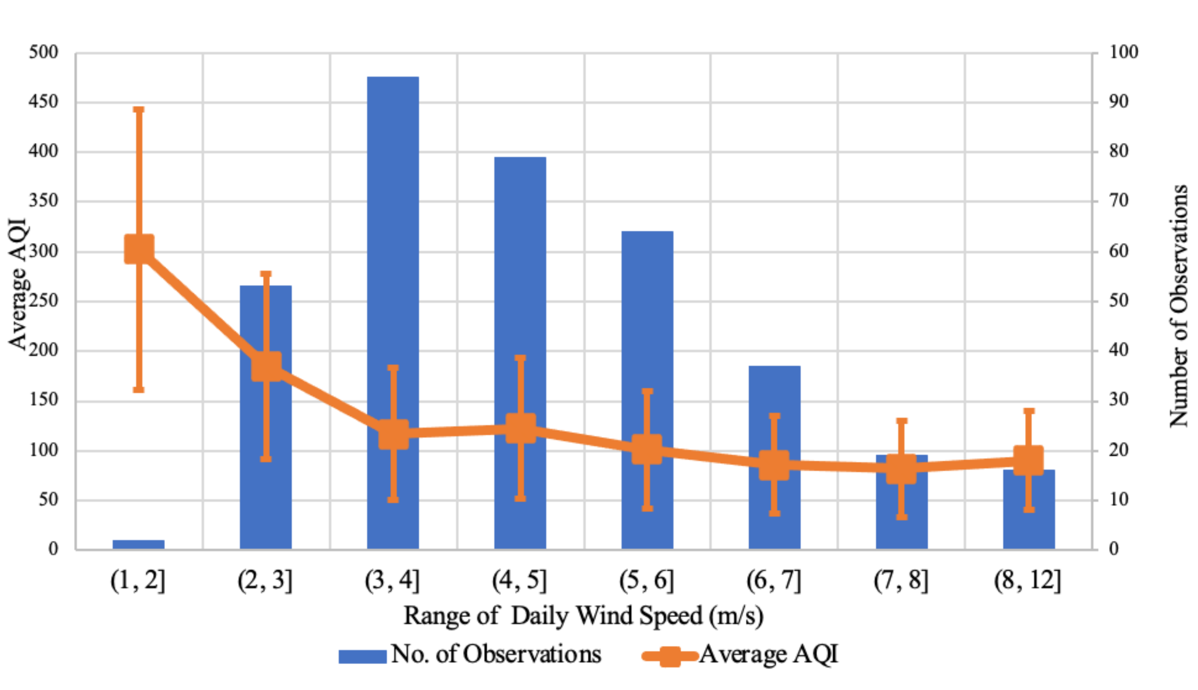

500
450
400
350
300
250
200
150
100
50
0
Average AQI
100
90
80
70
60
50
40
30
20
10
0
Number of Observations
(1, 2]
(2, 3]
(3, 4]
(4, 5]
(5, 6]
(6, 7]
(7, 8]
(8, 12]
Range of Daily Wind Speed (m/s)
No. of Observations
Average AQI

Figure 2. Policy Uncertainty

The area of the circle represents the magnitude of subsidy policy uncertainty in a city. The black portion represents to the amount attributable to wind and rain variability.