Health perception and commuting choice: a survey experiment measuring behavioral trade-offs between physical activity benefits and pollution exposure risks

Yichun Fan1,2, Juan Palacios1,2, Mariana Arcaya, Rachel Luo and Siqi Zheng1,2,*

1 Department of Urban Studies and Planning, Massachusetts Institute of Technology, Cambridge, MA, United States of America
2 Sustainable Urbanization Lab, and Center for Real Estate, Massachusetts Institute of Technology, Cambridge, MA, United States of America
* Author to whom any correspondence should be addressed.

Keywords: air pollution, physical activity, health, China

Supplementary material for this article is available online

Abstract

Previous literature suggests that active commuting has substantial health benefits. Yet, in polluted regions, it can also cause additional health risks by increasing riders’ pollution exposure and raising their inhalation rate. We examine the effect of perceived air pollution on stated commuting choices using an on-site survey experiment for 2285 non-automobile commuters in Zhengzhou, a heavily polluted city in central China. We integrate a sequential randomized controlled trial in a survey where individuals in the treatment group received tailored information on their commuting-related pollution exposure, based on our 2 week peak-hour pollution monitoring campaign across transportation modes in the city. We find that travelers in Zhengzhou have already adopted pollution prevention actions by favoring indoor commuting modes on polluted days. Individuals receiving personalized pollution exposure information by mode further decrease active commuting by 8.4 percentage points (95% CI: 5.1, 11.6), accompanied by a 14.7 percentage points (95% CI: 10.7, 18.3) increase in automobile commuting. Travellers make sub-optimal, overly risk averse choices by reducing active commuting even for trips where epidemiological research suggests the exercise benefits outweigh pollution exposure risks. This pollution avoidance tendency significantly attenuates the effect of policies encouraging active commuting. Our findings show the intricately intertwined relationships between the public health targets of promoting active lifestyles and reducing pollution exposure, and between individual pollution avoidance and societal pollution mitigation.

1. Introduction

Globally, 81% of the adolescent population and 23% of adults are insufficiently physically active (WHO 2018). Insufficient physical activity is among the 15 leading risk factors of the overall disease burden globally measured by attributable disability-adjusted life year (Murray et al 2020).

Inactive individuals have a higher risk to develop cardiovascular diseases (Blond et al 2016, Lear et al 2017, Cheng et al 2018), obesity (Di Pietro et al 2004, Gordon-Larsen et al 2009, Hankinson et al 2010), type 2 diabetes mellitus (Berentzen et al 2007, Katzmarzyk et al 2007, Demakakos et al 2010), cognitive impairment (Abbott et al 2004, Larson et al 2006) and mental health diseases like depression (Dunn et al 2001). Regular aerobic exercise is recommended to combat the epidemic of physical inactivity (Donnelly et al 2009, Quist et al 2018). Commuting offers an ideal setting to promote an active lifestyle since it substantially increases physical activity level (Donaire-Gonzalez et al 2015) and facilitate habit formation by integrating exercises into the daily routine (Götschi et al 2016). Both observational studies (Flint et al 2014, Flint and Cummins 2016) and randomized controlled trials (RCTs) (Møller et al 2011, Quist et al 2018) have demonstrated the effectiveness of active commuting (i.e. walking and biking) on promoting desirable health outcomes (de Nazelle et al 2011).
Nonetheless, in fast urbanizing countries like China, air pollution exposure creates substantial burdens to human health and well-being. People in some highly polluted regions lose over 5 years of life expectancy (Pope and Dockery 2013), perform more poorly at work (Dockery et al 1993, Chen et al 2013, Ebenstein et al 2017), and display lower happiness levels (Zheng et al 2019). Commuting is one of the daily activities where exposure to air pollution is the greatest, and the choice of commuting mode can be critical for the total intake of air pollutants by citizens over a lifetime. The concentration of air pollutants differs greatly across commuting modes (Cepeda et al 2017), which is magnified by the differences in inhalation and lung deposition due to different physical activity levels (Quist et al 2018). The awareness of differential exposure to air pollution by commute mode can thus facilitate mode switching as an avoidance channel. However, unlike other avoidance behaviors documented by previous studies, such as wearing face masks, installing air purifiers in their homes or reducing time spent outdoors (Sun et al 2017, Keiser et al 2018, Ito and Zhang 2020), transportation mode switching can generate negative social impacts to local communities if dirtier modes like motor vehicles are favored for the protection they provide against pollution exposure.

Public health literature has brought together the two public health crises to explore the health implications of exercising under air pollution. Exercise benefit rises steeply as activity time increases from zero, yet levels off quickly after eight metabolic equivalents (METs) hours per week (Kelly et al 2014). In contrast, the dose-response function of PM$_{2.5}$ is largely linear or convex as pollution increases (Burnett et al 2014). Recent studies develop optimal cycling times under different levels of air pollution considering the health trade-offs (Giles and Koehle 2014, Andersen et al 2015, Doorley et al 2015, Mueller et al 2015, Tainio et al 2016, Tao et al 2019). A natural question to ask is whether individual commuting behaviors adapt to air pollution in ways consistent with the theoretical trade-off curves? Examining actual behaviors is crucial for policy makers to decide the future direction of public information campaigns and to design balanced health and transport policies.

Although some studies show that people are less likely to bike (Zhao et al 2018) and more likely to choose motorized modes (Li and Kamargianni 2017) when ambient pollution level is high, no behavioral research has investigated how mode choice behavior under air pollution reflects this personal trade-off between perceived exercise benefit and pollution exposure risk. In addition, pure observational correlations between pollution and mode choice reflect a mixture of safety concerns (e.g. low visibility), restriction concerns (e.g. driving restriction is stronger on heavily polluted days), social responsibility concerns (e.g. avoiding driving for its contribution to pollution) and health concerns. Without an experimental approach to separate the health concerns from the non-health confounders, we cannot draw causal inferences on which factors induce transportation mode switch.

In this study, we report evidence from a large-scale experiment in which we experimentally shift the pollution exposure beliefs on a random set of participants (treatment group). We explore to what extent the information treatment affects participants’ stated commuting behavior to capture the causal effect of health perception on commuting behaviors. We examine three primary research questions: first, to what extent do health concerns about pollution exposure affect commuting mode choices? Second, how well do respondents trade off the health benefits of exercise against pollution exposure risks when compared with scientific evidence? Third, what are the corresponding implications for public health and sustainable transport policies which encouraging active commuting? This paper adds to the previous empirical studies by modelling how active commuting responds to air pollution; how such responses differ for people with different commuting distance considering the counteracting health forces; and sheds light on the negative impacts heavy air pollution would impose on public health and environment by reducing physical activity and increasing automobile dependency.

2. Methodology

2.1. Study context and intervention preparation

The study took place in Zhengzhou, a city of ten million inhabitants that is the capital of Henan province, China. The seasonal variation of air pollution is high, with winter heating leading to a monthly average PM$_{2.5}$ level above 100 µg m$^{-3}$ (figure 1(a)). Zhengzhou local government has made extensive efforts to combat air pollution, with a strong emphasis on active travel. Besides the dockless bike-sharing systems run by private companies, the local government sponsors a dock-based public bike system, offers free bike services to encourage active commuting and solve the last mile problems of public transit. Zhengzhou also has strict license plate-based driving restrictions alongside efforts to expand bus and subway networks. The severe air pollution accompanied by the extensive investment in public policies and infrastructure to promote green traveling makes Zhengzhou an ideal study setting for our research questions.

Our survey was conducted in July, 2019. Our sampling frame is non-automobile commuters, whose job location is around Zhengzhou’s new Central Business District (CBD) area. We visited 95 local companies covering 18 sectors around the CBD area (figure 1(b)). The surveys are administered online on Qualtrics platform while the information
Figure 1. Study context and sample composition. (a) 2019 daily average PM$_{2.5}$ pollution in Zhengzhou. The light red line shows the fluctuation in daily average PM$_{2.5}$ concentration while the dark red line displays the smoothed time series through locally estimated scatterplot smoothing (LOESS) algorithm. (b) Job locations of survey participants. The participants are recruited through visiting companies around the CBD area. (c) Commuting modes composition of survey participants. (d) Home-job walking distance distribution of survey participants. *68% of the participants own a car at home, though they are not currently using it for commuting, which preserves the possibility for them to switch to automobiles.

Interventions were presented to participants face-to-face by our surveyors; both were done using iPad (see supplementary note 3 (available online at stacks.iop.org/ERL/16/054026/mmedia) for the inclusion criteria of our sample; see supplementary note 4 for survey implementation details). Our final sample contained 2285 non-automobile commuters, of whom approximately 20% typically commute using active modes (i.e. biking or walking$^{1,2}$) (figure 1(c)). The average home-job walking distance is 7.92 km (figure 1(d)).

Air pollution exposure varies significantly across transportation modes (Cepeda et al 2017) and is very context-specific (Zhao et al 2018). To understand micro-level pollution exposure during local commuting, our research team rented four professional air pollution monitoring devices from Fairsense (www.fairsense.cn/) and conducted two-weeks’ on-site monitoring (see supplementary note 1 for more information). We prepared the information interventions by transportation modes based on pollution concentration from monitoring results, inhalation rate across modes from literature (Cepeda et al 2017), personal commuting time and distance querying from Amap$^3$, and a pollution-cigarette equivalent index from epidemiological findings (US Department of Health and Human Services 2014, Rohde and Muller 2015). Details about the indices used for intervention can be found in supplementary note 2.

2.2. Experimental design
Figure 2 displays the survey structure and group decompositions. All respondents were asked to state their commuting preferences four times. Among the four rounds of choices, the first two rounds depicted before the dashed line are under the pollution level of the survey day (clean day scenario; with average daily PM$_{2.5}$ less than 40 µg m$^{-3}$). In Round 1, respondents

---

$^1$ The biking mode choice here includes both public and private bikes. We bundled these two schemes as one mode choice option in our survey, which limits our capacity to test their differences.

$^2$ Electric bike users, which is similar to motorcycle users, are not counted as active commuters as that does not require heavy physical exertion.

$^3$ A web mapping service provided by Alibaba. https://m.amap.com/.
Figure 2. Survey flow and group decompositions. Treatment Group 1 and Control Group are used to construct the treatment effect of pollution exposure information on commuting choice. Treatment Group 2 and Control Group are used to estimate the treatment effect of the exercise nudge (i.e. for the policy implication section). O1 and O2 refer to basic travel information by modes and information unrelated to pollution or exercise, respectively. Details about the information interventions and survey structure are summarized in table S3. The treatment platform is displayed in figure S3.

were asked to report their real commuting mode in the past month. Next, all respondents were presented with personalized travel information regarding the time and cost of traveling by different commuting modes. Therefore, in Round 2, we can measure the commuting choice after counteracting the information asymmetry respondents face in their knowledge of the accessibility of alternative modes. For the next two rounds, respondents were put under a hypothetical polluted scenario the same as the average PM\(_{2.5}\) level of most polluted months in Zhengzhou in 2018 (117 \(\mu g m^{-3}\)). In each round, participants provided their preferred primary mode of commuting, whether they were willing to change (WTC) to active commuting (i.e. biking or walking) given a ‘reasonable amount of subsidy’, and the minimum willingness to accept (WTA) value for the subsidy. Participants who already chose active commuting in the first question were not asked these follow-up questions.

Respondents were randomly assigned to treatment and control groups. Observed socio-demographic characteristics are balanced across groups, suggesting our randomization was successful (see tables S4 and S5 for descriptive statistics and balance tests). Comparisons between treatment and control groups at different rounds enable us to quantify the causal impacts of the information treatments, after controlling for survey round fixed effects. Our primary treatment of interest is the pollution exposure treatment (P) before Round 4, in which we informed people of their personalized levels of pollution exposure by different transportation modes in cigarette equivalent under our pollution scenario, based on an actual pollution monitoring exercise our engineering team conducted (see figure S3 for treatment interface). Thus Round 3 represents respondents’ baseline preference on a polluted day, based on their own prior knowledge of pollution exposure risk. Round 4 captures the treatment effect of the pollution exposure intervention. In addition, we added another treatment arm (i.e. Treatment Group 2), where we manipulated their beliefs regarding the exercise benefits of commuting before Round 2. Individuals in this group received exercise benefits of active commuting in the format of tailored calorie consumption and expected weight loss if doing active commuting for a month.

2.3. Statistical analysis
Within-group comparisons of the mode choice before and after the treatment is limited by the fact that people might respond differently when answering another round of similar questions. We estimate the average treatment effects of the two information interventions on mode choice comparing between treatment and control groups using the following regression model:

\[ Y_{i,t} = \alpha Y_{i,0} + \beta T_i + X_i\gamma + \epsilon_i, \quad (1) \]
where $Y_{i,t}$ is a dummy variable indicating whether individual $i$ chose an active commuting modes in round $t$. $Y_{i,0}$ describes the commuting mode they were regularly taking prior to the experiment (i.e. choice in Round 1). $\beta_i$ measures the average treatment effect in round $t$, which can be interpreted as the additional percentage point change of people choosing active commuting modes over other modes. Ordinary least square is used to estimate the coefficients, and robust standard errors are used for inference. When we estimate the treatment effect on the WTC and WTA for the active commuting subsidy, we utilize the same empirical model but change the outcome variable $Y_{i,t}$. When estimating the effect of pollution exposure information, we compare Treatment Group 1 and Control Group in their choice and set round $t = 4$. When we estimate the treatment effect of exercise nudge treatment (H), we apply a similar regression by comparing Treatment Group 2, who received the exercise nudge, and the Control Group. To further understand whether individuals are making the optimal choice, we queried the biking time given an individual's home and job location, stratified our sample into six groups according to the biking time sextiles and model the treatment effect of pollution exposure information for each subgroup.

3. Results

3.1. Air pollution and commuting choice

Figure 3 depicts individual commuting mode choices under different scenarios for Treatment Group 1 (which received pollution exposure treatment). Compared polluted days (gray bars) with clean days (blue bars), respondents display higher preference for indoor commuting options (i.e. public transit or automobile) and decreased preference for outdoor modes (i.e. bike, walk or electric bike)—suggesting that our participants were aware that changing transportation modes can be a form of self-protection. After we presented to them their personal pollution exposure information (red bars), we see a further reduction in respondents choosing active commuting and a large increase in automobile use. The effects of information reveal a gap between people’s perceived pollution exposure risk and the reality.

We then estimate the treatment effect of pollution exposure information (P) on commuting choices by comparing the responses of participants who received the exposure information (Treatment Group 1) with those that did not receive it (Control Group) using the econometric model described in equation (1). The results show that when fully aware of the pollution exposure risk described in equation (1). The results show that when fully aware of the pollution exposure risk across modes, the stated active commuters further decreased by 8.4 percentage points (95% CI: 5.1, 11.6) and the automobile commuters\(^4\) increases by 14.7 percentage points (95% CI: 10.7, 18.3) (full sample sub-panel of figure 4 and table S7). Using multinomial logistics regressions gives similar results (table S8).

The effect of pollution exposure information on commuting choice is relatively stable across subgroups specified by gender, age, and family income. The two essential moderators are education and family car ownership (figure 4). The degree to which pollution exposure information reduces active commuting is twice as large for respondents without college degree than those with at least a college degree. This could be explained by the fact that less-educated people usually have a more significant initial knowledge gap of pollution exposure differences by mode. Moreover, we find suggestive evidence that if people own a car at home, they are more likely to reduce active commuting and increase automobile commuting (others can choose taxi/TNC which have higher, more visible marginal cost). Overall, the broadly uniform structure of estimated treatment effects across groups suggests that the decreased active commute and increased automobile commute due to pollution health concerns are highly universal across individuals and should receive policy attention.

3.2. Rationality in health trade-offs

To further understand whether individual behavioral responses are consistent with the optimal trade-offs between physical activity benefit and pollution exposure risk, we compare the theoretical risk-benefit breakeven curve (figure 5(a); data obtained from Tainio et al 2016) with behavioral responses to pollution exposure within our sample (figure 5(b); see method for the modeling approach). Figure 5(b) suggests that although biking within 30 min has exercise benefits that outweigh pollution cost under the given pollution scenario, many people having shorter commuter time than this threshold also intentionally switch from active commuting to other transportation modes, hedging against their subjective perception of exposure risk.

This risk-averse response is in line with our survey evidence showing that participants are very pessimistic about air pollution in Zhengzhou. From our survey, 82% of participants think winter air quality is bad or terrible. 73.48% think air pollution in Zhengzhou largely or severely impacts their health (figure S4(a); table S11). People who believe local air pollution severely impacts their health are more likely to reduce active commuting and increase motor vehicle commuting. These people also have a greater

\(^4\) Automobile mode includes driving, taxi, or services provided by Transportation Network Company (TNC; such as Uber/Didi).
tendency to reduce active commuting when the exercise benefit still outweighs the pollution exposure risk on average (figure S4(b)).

3.3. Implications for active commuting policies

Besides inducing people to switch from active to non-active modes, health concerns over air pollution can intensify non-active commuters’ reluctance to choose active commutes. Encouraging active commuting has been an important policy target to promote physical and psychological health (Avila-Palencia et al. 2017). It can also mitigate public transit congestion, which has been found to create social costs comparable to road congestion in busy metropolitan areas (Haywood et al. 2018). We mimicked the implementation of two hypothetical public policies aiming at increasing active commuting: financial subsidy and exercise nudge. Financial incentives such as taxes and subsidies are common policies to encourage active commute and have been extensively studied (Martin et al. 2012). Meanwhile, behavioral policy based on information provision, social comparisons and commitment devices (Bhattacharya et al. 2015) represent a new set of tools for making public policy more cost-efficient (Tannenbaum et al. 2017) and preserving an individual’s freedom of choice.5

Our results suggest that when faced with air pollution, active commuting subsidies mobilize changes for a smaller subgroup of the population, and the subsidy rate will need to be much higher than that of clean days. The proportion of people willing to change their mode choice given a subsidy decreases from 76.7% on a clean day to 63.4% on a polluted day; the minimum WTA for subsidy increases from 4.37 RMB/trip on a clean day to 5.04 RMB/trip on a polluted day (table S6). Regression results comparing treatment and control groups indicate that when fully informed about the pollution exposure by modes, respondents willing to take a green travel subsidy falls by a further 14.1% points (95% CI: 9.8, 18.2) while the average WTA increases by 1.1 RMB (95% CI: 0.3, 1.9)6 (columns 1 and 2 of table 1).

Similarly, our exercise nudge, informing participants about calorie burnt and expected weight losses, successfully increased active commuting by 9.7% points (95% CI: 6.7, 12.8) on clean days, yet had much smaller and insignificant effect under polluted day for people with all commuting times (see columns 3 and 4 of table 1 for overall effects (Milkman et al. 2011). Government agencies also increasingly adopt nudges to their policy toolkits (Benartzi et al. 2017). For example, the UK Cabinet Office created the Behavioural Insights Team (BIT) in 2010, and the U.S. government established the White House Social and Behavioral Science Team in 2014.

5 Nudges have been shown to be effective at shaping a diverse range of health behaviors including smoking cessation (Eyal 2014), exercise (Bhattacharya et al. 2015) and vaccination attainment (Milkman et al. 2011). Government agencies also increasingly adopt nudges to their policy toolkits (Benartzi et al. 2017). For example, the UK Cabinet Office created the Behavioural Insights Team (BIT) in 2010, and the U.S. government established the White House Social and Behavioral Science Team in 2014.

6 To put it into perspective, the bus ticket in Zhengzhou is a flat rate of 1 RMB.
Figure 4. Treatment effects of pollution exposure information on the percentage of respondents choosing active and automobile modes to commute (sample: Treatment Group 1 and Control Group). The regressions of equation (1) are run for each subgroup separately. Choosing an automobile includes choosing a private car and taxi/TNC. The dots are point estimates of the treatment effects comparing Treatment Group 1 and Control Group. Lines are 95% confidence intervals. Numeric results used to in the figure are summarized in table S9.

and figure S5 for results by time). The results after pollution exposure information treatment reinforce that health risk dimension completely overshadows exercise nudge and dominates people’s commuting choices (figure S6).

4. Discussion

In this paper, we provide the first empirical evidence on the interaction of two important public health challenges—physical inactivity and pollution exposure—in commuting mode choice; and provide an assessment of the unintended consequences pollution avoidance behaviors can have on both individuals and the society at large. The randomized experimental design allows us to separate out the impacts of confounding factors and provide robust causal inference.

First, we provide experimental evidence that people switch commuting modes as an air pollution avoidance strategy. In our sample, people are mostly aware of that cutting outdoor commuting can limit pollution exposure, yet they underestimate their pollution exposure taking public transit. Our results indicate that if people are informed about their personalized pollution exposure risk by commuting modes, active commuting would further decrease by 8.4 percentage points, while automobile commuting increases by 14.7 percentage points, creating a double challenge to both public health and pollution mitigation. As national air quality disclosure programs and the Personal Air Pollution Exposure
technology expand access to pollution exposure at micro-levels (Jerrett et al 2017, Larkin and Hystad 2017, Arano et al 2019, Mamun and Yuce 2019), the broader social impacts of pollution avoidance behaviors should receive added attention in policy making to balance mitigation and avoidance efforts.

Previous studies on pollution and commuting have mostly been conducted in the developed countries, where the main channel of pollution avoidance in transportation is switching to routes with lower proximity to motor vehicles (Cole-Hunter et al 2013, 2015, Good et al 2016). In developing country cities, ambient pollution levels are much higher than in Europe or the US and non-transportation sources (e.g. coal-based heating/manufacturing sector) contribute greatly to the heavy air pollution throughout the city. As a result, travel modes, rather than travel routes, tend to explain the greatest variability in commuters’ pollution exposure (deSouza et al 2020). Changing commuting mode can create a vicious cycle: heavy air pollution boosts the usage of automobiles, a dirtier yet more self-protective transportation mode for pollution avoidance, which further aggravates local air pollution. The omission of this behavioral reaction would lead to underestimation of air pollution’s social cost. Policymakers can partially mitigate this unintended consequence by running air purification systems in public transit vehicles when ambient pollution is high, or encouraging the usage of facemasks.

Second, our results suggest that people may overestimate the health risks of air pollution as compared to the health benefits of physical activity. Even for people with commuting times where epidemiological studies suggest that the exercise benefits outweigh pollution exposure risk, a substantial reduction in active commuting is documented due to pollution health concerns. We should be cautious about interpreting these more risk-averse behaviors as irrational, since citizens may not have adequate scientific knowledge to precisely compare health impacts across two dimensions. However, the results do suggest that although informing citizens about their personal pollution exposure can mobilize proactive pollution avoidance, these actions may crowd out the efforts to achieve other public health goals. Policymakers should acknowledge the intertwined relationship between different public health targets (i.e. reducing pollution exposure and increasing physical activities), and consider risk-averse behavioral tendencies before promoting public information campaigns for pollution alerts.

Third, we find that both financial subsidies and exercise nudges encouraging active commuting are likely to be ineffective in polluted contexts. We find that the proportion of sample willing to adopt active commuting given subsidy drops by 14 percentage points, and the minimum subsidy amount increases by 1.1 RMB when citizens are informed about the pollution exposure risk. Meanwhile, though low-cost

---

**Figure 5.** Scientific and behavioral health trade-off comparisons. (a) Theoretical break-even curve when exercise benefit equals exposure risk under different biking time and pollution levels. The theoretical model supporting this curve is from Tainio et al 2016. Our pollution scenario in the survey (117 μg m$^{-3}$) and its corresponding breakeven time per commuting trip (30 min; assuming two commuting trips per day) are denoted in the figure. (b) Treatment effect of pollution exposure information on the percentage of respondents active commute by each counterfactual biking time (sample: Treatment Group 1 and Control Group). Bars show the treatment effects comparing Treatment Group 1 and Control Group. Error bars show 95% confidence intervals of subgroup regression coefficients. Numeric results used for this figure are summarized in column (1) of table S10.

- Note that the results display percentage point decreases instead of percentage change (i.e. not been divided by the base percentage of active commuter within each group), thus the null effect of ‘>60 min’ group is due to the widely adoption of non-active modes before the treatment.

- Although people could choose walking as their active commuting choice, the breakeven time per day for walking is very large (7 h 45 min). We use biking time to build a lower bound of active commuting distance for which health benefits outweigh pollution exposure risk.
information interventions like nudges are effective in encouraging active commuting by 10 percentage points, such effects completely disappear under the polluted day scenario. These results show that reducing air pollution levels is essential if the governments wish to encourage active commuting, providing yet another motivation to reduce air pollution levels in addition to its well-documented direct health costs.

The results in this paper should be interpreted with caution for several reasons. First, the stated preference nature of the survey makes it susceptible to experimenter demand effects and reporting biases. RCTs relying on GPS tracking of actual commuting mode choices (combining smartphone GPS signals with machine learning algorithms to detect commuting mode) are preferred to those using self-reported commuting preferences. Second, due to the length constraint on the survey, our measurement of attitude and preferences are largely qualitative, which is susceptible to measurement errors. Further, we are only able to measure people’s commuting choice under the two discrete pollution scenarios, rather than building a continuous dose-response between air pollution and commuting preference. Third, our conclusion that people engage in suboptimal avoidance behavior in a risk-averse direction is dependent on trade-off curves published in the epidemiological literature, which are sensitive to dose-response function assumptions. Impacts of short-term air pollution episodes, where concentrations significantly exceed the average air pollution levels for a few days, may induce additional short-term health effects not captured by the experiment used in this paper. Fourth, although our research primarily focuses on the non-automobile commuters, we would expect the same pollution avoidance mechanism to intensify the reluctance to switch to active/non-active green transportation modes for drivers as well. How air pollution will cause similar ‘attenuation effects’ for broader green subsidies, and green nudge policies is an essential topic for future studies. Finally, we should be cautious when extrapolating the results to Western contexts due to the large differences in ambient pollution levels and transportation systems (see supplementary note 5 for more discussions). Further research in other cities and countries is needed to cross-validate the external validity of our quantitative findings.

5. Conclusion

This study presents the first empirical evidence on the stated behavioral trade-offs between exercise benefits and pollution exposure risk in individuals’ commuting mode choice. We find that perceived and learned pollution exposure information causally induce people to switch from active commuting modes to non-active ones, and cause a substantial proportion of people to choose automobile as the commuting mode. This avoidance behavior is observed even for the sub-population for whom the exercise benefits of active commuting outweigh its pollution exposure risk given their commuting distance, and can attenuate the effect of policies encouraging active commuting. It is thus vital for the governments to recognize the spillover effects between different public health problems and be aware of the crowding-out effect between policies targeting different goals.

Acknowledgements

The authors are grateful for the research support from the MIT Sustainable Urbanization Lab and its Zhengzhou City Living Lab Program. We thank Guochen ZHAI and Jianghao WANG for local coordination and organization; thank Yuchen CHAI for the development of intervention webpage; thank Binzhe WANG, Hui DENG, Bei HE, JunGAO, Shuyang YAO, and students from Zhengzhou University for assisting the reluctant to switch to active/non-active green transportation modes for drivers as well. How air pollution will cause similar ‘attenuation effects’ for broader green subsidies, and green nudge policies

Table 1. Air pollution and active commuting policies (subsidy and exercise nudge).

|                  | Panel A. Subsidy                                                                 | Panel B. Exercise nudge                                                                 |
|------------------|---------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------|
| Willing to change (%) (1) | Willing to accept (RMB) (2)                                                     | Exercise nudge treatment                                                                 |
| Pollution exposure | −14.05***                                                                     | 1.080***                                                                                |
| treatment         | (2.14)                                                                         | (0.405)                                                                                 |
| Observations      | 1507                                                                           | 872                                                                                     |
| R-squared         | 0.277                                                                          | 0.298                                                                                   |
| Controls          | Yes                                                                             | Yes                                                                                     |
|                   |                                    | R-squared                                                                                |
|                   |                                    | Observations                                                                             |
|                   |                                    | 1498                                                                                    |
|                   |                                    | 1498                                                                                    |
|                   |                                    | Controls                                                                                 |
|                   |                                    | Yes                                                                                    |
|                   |                                    | Yes                                                                                    |

Note: Robust standard errors in parentheses. Control variables include income, education, gender, marriage status, commuting distance, and baseline commuting choice. In columns 1 and 2, comparison between Treatment Group 1 (O1 + P) and Control Group (O1 + O2) in Round 4 is used to estimate the treatment effect of pollution exposure information. In columns 3 and 4, comparison between Treatment Group 2 (H + P) and Control Group (O1 + O2) in Round 2 and 3 are used to estimate the treatment effect of exercise nudge information under different pollution conditions. The observation number for willingness to accept (WTA) shrinks since only the people who said that they are willing to change (WTC) given a reasonable amount of subsidy were asked for their exercise nudge information under different pollution conditions. The observation number for willingness to accept (WTA) shrinks since only the people who said that they are willing to change (WTC) given a reasonable amount of subsidy were asked for their WTA. See section 2 for how WTC and WTA are measured in the survey. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.
the survey implementation; and thank the pollution monitoring team led by Priyanka deSouza.

**Data availability statement**

The data that support the findings of this study are available upon reasonable request from the authors.

**Permission**

The authors have confirmed that any identifiable participants in this study have given their consent for publication.

**ORCID iD**

Yichun Fan https://orcid.org/0000-0001-8400-3863

**References**

Abbott R D, White I R and Ross G W 2004 Walking and dementia in physically capable elderly men ACC Curr. J. Rev. 13 14

Andersen Z J, de Nazelle A, Mendez M A, Garcia-Aymerich J, Hertel O, Tjonneland A, Overvad K, Raaschou-Nielsen O and Nieuwenhuijsen M J 2013 A study of the combined effects of physical activity and air pollution on mortality in elderly urban residents: the Danish diet, cancer, and health cohort Environ. Health Perspect. 123 557–63

Arano K A G, Sun S, Ordieres-Mere J and Gong A B 2019 The use of the internet of things for estimating personal pollution exposure Int. J. Environ. Res. Public Health 16 3130

Avila-Palencia I, de Nazelle A, Cole-Hunter T, Donaire-Gonzalez D, Jerrett M, Rodriguez D A and Nieuwenhuijsen M J 2017 The relationship between bicycle commuting and perceived stress: a cross-sectional study BMJ Open 7 e013542

Benartzi S, Beshars J, Milkman K L, Sunstein C R, Thaler R H, Avila-Palencia I, de Nazelle A, Cole-Hunter T, Morawska L and Solomon C 2015 Bicycle commuting and exposure to air pollution: a questionnaire-based investigation of perceptions, symptoms, and risk management strategies J. Phys. Act. Health 12 490–9

De Nazelle A et al 2011 Improving health through policies that promote active travel: a review of evidence to support integrated health impact assessment Environ. Int. 37 766–77

Demakakos P, Hamer M, Stamatakis E and Steptoe A 2010 Low-intensity physical activity is associated with reduced risk of incident type 2 diabetes in older adults: evidence from the English Longitudinal Study of Ageing Diabetologia 53 1877–85

deSouza P, Lu R, Kinney P and Zheng S 2020 Exposures to multiple air pollutants while commuting: evidence from Zhengzhou, China Atmos. Environ. 247 118168

Di Pietro L, Dziura J and Blair S N 2004 Estimated change in physical activity level (PAL) and prediction of 5 year weight change in men: the Aerobics Center Longitudinal Study Int. J. Obes. Relat. Metab. Disord. 28 1541–7

Dockery D W, Pope C A, Xu X, Spengler J D, Ware J H, Fay M E, Ferris B G J and Speizer F E 1993 An association between air pollution and mortality in six US cities New Engl. J. Med. 329 1753–9

Donaire-Gonzalez D et al 2015 The added benefit of bicycle commuting on the regular amount of physical activity performed Am. J. Prev. Med. 49 842–9

Donnelly J E, Blair S N, Jakicic J M, Manore M M, Rankin J W and Smith B K (American College of Sports Medicine) 2009 American College of Sports Medicine Position Stand. Appropriate physical activity intervention strategies for weight loss and prevention of weight regain for adults Med. Sci. Sports Exerc. 41 459–71

Doorley R, Pakrashi V and Ghosh B 2015 Quantifying the health impacts of active travel: assessment of methodologies Transp. Rev. 35 559–82

Dunn A L, Trivedi M H and O’Neal H A 2001 Physical activity dose-response effects on outcomes of depression and anxiety Med. Sci. Sports Exerc. 33 5587–97

Ebenstein A, Fan M, Greenstone M, He G and Zhou M 2017 New evidence on the impact of sustained exposure to air pollution on life expectancy from China’s Huai River Policy Proc. Natl Acad. Sci. USA 114 10384–9

Eyal N 2014 Nudging by shaming, shaming by nudging Int. J. Health Policy Manage. 3 53–56

Flin E and Emmins S 2016 Active commuting and obesity in mid-life: cross-sectional, observational evidence from UK Biobank Lancet Diabetes Endocrinol. 4 420–35

Flin E, Emmins S and Sacker A 2014 Associations between active commuting, body fat, and body mass index: population based, cross sectional study in the United Kingdom BMJ 349 g4897

Giles I V and Koehle M S 2014 The health effects of exercising in air pollution Sports Med. 44 223–49

Good N et al 2016 The Fort Collins Commuter Study; impact of route type and transport mode on personal exposure to multiple air pollutants J. Expo. Sci. Environ. Epidemiol. 26 397–404

Gordon-Larsen P, Hou N, Sidney S, Sternfeld B, Lewis C E, Jacobs D R and Popkin B M 2009 Fifteen-year longitudinal

Cheng W, Zhang Z, Cheng W, Yang C, Yao L and Liu W 2018 Associations of leisure-time physical activity with cardiovascular mortality: a systematic review and meta-analysis of 44 prospective cohort studies Eur. J. Prev. Cardiol. 25 1864–72

Cole-Hunter T, Jayaratne R, Stewart I, Hadaway M, Morawska L and Solomon C 2013 Utility of an alternative bicycle commute route of lower proximity to motorised traffic in decreasing exposure to ultra-fine particles, respiratory symptoms and airway inflammation—a structured exposure experiment Environ. Health 12 29

Cole-Hunter T, Morawska L and Solomon C 2015 Bicycle commuting and exposure to air pollution: a questionnaire-based investigation of perceptions, symptoms, and risk management strategies J. Phys. Act. Health 12 490–9
trends in walking patterns and their impact on weight change Am. J. Clin. Nutr. 89 19–26
Götschi T, Garrard J and Giles-Corti B 2016 Cycling as a part of daily life: a review of health perspectives Transp. Rev. 36 45–71
Hankinson A L, Daviguas M L, Bouchard C, Carnethon M, Lewis C E, Schreiner P J, Liu K and Sidney S 2010 Maintaining a high physical activity level over 20 years and weight gain JAMA 304 2003–10
Haywood L, Koning M and Prud’homme R 2018 The economic cost of subway congestion: estimates from Paris Transp. Econ. Trans. 14 1–8
Ito K and Zhang S 2020 Willingness to pay for clean air: evidence from air purifier markets in China J. Polit. Econ. 128 1627–72
Jerret M et al 2017 Validating novel air pollution sensors to improve exposure estimates for epidemiological analyses and citizen science Environ. Res. 158 286–94
Katzmarzyk P T, Craig C L and Gauvin L 2007 Adiposity, physical fitness and incident diabetes: the physical activity longitudinal study Diabetologia 50 538–44
Keiser D, Lade G and Rudik I 2018 Air pollution and visitation at U.S. national parks Sci. Adv. 4 eaat1613
Kelly P, Kahlmeier S, Götschi T, Orsini N, Richards J, Roberts N, Scarborough P and Foster C 2014 Systematic review and meta-analysis of reduction in all-cause mortality from walking and cycling and shape of dose response relationship Int. J. Behav. Nutr. Phys. Act. 11 132
Larkin A and Hystad P 2017 Towards personal exposures: how technology is changing air pollution and health research Curr. Environ. Health Rep. 4 463–71
Larson E B, Wang L, Bowen J D, McCormick W C, Teri L, Crane P, Kelly P, Kahlmeier S, Götschi T, Int Panis L, Kahlmeier S and Nieuwenhuijsen M 2015 Health impact assessment of active transportation: a systematic review Prev. Med. 76 103–14
Murray C J L et al 2020 Five insights from the Global Burden of Disease Study 2019 Lancet 396 1135–59
Pope C A 3rd and Dockery D W 2013 Air pollution and life expectancy in China and beyond Proc. Natl Acad. Sci. USA 110 12861–2
Quist J S, Rosenkilde M, Petersen M B, Gram A S, Sjödin A and Stallknecht B 2018 Effects of active commuting and leisure-time exercise on fat loss in women and men with overweight and obesity: a randomized controlled trial Int. J. Obes. 42 469–78
Rohde R A and Muller R A 2015 Air pollution in China: mapping of concentrations and sources PLoS One 10 e0135749
Scarborough P and Foster C 2014 Systematic review and meta-analysis of reduction in all-cause mortality from walking and cycling and shape of dose response relationship Int. J. Behav. Nutr. Phys. Act. 11 132
Sun C, Kahn M E and Zheng S 2017 Self-protection investment exacerbates air pollution exposure inequality in urban China Ecol. Econ. 131 468–74
Taimio M, de Nazelle A J, Götschi T, Kahlmeier S, Rojas-Rueda D, Nieuwenhuijsen M J, de Sá T H, Kelly P and Woodcock J 2016 Can air pollution negate the health benefits of cycling and walking? Prev. Med. 87 233–6
Tannenbaum D, Fox C R and Rogers T 2017 On the misplaced politics of behavioural policy interventions Nat. Hum. Behav. 1 10130
Tao L, Li X, Zhang J, Liu J, Liu Y, Li H, Liu X, Luo Y and Guo X 2019 Association of commuting mode with dyslipidemia and its components after accounting for air pollution in the working population of Beijing, China BMC Public Health 19 622
US Department of Health and Human Services 2014 The Health Consequences of Smoking—50 Years of Progress: A Report of the Surgeon General (Atlanta, GA: U.S. Department of Health and Human Services, Centers for Disease Prevention and Control, National Center for Chronic Disease Prevention and Health Promotion, Office on Smoking and Health)
World Health Organization (WHO) 2018 Global action plan on physical activity 2018-2030: more active people for a healthier world (https://www.who.int/ncds/prevention/physical-activity/global-action-plan-2018-2030/en/)
Zhao P, Li S, Li P, Liu J and Long K 2018 How does air pollution influence cycling behaviour? Evidence from Beijing Transp. Res. D: Transp. Environ. 63 26–38
Zheng S, Wang J, Sun C, Zhang X and Kahn M E 2019 Air pollution lowers Chinese urbanites’ expressed happiness on social media Nat. Hum. Behav. 3 237–43