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Replication: Can Technology Solve the Principal-Agent Problem? Evidence from China's War on Air Pollution

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I4R DISCUSSION PAPER SERIES

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Can Technology Solve the Principal-Agent
Problem? Evidence from China's War on Air
Pollution**

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April 2024

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Replication: Can Technology Solve the Principal-Agent Problem? Evidence from China's War on Air Pollution

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REPLICATION: CAN TECHNOLOGY SOLVE THE PRINCIPAL-AGENT PROBLEM? EVIDENCE FROM CHINA'S WAR ON AIR POLLUTION

Cloé Garnache*, Arijit Ghosh†, Garreth Gibney‡

Abstract

Greenstone et al. examine the effect of the introduction of automatic air pollution monitoring on the reporting of local air pollution in China. Using 654 regression discontinuity designs (RDDs) based on city-level variation in the day that monitoring was automated, they find an immediate and lasting increase of 35 percent in reported PM10 concentrations post-automation. Moreover, they find that automation's introduction increases online searches for face masks and air filters by 200 percent and 28 percent, respectively, using an RDD. Results are consistent when using an event study design.

First, we were able to computationally replicate the results. Second, we find that results are robust to more flexible specifications of the weather variables, to re-constructed weather variables using the same matching procedure as the authors (i.e., closest station) and meteorological data with additional weather stations, to alternative construction of the weather variables using an inverse distance weighted approach of the surrounding weather stations, and to more flexible choices of fixed effects (up to the city level). Finally, we find limited evidence of discontinuity in objective measures of ground pollution (i.e., AOD) for a sub-sample using alternative weather variables. The estimate, however, is economically insignificant. Moreover, no discontinuity is observed in the full sample. Therefore, we believe this result does not invalidate the original study's findings.

JEL CODES: D82, O13, P28, Q53, Q55, Q58.

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1 Introduction

Greenstone et al. examine the introduction of automatic pollution monitoring, which was a key element of China’s “war on pollution.” Automatic pollution monitoring increases the costs of pollution reporting manipulation by local government officials. Their analysis exploits the exact date that automatic monitoring was implemented in 123 cities with 654 monitoring stations to run station-specific regression discontinuity (RD) designs to test for manipulation. Because the implementation date varies across cities, they also run event-study designs to investigate medium to long-term tests for manipulation.

The study reports two key findings. First, they find evidence of underreporting of air pollution concentrations before automation. The RD estimates based on city-level variation on the exact day that monitoring was automated indicate that reported PM10 concentrations increased by 35 $\mu\text{g}/\text{m}^3$ or 35 percent on average, immediately after monitoring was automated. They also find an increase in the natural logarithm of reported PM10 concentrations post-automation of 24 percent to 32 percent when exploiting the variation in the timing of automation across cities using difference-in-differences (DiD) designs.

The second key finding is that the introduction of automated monitoring led to an increase in online searches for face masks and air filters by 200 percent and 28 percent, respectively, using an RDD, and using an event study higher searches for face masks and air filters are sustained and still evident 7-12 months after automation.

Using the authors data and code, we were able to quantitatively reproduce their key results (computational reproducibility). Using the authors’ data, we find that results are quantitatively robust to more flexible specifications of the weather variables (robustness replicability). Furthermore, we find that results are qualitatively robust to more flexible choices of fixed effects (up to the city level) in the case of pollution but estimates change sign in the case of avoidance behavior, both for mask and air filter searches (robustness replicability). Finally, the authors’ examine potential differences in behavioral responses between ‘normal’ and ‘data-manipulating’ cities. We find that these results are robust to alternative, more stringent definitions for ‘data-manipulating’ cities.

Using the same database (NOAA, 2022) as the authors’, we attempted to re-construct the

original weather variables using the same matching procedure (i.e., closest station). We fail to replicate the weather variables used in the original study. In spite of this issue, we are able to quantitatively reproduce the key results using our re-constructed weather variables (direct replicability). We contacted the original authors to request 'raw weather data' (i.e., with information on weather station co-ordinates) and enquire if additional steps were used to select weather stations. After discussion with the original authors, the possible reason for this might be that the stations used were different in our and the original authors' study and/or issues with GPS coordinates, which can be inaccurate in China and could have varied between our data and authors data for the same sites.

Using additional weather stations and implementing an alternative construction of the weather variables using an inverse distance weighted approach of the surrounding weather stations, we were also able to quantitatively reproduce the key results (conceptual replicability). However, we find limited evidence of discontinuity, with an increase in the objective/actual level of ground pollution (i.e., AOD) for a sub-sample (Wave 2 cities). Although, the estimate is economically insignificant. Moreover, no discontinuity is observed in the full sample. Therefore, we believe that this result does not invalidate the findings in the original study. Our data and code are available at DOI [10.17605/OSF.IO/M8HFR](https://doi.org/10.17605/OSF.IO/M8HFR).

2 Reproducibility

We run the codes and reproduce the results in Tables 1 and 2. The structure of the table is the same as in the original study. We find that the point estimates are identical, with the sign, magnitude and statistical significance all being reproduced. No coding errors were encountered.

3 Replication

We now turn our attention to our replication. We perform a direct replication of the weather variables used in the original study. Using same matching procedures as the authors' (i.e., match the pollution monitor with closest weather station) with new meteorological data with

additional weather monitoring stations. A list of the Chinese weather stations could not be retrieved using the link provided by authors ¹. Therefore, we do not know which stations are 'new' in our sample. We used a package called 'GSDOR' in R to download the raw weather data from the same archive as the authors' (NOAA, 2022).

We test the robustness of the results to a conceptual replication using the new meteorological data to construct an inverse distance weighted algorithm to match pollution monitoring stations with a distance weighted average (DWA) of surrounding weather stations. Because air pollution is very sensitive to weather, approximating the local weather prevailing at a pollution monitoring station can be improved by using a weighted average (based on the inverse distance) of the weather reported at nearby weather stations, rather than using the weather at the closest weather station, which may still be very far and possibly inaccurate, as done in the original paper. However, it is important to note that 'closest matching' is widely employed in economics.

We run two other robustness replications by increasing the order of the weather polynomial to allow for non-linearity between weather and pollution and adding more flexible fixed effects in the difference-in-difference analysis to account for unobservables that may be correlated with the dependent variables.

The decision to conduct the inverse distance weighted algorithm was taken after reading the paper but prior to observing the codes/programs, while for the three other robustness checks and the direct replication, the decision was taken after reading the paper and after observing the codes/programs.

3.1 Short-run changes in PM10: RD designs

For our analysis, we rely on the same RD and event study specifications comparing the treated cities (that have adopted automation technology) to untreated cities (that have not yet adopted). The analysis is at the city/day level for the RDD and at the city/month level for the event study. See the original study for more details and equations.

¹This is the link provided by the authors in their supplementary material: <https://www7.ncdc.noaa.gov/CDO/cdoselect.cmd?datasetabbv=GSODcountryabbv=georegionabbv>

$$P_{ict} = \beta_1 I(t \geq Auto_{ict}) + \beta_2 f(t \geq Auto_{ict}) + \quad (1)$$

$$\beta_3 I(t \geq Auto_{ict}) \times f(t \geq Auto_{ict}) + \beta_4 W_{ict} + \alpha_i + month_t + \epsilon_{ict}. \quad (2)$$

Weather conditions, W_{ict} , include temperature, precipitation, relative humidity, and wind speed.

3.1.1 Re-constructed weather variables.

We investigate whether using a reconstructed weather variable generated from meteorological data with additional weather stations has an impact on the sign, magnitude, and statistical significance on the estimates of PM_{10} and AOD in the RD model. The dependent variables PM_{10} and AOD are daily station level measures of concentrations of PM_{10} and the total vertical distribution of particles and gases within a grid (10x10km) according to the light distinction coefficient, respectfully. The AOD measure can be used to objectively infer ground level pollution. The estimating procedures employed for the RD regression are the same as those employed by the authors. However, using the same matching procedures (i.e., matching the pollution monitoring station with the closest weather station) but with new meteorological data, we attempt to re-construct the original weather variables (referred to as 're-constructed weather variable' here after). We fail to replicate the weather variables used in the original study. Summary statistics of original and re-constructed weather variables are reported in Table 1. We note that our re-constructed variable contains more observations than the original study, approximately over 13,000 more observations. However, if we exclude additional observations in our re-constructed variables only 1.32, 41.65, 1.9 and less than 0.001 percent of observations of temperature, precipitation, wind speed and relative humidity are equal, respectfully. We are not certain why we failed to recreate the original weather data using closest matching. However, the original authors suggest that this could be due to using different weather stations and/or issues with the accuracy of GPS coordinates.

Our findings are reported in Table 2. Panel a. reports the point estimates from the original study, and panel b. reports the point estimates using re-constructed weather vari-

ables. The point estimates for the full sample (columns (1) and (2)) are quantitatively similar. While the point estimates for sub-samples (columns (3), (4) and (5)) are qualitatively similar. We note that point estimates are slightly higher for wave 1 cities (column (3)), approximately 1.5 percentage points, and also slightly higher for wave 2 (column (4)) and deadline cities (column (5)), including up to 3.8 percentage points for deadlines cities (column (5)). The sign and the statistical significance are the same for all point estimates.

3.1.2 Weather variables constructed from using inverse distance weights of multiple weather stations

We investigate whether constructing our weather variables using a distance-weighted average algorithm to match meteorological data with pollution monitoring stations impacts the sign, magnitude, and statistical significance of the RD model of PM_{10} and AOD. The estimating procedures employed for the RD regression are the same as the authors'. However, we employ an alternative procedure to match pollution monitors with meteorological data. We use a distance-weighted average algorithm to match each pollution monitor with all weather stations on a given day. The distance-weighted average is generated by the equation below:

$$W_{d,p} = \frac{\sum_{i=1}^n \frac{w_i}{d_i}}{\sum_{i=1}^n \frac{1}{d_i}} \quad (3)$$

Our findings using ‘distance weighted average’ (DWA) weather variables are reported in Table 2, panel c. The point estimates are qualitatively similar for PM_{10} . The point estimates are lower for all RD models, including weather controls (columns (2)-(5)), including up to 6.1 percentage points for deadline cities (column (5)). On average, our point estimates are 4.4 percentage points lower than the original estimates.

Turning to the AOD model, notably, all point estimates, except for wave 1 cities (column (3)) are qualitatively similar. The point estimate for wave 1 cities is positive and statistically significant. This result suggests discontinuity in ground-level pollution, questioning if the observed increase in PM_{10} is caused by automation of air pollution monitoring or potentially a spurious increase in air pollution. Although the increase in AOD level is very small – it

only increases by 0.076 percentage points. Thus, relative to the change in PM_{10} , the change in AOD may not be economically significant.

We test the robustness of our DWA findings by modifying our DWA algorithm to only include weather stations within 500km and 100km of pollution monitors. Although the DWA algorithm weights assigned to far away stations would be very small, these restrictions ensure that very far away stations, which likely do not measure the prevailing weather accurately at a given pollution station, do not have any effect on our DWA weather measure. The idea is to provide a more accurate measure of weather at a given pollution monitor. Summary statistics of the alternative DWA weather measures are reported in Table 1. We note large declines in observations in DWA weather measures under those more stringent restrictions.

Our findings are reported in Table A1. Panel a. reports the findings using DWA algorithm using only stations within 500km of each pollution monitor (referred to as DWA_500 hereafter), and panel b. reports the DWA algorithm using only stations within 100km of each pollution monitor (referred to as DWA_100 hereafter).

The point estimates for AOD using DWA_500 are qualitatively similar to our initial findings using DWA weather measures, with the exception of column (1). We note a small increase in the level of statistical significance for wave 1 cities (column (3)) with estimates now significant at the 10 percent level. The AOD point estimates for DWA_100 are qualitatively similar for wave 1 cities (column (3)), relative to our initial DWA findings. We note that the statistical significance and the magnitude of the estimate for wave 1 cities (column (3)) increase to a 99 percent level confidence level and by 0.109 percentage points. These findings suggest a discontinuity in ground-level pollution. However, AOD point estimates remain economically insignificant and remain statistically insignificant in the authors' preferred specification using all cities (column (2)). Turning to the other AOD point estimates, using DWA_500, we find that point estimates for all cities with no controls (including weather and fixed effects) are positive and statistically significant at 90 percent confidence level. In contrast, when using DWA_100 for wave 2 cities (column (4)), estimates are negative and statistically significant at 95 percent confidence level, while for deadline cities estimates are positive and statistically significant at 90 percent confidence level (column (5)). This again suggests discontinuity, but estimates are economically insignificant.

Turning to the PM_{10} RD model using more stringent DWA measures, we find that estimates are in general, qualitatively similar. There are significant differences in the magnitude of the point estimates relative to the original findings. However, it is not clear if this is driven by data quality (i.e., more accurate measure of weather at pollution stations) or the sample, as we find significant decreases in the number of observations when we limit distance to weather stations (see table 1).

3.1.3 More flexible weather polynomial

We investigate whether allowing for a more flexible weather polynomial has an impact on the sign, magnitude and statistical significance of the RD model of PM_{10} and AOD . For this analysis, an observation is a city/day. The dependent variables, PM_{10} and AOD , are the daily concentration of PM 10 in a given city and the monthly AOD level at a given pollution monitor, respectively. Robust standard errors are clustered by city. Our findings are reported in Table 3. Panel a. reports the estimates from the original study, while Panel b. reports the estimates for the quadratic polynomial and Panel c. for the cubic polynomial. The sample includes monitoring stations from all cities (columns (1) and (2)), only from cities part of wave 1 or wave 2 (column (3) or (4)), and only from cities that adopt automation at the deadline (column (5)). With the quadratic or cubic weather polynomial, we replicate both the sign and significance of the PM 10 and AOD estimates. The point estimates are qualitatively similar. We note that the effect on PM 10 becomes slightly lower when allowing for more flexible polynomials, including up to 1 percentage point lower for all cities with fixed effects (column (2)) and up to 3 percentage points lower for deadline cities with fixed effects (column (5)).

3.2 Medium-Run Changes in Reported PM10: Difference-in-Differences Estimates

The RD approach provides a test of the effect of automation immediately after its implementation. The authors complement the RD by examining the effect of automation on PM_{10} in the medium-run using Difference-in-Differences models.

$$P_{ict} = \gamma_{\tau} \sum_{\tau=-4}^{+3} Auto_{ict\tau} + \beta W_{ict} + \alpha_i + month_t + \epsilon_{ict}. \quad (4)$$

Weather conditions, W_{ict} , include temperature, precipitation, relative humidity, and wind speed. The fixed effects, $\alpha_i, month_t$ are the station FEs and the month or year-by-month FEs.

3.2.1 Re-constructed weather variables.

We investigate whether using a reconstructed weather variable using meteorological data with additional weather stations has an impact on the sign, magnitude, and statistical significance of the DiD/Event Study model of PM_{10} and AOD. The reconstructed weather variable is same as described in the previous section. We use the same estimating procedures as the authors. Our findings are reported in Table 4. Panel a. reports the estimates from the original study, while panel b. reports the estimates from using our re-constructed weather variable. The point estimates are qualitatively similar. The PM_{10} estimates are somewhat similar to the original estimates. They can be slightly larger or smaller across time periods, including 1.8 percentage points lower for deadline cities 5-6 months before automation adoption and 3.5 percentage points higher for deadline cities 5-6 months after automation (column (2)). In the authors' preferred specification with matching, our estimates are similar but tend to be both slightly higher or similar to the original estimates (columns (3)-(5)). Four point estimates change in terms of statistical significance, with two increasing in significance and two decreasing.

3.2.2 Weather variables constructed from using inverse distance weights of multiple weather stations

We investigate whether constructing our weather variables using a distance weighted average algorithm to match meteorological data with pollution monitors impacts the sign, magnitude, and statistical significance of the DiD/Event Study model of PM_{10} and AOD. The DWA variable is the same as described in the previous section. We use the same estimating procedures as the authors. Our findings are reported in Table 4. Panel a. reports the

estimates from the original study, while panel c. reports the estimates from using our DWA weather variable. The point estimates are qualitatively similar. The DWA effect on the point estimates of PM_{10} operates in both directions, including 1.2 percentage points lower for deadline cities 5-6 months before automation and 3.1 percentage points higher for deadline cities 5-6 months after automation (column (2)). In the authors' preferred specification with matching, our point estimates are similar but tend to be both slightly higher or similar to the original estimates (columns (3)-(5)). Six point estimates change in terms of statistical significance, with four increasing in significance and two decreasing.

3.2.3 More flexible weather polynomial

We investigate whether allowing for a more flexible weather polynomial has an impact on the sign, magnitude and statistical significance of the event study model of PM_{10} . For this analysis, an observation is a city/month. The dependent variable, PM_{10} , is the daily concentration of PM 10 in a given city. Robust standard errors are clustered by city. Our findings are reported in Table 5. Panel a. reports the estimates from the original study, while Panel b. reports the estimates for the quadratic polynomial and Panel c. for the cubic polynomial. The sample includes monitoring stations from cities that adopt automation at the deadline (columns (1) and (2)). Treatment monitors are from Wave 1 cities where automation occurred on January 1, 2013, and control monitors are from Wave 2 cities where automation never occurred during this two-year period. In addition, in columns (3)-(5) each monitoring station in the Wave 1 (deadline) cities is matched to its (geographically) nearest monitoring station in the Wave 2 (deadline) cities with replacements. With the quadratic or cubic weather polynomial, we replicate both the sign and significance of the PM 10 estimates. The point estimates are qualitatively similar. We note that the effect on PM 10 becomes slightly lower when allowing for more flexible polynomials, including up to 1 percentage point lower for deadline cities in the 7-12 months before and after automation adoption (columns (1) and (2)). In the authors' preferred specification with matching, our estimates are quantitatively similar to theirs (columns (3)-(5)).

3.2.4 More flexible fixed effects

We investigate whether allowing for more flexible city controls, in the form of a city trend or additional city fixed effects to control for unobservables at the city level that may correlate with PM 10 has an impact on the sign, magnitude and statistical significance of the event study model of PM_{10} . For this analysis, an observation is a city/month. The dependent variable, PM_{10} , is the daily concentration of PM 10 in a given city. Robust standard errors are clustered by city. Our findings are reported in Table 6. (Table 5, Panel a. reports the estimates from the original study.) The sample includes monitoring stations from cities that adopt automation at the deadline (columns (1)-(3)). Treatment monitors are from Wave 1 cities where automation occurred on January 1, 2013, and control monitors are from Wave 2 cities where automation never occurred during this two-year period. In addition, in columns (4)-(9) each monitoring station in the Wave 1 (deadline) cities is matched to its (geographically) nearest monitoring station in the Wave 2 (deadline) cities with replacements. We introduce yearly linear city trends (columns (1), (4), and (7)), city-by-year FEs (columns (2), (5), and (8)), and city-by-year-by-month FEs (columns (3), (6), and (9)). Fewer estimates are significant in the post period. With the exception of column (9), estimates are significant only for the 1-2 months post automation. In column (8), estimates are not significant at the 10% level in the post period, while in column (7) estimates are significant only at the 10% level and only for the 1-2 months post automation. Some estimates also change sign (become positive and highly significant) in the 7-12 months before automation adoption with city trends (columns (1) and (4)). However, overall, the results are qualitatively similar to the author's original results.

3.3 Behavioral Responses

The original study defines a city as a data-manipulating one if its RD estimate is positive and statistically significant at the 5 percent level.

3.3.1 Re-constructed weather variables.

We investigate whether using a reconstructed weather variable generated from meteorological data with additional weather station has an impact on the sign, magnitude and statistical significance of the RD model of face mask and air filter searches. Our findings are reported in Table 7. Panel a reports the estimates from the original study, while panel b. reports the estimates using our re-constructed weather variable. We find that the point estimates are strikingly similar, with the sign, magnitude and statistical significance being remarkably similar.

3.3.2 Weather variables constructed from using inverse distance weights of multiple weather stations

We investigate whether constructing our weather variables using a distance weighted average algorithm to match meteorological data with pollution monitors impacts the sign, magnitude, and statistical significance of the RD model of face mask and air filter searches. Our findings are reported in Table 7. Panel a reports the estimates from the original study, while panel c. reports the estimates using our DWA weather variable. We find that the point estimates are strikingly similar, with the sign, magnitude and statistical significance being remarkably similar.

3.3.3 More flexible weather polynomial for the RD design

We investigate whether allowing for a more flexible weather polynomial has an impact on the sign, magnitude and statistical significance of the RD model of face mask and air filter searches. For this analysis, an observation is a city/month. The dependent variables are the monthly number of face mask and air filter searches (in level or in log +1) in a given city. Robust standard errors are clustered by city. Our findings are reported in Table 8. Panel a. reports the estimates from the original study, while Panel b. reports the estimates for the quadratic polynomial and Panel c. for the cubic polynomial. The sample includes all cities (columns (1) and (2)), only normal cities (column (3)), and only manipulating cities, defined as those with RD estimates positive and statistically significant at 5 percent level,

(column (5)). With the quadratic or cubic weather polynomial, we replicate both the sign and significance of the face mask and air filter searches estimates. The point estimates are quantitatively similar.

3.3.4 Alternative definition of normal or manipulating cities

We investigate whether allowing for different definitions of “normal” or “manipulating” cities has an impact on the sign, magnitude and statistical significance of the RD model of face mask and air filter searches. A more stringent definition of manipulating cities leads to a smaller (larger) sample for the manipulating (normal) cities, which may reduce the occurrence of false positives but also reduce statistical power. For this analysis, an observation is a city/month. The dependent variables are the monthly number of face mask and air filter searches (in level or in log +1) in a given city. Robust standard errors are clustered by city. Our findings are reported in Table 8, Panel d. When redefining manipulating (normal) cities as those for which the RD estimate is (not) statistically significant at the 1 percent level – instead of 5 percent level, we observe that the estimates become smaller and lose significance for the manipulating cities (column (2)), while they increase in magnitude and somewhat in significance for the normal cities (column (1)). When redefining manipulating (normal) cities as those for which the RD estimate is greater (lower) than 2 standard deviation, the estimates are qualitatively similar to those of the authors, although slightly higher (columns (3)-(4)).

3.3.5 More flexible weather polynomial for the event study design

We investigate whether allowing for a more flexible weather polynomial has an impact on the sign, magnitude and statistical significance of the event study model of face mask and air filter searches. For this analysis, an observation is a city/month. The dependent variables are the monthly number of face mask and air filter searches (in level) in a given city. Robust standard errors are clustered by city. Our findings are reported in Table 9. Panel a. reports the estimates from the original study, while Panel b. reports the estimates for the quadratic polynomial (columns (1) and (3)) and cubic polynomial (columns (2) and (4)). The sample includes all cities (columns (1) and (2)), only normal cities (column (3)), and only manip-

ulating cities, defined as those with RD estimates positive and statistically significant at 5 percent level, (column (5)). With the quadratic or cubic weather polynomial, we replicate both the sign and significance of the face mask and air filter searches estimates of columns (2) and (4) in Panel a. (Note that columns (1) and (3) of Panel a. do not include any weather controls.) with linear weather controls. The point estimates are quantitatively similar.

3.3.6 More flexible fixed effects

In Table 10, we report the estimates when allowing for more flexible fixed effects. (Table 9, Panel a. reports the estimates from the original study.) In column (1), with yearly city trend, weather controls, and month fixed effects, point estimates for mask searches are similar to those in the original study (column (1) in Table 9, Panel a; with year-month fixed effects). However, by including city-year FE in column (2), we note a smaller increase in online searches for masks 1 to 2 and 3 to 4 months after policy implementation. Additionally, there is a decrease, 5 to 6 months after the policy implementation. Turning now to filter searches (columns (3)-(4)), we note some important differences with the original study. Specifically, the estimates are positive and statistically significant before the policy implementation and tend to become negative in the post-period. Using within city and year variation, the evidence is less clear that the introduction of automatic air pollution monitoring in the reporting of local air pollution in China caused the change in avoidance behaviours, in particular, for air filter searchers.

4 Conclusion

We are able to quantitatively reproduce the key results using the authors' data and code (computational reproducibility). Using the authors' data, we find the results are quantitatively robust to more flexible specifications of the weather variables (robustness replicability). Furthermore, the results are qualitatively robust to more flexible choices of fixed effects (up to the city level) in the case of pollution but estimates change sign in the case of avoidance behavior, both for mask and air filter searches (robustness replicability). Finally, the authors' examine if there are difference in behavioral responses between 'normal' and 'data-manipulating' cities. We find that these results are robust to alternative definitions for 'normal' and 'data-manipulating' cities.

Using the same database (NOAA, 2022) as the authors, we attempted to re-construct the original weather variables using the same matching procedure (i.e., closest station). We fail to replicate the weather variables used in the original study. Despite this, we are able to quantitatively reproduce the key results using our re-constructed weather variables (direct replicability). The authors suggested that this could be due to using different weather stations and/or issues with the accuracy of GPS coordinates. Moreover, using additional weather stations and implementing an alternative construction of the weather variables using an inverse distance weighted approach of the surrounding weather stations. We were also able to quantitatively reproduce the key results (conceptual replicability). We find limited evidence of discontinuity, with an increase in the objective/actual level of ground pollution (i.e., AOD) for a sub-sample (Wave 2 cities) – however, the estimate is economically insignificant. Moreover, no discontinuity is observed in the full sample. Therefore, we believe that this result does not invalidate the findings in the original study.

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Tables

Table 1 Summary Statistics of Weather Variables

VARIABLES	(1) Observations	(2) Mean (SD)	(3) Min	(4) Max
Temperature				
Original	1,420,074	15.2(10.99)	-29.54	37.41
Nearest Weather Station	1,433,568	13.06(12.09)	-43.9	40.4
Distance Weighted Average	1,433,568	12.64(9.28)	-15.22	31.03
Within 500km	890,212	13.35(11.27)	-43.9	40.40
Within 100km	109,490	12.77(12.74)	-34.5	36.9
Rain				
Original	1,420,074	3.4(10.5)	0	290
Nearest Weather Station	1,433,568	2.72(9.52)	0	455.42
Distance Weighted Average	1,433,568	2.63(2.25)	0	93.36
Within 500km	890,212	2.73(8.4)	0	440.9
Within 100km	109,490	2.56(9.24)	0	440.9
Wind Speed				
Original	1,420,074	2.59(1.40)	0	25.14
Nearest Weather Station	1,433,568	2.46(1.43)	0	25.2
Distance Weighted Average	1,433,568	2.52(0.35)	0.85	6.2
Within 500km	890,212	2.44(1.27)	0	22.1
Within 100km	109,490	2.66(1.48)	0	22.1
Relative Humidity				
Original	1,420,074	65.48(18.91)	4.98	110.72
Nearest Weather Station	1,433,568	61.94(20.49)	2.3	25.2
Distance Weighted Average	1,433,568	61.88(6.95)	25	91.69
Within 500km	890,212	62.67(17.45)	0	100
Within 100km	109,490	60.28(19.35)	0	100

Table 2 (Referring to Table 1 in the original paper) Automating Air Quality Monitoring System and Reported PM10: Direct and Conceptual Replication

	(1)	(2)	(3)	(4)	(5)
<i>Panel A. RD estimates</i>					
Panel a. Original - Linear weather variables					
RD in PM ₁₀ (daily)	34.7*** (10.7)	34.9*** (5.8)	27.5*** (9.8)	64.7*** (9.9)	57.1*** (8.6)
RD in AOD	0.065 (0.044)	-0.005 (0.021)	0.026 (0.031)	-0.030 (0.029)	-0.003 (0.025)
Obs.(Daily)	91470	232326	81950	68456	86042
Bandwidth (Days)	109	263	140	234	184
Obs.(Monthly)	5057	5851	3173	2316	4894
Bandwidth (Months)	6	7	7	6	10
Panel b. Conceptual Replication - Nearest Weather Station					
RD in PM ₁₀ (daily)	34.8*** (10.7)	34.7*** (5.8)	29.1*** (9.4)	67.4*** (10.8)	60.9*** (7.9)
RD in AOD	0.065 (0.044)	0.003 (0.023)	0.047 (0.035)	-0.028 (0.030)	0.027 (0.031)
Obs.(Daily)	91474	227739	84891	57412	89997
Bandwidth (Days)	109	258	145	202	191
Obs.(Monthly)	5057	5851	4075	1932	3802
Bandwidth (Months)	6	7	9	5	8
Panel c. Robustness Replication - Distance Weighted Average (DWA)					
RD in PM ₁₀ (daily)	34.8*** (10.7)	30.9*** (6.1)	25.6*** (9.1)	59.0*** (10.0)	51.0*** (7.8)
RD in AOD	0.065 (0.044)	0.022 (0.023)	0.076** (0.038)	-0.042 (0.027)	0.043 (0.029)
Obs.(Daily)	91474	182274	100043	69206	97073
Bandwidth (Days)	109	209	171	236	204
Obs.(Monthly)	5057	6626	3594	2678	4385
Bandwidth (Months)	6	8	8	7	9
Sample	All	All	Wave 1	Wave 2	Deadline
Station FE		Y	Y	Y	Y
Month FE		Y	Y	Y	Y
Weather Controls		Y	Y	Y	Y

Note: * p<0.10, ** p<0.05, *** p<0.01.

Table 3 (Referring to Table 1 in the original paper) Automating Air Quality Monitoring System and Reported PM10: More flexible weather polynomials

	(1)	(2)	(3)	(4)	(5)
<i>Panel A. RD estimates</i>					
Panel a. Original - Linear weather variables					
RD in PM ₁₀ (daily)	34.7*** (10.7)	34.9*** (5.8)	27.5*** (9.8)	64.7*** (9.9)	57.1*** (8.6)
RD in AOD	0.065 (0.044)	-0.005 (0.021)	0.026 (0.031)	-0.030 (0.029)	-0.003 (0.025)
Obs.(Daily)	91470	232326	81950	68456	86042
Bandwidth (Days)	109	263	140	234	184
Obs.(Monthly)	5057	5851	3173	2316	4894
Bandwidth (Months)	6	7	7	6	10
Panel b. Quadratic weather variables					
RD in PM ₁₀ (daily)		34.2*** (6.0)	26.2*** (9.7)	61.5*** (9.7)	54.5*** (8.5)
RD in AOD		-0.004 (0.021)	0.031 (0.031)	-0.033 (0.028)	-0.005 (0.026)
Obs.(Daily)		211764	82524	71696	87773
Bandwidth (Days)		241	141	244	187
Obs.(Monthly)		5851	3594	2316	4385
Bandwidth (Months)		7	8	6	9
Panel c. Cubic weather variables					
RD in PM ₁₀ (daily)		33.7*** (6.2)	25.9*** (9.7)	61.3*** (9.8)	54.0*** (8.5)
RD in AOD		-0.002 (0.020)	0.027 (0.030)	-0.029 (0.028)	-0.001 (0.026)
Obs.(Daily)		195154	83064	72245	87192
Bandwidth (Days)		223	142	246	186
Obs.(Monthly)		6626	4075	2316	4385
Bandwidth (Months)		8	9	6	9
Sample	All	All	Wave 1	Wave 2	Deadline
Station FE		Y	Y	Y	Y
Month FE		Y	Y	Y	Y
Weather Controls		Y	Y	Y	Y

Note: * p<0.10, ** p<0.05, *** p<0.01.

	(1)	(2)	(3)	(4)	(5)
	PM ₁₀	PM ₁₀	PM ₁₀	PM ₁₀	log(PM ₁₀)
Panel a. Original - Linear weather variables					
treat_m712_before2	-8.5* (4.7)	-17.2** (6.7)	-10.7 (7.7)	-10.8 (9.7)	-0.13* (0.07)
treat_m56_before2	6.8 (6.0)	-19.2** (9.3)	10.5 (8.5)	-2.2 (12.1)	0.02 (0.11)
treat_m34_before2	-6.4 (5.6)	-12.0* (6.9)	-2.8 (7.3)	-5.2 (9.2)	-0.03 (0.09)
treat_m12_after2	60.3*** (11.0)	31.4*** (11.1)	66.5*** (14.3)	45.6*** (16.3)	0.24*** (0.09)
treat_m34_after2	45.0*** (7.8)	33.6*** (8.8)	47.2*** (10.7)	32.5** (14.2)	0.32** (0.12)
treat_m56_after2	28.1*** (6.7)	22.2*** (8.0)	33.4*** (9.7)	29.0** (13.7)	0.29** (0.12)
treat_m712_after2	40.0*** (6.1)	9.8 (8.8)	42.9*** (7.7)	15.8 (14.0)	0.24* (0.15)
Constant	72.3*** (11.6)	84.6*** (11.4)	61.5*** (15.5)	68.9*** (15.5)	4.19*** (0.14)
Observations	176,426	176,426	186,499	186,499	186,469
Panel b. Nearest Weather Station					
treat_m712_before2	-7.9 (4.8)	-18.9*** (6.3)	-10.3 (8.0)	-12.0 (9.1)	-0.14* (0.07)
treat_m56_before2	8.3 (5.7)	-21.0** (7.9)	9.2 (7.5)	-4.3 (9.4)	-0.00 (0.08)
treat_m34_before2	-6.3 (5.6)	-14.4** (6.3)	-3.8 (6.6)	-7.7 (7.7)	-0.06 (0.08)
treat_m12_after2	64.1*** (10.8)	32.9*** (11.1)	69.4*** (14.6)	46.0*** (16.5)	0.25*** (0.09)
treat_m34_after2	44.9*** (7.6)	31.5*** (8.5)	46.4*** (10.9)	31.7** (14.3)	0.32** (0.13)
treat_m56_after2	26.3*** (6.6)	18.7** (7.7)	30.7*** (9.2)	25.8** (12.0)	0.26** (0.11)
treat_m712_after2	41.2*** (5.7)	5.9 (7.3)	44.2*** (7.3)	10.4 (11.5)	0.19 (0.13)
Constant	81.9*** (6.9)	95.3*** (7.4)	80.4*** (7.4)	88.6*** (8.5)	4.28*** (0.07)
Observations	176,428	176,428	186,533	186,533	186,503
Panel c. DWA Weather Variables					
treat_m712_before2	-11.6** (4.8)	-18.4*** (6.4)	-12.3 (7.8)	-11.5 (9.2)	-0.13* (0.07)
treat_m56_before2	1.9 (5.6)	-20.4** (8.0)	4.9 (7.3)	-3.6 (9.6)	0.01 (0.08)
treat_m34_before2	-11.9** (5.5)	-13.6** (6.2)	-8.1 (6.6)	-7.5 (7.9)	-0.05 (0.08)
treat_m12_after2	56.3*** (10.4)	32.3*** (11.1)	62.6*** (14.1)	45.3*** (16.5)	0.24*** (0.09)
treat_m34_after2	40.0*** (7.6)	31.6*** (8.5)	43.3*** (10.9)	32.8** (14.6)	0.33** (0.13)
treat_m56_after2	27.9*** (6.8)	19.1** (7.8)	34.0*** (9.5)	27.1** (12.7)	0.28** (0.11)
treat_m712_after2	38.5*** (5.9)	7.0 (7.4)	42.3*** (7.6)	11.7 (12.3)	0.21 (0.14)
Constant	129.5*** (16.9)	127.3*** (17.1)	118.4*** (22.0)	115.6*** (20.3)	4.58*** (0.21)
Observations	176,428	176,428	186,533	186,533	186,503
Sample	Deadline	Deadline	+Matching	+Matching	+Matching
Weather Controls	Y	Y	Y	Y	Y
Station FE	Y	Y	Y	Y	Y
Month FE	Y		Y		
Year-Month FE		Y		Y	Y

Note: * p<0.10, ** p<0.05, *** p<0.01.

Table 5 (Referring to Table 1 in the original paper) Automating Air Quality Monitoring System and Reported PM10: More flexible weather polynomials

	(1)	(2)	(3)	(4)	(5)
	PM ₁₀	PM ₁₀	PM ₁₀	PM ₁₀	log(PM ₁₀)
<i>Panel B. Event-study estimates</i>					
Panel a. Original - Linear weather variables					
treat_m712_before2	-8.5* (4.7)	-17.2** (6.7)	-10.7 (7.7)	-10.8 (9.7)	-0.13* (0.07)
treat_m56_before2	6.8 (6.0)	-19.2** (9.3)	10.5 (8.5)	-2.2 (12.1)	0.02 (0.11)
treat_m34_before2	-6.4 (5.6)	-12.0* (6.9)	-2.8 (7.3)	-5.2 (9.2)	-0.03 (0.09)
treat_m12_after2	60.3*** (11.0)	31.4*** (11.1)	66.5*** (14.3)	45.6*** (16.3)	0.24*** (0.09)
treat_m34_after2	45.0*** (7.8)	33.6*** (8.8)	47.2*** (10.7)	32.5** (14.2)	0.32** (0.12)
treat_m56_after2	28.1*** (6.7)	22.2*** (8.0)	33.4*** (9.7)	29.0** (13.7)	0.29** (0.12)
treat_m712_after2	40.0*** (6.1)	9.8 (8.8)	42.9*** (7.7)	15.8 (14.0)	0.24* (0.15)
R-squared	0.3	0.4	0.3	0.3	0.38
Panel b. Quadratic weather variables					
treat_m712_before2	-8.7* (4.5)	-18.0** (6.8)	-9.9 (7.5)	-10.4 (9.4)	-0.13* (0.07)
treat_m56_before2	6.0 (5.8)	-20.2** (9.3)	9.8 (7.8)	-3.3 (11.5)	0.00 (0.10)
treat_m34_before2	-6.8 (5.5)	-13.3* (6.8)	-3.2 (6.9)	-5.4 (8.6)	-0.04 (0.09)
treat_m12_after2	59.8*** (11.0)	32.8*** (11.1)	65.2*** (14.5)	45.4*** (16.3)	0.24*** (0.09)
treat_m34_after2	43.9*** (8.2)	32.4*** (9.0)	47.8*** (11.1)	33.5** (14.3)	0.33*** (0.12)
treat_m56_after2	27.0*** (7.0)	21.0** (8.2)	32.7*** (9.8)	29.1** (13.0)	0.29** (0.11)
treat_m712_after2	39.0*** (6.1)	10.9 (8.7)	41.8*** (7.5)	16.1 (12.8)	0.25* (0.14)
R-squared	0.4	0.4	0.3	0.4	0.40
Panel c. Cubic weather variables					
treat_m712_before2	-9.1** (4.5)	-18.3*** (6.9)	-10.3 (7.6)	-10.7 (9.4)	-0.13* (0.07)
treat_m56_before2	5.3 (5.7)	-20.4** (9.3)	9.6 (7.8)	-3.2 (11.5)	0.00 (0.10)
treat_m34_before2	-7.0 (5.4)	-13.1* (6.7)	-3.3 (6.9)	-5.4 (8.6)	-0.04 (0.09)
treat_m12_after2	59.4*** (11.2)	32.6*** (11.0)	64.8*** (14.6)	45.5*** (16.3)	0.24** (0.09)
treat_m34_after2	43.5*** (8.4)	32.0*** (9.3)	47.3*** (11.2)	33.0** (14.3)	0.32*** (0.12)
treat_m56_after2	26.9*** (7.1)	20.9** (8.2)	32.5*** (9.8)	29.5** (13.2)	0.29** (0.11)
treat_m712_after2	38.9*** (6.1)	11.5 (8.5)	41.8*** (7.4)	16.7 (12.8)	0.26* (0.14)
R-squared	0.4	0.4	0.3	0.4	0.41
Observations	176,426	176,426	186,499	186,499	186,469
Sample	Deadline	Deadline	+Matching	+Matching	+Matching
Weather Controls	Y	Y 20	Y	Y	Y
Station FE	Y	Y	Y	Y	Y
Month FE	Y		Y		
Year-Month FE		Y		Y	Y

Table 6 (Referring to Table 1 in the original paper) Automating Air Quality Monitoring System and Reported PM10: More flexible trends and fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Panel B. Event-study estimates</i>									
Different FEs and trend									
VARIABLES	PM10	PM10	PM10	PM10	PM10	PM10	log_PM10	log_PM10	log_PM10
treat_m712_before2	30.0*** (8.4)	-2.2 (4.4)	-6.4*** (0.6)	30.8*** (10.3)	-5.0 (7.3)	-6.0** (2.8)	0.13 (0.09)	-0.12** (0.06)	-0.04 (0.03)
treat_m56_before2	16.9*** (5.9)	12.2** (5.7)	-9.3*** (0.5)	25.5*** (8.6)	14.1* (8.2)	-3.3*** (0.1)	0.14 (0.09)	0.06 (0.08)	0.03 (0.04)
treat_m34_before2	-2.3 (5.5)	-4.4 (5.2)	-17.3*** (1.9)	3.3 (7.4)	-2.0 (7.1)	-17.3*** (0.6)	-0.04 (0.08)	-0.07 (0.07)	-0.21*** (0.05)
treat_m12_after2	32.1*** (11.6)	36.8*** (10.7)	19.6*** (5.2)	40.6** (16.9)	38.2** (14.4)	19.3*** (4.0)	0.19* (0.10)	0.18 (0.11)	0.15*** (0.00)
treat_m34_after2	10.6 (9.3)	21.1** (10.1)	15.6 (11.1)	13.3 (14.2)	18.0 (13.0)	16.9 (10.9)	0.10 (0.10)	0.13 (0.10)	0.14** (0.06)
treat_m56_after2	-10.5 (10.0)	6.4 (9.7)	13.1** (6.2)	-6.7 (14.7)	5.2 (12.4)	8.1* (4.7)	-0.00 (0.10)	0.08 (0.10)	0.13*** (0.02)
treat_m712_after2	-26.0* (13.6)	15.4 (9.6)	2.8 (5.8)	-23.7 (17.5)	11.1 (11.6)	6.7 (10.4)	-0.11 (0.14)	0.13 (0.10)	0.16 (0.11)
Constant	-21.6 (20.0)	86.2*** (9.3)	46.0*** (9.5)	24.5 (18.6)	74.9*** (13.9)	30.8** (12.5)	3.90*** (0.16)	4.26*** (0.13)	3.83*** (0.12)
Observations	176,426	176,426	176,426	186,499	186,499	186,499	186,469	186,469	186,469
R-squared	0.4	0.4	0.5	0.4	0.4	0.5	0.41	0.42	0.55
Sample	Deadline	Deadline	Deadline	+Matching	+Matching	+Matching	+Matching	+Matching	+Matching
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Station FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Yearly city trend	Y	Y	Y	Y	Y	Y	Y	Y	Y
City-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
City-Year-Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: * p<0.10, ** p<0.05, *** p<0.01.

Table 7 (Referring to Table 2 in the original paper) Automating Air Quality Monitoring System and Avoidance Behaviors: Direct and Conceptual Replication

	(1)	(2)	(3)	(4)
<i>Panel A. RD estimates</i>				
Panel a. Original - Linear weather variables				
RD in face mask searches (preautomation mean = 0.62)	10.10*** (1.58)	11.03*** (1.66)	6.46*** (2.03)	18.77*** (2.63)
RD in air filter searches (preautomation mean = 35.5)	7.36** (3.60)	8.73*** (1.86)	5.16** (2.50)	16.30*** (2.39)
RD in log (face mask searches + 1) (preautomation mean = 0.16)	1.06*** (0.17)	1.15*** (0.17)	0.90*** (0.21)	1.72*** (0.25)
RD in log (air filter searches + 1) (preautomation mean = 3.30)	0.18* (0.10)	0.16*** (0.04)	0.12** (0.05)	0.25*** (0.06)
Panel b. Nearest Weather Station				
RD in face mask searches	10.22*** (1.57)	11.21*** (1.64)	6.66*** (2.00)	18.90*** (2.59)
RD in air filter searches	7.52** (3.63)	8.83*** (1.85)	5.24** (2.48)	16.07*** (2.28)
RD in log (face mask searches + 1)	1.07*** (0.17)	1.16*** (0.17)	0.91*** (0.20)	1.77*** (0.24)
RD in log (air filter searches + 1)	0.18* (0.10)	0.16*** (0.04)	0.12** (0.05)	0.25*** (0.06)
Panel c. Distance Weighted Average Weather Variables				
RD in face mask searches	10.22*** (1.57)	10.87*** (1.67)	6.31*** (1.99)	18.30*** (2.75)
RD in air filter searches	7.52** (3.63)	8.12*** (1.82)	4.47* (2.41)	14.80*** (2.24)
RD in log (face mask searches + 1)	1.07*** (0.17)	1.04*** (0.17)	0.80*** (0.20)	1.65*** (0.24)
RD in log (air filter searches + 1)	0.18* (0.10)	0.14*** (0.04)	0.09** (0.04)	0.23*** (0.05)
Sample	All	All	Normal	Manipulate
City FE		Y	Y	Y
Month FE		Y	Y	Y
Weather Controls		Y	Y	Y

Note: * p<0.10, ** p<0.05, *** p<0.01.

Table 8 (Referring to Table 2 in the original paper) Automating Air Quality Monitoring System and Avoidance Behaviors: More flexible weather polynomials and alternative definition for normal and manipulating cities

	(1)	(2)	(3)	(4)
<i>Panel A. RD estimates</i>				
Panel a. Original - Linear weather variables				
RD in face mask searches (preautomation mean = 0.62)	10.10*** (1.58)	11.03*** (1.66)	6.46*** (2.03)	18.77*** (2.63)
RD in air filter searches (preautomation mean = 35.5)	7.36** (3.60)	8.73*** (1.86)	5.16** (2.50)	16.30*** (2.39)
RD in log (face mask searches + 1) (preautomation mean = 0.16)	1.06*** (0.17)	1.15*** (0.17)	0.90*** (0.21)	1.72*** (0.25)
RD in log (air filter searches + 1) (preautomation mean = 3.30)	0.18* (0.10)	0.16*** (0.04)	0.12** (0.05)	0.25*** (0.06)
Panel b. Quadratic weather variables				
RD in face mask searches	7.93*** (1.22)	10.98*** (1.67)	6.28*** (2.04)	18.91*** (2.63)
RD in air filter searches	6.94* (3.55)	8.72*** (1.86)	5.17** (2.51)	16.30*** (2.41)
RD in log (face mask searches + 1)	1.26*** (0.15)	1.15*** (0.18)	0.90*** (0.21)	1.73*** (0.25)
RD in log (air filter searches + 1)	0.20** (0.09)	0.16*** (0.04)	0.12** (0.05)	0.25*** (0.06)
Panel c. Cubic weather variables				
RD in face mask searches	7.93*** (1.22)	10.98*** (1.67)	6.29*** (2.04)	18.92*** (2.63)
RD in air filter searches	6.94* (3.55)	8.64*** (1.85)	5.19** (2.50)	16.20*** (2.43)
RD in log (face mask searches + 1)	1.26*** (0.15)	1.16*** (0.17)	0.91*** (0.21)	1.73*** (0.25)
RD in log (air filter searches + 1)	0.20** (0.09)	0.16*** (0.04)	0.12** (0.05)	0.24*** (0.06)
Sample	All	All	Normal	Manipulate
City FE		Y	Y	Y
Month FE		Y	Y	Y
Weather Controls		Y	Y	Y
Panel d. Different cutoff for normal and manipulating cities				
RD in face mask searches	12.24*** (1.83)	0.27 (1.72)	9.50*** (1.67)	32.70*** (6.89)
RD in air filter searches	9.17*** (2.01)	4.65* (2.45)	7.64*** (1.90)	23.90*** (4.93)
RD in log (face mask searches + 1)	1.29*** (0.19)	-0.36 (0.37)	1.04*** (0.18)	2.97*** (0.40)
RD in log (air filter searches + 1)	0.18*** (0.04)	-0.08 (0.10)	0.13*** (0.04)	0.53*** (0.12)
Sample	Normal 1%	Manipulate 1%	Normal 2*SD	Manipulate 2*SD
City FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y

Note: * p<0.10, ** p<0.05, *** p<0.01.

Table 9 (Referring to Table 2 in the original paper) Automating Air Quality Monitoring System and Avoidance Behaviors: More flexible weather polynomials

	(1)	(2)	(3)	(4)
<i>Panel B. DiD estimates</i>				
	Mask searches	Mask searches	Filter searches	Filter searches
Panel a. Original - Linear weather variables				
treat_m712_before2	-0 (0.0)	-0.0471 (0.615)	-0.152 (0.908)	-0.136 (0.917)
treat_m56_before2	-0 (0.0)	0.121 (0.539)	0.622 (0.593)	0.861 (0.485)
treat_m34_before2	-0 (0.0)	0.166 (0.143)	0.910 (0.419)	1.160 (0.317)
treat_m12_after2	18.60 (18.52*** (3.80e-09)	2.870 (0.135)	2.803 (0.138)
treat_m34_after2	17.39	17.31*** (5.97e-08)	6.111*** (0.00103)	6.097*** (0.00100)
treat_m56_after2	5.425	5.370*** (1.56e-05)	2.477 (0.136)	2.580 (0.119)
treat_m712_after2	14.45	14.62*** (1.56e-08)	6.000*** (0.000820)	6.216*** (0.000647)
Observations	51,901	51,900	51,170	51,169
R-squared	0.32	0.32	0.53	0.53
City FE	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y
Weather Controls		Y		Y
Panel b. Quadratic or Cubic weather variables				
treat_m712_before2	-0.04 (0.10)	-0.05 (0.12)	-0.17 (1.29)	-0.19 (1.29)
treat_m56_before2	0.15 (0.25)	0.10 (0.27)	0.81 (1.16)	0.78 (1.16)
treat_m34_before2	0.31 (0.19)	0.28 (0.22)	0.92 (1.12)	0.88 (1.13)
treat_m12_after2	18.45*** (2.75)	18.42*** (2.75)	2.94 (1.86)	2.93 (1.85)
treat_m34_after2	17.35*** (2.86)	17.37*** (2.87)	6.07*** (1.73)	6.05*** (1.72)
treat_m56_after2	5.42*** (1.18)	5.39*** (1.19)	2.52 (1.58)	2.45 (1.57)
treat_m712_after2	14.64*** (2.30)	14.63*** (2.30)	6.15*** (1.69)	6.12*** (1.69)
Observations	51,900	51,900	51,169	51,169
R-squared	0.32	0.32	0.53	0.53
City FE	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y
Quadratic Weather Controls	Y		Y	
Cubic Weather Controls		Y		Y
Sample	Deadline	Deadline	Deadline	Deadline

Note: * p<0.10, ** p<0.05, *** p<0.01.

Table 10 (Referring to Table 2 in the original paper) Automating Air Quality Monitoring System and Avoidance Behaviors: More flexible trends and fixed effects

	(1)	(2)	(3)	(4)
<i>Panel B. DiD estimates</i>				
	Mask searches	Mask searches	Filter searches	Filter searches
	Different FEs and trend			
treat_m712_before2	0.51 (0.39)	6.73*** (1.12)	24.10*** (2.67)	7.55*** (1.26)
treat_m56_before2	7.79*** (1.66)	13.27*** (2.01)	17.83*** (1.51)	12.26*** (1.44)
treat_m34_before2	2.84*** (1.02)	8.13*** (1.23)	10.87*** (1.28)	8.10*** (1.22)
treat_m12_after2	22.33*** (2.83)	6.69*** (1.05)	5.54*** (1.68)	-0.24 (1.16)
treat_m34_after2	18.37*** (3.03)	2.68** (1.21)	1.41 (1.70)	-1.30 (1.17)
treat_m56_after2	5.01*** (1.59)	-10.79*** (1.39)	-10.25*** (1.67)	-9.99*** (1.06)
treat_m712_after2	17.10*** (2.79)		-10.97*** (2.55)	
Constant	-4.89*** (0.82)	0.92 (0.99)	14.30*** (3.23)	34.43*** (1.10)
Sample	Deadline	Deadline	Deadline	Deadline
Month FE	Y	Y	Y	Y
Yearly city trend	Y		Y	
City-Year FE		Y		Y
Weather Controls	Y	Y	Y	Y
Observations	51,900	51,900	51,169	51,169
R-squared	0.35	0.37	0.49	0.53

Note: * p<0.10, ** p<0.05, *** p<0.01.

Appendix

This section reports auxiliary results.

Table A1 (Referring to Table 1 in the original paper) Automating Air Quality Monitoring System and Reported PM10: Distance weighted average Variables with distance limits

	(1)	(2)	(3)	(4)	(5)
<i>Panel A. RD estimates</i>					
Panel a. DWA - Limited to weather stations within 500km.					
RD in PM ₁₀ (daily)	37.1*** (11.7)	29.7*** (4.9)	31.6*** (9.2)	74.2*** (10.6)	57.7*** (8.1)
RD in AOD	0.101* (0.052)	0.012 (0.026)	0.072* (0.040)	-0.058 (0.036)	0.034 (0.033)
Obs.(Daily)	69556	206568	62906	26447	59773
Bandwidth (Days)	133	366	174	160	189
Obs.(Monthly)	3133	4099	2234	1432	2243
Bandwidth (Months)	6	8	8	6	7
Panel b. DWA - Limited to weather stations within 100km					
RD in PM ₁₀ (daily)	52.6*** (14.8)	49.3*** (8.0)	47.1*** (9.2)	36.9 (23.0)	47.8*** (8.1)
RD in AOD	0.117 (0.104)	0.032 (0.057)	0.185*** (0.067)	-0.110** (0.054)	0.119* (0.065)
Obs.(Daily)	12296	15008	6692	10580	17919
Bandwidth (Days)	197	234	167	398	350
Obs.(Monthly)	712	643	326	283	405
Bandwidth (Months)	10	9	9	8	8
Sample	All	All	Wave 1	Wave 2	Deadline
Station FE		Y	Y	Y	Y
Month FE		Y	Y	Y	Y
Weather Controls		Y	Y	Y	Y

Note: * p<0.10, ** p<0.05, *** p<0.01.