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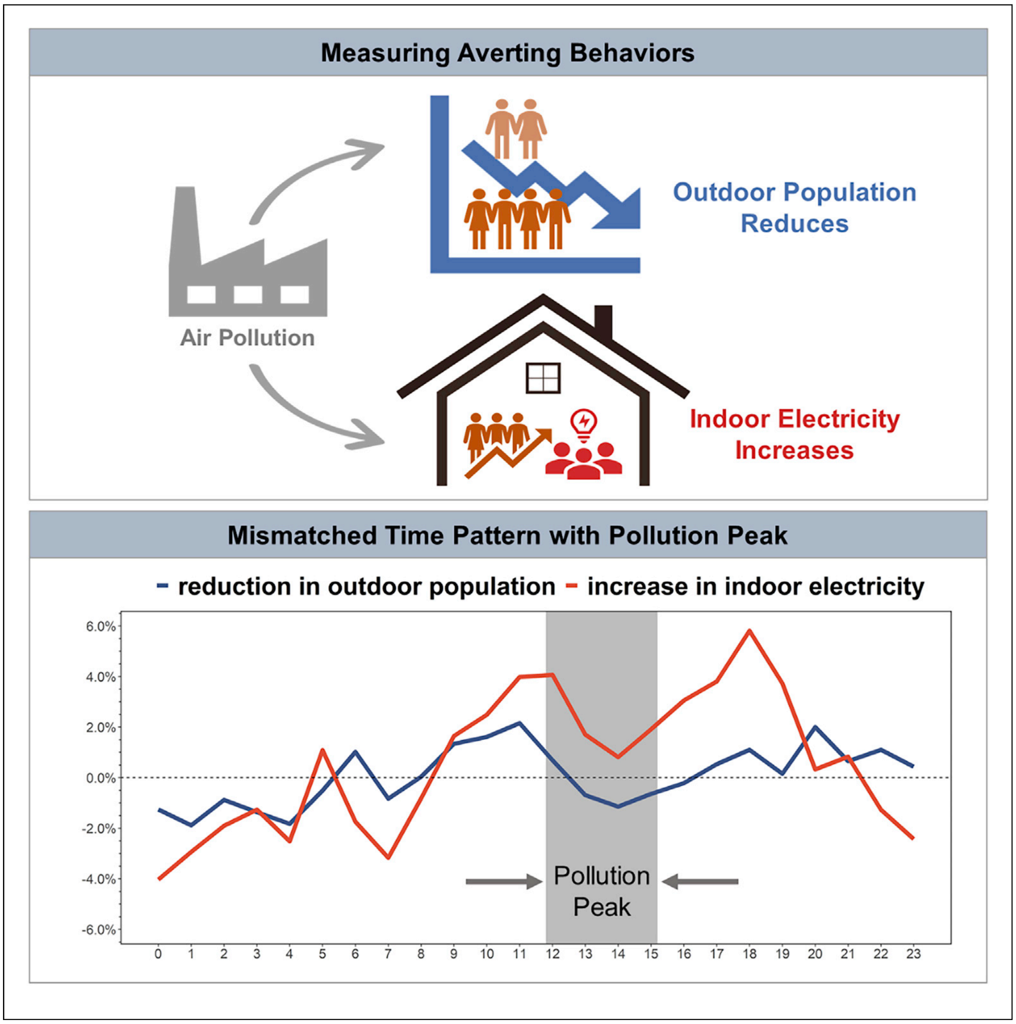


Qingran Li, Yang Zhou, William A. Pizer, Libo Wu

wulibo@fudan.edu.cn

## Highlights

Averting behavior follows a "double-peaked" pattern during the day

Peak averting responses fail to match the peak pollution

Averting behavior induces a higher marginal response indoors than outdoors

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# The unbalanced trade-off between pollution exposure and energy consumption induced by averting behaviors

Qingran Li,[1,2,7] Yang Zhou,[3,4,7] William A. Pizer,[5] and Libo Wu[3,6,8,*]

## SUMMARY

**Behavioral responses to environmental risks create gains and losses. We use high-frequency datasets to elucidate such behavior responses against air pollution and find a "double-peaked" time pattern in reducing outdoor exposure and in increasing electricity consumption. Despite that one standard deviation increase in the Air Quality Index induces 2% less outdoor population and 6% more household electricity consumption at peak, most responses fail to match with the intra-day pollution peaks, implying ineffective exposure avoidance. We find an unbalanced trade-off between health benefits and energy co-damages. The behavior-induced change in annual residential power consumption (+1.01% to +1.20%) is estimated to be 20 times more than that in the population-based exposure (−0.02% to −0.05%), and generates 0.13–0.15 million more metric tons of citywide carbon emissions. Our results imply that by targeting peak pollution periods, policies can shrink the trade-off imbalance and achieve mutual improvements in exposure reduction and energy conservation.**

## INTRODUCTION

Exposure to air pollution adversely affects adult and infant health,[1,2] human capital development,[3,4] labor productivity,[5–8] and subjective well-being.[9–11] This leads to economic costs, estimated by environmental-health models, which are critical in making welfare-improving policies. There are in general two channels to lower the public exposure to environmental risks — reducing pollutant concentration via regulatory emission controls and spontaneous individual averting behaviors.[12,13] Our research focuses on the second channel. Averting behaviors are often associated with costs burdened on consumers, such as increasing energy usage and purchasing masks and air purifiers.[14–16] The associated increase in consumption due to averting behaviors can be quite significant leading to co-damages.[17,18] The co-damages depend on the intensity of responses to pollution, while the health benefits depend on the effectiveness of such responses in averting exposure. The co-damages could outweigh the potential health benefits if the averting behaviors are not merely responses to pollution concentrations but are also constrained by other factors. The previous literature[3,10,13–17,19] tends to ignore the complexity of human behaviors when subject to such constraints. Our paper contributes to this deficiency in examining the time pattern as an imposed constraint to averting behaviors and in accessing the coupled exposure reduction and energy consumption under such a time pattern.

Our paper focuses on the most common and costless response to air pollution, i.e., moving activities from outdoors to indoors, which usually occurs during certain hours of the day. Though this type of averting behavior is temporary, the associated exposure reduction is not trivial, as pollutant concentrations such as indoor PM2.5 in residential dwellings can be up to 80% lower than those outdoors.[20] In the occurrence of high pollution, residents tend to reduce time spent in open-space outdoor areas and stay longer time indoors thus leading to increased household electricity consumptions.[17,18,21] This type of averting response generates the two complementary outcomes analyzed in our study — reduced population outdoors and increased electricity consumption indoors. Existing studies rarely keep track of both outcomes, thus failing to discuss the comparable magnitudes between the co-damages and the health benefits induced by averting behaviors. This likely leads to biased perceptions about how effective averting behaviors are. Our paper contributes to empirically analyzing the two behavioral outcomes simultaneously and provides a crucial reference for policy-making that needs to consider the welfare trade-off between exposure and co-damages.

[1]David D. Reh School of Business, Clarkson University, Potsdam, NY, USA

[2]Institute for a Sustainable Environment, Clarkson University, Potsdam, NY, USA

[3]Institute for Big Data, Fudan University, Shanghai, China

[4]Department of ORFE, Princeton University, Princeton, NJ, USA

[5]Resources for the Future, Washington, DC, USA

[6]School of Economics, Fudan University, Shanghai, China

[7]These authors contributed equally

[8]Lead contact

*Correspondence: wulibo@fudan.edu.cn

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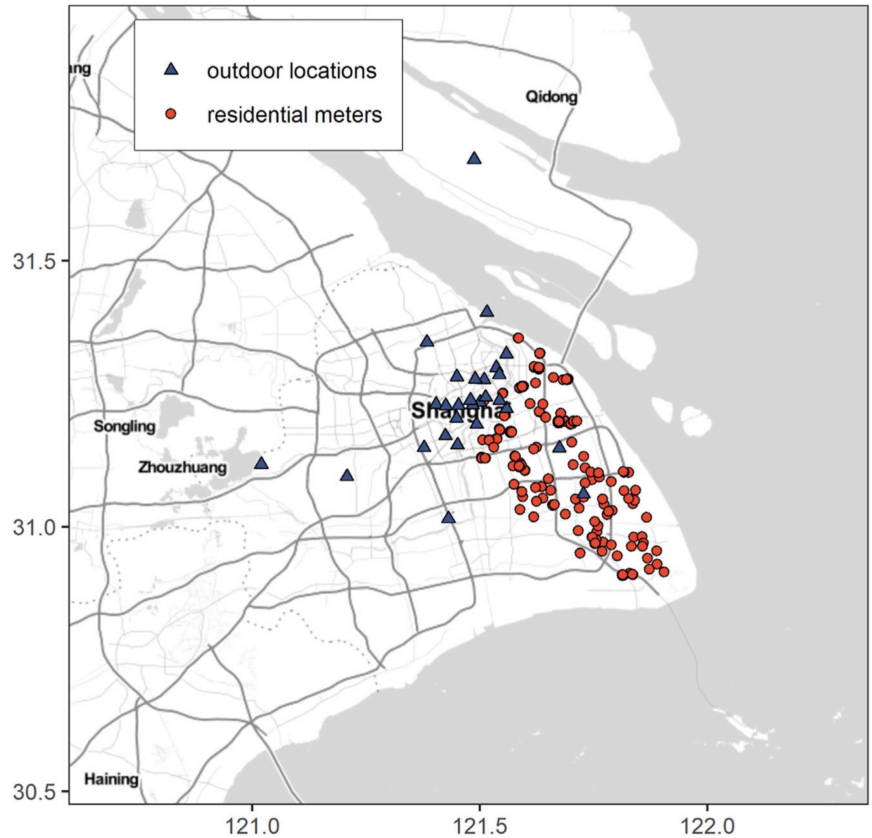


**Figure 1. Map of electricity meters and public areas in the indoor and outdoor samples**
Notes: Household meters are depicted by orange dots and public areas with blue triangles.

To measure the two complementary outcomes of averting behaviors, our study utilized two high-frequency datasets — the hourly household electricity consumption data and outdoor mobile tracking data (see data and code availability). Locations of observations from the indoor and outdoor samples are shown in Figure 1. Our indoor electricity consumption data cover 588 residential smart meters in the Pudong district of Shanghai from March 2016 to March 2018. The outdoor sample contains 28 public areas (e.g., parks, plazas, and stadiums) across the city from June 2018 to February 2019. Observations in the two datasets are matched with hourly Air Quality Index (AQI) readings and weather variables from the nearest monitoring station. Summary statistics of the main variables are provided in Table S1. Though the sample size was limited by the availability of high-frequency data, the comparison between the summary social attributes of our sample and the entire city of Shanghai (see Table S2) justifies the representativeness of our sample and the internal validity of our analytical results.

Behaviors such as moving outdoor activities indoors are associated with people's decisions to reallocate time within a day. The costs of alternating these activities need not be constant over time, and they may not follow a uniform pattern during the day nor directly correlate with outdoor pollution concentrations. The high-frequency feature of our data allows us to identify the temporal variability of human responses to environmental risks. This is a critical contribution as using aggregated measurements would result in biased estimates of averting behaviors. Studies using low-frequency data (e.g., daily or monthly) aggregate away from the variation of pollution levels but instead provide only average or aggregated estimates.[13,17,22–25] The magnitude of averting behaviors could be underestimated as peak response periods could be smoothed out in the average estimates. We find that averting behaviors have a "double-peaked" pattern with higher responses during late morning (9 a.m.–12 p.m.) and evening hours (5–9 p.m.). Quantitatively, this amounts to a 1%–2% population reduction outdoors and a 4%–6% household electricity consumption increase indoors for each standard deviation increase in the AQI (27 AQI units for the outdoor sample period and 38 units for the indoor sample period). However, the mean outdoor population reduction is just 0.5% and there is no effect on indoor electricity usage when we assume no temporal variation, i.e., the same effect for all hours (Table S4).

Despite that people do respond to air pollution by reducing outdoor exposure and moving indoors, our paper demonstrates that the effectiveness of averting behaviors in reducing exposure would be considerably overestimated. This is because pollution concentrations mostly peak in the middle of the day and early afternoon when the "double-peaked" behavioral pattern presents the least significant response. Peak pollution as measured by AQI is on average 3 times the daily average (Figure S1). Failing to respond to high peak pollution would minimize the exposure-related health benefits. Such results are likely to be subject to other constraints imposed by how other activities are scheduled during the day, such as a pre-planned visit to the park or work-related transit between locations. When these unobserved constraints are significantly binding averting behaviors associated with mobility, people might be irresponsive to pollution alerts without better temporal information on the pollution level. We can validate the potential mechanism underlying the mismatched time patterns by comparing averting responses during workdays and non-workdays. The mismatched temporal patterns between averting behaviors and intra-day pollution levels exacerbate the co-damage problem, as most responses are ineffective in averting pollution exposure while still inducing energy consumption and expenditures by the households. Using the hourly average AQI in 2018, our simulation shows that averting behaviors only attribute to a 0.02% reduction in our population-based exposure measure, which could lead to approximately 247 MWh more residential electricity consumption in Shanghai. The novelty in our findings emphasizes the need to analyze complementary outcomes for policy designs to enhance public health benefits while minimizing the co-damages from behavioral responses.

The context and the temporal variability focus of our analyses suggest that our findings contribute to the environmental health discussions in developing countries, which have been experiencing high pollution due to economic growth. While abatement policies that directly control pollutant emissions are rolling out and a global monitoring network is expanding to facilitate awareness of the environmental risks, people living in less-developed regions often lack the accessible resources to make the defensive investment. However, reliable information is rare on personal activity patterns and temporal decisions of households in the developing world.[26] Even though staying indoors is usually the first "go-to" option to reduce environmental risk exposure, our analyses unveil nontrivial costs of taking action during the high-pollution hours, which potentially imply limited attention or lack of access to air quality information for the residents.

## RESULTS

### The "double-peaked" time pattern of averting behaviors

We investigate the hourly marginal responses in outdoor population counts and indoor electricity consumption induced by variations in ambient air quality. However, electricity consumption and air pollution could be endogenously correlated, leading to a dual causality problem in the regression analysis. To address this identification issue, we have utilized the high-frequency nature of our dataset, by regression of the individual household's hourly electricity consumption and the outdoor hourly observation of the air pollution level of the previous hour, while controlling the fixed effects in the most saturated manner. Details of our models and identification strategies can be found in the STAR Methods section (baseline regression model). The empirical results of our baseline model are presented in Figure 2, where we find the marginal averting responses to AQI variations are not uniform across the day. We find that the patterns of both outdoor (Figure 2A) and indoor (Figure 2B) responses resemble each other in demonstrating a "double-peaked" pattern —in the evening period (5–9 p.m.) and the late morning (9 a.m.–12 p.m.). As AQI increases by one standard deviation, outdoor populations in the evening decline by approximately 2%, with less reduction in the morning, and indoor electricity usage increases between 4% and 6% in the morning and evening (Table S3).

The negative values, which are largely insignificant, for some hours, imply that a portion of the averting behavior may reflect a shift in when activities occur rather than a change in the average daily level. As air quality deteriorates, people tend to spend more time indoors to reduce outdoor exposure. They may also rearrange activities which are usually conducted in other hours of the day to hours cut from outdoor activities. For example, residents might choose to do laundry at an earlier time of the day, thus leading to electricity consumption drops during the nighttime. Similarly, for outdoor activities, someone might

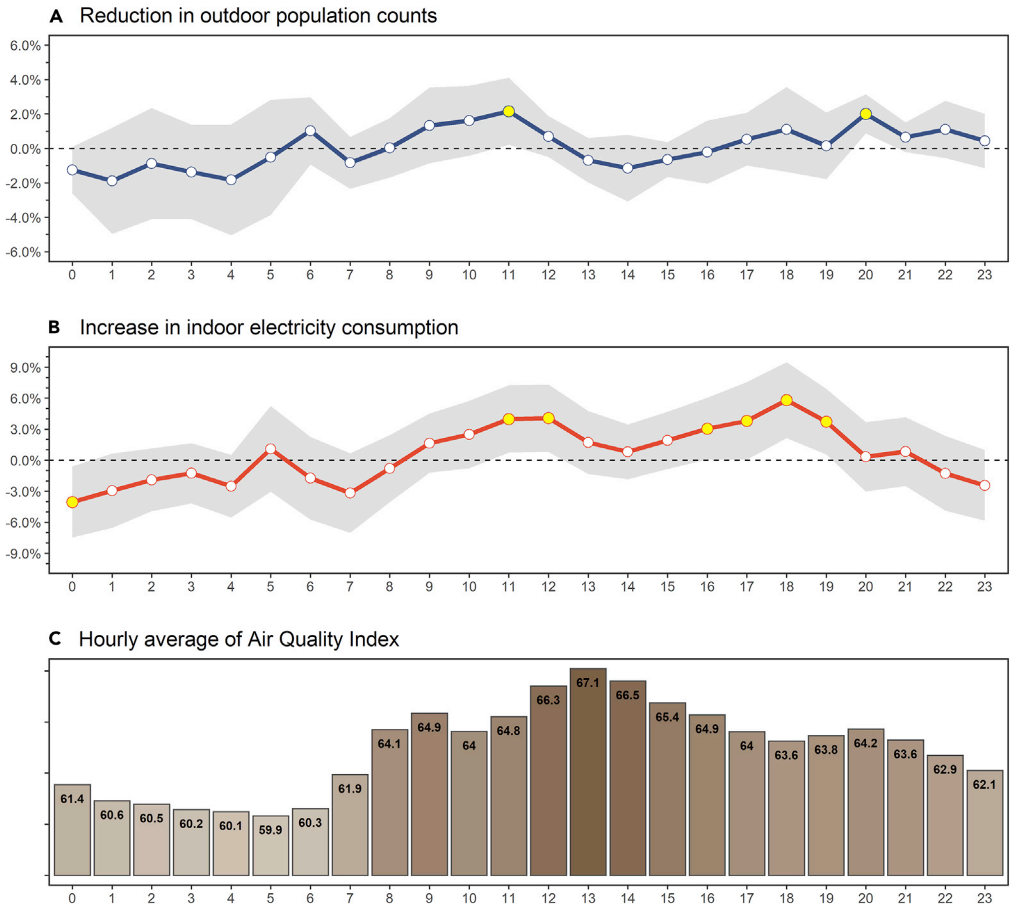


**Figure 2. Averting responses to one standard deviation increase in AQI and hourly average AQI levels**

(A–C) Notes: Panel (A) illustrates the estimated marginal response measured by percentage reduction in outdoor populations (negative numbers indicate increases) and (B) illustrates the estimated marginal response measured by percentage increase in indoor electricity consumption. The point estimates depict the percentage change in outdoor and indoor measures to a one standard deviation increase in AQI. The band around the lines indicates the 95% confidence interval of the point estimates. Panel (C) plots the hourly average AQI levels. The 5% significant estimates are highlighted by yellow color points in (A–B).

postpone a morning trip until the early afternoon, which leads to an increase in population counts, i.e., a negative reduction in the outdoor population.

Our finding of the time pattern in averting behaviors suggests that ignoring such temporal variation would lead to bias in the empirical estimation. We validate the existence of this bias by regressing the outcome variables (population and electricity consumption) on AQIs using their average values instead. Such an aggregated model with an equal averting effect across all hours leads to unchanged indoor electricity consumption and a mildly declined outdoor population by about 0.5% (Table S4). The latter is about 1/4 of the magnitude of the peak reduction in evening hours. This is an important finding as it shows that although previous studies using aggregated data without intra-day variations might be able to identify averting behaviors, those estimates are likely to be biased — significant underestimates in people's responses to environmental risks during those peak hours and overestimates in others.[25] A side benefit of our analysis comes from the use of the two complementary indoor and outdoor activity measures, which allows us to test the robustness of our time-pattern findings. We find highly symmetric results for outdoor and indoor averting behavior patterns, with both peaking during late morning and evening hours. This timing coincides with the existing windows when data show people are going outside, suggesting changes along with both extensive (going out or not) and intensive margins (duration) of outdoor activities. The complementary results verify the correlation between outdoor and indoor measurements of averting behaviors, i.e., the increase in residential electricity consumption is partly attributed to the movement of human activities from outdoors to indoors. We noticed that the ''peak'' hours are not fully synchronized between the outdoor and indoor responses, probably because only part of the population moving away from those outdoor areas went to residential houses. The rest might go to non-residential buildings, which are not captured in our data sample. Moreover, as our outdoor population counts only measure mobility in public open spaces, the electricity consumption increase may reflect stronger averting behavior than is detectable with our outdoor sample.

Our results carry an important message that the existence of averting behaviors does not grant their effectiveness in reducing environmental risk exposures. Comparing the temporal patterns in Figures 2A and 2B with the hourly AQI distribution in Figure 2C, we found a mismatch between averting behavior and air pollution that the double-peaked pattern seems to only align with the shoulder of the AQI pattern with limited elastic response to the midday peak. Since most people are staying outdoors during that time (see Figure S2), such results lead to more severe negative outcomes for residents' health. This mismatched result also implies that the exposure reduction benefits from averting behavior are quite limited, especially when compared with the co-damages from increased electricity consumption (not even including the deducted subjective well-being due to lost outdoor time).

## Time patterns on workdays versus non-workdays

Given the temporal pattern of averting behavior is mismatched to air quality, we speculate that people might be less willing to adjust behaviors during the early afternoon period when there are increased levels of pollution. This willingness can be directly associated with the opportunity costs of behavioral obligations. Naturally, these obligations are observed to differ between different types of days: activities tend to be more flexibly scheduled when they do not have to compete with work thus less constrained by the time pattern. We, therefore, test this hypothesis by comparing the heterogeneous averting behavior patterns on workdays versus non-workdays (i.e., weekends and public holidays). The results are summarized in Figure 3. Note that due to less production during non-workdays, there is an improvement in air quality in general, but still, the time-variant distribution of AQI, in general, reveals a similar pattern — midday peak with shoulder periods in the late morning and early evening hours (Figure S2).

We found that on workdays, both the magnitude and pattern of averting responses (indoor and outdoor) resemble a ''double-peaked'' shape (Table S3). However, there are significant changes in averting behaviors during non-workdays. Firstly, the behavior pattern has a more concentrated reduction of outdoor activities between early morning and noon compared to the evening ''peak''. This population reduction represents a larger, statistically significant response (3.3% at 10 a.m.) compared to estimates using the full sample (2.2% at 11 a.m.). The pattern of indoor averting behavior also shows a change in shape. But rather than one or two sharp peaks over 4–5 h, there is a relatively small but similar response during all daylight hours with a significant midday peak (5.3% at 1 p.m.). These results help to explain the mismatch issue discovered in the previous section; it could be caused by time-variant opportunity costs associated with altering outdoor activities to indoors. The divergent pattern on non-workdays implies the impact of lower opportunity costs on increasing behavior elasticity on those days. This leads to a better alignment between averting behavior and the AQI pattern on non-workdays: i.e., the disappearance of the evening peaking response and higher intensity of daytime peaks. On workdays, the opportunity costs of altering scheduled activities are higher than that on non-workdays, thus persisting the issue of the ''least response to high pollution'' mismatch.

## The unbalanced trade-off between exposure and energy consumption

As has been shown by our empirical analyses, there are two direct outcomes of the averting behaviors — reduced exposure and increased electricity consumption. The former transfers to health benefits while the latter generates co-damages. The mismatched temporal patterns between averting behaviors and intra-day pollution levels exacerbate the trade-off between the two, as most responses fail in averting peak pollution while still inducing energy usage by the households. To explore the magnitude of this unbalanced trade-off, we utilize our estimates to compute the changes in a population-based exposure measure and compare them with the changes in residential energy consumption of the city due to averting behaviors (see STAR Methods: Scenario simulations and Table S5). To investigate the amount of pollution exposure reduced by averting behaviors, we calculate the difference in our population-based exposure measures between that with behavioral responses and when assuming no responses.

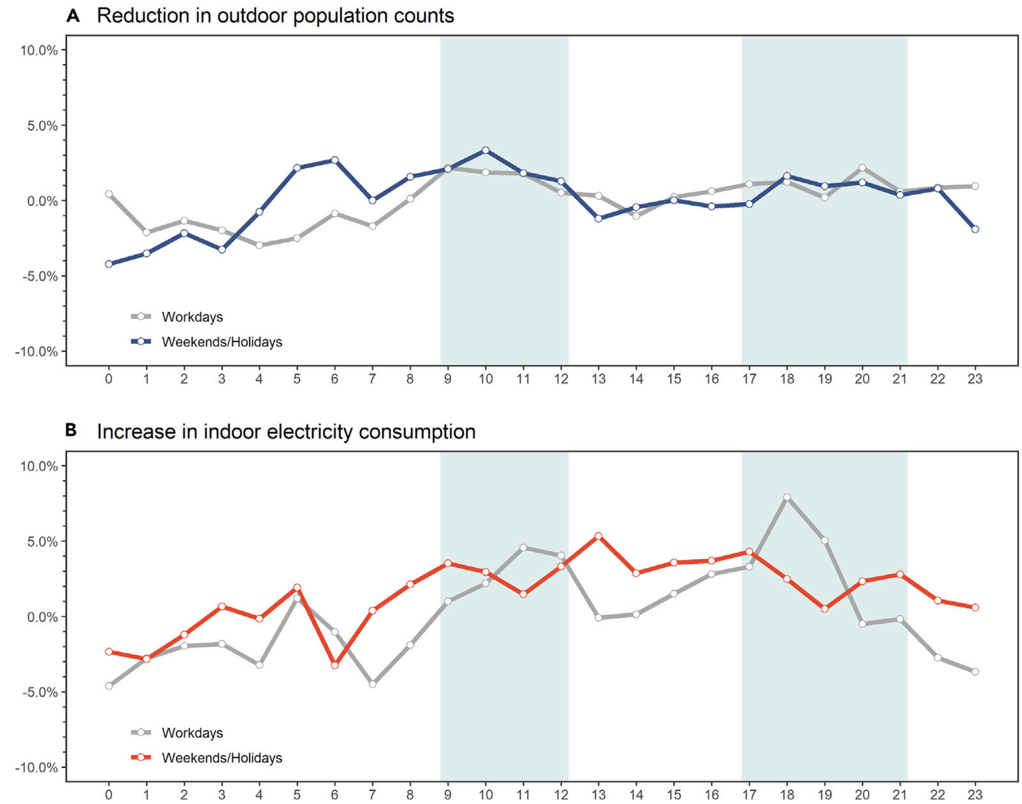


**Figure 3. Averting responses to one standard deviation increase in AQI on workdays versus non-workdays**

(A and B) Notes: The shadowed areas illustrate the double-peak response periods in our main results. The lines depict the point estimates of marginal responses between workdays and non-workdays: panel (A) is the percentage reduction in outdoor population counts, and panel (B) is the percentage increase in indoor electricity consumption. The outdoor responses are significant during 9–10 a.m. and 8 p.m. on workdays and 9–10 a.m. on non-workdays. The indoor responses still demonstrate the "double-peaked" pattern on workdays but have a significant midday peak at 1 p.m. on non-workdays.

Comparing the values in Table 1, the averting behavior-induced reduction in exposure is assessed to be much smaller than the associated increase in electricity consumption (from −0.05% to −0.01% in reduced exposure, from +1.20% to +0.95% in increased energy usage). Even though the overall air quality is improving as time proceeds and averting behaviors have been attributed to fewer changes in the two outcomes, the gap remains, that they are significantly disproportional. The increased residential electricity consumption due to averting behaviors is equivalent to about 250 MWh per year. Using the carbon intensity factor from Ember Climate (Data: https://ourworldindata.org/grapher/carbon-intensity-electricity), we then calculated the carbon emissions associated with these energy co-damages (fifth row in Table1) to be between 0.13 and 0.15 million metric tons per year. This is likely a lower bound of the co-damage estimate as electricity consumption in commercial buildings and other non-residential districts could also increase when people go indoors to avert air pollution, which is not included in our data sample. The carbon intensity of electricity in China illustrates a decreasing trend. If the carbon intensity factor continues a declining trend as China pushes forward with the carbon neutrality goal, the averting behavior-induced trade-off between less exposure reduction and more electricity consumption might become less of a concern due to shrinking effects on carbon emissions. However, health co-damages from ineffective averting behaviors would still be a concern, if other health co-damages from other non-carbon local pollutants are not decreasing significantly under carbon neutrality.

As the mismatched time pattern weakens the effectiveness of averting behaviors, policies that shave off-peak pollution could achieve the dual benefits of exposure reduction and energy conservation. We simulate two counterfactual scenarios to demonstrate how time-variant pollution reductions can affect exposure and electricity consumption (see STAR Methods: scenario simulations). The baseline scenario ("scenario 0" in Figure 4 versus "real AQI in 2017") is the observed reduction of average AQIs across

**Table 1. Simulated changes in exposure, energy consumption, and carbon emissions due to averting behaviors**

| | Using AQIs and citywide load data | | | |
|---|---|---|---|---|
| | in 2016 | in 2017 | in 2018 | in 2019 |
| Change in population-based exposure attributed to averting behaviors (percentage) | −0.05% | −0.04% | −0.02% | −0.01% |
| Change in residential electricity consumption attributed to averting behaviors (percentage) | +1.20% | +1.16% | +1.01% | +0.95% |
| Change in residential electricity consumption attributed to averting behaviors (megawatt-hours per year) | 260.8 | 264.4 | 246.6 | 232.5 |
| Carbon intensity of electricity (gCO2e per kWh) | 584 | 579 | 574 | 560 |
| Carbon emissions associated with increased electricity consumption (million metric tons of CO2e per year) | 0.152 | 0.153 | 0.142 | 0.130 |

different hours. Compared with the previous year, air quality across all hours was improved in 2018 with some hours experiencing a larger pollution reduction than others. The two hypothetical AQI improvement scenarios are illustrated in Figure 4 by comparing the "scenario 1/2" AQI level to that in 2017. Scenario 1 assumes a proportional improvement in the AQI in all hours, which, compared to scenario 0, represents a *worsening of* (higher) peak emissions. Scenario 2 assumes smoothing out the hourly emissions, which, compared to scenario 0, represents an *improvement in* (lower) peak emissions.

The two hypothetical scenarios represent two extreme cases — "scenario 1" is a parallel shift down of the intra-day AQI distribution in the previous year with no change in time pattern, and "scenario 2" is a complete smooth out of the hourly pattern. Compared with our baseline scenario, "scenario 1" is estimated to result in 7.99% less population-based exposure reduction and 42.10% less energy conservation as shown in Figure 4. That is, there is higher exposure and electricity use than the baseline scenario, leading to an unambiguously *worse* counterfactual than the actual AQI pattern in 2018. On the contrary, both outcomes are improved in "scenario 2" compared with the baseline — 12.67% more exposure reduction and 81.83% more conserved energy in terms of residential electricity consumption. That is, there is lower exposure and electricity use than in the baseline scenario; this is an unambiguously better counterfactual. The pollution peak-emphasized reductions in "scenario 2" can better align the time pattern of averting behaviors to that of the pollution level, leading to less electricity consumption and less averting behavior in those "inelastic" response periods — but also less exposure because the peak pollution hours are also the peak exposure hours with more people outside.

## DISCUSSION

This study explores the time pattern of averting behaviors and the impact of it on exacerbating the trade-off between exposure reduction and co-damages associated with energy usage. Our analytical model uses high-frequency datasets to proxy the changes in outdoor and indoor activities responding to variations in air pollution. This simplest form of averting behaviors in terms of shifting outdoor activities indoors, though quite common in practice, especially in the developing world context, is rarely measured directly, and their temporal variability is largely ignored in previous literature. The complementary patterns of the outdoor and indoor results in our study further verify the time-dependent characteristics of averting behaviors. Residents are not just reducing their appearance in outdoor public spaces, but are also increasing their appearance at home (via higher household electricity consumption).

Our research demonstrates the potential bias in the estimates of averting behaviors when using aggregated data with average values. We find that if modeling efforts disallow the intra-day time pattern in behaviors, the estimates would be flattened by averaging responses of each hour that the magnitude of behavioral responses to air pollution will be significantly underestimated. This is especially true during the late morning and evening periods in our sample when the time-relevant constraints are less binding and/or impose lower opportunity costs on changing outdoor times. We find that the time patterns of averting behaviors are likely to align better with the intra-day pollution levels, i.e., more elastic responses in higher pollution hours in the morning and early afternoon on non-workdays. We further explore if this

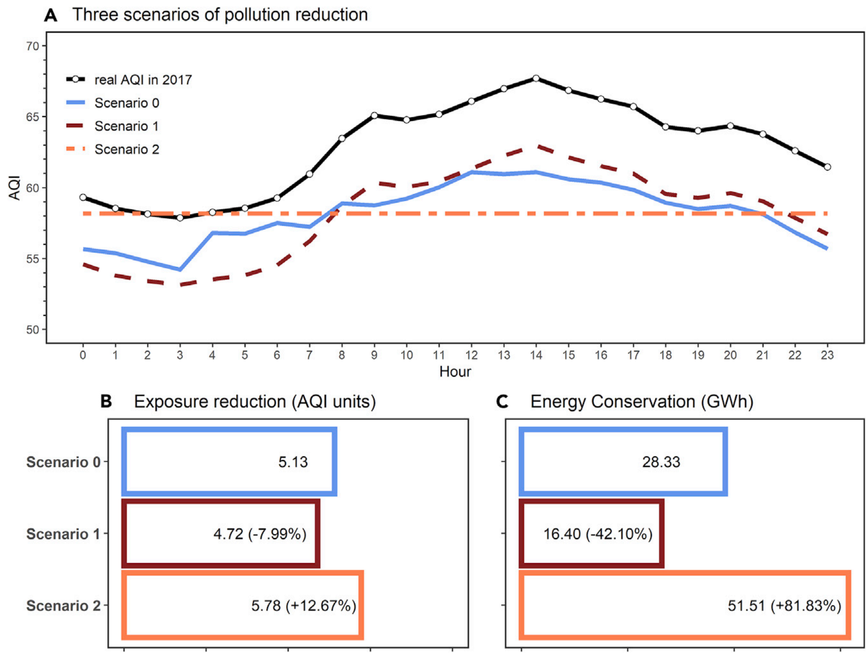


**Figure 4. Exposure reduction and energy conservation outcomes under three scenarios of time-variant pollution reduction**

(A) Notes: The black line with circle markers in (A) shows the hourly average AQI in 2017 for Shanghai. The baseline scenario is depicted by the observed AQI reductions resulting in the "scenario 0" intra-day AQI distribution in 2018 (blue solid line). The two hypothetical scenarios are depicted by the time-variant AQI reductions in "scenario 1" (brown dash line) and "scenario 2" (coral dash-dotted line) as compared with "real AQI in 2017" (black circle line). We controlled the 2018 post-abatement averages of the 24-h AQI values depicted in scenario 0, 1, and 2 to be the same. Simulated exposure reductions are illustrated in (B). Energy conservation estimates are presented in (C). The values in the colored bars correspond to the simulated estimates in each scenario. The values in the parentheses in (B and C) are percentage changes compared to scneario 0.

time pattern can also be linked with the cross-sectional attributes of our sample by carrying out some heterogeneity analyses (see STAR Methods: heterogeneity analyses). The regression models for the heterogeneity analyses are described in the STAR Methods section. The indoor responses however do not demonstrate significant heterogeneity across household attributes (Figure S3). Constrained by the size and scale of the sample (i.e., electricity meters all located in an urban district), the lack of significance cannot rule out the possibility of existing cross-household differences in averting patterns. The external validity of our analytical results should be treated with caution, as the studied sample is located in an urban area with high population density and higher income compared to other regions in the nation (see Table S2). Magnitudes of the time-variant averting behaviors are likely to vary for a population with different geo-demographic features, even though the time pattern results would hold qualitatively.

The critical finding of the mismatched time pattern reveals the problem of ineffective averting behaviors nevertheless leveling up co-damages in the energy sector. Averting responses are least elastic during peak pollution hours when the outdoor population is the densest and when most residential households are not consuming the most electricity. This research demonstrates that this would disproportionately diminish the exposure reduction benefits for the population as compared with the additional power consumption induced by averting behaviors. The results of our paper hence provide critical insights into improving the design of environmental health policies and pollution control policies. On the one hand, public health policies that aim at reducing exposure to environmental risk should consider this internal bias imposed by time-dependent human behaviors and should incorporate designs to lessen such bias. For example, alerts need to be more salient in warning the outdoor population about midday peak pollution. Given that the time-dependent averting behaviors are subject to constraints from other activities, day-ahead forecasts on peak pollution occurrence would relax these constraints as people can schedule outdoor activities around these hours. On the other hand, policymakers need to consider the trade-off between exposure reduction and energy co-damages and how such dynamics shift when abatement policies or clean technologies drastically curtail peak-hour pollutants. The hypothetical scenarios in our analyses demonstrate the two extreme ends of policy outcomes — minimal exposure reduction and energy conservation versus dual improvements in both. In practice, episodic or seasonal pollution controls are not novel,[27–30] as the temporal feature of pollution concentrations is usually associated with different emission inventories or economic activities. On an intra-day level, policies such as critical events or peak pricing for energy-intensive industries have also been implemented, though usually with the cost-saving objective of power grid operations. Of course, designing policies to integrate these co-benefits require the regulators to make the trade-off between these welfare gains with both the complexity of higher frequency regulation and potentially higher pollution abatement costs. Our finding implies potential public health co-benefits associated with such policies. The current literature has insufficient discussions on policy impacts attributed to alternative designs along the time dimension. Though this study is quite explorational in this research field, the presented results highlight the need for further investigating the human behavior feedback on environmental risks and the resulting uncertainties in policy decisions.

### Limitations of the study

There are several limitations to our study that could inspire future research. First, this study focuses on short-term averting behaviors in an urban area with high population density and higher income compared to other regions in the nation. There might be disparities in the quantitative findings between our sample and rural areas and disadvantaged communities, which likely have liquidity constraints in both the short and long terms. Second, our mobility data cannot track the destinations or measure the risk of exposure in various destinations. People might be moving from open spaces to non-residential locations with better or worse pollution control devices. Complementary data sources (e.g. transit choices and patterns) are needed to fill in this research gap. Lastly, the datasets analyzed in this study do not have dynamic policy variables (e.g. pollution alerts) that can affect intra-day averting behaviors. Future research should evaluate the dynamic policy effect on reducing the trade-off imbalance between health benefits and energy co-damages.

## STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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  - Materials availability
  - Data and code availability
- METHOD DETAILS
  - Baseline regression model
  - Heterogeneity analyses
  - Scenario simulations
- QUANTIFICATION AND STATISTICAL ANALYSIS

## SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2022.105597.

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## AUTHOR CONTRIBUTIONS

L.W. conceptualized this research. Q.L. and Y.Z. are leading co-authors and contributed equally. Q.L. and Y.Z. designed the research methods, collected, processed, and analyzed the data, performed the research, and wrote and revised the paper. Q.L., Y.Z., W.P., and L.W. made revisions to the paper. All the authors conceived the paper and designed the research.

## DECLARATION OF INTERESTS

The authors declare no competing interests.

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## STAR★METHODS

### KEY RESOURCES TABLE

| REAGENT or RESOURCE | SOURCE | IDENTIFIER |
|---|---|---|
| Deposited data | | |
| Weather data | National meteorological information center | http://data.cma.cn/ |
| Air pollution data | China's Ministry of Environmental Protection website | http://www.mee.gov.cn/ |
| Residential electricity consumption data | State Grid Corporation of China | Data is under a confidential agreement with the provider. |
| Outdoor mobile tracking data | China Telecom | Data is under a confidential agreement with the provider. |
| Software and algorithms | | |
| R software | Bell Laboratories | https://www.r-project.org/; RRID:SCR_001905 |

## RESOURCE AVAILABILITY

### Lead contact

Further information and requests for data and code files should be directed to and will be fulfilled by the lead contact, Libo Wu (wulibo@fudan.edu.cn).

### Materials availability

This study did not generate new unique materials.

### Data and code availability

Data: Residential electricity consumption

The State Grid Corporation of China (SGCC) has installed smart meters for all the 1.8 million residential households in Pudong District, Shanghai. Among these, a randomly picked sub-sample with about 60,000 meters records electricity consumption every 15 minutes from 0:00 AM to 11:45 PM, thus named 96-Point record (i.e. 96 readings per day). The electricity consumption data is stored in a data center established by SGCC in Shanghai and is only available for research purposes under confidential agreements. A random sample of 769 households is picked in this paper from the 96-Point dataset with two years of kWh readings from 3/18/2016 to 3/31/2018. All the 96-Point households are enrolled in a Time-of-Use retail tariff design with the same peak hours (6 AM to 9 PM) across the year, and the peak kWh charge is approximate twice the off-peak charge.

In our analysis, we aggregated the 15-minute meter readings into the hourly kWh consumption of each household to avoid potential sensitivity gaps in the performance of smart meters. This is because sometimes the meter is not sensitive enough to record a tiny level of energy consumption within this 15-minute interval, showing a zero-reading record, even though the household is consuming electricity. Moreover, when this occurs, the readings will be automatically accumulated and added to the next interval. We then proceed to drop certain outlier observations, where an observation is defined as a "household day" or a "24-hour load profile". We dropped the households which had an average daily consumption below 0.3 kWh or above 30 kWh. This is because we want to exclude observations that are likely to be vacant houses or have been repurposed to abnormal activities of the residents (e.g. running a home-based private business). The lower threshold is computed according to the labeled power capacity of an average energy-efficient one-door refrigerator which consumes approximately 0.3 kWh per day. The upper threshold is around the 98% quantile of the data. The data set after cleaning has 588 households.

Data: Outdoor activity

Since residents' outdoor activities cannot be directly observed, we construct the total number of outdoor people as a proxy by using the mobile location data from residents' smartphones and other mobile operators. Smartphones will connect with the base station when asking for an internet connection including social contact app, website, messages, and phone calls since all network connection is provided by the base station of the operator. Thus, the base stations can locate smartphones from each information connection, by which the number of smartphones in a specific location can be counted. However, the location information collected from the base station cannot cover too small areas such as community areas, or small squares due to the large covering area. Therefore, we picked 30 over-scale public areas in Shanghai as our statistical samples (parks, stadiums, public squares). These public areas in our dataset cover parks, public plazas, and outdoor stadiums which are open-air with locations near the city center as well as suburban areas in Shanghai. Since 2 of these 30 areas cannot be divided, 28 areas are left in our final sample. By collaborating with one of the three licensed network operators in China, China Telecom, the hourly count of the outdoor population in these 28 public squares in Shanghai is obtained from 6/1/2018 to 3/1/2019. Unfortunately, historical records before June 2018 have been removed from the server of the company due to the limitation on storage.

Data: Ambient air quality

The air pollution data was posted hourly by China's Ministry of Environmental Protection website (Data: http://www.mee.gov.cn/). In our analysis, the hourly Air Quality Index (AQI) is used as the pollution measurement, since this value is the primary reference posted to or checked by local inhabitants. AQI is calculated based on the primary pollutant of the hour. There are six color-coded AQI categories to provide information on levels of health concerns: Good (AQI = 0 to 50), Moderate (AQI = 51 to 100), Unhealthy for Sensitive Groups (AQI = 101 to 150), Unhealthy (AQI = 151 to 200), Very Unhealthy (AQI = 201 to 300), Hazardous (AQI = 301 to 500). For the indoor averting behavior analysis, we use the air quality data from three monitoring stations in Pudong. Household meters are matched with the AQI information from the nearest station within a 15km radius and with the average AQI from the three stations if outside this radius. For the outdoor averting behavior analysis, as locations of the public areas are more dispersed across different districts in Shanghai, the activity data is matched to the nearest air quality monitoring station in terms of geographical distance.

Data: Meteorological information

Weather data are collected from the National Meteorological Information Center of China (Data: http://data.cma.cn/). For each district in Shanghai, the weather variables are reported by the primary weather monitoring station in that district. Since all household electricity meters are located in Pudong, they were matched with the weather record series collected by the Pudong District Station. Therefore, when matched with the activity data set, there are cross-id variations in weather variable values in the outdoor analysis, while only cross-time variations in the indoor analysis. We, therefore, dropped the weather covariates in the indoor regression model and control these with the date-hour fix effect. Weather variables include hourly mean temperature, rain, humidity, wind speed, and wind direction. In Supplementary Figure S5, we compare the prediction power of instrumental variables versus the previous hour's AQI. The two instrumental variables – wind direction and thermal inversion – were downloaded from the Integrated Surface Database and the Integrated Global Radiosonde Archive of the National Oceanic and Atmospheric Administration (IGRA: https://www.ncei.noaa.gov/products/weather-balloon/integrated-global-radiosonde-archive).

Code

This paper does not report original codes.

Additional Information

Any additional information required to reanalyze the data reported in this section is available upon request to the lead contact, or Qingran Li (qli@clarkson.edu) and Yang Zhou (yangzhou@fudan.edu.cn).

## METHOD DETAILS

### Baseline regression model

To investigate the average effect of behavioral responses to air pollution, we estimate Equation 1 using a fixed effect panel regression approach:

$$\log(y_{idh}) = \sum_t \left[\alpha_t * 1(h = t) * AQI_{id(h-1)}\right] + \beta W_{idh} + \eta_{id} + \gamma_{ih} + \varphi_{dh} + \varepsilon_{idh} \qquad \text{(Equation 1)}$$

where outcome variable $y_{idh}$ for the outdoor sample is the size of the population at location $i$ in hour $h$ on day $d$ and for the indoor sample is the kilowatt-hours of electricity consumed by households $i$ in hour $h$ on day $d$.

We use $AQI_{id(h-1)}$ to control for endogeneity between air quality and our indoor and outdoor behavior measures, which is the lagged (one-hour) observed air quality index. Air pollution is highly correlated with energy consumption since coal-fired power plants are still the major method of power generation in China. Therefore, there exists an endogenous relationship between air quality and indoor electricity consumption — bad air quality causes people to increase electricity consumption via shifting outdoor activities indoors and using air purifiers, and higher electricity consumption contributes to higher emissions and thus polluted air. There might be an endogeneity issue with the outdoor sample as well — more outdoor activities thus less indoor energy use could reversely lead to lower pollution. We tested an instrumental variables (IV) approach to address the endogeneity bias. Our initial choice of IVs – indicators of wind directions and thermal inversion – had weak power in predicting real-time air quality, especially at higher pollution levels. Hence, instead of using the IV approach, we show in Figure S5 that using the first-lag AQI in OLS regression is a preferred approach to avoid reverse causality with high-frequency data.

Weather variables in the model include bins of hourly mean temperature, humidity, humidity squared, and rain. For the outdoor sample, as weather variables in $W_{idh}$ are collected from a range of stations, adding $W_{idh}$ controls the exogenous variations which are not included in the fixed effects. For the indoor sample, as households are more concentrated in a location with a single weather station nearby, the weather variables $W_{dh}$ do not have cross-section variations and are thus controlled by the day-hour fixed effects ($\varphi_{dh}$).

Unbiased identification of the magnitude of such behavioral responses needs to control for three types of unobservables that may correlate with air quality:

- **unit-hour-specific unobservables** that affect a unit's "innate" behavior, such as the routine use of home appliances, and scheduled outdoor events in public parks.
- **unit-day-specific unobservables**, such as changes in baseload electricity consumption due to changing income, adding new appliances, energy efficiency investment, etc., or changes in population counts due to road and infrastructure constructions nearby.
- **day-and-hour-specific common trends** in electricity consumption and outdoor population counts.

We compared five models with different fixed effects estimators applied to the high-frequency panel data. The time pattern estimation results are illustrated in Table S9. We found that the fixed effects selection can significantly affect the robustness of the estimators. As our data sample has a high-frequency nature, it is unlikely that marginal responses are homogeneous across units, days, and hours. Both electricity consumption, as well as outdoor population counts, may have temporal patterns and correlations between the periods (see Figure S4 and Table S9). To control for unobserved idiosyncratic factors, we applied fixed effects with two dimensions in the baseline model. These fixed effects allow this model to achieve consistent estimators with control on the variation of unit-hour intercepts ($\gamma_{ih}$), day-hour trend ($\varphi_{dh}$) and more importantly, the unit-specific daily trend ($\eta_{id}$), which is most likely to be omitted if splitting the sample by hour. Our model follows the recent practical guide[25] for high-frequency panel data analyses to avoid inconsistency in fixed effects estimators.

### Heterogeneity analyses

For the heterogeneity analyses, we focused on varying behaviors across specific days (workday/non-workday), public space, and household characteristics. For the analysis between workdays and non-workdays, we repeat the model in Equation 1 but simply estimate it on sub-groups based on day attributes.

However, to show the cross-sectional difference in averting behavior, we further extended the original model:

$$\log(y_{idh}) = \sum_{t}\left[1(h = t)AQI_{id(h-1)} * (\alpha_t + \theta_t D\_Attri_i)\right] + \beta W_{idh} + \eta_{id} + \gamma_{ih} + \varphi_{dh} + \varepsilon_{idh} \quad \text{(Equation 2)}$$

where all other variables have the same meaning as Equation 1, and $D\_Attri_i$ is the Dummy variable of a specific attribute of an individual or outdoor area $i$. For example, when we studied the outdoor heterogeneous response between free and ticketed public spaces, $D\_Attri_i$ is 1 for public areas requiring tickets and 0 for freely accessible public areas. Therefore, Equation 2 provides results on the response difference in terms of the marginal effect of individual attributes, relative to those without the attribute, as shown in Figure S3 and Tables S6–S8.

## Scenario simulations

### *Part A: Estimation of population-based exposure*

To reveal the unbalanced tradeoff between exposure reduction and co-damages from energy consumption, we built an index as "population-based AQI" which is the average AQI weighted by hourly outdoor population. Since the current observation of the outdoor population already covered the effect of averting behavior, we calibrated the population data based on the regression parameters in Table S3 and estimated the original population with no averting behavior. After that, we were able to estimate the outdoor population as well as the population-based exposure indexes according to the hourly AQI data each year.

First, the basic description of the population-based exposure index can be written as,

$$Exposure = \frac{\sum_{t=1}^{8760}\left(\widehat{p}_t \times A_t\right)}{\sum_{t=1}^{8760}\widehat{p}_t}$$

where $\widehat{p}_t$ and $A_t$ are the average hourly population and the AQI of all areas in our sample on hour $t$. Based on whether there is averting behavior, we recalculated and calibrated the key variable $\widehat{p}_t$ and estimated the true reduction of exposure to averting behavior. This index could clearly show the true air pollution exposure with consideration of outdoor activity. Therefore, the comparison of "population-based exposure" reduction with and without averting behaviors each year can be used to evaluate the health/exposure effect of averting behavior.

Based on the regression model in Equation 1, we can further estimate the counterfactual outcomes by

$$\log(\widehat{y}_{dh}) = \log(y_{dh}) + \sum_{t}[\alpha_t * 1(h = t) * (\widehat{AQI}_{dh} - AQI_{dh})] + \beta(\widehat{W}_{idh} - W_{idh})$$

where the $\widehat{y}_{dh}$, $\widehat{AQI}_{dh}$, and $\widehat{W}_{idh}$ are the outdoor population or energy, AQI, and weather conditions during the target year, such as the years 2016,2017, 2018, and 2019. For the scenario with averting behaviors, we would calibrate $\widehat{p}_t$ considering the difference between the AQI during our sample period and the target year, to reveal the true population level. For the counterfactual scenario without averting behaviors, we "added" back the outdoor population change, where the $\widehat{AQI}_{dh}$ is set as 0, and then used the calibrated $\widehat{p}_t$ as the weights of the index. For indoor energy consumption, we followed the same process but didn't weigh it with the population. By comparing the energy consumption with and without behavior, we could estimate the co-damages of air pollution from increasing energy consumption.

### *Part B: Outcomes simulated under the counterfactual policy scenarios*

To clearly show how the resident's response contributes to policymaking, we further simulated several policy scenarios with environmental policy based on our results. The scenarios are set in Shanghai from 2017 to 2018. Following the same process, in Part A, we first calibrated the outdoor activity (amount of people) and household energy consumption by using the coefficient in Table S3 in terms of the difference in air quality. Scenario 0 is the comparison between observed AQI in the years 2017 and 2018, which is also set as the baseline policy effect in Table S5. In scenario 1, we estimated the related measurements (welfare-related outcomes) with uniform and proportional AQI reduction in each hour, but equal to the average reduction level in scenario 0. In contrast, scenario 2 will focus only on the peak hours in terms of air pollution and will flat the AQI pattern, with the same amount of aggregated AQI reduction compared to the baseline.

## QUANTIFICATION AND STATISTICAL ANALYSIS

Statistical significance was calculated in R with an unpaired two-sided t-test if not stated differently. p-values are reported in the figures with a p-value $<0.10$ considered significant. All data were visualized using R with the packages ggplot2 and other built-in functions.