Air Pollution, Avoidance Behaviors, and Neglected Social Costs: Evidence from Outdoor Leisure and Commuting Behaviors

by

Yichun Fan

Bachelor of Engineering, Tsinghua University (2018)

Submitted to the Department of Urban Studies and Planning
in partial fulfillment of the requirements for the degree of

Master in City Planning

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 2020

Author . . . .
Department of Urban Studies and Planning
May 15, 2020

Certified by . . . .
Professor Siqi Zheng
Department of Urban Studies and Planning
Thesis Supervisor

Accepted by . . . .
Ceasar McDowell
Professor of the Practice
Chair, MCP Committee
Department of Urban Studies and Planning

Air Pollution, Avoidance Behaviors, and Neglected Social Costs: Evidence from Outdoor Leisure and Commuting Behaviors

by

Yichun Fan

Submitted to the Department of Urban Studies and Planning
on May 15, 2020, in partial fulfillment of the
requirements for the degree of
Master in City Planning

Abstract

The social cost of air pollution depends on both its biophysical impacts on health and productivity and the dynamic avoidance behaviors citizens proactively adopt. The literature has almost exclusively focused on the direct impacts, and the limited research looking into the avoidance behaviors has only considered monetary defensive expenditure. Building upon a theoretical framework incorporating the broader pollution costs into existing economic models, I derive empirical evidence of the hidden opportunity cost and social cost of pollution avoidance behaviors. For opportunity cost, I focus on the foregone outdoor leisure activities and the related welfare loss due to pollution avoidance, relying on billions of cell phone location inquiries from 10,499 parks all over China. Using the pollution blown from upwind cities as the instrumental variable for local pollution, I show that heavy PM2.5 pollution reduces park visitation by 10% in northern Chinese cities. If the number of heavily-polluted days reduces by 25% in northern China, the welfare gain from leisure activity is about 83.5 million USD. For social cost, I show that pollution awareness affects commuting behaviors, by conducting a survey for 2,258 non-vehicle commuters in Zhengzhou, China. If fully aware of exposure risk, up to 14.8% of non-vehicle travelers intend to switch to motor vehicle commuting (private car/ taxi) on polluted days, 13.9% fewer people are willing to choose active commuting even if they can receive a subsidy, and soft policies like Green Nudge completely lose effect. This avoidance behavior generates more emissions for the society and creates a “mitigation-avoidance dilemma” for transportation policies. The thesis calls for more attention to quantifying the broader social impacts of pollution by including the non-market value of avoidance behaviors; these impacts create substantial welfare loss and social challenges awaiting more balanced policy decision-making to consider these trade-offs.

Thesis Supervisor: Professor Siqi Zheng
Title: Professor in Department of Urban Studies and Planning

Acknowledgments

Conducting two empirical studies with different skills required (i.e., analyzing big data and designing experiment) and synthesizing the results into a coherent theoretical framework is a challenging yet rewarding experience. It is impossible for me to put all pieces together without the support from my advisor, colleagues in lab, my family and my friends.

I am grateful to my advisor Professor Siqi Zheng, who has guided me through the whole process of research and provided many valuable insights into enhancing the robustness of the findings. Due to the Covid-19 outbreak, my original thesis proposal was not able to be implemented. It was Siqi who encouraged me to directly face the challenge and provided helpful suggestions for producing the thesis with highest quality of possible given the constraints. I also wish to thank Professor Jinhua Zhao for being my thesis reader and providing valuable feedbacks for me to continuously improve my studies after graduation.

I also wish to express my deep appreciation to the research community of Sustainable Urbanization Lab (SUL). My thesis is comprised of two empirical chapters, which have received tremendous help from Jianghao Wang and Juan Palacios, the Research Scientist and Post-doctoral Researcher of SUL. The successful implementation of the July survey is owing to the joint efforts of Rachel Luo, Binzhe Wang, Yuchen Chai, Priyanka de Souza, me and many other researchers in US and in China. Meanwhile, the project was almost impossible to take place without the support of Guochen Zhai, the Innovative Fellow of SUL. I feel very lucky to be part of such a great research community and looking forward to have more research collaboration with you in the future.

Last but not least, I wish to thank for the continuous support from my family, friends, and the DUSP family. Studying at MIT is accompanied with challenges and stress. The unconditional love from my parents, husband and friends always charge me to conquer any difficulty in studying and in life.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Motivation

Particulate matter (PM) air pollution, which is predominantly the result of fossil fuel combustion, is recognized as the most deadly form of air pollution globally. In 2015, ambient air pollution was considered the fifth ranking mortality risk factor with exposure to PM2.5 estimated to have caused 4.2 million deaths (Cohen et al. 2017). About 98% of cities in low- and middle-income countries and 56% of cities in high-income countries fail to meet the World Health Organization (WHO) air quality guidelines (Organization and Others 2016). According to the Air Quality Life Index (AQLI), particular air pollution cuts global life by nearly 2 years relative to the level deemed safe by the WHO, which makes it more serious than communicable diseases like HIV/ AIDs or behavioral killers like cigarette smoking and even wars [1]. In China, the life expectancy loss exceeds 5 years in many northern cities where coal burning factories are located in clusters. Recently, scholars also notice that air pollution severely affects human capital and productivity (Graff Zivin and Neidell 2013). A growing literature has begun to establish the causal link between pollution and outcomes ranging from labor supply, productivity, cognitive performance, etc. Given the importance of human capital as an engine for economic growth and innovations, the lasting impacts on productivity could be more severe than the acute morbidity.

[1] https://aqli.epic.uchicago.edu/pollution-facts/

Understanding the likely economic impacts of air pollution is of tremendous practical value to both the policymakers and the public since the perspectives on how pollution risk matters compared with other local challengings are largely inconsistent due to their incomparability. In the United States, the Office of Management and Budget (OMB) must report to the Congress annually on the benefits and costs of major federal regulation. How to identify, quantify and even monetize the marginal costs and benefits associated with environmental policies has become a crucial issue in the policy debates, so that different dimensions of policy decisions can be made comparable and negotiable. Given the seminal role of such quantification, researchers have struggled to provide empirically founded estimates of both the non-market economic value of pollution damages and their distributive impacts on diverse population groups accounting for the heterogeneous behavioral responses. To communicate policy impacts in economic values, researchers have begun to quantify the mortality cost using the Value of Statistical Life (VSL) (Ashenfelter and Greenstone 2004), calculate morbidity burden through cost-of-illness (Jo 2014), and estimate the labor market outcomes affected by pollution (T. Chang et al. 2016). These significant efforts have greatly increased the saliency of air pollution consequences, yet the hidden cost in avoidance behaviors are still omitted in the cost structure of pollution and thus in the benefits of mitigation policies as well.

In fact, although existing literature predominantly focus on the health and productivity impacts of pollution exposure, individuals are rarely passive victims who take no actions to self-protect. When people take avoidance behaviors, they either have extra consumption or change behaviors (Figure 1-1). Given that these choices are not preferred in the counterfactual scenario where no pollution exists, they inevitably create new costs. While it is clear that defensive expenditure carries cost, the significance of the behavioral responses without market price is much less obvious. Understanding these hidden costs is not trivial. On one hand, neglecting the hidden costs of behavioral adjustments will underestimate the benefit pollution mitigation policies can create, thus slowing the progress of pollution control if decisions are made based on cost-benefit analysis. On the other hand, it is important for the policy makers to acknowledge the cost of individual avoidance behaviors, so that the health benefits of public information encouraging voluntary self-protection can be better balanced with its costs on society.

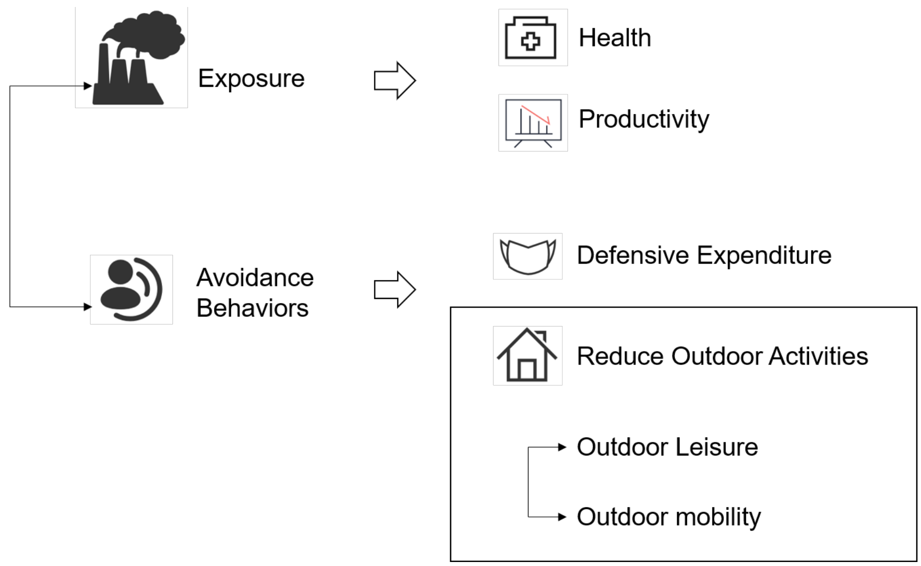


Figure 1-1: Structure of social cost of pollution.

In this thesis, I aim to incorporate individual behavioral responses in the wide-applied health economic model and to characterize the hidden costs of these avoidance behaviors. Specifically, with theoretical advancement motivating conceptual thinking, I enrich the policy optimization model by adding the opportunity cost and social cost of avoidance behaviors. I then derive rich empirical evidence using quasi-experimental and experimental designs to demonstrate how the two cost elements are reflected in real-world behavioral decisions of outdoor leisure (i.e., park visitation) and outdoor mobility (i.e., commuting) activities (Figure 1-1). The implicit value of subjective well-being lost tied with the forgone leisure activity constitutes the opportunity cost. While the avoidance behaviors in the transportation sector create social cost since citizens can become emission producers. Air pollution can be substantial determinants of behavioural patterns that underlie costly public crises. Understanding the interaction between nature and human systems will help the policy makers to better understand the toll of air pollution and its distributive impacts, so that tailored regulation can be implemented to preserve public welfare.

1.2 Research questions

This thesis aims to unveil the hidden cost of air pollution through quantifying the behavioral responses in outdoor leisure and outdoor mobility activities to reduce pollution exposure. Efforts are made to investigate the non-market value and behavioral mechanisms underlying the avoidance behaviors. Specifically, I answer the following research questions in this thesis:

(1) How does air pollution impede outdoor park visitation?

Several sub-questions are asked in this chapter to fulfill the goals stated above: What are the average effects of marginal PM2.5 concentration increase and that of heavy pollution? What is the inter-day temporal dynamics of the impacts? What is the dose-response function of this impact? How does the impact vary by regions, income, park types and time? And finally, what is the implicit economic cost bundled with the foregone leisure?

When answering these questions, big data analytical strategies are utilized to maximize the generalizability and comprehensiveness of the empirical evidence. Special identification strategies are designed to make causal inferences, and back-of-envelope analysis is used to make nationwide estimation on non-market cost generated through foregone outdoor leisure activities. The quantification of opportunity cost provides evidence that people's voluntary avoidance behaviors, though reducing the health impacts of air pollution, still causes substantial welfare loss to the urbanites.

(2) How does air pollution alter commuting behaviors?

Similarly, the research thread in this chapter is driven by several sub-questions: How does the health perception on ambient PM2.5 pollution exposure affect mobility choices? Would the avoidance behaviors in the transportation sector create social cost and render policy dilemmas for promoting public health and urban sustainability? What are the behavioral pathways and individual heterogeneity underlying the decisions? What are the implications for green transportation policies encouraging active commuting?

Since commuting behaviors are largely constrained by home-job locations and the availability of transportation alternatives, there can be huge heterogeneity across individuals. I thus lay specific emphasis on understanding the decision-making mechanisms by conducting a large scale survey. Taking advantage of the survey data, I have detailed information on individual's home-job locations, mobility constraints, tailored exposure risk during commuting, socio-demographics, risk preferences and personal habits to help predict what types of people will be more affected by pollution in their mobility choice. Furthermore, I designed a Randomized Controlled Trial with information interventions treatment to project the commuting choice landscape when people are increasingly informed about the individual level health information, and evaluate the broader impacts on the effectiveness of hypothetical transportation policies. These exercises have direct policy implications for the government.

1.3 Thesis structure

For the rest of this paper, Chapter 2 reviews the recent empirical studies quantifying the social cost of air pollution, including both the biological impacts on health and productivity, and the human avoidance behaviors related to outdoor leisure activities and transportation behaviors. The research gap and contribution of this paper are also integrated in the review chapter. Chapter 3 introduces the modeling framework of optimal policy designs of pollution regulation, and promotes theoretical advancement in encompassing broader social cost beyond health and productivity in the cost structure of air pollution. Chapter 4 illustrates the empirical strategies and evidence with respect to pollution and outdoor leisure activities. Chapter 5 presents the analysis of pollution and commuting behaviors. Chapter 6 synthesizes the findings and discusses future work and policies.

Chapter 2

Literature Review

This study fits into the growing literature on empirically-derived estimates of the social cost of air pollution. The following sections summarize the existing empirical evidence of the impacts of air pollution on health and productivity, outdoor leisure activities and commuting behaviors. While the first one is more well-developed, the other two research realms are relatively under-studied, and thus become the focus of this thesis. I summarize the gaps and limitations of existing research and explain how that motivates me to explore the research questions I listed in the previous chapter.

2.1 Impacts of pollution on health and productivity

Particular matter (PM) is a mixture of many organic and inorganic chemical components (Sillanpää et al. 2006), with some of them directly toxic or lead to systemic inflammation leading to adverse health outcomes (Y. Chen et al. 2013; Ebenstein et al. 2017; Dockery et al. 1993). The relationship between pollution and health has been well-documented. Many environmental health and economics research has utilized quasi-experimental designs to quantify the impacts of air pollution on mortality and monetize the cost through Value of Statistical Life (VSL) (Ashenfelter and Greenstone 2004). Similar studies are conducted all over the world, including US (Chay and Greenstone 2003; Dockery et al. 1993), Europe (Luechinger 2014), China (C. W. Cheung, He, and Pan 2020; H. Zhao et al. 2019; Ebenstein et al. 2017), Korea (Bae, Lim, and Hong 2020), India (Greenstone and Hanna 2014), etc. Lelieveld et al. 2015 has presented global evidence on how pollution affects premature mortality worldwide synthesizing the data from the global atmospheric chemistry model and global burden of disease. In addition, As many of the chronic health impacts are reflected in morbidity rather than death, there are rich papers documenting the link between pollution and communicable diseases, such as lung cancer (Pope et al. 2011), cardiovascular and respiratory diseases (Williams et al. 2019; Moretti and Neidell 2011; Neidell 2009). Some of these papers proxy the social cost of pollution through medical and hospitalization costs (Deryugina et al. 2016; Giaccherini, Kopinska, and Palma, n.d.).

In addition, the adverse effect of pollution is not only reflected in physiological systems, but also in the cognitive systems of human-being. Previous research has quantified the cognitive impacts of pollution using exam scores (X. Zhang, Chen, and Zhang 2018; X. Chen, Zhang, and Zhang 2017; Marcotte 2017; Lavy, Ebenstein, and Roth 2014) and cognitive biases observed in the financial market (J. J. Li et al. 2017; Heyes, Neidell, and Saberian 2016). These cognitive shocks not only happen contemporaneously. The nascent empirical literature has also found that childhood exposure can have lasting impacts on the human capital outcome later in life (Currie et al. 2014). Pollution, as a consequence, significantly impedes human capital formation and reduces labor output. (Hanna and Oliva 2015) presents evidence that air pollution in Mexico reduces labor supply. (T. Chang et al. 2016) finds that ambient PM2.5 of $10 \mu g/m^3$, which readily penetrates indoors, reduces the productivity of indoor pear-packing workers by \$0.41 per hour (approximately 6% of hourly earnings). The productivity impacts on service and knowledge sectors are equally significant. According to (T. Y. Chang et al. 2019) , a 10-unit increase in the air pollution index (API) decreases the number of daily calls handled by a worker of Ctrip by 0.35% on average which declines largely linearly with pollution levels.

2.2 Pollution and outdoor leisure activities

Beyond mortality, morbidity and productivity, air pollution also impacts the mental well-being of humans, which has been measured by expressed sentiment on social media (Zheng et al. 2019), interviews (Smyth, Mishra, and Qian 2008) and surveys (Barrington-Leigh and Behzadnejad 2017; X. Zhang, Zhang, and Chen 2017; Zijlema et al. 2016; Power et al. 2015; Luechinger 2009). However, the specific behavioral mechanisms directing those changes, though crucial for risk modelling and effective interventions, is not well-understood.

The sacrifice of outdoor leisure activities for pollution avoidance is one of the most important moderators between pollution and subjective well-beings. Rich literature has documented that outdoor leisure activity has significant non-market contributions to both physiological health and psychological well-being (Brajša-Žganec, Merkaš, and Šverko 2011; Kerr et al. 2012; Wolsko and Lindberg 2013; Korpela et al. 2014; Manferdelli, La Torre, and Codella 2019). This is especially important for China, which has a culturally rooted lifestyle of participation in outdoor physical and leisure activity (Lü et al. 2015). Some literature leverage surveys to document the impacts of pollution on mundane urban park activities. (Jiang, Huang, and Fisher 2019) relies on stated preference survey and faceto-face survey in a specific urban park of Beijing to show that pollution has a negative impact on the maximum number of visits a park may receive. (Roberts, Voss, and Knight 2014) uses self-reported survey data with logistic regression models and estimates statistically significant linkages between PM2.5 and leisure-time physical inactivity in the US. The impacts on leisure activities constitute a key social cost of pollution that has heretofore been absent from policy discussions.

Beyond the contribution to well-being, outdoor leisure activity is closely related to the tourism sector, which constitutes 10.4% of global GDP (World Travel & Tourism Council 2019). As proposed by (Sönmez and Graefe 1998), health risk is an important component of travel risks, and perceived travel risks have negative impacts on tourists' travel intention (Qi, Gibson, and Zhang 2009). Several empirical research using survey data to document the linkage between pollution and general travel intention. (Peng and Xiao 2018) uses structural equation modelling (SEM) and confirms that smog in Beijing induces perception of experience risk and directly influences Chinese residents' travel dissatisfaction. (Law and Cheung 2007) finds that visitors are willing to pay additional departure tax to fund air quality improvements in Hong Kong. The major limitation of the survey studies is that there might be reporting issues such as memory bias. Alternatively, some literature begins to look at how air pollution affects visitation of a specific type of park using objective data. (Poudyal, Paudel, and Green 2013) fits monthly visitation data of the Great Smoky Mountain National Park (GSMNP) into a number of time-series econometric models, and finds that improving the average visibility by 10% (5.5 km) could increase one million recreational visits annually. (C.-M. Chen, Lin, and Hsu 2017) shows that as the number of bad-air-quality days increases by one, the tourists traveling at the Sun Moon Lake in Waiwan would fall by 25,725 people. (Graff Zivin and Neidell 2009) documents the impact of consequent ozone alerts on visitation of Los Angeles Zoo and Botanical Gardens and Griffith Park Observatory, and finds the phenomenon of "alert fatigue" on the second successive day receiving the alert. The largest scale of research in this thread of literature is (Keiser, Lade, and Rudik 2018), who uses instrumental variable regression to estimate the impacts of ozone pollution on visitation of US national parks which have hundreds of millions of visitors travelled to every year. Nevertheless, due to data availability constraints, these research predominantly look at only one park or one type of park. Which makes it difficult to understand the distributive impacts across park types. For example, the city parks where local citizens use for exercise and leisure might have completely pollution sensitivity compared with tourism attractions. Meanwhile, the limited geographical coverage of park case studies poses difficulties in quantifying the social cost due to the lack of generalizability to the national level. In Chapter 4, I exploit the richness of the dataset to look into the impacts for different types of parks and in cities of different regions with different income levels, not only providing representative qualifications for the whole nation, but also supporting the mapping of distributive effects rarely encompassed in previous studies.

Finally, from a policy perspective, scholars predominantly view the avoidance behavior of reducing outdoor activities as the policy target, and intensively investigate how pollution alerts can better assist voluntary self-protections (Lee et al. 2020; H. Chen et al. 2018). However, few papers ever look at the foregone leisure as an unignorable opportunity cost accompanying this avoidance behavior. The neglection of this hidden cost will lead to over-emphasis on citizens' self-protection and lack of incentives for top-down pollution mitigation policies, since information campaigns encouraging self-protection are usually very cheap. To fill in this gap, I not only comprehensively estimate the nation-wide impacts of pollution on visitation for all types of park, but also monetize the lost economic value of those foregone activities to better support the policy decision-makings. This valuation is especially important in the context of a developing country with relatively severe air pollution problems like China, since the saliency of pollution issue induces avoidance behaviors.

2.3 Pollution and commuting behaviors

When quantifying the cost of avoidance behaviors itself, existing literature predominantly focus on the defensive expenditure, such as air purifiers (Liu, He, and Lau 2018), face masks (J. Zhang and Mu 2018; Sun, Kahn, and Zheng 2017; Ito and Zhang 2016), and pharmaceutical purchases (Deschênes, Greenstone, and Shapiro 2017). These market costs are easily quantifiable into monetary value due to the availability of market price, however, it neglects the broader social consequences of pollution avoidance from broader channels of behavioral changes. It is known that transportation contributes significantly to local air pollution in urban context (Kheirbek et al. 2016; Abu-Allaban et al. 2007), while at the same time, travel modes explained much more of commuters' exposure variability than meteorology (Caplin et al. 2019). Urban mobility would be one of the most important behavioral dimensions to look at due to its uniqueness in individual's choice architecture where social responsibility and self-protection might contradict in transportation mode choice.

Since different commuting modes are exposed to different pollution concentrations (Cepeda et al. 2017), and have varied inhalation and lung deposition (Quist et al. 2018), knowledgeable citizens might switch commuting modes as a channel of self-protection. On one hand, previous literature has found that people significantly reduce physical activities (Yu, An, and Andrade 2017) and biking (P. Zhao et al. 2018) in response to high air pollution levels in developing countries. This poses a policy dilemma to balance the two interrelated factors of minimising environmental hazards and promoting active lifestyles (F. Li et al. 2015). Recently, an emerging thread of science literature considers exposure risk and exercise benefit together to investigate the optimal balance of cycling under pollution as a function of time (Tainio et al. 2016; Giles and Koehle 2014; Mueller et al. 2015; Doorley, Pakrashi, and Ghosh 2015; Z. J. Andersen et al. 2015). Yet whether behavioral choices follow the same pattern remains to be undiscovered.

On the other hand, the specific uniqueness of avoidance behaviors in the transportation sector is that residents themselves can act as a pollution emitter themselves if motor vehicles are preferred under pollution. Some studies begin to acknowledge the importance of this problem by testing the effectiveness of public voluntary information programs related to pollution alert on reducing driving on polluted days. However, the results are largely inconsistent. Cutter and Neidell (2009) relies on regression discontinuity (RD) design and finds daily traffic volumes decrease by 3-3.5% when information programs like 'Spare the Air' (STA) advisories are issued in California. Applying a similar identification strategy, Noonan (2014) fails to find any effect of ozone alert in Atlanta on driving and argues that the free transit offer California was promoting along with STA might bias the previous estimation. Welch, Gu, and Kramer (2005) also fails to find significant effects of ozone alert on overall ridership on Chicago Transit Authority trains, but admits that an aggregate measure of ridership might mask subtle and complex shifts in travel behavior (e.g., some reduce traveling while others increase). More detailed investigation into the heterogeneity across population and the underlying behavioral mechanisms is essential to understand the inconsistency of observed transportation behaviors in response to air pollution, which might be more multifaceted and subtle than health and leisure behaviors.

A key difference between the US and Chinese context is that China has a much more severe pollution problem, and the pollution alert in China sets public health avoidance rather than the green nudge advisories as the primary goal. Meanwhile, like most developing countries, the primary pollutant in China is particulate matter rather than ozone, and public health literature has documented a more severe health impact of particulate matter (OECD 2016). If we look at the commuting choice as an individual trade-off between self-protection and altruism, the balance point is likely to shift towards the risk averse side due to the apparent larger private cost compared with the limited public benefit reducing one car on the road could provide. There is already some evidence which suggests more unwillingness to reduce driving for people with lung diseases who weigh the health impacts higher (Skov et al. 1991). Whether the health perception of pollution will cause normal citizens to adopt more frequently the motor vehicle for commuting under a heavy polluted scenario is thus a highly relevant yet largely understudied empirical question which Chapter 5 will try to approach.

Chapter 3

Theoretical Framework

Understanding the value of reducing air pollution matters for pollution regulation policy and risk management, yet synthesizing the quantification evidence from multifaceted impact domains requires a comprehensive theoretical framework. In this chapter, I will first present the schematic architecture of social cost of pollution accounting for avoidance behaviors, and then incorporate the relationships into existing economic models to facilitate optimal pollution policy derivation.

3.1 Social cost of air pollution

The estimation structure of social cost of air pollution usually follows the impact pathway approach, which calculates the economic costs of air pollution tracing from emissions, exposure, biophysical impacts and valuation of economic costs (OECD 2016). This methodology has been used in many policy contexts to provide empirical evidence. For example, previous studies have used the impact pathway approach to study the benefits of several directives and technology options aimed to improve air quality in the EU (European Commission 2013). And the US EPA has also evaluated the benefits of the Clean Air Act (DeMocker 2003) using this method.

A distinct feature of the structure I presented in Figure 3-1 is the integration of a behavioral layer where an individual's dynamic avoidance behaviors and its corresponding economic costs are also considered in the equilibrium. The new structure wishes to emphasize the fact that what public health and economic statistics can capture are the residual impacts after individuals' voluntary avoidance behaviors. Citizens already paid the avoidance toll to reduce adverse biophysical impacts. Ignoring the avoidance costs will underestimate the damage of pollution on the whole society, especially for the group of people who are health conscious and adopt abundant precautionary measures to reduce exposure. Learning from social cost of climate presented by (Diaz and Moore 2017), the social cost of pollution I formulated takes into account both the biophysical impacts with its corresponding productivity consequences (as the health and productivity outcomes discussed in the literature of Section 2.1) and the avoidance behaviors with its monetary and non-market costs (the emphasis for this research). I also add in policies in the framework. The mitigation policy will directly impact pollution drivers, while information policies like alerts and education campaigns will nudge avoidance behaviors. Both policies will reduce the health and economic damages of pollution, yet the avoidance costs should be taken into account when making the judgement of which policy is most efficient in achieving the goal.

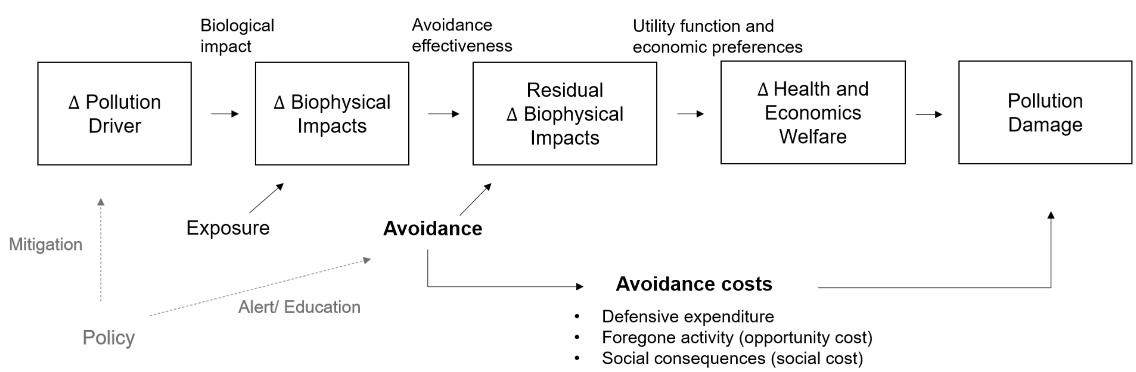


Figure 3-1: Schematic representation of air pollution social cost estimations.

Having the improved estimation structure not only fills in the gap of the neglected social cost, but also conveys an important message that the impacts of pollution on our human system is beyond the vulnerable groups (e.g., child and elderly) and occupations (e.g., outdoor low-skilled workers). The mass citizens need to spend extra money on defensive expenditure, reduce their engagement in welfare-enhancing outdoor leisure and physical activities. This creates economic, physiological and psychological burdens on individual citizens. Furthermore, in the urban system, personal avoidance behaviors can create social consequences. It is especially of relevance in transportation systems where urbanites are not only victims of pollution, but the emission generator themselves. This neglected dimension of social cost is projected to further increase when citizens are more informed about the micro-level pollution conditions and better educated about its corresponding health risk. And when the governments increasingly favor information policies to encourage voluntary avoidance behaviors.

3.2 Economic model with broader avoidance cost

Upon the social cost estimation structure, it is crucial for us to understand how the empirical evidence researchers document for each impact pathway can be organized to formulate the economic model of optimal environmental policy designs. The economic model I develop builds on the seminal model characterizing health as an investment goods (Grossman 1972), its derivation to examine environmental health (Graff Zivin and Neidell 2013), and the nascent work on the economics of climate change adaptation (Carleton et al. 2019).

For simplicity, health is modeled as a function of pollution level p and the avoidance behaviors taken $\mathbf{b}$, which is a vector K of endogenous variables $\mathbf{b} = \{b_1, ...b_k\}$ including all avoidance behavior choices available to individuals. Such as purchasing defensive equipment, reducing outdoor activities, etc. The health production function would be characterized as:

$$H = f(\mathbf{b}(p), p) \tag{3.1}$$

Which allows the pollution avoidance behaviors to enter the health function. And since the change in pollution level affects health outcomes through both the direct biophysical impacts and the behavioral adjustment, the health cost of air pollution by changing the received pollution level from p_1 to p_2 would thus be:

$$Health\ impacts = f(\mathbf{b}(p_2), p_2) - f(\mathbf{b}(p_1), p_1) \tag{3.2}$$

Formula 3.2 is the residual biophysical effect from the health dimension. A full measure of the economic damage of pollution must account not only for the net effect accounting for avoidance behavior adjustment, but also the cost of the behaviors themselves. Thus the total cost of health impacts tied with increased pollution level from p_1 to p_2 is:

$$Value\ of\ health\ impacts = \frac{\partial U}{\partial H}[f(\mathbf{b}(p_2, p_2)) - f(\mathbf{b}(p_1, p_1))]\frac{1}{\lambda} + [A(\mathbf{b}(p_2)) - A(\mathbf{b}(p_1))] \tag{3.3}$$

Where $\frac{\partial U}{\partial H}$ is the utility change with respect to the change in health, and $\frac{1}{\lambda}$ is the shadow price of utility change which can be obtained through individual utility maximization and lagranene theory (i.e., first order condition). If we simplify x to a numeraire good, $\frac{1}{\lambda}$ would simply take the form of $\frac{1}{\frac{\partial U}{\partial x}}$. From the formula we can see that if the costs of avoidance $A(\mathbf{b})$ were omitted from this calculation, we could underestimate the overall economic burden of pollution.

To have a more complete view of the pollution impacts beyond health, we can characterize the utility function of individuals U= U (X, L, H) to depend on health (H), consumption (X) and leisure (L). Letting I denote non-wage income, such as interest, dividends etc, and W denote wage. Since pollution will affect productivity, wage W will be characterized as a function of pollution as well which could be affected through reduced working time or reduced labor productivity: $W = g(\mathbf{b}(p), p)$. When individual maximize their utility given the budget constraints, the maximization problem can be expressed as:

$$max_{X,L,b}\Gamma = U(X, L, H) + \lambda[I + W - c_x X - h(b)b)] \tag{3.4}$$

Where h(b) denotes the pecuniary cost of avoidance behavior b. Solving the first order conditions will give us the shadow price of utility $\frac{1}{\lambda}$ as mentioned in the last paragraph. Under this framework, individual citizens will choose the avoidance investment to equalize the marginal cost of avoidance with the marginal benefit of health improvement. The optimal level of avoidance behavior individual chooses after the optimization would be denoted as $\mathbf{b}^*$.

Optimal regulation requires policy choices that balance the costs and benefits of regulation to maximize social welfare. Denoting the cost of pollution regulation as c_R, optimal pollution regulation occurs at the point where the marginal cost of regulation R is equal to the marginal benefit associated with reduced health and productivity loss, as well as the saved avoidance cost:

$$\begin{aligned}\frac{\partial P}{\partial R}c_R &= \frac{dW}{dP} + \frac{\partial U}{\partial H}\frac{dH}{dP}\frac{1}{\lambda} + \frac{\partial b}{\partial P}c_A \\ &= \underbrace{\frac{dg(\mathbf{b}(p),p)}{dP}}_{\text{productivity}} + \underbrace{\frac{\partial U}{\partial H}\frac{df(\mathbf{b}(p),p))}{dP}\frac{1}{\lambda}}_{\text{health welfare impacts}} + \underbrace{\frac{\partial b}{\partial P}(\sum_k \frac{\partial}{\partial b_k}[h(b^*) + u(b^*) + s(b^*)]])}_{\text{avoidance behavior costs}}\end{aligned} \tag{3.5}$$

Where the three main chunks of the formula represents the economic impact due to productivity changes, the welfare value of health impact, and the avoidance behavior changes. The key distinction between the formula 3.5 and conventional wisdom to calculate the benefit of pollution is the acknowledgement of the behavioral responses to pollution change $\frac{\partial b}{\partial P}$ and the quantification of broader welfare impacts of avoidance behaviors accounting for the pecuniary cost h(b*), utility cost u(b*)of foregone activities (opportunity cost), and the social cost of self-protection behaviors s(b*). The sum of these three types of avoidance costs are denoted as A(b*). To quantify the impacts of non-marginal change could simply build the integration of the marginal impacts. For example, the avoidance cost change given the budget constraint $h(b)b + xc(x) = I + W$. Then a pollution change from p_1 to p_2 would be characterized as:

$$A(b^*(p_2, I+Q)) - A(b^*(p_1, I+W)) = \int_{p_1}^{p_2} \frac{\partial[h(b^*) + U(b^*) + s(b^*)]}{\partial b}\frac{db^*}{dP}dP \tag{3.6}$$

In this thesis, I focus on the u(b*)and s(b*)dimensions which are rarely explored in existing research. Outdoor leisure activity would be the major part of foregone utility u(b*), and we can further formulate u(b*)as $\frac{\partial U}{\partial L}\frac{1}{\lambda}$: the welfare cost of leisure. In Chapter 4, I will quantify the impact of air pollution on avoidance behavior of reducing outdoor leisure activity measured by park visitation, and utilize the existing evidence of the utility value of leisure to quantify the opportunity cost. For the social cost of avoidance behavior s(b*), I focus on transportation behaviors, since it is the most typical urban activity likely to be affected by air pollution and at the same time imposes significant social consequences. In Chapter 5, I study how health perception of air pollution affects commuting mode choice. The characterization of s(b*)need large scale panel data covering the whole nation to quantify the feedback system between personal avoidance transportation behaviors to societal pollution rebound. I can only illuminate the importance of accounting for this unintended social impact based on the empirical evidence from a case study at this stage. But the detailed survey data allows me to look into the deterministic factors of behavioral changes, and uses information intervention to test out its potential impacts on sustainable transportation policies.

Chapter 4

Pollution and Outdoor Leisure Activity

When people reduce pollution exposure by canceling outdoor leisure activities, they have implicitly conveyed the message that the health costs of pollution exposure outweighs the utility they can get from outdoor leisure. As a result, the value of forgone outdoor leisure, reflects the lower bound of the part of pollution costs neglected from previous research. In this chapter, I focus on one of the most common outdoor leisure, park visitation. I empirically estimate the impacts of air pollution on park visitation, and take one-step further to make a back-of-envelope analysis of the corresponding opportunity costs of the foregone leisure activity.

4.1 Data

The primary data for our analysis come from three sources: mobile phone (MP) positioning data from Tencent's location-based service (`https://heat.qq.com`), weather data from national meteorological monitoring stations and air pollution data from national monitoring stations. All these data cover all cities in China for the whole year of 2017 and are on hourly resolution.

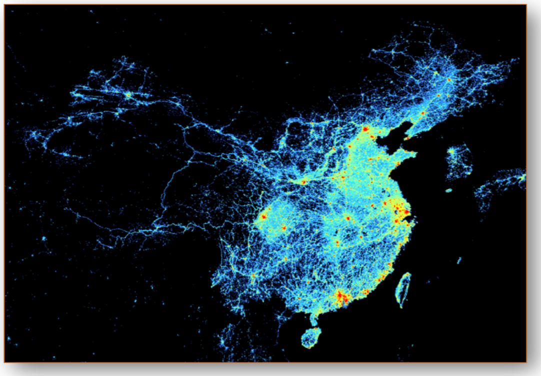
The mobile phone (MP) positioning data from Tencent contains the real-time geographic coordinates of more than 900 million users and more than 60 billion location requests per day all over China in 2017 (Figure 4-1a). In total, I have 10,499 parks all over China in the data set, comprehensively including 19 categories (Figure 4-1b). I calculate the number of location points lying within the boundary of each park on an hourly basis to formulate the panel data set of park visitation. Thus each park visitation unit represents one activity hour for a person.

I match the park-level hourly visitation index with hourly weather data from the closest station of the 2000 national meteorological monitoring stations. Weather variables comprehensively include temperature, precipitation, relative humidity, wind speed, wind direction, and air pressure. The cloud coverage data is collected from MERRA-2, M2T1NXRAD project (`https://disc.gsfc.nasa.gov/datasets/M2T1NXRAD_V5.12.4/summary`). Meanwhile, I collect hourly air pollution data including PM10, PM2.5, O3 and overall Air Quality Index (AQI) from 1500 pollution monitoring stations in China. Hourly air quality data has been published by the Ministry of Ecology and Environment of China on its official website since 2013. Compared with weather monitoring stations, pollution monitoring stations are more clustered in high population density areas which leave some parks without a station close enough to be representative (Figure 4-1c and 4-1d). As a result, I constructed the pollution level of each park through spatial interpolation applying the kriging spatial prediction method (Cressie 2015).

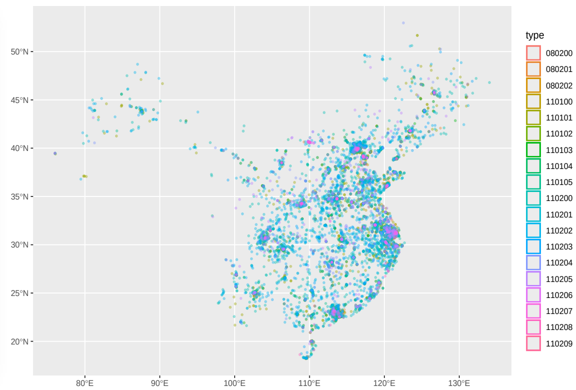
Table 4.1 displays the summary statistics for each of the variables used in estimation. On average, there are more than 4000 park visitation (i.e., person activity hour) per day. The average PM2.5 level all over China across the whole year is around 45 $\mu g/m^3$, about five times the US average PM2.5 level. The distribution of weather controls are also presented for references.

4.2 Empirical Strategy

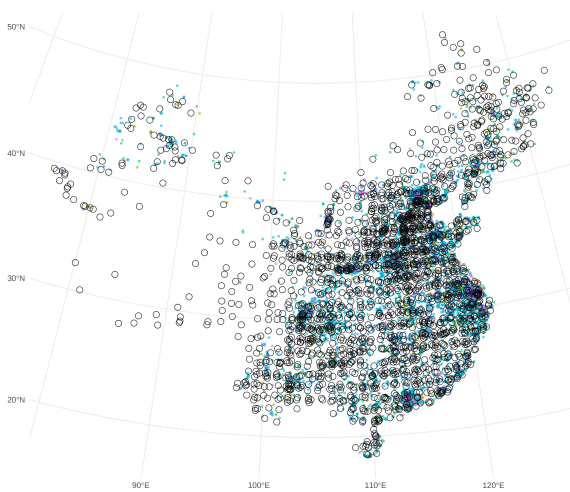
Careful quasi-experimental designs are required to obtain the reliable estimation of pollution cost. To investigate the impacts of local air pollution on park visitation, I



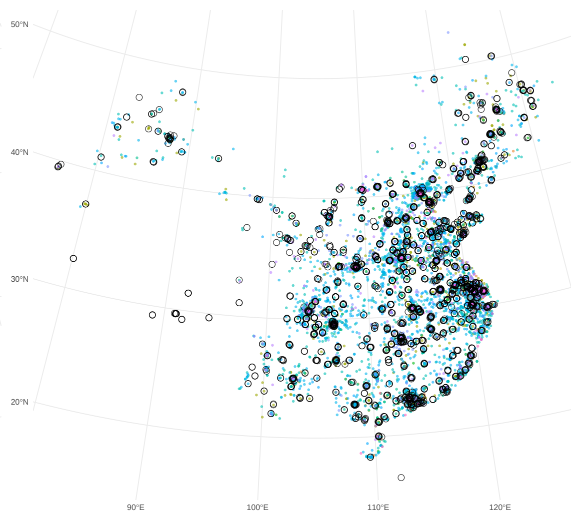
(a) Cell-phone location data from Tencent



(b) Park distribution by categories



(c) Meteorology monitoring stations



(d) Air pollution monitoring stations

Figure 4-1: Display of core data sets.

model the impacts of local pollution (i.e., PM2.5) through a fixed-effect model:

$$log(Y_{ict} + 1) = \beta_{PM} PM25_{ict} + X_{ict}\gamma + \delta_i + \theta_{dow} + \mu_{ct} + \varepsilon_{ict} \tag{4.1}$$

Where i indexes park, c indexes the city the park falls in, t indexes time which is detailed into an hourly level. The outcome variable of interest Y_{ict} is the visitation number for park i in city c on date t. Only day-time between 6 AM to 9 PM is considered since there should be limited activity at night yet the pollution level might still be high. I exclude the small parks with daily visitation less than 1000, and add one to ensure non-negative when taking log transformation. $PM25_{ict}$ is the average PM2.5

Table 4.1: Summary Statistics of Data.

Variables	Mean	SD	Min	Max	N
Park visitation					
Average whole nation	4394.92	9336.02	6	1,001,180	2,483,865
(northern cities)	3918.576	6462.66	6	347,600	959,647
(southern cities)	4698.29	10778.8	6	1,001,180	1,513,633
Pollution					
AQI	72.01	45.84	1	500	2,476,983
PM2.5 (g/m^3)	44.68	38.1	1.33	496	2,476,871
PM2.5 (IV)	1.6	1.58	0	22.52	2,436,116
Weather					
Temperature ($^{\circ}C$)	17.68	10.17	-35.61	43.48	2,481,672
Wind Speed (m/s)	2.92	1.26	0	21.39	2,481,668
Relative Humidity (%)	64.77	19.29	1.38	100	2,481,672
Cloud coverage (%)	49.44	30.96	0	100	2,483,865
Precipitation (mm)	2	7.95	0	289.7	2,483,865

Note: All variables are summarized per park per day level.

level at park i in city c on date t. Control variable X_{ict} includes other weather variables (i.e., temperature, temperature2, precipitation, wind speed, humidity, air pressure, and cloud coverage) and a dummy variable indicating holidays. Taking advantage of the panel data structure, we include park fixed effect (δ_i), day-of-week fixed effect (θ_{dow}), and city by month fixed effects (μ_{ct}). This setting allows me to control for the unobservable spatial, cyclical within-week, and locally seasonal variations in pollution and park visitation, and exploit the exogenous daily fluctuations in temperature across the same park within the same hour overtime to identify the causal effect. Including a series of high-dimensional fixed effects can largely address the endogeneity problem caused by omitted variables. The standard errors are clustered at the park level to non-parametrically adjust for arbitrary within-unit autocorrelation in the disturbance term ε_{ict}.

Since local air pollution is endogenous to local activities. For example, as more people drive to the parks, the emissions around the park will increase, causing a positive correlation between pollution and park visitation. To avoid this bias, I employ the imported pollution from upwind cities as an instrument for the air pollution level of the city of interest. Since the pollutant transmission process is not instant, we use daily and city level pollution instead of hourly and park level air pollution to proceed the IV estimates. Specifically, we instrument the $PM25_{ct}$ variable in equation 4.1 by $Pollution^{up}_{ct}$ which is calculated by the following formula:

$$\begin{aligned} Pollution^{up}_{ct} &= \sum_j max(\cos\theta_{cjt}, 0) \times \frac{Pollution_{jt}}{Distance_{cj}} \\ 60km &< Distance_{cj} < 300km \end{aligned} \tag{4.2}$$

The imported pollution of city c is obtained through all cities j which have distance to city c within the range between 60 km to 300 km. The lower bound of distance is set to circumvent the autocorrelation among closed cities, while the upper limit is set to exclude the cities so far away which cannot be reached by wind. We add a cosine function applying to the angle between wind direction and the line connecting city c with city j to ensure that only upwind cities are considered. Similar methods are applied by (Bayer, Keohane, and Timmins 2009; Keiser, Lade, and Rudik 2018; Zheng et al. 2019). Large and significant first stage results of the IV regressions are presented in the main regression table to consolidate that weak instrument bias is not a concern in our setting.

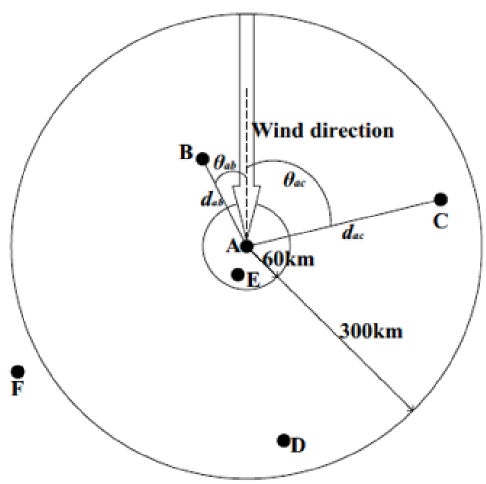


Figure 4-2: PM2.5 instrument construction illustrations.

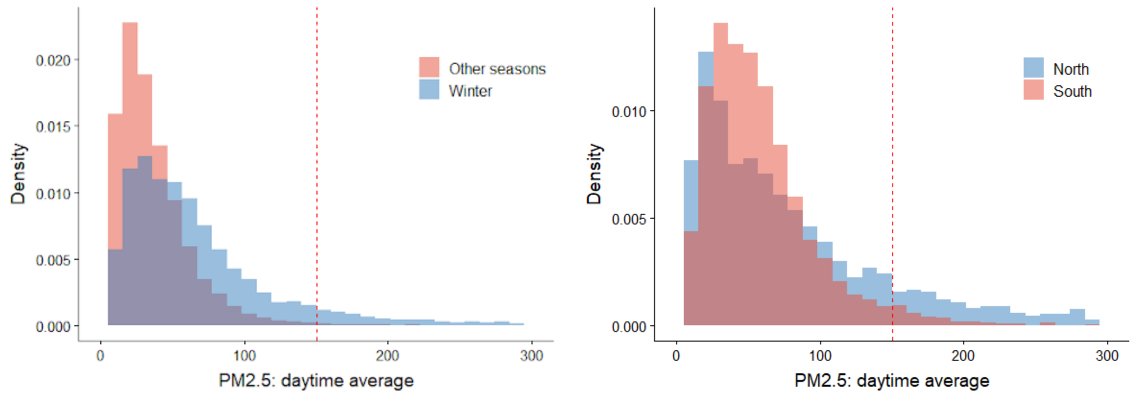
4.3 Results

In the results section, I will first present a series of specifications to demonstrate the impacts of pollution on park visitation. I then explore the temporal dynamic of inter-day activity substitution. Third, I investigate the dose response function to map the non-linear relationship between pollution and activity. Fourth, I compare the coefficient estimates by different park types, by cities with different income levels, and by time to explore the heterogeneity. Finally, I make a back-of-envelope analysis of the economic cost of the foregone leisure induced by heavy air pollution taking into account the contingent valuation of outdoor leisure by Chinese citizens.

4.3.1 Main effect

Due to winter heating and more adverse meteorological conditions such as frequent temperature inversion formation, most of the heavy pollution sequences take place in winter (Figure 4-3a). Given the data pattern, I will mainly focus on the winter period (from December to February) to investigate how air pollution impedes outdoor leisure activity in China. The pollution situation gets worse as we pass across Huai River to the northern part of China (Figure 4-3b), since the central heating is implemented in northern China, which has more than 83% generated by coal burning in 2016 (Myllyvirta and Shen 2018).

Table 4.2 displays the results from both fixed effect regressions and instrumental variable models. All regressions control for weather (i.e., temperature, precipitation, wind speed, humidity, cloud coverage, air pressure), common seasonal factors by cities (city-month fixed effects), and unobserved factors specific to each park (park fixed effects). Column 1 and 4 of Table 4.2 present the fixed-effects estimate of the response of daily log visitation to daytime average PM2.5, which is smaller than the IV specification (Column 2 and 5) using PM2.5 concentration in upwind cities. Since local PM2.5 concentration is endogenous, i.e., park visitation will reversely increase pollution if people drive to the parks, we rely on the IV specification as our preferred empirical strategy. Column 3 and 6 present the first stage of IV estimation, and we



(a) Season (b) Region

Figure 4-3: Pollution distribution by seasons and regions.
(a) PM2.5 concentration distribution in winter and other seasons all over China. (b) Pollution distribution of northern and southern China in winter.
Note: the vertical dashed line displays 150 $\mu g/m^3$, which is the threshold for heavy pollution of PM2.5 in China.

can see that PM2.5 concentration in upwind cities is a good predictor of local air pollution thus is valid to provide the exogenous shocks in local pollution which we are looking for. The parameters estimated in Column 2 and 5 of Table 4.2 suggests that a 10 $\mu g/m^3$ increase in PM2.5 is associated with about 0.2% decrease in park visitation on average nationwide. When PM2.5 level is above 150 $\mu g/m^3$, that is, lying in the heavy or severe pollution range defined by Chinese Ministry of Ecology and Environment, daily park visitation falls by 4.8% on average.

Our primary estimates suggest that daily increases in PM2.5 do have a small negative effect on outdoor leisure activity, yet there are stark differences across regions. Table 4.3 displays the IV estimates by regions (i.e., northern or southern China). The results indicate that only citizens in northern China are adjusting outdoor leisure activities in response to air pollution. Even under heavy PM2.5 conditions, people in southern China still remain their activity patterns as usual. These differences could be attributed to the differences in living style, yet more likely, to the differences in pollution awareness. Higher frequency of heavily polluted events in northern cities increases people's awareness of air pollution problems and behaviors like checking the pollution index and alerts more oftenly. This is consistent with a survey research on

Table 4.2: Impacts of PM2.5 on park visitation in winter.

	Marginal contribution			Heavy PM2.5 (> 150 g/m^3)		
	(1) FE (log visit)	(2) IV (log visit)	(3) FS (PM2.5)	(4) FE (log visit)	(5) IV (log visit)	(6) FS (heavy PM2.5)
PM2.5	-0.0001***	-0.0002***		-0.0118***	-0.0475***	
	(0.00001)	(0.00002)		(0.0015)	(0.0063)	
IV_PM2.5			11.3154***			0.0396***
			(0.1139)			(0.0006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
IV	No	Yes		No	Yes	
Adjusted R2	0.8962	0.8956	0.579	0.8966	0.8958	0.3363
N	612,679	603,142	603,142	617,061	604,910	604,910

Note: Control variables include daily weather conditions (i.e., temperature, the square of temperature, precipitation, wind speed, relative humidity, air pressure, and cloud coverage) and holiday dummy. Fixed effects include day-of-week FE, park FE and city-by-month FE. Standard errors cluster within parks.
** p<0.01; ** p<0.05; * p<0.1

tourism in Hong Kong finding that Asian tourists appear to be more conscious of air quality than Western vitistors (C. Cheung and Law 2001).

4.3.2 Temporal lag

Previous results suggest that park visitation responds contemporaneously to changes in PM2.5 pollution level as people having the health awareness to make avoidance behaviors. Yet from the behavioral perspective, the responses to air pollution may be more dynamic. For example, the temporary fall in outdoor activities on a given day caused by air pollution could be compensated for by an increase in activities in the subsequent clean days. However, a polluted day could also have enduring negative impacts on the activities in the following days if people fail to update the pollution situation in time or fall into an inertia to stay home on the couch. Which of these two effects dominates is an empirical question.

To clearly understand the temporal dynamic of pollution impacts, I next test for the lagged effects of air pollution. Since the pollution levels of consecutive days are

Table 4.3: Impacts of PM2.5 on park visitation by regions.

	Marginal contribution		Heavy PM2.5 (> 150 g/m^3)	
	(1) North	(2) South	(3) North	(4) South
PM2.5	-0.0004***	0.00004	-0.0987***	0.0183
	(0.00004)	(0.00003)	(0.0083)	(0.0135)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
IV	Yes	Yes	Yes	Yes
Adjusted R2	0.8867	0.8998	0.8859	0.9001
N	235,131	368,011	235,189	369,721

Note: Control variables include daily weather conditions (i.e., temperature, the square of temperature, precipitation, wind speed, relative humidity, air pressure, and cloud coverage) and holiday dummy. Fixed effects include day-of-week FE, park FE and city-by-month FE. Standard errors cluster within parks.
** p<0.01; ** p<0.05; * p<0.1

highly correlated, simply including the lagged variables in regression can cause severe multicollinearity problems. The inconsistency caused by including lagged variables are especially problematic when unobserved individual effects are controlled and the differences residuals are used for estimation (Nickell 1981). In order to address this issue, a cubic distributed lag function is applied here to estimate the temporal lagged effect of pollution. The model assumes that the effect over time is a smooth cubic function, which is more suitable for the case at hand. Similar estimation strategy was adopted by (Burkhardt et al. 2019) to study the lagged impact of air pollution on crime. By including a cubic lag function of three-day lags of PM2.5 in the primary model, I find that same day PM2.5 has the largest impacts which is slightly lower than the impact captured by primary specification due to serial correlation in air pollution (Figure 4-4). The impact of 1 day lag is about one half the contemporaneous effect, and the negative coefficient remains to be significantly negative even till 3-day lags. It seems that instead of making up for the loss in outdoor activities in previous pollution sequences, people have the inertia to stay home even when the pollution level declines, which further magnifies the negative impacts pollution will have on outdoor leisure.

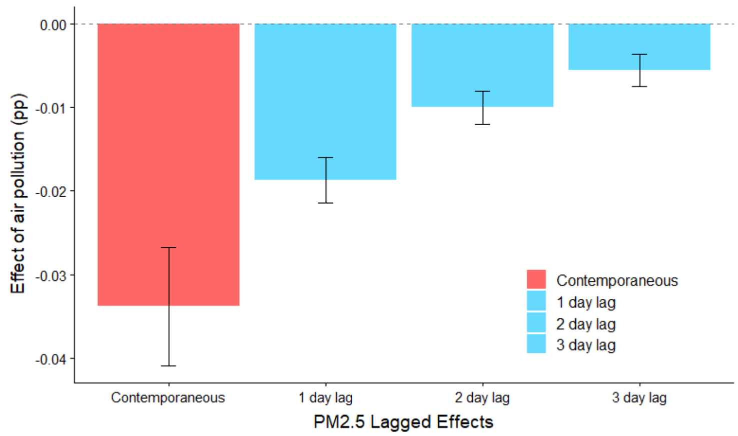
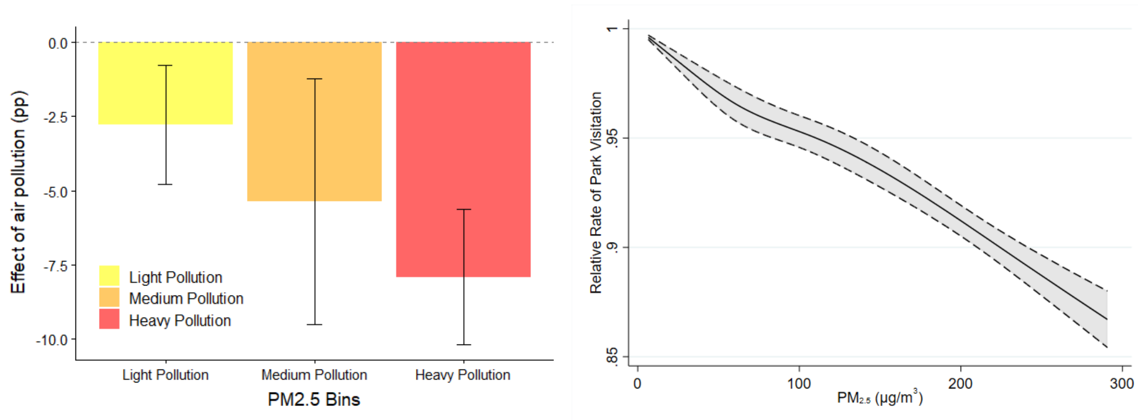


Figure 4-4: Lagged marginal effects.
Note: the y axis indicates how 1 $\mu g/m^3$ PM2.5 increase affect park visitation.

4.3.3 Dose response

Since the impacts of pollution might not be linear, I apply two strategies to capture the nonlinear effects. First, I rely on non-parametric binned regressions which decompose PM2.5 level into categories according to the classification of Technical Regulation on Ambient Air Quality Index (HJ633-2012) of China. Compared with Excellent or Good pollution level (i.e., PM2.5 < 75 $\mu g/m^3$), park visitation drops by 2.8%, 5.4% and 7.9% during light (PM2.5: 75 115 $\mu g/m^3$), medium (PM2.5: 115 150 $\mu g/m^3$) and heavy pollution (PM2.5$>$ 150$\mu g/m^3$) respectively (Figure 4-5a).

Second, I try to model the dose response functions of pollution on park activity in a flexible format, thus I replace the PM2.5 level with a restricted cubic spline with knots at the 25th, 50th, 75th and 95th percentiles (equivalent to PM2.5 level at 30, 61, 109, 232 $\mu g/m^3$ respectively). In this way, instead of binning into categories, I separately fit the regression curves with a polynomial of degree 3 between the knots and require that the individual curves be defined in such a way that they meet at the knots to support "smooth" joins. As shown in Figure 4-5b, the negative impacts of PM2.5 on park visitation continuous to increase as the pollution level moves away from 0 in an approximate linear format, with the slope only slightly larger after 100 $\mu g/m^3$.



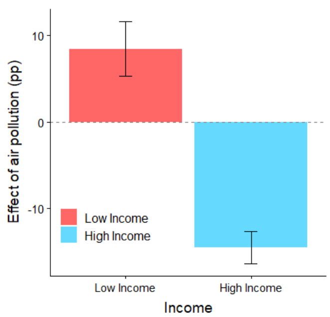
(a) Binned regression (b) Restricted cubic spline

Figure 4-5: Dose response function of PM2.5 on park visitation in northern China.

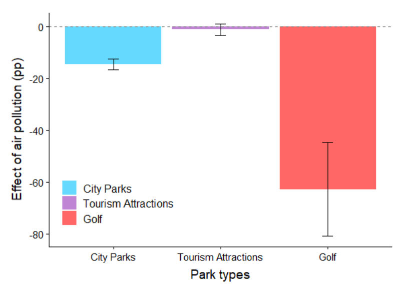
4.3.4 Heterogeneous effects

The average treatment effect identified is likely to mask important differences in the sensitivity across diverse populations. To inform environmental policies, researchers must produce rigorous and balanced evidence not only of the breadth and magnitude of the impacts, but also of how they are distributed across regions and time. To examine the potential distributive impacts of air pollution on park activities in northern China, I separately estimate the impacts for cities with high and low income (delineated by the medium value of per capita income for all northern cities) with the same instrumental variable and two stage least square estimation strategy as the main model. There are sizable differences across cities. The results (Figure 4-6a) show that only people in northern cities with high average income are actively avoiding exposure by reducing outdoor leisure in response to air pollution. This depicts a health awareness inequality across income groups which might induce people in poorer regions to be more exposed to air pollution. I further consolidate the income differences in avoidance behaviors by mapping the impacts of pollution on golf court visitation, an activity type which is mostly adopted by the urban rich. The result shows that golf activities are indeed much more affected (around -60%, nearly six times more responsive) compared with other parks (Figure 4-6b).

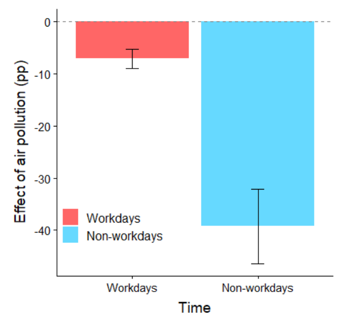
Taking advantage of the broad coverage of our big data, I not only tested the differential impacts across regions, but also how different activity types (i.e., different park destinations at different times) are unevenly impacted by pollution within the same city. From the spatial dimension, I find that tourism attraction is not as pollution sensitive compared as normal city parks (Figure 4-6b), probably because tourists have their plans for vacation which will not be easily modified by pollution once they arrive in the new city. Similar evidence that tourists are less affected has been documented in the impacts of pollution on broader urban activities in China (Yan et al. 2019). Further results for temporal heterogeneity depict that leisure activities on weekends and holidays are much more affected by pollution than daily recreation and exercising activities on workdays (Figure 4-6c).



(a) By city incomes



(b) By park types



(c) By time

Figure 4-6: Heterogeneous impacts of heavy PM2.5 pollution on park visitation.

4.3.5 Economic Valuation

Finally, we can put the estimated results into context by generating some back of the envelope estimates of the value of foregone leisure to support the cost-benefit analysis for policy designs. In the previous section, I show that heavy PM2.5 pollution in northern cities decreases park visitation activities by 9.87% in winter per city per day (no significant effect for southern cities). Since the park activity is measured by the number of cell-phone location requests within each park on an hourly basis, each unit represents one person activity hour. In northern China, the average park activity hours on the not heavily polluted days is 3,356 (95% CI: 3,142, 3,570) across all parks in winter. This translates into 331 (95% CI: 310, 352) less park activity hours per day per park, or 0.88 million (95% CI: 0.82 million, 0.94 million) less park activity hours per day across the 2,658 parks in northern cities in our dataset because of the heavy air pollution.

To understand the economic implications, studies in North America usually refer to the Recreational Use Values Database which was published by Oregon State University, summarizing the consumer surplus (non-market value) derived from different outdoor recreational activities obtained through 421 economic valuation studies (such as (Chan and Wichman 2017)) in $ per person per activity day. Yet the studies for China is very limited. I source my economic valuation data from a meta-analysis study (Wang et al. 2013), in which the authors collected literature by searching the Chinese National Knowledge Infrastructure (CNKI) database and use the benefit transfer model based on meta-analysis to construct the valuation index. Across their results, the valuation of activities likely to take place in parks (such as hiking and sightseeing) is $53.73 (in 2005 USD) per person per activity day, which is $71.17 in 2020 USD.

Using these values and conservatively assuming that people spent 3 hours in park per day (Since hour data is at person-hour unit rather than person-day), I estimate that the costs of heavy pollution events on park visitation in China is $20.8 million [1] (CI: $19.5 million, $22.3 million) in 2020 USD per day across all cities in northern China. This data can also be used to understand the potential social impacts of Chinese national mitigation strategies to meet the air pollution targets. According to the "Defend the Blue Sky Three Year Action Plan" (《打赢蓝天保卫战三年行动计划》), China has established the goal towards 2020, aiming at reducing the heavy and severe polluted days by 25% compared with 2015. The heavy polluted days are predominantly driven by the IAQI index of PM2.5. By collecting data for all cities in 2015, I calculate that the average PM2.5 heavy and above pollution sequences in northern China is 16 days per year. Improving by 25% would translate into an improvement of at least 4 days per year. That translates into dollar value indicating that the policy will have $83.5 million (CI: $77.8 million, $89.2 million)

[1] (0.88 million park activity hour reduction/ day * $71.17 welfare loss/ day) / (3 hours/day)

benefit per year in removing the outdoor leisure activity constraints created by air pollution in northern China. If accounting for the park tickets of many parks and the benefits from reducing the medium and light polluted days, the total benefits of pollution mitigation policy would be even higher. These costs demonstrate real additional benefits of reducing pollution which will not be captured in the mortality and morbidity data.

This value is much smaller than the estimation from the World Bank based on VSL and labor output, which estimates the air pollution cost in 2013 for China was about 1,634 billion USD (Bank, World Bank, and Institute for Health Metrics and Evaluation 2016). However, these two estimations are not comparable since I only measure one typical outdoor leisure activity and only look at the heavy polluted days which has direct linkage to the environmental policy documents of China to deliver quantifiable benefits of mitigation policies. The World Bank, instead, measures the aggregated impacts of all days above WHO standard (i.e., 10 $\mu g/m^3$) and attributes all the welfare value bundled with the life expectancy loss to the costs of pollution. Whenever things come to death, the value is huge. However, valuing human life is usually controversial and makes the estimation biased towards a limited proportion of vulnerable people. A more comparable research would be a recent paper investigating the defensive expenditure in China during the heavily polluted sequences (J. Zhang and Mu 2018). It quantifies the total saving for the society on defensive expenditure of facemask given pollution improvement would be 187 million USD. The foregone leisure cost from park visitation is on the same magnitude as the monetary expenditure of defensive devices. And as people become more educated about the pollution impacts, both costs are expected to increase, though the cost of pollution measured by mortality, morbidity, and productivity might be decreasing with more avoidance behaviors.

4.4 Discussion and Policy Implications

The leisure cost of pollution avoidance presented in this chapter sheds new light on the value of air pollution mitigation policies. It illuminates a part of opportunity cost, which has a wide impact beyond the health vulnerable groups, yet has not been captured in the mortality, morbidity or economic data researchers are able to rely on for empirical evaluation. When individuals make the choice to stay home and sacrifice the leisure activities they can possibly enjoy outdoors, the behavior itself reveals their trade-offs between the pollution risk and welfare gained in leisure. As a result, the foregone benefits of leisure can be viewed as a private opportunity cost to create better "personal air quality", and should be viewed as part of the pollution cost. To my knowledge, this is the first paper to comprehensively evaluate the welfare cost of foregone leisure caused by pollution using a large scale objective data set covering different types of parks. And the first paper tries to quantify the non-market cost of pollution avoidance behavior in a developing country.

The preferred model estimates that heavy PM2.5 pollution in China leads to a 5% decrease in park visitation on average across all parks all over China in 2017 winter. Only northern cities of China, where pollution problem is more severe, have shown a significant leisure reduction, with about 10% decrease in response to pollution. In contrast to inter-day substitutions to compensate for the lost activity, I document that the impact of pollution can last more than 3 days by creating an inertia for people to go out. Furthermore, I estimate the dose response function of pollution on park visitation, and find a nearly linear decrease in activity as pollution increases, suggesting a continuous impact of pollution on days well below the heavy pollution threshold. The avoidance behavior in reducing outdoor leisure is more concentrated in higher income regions, has higher sensitivity for daily activities taking place at normal city parks than tourism attractions, and having large impacts for non-working days. I estimate that heavy air pollution events in northern China creates a welfare cost of $334 million per year. And thus the 25% reduction of heavy and severe polluted days by 2020 promoted by China can have the benefit in leisure for at least 83.5 million

(CI: \$77.8 million, \$89.2 million) per year.

Quantifying and communicating the opportunity cost of foregone urban activities can instill the sense of relevance of the pollution impacts to the larger population beyond vulnerable groups. It conveys the message that air pollution is not simply a health invader, but is forcing the mass urbanites to sacrifice their quality of life which most urban policies are striving to improve. However, the estimations used in this chapter still have some limitations. First, these are lower bound results since I only estimate the impacts of the heavily polluted days, which have the largest impacts on leisure activities and can be reflected in policy targets to make projections. However, people start to respond in even less polluted scenarios according to the dose response function presented in the result section. And even for people who still go to the park, the experience satisfaction might be lower due to lower visibility which cannot be captured in my evaluation. Second, I only focus on northern cities for the valuation since there lacks the empirical evidence to show that southern cities are responsive. This might mask the impacts on particular cities or on particular groups of people in the south who have higher pollution awareness. Third, there lacks a reliable leisure value dataset for developing countries like China, thus more research in non-market valuation is required to have a more accurate estimation of social cost. The improvement in the advancement in non-market valuation in developing countries can also allow for more papers to investigate other types of leisure activities potentially sacrificed due to air pollution.

Chapter 5

Pollution and Commuting Behavior

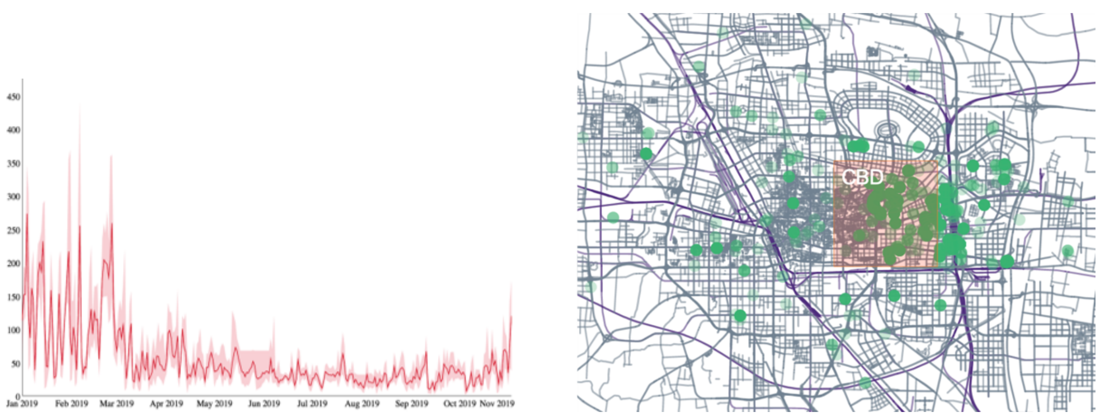
Beyond leisure activity, other human behaviors such as mobility choice will be impacted by air pollution as well. In this chapter, I focus on the impact of pollution on commuting behaviors relying on a large scale survey in Zhengzhou, China. Unlike leisure activities, commuting trips are defined by home-job locations and are constrained by the availability of transportation alternatives. I designed and conducted a sequential randomized controlled trial (RCT) with a team from MIT Sustainable Urbanization Lab (SUL) to explore the avoidance behaviors reflected in commuting choices. I model the decision-making mechanisms as a function of objective exposure risk and personal characteristics. And use hypothetical scenarios to investigate the implications of pollution avoidance for transportation policies.

5.1 Study context and pollution monitoring

The study takes place at Zhengzhou, the capital city of Henan province, China. The seasonal variation of air pollution in Zhengzhou is huge, with winter heating leading to a substantial increase in air pollution (Figure 5-1a). In about three months in a year, the average PM2.5 level is above 100 $\mu g/m^3$.

The Zhengzhou local government has made great efforts to combat air pollution over the past years. First, Zhengzhou has plate-based driving restrictions, forbidding private cars to circulate one day per week on weekdays from 7 AM to 9 PM. Since

2017. This restriction was strengthened in December due to year-end air quality performance evaluation. Instead of restricting two last digits for each day, the restriction is based on an even/odd number in December, meaning half of the cars are forbidden to drive on each workday. Second, Zhengzhou is planning to expand the subway network from 5 lines to 21 lines (Wikipedia contributors 2019) and is expanding their BRT system all over the city. Third, though having the dockless bike-sharing systems run by private companies, the Zhengzhou government also sponsors dock-based public bike systems to offer free bike services for local residents in order to solve the last mile problem and encourage active commuting. Recently, in the new "Green Travel Action Plan (2019-2022)" (《绿色出行行动计划（2019—2022年）》) published by Zhengzhou government describing the strategies in the recent three years to promote green travel, more emphasis on encouraging green travel is laid on cultivating green travel habits and culture than the command and control policies. The severe air pollution problem accompanied with the extensive investments in public policies and public infrastructure to promote green traveling makes Zhengzhou the ideal context to study the relationship between air pollution and sustainable commuting behaviors, as well as how these interactions will potentially impact local green transportation policies.



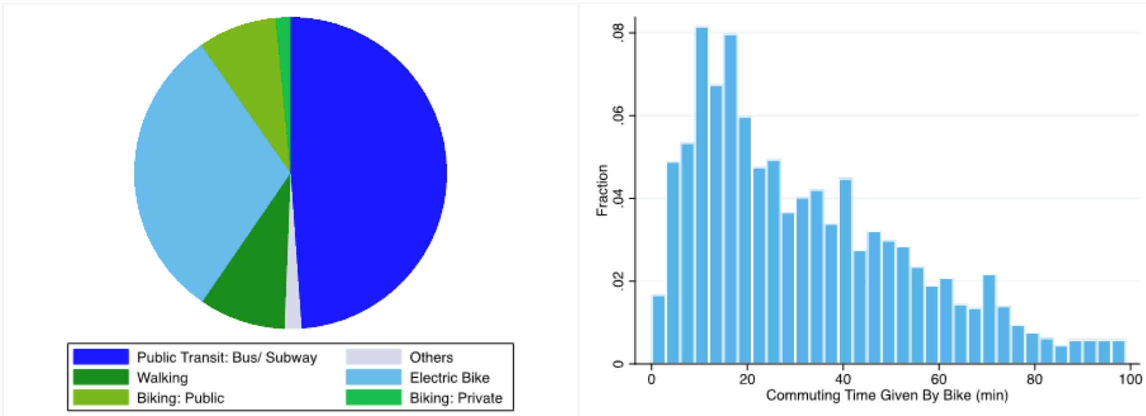
(a) PM2.5 trend (b) Job Location

Figure 5-1: Pollution context and sample distribution.

The survey was conducted in July, 2019. Our major target group is non-vehicle commuters whose job location is around Zhengzhou CBD area, with a total 2285 valid participants. Figure 5-1b shows the spatial distribution of the job locations of our respondents. We focus on non-vehicle users because those commuters are more affected by air pollution, and also because we want to partially avoid the experimenter demand effect since vehicle users have a strong incentive to under report driving for social image concerns. Among all participants, approximately 20% of people use active modes (i.e., biking or walking) for daily commuting (Figure 10 (a)) and average home-job walking distance is 7.92 km (Figure 10 (b) for distance distribution).

To enhance the representativeness of survey participants to local citizens, we conducted stratified randomization based on employment sectors to diversify the sectoral coverage and to approximate the distribution with local census data. To ensure survey quality, we contacted dozens of local companies around CBD and recruited 60 local college graduate students to assist us implementing one-on-one surveys by visiting those local companies (Fig B-1). All those volunteer surveyors have taken our training courses and were supervised by one group leader from our core research team on the ground. The information interventions are presented using a standard template designed by our team, so that every participant receives information with the same displaying format and wordings. Researchers informed the respondents that they will not peer at their answers, and respondents committed to telling the truth at the beginning of the survey. If any respondents answered questions too fast or appeared to be very impatient, the student will inform the group leader to record the questionnaire ID so that we can delete those answers from the server in real time.

Air pollution level varied significantly across transportation modes (Cepeda et al. 2017). In order to understand the micro-level pollution exposure during commuting and provide individual tailored exposure information, our research team rented four professional air pollution monitoring equipment of Fairsense to conduct two-weeks' on-site monitoring. We chose three representative commuting routes around Zhengzhou New District CBD (Fig B-2), and along each route, peak-hour air pollution concentration in different transportation environments (i.e., bus, subway, car, bike/ walk) were monitored two times per day. The final pollution levels were translated into exposure indices per commuted mode inputting inhalation rate and individual tailored



(a) Commuting modes

(b) Home-job walking distance

Figure 5-2: Commuting modes and home-job distance of the survey participants.

commuting time for each transportation mode suggested by (Cepeda et al. 2017) (Table A.1). To make the index easily accessible for the local residents, we translated the exposure amount into smoking index referring to the epidemiological findings that "one cigarette per day is the rough equivalent of a PM2.5 level of 22 $\mu g/m^3$" ("Air Pollution and Cigarette Equivalence - Berkeley Earth", 2015), and adjusting by pollution concentration and exposure time. Cigarettes equivalent for monthly commuting by modes are displayed in bar charts for pollution exposure information intervention (Fig B-3). The exposure magnitude and relative exposure by modes are displayed in Fig B-4a.

5.2 Survey designs

Questionnaires are designed and collected through Qualtrics. Survey takes 15-20 minutes, including an opening video introducing the iPad interface of electronic questionnaire, informed consent, four rounds of commuting choices questions, two information intervention, and some socio-demographics habits and preferences characterization questions (Figure 10). All respondents are asked to make four rounds of commuting choices. Each round of choices is bundled with three questions: their primary mode of commuting, whether they are willing to switch to active commuting (i.e., biking or walking) given a reasonable amount of subsidy, and what is the minimum amount of subsidy they are willing to accept for the switch. People who already choose active commuting in the first question will not be asked follow-up questions.

Among the four rounds of choices, the first two rounds before the dash line are under current pollution level (i.e., clean day scenario, since we conducted the survey in July when PM2.5 concentration is less than 40 $\mu g/m^3$, while the second two rounds are under hypothetical polluted scenario (i.e., with PM2.5 117 $\mu g/m^3$ [1], the average of the most polluted month in Zhengzhou 2018). A picture of Zhengzhou under this pollution scenario is displayed in the survey (Fig B-4). We use the answers to commuting behavior of Choice 1 to Choice 4 to get people's baseline preference on a clean day, updated preference on a clean day after first information intervention (O1 or H, illustrated in the next paragraph), preference under pollution scenario, and the updated preference under pollution scenario given the second information treatment (O2 or P) respectively.

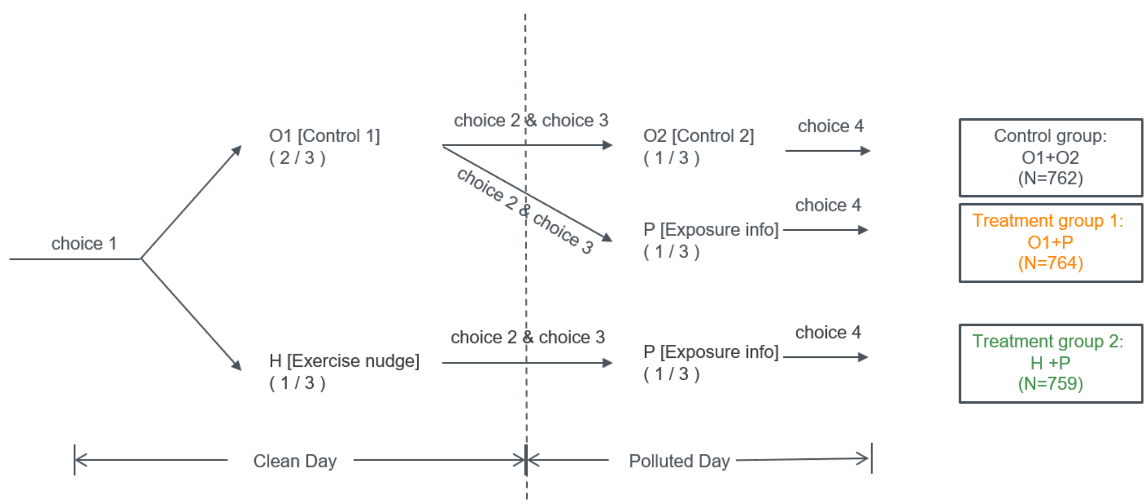


Figure 5-3: Survey structure and group decompositions.

Based on the respondents' job and home location, we formulate all information treatment in an individual-tailored format to enhance effectiveness. Respondents are randomly assigned into three groups, getting an information bundle of (O1 + O2), (O1+P), (H+P) respectively (Figure 5-3). The exercise nudge intervention (H)

[1]We used the monthly average PM2.5 pollution level of the most polluted month in Zhengzhou, 2018. Due to the winter heating and adverse climate conditions in winter, Zhengzhou has about three months having approximate this pollution level every year.

shows the counterfactual time and cost during their commuting by different modes and highlights exercise benefits of active commuting and quantifies the tailored calorie consumption and expected weight loss if doing active commuting for a month. The corresponding control information (O1) only shows time and cost by modes. For the treatment 2 in polluted scenario, individual tailored pollution exposure by modes and corresponding cigarettes equivalent were presented for information (P) in the format displayed in Fig B-3, while irrelevant information was displayed for the control (O2). Comparisons between treatment and control groups at different rounds enable us to quantify the impacts of information controlling for survey round fixed effects. Due to the large sample and stratified randomization designs, socio-demographics, health condition and personal habits, as well as economic preferences are balanced across groups (Table 5.1).

5.3 Results

In this section, I will answer four primary research questions relying on the survey of 2,258 non-vehicle commuters with a series of controlled experimental designs. First, does air pollution alter the commuting mode choices due to health concerns? Second, are people's behavioral trade-offs between health benefit and cost for active commuting in pollution consistent with scientific findings? Third, are there changes on the intensive margin (i.e., people whose actual commuting modes unchanged yet unobserved perception change) and what are the implications for transportation policies? Fourth, what are the underlying determinants of the decision-making process? This research differs from the previous empirical studies by modelling a non-homogeneous response elasticity as a function of real exposure risk and rich personal characteristics to depict behavioral rationality, and sheds light on the potential social consequences of pollution avoidance behaviors.

Table 5.1: Descriptive Statistics of Survey.

	O1 + O2 (N = 762)		O1 + P (N = 764)		H + P (N = 759)		All (N= 2285)	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Socio-Demographics								
Gender, 1=Female	0.559	0.497	0.559	0.497	0.539	0.499	0.552	0.497
Age	29.676	7.082	30.131	7.229	29.87	7.315	29.893	7.209
Marital Status, 1=Married	0.488	0.5	0.484	0.5	0.484	0.5	0.485	0.5
Household size								
3 or less	0.424	0.494	0.424	0.495	0.415	0.493	0.421	0.494
4 or 5	0.446	0.497	0.441	0.497	0.476	0.5	0.454	0.498
6 or more	0.129	0.335	0.135	0.342	0.107	0.309	0.123	0.329
Household income								
Less than 50 thousand RMB	0.186	0.39	0.179	0.384	0.173	0.378	0.179	0.384
50-150 thousand RMB	0.543	0.498	0.529	0.499	0.528	0.5	0.533	0.499
150-300 thousand RMB	0.211	0.408	0.233	0.423	0.24	0.427	0.228	0.42
More than 300 thousand RMB	0.05	0.218	0.052	0.223	0.05	0.218	0.051	0.22
Education								
High school or lower	0.121	0.326	0.105	0.306	0.121	0.327	0.116	0.32
Some college	0.273	0.446	0.266	0.442	0.281	0.45	0.273	0.446
BA degree	0.508	0.5	0.495	0.5	0.472	0.5	0.491	0.5
Master degree or higher	0.093	0.291	0.13	0.336	0.117	0.322	0.113	0.317
Health and habits								
Health condition								
Not so good	0.22	0.415	0.186	0.389	0.182	0.386	0.196	0.397
Good	0.619	0.486	0.628	0.484	0.631	0.483	0.626	0.484
Excellent	0.16	0.367	0.186	0.389	0.184	0.388	0.177	0.382
Exercise habit								
Never	0.282	0.45	0.287	0.452	0.312	0.464	0.294	0.456
Less than 3 days/ week	0.374	0.484	0.373	0.484	0.365	0.482	0.371	0.483
3 days or more/ week	0.184	0.388	0.203	0.402	0.181	0.385	0.189	0.392
Smoking habit, 1=yes	0.16	0.367	0.136	0.343	0.142	0.35	0.215	0.411
Economic Preferences								
Risk preference								
averse	0.26	0.439	0.255	0.436	0.283	0.451	0.266	0.442
neutral	0.515	0.5	0.489	0.5	0.495	0.5	0.5	0.5
seeking	0.225	0.418	0.256	0.437	0.222	0.416	0.235	0.424
Patient								
low	0.119	0.324	0.121	0.326	0.105	0.306	0.115	0.319
medium	0.461	0.499	0.469	0.499	0.45	0.498	0.46	0.499
high	0.42	0.494	0.41	0.492	0.445	0.497	0.425	0.494

5.3.1 Air pollution and commuting choice

I first examine whether people are switching commuting modes as a way of self-protection. I try to first understand people's choices on polluted days based on their existing knowledge structure of the health impacts of pollution as well as exposure by modes (Choice 3 of Figure 5-3), and then model the behavioral changes when exposure information is presented (Choice 4).

Figure 5-4 depicts the commuting mode choices of Treatment Group 1 (O1+P) under different scenarios. On polluted days, people already have the awareness to change transportation modes for self-protection, and their status quo behaviors are to increase indoor commuting (i.e., public transit or car) while decreasing outdoor ones (i.e., bike, walk or electric bike). However, after we present with people their personal pollution exposure information, we see a large reduction in respondents choosing public transit and a large increase in motor vehicles (i.e., car/ taxi). Assuming information is the only thing updated about their beliefs, the result indicates a knowledge gap between people's perceived pollution exposure and the reality, specifically, people seem to underestimate the exposure in public transit. The high pollution exposure of public transit compared to vehicles (Fig B-4a) is primarily caused by two reasons. First, there are only two subway lines crossing the Zhengzhou New District currently, thus public transit involves active commuting for the last mile transition. Second, public transit has less insulated in-carriage environment compared to the closed window private car or taxi.

One concern for this within-group comparison is that people might behave differently when we sequentially ask them one more round of question after the second information intervention. To address this confounding factor, we calculate the treatment effect of pollution exposure information (P) on commuting choices by comparing Treatment Group 1 (O1+P) with Control (O1+O2) in Choice 4 controlling for baseline mode choice, commuting distance and socio-demographic information (Table 5.2). The only difference between the two groups is the provision of Commute Exposure information by commuting modes. The results show that if fully aware of the pollu-

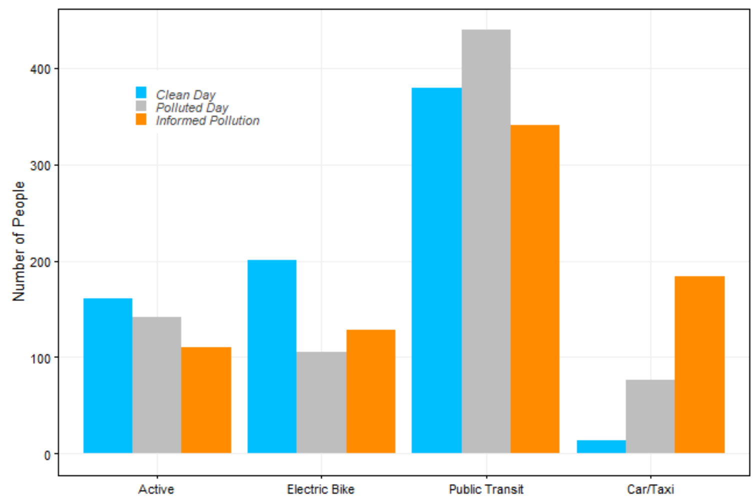


Figure 5-4: Descriptive analysis of commuting choice.
Note: For Treatment Group 1 under different pollution scenarios.

tion exposure, active commuters will further reduce by 8.5% (95% CI: 5.3%, 11.7%) and vehicle commuters (driving, taxi, or Uber/ Didi) will increase by 15% (95% CI: 11.1%, 18.5%) among all initial non-vehicle commuters. Therefore, when modeling the pollution exposure risk and making a projection of emissions from driving, researchers cannot naively assume that travelers are passive victims of pollution and they won't take any avoidance behavior to protect themselves. Our findings in Table 5.2 support the existence of such self protection behaviors and the resulting feedback loop of aggravated emissions induced by such self-protection choices towards more driving.

5.3.2 Health trade-offs in active commuting

Though significant effects of reduction in active commuting is documented, the real-world decisions are likely quite heterogeneous and structured as a function of commuting time. Specifically, the exposure risk continuously increases with active commuting time, while the exercise benefits gradually level-off, constituting a break-even point at which the health benefit and health cost cancel out with each other. Though in western context, the benefits of exercise usually outweigh the adverse effect of pollution exposure at the population level (Caplin et al. 2019), the high ambient pollution

Table 5.2: Treatment effect of pollution exposure information on commuting choice.

VARIABLES	(1) Active Tendency	(2) Active Tendency	(3) Drive Tendency	(4) Drive Tendency
Commute Exposure	-0.0870***	-0.0847***	0.149***	0.148***
(1=Yes)	(0.0199)	(0.0164)	(0.0187)	(0.0188)
Constant	0.231***	0.259***	0.0919***	0.106*
	(0.0153)	(0.0592)	(0.0105)	(0.0602)
Observations	1,526	1,505	1,526	1,505
R-squared	0.012	0.337	0.04	0.053
Controls	NO	YES	NO	YES
Choice	4	4	4	4
Group	O1+P vs O1+O2	O1+P vs O1+O2	O1+P vs O1+O2	O1+P vs O1+O2

Note: Robust standard errors in parentheses. Control variables include income, education, gender, marriage status, commuting distance and baseline commuting choice.
*** p<0.01; ** p<0.05; * p<0.1

level of many developing countries might change the story for long-time commuters. From a scientific study by (Tainio et al. 2016), at the given pollution scenario in the survey, the break-even point is 60 minutes' cycling. Since commuting is composed of two-way trips, active commuting within 30 minutes per trip would likely have exercise benefits that outweighs exposure cost in our scenario context.

To compare people's real behaviors with this scientific finding, I queried the biking time given individual's home and job location from Amap and modelled the treatment effect of pollution exposure information (P) by biking time sextiles (i.e., I calculate the treatment effect showed in Table 5.2 by each sub-group, comparing Treatment Group I and Control Group). Figure 5-5 shows that though biking within 30 minutes has exercise benefit outweighs pollution cost, people who live close to the job location also intentionally switch from active commuting to other transportation modes to hedge against their subjective perception of exposure risk.

This risk averse response pattern can be partially explained by the anecdotal evidence that local residents are very pessimistic about air pollution in Zhengzhou. From our survey, 82% think winter air quality is bad or terrible. 73.48% think air pollution in Zhengzhou largely or severely impacts their health (Figure 5-6a); Table A.2). The fact that behavioral trade-offs are more sensitive towards self-protection should be cautiously interpreted as bounded rationality, since citizens do not have the scientific knowledge to precisely compare health impacts across two dimensions. However, the results suggest that when putting forward information policies like pollution exposure education or air pollution alert, policy makers should acknowledge the negative interaction between public health targets of reducing pollution risk and increasing physical activities, and be cautious about the potential unintended consequences of increased transportation emissions caused by increased usages of motor vehicles when people being risk averse and over-protective.

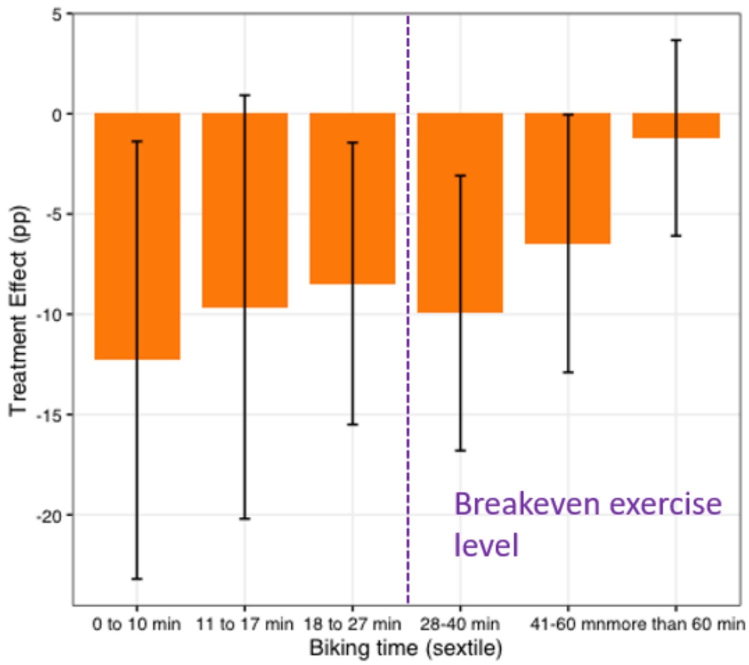
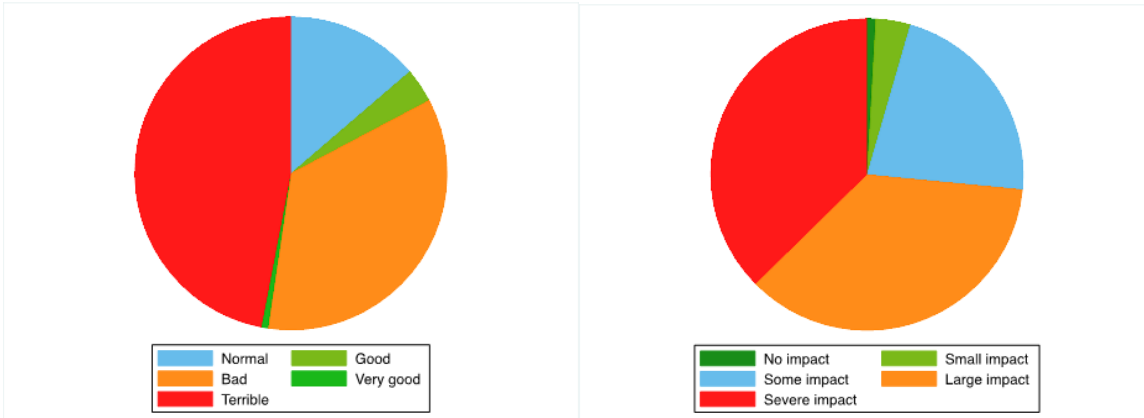


Figure 5-5: Active commuting reduction after informed pollution exposure by counterfactual biking time.

5.3.3 Implications for active commuting policies

According to the "Green Travel Action Plan 2019-2022" of Zhengzhou, a shift from top-down command and control transportation policies to financial and soft policies encouraging green travel is emphasized. In this section, I model the transportation behaviors and perceptions under two public policies aiming at increasing active commuting: financial subsidy and green nudge. This will not only provide us insights



(a) Zhengzhou air quality in winter (b) Pollution health impacts

Figure 5-6: Participants' perception of air quality.

into the effectiveness of green policies in breaking the vicious circle created by air pollution, but also help us understand the changes on the intensive margin where the revealed transportation choice remained unchanged yet the reluctance for active commuting still be intensified by air pollution.

Financial incentives such as taxes and subsidies are common policies to encourage active commuting and are extensively studied in existing literature (Martin, Suhrcke, and Ogilvie 2012). For the four rounds of commuting choices in the survey, I not only elicited people's mode choices, but also asked non-active commuters whether they are willing to switch to active commuting given a reasonable amount of subsidy and what is their minimum willingness to accept (WTA). Similar to the last section, I first make a descriptive analysis of Treatment Group 1 (O1+P) to exploratively understand people's choices under perceived and informed pollution scenarios compared to the baseline. I find that the proportion of people willing to change provided subsidy decreases from 76.7% to 63.4% on a polluted day, and further decreases to 55.8% when citizens are more educated about the pollution exposure in different transportation environments. Assuming the government has the capacity to provide tailored subsidy according to each one's willing to accept, the average cost needed to subsidize people's active travel increases from 4.37 RMB/trip to 5.04 RMB/trip on a polluted day and further increase to 5.51 RMB/trip if micro-environment pollution exposure is available.

To get a pure treatment effect, I compare the answers to questions related to subsidy on Choice 4 by comparing Treatment Group 1 (O1+P) and the Control Group (O1+O2) controlling for socio-demographics, baseline and commuting distance. Table 5.3 and Table 5.4 show that when people are fully informed of the pollution exposure by modes, 13.9% (95% CI: 10.0%, 17.8%) fewer people can be potentially affected by the financial subsidy and the average willing-to-accept (WTA) increases by 1.6 RMB (95% CI: 0.8, 2.3).

Table 5.3: Treatment effect of pollution exposure information on willingness to change to active modes.

VARIABLES	(1) Willing to change (WTC)	(2) Willing to change	(3) Change of WTC
Commute Exposure	-0.146***	-0.140***	-0.139***
(1=Yes)	(0.0244)	(0.0214)	(0.0199)
Constant	0.703***	0.648***	-0.00857
	(0.0166)	(0.0716)	(0.0628)
Observations	1,526	1,507	1,507
R-squared	0.023	0.277	0.036
Controls	NO	YES	YES
Choice	4	4	4
Group	O1+P vs O1+O2	O1+P vs O1+O2	O1+P vs O1+O2

Note: Robust standard errors in parentheses. Control variables include income, education, gender, marriage status, commuting distance and baseline commuting choice.
*** $p<0.01$; ** $p<0.05$; * $p<0.1$

In order to understand people's trade-offs perception on the intensive margin, I model the willingness to change (WTC) and willingness to accept (WTA) as by counterfactual biking time. Figure 5-7a indicates that people with counterfactual biking time 28-60 minutes value the health cost of pollution exposure the most, by either unwilling to change or substantially increasing WTA. The differences for extensive and intensive margin can be partially explained by the selection bias, since people who adopt active commuting for biking time longer than 30 minutes usually have greater preferences for physical activities or having limited alternative transportation choice. This highlights the crucialness of conducting a first hand survey to collect information on the subjective dimensions which cannot be observed through revealed studies.

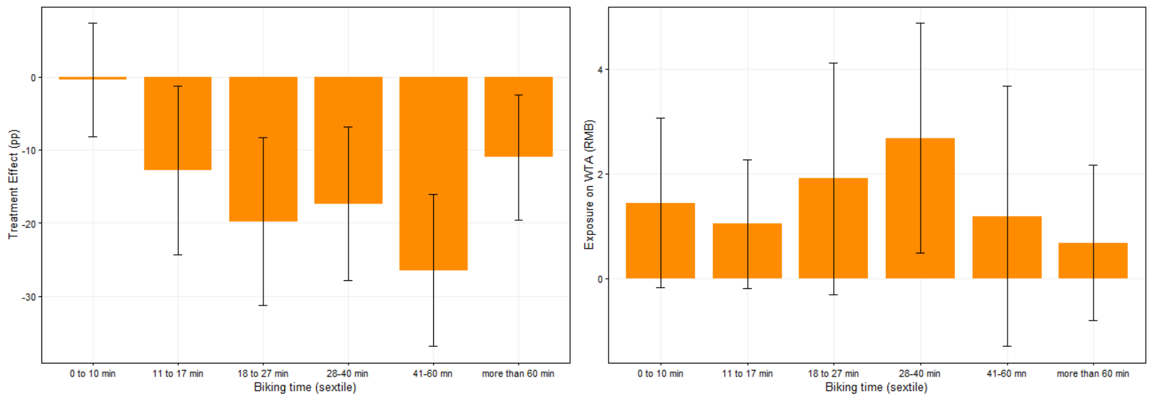
Table 5.4: Treatment effect of pollution exposure information on willingness to accept (subsidy) to active modes.

VARIABLES	(1) Willing to accept	(2) Willing to accept	(3) Change of WTA
Commute Exposure	0.999**	1.080***	1.563***
(1=Yes)	(0.4760)	(0.4050)	(0.3810)
Constant	4.515***	-1.345	0.241
	(0.2950)	(1.0100)	(1.0930)
Observations	962	872	838
R-squared	0.005	0.298	0.033
Controls	NO	YES	YES
Choice	4	4	4
Group	O1+P vs O1+O2	O1+P vs O1+O2	O1+P vs O1+O2

Note: Robust standard errors in parentheses. Control variables include income, education, gender, marriage status, commuting distance and baseline commuting choice.
*** p<0.01; ** p<0.05; * p<0.1

Besides financial policies, behavioral policy intervention like nudge represents a new set of tools for making public policy more cost efficient (Tannenbaum, Fox, and Rogers 2017) and are increasingly adopted by government agencies to their policy toolkits (Benartzi et al. 2017). Since green nudge is low-cost and preserves the freedom of choice, this has been one of the most popular policy instruments to encourage active commuting. To understand the causal impact of green nudge in a clean and polluted day scenario, I construct the comparisons between Treatment Group 2 (H+P) Control (O1+O2) for Choice 2, 3 and 4 (see Figure 5-3). The differences in choices in Choice 2 and Choice 3 uncover the treatment effect of exercise nudge on active commuting choice on clean and polluted days respectively. And the differences in Choice 4 indicate the combined effect of exercise nudge and pollution exposure education.

Table 8 shows that exercise nudge can increase active commuting by 9.7% (95% CI: 6.7%, 12.8%) (Column 2) in clean days, with especially strong effects for people having counterfactual biking time between 11 to 17 minutes (Figure 5-8a). However, soft policies like nudge completely lost effect under polluted scenarios (Column 4) in all biking time groups (Figure 5-8a). When both health benefit and health cost information are presented, health cost completely dominates in directing people's



(a) Willingness to go active given subsidy

(b) Minimum acceptable subsidy

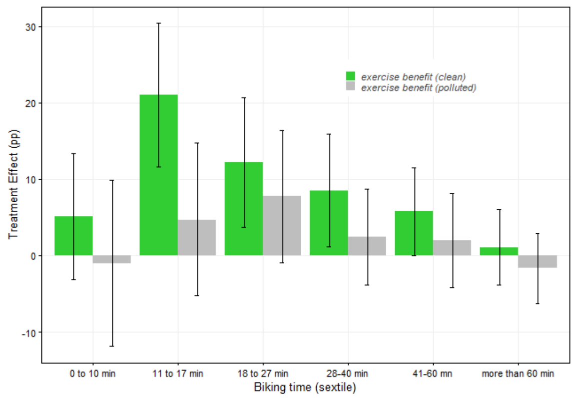
Figure 5-7: Impact of pollution exposure information on changes on intensive margin by counterfactual biking time.

commuting choices (Column 6) and the choices of Treatment Group 2 (H+P) in Choice 4 are not distinguishable with those of Treatment Group 1 (O1+P) where only pollution exposure treatment is presented (Figure 5-8b).

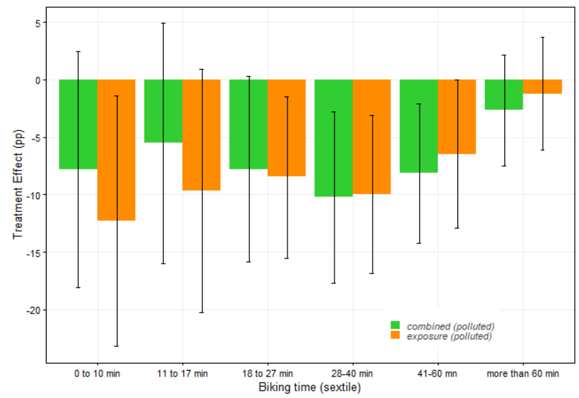
Table 5.5: Effectiveness of active nudge under different scenarios.

VARIABLES	(1) Active (clean)	(2) Active (clean)	(3) Active (polluted)	(4) Active (polluted)	(5) Combined (polluted)	(6) Combined (polluted)
Exercise nudge	0.0983***	0.0973***	0.0231	0.0242	-0.0716***	-0.0699***
(1=Yes)	(0.0221)	(0.0157)	(0.0201)	(0.0169)	(0.0203)	(0.0167)
Constant	0.202***	0.141***	0.177***	0.353***	0.231***	0.310***
	(0.0146)	(0.0534)	(0.0138)	(0.0592)	(0.0153)	(0.0601)
Observations	1,521	1,496	1,521	1,496	1,521	1,496
R-squared	0.013	0.526	0.001	0.32	0.008	0.351
Controls	NO	YES	NO	YES	NO	YES
Choice	2	2	3	3	4	4
Group	H+P vs O1+O2	H+P vs O1+O2	H+P vs O1+O2	H+P vs O1+O2	H+P vs O1+O2	H+P vs O1+O2

Note: Robust standard errors in parentheses. Control variables include income, education, gender, marriage status, commuting distance and baseline commuting choice.
p<0.01; ** p<0.05; * p<0.1



(a) Exercise nudge



(b) Exercise nudge and pollution exposure

Figure 5-8: Treatment effect of exercise nudge under different scenarios.
(a) Treatment effect of exercise nudge on active commuting under different pollution scenario; (b) Combined effect of exercise nudge and pollution exposure information on active commuting.

5.3.4 Determinants of the response

Beyond objective factors like built environment, a wide range of individual characteristics determine travel decision making, such as socio-demographics, economic preference, health conditions, and personal habits. In Figure 5-9, the responsive elasticity to air pollution for different outcomes is modelled as a function of one characteristic variable within each category. The full dimensions of all the covariates available are summarized in Table A.5, Table A.6 and Table A.7.

The most important determinant of behavior is knowledge. I find that people with higher education levels are less affected by pollution exposure information, suggesting a lower knowledge gap before intervention. Unlike pollution exposure treatment, the impact of active commuting nudge is homogeneous across education groups, having significant positive effect on clean days and completely losing impact on polluted days. Meanwhile, consistent with previous literature, I find that females are more sensitive to pollution exposure risk (Table A.5 & Table A.6) while males are more responsive to exercise nudge (Table A.7).

Many theories of human behavior assume a set of economic preferences driving individual decision making (Falk et al. 2018). Among which, risk preference is most relevant for behavioral changes when faced with air pollution exposure. To my knowledge, no one has linked economic preferences with air pollution adaptation behavior. I measure risk preferences using the survey instruments suggested and validated by (Falk et al. 2018)[2] and show that people's risk preference has good predictive power on travel behaviors. Row 2 of Figure 5-9 depicts that risk averse people are more sensitive to pollution exposure information by reducing active commuting more and having higher increase in WTA, which is consistent with existing literature since risk averse people weight losses more heavily than gains (Kahneman and Tversky 1979). On the other hand, risk seeking people are more responsive to exercise nudge, and gain information. Yet again, exercise nudge loses effects for all kinds of people under the pollution scenario. Similarly, hyperbolic discounting in time preferences leads to overweighting of near-term costs and underweighting of delayed benefits (Bhattacharya, Garber, and Goldhaber-Fiebert 2015). I find that people with patient time preferences are indeed more responsive to active commuting nudge yet the effect also goes to zero when met with air pollution (Table A.7).

Habit is an essential element determining people's exercise-related behaviors (Bhattacharya, Garber, and Goldhaber-Fiebert 2015). When evaluating the benefits of public policies, it is important to ask which group of people are responsive. Row 3 of Figure 5-9 shows that active commuting nudge is not effective for people who do not exercise at all, although this group of people would have the largest health benefits gained from active commuting (Fishman 2016). And I find that people who exercise more than 5 days per week are almost the only group who still outweighs exercise benefit over pollution exposure on polluted days.

5.4 Discussion and Policy Implications

In this chapter, I provide evidence that people have the intention of switching commuting modes as a channel of air pollution avoidance behavior. Specifically, we see

[2]Though quantitative questions tend to have smaller measurement error, the length of survey does not allow us to add in a complicated choice matrix to measure risk. (Falk et al. 2018) finds that qualitative and quantitative questions give similar results under their questionnaire framing, thus we exactly apply their qualitative question framing to measure the economic preferences.

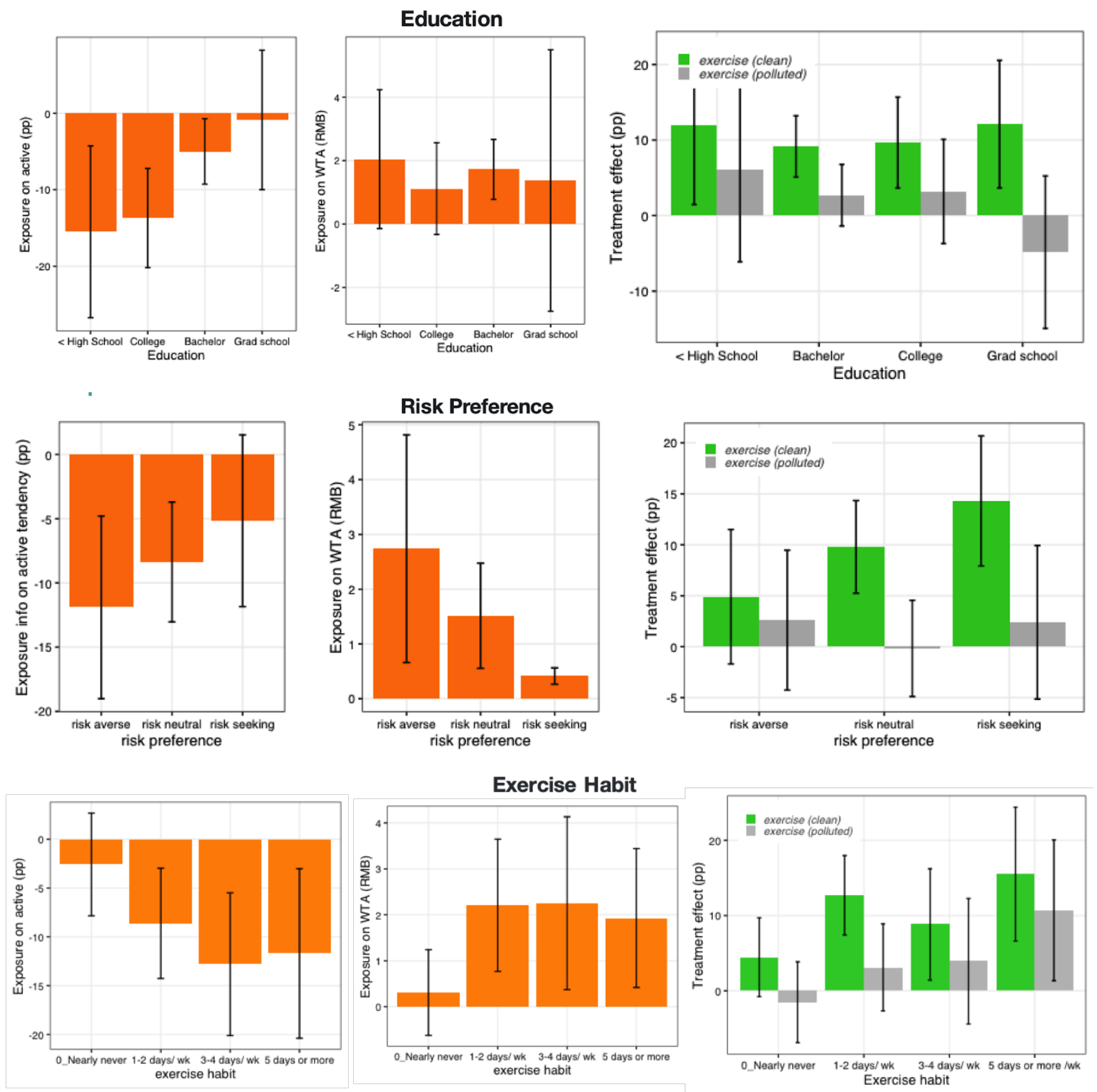


Figure 5-9: Heterogeneous treatment effect.

Impacts of pollution exposure treatment on active commuting tendency (Column 1 and WTA (Column 2); Impacts of exercise nudge treatment on active commuting tendency (Column 3).

Note: Consistent with the results section, the first two columns rely on Treatment Group 1 and Control Group to calculate the treatment effect of pollution exposure information on active commuting behaviors and perceptions. The third column relies on Treatment Group 2 and Control Group to calculate the treatment effect of active commuting's health benefit information on commuting choice on clean and polluted days respectively.

a clear tendency for people to reduce outdoor commuting for exposure avoidance, yet people underestimate the pollution exposure of public transits in Zhengzhou. Recently, we see continuous technology advancement in environmental Internet of Things (IoT) applications to measure personal micro-environment pollution exposure, accompanied with the increasing demand for fine-grained air quality data (Mamun and Yuce 2019; Caplin et al. 2019). My results give the prediction that if people are more educated about the personalized pollution exposure by commuting modes, active commuting would further decrease by 8.5%, while driving increases by 14.8%, creating double challenges to both public health and pollution mitigation. The commuting choices show a pessimistic feedback loop, in which the advertent behaviors of citizens in response to air pollution further aggravate the local air pollution through choosing dirtier yet more protective transportation modes. Given that transportation contributes significantly to local air pollutants and greenhouse gas emissions, the omission of which will drive a wedge between ex ante engineering estimates of program costs and ex post estimates of true social cost. The discrepancy can bias our future projection of anthropogenic environmental changes and make policy makers under-estimate the cost caused by environmental stressors in the social system.

Second, my results suggest that people seem to overreact to air pollution. Even for people having much shorter commuting time than the break-even point (i.e., 30 minutes/ trip in our scenario), a substantial reduction in active commuting is documented. The results depict that people are not sophisticated enough to balance the health gain and health loss of biking/ walking in pollution, instead, they tend to react in an overly-protective way caused by the deep rooted negative impressions on local air pollution. The results indicate a sad dilemma between intertwined public health goals, reducing pollution exposure and advocating active living. And the contradicted environmental policy targets of encouraging voluntary pollution avoidance and pollution mitigations. More importantly, it emphasizes that policy makers should not narrowly look at air pollution as a public health threat in objective exposure and focus their efforts only on one policy goal: reducing exposure by alerting public information. An integrated policy design can help exploit synergies between different policy objectives while avoiding harmful contradictions. For instance, a policy maker who recognizes the unintended consequences of avoidance behaviors in the transportation sector should improve the air quality in public transits by purifier operations, rather than simply alerting people about high pollution which could nudge people to drive.

Third, I find that both financial subsidy and green nudge policies to encourage active commuting are likely to be in vain under air pollution. Unlike previous research, I model changes take place on the intensive margin by eliciting people's willingness to change and willingness to accept in addition to mode choices. I document that people willing to adopt active commuting given subsidy decreases by 14% and minimum subsidy requirement increases by 1.56 RMB on average when fully informed about the pollution exposure risk. Meanwhile, though low-cost soft policies like nudge are effective in encouraging active commuting by 10%, the effect completely goes away in almost all sub-populations under the pollution scenario.

The results should be interpreted cautiously. First, the stated preference nature of the survey makes the social image concerns and arbitrary answers hard to be eliminated. Randomized controlled trials relying on objective documentation of commuting choices such as using smartphone GPS are preferred to validate the stated preferences with revealed behaviors. Second, the current conclusion of risk averse is in comparison with the trade-off curves suggested by science literature, which is sensitive to the dose response function assumptions for the benefits and cost of pollution and exercise. 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. Last but not the least, more research efforts in different cities and countries are required to cross-validate the external validity of the conclusions. This case study in Zhengzhou is only a starting point to shed light on the neglected social cost tied with pollution avoidance behaviors which is largely understudied in existing literature, and to advocate for a more holistic view when designing public policies to satisfy conflicting public goals. Nonetheless, the results should not be interpreted as a deterministic evidence of human behaviors across all contexts.

Chapter 6

Conclusion

The avoidance behaviors of human-being under air pollution are not well-studied, and the limited research on avoidance behaviors mainly focus on the monetary cost bundled with defensive expenditure. For this paper, I empirically investigate the impacts of two short-term avoidance behaviors with non-market opportunity cost and unintended social cost respectively: reducing outdoor leisure activities and switching transportation modes.

On one hand, I display that avoidance behaviors, though effective in reducing exposure, can create welfare loss due to the foregone leisure activities. Cancelling and reducing the duration of park visitation when faced with heavily polluted events can deprive citizens from enjoying the social, physical and psychological well-being benefits city parks can provide (van Wagoner n.d.). In this research, I quantify not only the net effect of pollution on park activities, but also the temporal lagged effects and dose-response function accounting for the non-linearity. Furthermore, I take advantage of the detailedness of the dataset to show the distributive impacts, including the heterogeneity across geographical regions, cities with different income, parks with different functionality, as well as activity patterns at different times. A back-of-envelope investigation of the social cost of the foregone leisure was conducted and the results show a comparable economic value to the market value of defensive expenditure, indicating that incorporating the non-market value is not a trivial thing.

On the other hand, I show that self-protected commuting behaviors can generate social consequences in building a vicious feedback loop between pollution and motor vehicle usages. The risk averse tendency to protect one's own health could make public policies encouraging green travels powerless during the pollution events. Although does not have the capacity to quantify the monetary cost of behavioral adjustment in urban transportation sector, this is the first paper to look at the social consequences of individual avoidance behaviors, and to project how this neglected dimension of cost can be increasingly critical when urban citizens are getting more informed and educated about micro-level pollution exposure risk. I acknowledge the fact that stated preferences in surveys might be different from people's actual behaviors due to the potential report bias and experimenter demand effect. As the next step, we will implement a Randomized Controlled Trial using smartphone App to objectively track individual's commuting choices and follow the participants for six weeks to map out the within-subject differences for clean and polluted days. The effects of individual tailored pollution exposure information and green travel subsidy will also be evaluated through revealed behaviors to support more robust program evaluation and future prediction.

As developed in the theoretical framework, I believe the two dimensions of hidden costs (i.e., opportunity costs and social cost) of pollution impacts linked with avoidance human behaviors should be included in the estimation of social damages of pollution and the benefits of mitigation policy. These cost elements are closely related to urbanites' quality of life and the establishment of green culture and social cohesion. Though challenging, it is essential for researchers to seek innovative ways to quantify the hidden costs with novel data, and incorporate these costs into policy conversations. In addition, understanding avoidance behaviors are not cheap panacea will help the policy makers to model the cost and benefits of industrial and pollution mitigation policies more comprehensively, and be able to judge the public information campaign nudging people to self-protect more critically.

The research question of interest and the methodologies developed in this thesis is not only relevant in the Chinese setting, but also useful to study pollution avoidance in other developing countries. For example, some Indian cities are becoming the most polluted ones in the world, with nearly a 9-years reduction in life expectancy because of pollution. Since a large percentage of Indian households rely on biomass cooking and agricultural practices like burning crop stubble is widespread, the pollution visibility is higher in Indian than in China. This, accompanied with the warmer temperature supporting outdoor activities, can cause the hidden costs of the avoidance behaviors to be even larger. Similarly, the estimation strategy is also readily applicable to study other environmental problems, such as extreme temperature. As well as the interactive effects of multiple environmental hazards on human behaviors. There have been dramatic advances in understanding the physical science of pollution and climate change, yet the social value of these advances depends on understanding their broader social impacts on our human system. Understanding the social cost of the environmental degradation is a domain requiring substantive research efforts, otherwise, effective policy solutions with broad societal support will remain elusive.

Having said that, the estimation results and policy simulations practiced in this research should be interpreted contingently. First, it is likely that the monetary estimation only quantifies a small part of the avoidance cost, since I only measure one of the many types of leisure activities which are likely to be affected by air pollution. Second, the survey data used to analyze commuting behaviors, though having the advantage of supporting behavioral pathways analysis at individual level, are limited in its geographical and population coverage to generalize to larger urban contexts. Third, many long-term avoidance and adaptation strategies people could adopt, such as migrating to cleaner cities (S. Chen, Oliva, and Zhang 2017) or spending longer holidays in cleaner cities, are still missing in the improved evaluation picture I proposed in Figure 1-1. With all these cautions in mind, I believe that this paper has highlighted the key role of a systematic empirical analysis building the causal impacts of air pollution on broader social sectors accounting for dynamic behavioral adjustments. I hope that my work could draw more attention to the neglected avoidance costs to support comprehensive behavioral modelling in pollution risk management and more well-informed policy decision-makings.

Appendix A

Supplementary Tables

Table A.1: Pollution and inhalation factors.

	Pollution factor	Inhalation factor
Car (with AC)	0.8	0.16
Bus	1.1	0.72
Subway	1.2	0.49
Bike	1	1
Walk	1	1

Note: Exposure of mode i for individual j = ambient PM2.5 level pollution factor of mode i inhalation factor of mode i counterfactual commuting time taking mode i for individual j. Cigarettes equivalent of mode i for individual j/ month= (ambient PM2.5 level $\times$ pollution factor of mode i /22) $\times$ inhalation factor of mode i $\times$ (counterfactual commuting time taking mode i for individual j /24) $\times$ 2 $\times$ 20.

Table A.2: Ways to judge pollution information.

rank	Number of people	fraction
Cell phone App	1693	74.09%
Judge from visibility	1048	45.86%
From searching engine main page	186	8.14%
EPA official website	167	7.31%
Monitor themselves	47	2.06%
Never check	41	1.79%

Table A.3: Perception of Zhengzhou air pollution in winter.

Perception	Number of people	fraction
Terrible	1063	46.95%
Bad	794	35.07%
Normal	311	13.74%
Good	80	3.53%
Very good	16	0.71%

Table A.4: Perception of Zhengzhou air pollution on their personal health.

Perception	Number of people	fraction
Severe impact	845	37.36%
Large impact	817	36.12%
Some impact	499	22.06%
Small impact	81	3.58%
No impact	20	0.88%

Table A.5: Heterogeneity of treatment effect of pollution exposure education.

	Active tendency		Driving tendency	
	TE	SE	TE	SE
All	-0.084***	(0.0164)	0.147***	(0.0189)
Demographics				
Gender				
Female	-0.092***	(0.0435)	0.160***	(0.0260)
Male	-0.068***	(0.0244)	0.125***	(0.0269)
Income				
Less than 50 thousand	-0.106**	(0.0432)	0.161***	(0.0431)
50-150 thousand	-0.0771***	(0.0227)	0.153***	(0.0248)
150-300 thousand	-0.0826**	(0.0330)	0.130***	(0.0403)
More than 300 thousand	-0.0642	(0.0623)	0.184*	(0.1020)
Education				
$<$ High school	-0.155***	(0.0573)	0.175***	(0.0464)
College	-0.137***	(0.0331)	0.163***	(0.0355)
BA	-0.0499**	(0.0219)	0.144***	(0.0266)
Grad school	-0.00883	(0.0465)	0.125*	(0.0663)
Habits				
Exercise habit				
Nearly never	-0.0259	(0.0268)	0.0713*	(0.0367)
1-2 days/ wk	-0.0862***	(0.0288)	0.191***	(0.0318)
3-4 days/wk	-0.128***	(0.0373)	0.174***	(0.0386)
$>=$5 days/wk	-0.117***	(0.0443)	0.145***	(0.0516)
Smoking habit				
No	-0.0758***	(0.0186)	0.144***	(0.0213)
Yes	-0.115***	(0.0361)	0.157***	(0.0400)
Health Perception and Condition				
Health impact of pollution				
Not severe	-0.0489	(0.0353)	0.181***	(0.0353)
Severe	-0.0933***	(0.0185)	0.138***	(0.0224)
Health condition				
Bad/ Normal	-0.0833**	(0.0345)	0.0925**	(0.0422)
Good	-0.0807***	(0.0211)	0.174***	(0.0239)
Very good	-0.126***	(0.0429)	0.113**	(0.0468)
Economic Preference				
Risk preference				
Averse	-0.119***	(0.0363)	0.154***	(0.0378)
Neutral	-0.0837***	(0.0238)	0.185***	(0.0281)
Seeking	-0.0515	(0.0341)	0.0816**	(0.0409)
Time preference				
Impatient	-0.0515*	(0.0306)	0.142***	(0.0333)
Patient	-0.0806***	(0.0304)	0.105***	(0.0366)
Very patient	-0.0832***	(0.0263)	0.190***	(0.0302)

Table A.6: Heterogeneity of treatment effect of exposure information on WTC and WTA.

	Active tendency		Driving tendency	
	TE	SE	TE	SE
All	-0.139***	(0.0199)	1.563***	(0.3810)
Demographics				
Gender				
Female	-0.142***	(0.0283)	1.772***	(0.5720)
Male	-0.134***	(0.0277)	1.327***	(0.4830)
Income				
Less than 50 thousand	-0.152***	(0.0496)	1.971*	(1.1530)
50-150 thousand	-0.151***	(0.0278)	1.493***	(0.4820)
150-300 thousand	-0.104**	(0.0407)	1.520**	(0.6570)
More than 300 thousand	-0.144**	(0.0715)	1.681	(1.3660)
Education				
< High school	-0.121**	(0.0582)	2.045*	(1.1180)
College	-0.114***	(0.0361)	1.116	(0.7380)
BA	-0.172***	(0.0295)	1.720***	(0.4820)
Grad school	-0.0642	(0.0578)	1.372	(2.1040)
Habits				
Exercise habit				
Nearly never	-0.0853**	(0.0361)	0.308	(0.4760)
1-2 days/ wk	-0.209***	(0.0339)	2.208***	(0.7350)
3-4 days/wk	-0.129***	(0.0450)	2.253**	(0.9590)
>=5 days/wk	-0.0695	(0.0572)	1.930**	(0.7710)
Smoking habit				
No	-0.147***	(0.0227)	1.648***	(0.4500)
Yes	-0.112***	(0.0420)	1.168*	(0.7000)
Health Perception and Condition				
Health impact of pollution				
Not severe	-0.123***	(0.0372)	0.194	(0.4680)
Severe	-0.144***	(0.0234)	2.125***	(0.5030)
Health condition				
Bad/ Normal	-0.154***	(0.0497)	0.946	(0.5830)
Good	-0.146***	(0.0245)	1.497***	(0.4560)
Very good	-0.112**	(0.0480)	2.496**	(1.2360)
Economic Preference				
Risk preference				
Averse	-0.135***	(0.0408)	2.739**	(1.0600)
Neutral	-0.152***	(0.0306)	1.515***	(0.4890)
Seeking	-0.156***	(0.0419)	0.414	(0.7640)
Time preference				
Impatient	-0.147***	(0.0355)	1.022	(0.6830)
Patient	-0.0853**	(0.0377)	2.323***	(0.7540)
Very patient	-0.175***	(0.0328)	1.236***	(0.4730)

Table A.7: Heterogeneity of treatment effect of exercise nudge on clean and polluted days.

	Active tendency		Driving tendency	
	TE	SE	TE	SE
All	0.097***	(0.0157)	0.0253	(0.0169)
Demographics				
Gender				
Female	0.089***	(0.0208)	0.0273	(0.0227)
Male	0.103***	(0.0239)	0.0301	(0.0253)
Income				
Less than 50 thousand	0.135***	(0.0382)	0.0327	(0.0432)
50-150 thousand	0.101***	(0.0208)	0.0228	(0.0229)
150-300 thousand	0.0437	(0.0331)	0.0173	(0.0336)
More than 300 thousand	0.160*	(0.0855)	0.0895	(0.0692)
Education				
< High school	0.120**	(0.0538)	0.0616	(0.0627)
College	0.0966***	(0.0307)	0.032	(0.0352)
BA	0.0916***	(0.0207)	0.0271	(0.0208)
Grad school	0.121***	(0.0431)	-0.0485	(0.0515)
Habits				
Exercise habit				
Nearly never	0.0447*	(0.0267)	-0.0151	(0.0274)
1-2 days/ wk	0.127***	(0.0269)	0.0312	(0.0295)
3-4 days/wk	0.0883**	(0.0377)	0.0394	(0.0425)
>=5 days/wk	0.155***	(0.0453)	0.107**	(0.0477)
Smoking habit				
No	0.101***	(0.0178)	0.0281	(0.0187)
Yes	0.0819**	(0.0359)	0.0225	(0.0401)
Health Perception and Condition				
Health impact of pollution				
Not severe	0.0916***	(0.0372)	0.0043	(0.0304)
Severe	0.102***	(0.0234)	0.0403**	(0.0201)
Health condition				
Bad/ Normal	0.0261	(0.0335)	0.0205	(0.0332)
Good	0.0985***	(0.0197)	0.0158	(0.0209)
Very good	0.165***	(0.0406)	0.0587	(0.0475)
Economic Preference				
Risk preference				
Averse	0.0491	(0.0337)	0.026	(0.0350)
Neutral	0.0979***	(0.0232)	-0.0017	(0.0241)
Seeking	0.143***	(0.0325)	0.024	(0.0384)
Time preference				
Impatient	0.0555*	(0.0315)	-0.0095	(0.0314)
Patient	0.103***	(0.0280)	0.0289	(0.0295)
Very patient	0.131***	(0.0242)	0.0419	(0.0268)

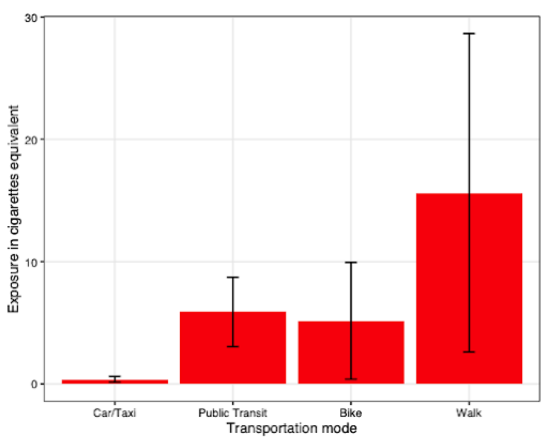
Appendix B

Supplementary Figures

Figure B-1: Survey implementation on the ground in collaborated companies.

Figure B-2: Air pollution monitoring road map.

Figure B-3: Information intervention webpage interface.



(a) Exposure by modes

(b) PM2.5 scenario picture

Figure B-4: Pollution by modes and scenario picture.

References

Abu-Allaban, M., J. A. Gillies, A. W. Gertler, R. Clayton, and D. Proffitt (2007, September). Motor vehicle contributions to ambient PM10 and PM2.5 at selected urban areas in the USA. *Environ. Monit. Assess. 132*(1-3), 155–163.

Adhvaryu, A., N. Kala, and A. Nyshadham (2014). Management and shocks to worker productivity: evidence from air pollution exposure in an indian garment factory. *Unpublished working paper, University of Michigan*.

Allen, J. L., C. Klocke, K. Morris-Schaffer, K. Conrad, M. Sobolewski, and D. A. Cory-Slechta (2017, June). Cognitive effects of air pollution exposures and potential mechanistic underpinnings. *Curr Environ Health Rep 4*(2), 180–191.

An, R., S. Zhang, M. Ji, and C. Guan (2018, March). Impact of ambient air pollution on physical activity among adults: a systematic review and meta-analysis. *Perspect. Public Health 138*(2), 111–121.

Ashenfelter, O. and M. Greenstone (2004). Estimating the value of a statistical life: The importance of omitted variables and publication bias. *Am. Econ. Rev. 94*(2), 454–460.

Bae, S., Y.-H. Lim, and Y.-C. Hong (2020, March). Causal association between ambient ozone concentration and mortality in seoul, korea. *Environ. Res. 182*, 109098.

Bank, W., World Bank, and Institute for Health Metrics and Evaluation (2016). The cost of air pollution.

Barrington-Leigh, C. and F. Behzadnejad (2017). Evaluating the short-term cost of low-level local air pollution: a life satisfaction approach.

Bartik, T. J. (1988, March). Evaluating the benefits of non-marginal reductions in pollution using information on defensive expenditures. *J. Environ. Econ. Manage. 15*(1), 111–127.

Bayer, P., N. Keohane, and C. Timmins (2009, July). Migration and hedonic valuation: The case of air quality. *J. Environ. Econ. Manage. 58*(1), 1–14.

Benartzi, S., J. Beshears, K. L. Milkman, C. R. Sunstein, R. H. Thaler, M. Shankar, W. Tucker-Ray, W. J. Congdon, and S. Galing (2017, August). Should governments invest more in nudging? *Psychol. Sci. 28*(8), 1041–1055.

Bhattacharya, J., A. M. Garber, and J. D. Goldhaber-Fiebert (2015, July). Nudges in exercise commitment contracts: A randomized trial.

Brajša-Žganec, A., M. Merkaš, and I. Šverko (2011, May). Quality of life and leisure activities: How do leisure activities contribute to subjective Well-Being? *Soc.*

Indic. Res. 102(1), 81–91.

Burkhardt, J., J. Bayham, A. Wilson, E. Carter, J. D. Berman, K. O'Dell, B. Ford, E. V. Fischer, and J. R. Pierce (2019, November). The effect of pollution on crime: Evidence from data on particulate matter and ozone. *J. Environ. Econ. Manage. 98*, 102267.

Caplin, A., M. Ghandehari, C. Lim, P. Glimcher, and G. Thurston (2019, March). Advancing environmental exposure assessment science to benefit society. *Nat. Commun. 10*(1), 1236.

Carleton, T., M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, A. Jina, R. E. Kopp, K. McCusker, I. Nath, J. Rising, A. Rode, H. K. Seo, J. Simcock, A. Viaene, J. Yuan, and A. T. Zhang (2019, July). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits.

Carleton, T. A. and S. M. Hsiang (2016, September). Social and economic impacts of climate. *Science 353*(6304).

Cepeda, M., J. Schoufour, R. Freak-Poli, C. M. Koolhaas, K. Dhana, W. M. Bramer, and O. H. Franco (2017). Levels of ambient air pollution according to mode of transport: a systematic review.

Chan, N. W. and C. J. Wichman (2017). The effects of climate on leisure demand: evidence from north america. Technical report, Working Paper Version: December 5.

Chang, P.-J., R. Song, and Y. Lin (2019). Air pollution as a moderator in the association between leisure activities and Well-Being in urban china. *J. Happiness Stud. 20*(8), 2401–2430.

Chang, T., J. Graff Zivin, T. Gross, and M. Neidell (2016, August). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy 8*(3), 141–169.

Chang, T. Y., J. Graff Zivin, T. Gross, and M. Neidell (2019, January). The effect of pollution on worker productivity: Evidence from call center workers in china. *Am. Econ. J. Appl. Econ. 11*(1), 151–172.

Chay, K. Y. and M. Greenstone (2003, August). The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession. *Q. J. Econ. 118*(3), 1121–1167.

Chen, C.-M., Y.-L. Lin, and C.-L. Hsu (2017, June). Does air pollution drive away tourists? a case study of the sun moon lake national scenic area, taiwan. *Transp. Res. Part D: Trans. Environ. 53*, 398–402.

Chen, H., Q. Li, J. S. Kaufman, J. Wang, R. Copes, Y. Su, and T. Benmarhnia (2018, January). Effect of air quality alerts on human health: a regression discontinuity analysis in toronto, canada. *Lancet Planet Health 2*(1), e19–e26.

Chen, S., P. Oliva, and P. Zhang (2017, November). The effect of air pollution on migration: Evidence from china.

Chen, X., X. Zhang, and X. Zhang (2017, March). *Smog in our brains: Gender differences in the impact of exposure to air pollution on cognitive performance in China.* Intl Food Policy Res Inst.

Chen, Y., A. Ebenstein, M. Greenstone, and H. Li (2013, August). Evidence on the impact of sustained exposure to air pollution on life expectancy from china's huai river policy. *Proc. Natl. Acad. Sci. U. S. A. 110*(32), 12936–12941.

Cheung, C. and R. Law (2001). THE IMPACT OF AIR QUALITY ON TOURISM: THE CASE OF HONG KONG. *Pacific Tourism Review 5*(1-2), 69–74.

Cheung, C. W., G. He, and Y. Pan (2020, March). Mitigating the air pollution effect? the remarkable decline in the pollution-mortality relationship in hong kong. *J. Environ. Econ. Manage.*, 102316.

Cohen, A. J., M. Brauer, R. Burnett, H. R. Anderson, J. Frostad, K. Estep, K. Balakrishnan, B. Brunekreef, L. Dandona, R. Dandona, V. Feigin, G. Freedman, B. Hubbell, A. Jobling, H. Kan, L. Knibbs, Y. Liu, R. Martin, L. Morawska, C. A. Pope, H. Shin, K. Straif, G. Shaddick, M. Thomas, R. van Dingenen, A. van Donkelaar, T. Vos, C. J. L. Murray, and M. H. Forouzanfar (2017, May). Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the global burden of diseases study 2015. *Lancet 389*(10082), 1907–1918.

Cressie, N. (2015, March). *Statistics for Spatial Data.* John Wiley & Sons.

Currie, J., J. G. Zivin, J. Mullins, and M. Neidell (2014, November). What do we know about short- and Long-Term effects of Early-Life exposure to pollution? *Annu. Rev. Resour. Econ. 6*(1), 217–247.

Cutter, W. B. and M. Neidell (2009). Voluntary information programs and environmental regulation: Evidence from 'spare the air'. *J. Environ. Econ. Manage. 58*(3), 253–265.

DeMocker, M. J. (2003). Benefits and costs of the clean air act 1990-2020: Revised analytical plan for EPA's second prospective analysis. *Industrial Economics Incorporated, Cambridge, MA*.

Deryugina, T., G. Heutel, N. H. Miller, D. Molitor, and J. Reif (2016, November). The mortality and medical costs of air pollution: Evidence from changes in wind direction.

Deschênes, O., M. Greenstone, and J. S. Shapiro (2017, October). Defensive investments and the demand for air quality: Evidence from the NOx budget program. *Am. Econ. Rev. 107*(10), 2958–2989.

Diaz, D. and F. Moore (2017, November). Quantifying the economic risks of climate change. *Nat. Clim. Chang. 7*(11), 774–782.

Dockery, D. W., C. A. Pope, X. Xu, J. D. Spengler, J. H. Ware, M. E. Fay, B. G. Ferris, Jr, and F. E. Speizer (1993). An association between air pollution and mortality in six US cities. *N. Engl. J. Med. 329*(24), 1753–1759.

Dundas, S. J. and R. H. von Haefen (2020, March). The effects of weather on recreational fishing demand and adaptation: Implications for a changing climate. *Journal of the Association of Environmental and Resource Economists 7*(2), 209–242.

Ebenstein, A., M. Fan, M. Greenstone, G. He, P. Yin, and M. Zhou. Growth, pollution, and life expectancy: China from 1991-2012.

Ebenstein, A., M. Fan, M. Greenstone, G. He, and M. Zhou (2017, September). New evidence on the impact of sustained exposure to air pollution on life expectancy from china's huai river policy. *Proc. Natl. Acad. Sci. U. S. A. 114*(39), 10384–

10389.

European Commission (2013). The clean air policy package. *Commission Staff Working Document. Impact Assessment, No. SWD(2013)531,*.

Falk, A., A. Becker, T. Dohmen, B. Enke, D. Huffman, and U. Sunde (2018, November). Global evidence on economic preferences. *Q. J. Econ. 133*(4), 1645–1692.

Fishman, E. (2016, January). Cycling as transport. *Transp. Rev. 36*(1), 1–8.

Giaccherini, M., J. Kopinska, and A. Palma. When particulate matter strikes cities. social disparities and health costs of air pollution.

Graff Zivin, J. and M. Neidell (2009, September). Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *J. Environ. Econ. Manage. 58*(2), 119–128.

Graff Zivin, J. and M. Neidell (2012, December). The impact of pollution on worker productivity. *Am. Econ. Rev. 102*(7), 3652–3673.

Graff Zivin, J. and M. Neidell (2013, September). Environment, health, and human capital. *J. Econ. Lit. 51*(3), 689–730.

Greenstone, M. and R. Hanna (2014, October). Environmental regulations, air and water pollution, and infant mortality in india. *Am. Econ. Rev. 104*(10), 3038–3072.

Greenstone, M., J. Nilekani, R. Pande, N. Ryan, A. Sudarshan, and A. Sugathan (2015). Lower pollution, longer lives: life expectancy gains if india reduced particulate matter pollution. *Econ. Polit. Wkly. 50*(8).

Grossman, M. (1972). On the concept of health capital and the demand for health. *J. Polit. Econ. 80*(2), 223–255.

Hanna, R. and P. Oliva (2015, February). The effect of pollution on labor supply: Evidence from a natural experiment in mexico city. *J. Public Econ. 122*, 68–79.

Heyes, A., M. Neidell, and S. Saberian (2016, October). The effect of air pollution on investor behavior: Evidence from the S&P 500.

Heyes, A. and M. Zhu (2019, November). Air pollution as a cause of sleeplessness: Social media evidence from a panel of chinese cities. *J. Environ. Econ. Manage. 98*, 102247.

Ito, K. and S. Zhang (2016, June). Willingness to pay for clean air: Evidence from air purifier markets in china.

Jiang, Y., G. Huang, and B. Fisher (2019, December). Air quality, human behavior and urban park visit: A case study in beijing. *J. Clean. Prod. 240*, 118000.

Jo, C. (2014). Cost-of-illness studies: concepts, scopes, and methods.

Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk.

Keiser, D., G. Lade, and I. Rudik (2018, July). Air pollution and visitation at U.S. national parks. *Sci Adv 4*(7), eaat1613.

Kerr, J., S. Marshall, S. Godbole, S. Neukam, K. Crist, K. Wasilenko, S. Golshan, and D. Buchner (2012, December). The relationship between outdoor activity and health in older adults using GPS. *Int. J. Environ. Res. Public Health 9*(12), 4615–4625.

Kheirbek, I., J. Haney, S. Douglas, K. Ito, and T. Matte (2016, August). The contribution of motor vehicle emissions to ambient fine particulate matter public health impacts in new york city: a health burden assessment. *Environ. Health 15*(1), 89.

Kilian, J. and M. Kitazawa (2018, June). The emerging risk of exposure to air pollution on cognitive decline and alzheimer's disease - evidence from epidemiological and animal studies. *Biomed. J. 41*(3), 141–162.

Korpela, K., K. Borodulin, M. Neuvonen, O. Paronen, and L. Tyrväinen (2014, March). Analyzing the mediators between nature-based outdoor recreation and emotional well-being. *J. Environ. Psychol. 37*, 1–7.

Lavy, V., A. Ebenstein, and S. Roth (2014). The impact of short term exposure to ambient air pollution on cognitive performance and human capital formation.

Law, R. and C. Cheung (2007, July). Air quality in hong kong: A study of the perception of international visitors. *J. Sustainable Tour. 15*(4), 390–401.

Lee, K.-K., Y. Park, S.-P. Han, and H. C. Kim (2020, January). The alerting effect from rising public awareness of air quality on the outdoor activities of megacity residents. *Sustain. Sci. Pract. Policy 12*(3), 820.

Lelieveld, J., J. S. Evans, M. Fnais, D. Giannadaki, and A. Pozzer (2015, September). The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature 525*(7569), 367–371.

Li, F., Y. Liu, J. Lü, L. Liang, and P. Harmer (2015, March). Ambient air pollution in china poses a multifaceted health threat to outdoor physical activity. *J. Epidemiol. Community Health 69*(3), 201–204.

Li, J. J., M. Massa, H. Zhang, and J. Zhang (2017). Behavioral bias in haze: Evidence from air pollution and the disposition effect in china. *Massimo and Zhang, Hong and Zhang, Jian, Behavioral Bias in Haze: Evidence from Air Pollution and the Disposition Effect in China (June 28, 2017)*.

Liu, T., G. He, and A. Lau (2018, April). Avoidance behavior against air pollution: evidence from online search indices for anti-PM2.5 masks and air filters in chinese cities. *Environ. Econ. Policy Stud. 20*(2), 325–363.

Lü, J., L. Liang, Y. Feng, R. Li, and Y. Liu (2015, November). Air pollution exposure and physical activity in china: Current knowledge, public health implications, and future research needs. *Int. J. Environ. Res. Public Health 12*(11), 14887–14897.

Luechinger, S. (2009, March). Valuing air quality using the life satisfaction approach. *Econ J 119*(536), 482–515.

Luechinger, S. (2014, September). Air pollution and infant mortality: a natural experiment from power plant desulfurization. *J. Health Econ. 37*, 219–231.

Mamun, M. A. A. and M. R. Yuce (2019, September). Sensors and systems for wearable environmental monitoring toward IoT-Enabled applications: A review. *IEEE Sens. J. 19*(18), 7771–7788.

Manferdelli, G., A. La Torre, and R. Codella (2019, May). Outdoor physical activity bears multiple benefits to health and society. *J. Sports Med. Phys. Fitness 59*(5), 868–879.

Marcotte, D. E. (2017, February). Something in the air? air quality and children's educational outcomes. *Econ. Educ. Rev. 56*, 141–151.

Martin, A., M. Suhrcke, and D. Ogilvie (2012, December). Financial incentives to promote active travel: an evidence review and economic framework. *Am. J. Prev. Med. 43*(6), e45–57.

Moretti, E. and M. Neidell (2011, January). Pollution, health, and avoidance behavior: Evidence from the ports of los angeles. *J. Hum. Resour. 46*(1), 154–175.

Myllyvirta, L. and X. Shen (2018, January). China plans to cut coal heating again, but can it avoid another crisis? `https://unearthed.greenpeace.org/2018/01/10/china-coal-heating-winter-crisis-pollution/`. Accessed: 2020-4-18.

National Research Council, Division on Earth and Life Studies, Board on Atmospheric Sciences and Climate, and Committee on the Significance of International Transport of Air Pollutants (2010, February). *Global Sources of Local Pollution: An Assessment of Long-Range Transport of Key Air Pollutants to and from the United States*. National Academies Press.

Neidell, M. (2009). Information, avoidance behavior, and health.

Neidell, M. J. (2004, November). Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma. *J. Health Econ. 23*(6), 1209–1236.

Neidell, M. J. (2008, July). Information, avoidance behavior, and health: The effect of ozone on asthma hospitalizations.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica 49*(6), 1417–1426.

Noonan, D. S. (2014). Smoggy with a chance of altruism: The effects of ozone alerts on outdoor recreation and driving in atlanta.

OECD (2016, June). *The Economic Consequences of Outdoor Air Pollution*. OECD Publishing.

Organization, W. H. and Others (2016). WHO global urban ambient air pollution database (update 2016). *Geneva, Switzerland: WHO*.

Peng, J. and H. Xiao (2018, December). How does smog influence domestic tourism in china? a case study of beijing. *Asia Pacific Journal of Tourism Research 23*(12), 1115–1128.

Pope, III, C. A., R. T. Burnett, M. C. Turner, A. Cohen, D. Krewski, M. Jerrett, S. M. Gapstur, and M. J. Thun (2011). Lung cancer and cardiovascular disease mortality associated with ambient air pollution and cigarette smoke: shape of the exposure–response relationships. *Environ. Health Perspect. 119*(11), 1616–1621.

Poudyal, N. C., B. Paudel, and G. T. Green (2013, April). Estimating the impact of impaired visibility on the demand for visits to national parks. *Tourism Econ. 19*(2), 433–452.

Power, M. C., M.-A. Kioumourtzoglou, J. E. Hart, O. I. Okereke, F. Laden, and M. G. Weisskopf (2015, March). The relation between past exposure to fine particulate air pollution and prevalent anxiety: observational cohort study. *BMJ 350*, h1111.

Qi, C. X., H. J. Gibson, and J. J. Zhang (2009, February). Perceptions of risk and travel intentions: The case of china and the beijing olympic games. *J. Sport Tourism 14*(1), 43–67.

Quist, J. S., M. Rosenkilde, M. B. Petersen, A. S. Gram, A. Sjödin, and B. Stallknecht (2018, March). 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*(3), 469–478.

Roberts, J. D., J. D. Voss, and B. Knight (2014, March). The association of ambient air pollution and physical inactivity in the united states. *PLoS One 9*(3), e90143.

Sillanpää, M., R. Hillamo, S. Saarikoski, A. Frey, A. Pennanen, U. Makkonen, Z. Spolnik, R. Van Grieken, M. Braniš, B. Brunekreef, M.-C. Chalbot, T. Kuhlbusch, J. Sunyer, V.-M. Kerminen, M. Kulmala, and R. O. Salonen (2006, January). Chemical composition and mass closure of particulate matter at six urban sites in europe. *Atmos. Environ. 40*, 212–223.

Skov, T., T. Cordtz, L. K. Jensen, P. Saugman, K. Schmidt, and P. Theilade (1991). Modifications of health behaviour in response to air pollution notifications in copenhagen. *Soc. Sci. Med. 33*(5), 621–626.

Smyth, R., V. Mishra, and X. Qian (2008, December). The environment and Well-Being in urban china. *Ecol. Econ. 68*(1), 547–555.

Sönmez, S. F. and A. R. Graefe (1998, November). Determining future travel behavior from past travel experience and perceptions of risk and safety. *J. Travel Res. 37*(2), 171–177.

Sun, C., M. E. Kahn, and S. Zheng (2017, January). Self-protection investment exacerbates air pollution exposure inequality in urban china. *Ecol. Econ. 131*, 468–474.

Tainio, M., A. J. de Nazelle, T. Götschi, S. Kahlmeier, D. Rojas-Rueda, M. J. Nieuwenhuijsen, T. H. de Sá, P. Kelly, and J. Woodcock (2016, June). Can air pollution negate the health benefits of cycling and walking? *Prev. Med. 87*, 233–236.

Tannenbaum, D., C. R. Fox, and T. Rogers (2017, July). On the misplaced politics of behavioural policy interventions. *Nature Human Behaviour 1*(7), 0130.

van Wagoner, C. Why city parks matter - powerful tools for cities | city parks alliance. `https://cityparksalliance.org/about-us/why-city-parks-matter/`. Accessed: 2020-4-15.

Wang, E., L. Zhao, Y. Zhou, and B. B. Little (2013, April). Valuing outdoor recreation activities using a Meta-Analysis model in china: An empirical study. *Tourism Econ. 19*(2), 415–432.

Wikipedia contributors (2019, November). Zhengzhou metro. `https://en.wikipedia.org/w/index.php?title=Zhengzhou_Metro&oldid=927286595`. Accessed: 2019-12-1.

Williams, A. M., D. J. Phaneuf, M. A. Barrett, and J. G. Su (2019, March). Short-term impact of PM2.5 on contemporaneous asthma medication use: Behavior and the value of pollution reductions. *Proc. Natl. Acad. Sci. U. S. A. 116*(12), 5246–5253.

Wolsko, C. and K. Lindberg (2013, June). Experiencing connection with nature: The matrix of psychological Well-Being, mindfulness, and outdoor recreation. *Ecopsychology 5*(2), 80–91.

World Travel & Tourism Council (2019). TRAVEL & TOURISM ECONOMIC IMPACT 2019 WORLD. Technical report.

Yan, L., F. Duarte, D. Wang, S. Zheng, and C. Ratti (2019, August). Exploring the effect of air pollution on social activity in china using geotagged social media check-in data. *Cities 91*, 116–125.

Yu, H., R. An, and F. Andrade (2017, July). Ambient fine particulate matter air pollution and physical activity: A longitudinal study of university retirees in beijing, china. *Am. J. Health Behav. 41*(4), 401–410.

Zhang, A., L. Zhong, Y. Xu, H. Wang, and L. Dang (2015). Tourists' perception of haze pollution and the potential impacts on travel: Reshaping the features of tourism seasonality in beijing, china. *Sustain. Sci. Pract. Policy 7*(3), 2397–2414.

Zhang, J. and Q. Mu (2018). Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks.

Zhang, X., X. Chen, and X. Zhang (2018, September). The impact of exposure to air pollution on cognitive performance. *Proc. Natl. Acad. Sci. U. S. A. 115*(37), 9193–9197.

Zhang, X., X. Zhang, and X. Chen (2017, September). Happiness in the air: How does a dirty sky affect mental health and subjective well-being? *J. Environ. Econ. Manage. 85*, 81–94.

Zhao, H., G. Geng, Q. Zhang, S. J. Davis, X. Li, Y. Liu, L. Peng, M. Li, B. Zheng, H. Huo, L. Zhang, D. K. Henze, Z. Mi, Z. Liu, D. Guan, and K. He (2019, September). Inequality of household consumption and air pollution-related deaths in china. *Nat. Commun. 10*(1), 4337.

Zhao, P., S. Li, P. Li, J. Liu, and K. Long (2018, August). How does air pollution influence cycling behaviour? evidence from beijing. *Transp. Res. Part D: Trans. Environ. 63*, 826–838.

Zheng, S., J. Wang, C. Sun, X. Zhang, and M. E. Kahn (2019, March). Air pollution lowers chinese urbanites' expressed happiness on social media. *Nat Hum Behav 3*(3), 237–243.

Zijlema, W. L., K. Wolf, R. Emeny, K. H. Ladwig, A. Peters, H. Kongsgård, K. Hveem, K. Kvaløy, T. Yli-Tuomi, T. Partonen, T. Lanki, M. Eeftens, K. de Hoogh, B. Brunekreef, BioSHaRE, R. P. Stolk, and J. G. M. Rosmalen (2016, March). The association of air pollution and depressed mood in 70,928 individuals from four european cohorts. *Int. J. Hyg. Environ. Health 219*(2), 212–219.