Clear Skies, Clear Minds?
—Evidence from NSFC Grant Applications

Chenzhe Zhang

Duke University

November 17, 2025

Abstract

This paper examines how short-run exposure to air pollution affects participation in scientific innovation. Using plausibly exogenous variation in upwind pollution transported by wind, and administrative data on NSFC grant applications from 2013–2019, we find that pollution in the one- to three-month period preceding the application deadline significantly reduces the number of submissions. These effects are consistently identified across city- and institution-level analyses and supported by strong first-stage relationships. By contrast, conditional on applying, pollution has no detectable impact on funding success. The results indicate that air pollution primarily affects innovation through the participation margin, suggesting that short-term environmental disruptions can meaningfully shape entry into high-stakes scientific competitions.

1 Introduction

Innovation plays a central role in economic growth, and competitive grant programs are a key mechanism through which governments support scientific research. Preparing a grant proposal, however, requires sustained attention, cognitive effort, and intensive coordination, especially in the weeks leading up to fixed submission deadlines. These features raise the possibility that short-run environmental disruptions—such as temporary declines in air quality—may influence not only research productivity but also the decision to participate in the innovation process.

This paper examines whether short-run exposure to air pollution affects participation in China's National Natural Science Foundation (NSFC), the country's largest and most influential research funding program. Leveraging variation in upwind pollution transported by wind, we study how pollution immediately before the application window influences both the number of submissions and subsequent funding success.

A growing literature documents that air pollution affects human behavior and decision-making through several channels. Studies show that pollution can impair cognitive performance (Carneiro et al., 2021; Cui et al., 2023), reduce physical health and labor supply (Barwick et al., 2024), and worsen mental well-being (Sass et al., 2017). Pollution has also been shown to reduce outdoor activity and alter time allocation decisions (Fan, 2024).

Despite these advances, little is known about how pollution affects the behavior of researchers in higher-education institutions—a population whose work differs fundamentally from typical labor markets. Researchers have substantial discretion over how to allocate their time, often face fewer formal constraints on daily work schedules, and concentrate effort intensively around grant deadlines rather than spreading it evenly throughout the year. These features make them simultaneously more flexible yet potentially more vulnerable to short-run disruptions that interfere with high-stakes tasks requiring sustained focus.

This setting motivates our research questions: does short-run exposure to air pollution reduce researchers' effective work capacity during the critical pre-application period, and affect the quantity or quality of research output submitted for competitive funding?

2 Data Resources

Our data come from the National Natural Science Foundation of China (NSFC), publicly released daily Air Quality Index (AQI) records, weather condition data, and various statistical yearbooks. These include city-level yearbooks, such as *Dongguan Statistical Yearbook 2022*; province-level yearbooks, such as *Hebei Economic Yearbook 2015*; and national-level yearbooks, such as *China City Statistical Yearbook 2021*.

From the raw data, we construct two panel datasets: (1) a university-level panel dataset, and (2) a city-level panel dataset. For both datasets, our key variables include the number of NSFC grant applications and the NSFC funding rate at the university and city levels. The independent variables consist of air quality indicators and weather condition indicators. Control variables capture the level of city development, such as GDP per capita.

Finally, our panel data contain 659 universities and their NSFC application and funding outcomes from 2013 to 2019. Deatils can be found in Table 1 below.

Table 1: Summary Statistics

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Year	4613	2016	2	2013	2019
Application Number	4613	69.96	151.20	0	1912
Funded Number	4613	14.34	40.45	0	493
GDP per Capita	4597	1,699,564.4	34,706,166	10,090	7.449e+08
AQI	4513	80.32	25.93	22.83	217.97
Temperature Range	4613	9.17	1.87	5.12	15.37
Average Temperature	4613	15.79	4.57	1.03	26.89
Precipitation	4613	2.94	1.51	0.29	7.73

3 Model Set Up

3.1 Model Assumption

Based on the We assume the effect of air quality and weather condition on academic research output may accumulate for either 1 months, 2 months, 3 months, 6 month or 12 months, hence our air quality indicator variables and weather condition indicator variables are defined for different time hrizon prior to the start of the NSFC grant application date, which is typically March 1st for the years we study (see Figure 1). Our time lag and accumulated effect assumption are reasonable, since they are frequently applied strategies in pollution effect studies (see Sass et al., 2017). We also consider alternative measures of using natural years for pollution indicator variables, the regression results are similar and available upon request. Our control variables, however, due to the fact that statistical year books only publish annual values, are limited to natural years.

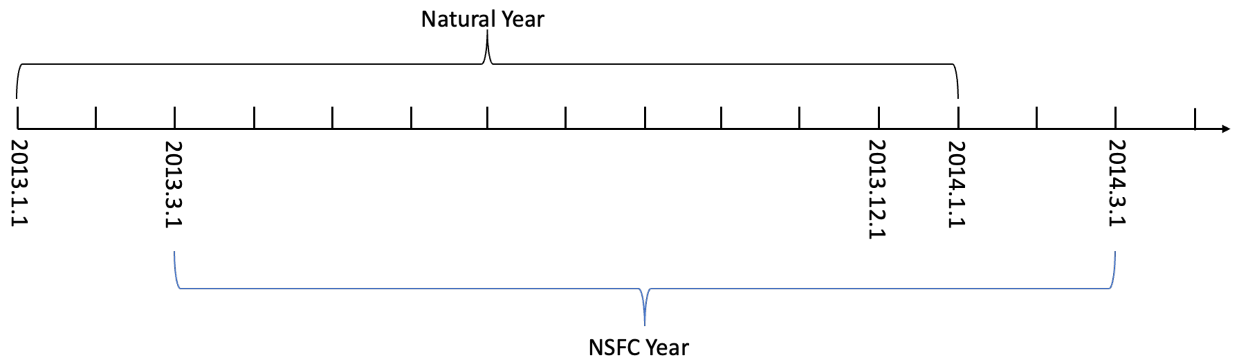

Figure 1: NSFC Submission Time Line

3.2 Instrument Variable and Control Function

We employ a two-stage control function approach to address endogeneity concerns in estimating the impact of air pollution. Our empirical model is specified as follows:

$$\text{First Stage:} \quad AQI_{it} = \pi_0 + \pi_1 UP_{it} + X'_{it}\pi + \alpha_i + \delta_t + \epsilon_{it},$$

$$\text{Second Stage:} \quad E[y_{it} \mid X] = \exp(\beta_0 + \beta_1 AQI_{i,t-1} + \beta_2 \hat{\epsilon}_{i,t-1} + X'_{it}\beta + \alpha_i + \delta_t)\,.$$

where AQI_{it} represents the air quality index, treated as an endogenous variable; UP_{it} denotes the instrument, capturing air pollution transported from upwind cities relative to the central city; X_{it} is a vector of control variables; $\hat{\epsilon}_{i,t-1}$ is the residual from the first-stage regression, included to control for endogeneity; and α_i and δ_t represent city and year fixed effects, respectively.

Compared to conventional Two-Stage Least Squares (2SLS), we adopt the control function approach (Wooldridge, 2015). This choice is motivated by the nature of our outcome variable, which is a count measure that may not satisfy the continuity assumptions of standard OLS. Consequently, we employ Poisson Pseudo-Maximum Likelihood (PPML) estimation in the second stage (Correia et al., 2019), which provides consistent estimates for count data while accommodating fixed effects.

3.3 Instrument Variable Construction

Our identification strategy exploits exogenous variation in air pollution originating from upwind cities. The instrument UP_{it} captures transboundary pollution flows that influence local air quality while remaining plausibly exogenous to local economic conditions, thus satisfying the exclusion restriction.

Following Chen et al. (2021), we construct our instrumental variable as follows:

$$UP_{it} = \sum_{i' \neq i} \frac{P_{i't} \cdot WD_{i't}}{D_{i'i}^2} \cos\theta_{i'it},$$

where the directional component is defined as:

$$\cos\theta_{i'it} = \max\{\cos\alpha_{i'it},\, 0\}.$$

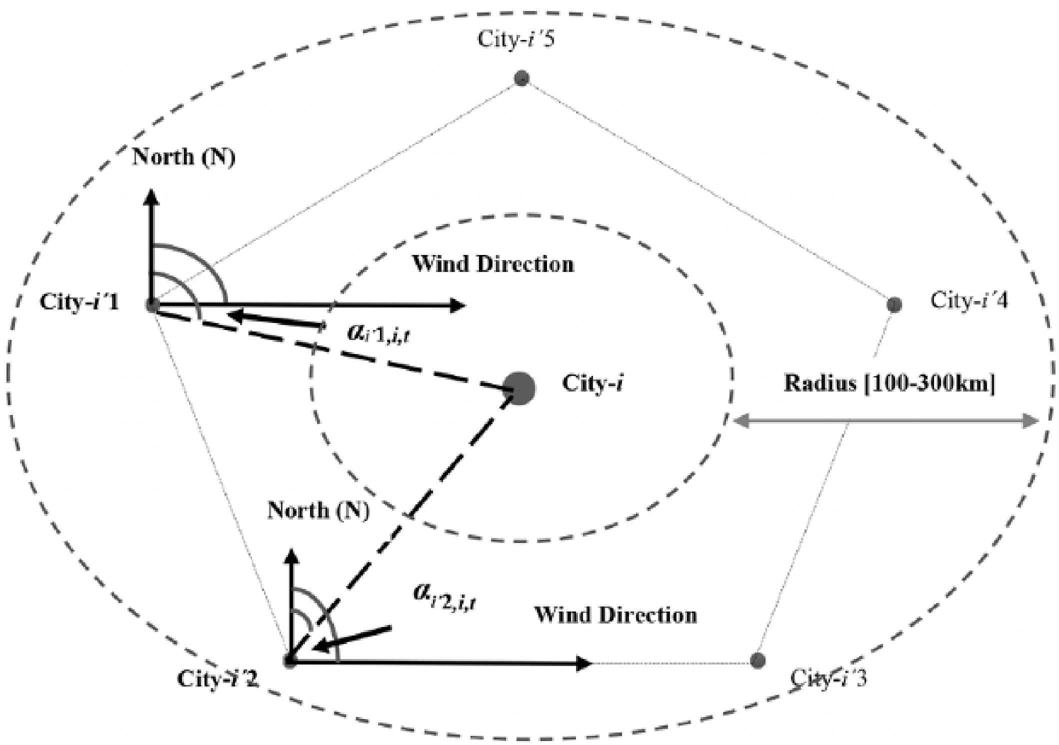

Figure 2: Instrumental Variable Construction (following Chen et al., 2021)

The construction proceeds through several intuitive steps. First, we identify the central city and define a surrounding radius of 100–300 km, within which we identify neighboring cities. This distance range is carefully chosen: too close a radius may violate the exclusion condition due to spatial spillovers, while too distant a radius may yield weak instruments.

Next, we identify upwind cities relative to the central city. For each time period t, we observe wind direction in neighboring cities and calculate the angle between each neighbor and the central city. We compute the angle difference (α in the Figure 2) between these two directions and take its cosine value. Cities with positive cosine values (indicating wind blowing toward the central city) are classified as upwind cities.

Finally, the total upwind pollution contribution aggregates pollution from all qualifying neighbors, weighted by wind speed, inverse squared distance, and the directional cosine component.

4 Discussion

We focus our interpretation on specifications with a strong first stage (KP F-statistic $>$ 10), which correspond to the one- to three-month exposure windows. Results for six- and twelve-month lags are reported for completeness but interpreted cautiously.

Tables 2 and 3 show that air pollution significantly depresses application activity in the short run. At the city level, higher pollution in the one- to three-month period preceding the submission deadline leads to a clear reduction in the number of NSFC applications, supported by strong first-stage relationships and precisely estimated endogenous components. Institution-level results exhibit the same qualitative pattern, although with a somewhat weaker instrument, reinforcing that short-term pollution exposure lowers participation across both levels of aggregation.

The timing of exposure is central to interpretation. The instrument weakens sharply for the six-month horizon, making medium-run effects difficult to assess. Although the first stage strengthens again at twelve months, the corresponding coefficient is unstable in sign and sensitive to specification, indicating that it should not be interpreted as evidence of a meaningful long-run effect. Instead, the consistent and well-identified estimates for the one- to three-month windows point to a short-run mechanism: pollution occurring close to the application deadline interferes with the intensive preparation, coordination, and cognitive effort required for submission. Beyond this immediate period, the data provide little evidence of systematic longer-run responses.

Funded-rate results tell a different story. As shown in Tables 4 and 5, short-run pollution exposure does not meaningfully alter the probability of obtaining support conditional on submitting a proposal. The coefficients for the one- to three-month lags are small and statistically insignificant even when the instrument is strong, and the longer-run estimates are similarly centered around zero. There is no evidence of a negative short-term effect or a compensatory long-run response.

Taken together, the findings point to a single dominant channel: pollution reduces participation rather than performance. It discourages researchers from applying during the period of highest cognitive and logistical demand, but conditional on participation, prior pollution exposure does not materially affect funding success. This distinction highlights that the timing of environmental shocks matters for innovation outcomes; disruptions need not have persistent effects to influence entry into competitive scientific contests.

Table 2: Effect of Air Pollution on Application Number (City Level)

	(1)	(2)	(3)	(4)	(5)
	1m	2m	3m	6m	12m
IV on Local AQI	271.077***	293.620***	295.562***	8.984	-296.518***
	(71.803)	(61.788)	(44.825)	(60.922)	(84.479)
Local AQI	-0.0053**	-0.0075***	-0.0053***	-0.2631***	0.0116***
	(0.0023)	(0.0024)	(0.0021)	(0.0879)	(0.0037)
Endogenous	0.0058**	0.0085***	0.0063***	0.2647***	-0.0094***
	(0.0024)	(0.0025)	(0.0022)	(0.0882)	(0.0033)
Number of Obs.	1144	1144	1144	1144	1144
R^2 (1st Stage)	0.824	0.880	0.892	0.881	0.857
KP F-stat	14.253	22.582	43.477	0.022	12.320
Pseudo R^2	0.9859	0.9859	0.9860	0.9859	0.9860

Notes: Standard errors in parentheses, clustered by City ID. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Effect of Air Pollution on Application Number

	(1) 1m	(2) 2m	(3) 3m	(4) 6m	(5) 12m
IV on Local AQI	243.486**	281.567***	232.003***	26.798	-105.610
	(101.711)	(86.663)	(67.221)	(70.192)	(96.595)
Local AQI	-0.0059**	-0.0078***	-0.0070***	-0.0871***	0.0286***
	(0.0026)	(0.0025)	(0.0026)	(0.0293)	(0.0095)
Endogenous	0.0064**	0.0089***	0.0080***	0.0888***	0.0263***
	(0.0027)	(0.0025)	(0.0028)	(0.0296)	(0.0092)
Number of Obs.	3838	3838	3838	3838	3838
R^2 (1st Stage)	0.800	0.862	0.876	0.882	0.872
KP F-stat (1st Stage)	5.731	10.556	11.912	0.146	1.195
Pseudo R^2	0.9472	0.9473	0.9473	0.9472	0.9473

Notes: Standard errors in parentheses, clustered by City ID. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: Effect of Air Pollution on Funded Rate (City Level)

	(1) 1m	(2) 2m	(3) 3m	(4) 6m	(5) 12m
IV on Local AQI	254.665***	291.499***	282.209***	19.133	-226.438**
	(91.541)	(81.187)	(54.099)	(66.156)	(96.595)
Local AQI	0.0016	0.0017	0.0018	0.0518*	-0.0033
	(0.0018)	(0.0017)	(0.0014)	(0.0273)	(0.0026)
Endogenous	-0.0014	-0.0018	-0.0017	-0.0514*	-0.0033
	(0.0018)	(0.0017)	(0.0015)	(0.0274)	(0.0026)
Number of Obs.	624	624	624	624	624
R^2 (1st Stage)	0.818	0.870	0.884	0.879	0.858
KP F-stat	7.739	12.892	27.213	0.084	5.822
Pseudo R^2	0.9764	0.9764	0.9764	0.9764	0.9764

Notes: Standard errors in parentheses, clustered by City ID. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5: Effect of Air Pollution on Funded Rate

	(1) 1m	(2) 2m	(3) 3m	(4) 6m	(5) 12m
IV on Local AQI	245.182**	271.629***	208.272***	-2.930	-106.359
	(110.472)	(96.759)	(79.523)	(81.170)	(94.458)
Local AQI	0.0013	0.0016	0.0019	-0.2776	-0.0062
	(0.0019)	(0.0019)	(0.0020)	(0.1799)	(0.0055)
Endogenous	-0.0009	-0.0013	-0.0015	0.2784	0.0071
	(0.0019)	(0.0019)	(0.0021)	(0.1798)	(0.0054)
Number of Obs.	1933	1933	1933	1933	1933
R^2 (1st Stage)	0.799	0.858	0.872	0.881	0.878
KP F-stat	4.926	7.881	6.859	0.001	1.268
Pseudo R^2	0.9472	0.9473	0.9473	0.9472	0.9473

Notes: Standard errors in parentheses, clustered by City ID.* p<0.10, ** p<0.05, *** p<0.01.

5 Conclusion

This paper documents a clear and economically meaningful link between short-run air pollution exposure and participation in scientific innovation. Using plausibly exogenous variation in upwind pollution transported by wind, we show that higher pollution in the months immediately preceding the NSFC application deadline significantly reduces the number of grant submissions. These effects are consistently identified across city- and institution-level analyses and are supported by strong first-stage relationships. By contrast, we find no corresponding impact on funding success conditional on applying, indicating that pollution influences the decision to participate rather than the quality or competitiveness of submitted proposals.

Taken together, the results underscore the importance of timing in environmental shocks. Pollution experienced during periods of high cognitive and organizational demand meaningfully deters entry into high-stakes research competitions, while exposures farther from the decision window do not generate systematic effects. These findings highlight a underappreciated channel through which environmental conditions influence innovation outcomes and point to the broader relevance of short-term disruptions in shaping scientific productivity.

References

Barwick, P. J., Li, S., Rao, D., and Zahur, N. B. (2024). The healthcare cost of air pollution: evidence from the world's largest payment network. *Review of Economics and Statistics*, pages 1–52.

Carneiro, J., Cole, M. A., and Strobl, E. (2021). The effects of air pollution on students' cognitive performance: evidence from brazilian university entrance tests. *Journal of the Association of Environmental and Resource Economists*, 8(6):1051–1077.

Chen, S., Chen, Y., Lei, Z., and Tan-Soo, J.-S. (2021). Chasing clean air: Pollution-induced travels in china. *Journal of the Association of Environmental and Resource Economists*, 8(1):59–89.

Correia, S., Guimarães, P., and Zylkin, T. (2019). Verifying the existence of maximum likelihood estimates for generalized linear models.

Cui, J., Huang, S., and Wang, C. (2023). The impact of air quality on innovation activities in china. *Journal of Environmental Economics and Management*, 122:102893.

Fan, Y. (2024). Social cost of lifestyle adaptation: Air pollution and outdoor physical exercise. *Journal of Environmental Economics and Management*, 127:103042.

Sass, V., Kravitz-Wirtz, N., Karceski, S. M., Hajat, A., Crowder, K., and Takeuchi, D. (2017). The effects of air pollution on individual psychological distress. *Health & place*, 48:72–79.

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*, 50(2):420–445.