Prolonged Pollution Days in China:

How Does Air Pollution Duration Affect Subjective Well-Being (SWB)?

Gengyi (Rebecca) Chen

February 21, 2022
Carleton College Department of Economics
Senior Integrative Exercise

Acknowledgments

I would like to thank my advisor, Faress Bhuiyan, for all the support, guidance, and countless meetings since freshman year. In addition, I would like to thank all the faculty members in the Economics Department, the Library staff, the Quantitative Resources Center, my suitemates, friends, and family for technical and moral support- especially my roommate Leah Johnson, who is there every step of the way.

Abstract

This study examines the effect of prolonged air pollution on subjective well-being in China. Rapid economic growth in recent decades has contributed to hazardous levels of air pollution across different regions in China. Although tangible health risks of air pollution are well established, the effect of air pollution on subjective well-being is often overlooked.

I use a panel fixed-effects model with the various forms of air pollution duration as the independent variables and subjective well-being measures as the dependent variables. I find that exposure to prolonged pollution has negative effects on both hedonic happiness and life satisfaction. I also find that hedonic adaptation, a psychological process that protects individuals from mental stress by reducing the impacts of unfavorable situations, may potentially mute the effects of prolonged air pollution.

Contents

1. Introduction

China has experienced rapid economic growth over the past few decades, but the fossil-fuel-dependent economy also contributes to heavy air pollution across the country (Lu et al., 2020). Approximately 70% of all 338 municipal cities did not meet the national standard in 2017 (Lu et al., 2020). Recent studies in China also linked lung cancer mortality rates with air pollutant concentration, highlighting the need for continued pollution control and improvement in public health (Wu et al., 2021; Zhang & Cao, 2015),.

However, air pollution is associated with more than tangible health risks. Prolonged pollution can limit outdoor time and give individuals the perception of unhealthy living conditions, which also take an emotional toll (Ye & Zhang, 2020). Past studies on air pollution have established that exposure to pollutants increases health risks, including cardiovascular diseases and respiratory diseases (Afoakwah et al., 2020; Moretti & Neidell, 2011; Zhang et al., 2017), but research regarding the effect of air pollution on subjective well-being (SWB) has not yet been extensively studied (Zhang et al., 2017).

I investigate the relationship between air pollution and SWB in China using panel fixed effects models with individual-level data from the China Family Panel Studies (CFPS). Knowing that prolonged air pollution has significant impacts on public health (Liang et al., 2020; Liu et al., 2018), I explore the following research question – how does the duration of polluted days (number of polluted days in a month) affect SWB? I hypothesize that a longer pollution duration lowers individuals' short term happiness, but its effect on life satisfaction is muted due to hedonic adaptation, a psychological process that protects people from mental stress by reducing the impacts of unfavorable situations. My study contributes to the

intersection of environmental and happiness economics in two major ways. First, previous studies only examine the effects of pollution level on SWB while my study explores the effects of pollution duration. Second, I construct theoretical and econometric models to differentiate the mechanisms by which air pollution duration affects SWB – one through outdoor time and the other through hedonic adaptation. My empirical results suggest that exposure to prolonged pollution has negative effects on both hedonic happiness and life satisfaction, and hedonic adaptation is a potential mechanism that mutes the effect of long-term air pollution.

The structure of this paper is as follows. In section 2, I examine the context of air pollution in developing countries, which follows by a review of the current literature on prolonged pollution, SWB, and economic development in section 3. I construct the theoretical and econometric modeling in section 4 and 5, respectively. In section 6, I describe the data used in the study. I present my results and discussions in section 7 and 8. Section 9 concludes.

2. Context: Air Pollution and SWB Studies in China

To contextualize the air pollution situation in China, imagine you're a high school student in Beijing doing homework on a normal Wednesday night. A notification on your phone pops up, "…school is canceled until further notice due to hazardous levels of air quality." *Second time this month,* you think to yourself, *but at least I can avoid the crowded subway tomorrow.* You also know that the factories will be shut down and half of the cars

cannot be on the road, and it is time to get face masks and air filters out. In major industrial cities like Beijing, it is more common for schools to have "smog days off" than snow days off, as commuting to schools puts millions of children at risk of hazardous levels of pollution.

China provides an ideal case study on air pollution and subjective well-being (Apergis & Ozturk, 2015).[1] On one hand, with its rapid economic development over the past few decades, China faces severe pollution in major industrialized cities – less than 1% of the major cities in China met the World Health Organization (WHO) air quality standard in 2012 (Zhang & Crooks, 2012). Specifically, emissions of PM 2.5 and sulfur dioxide (SO_2) concentrations exceeded cities' environmental absorptive capacity by 80% and 50% respectively in 2015 (The World Bank, 2020). On the other hand, there is a growing interest in using life satisfaction as an alternative to objective economic measures in China (Clark et al., 2019). Although the majority of the studies focus on the recent economic growth and changes in life satisfaction, the increasing number of subjective well-being datasets available also allow for refined SWB studies that examine the role of environmental context (Clark et al., 2019; Ma & Chen, 2021).

[1] Subjective Well-being is defined as "good mental states, including all of the various evaluations, positive and negative, that people make of their lives, and the affective reactions of people to their experiences" by Organization for Economic Co-operation and Development (OECD). There are different measurements of SWB, and the most common distinction is between life evaluation (also known as life satisfaction) and measures of affect (also known as hedonic happiness) where life evaluation involves a cognitive evaluation of the person's life as a whole and the later refers to the feelings experienced by a person at a particular point in time (OECD, 2013). There is also the eudaimonic aspect of SWB which refers to a person's sense of purpose and engagement, but this concept will not be explored within the scope of this paper.

3. Literature Review

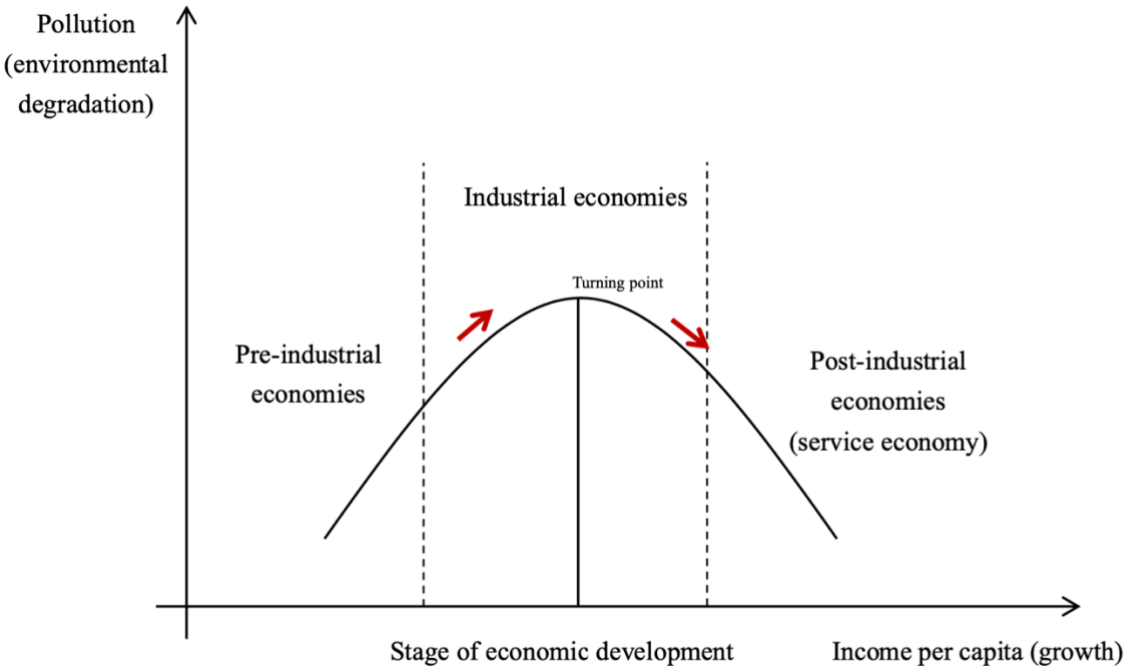
This section covers the existing literature on measures of air pollution and subjective well-being. It serves to bridge the gap of Environmental and Happiness Economics. The three subsections are air pollution and economic development, subjective well-being and air pollution, and the effects of prolonged pollution.

3.1 Air pollution and Economic Development

Developing countries constantly face the conundrum of balancing environmental protection and economic development when going through rapid industrialization. Environmental Kuznets Curve predicts an inverted "U" shaped relationship between economic growth and level of environmental degradation (Figure 1.) – environmental degradation increases with GDP per capita in early stages of growth and declines after reaching a threshold (Apergis & Ozturk, 2015; Grossman & Krueger, 1995). Countries experiencing rapid growth tend to prioritize industrialization as a means for sustained development, which leads to a higher level of pollution. As the economy grows, two factors lead to a turning point in the curve. First, the service sector grows stronger, and industrial production shifts to a less prominent position, which results in a lower pollution level. Second, countries are more likely to address environmental concerns, with their citizens becoming wealthier and more environmentally aware. This empirical trend has proven to be

true across Asian countries that are experiencing disharmonic industrialization, urbanization, and transportation development (Apergis & Ozturk, 2015).

Figure 1. Environmental Kuznets Curve with inverted "U" shaped relationship between economic growth and pollution



In developing countries, however, social and economic disparities tend to coexist with the high level of pollution (Mannucci & Franchini, 2017). The poor ambient air quality resulting from rapid industrialization puts vulnerable populations in developing countries more at risk than those in developed countries. Women and children are more likely to suffer from both short-term and long-term negative health consequences (Deng et al., 2015; Mannucci & Franchini, 2017). In addition, there are fewer preventative health services in developing countries, which increase the risk of air pollution exposure (Clark et al., 2019).

3.2 The Validity of Subjective Well-being measures

Easterlin first brought forth the observation that happiness is not strongly correlated with economic growth in his seminal work and introduced happiness studies to the field of Economics (Zhang et al., 2017). Since then, a growing literature continued to examine the Easterlin paradox and the validity of happiness measures, and the number of studies on SWB grew more than twentyfold from 1995 to 2005 in an economic journal database (Kahneman & Krueger, 2006). There is a consensus among economists that data on SWB are reliable for analyses (Diener et al., 2013; Rehdanz & Maddison, 2008; Zhang et al., 2017),

As opposed to objective measurements of individual well-being such as health outcomes, subjective well-being focuses on a person's cognitive and affective evaluations of their life and is typically measured through survey questions where participants are asked to rank their level of happiness (Diener et al., 2013; Zhang et al., 2017). There are two main measures of SWB that I examine in this study – life satisfaction and hedonic happiness. Life satisfaction is a life evaluation measurement that involves an overall cognitive evaluation of the person's life while hedonic happiness refers to the feelings experienced by a person at a particular point in time (OECD, 2013).

SWB studies reveals what cannot be captured by traditional economic analyses, and research conclusions can inform policymaking (MacKerron & Mourato, 2009). Economic conditions such as relative income and unemployment all influence SWB, suggesting that "happiness" is not just a personal feeling that is irrelevant to economic research (Clark et al., 2008; Frey, 2010; Rehdanz & Maddison, 2008). An understanding of how pollution affects citizens' SWB outcomes can give policymakers information to properly weigh the cost and

benefits of environmental regulations – only considering physical health-related costs would understate the cost of pollution (Zhang et al., 2017).

3.3 Subjective well-being and air pollution

Although studies on happiness economics have been growing, analyses on environmental issues are still the minority in the literature. Welsch first examined the ambient environmental quality and SWB using cross-national data in 2002, however, using cross-sectional approach could result in unobserved heterogeneity (Welsch, 2006). Studies in Europe conclude that both the objective measure of air pollution and the perceived pollution level reduce SWB (MacKerron & Mourato, 2009; Rehdanz & Maddison, 2008). Later studies also indicate that researchers need to consider endogeneity for perceived pollution levels, because a happy person could be less sensitive of heavy pollution and perceive pollution level to be lower. Overall, the literature concludes that air pollution level generally affects SWB negatively (Dolan & Laffan, 2016; MacKerron & Mourato, 2009; Zhang et al., 2017), and studies published in Chinese journals also confirm the negative correlation (Liu et al., 2021; Ye & Zhang, 2020; Zhu et al., 2020).

Some journal articles use life satisfaction, affect, and happiness interchangeably, but other studies make distinctions in the terminology to capture the nuances. While studies find air pollution lower life satisfaction (Laffan, 2018; MacKerron & Mourato, 2009), a few recent studies using datasets in China conclude that hedonic happiness is affected by air

pollution negatively but life satisfaction is not affected (Ye & Zhang, 2020; Zhang et al., 2017).

A potential explanation is the presence of hedonic adaptation, a psychological process that reduces long-term emotional impact of unfavorable circumstances. This strategy is evolutionarily favorable in protecting individuals from mental stress, and it helps individuals to save energy on attempts to change unchangeable situations (Diener et al., 2009; Zhang et al., 2017). In the case of air pollution, unhealthy air pollution is an unfavorable yet unchangeable situation. Thus, this evolutionary process could potentially counteract the effect of the duration of pollution on SWB. Hedonic happiness might not be subject to this process because it is a measurement of short-term SWB while hedonic adaptation is rather a long-term process. Life satisfaction, which captures the overall evaluation of one's life, could be influenced by hedonic adaptation. As a result, the effect of prolonged pollution on life satisfaction is be muted (Zhang et al., 2017).

3.4 Effects of prolonged pollution

Both short-term and long-term exposure to air pollutants negatively impact health (World Health Organization, 2019). Research has established that the duration of air pollution is an important factor in health outcomes and that prolonged exposure has significant impacts on public health (W. Liu et al., 2018). Specifically, longer exposure to outdoor pollutants such as PM2.5 increases mortality rates from respiratory causes, even if the exposure is at low pollution level (Eilstein, 2009; Strak et al., 2021).

Furthermore, individuals living in environments with prolonged pollution also reduce their outdoors time and physical activity levels (Laffan, 2018). The growing literature on home quarantine and mental health also sheds light on the effects of prolonged pollution as a restriction of mobility (Li et al., 2021). Economic literature has not yet been investigating the effect of pollution duration on SWB measures.

Thus, I conclude the gap from literature to be twofold. First, although there is evidence suggests the effect of air pollution on SWB is muted due to hedonic adaptation, there has not been a consensus among economists, and my research will contribute to the current literature on whether life satisfaction is resistant to air pollution. More importantly, although prolonged pollution negatively affects objective health outcomes, the relationship between duration of pollution and SWB has not been explored and my research aims to bridge that gap in the existing literature.

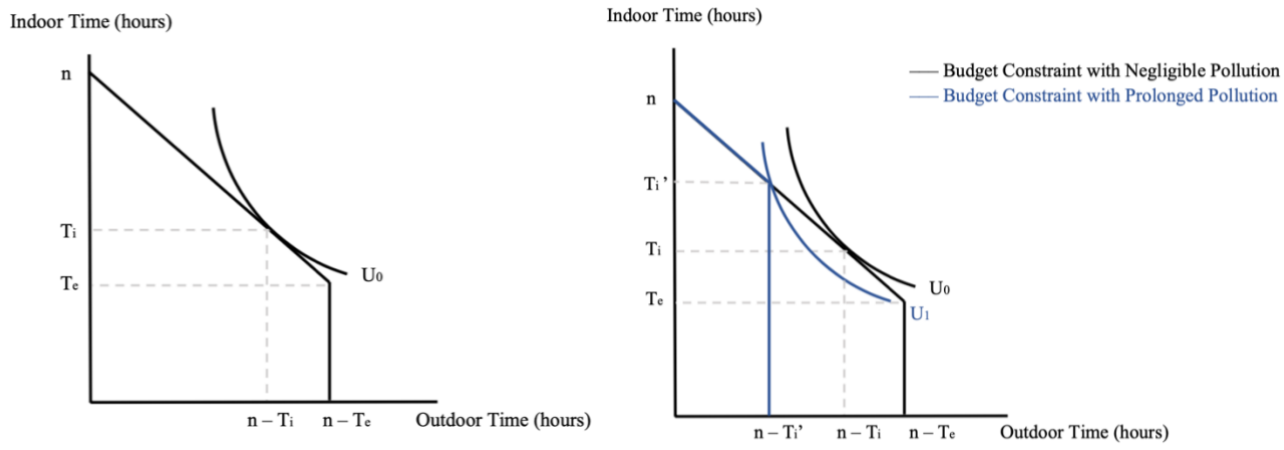
4. Theoretical Underpinnings

I examine two underlying mechanisms relating to SWB to test my hypothesis that the duration of air pollution has a negative effect on hedonic happiness whereas its effect on life satisfaction is muted. The feasible choice model predicts that prolonged pollution lowers SWB whereas the hedonic adaptation theory suggests the effects of prolonged pollution on life satisfaction could be muted by evolutionary processes.

4.1 Feasible Choice Sets and Utility Maximization

Behavioral studies indicate that physical environments affect individuals' perceptions and behaviors (Foster et al., 2004; Roberts et al., 2014). For individuals living in polluted environments, not only do their frequencies visiting the outdoors decrease by the presence of air pollution but their physical activity levels are reduced as well (Laffan, 2018). The behavioral change could in turn affect an individual's SWB. Studies find a positive correlation between both outdoor activities and life satisfaction (Ardahan & Mert, 2013) and physical activities and life satisfaction (Kim et al., 2018). Prolonged pollution could significantly reduce the amount of time individuals spend outdoors because they are aware of the negative health effects associated with air pollution. Moreover, the "smog days off" policy in China where school and work move online during prolonged pollution days could increase time individuals spend indoors (Hernández, 2015). Therefore, I posit that individuals would spend more time indoors if prolonged pollution is present, and SWB will be negatively affected.

Figure 2. Individual Utility Maximization Models with Indoor and Outdoor Time



(a) Negligible pollution scenario (b) Prolonged pollution scenario

Figure 2 presents the theory in a utility maximization model. The budget constraints illustrate an individual choosing between spending time indoors and outdoors. Figure 2 (a) depicts a scenario where the individual faces negligible air pollution. n is the total hours of time within a given time period (day, month, week, etc.), and T_e represents time spent indoors doing essential activities like sleeping, doing chores, and eating. The individual maximizes their utility U_0, with T_i hours of indoors time and (n - T_i) hours of outdoor time with their given preferences. Figure 2 (b) illustrates a situation where prolonged pollution increases the time people spend indoors because of health concerns and governmental regulations. Assuming individual's preference stays the same and the bundle chosen in 2 (a) is no longer feasible with the new budget constraint, and the individual's time spend indoors T_i' is greater than T_i and time outdoors (n - T_i') is lower than (n - T_i) in 2 (a). The maximized utility U_1, is on a lower indifference curve, indicating a lower level of SWB with the presence of prolonged air pollution.

4. 2 Hedonic Adaptation

Hedonic adaptation is a psychological process of reducing the long-term emotional impact of unfavorable circumstances. This strategy is evolutionarily favorable in protecting people from mental stress and helping people to save energy in attempts to change the unchangeable situations (Zhang et al., 2017). In the case of air pollution, unhealthy air pollution is an unfavorable yet unchangeable situation from the individual point of view. Thus, this evolutionary process could potentially counteract the effect of the duration of pollution on SWB. Hedonic happiness (affect) might not be subject to this process because it

is a measurement of short-term SWB while hedonic adaptation is rather a long-term process, but life satisfaction, which captures the overall evaluation of one's life, could be influenced by hedonic adaptation (Zhang et al., 2017). As a result, the effect of prolonged pollution on life satisfaction might be muted.

$$U = f\left(\frac{Outdoor\ Time}{Reference\ Outdoor\ Time},\ other\ factors\right) \qquad (1)$$

Equation (1) captures hedonic adaptation regarding outdoor and indoor time. The utility of an individual is derived from both the time spent outdoors and the reference point of outdoor time, which is what is perceived as the normal amount of time spent outdoors. Intuitively, the more hours spent outdoors, the higher the utility it is. The lower the reference hour is, the higher the level of utility is. If an individual is in an environment with heavy pollution, initially their outdoor time decreases but their reference outdoor time remains constant. The total utility of this individual will decrease as a result. However, if pollution continues and hedonic happiness takes place, reference outdoor time may start to decrease as well. As a result, utility of this individual could return to the initial level – or even higher depending on the magnitude of the change in reference.

5. Econometric Modelling

I use two econometric specifications to test my hypothesis: the first one explores the functional relationship between pollution duration and subjective well-being measures while the second specification employs a more nuanced analysis based on hedonic adaptation.

The first specification is as follows:

$$H_{ijt} = \beta_0 + \beta_1 f(D_{ijt}) + \boldsymbol{\beta_2 X_{ijt}} + \boldsymbol{\beta_3 W_{jt}} + \lambda_i + \delta_j + \eta_t + \varepsilon_{ijt} \qquad (2)$$

The dependent variable H_{ijt} is the SWB measures of respondent *i* in county *j* at time *t.* The two variables used for SWB are life satisfaction and hedonic happiness. The variable of interest D_{ijt} is the measure of duration of polluted days for respondent *i* in county *j* at time *t.* D_{ijt} is determined by the total number of days that are categorized as "Unhealthy" or worse in the past month.[2] The Environmental Protection Agency (EPA) suggests that when air quality falls in or above the unhealthy range, everyone can experience negative effects of air pollution if they are active outdoors. (US EPA, 2016).

$\boldsymbol{X_{ijt}}$ is a vector of control variables that includes absolute income, relative income, age and its square term, gender, marital status, years of education, unemployment status, party membership, and self-rated health status (A. E. Clark, 2016; Song & Appleton, 2008; Zhang et al., 2017; Zhu et al., 2020).[3] $\boldsymbol{W_{jt}}$ is a vector of weather controls that includes mean temperature and its square term and average precipitation. λ_i denotes individual fixed effect, δ_j represents county fixed effect, η_t indicates month and year fixed effect, and ε_{ijt} is the error term.

[2] United States Environmental Protection Agency (EPA) has six levels of air pollution standards based on pollution concentration, and I will discuss the standards more in details in the data section.
[3] Party membership indicates whether the induvial is part of the Chinese Communist Party. This control is commonly used in literature (Zhang et al., 2017; Zhu et al., 2020)

I test three different functional forms, *i)* $aD_{ijt} + b$, *ii)* $c\ ln\ D_{ijt}$, and *iii)* $gD_{ijt} + hD_{ijt}{}^2$. This allows me to show whether diminishing effect between the pollution duration and SWB is present. The second specification is as follows:

$$H_{ijt} = \alpha + \alpha_1\ D_{1ijt} + \alpha_2\ D_{2ijt} + \alpha_3\ D_{3ijt} + \alpha_4\ D_{1\&2ijt} + \alpha_5\ D_{1\&3ijt} + \alpha_6\ D_{2\&3ijt}$$
$$+\alpha_7\ D_{1\&2\&3ijt} + \alpha_{\mathbf{8}}\boldsymbol{X_{ijt}} + \alpha_{\mathbf{9}}\boldsymbol{W_{jt}} + \lambda_i + \delta_j + \eta_t + \varepsilon_{ijt} \qquad (3)$$

In this specification, D_{1ijt} to $D_{1+2+3ijt}$ are dummy variables representing whether the month(s) leading to the interview month are considered heavy pollution month(s). For example, if the interview is conducted in May, then D_{1ijt} represents whether April is a heavy pollution month for individual *i* in county *j* at time *t*. Table 1 presents detailed information on how each dummy variable is determined. A month (or combined months) is considered a pollution month if it has 70% or more of the days with AQI greater than 151 ("Unhealthy" or higher level). [4] All the dummy variables are mutually exclusive. If all previous three months are considered polluted, $D_{1+2+3ijt}$ is the only variable that takes the value of 1, all the other variables take the value of 0. The base group is D_{0ijt} where all three months in the past are not polluted. Different dummy variables provide a more nuanced regression result – if the prolonged pollution from the three months combined has less effect than that of one-month, hedonic adaptation could be the driving force.

[4] This analysis is ad hoc, and the level will also be tested at 50% level.

Table 1. Pollution dummy variables of months leading to the interview month

	Month		
Variables	T-1	T-2	T-3
D_{0ijt}			
D_{1ijt}	✓		
D_{2ijt}		✓	
D_{3ijt}			✓
D_{1+2ijt}	✓	✓	
D_{1+3ijt}	✓		✓
D_{2+3ijt}		✓	✓
$D_{1+2+3ijt}$	✓	✓	✓

Note: T-1 is the first month leading to the interview month, T-2 is the second month leading to the interview month, and T-3 is the third month leading to the interview month. For example, if May is the interview month, then T-1 is April, T-2 is March, and T-3 is February. For a particular variable, a check mark(s) means the month(s) is polluted (AQI>151).

There are potential biases in regression models that pose limitation to the study. Omitted variable bias could affect my econometric modeling. For example, individuals could be aware of governments in developing countries prioritizing the economy over pollution abatement and see that as a sign for economic prosperity (Ye & Zhang, 2020). There is no control for the perception of economic development in the dataset, therefore could result in biases in results. The potential issue is not concerning because I include controls from demographic and socioeconomic backgrounds as well as monthly weather conditions, consistent with previous literature (Ye & Zhang, 2020; Zhang et al., 2017; Zhu et al., 2020). I also use fixed-effects model to account for time-invariant characteristics like culture, religion, and other factors that are not easily observed or measured.

Measurement errors and attenuation bias could be another source of limitation. Chinese officials claimed that air quality data misreporting had ended after a series of reforms in 2012, however, a recent study using satellite data suggests that misreporting continued in local government that could lead to biased study results (Turiel & Kaufmann, 2021). Measurement inaccuracy from merging air pollution, SWB, and weather data could also contribute to attenuation bias.

Although the survey is nationally represented, selection bias could take place because the western half of the country tend to be less polluted but also more secluded. There are regions that might not be accessible for interviewers to go and therefore selection bias could occur. Simultaneity bias is not an issue in this study because the effect of air pollution on subjective well-being is likely to be one sided. The happiness level of a person cannot affect the pollution level of a city.

6. Data

6.1 Subjective Well-Being Measures

For this study, I use individual-level panel data from China Family Panel Studies (CFPS) for the subjective well-being information. This survey is nationally representative and offers insights into both the economic and non-economic wellbeing of contemporary Chinese families and individuals. The bi-annual survey was launched by the Institute of Social Science Survey (ISSS) and Peking University in 2010 (Institute of Social Science Survey,

2021). The CFPS covers 162 counties in 25 provinces that were randomly chosen to represent Chinese Society (Xie & Hu, 2014). I use data from 2014, 2016, 2018, and 2020 because air quality data are only available beginning 2014. All members of the household over age 9 were interviewed. Detailed summary statistics are presented in Appendix A.

Figure 3. China Family Panel Studies (CFPS) geographical reach [5]

The two SWB measures taken from this survey are questions on life satisfaction and hedonic happiness. The first one "Overall, how satisfied are you with your life?" measures life satisfaction on a scale of 1 (*not satisfied at all*) to 5 (*very satisfied*). Because the question does not specify a time frame, this measurement indicates a the individual's overall perception of their happiness levels (Zhang et al., 2017). The second SWB-related question is "to what extent did you agree with the statement 'I feel happy' in the past week according to

[5] The map polygons represent the Level 2 Administrative Boundaries (a sublevel of provincial boundaries), which mostly includes prefecture-level city (81%). Municipality (i.e., Beijing and Shanghai), autonomous prefecture, autonomous county, county-level city, prefecture, special administrative region, sub-prefecture-level city, and sub-province-level prefecture compose the other 19%. Boundary information obtained from China (CHN) Administrative Boundary Common Operational Database (COD-AB). The northern and western part of the country seem to be less represented than the other regions, suggesting selection bias could limit the study.

your mental statuses?". It measures hedonic happiness where 1 is *never (less than one day)*, 2 is *sometimes* (*1-2 days*), 3 is *often* (*3-4 days*), and 4 is *most of the time* (*5-7 days*).[6] The higher the score is, the happier and more satisfied the respondents are. Both life satisfaction and hedonic happiness scores are reported on an ordinal scale, however, the data in this study are treated as cardinal because past studies acknowledged that treating the data as cardinal and ordinal yields very similar results (Frey, 2010; Luechinger, 2010). The survey also presents data on economic activities, education status, health, relationships that allows me to control for a wide range of variables (Table 2).

Table 2. Demographic and Socioeconomic Controls from CFPS

	Survey questions and measurements	Categorical responses
Urban	Whether the individual lives in an urban or rural area	0- Rural and 1- Urban
Age	Age of the individual	N/A
Gender	Gender of the individual	0- Female and 1- Male
Marital	Marital status	1- Never married, 2- Married, 3- Cohabitation, 4- Divorced, 5- Widowed
Party Membership	Are you a member of the Communist Party?	0- No, 1-Yes
Health	How would you rate your health status?	1- Poor, 2- Fair, 3- Good, 4- Very good, 5- Excellent
Years of Education	Years of education the individual received	N/A
Employment Status	Current employment status	0- Unemployed, 2- Employed, 3- Out of labor market
Income	Total monthly income of all jobs	N/A
Relative Income	What is your relative income level in your local area?	1- very low to 5- very high

[6] The question in 2014 was asked with a time frame of last month, therefore excluded in the analyses of this paper.

6.2 Merging Air Pollution and Weather Data

The pollution data were obtained from The World Air Quality Index, a non-profit project providing transparent air quality information for more than 130 countries and 30, 000 stations. I generate the composite Air Quality Index (AQI) from individual pollutant AQI, including $AQI_{PM2.5}$, AQI_{PM10}, AQI_{O3}, AQI_{NO2}, AQI_{SO2}, and AQI_{CO}. [7] The composite AQI was calculated via the function:

$$AQI = max\ (AQI_{PM2.5}, AQI_{PM10}, AQI_{O3}, ...) \qquad (4)$$

AQI is one of the most common indices that indicate the pollution level of a region and ranges from 0 to 500. I use daily AQI data to calculate the number of days in a month with an unhealthy air quality. If the daily AQI is above the level of "Unhealthy" (AQI of 151 or higher) in the past month, it counts as a pollution day.[8] The Environmental Protection Agency (EPA) suggests that when air quality is in or above the unhealthy range, everyone can experience negative effects of air pollution if they are active outdoors. In addition, members of sensitive groups, such as children and those with pre-existing conditions, are likely to suffer negative effects if AQI is above 101.

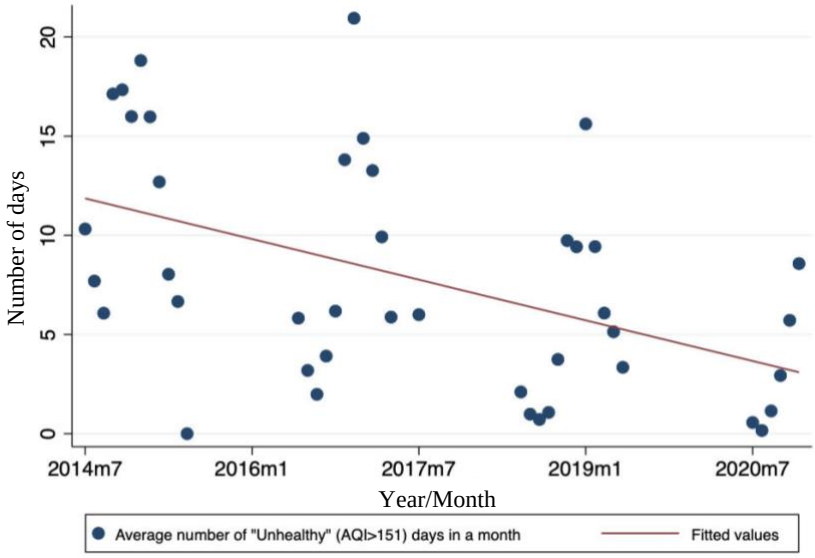
In addition, Over the past few years, China has been making continuous efforts to enforce air pollution controls since Premier Li Keqiang declared a war on pollution in 2014

[7] PM2.5 and PM10 are the two common characteristics of haze or smog episodes in China. They are both high fine particulate matter with aerodynamic diameters not larger than 2.5 μm for PM2.5 and 10 μm for PM10 (Zhang & Cao, 2015). The PM2.5 mean level is around 3 times as high as that of the global mean, suggesting a serious health risk(Zhang & Cao, 2015).

[8] The levels of air pollution are listed as follows according to United States Environmental Protection Agency (EPA): "Good" (AQI<50), "Moderate" (AQI in 51–100), "Unhealthy for Sensitive Groups" (AQI in 101–150), "Unhealthy" (AQI in 151–200), "Very Unhealthy" (AQI in 201–300), and "Hazardous" (AQI>301) (US EPA, 2016).

(Wu, 2018). My data also show a decreasing trend of air pollution duration since 2014 (Figure 2), with seasonal fluctuations of pollution level – winter months tend to have longer pollution duration, largely due to coal-burning (Zhang & Cao, 2015).

Figure 2. National average of polluted days per month from July 2014 to December 2020 [9]



I obtain the weather pattern data from National Climatic Data Center (NCDC) under the National Center for Environmental Information (NCEI) and Oceanic and Atmospheric Administration of the United States (NOAA). The measurements taken from NCDC are daily average temperature, daily precipitation, and daily snowfall. The data were aggregated to monthly data, namely, month average temperature, month average precipitation, and month average snowfall. I also add a weather-related control which indicates whether the province is a coastal province, which affect the climate of the regions (Sun et al., 2017). Air pollution duration and weather pattern data were matched to county-level data in the CFPS survey with

[9] With missing months where no interviews were conducted.

county, year, and month information as identifiers.[10] Survey results from CFPS were matched with the city-level AQI and weather data. If city-level data were not available, county data were matched to stations that are within 80 km radius of the county, or else data were coded as missing (Zhang et al., 2017). The total merged data contain 135 counties from 25 provinces (Table 3).

Table 3. Percentage of survey data matched to pollution and weather data by province

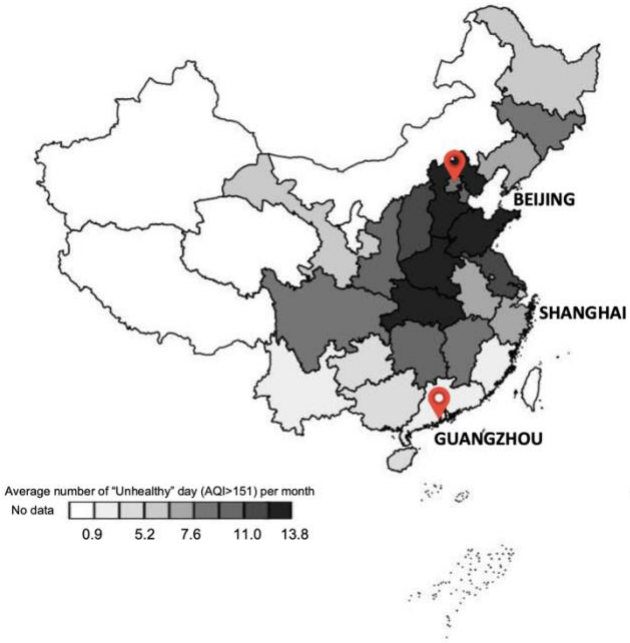
Province	Shanghai	Tianjin	Beijing	Chongqing	Jiangxi	Jilin	Yunnan
%	99.9	99.8	99.6	99.2	94.0	93.9	93.2
Province	Guizhou	Guangxi	Hebei	Hubei	Heilongjiang	Hunan	Anhui
%	92.8	92.4	91.9	89.6	89.2	88.0	87.4
Province	Shaanxi	Shandong	Shanxi	Gansu	Jiangsu	Sichuan	Liaoning
%	86.9	86.7	85.5	85.4	84.1	83.8	83.5
Province	Guangdong	Fujian	Henan	Zhejiang			
%	82.7	82.1	80.0	68.0			

Figure 3 presents air pollution and SWB summary statistics in maps. Figure 3 (a) and (b) illustrate pollution duration across China while Figure 3 (c) and (d) show SWB measures geographical distribution. All county-level data are aggregated to province-level. Pollution duration is longer in northern region than that of the southern region, with the most severe prolonged pollution occurs around Beijing-Tianjin-Hebei region, consistent with public perception and existing literature (Xiao et al., 2020). SWB distribution did not have a clear pattern across provinces.

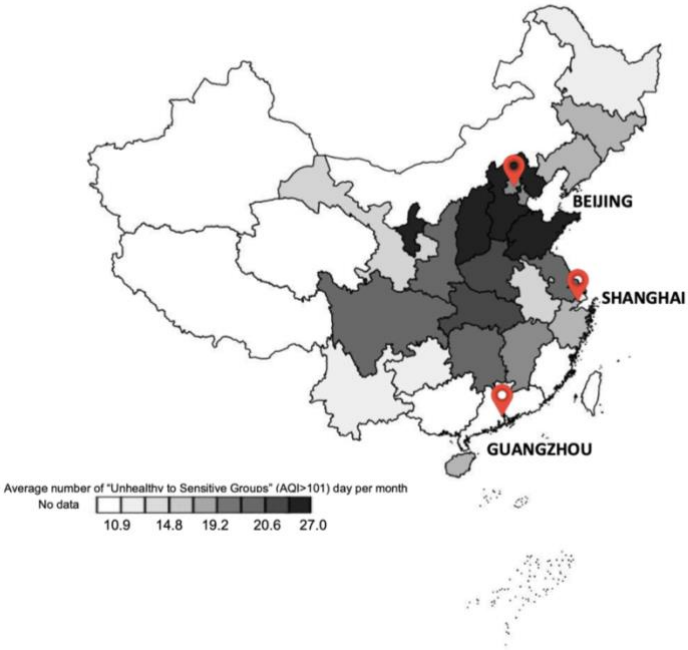
[10] Counties are given unique numeric values for identification, but the names of the county are currently withheld by CFPS for remote users. Thus, I use county-level population data (obtained from China Data Online) as an approximation to identify the counties listed in CFPS as it is a nationally representative survey. For example, the county with the highest population in Guangdong province is matched with the county with the largest number of respondents in the CFPS survey. Direct-administered municipalities- Beijing, Shanghai, Tianjin, and Chongqing- are excluded from this process of county matching. This process could contribute to measurement errors and attenuation bias.

Figure 3. Air pollution and SWB data summary statistics with geographical information[11]

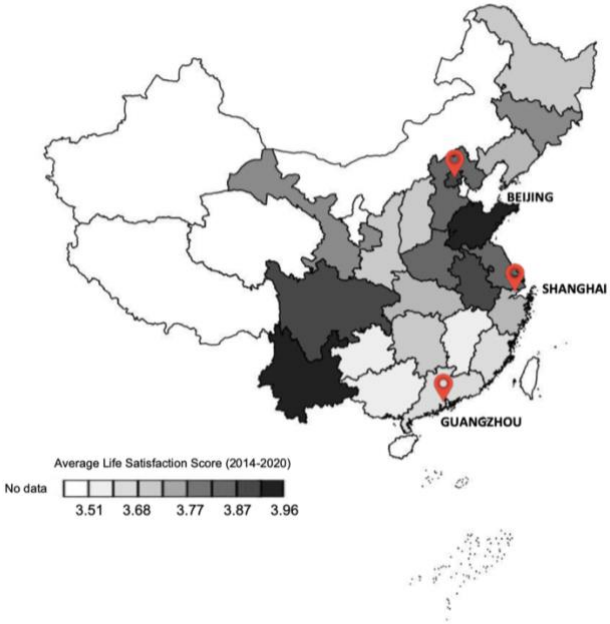
(a) Average number of "Unhealthy" day (AQI>151) per month in China (2014-2020)



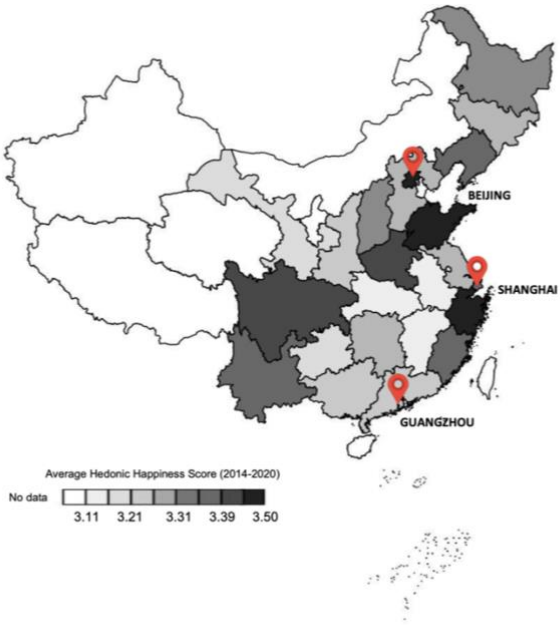
(b) Average number of "Unhealthy to Sensitive Groups" day (AQI>101) per month in China (2014-2020)



(c) Average satisfaction score in China (2014-2020)



(d) Average hedonic happiness score in China (2014-2020)



[11] Provincial boundary data was obtained from China Data Institute (Digital Map Database of China, 2020).

7. Results

7.1 Baseline Regression Results

Table 4 presents the baseline regression results with different functional forms from equation (2).[12] All regressions include control for demographic and socioeconomic factors, weather, individual fixed effects, county fixed effects, and month and year fixed effects. In addition, I use robustness standard errors for the following regressions to account for heteroscedasticity, where systematic change occurs in the variance of residuals over a range of values. Columns (1) to (3) describe the functional relationship of pollution duration and hedonic happiness. There is no significant relationship between both the linear and quadratic functional forms of pollution duration and hedonic happiness, but the natural log of pollution duration is positively correlated with hedonic happiness. Columns (4) to (6) describe the functional relationship of pollution duration and life satisfaction. There is no significant relationship between pollution duration in the functional forms and life satisfaction, but the natural log transformed pollution duration is negatively correlated with life satisfaction. A one-percent increase in pollution duration is associated with a decrease of 0.000047 in life satisfaction measure. Consistent with previous studies, both relative income and self-rated health status have positive and significant effects on both measures of SWB, regardless of the functional forms (Zhang et al., 2017).

[12] I conduct Hausman Test for all the functional forms. All the functional form regressions with life satisfaction indicate a fixed effects model is more appropriate. For the hedonic happiness regressions, even though the tests do not indicate fixed effects models as more appropriate, I assume that something within the panel (individual) may impact or bias the predictor variables.

Table 4. Baseline Pollution Duration Regression Models with Different Functional Forms

	Hedonic Happiness			Life Satisfaction		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Duration	0.00258	0.000389		0.000738	0.000109	
	(0.00202)	(0.00584)		(0.00221)	(0.00611)	
Duration^2		7.62e-05			2.19e-05	
		(0.000185)			(0.000197)	
ln (Duration)			0.0501**			-0.00476
			(0.0213)			(0.0249)
Urban	-0.0938	-0.0937	-0.0993	0.0132	0.0132	0.0111
	(0.0595)	(0.0595)	(0.0626)	(0.0576)	(-0.0281)	(-0.0592)
Age	-0.0142	-0.0138	0.00652	-0.0282	-0.0281	-0.0189
	(0.0318)	(0.0319)	(0.0388)	(0.0239)	(0.0240)	(0.0322)
Age^2	-8.19e-06	-9.75e-06	-4.52e-05	0.000547***	0.000547***	0.000642***
	(0.000206)	(0.000206)	(0.000214)	(0.000202)	(0.000202)	(0.000212)
Marital Status	**0.156****	**0.157****	**0.163****	0.0520	0.0522	0.0522
	(0.0691)	(0.0691)	(0.0730)	(0.0785)	(0.0785)	(0.0816)
Party Membership	0.0318	0.0312	0.0524	0.100	0.1000	0.0751
	(0.0862)	(0.0863)	(0.0902)	(0.0897)	(0.0897)	(0.0942)
Health	**0.0805*****	**0.0804*****	**0.0784*****	**0.0938*****	**0.0938*****	**0.0902*****
	(0.0129)	(0.0129)	(0.0134)	(0.0139)	(0.0139)	(0.0144)
Years of Education	0.00176	0.00152	0.00611	-0.00753	-0.00760	-0.0164
	(0.0171)	(0.0171)	(0.0183)	(0.0198)	(0.0198)	(0.0208)
Employment Status	0.110	0.110	0.143	0.233**	0.233**	0.213*
	(0.0998)	(0.0998)	(0.106)	(0.105)	(0.105)	(0.113)
Income	-3.74e-08	-3.70e-08	2.05e-07	7.40e-08*	7.41e-08*	6.36e-07*
	(3.17e-08)	(3.18e-08)	(3.81e-07)	(4.31e-08)	(4.31e-08)	(3.73e-07)
Relative Income	**0.0278****	**0.0277****	**0.0263***	**0.165*****	**0.165*****	**0.165*****
	(0.0139)	(0.0139)	(0.0144)	(0.0159)	(0.0159)	(0.0166)
Constant	3.032**	3.031**	2.065	2.706***	2.705***	2.315*
	(1.379)	(1.384)	(1.701)	(0.959)	(0.960)	(1.361)
Observations	23,002	23,002	22,094	23,016	23,016	22,108
R-squared	0.116	0.116	0.119	0.132	0.132	0.131
Number of Individual	17,585	17,585	17,079	17,595	17,595	17,090
Individual FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Note: 1. *** p<0.01, ** p<0.05, * p<0.1, and robust standard errors are included in parentheses

2. I also control for weather: average monthly temperature and square, coastal dummy, and monthly average precipitation

For the linear functional form of pollution duration and hedonic happiness, a one-point increase in the relative health status is associated with a 0.0805 point increase in hedonic happiness measures. A one-point increase in the relative income score is associated with a 0.0278 point increase in hedonic happiness measures. [13]

Table 5 present the baseline pollution duration regression models with pollution duration dummy variables from equation (3). Column (1) represents the regression results of pollution duration dummy variables and hedonic happiness measure. D_{1ijt} is negatively correlated with hedonic happiness and is significant at a 0.05 significance level.[14] This suggests that for individuals who were in a polluted environment only for the month prior to their interview, their hedonic happiness measure is 0.190 lower compared to those in the base group D_{0ijt}. The coefficient for D_{1+2ijt} suggests that for individuals who were in a polluted environment only for the first and second month prior to their interview, their hedonic happiness measure is 0.336 higher than those in the base group.[15] Column (2) represents the regression results of pollution duration dummy variables and life satisfaction measure. The coefficient of D_{2+3ijt} suggests that for individuals in this group, their life satisfaction measure is 0.161 lower compared to the base group. [16] [17]

[13] Health status ranges from 1 "Poor" to 5 "Excellent" and relative income ranges from 1 "very low" to 5 "very high"
[14] The robust standard error is 0.0943
[15] The robust standard error is 0.142
[16] The robust standard error is 0.0718
[17] All dummy variables are mutually exclusive. *D1ijt* suggests that the first month leading to the interview month is the *only* polluted month and *D2+3ijt* suggests that both the second and third months are considered polluted but the first month leading to the interview month is *not* polluted. *D0ijt* is the base group with no pollution months.

Table 5. Baseline Pollution Duration Regression Models with Dummy Variables

	(1) Hedonic Happiness	(2) Life Satisfaction
D_{1ijt}	**-0.190****	-0.0743
	(0.0943)	(0.110)
D_{2ijt}	0.0659	0.0639
	(0.0878)	(0.0899)
D_{3ijt}	-0.0218	-0.0352
	(0.0564)	(0.0599)
D_{1+2ijt}	**0.336****	0.213
	(0.142)	(0.174)
D_{1+3ijt}	0.0917	0.0859
	(0.239)	(0.318)
D_{2+3ijt}	-0.0284	**-0.161****
	(0.0745)	(0.0718)
$D_{1+2+3ijt}$	-0.00326	0.0336
	(0.0420)	(0.0456)
Constant	3.183***	2.686***
	(1.155)	(0.837)
Observations	23,660	23,674
R-squared	0.118	0.132
Number of Individuals	17,989	17,999
Individual FE	YES	YES
County FE	YES	YES
Time FE	YES	YES

Note: 1. *** p<0.01, ** p<0.05, * p<0.1, and robust standard errors are included in parentheses
2. I control for weather, demographic, and socioeconomic factors referred in data section

7.2 Heterogeneous Effects

I test for heterogeneous effects by constraining the sample into different groups. Table 6 presents the heterogeneous effects of pollution levels – with high and low pollution. Column (1) and (2) represent regression results from low pollution counties. For individuals in low

pollution regions, having only the first month as polluted month decreases hedonic happiness by 1.445 and life satisfaction by 1.220 compared to those in the base group.[18] For those in the $D_{1+2+3ijt}$ group, the life satisfaction score is 0.638 lower compared to those in the base group.[19] Column (3) and (4) represent regression results from high pollution counties. For individuals in high pollution regions and in the D_{2+3ijt} group, the life satisfaction score is 0.215 lower compared to those in the base group.[20]

Table 7 presents the heterogeneous effects on rural and urban areas. Column (1) and (2) represent regression results from urban region. The coefficient of D_{2+3ijt} indicates that only having the second and third as polluted month decrease life satisfaction by 0.209 compared to those in the base group. Rural area is represented in column (3) and (4), all the other coefficients are not significant except for the D_{1+2ijt} dummy, which have a positive and significant effect on hedonic happiness.

[18] The robust standard errors for hedonic happiness and life satisfaction are 0.573 and 0.567, respectively
[19] The robust standard error is 0.290
[20] The robust standard errors is 0.0831

Table 6. Heterogeneous Effects of Pollution Duration on SWB by Pollution Level

	Low Pollution		High Pollution	
	(1) Hedonic Happiness	(2) Life Satisfaction	(3) Hedonic Happiness	(4) Life Satisfaction
D_{1ijt}	**-1.445****	**-1.220****	-0.178	0.0840
	(0.573)	(0.567)	(0.120)	(0.147)
D_{2ijt}			0.0764	0.0373
			(0.0912)	(0.0944)
D_{3ijt}	-0.283	-0.762	-0.000617	-0.0515
	(0.486)	(0.589)	(0.0699)	(0.0732)
D_{1+2ijt}			0.308	0.323
			(0.205)	(0.266)
D_{1+3ijt}			0.0745	0.104
			(0.249)	(0.326)
D_{2+3ijt}	0.00852	-0.483	-0.0180	**-0.215*****
	(0.549)	(0.508)	(0.0880)	(0.0831)
$D_{1+2+3ijt}$	-0.139	**-0.638****	0.0201	-0.0245
	(0.283)	(0.290)	(0.0567)	(0.0607)
Constant	3.850**	0.878	2.792	3.250***
	(1.913)	(2.218)	(1.931)	(1.195)
Observations	6,838	6,839	16,822	16,835
R-squared	0.114	0.204	0.121	0.148
Number of Individual	6,074	6,076	13,723	13,733
Time FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Weather Controls	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES

Note 1. *** p<0.01, ** p<0.05, * p<0.1, and robust standard errors are included in parentheses

2. A county with more than half of the year (182 days) falls into the "Unhealthy to Sensitive Group" pollution level or above is considered a high pollution region at any given year. I chose "Unhealthy to Sensitive Group" instead of "Unhealthy" as a cut-off level because the possibility of under reporting and overall lower air pollution standard (Lu et al., 2020; Turiel & Kaufmann, 2021).

For robustness check, I run regressions for the baseline and heterogeneous effects with a different cutoff percent for a month to be considered a prolonged pollution month. Instead of using 70% as the cutoff, I use 50% as the standard for prolonged pollution. Baseline coefficients are not significant, but the heterogeneous effects yield similar results. I also include regressions with other groups for heterogeneous effects, including age, gender, and education level. All the robustness results are in Appendix B.

Table 7. Heterogeneous Effects of Pollution Duration on SWB by Rural and Urban

	Urban		Rural	
	(1) Hedonic Happiness	(2) Life Satisfaction	(3) Hedonic Happiness	(4) Life Satisfaction
D_{1ijt}	-0.183	-0.147	-0.197	-0.0717
	(0.134)	(0.180)	(0.135)	(0.146)
D_{2ijt}	0.170	0.154	-0.0701	-0.00896
	(0.122)	(0.127)	(0.130)	(0.130)
D_{3ijt}	-0.0656	-0.00134	-0.0141	-0.0984
	(0.0785)	(0.0815)	(0.0843)	(0.0896)
D_{1+2ijt}	0.352	0.178	**0.375***	0.198
	(0.252)	(0.296)	(0.200)	(0.246)
D_{1+3ijt}	0.0972	0.566	0.155	-0.122
	(0.578)	(0.525)	(0.239)	(0.396)
D_{2+3ijt}	-0.0686	**-0.209****	-0.00604	-0.159
	(0.101)	(0.106)	(0.115)	(0.101)
$D_{1+2+3ijt}$	0.0271	0.113*	-0.0739	-0.0729
	(0.0571)	(0.0659)	(0.0662)	(0.0691)
Constant	5.766***	4.173***	1.197	2.776***
	(1.221)	(1.152)	(1.090)	(1.076)
Observations	11,524	11,529	12,136	12,145
R-squared	0.136	0.135	0.107	0.128
Number of Individuals	8,609	8,612	9,744	9,751
Individual FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Note 1. *** p<0.01, ** p<0.05, * p<0.1, and robust standard errors are included in parentheses

2. Demographic, socioeconomic, and weather control are also included

8. Discussion

In this study, I find that prolonged pollution days have negative effects on SWB – both on hedonic happiness and life satisfaction, and hedonic adaptation is a potential mechanism that mutes the effects of long-term air pollution. I focus my analysis on the dummy variable regressions because the functional form regression results are not significant. I first discuss the main findings on the two measures of SWB and the theoretical underpinnings of outdoor time. I then discuss the presence of hedonic adaptation in results, follow by a discussion on the limitations of my study and implications to future ones.

8.1 Prolonged Pollution and Subjective Well-being

Pollution duration has a negative and significant effect on both hedonic happiness and life satisfaction (Table 5). In other words, prolonged pollution negatively affects an individual's short-term and long-term happiness. This finding aligns with previous literature that concludes high pollution levels lower individuals' life satisfaction (J. Liu et al., 2021; MacKerron & Mourato, 2009; Rehdanz & Maddison, 2008; Zhu et al., 2020) and hedonic happiness (Zhang et al., 2017). I expect the effect on life satisfaction to be muted due to hedonic adaptation according to a few studies in China (Ye & Zhang, 2020; Zhang et al., 2017), however, previous research focuses on the effect of the level of pollution instead of the duration of pollution. In other words, although the effect of high pollution levels might be reduced by hedonic adaptation, my study suggests that the presence of prolonged pollution could still negatively affect individuals' life satisfaction.

Another nuance between the two measures lies in which dummy variables, or which month(s), are affected by prolonged pollution exposure. For hedonic happiness, the significant negative effect is only present in the D_{1ijt} group. Only prolonged pollution in the first month (and not the second and third month) prior lowers hedonic adaptation. For life satisfaction, the significant negative effect is present in the D_{2+3ijt} group. Prolonged pollution in the second and third months (and not the first month) prior lowers life satisfaction. Results indicate that hedonic happiness is affected by prolonged pollution in a shorter time frame whereas life satisfaction is affected with a longer time frame. The result is expected based on how these two variables are measured, with hedonic happiness asking respondents' happiness level in the past week and life satisfaction without any time frame. The difference in regression coefficients and significance suggests that the two measures capture different aspects of SWB, which further indicates that prolonged exposure to air pollution lowers both short-term and long-term happiness.

The results align with the theoretical underpinning of the utility maximization model with indoor and outdoor time. With prolonged pollution, outdoor time could be significantly reduced because of the government mandate for remote work and the worry for adverse health factors. Shorter outdoor time could lead to budget constrain shrinking, and in turn, a lower level of utility. The utility maximization model can be used for both hedonic adaptation and life satisfaction because indoor and outdoor times are not constrained to a certain time frame. The total available hours n for an individual could be any amount.

It is important for government agencies to be aware that the cost of air pollution is more than the tangible health outcomes but also the mental well-being of the citizens. In addition,

Recent studies suggest that there is a decline in worker and student productivity because of air pollution exposure, in addition to the physiological pathway, there might be a psychological explanation related to lower physical activities (Chang et al., 2016; Ebenstein et al., 2016).

8.2 Prolonged Pollution and Hedonic Adaptation

I find that hedonic adaptation is a potential mechanism that mutes the effect of prolonged air pollution. Results from heterogeneous effects of high and low pollution counties allude to the presence of hedonic adaptation. In low pollution counties, the effect of prolonged pollution is mostly negative and significant, but in high pollution counties, the effect is mostly not significant for both hedonic happiness and life satisfaction. High pollution counties are defined to have more than half of the year with AQI greater than 101, in other words, prolonged pollution is the norm in these counties. As a result, exposure to long-term air pollution could shift individuals' frames of reference, therefore muting the effect of air pollution through hedonic adaptation. Specifically, chronically reduced outdoor time could lead to a lower reference outdoor time outlined in equation (1). The utility level could rise from the initial drop as hedonic adaptation takes place.

Overall, the psychological mechanism of hedonic adaptation could counteract the negative effects associated with prolonged pollution through examining the heterogeneity results of high and low pollution regions. Policymakers and think tanks should be aware when less stringent environmental regulations are put forth using the argument that life

satisfaction is not affected by air pollution. Despite people has adapting to air pollution, it does not make poor air quality acceptable.

8.3 Limitations and Implications for Future Studies

There are several limitations and implications that could help inform future research to better understand the relationship between prolonged pollution and subjective well-being. First, regressions on heterogeneous effects between rural and urban areas show a positive coefficient between D_{1+2ijt} and hedonic happiness for rural population (Table 7). This helps to explain the positive in the baseline coefficient but also suggests the possible omitted variable bias. There could be a factor that can capture the positive perception of air pollution as economic prosperity in rural area. Researchers could investigate the interaction of the Environmental Kuznets Curve and the perception of economic wellbeing.

Future research could also minimize measurement errors with full access to CFPS data. There are data withheld by CFPS for remote users. The interview date and county names are only available for in-person user. Future research could refine the study by using week as a measurement for hedonic happiness.[21] In addition, county names will allow a more accurate matching results compared to my current methodology, and therefore reducing attenuation bias.

[21] The question was phrased with the time frame of a week.

9. Conclusion

This study examines the intersection of Environmental and Happiness Economics to explore the effects of prolonged pollution on subjective well-being. This is especially relevant in developing countries like China that face serious pollution problems. Using China Family Panel Study (CFPS) data from 2014, 2016, 2018, and 2020, I show that exposure to prolonged air pollution negatively affects both individual hedonic happiness and life satisfaction. The potential mechanism by which pollution affects SWB is through reducing outdoor activities time.

Furthermore, I find that hedonic adaptation, a psychological process that protects individuals from mental stress by reducing the impacts of unfavorable situations, may mute the effects of prolonged air pollution. Despite limitations of the research, my study results add to the literature of air pollution and SWB. Policymakers should note that the cost of air pollution is not only the negative tangible health outcomes but also the happiness of the citizens. An understanding of how pollution affects citizens' SWB outcomes can provide better information to properly weigh the cost and benefits of environmental regulations.

Work Cited

Afoakwah, C., Nghiem, S., Scuffham, P., Huynh, Q., Marwick, T., & Byrnes, J. (2020). Impacts of Air Pollution on Health: Evidence from Longitudinal Cohort Data of Patients with Cardiovascular Diseases. *European Journal of Health Economics*, *21*(7), 1025–1038. http://dx.doi.org/10.1007/s10198-020-01198-5

Apergis, N., & Ozturk, I. (2015). Testing Environmental Kuznets Curve hypothesis in Asian countries. *Ecological Indicators*, *52*, 16–22. https://doi.org/10.1016/j.ecolind.2014.11.026

Ardahan, F., & Mert, M. (2013). Impacts of Outdoor Activities, Demographic Variables and Emotional Intelligence on Life Satisfaction: An Econometric Application of a Case in Turkey. *Social Indicators Research*, *113*(3), 887–901. https://doi.org/10.1007/s11205-012-0118-5

Chang, T., Graff Zivin, J., Gross, T., & Neidell, M. (2016). Particulate Pollution and the Productivity of Pear Packers. *American Economic Journal: Economic Policy*, *8*(3), 141–169. https://doi.org/10.1257/pol.20150085

Clark, A. E. (2016). Adaptation and the Easterlin Paradox. In T. Tachibanaki (Ed.), *Advances in Happiness Research: A Comparative Perspective* (pp. 75–94). Springer Japan. https://doi.org/10.1007/978-4-431-55753-1_6

Clark, A. E., Frijters, P., & Shields, M. A. (2008). Relative Income, Happiness, and Utility: An Explanation for the Easterlin Paradox and Other Puzzles. *Journal of Economic Literature*, *46*(1), 95–144. https://doi.org/10.1257/jel.46.1.95

Clark, W. A. V., Yi, D., & Huang, Y. (2019). Subjective well-being in China's changing society. *Proceedings of the National Academy of Sciences*, *116*(34), 16799–16804. https://doi.org/10.1073/pnas.1902926116

Deng, Q., Lu, C., Norbäck, D., Bornehag, C.-G., Zhang, Y., Liu, W., Yuan, H., & Sundell, J. (2015). Early life exposure to ambient air pollution and childhood asthma in China. *Environmental Research*, *143*, 83–92. https://doi.org/10.1016/j.envres.2015.09.032

Diener, E., Inglehart, R., & Tay, L. (2013). Theory and Validity of Life Satisfaction Scales. *Social Indicators Research*, *112*(3), 497–527. https://doi.org/10.1007/s11205-012-0076-y

Diener, E., Lucas, R. E., & Scollon, C. N. (2009). Beyond the Hedonic Treadmill: Revising the Adaptation Theory of Well-Being. In E. Diener (Ed.), *The Science of Well-Being: The Collected Works of Ed Diener* (pp. 103–118). Springer Netherlands. https://doi.org/10.1007/978-90-481-2350-6_5

Digital Map Database of China. (2020). *Provincial Boundary* (V1 ed.). Harvard Dataverse. https://doi.org/10.7910/DVN/DBJ3BX

Dolan, P., & Laffan, K. (2016). Bad Air Days: The Effects of Air Quality on Different Measures of Subjective Well-Being. *Journal of Benefit-Cost Analysis*, *7*(1), 147–195. https://doi.org/10.1017/bca.2016.7

Ebenstein, A., Lavy, V., & Roth, S. (2016). The Long-Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution. *American Economic Journal: Applied Economics*, *8*(4), 36–65. https://doi.org/10.1257/app.20150213

Eilstein, D. (2009). [Prolonged exposure to atmospheric air pollution and mortality from respiratory causes]. *Revue Des Maladies Respiratoires*, *26*(10), 1146–1158. https://doi.org/10.1016/s0761-8425(09)73532-6

Foster, C., Hillsdon, M., & Thorogood, M. (2004). Environmental perceptions and walking in English adults. *Journal of Epidemiology & Community Health*, *58*(11), 924–928. https://doi.org/10.1136/jech.2003.014068

Frey, B. S. (2010). *Frey, B. S. (2010). Happiness: A revolution in economics. The MIT Press.* The MIT Press.

Grossman, G. M., & Krueger, A. B. (1995). Economic Growth and the Environment*. *The Quarterly Journal of Economics*, *110*(2), 353–377. https://doi.org/10.2307/2118443

Hernández, J. C. (2015, December 9). In Beijing, a Day Off School for Smog Is No Fun for Anyone. *The New York Times*. https://www.nytimes.com/2015/12/10/world/asia/in-beijing-a-day-off-school-for-smog-is-no-fun-for-anyone.html

Institute of Social Science Survey, P. U. (2021). *China Family Panel Studies (CFPS)* [Data set]. Peking University Open Research Data Platform. https://doi.org/10.18170/DVN/45LCSO

Kahneman, D., & Krueger, A. B. (2006). Developments in the Measurement of Subjective Well-Being. *Journal of Economic Perspectives*, *20*(1), 3–24. https://doi.org/10.1257/089533006776526030

Kim, J., Heo, J., Dvorak, R., Ryu, J., & Han, A. (2018). Benefits of leisure activities for health and life satisfaction among Western migrants. *Annals of Leisure Research*, *21*(1), 47–57. https://doi.org/10.1080/11745398.2017.1379421

Laffan, K. (2018). Every breath you take, every move you make: Visits to the outdoors and physical activity help to explain the relationship between air pollution and subjective wellbeing. *Ecological Economics*, *147*, 96–113. https://doi.org/10.1016/j.ecolecon.2017.12.024

Liu, J., Dang, X., Zhang, W., & Wei, L. (2021). 中国城市 PM2.5 污染对居民主观幸福感的影响及支付意愿研究. 地理科学, *41*(12), 2096–2106. https://doi.org/10.13249/j.cnki.sgs.2021.12.003.

Liu, W., Xu, Z., & Yang, T. (2018). Health Effects of Air Pollution in China. *International Journal of Environmental Research and Public Health*, *15*(7), 1471. https://doi.org/10.3390/ijerph15071471

Lu, X., Zhang, S., Xing, J., Wang, Y., Chen, W., Ding, D., Wu, Y., Wang, S., Duan, L., & Hao, J. (2020). Progress of Air Pollution Control in China and Its Challenges and Opportunities in the Ecological Civilization Era. *Engineering*, *6*(12), 1423–1431. https://doi.org/10.1016/j.eng.2020.03.014

Luechinger, S. (2010). Life satisfaction and transboundary air pollution. *Economics Letters*, *107*(1), 4–6.

Ma, Y., & Chen, D. (2021). Openness, Income Inequality, and Happiness: Evidence from China. *The Journal of Economic Inequality*, 1–23. https://doi.org/10.1007/s10888-021-09507-5

MacKerron, G., & Mourato, S. (2009). Life satisfaction and air quality in London. *Ecological Economics*, *68*(5), 1441–1453. https://doi.org/10.1016/j.ecolecon.2008.10.004

Mannucci, P. M., & Franchini, M. (2017). Health Effects of Ambient Air Pollution in Developing Countries. *International Journal of Environmental Research and Public Health*, *14*(9), 1048. https://doi.org/10.3390/ijerph14091048

Moretti, E., & Neidell, M. (2011). Pollution, Health, and Avoidance Behavior Evidence from the Ports of Los Angeles. *Journal of Human Resources*, *46*(1), 154–175. https://doi.org/10.3368/jhr.46.1.154

OECD. (2013). *OECD Guidelines on Measuring Subjective Well-being*. OECD. https://doi.org/10.1787/9789264191655-en

Rehdanz, K., & Maddison, D. (2008). Local environmental quality and life-satisfaction in Germany. *Ecological Economics*, *64*(4), 787–797. https://doi.org/10.1016/j.ecolecon.2007.04.016

Roberts, J. D., Voss, J. D., & Knight, B. (2014). The Association of Ambient Air Pollution and Physical Inactivity in the United States. *PLOS ONE*, *9*(3), e90143. https://doi.org/10.1371/journal.pone.0090143

Song, L., & Appleton, S. (2008). *Life satisfaction in urban China: Components and determinants* (Working Paper No. 3443). IZA Discussion Papers. https://www.econstor.eu/handle/10419/34904

Strak, M., Weinmayr, G., Rodopoulou, S., Chen, J., Hoogh, K. de, Andersen, Z. J., Atkinson, R., Bauwelinck, M., Bekkevold, T., Bellander, T., Boutron-Ruault, M.-C., Brandt, J., Cesaroni, G., Concin, H., Fecht, D., Forastiere, F., Gulliver, J., Hertel, O., Hoffmann, B., … Samoli, E. (2021). Long term exposure to low level air pollution and mortality in eight European cohorts within the ELAPSE project: Pooled analysis. *BMJ*, *374*, n1904. https://doi.org/10.1136/bmj.n1904

Sun, C., Li, X., Zou, W., Wang, S., & Wang, Z. (2017). Chinese Marine Economy Development: Dynamic Evolution and Spatial Difference. *Chinese Geographical Science*, *28*. https://doi.org/10.1007/s11769-017-0912-8

The World Bank. (2020, June 21). *China: Fighting Air Pollution and Climate Change through Clean Energy Financing*.

https://www.worldbank.org/en/results/2020/06/21/china-fighting-air-pollution-and-climate-change-through-clean-energy-financing

Turiel, J. S., & Kaufmann, R. K. (2021). Evidence of air quality data misreporting in China: An impulse indicator saturation model comparison of local government-reported and U.S. embassy-reported PM2.5 concentrations (2015–2017). *PLOS ONE*, *16*(4), e0249063. https://doi.org/10.1371/journal.pone.0249063

US EPA, O. (2016, August 30). *Air Data Basic Information* [Data and Tools]. https://www.epa.gov/outdoor-air-quality-data/air-data-basic-information

Welsch, H. (2006). Environment and happiness: Valuation of air pollution using life satisfaction data. *Ecological Economics*, *58*(4), 801–813. https://doi.org/10.1016/j.ecolecon.2005.09.006

World Health Organization. (2019, November 15). *Health consequences of air pollution on populations*. https://www.who.int/news/item/15-11-2019-what-are-health-consequences-of-air-pollution-on-populations

Wu, L. (2018). *WHO Issues Latest Global Air Quality Report: Some Progress, but More Attention Needed to Avoid Dangerously High Levels of Air Pollution*. World Health Organization. https://www.who.int/china/news/detail/02-05-2018-who-issues-latest-global-air-quality-report-some-progress-but-more-attention-needed-to-avoid-dangerously-high-levels-of-air-pollution

Wu, X., Zhu, B., Zhou, J., Bi, Y., Xu, S., & Zhou, B. (2021). The epidemiological trends in the burden of lung cancer attributable to PM2.5 exposure in China. *BMC Public Health*, *21*(1), 737. https://doi.org/10.1186/s12889-021-10765-1

Xiao, C., Chang, M., Guo, P., Gu, M., & Li, Y. (2020). Analysis of air quality characteristics of Beijing–Tianjin–Hebei and its surrounding air pollution transport channel cities in China. *Journal of Environmental Sciences*, *87*, 213–227. https://doi.org/10.1016/j.jes.2019.05.024

Xie, Y., & Hu, J. (2014). An Introduction to the China Family Panel Studies (CFPS). *Chinese Sociological Review*, *47*(1), 3–29. https://doi.org/10.2753/CSA2162-0555470101.2014.11082908

Ye, L., & Zhang, W. (2020). 主观空气污染、收入水平与居民幸福感. 财经研究, *46*(1), 126–140. https://doi.org/10.16538/j.cnki.jfe.2020.01.009

Zhang, & Cao, F. (2015). Fine particulate matter (PM2.5) in China at a city level. *Scientific Reports*, *5*(1), 14884. https://doi.org/10.1038/srep14884

Zhang, Q., & Crooks, R. (2012). *Toward an Environmentally Sustainable Future: Country Environmental Analysis of the People's Republic of China* (China, People's Republic of). Asian Development Bank. https://www.adb.org/publications/toward-environmentally-sustainable-future-country-environmental-analysis-prc

Zhang, Zhang, & Chen. (2017). Happiness in the air: How does a dirty sky affect mental health and subjective well-being? *Journal of Environmental Economics and Management*, *85*, 81–94. https://doi.org/10.1016/j.jeem.2017.04.001

Zhu, H., Yan, J., & Wang, X. (2020). The Impact of Air Pollution on Residents' Life Satisfaction. 环境经济研究, *4*.

Technical Appendix A: Additional Summary Statistics

Table A. 1 Summary Statistics of Control Variables

Variables	N	Mean	SD	Min	Max
Urban	102991	0.467	0.499	0	1
Age	104400	46.236	18.506	9	104
Gender	104401	0.493	0.5	0	1
marital	96659	2.091	0.877	1	5
Party	82188	0.072	0.258	0	1
Health	104085	3	1.251	1	5
Year of Education	91972	7.524	4.809	0	22
Employment Status	88663	1.47	0.868	0	3
Income	36470	27092.77	65073.134	0	10299996
Relative Income	84285	2.669	1.068	1	5
Hedonic Happiness	94458	3.016	0.918	1	4
Life Satisfaction	90867	3.846	1.021	1	5
Pollution Duration	102986	4.236	6.651	0	31
Monthly Temperature	104412	73.993	13.686	-5.355	88.355
Monthly Precipitation	100771	0.341	0.261	0	1.765

Table A. 1 Summary Statistics of Control Variables (continued)

Marital Status	N	Percent
Never Married	13307	13.77
Married	75136	77.73
Cohabitation	378	0.39
Divorced	1823	1.89
Widowed	6015	6.22
Employment Status		
Unemployed	1021	1.15
Employed	66308	74.79
Out of Labor Market	21334	24.06

Table A. 2 Key Variable Summary Statistics by Year

	N	Mean	SD	Min	Max
2014					
Pollution Duration	20963	9.725	8.608	0	31
Hedonic Happiness	20684	3.31	0.764	1	4
Life Satisfaction	20717	3.802	1.011	1	5
2015					
Pollution Duration	1339	15.001	6.531	0	28
Hedonic Happiness	545	3.406	0.739	1	4
Life Satisfaction	545	3.741	1.028	1	5
2016					
Pollution Duration	27511	3.663	5.435	0	31
Hedonic Happiness	24581	2.919	0.955	1	4
Life Satisfaction	24579	3.634	1.073	1	5
2017					
Pollution Duration	3610	13.309	7.907	0	31
Hedonic Happiness	3359	2.936	0.942	1	4
Life Satisfaction	3358	3.465	1.126	1	5
2018					
Pollution Duration	28278	1.362	2.581	0	26
Hedonic Happiness	25817	2.907	0.928	1	4
Life Satisfaction	23816	4.029	0.96	1	5
2019					
Pollution Duration	892	10.189	7.936	0	30
Hedonic Happiness	761	2.888	0.926	1	4
Life Satisfaction	734	3.817	1.022	1	5
2020					
Pollution Duration	20393	0.778	1.736	0	18
Hedonic Happiness	18711	2.978	0.939	1	4
Life Satisfaction	17118	4.025	0.926	1	5

Note: Surveys were done bi-annually, but the process starts from the June instead of January, therefore there are seven years recorded.

Technical Appendix B: Additional Regression Results

Table B. 1 Baseline Pollution Duration Regression Models with Dummy Variables using 50% Cutoff for a Pollution Month

	(1) Hedonic Happiness	(2) Life Satisfaction
D_{1ijt}	0.0335	-0.123
	(0.0913)	(0.0943)
D_{2ijt}	0.0403	0.0543
	(0.0682)	(0.0669)
D_{3ijt}	-0.000520	-0.0463
	(0.0447)	(0.0450)
D_{1+2ijt}	-0.0983	0.0263
	(0.0966)	(0.107)
D_{1+3ijt}	0.0371	0.164**
	(0.0709)	(0.0750)
D_{2+3ijt}	-0.0719	0.0535
	(0.0563)	(0.0563)
$D_{1+2+3ijt}$	-0.0110	0.0394
	(0.0426)	(0.0450)
Constant	3.265***	2.681***
	(1.155)	(0.838)
Observations	23,660	23,674
R-squared	0.117	0.132
Number of individuals	17,989	17,999

Note: 1. *** p<0.01, ** p<0.05, * p<0.1, and robust standard errors are included in parentheses

2. I control for weather, demographic, and socioeconomic factors referred in data section

Table B. 2 Heterogeneous Effects of Pollution Duration on Life Satisfaction by Area and Pollution Level using 50% Cutoff for a Pollution Month

	Area		Pollution Level	
	Urban	Rural	High	Low
D_{1ijt}	**-0.361****	0.0326	-0.124	-0.751
	(0.156)	(0.120)	(0.117)	(0.552)
D_{2ijt}	0.0352	0.0316	0.0244	0.322
	(0.0938)	(0.0991)	(0.0811)	(0.387)
D_{3ijt}	**-0.113***	-0.0144	-0.0600	**-0.998***
	(0.0669)	(0.0639)	(0.0514)	(0.598)
D_{1+2ijt}	0.0961	-0.0850	0.0418	-0.629
	(0.147)	(0.167)	(0.129)	(0.450)
D_{1+3ijt}	0.151	0.188*	**0.194****	
	(0.108)	(0.113)	**(0.0962)**	
D_{2+3ijt}	0.0633	-0.0147	0.0367	**-0.545**
	(0.0878)	(0.0829)	(0.0731)	(0.737)
$D_{1+2+3ijt}$	0.0474	-0.00658	0.00786	**-0.622****
	(0.0619)	(0.0729)	(0.0672)	(0.285)
Constant	3.292***	2.688**	1.769*	3.257***
	(1.067)	(1.103)	(0.998)	(1.251)
Observations	11,529	12,145	16,835	6,839
R-squared	0.137	0.128	0.148	0.208
Number of Individual	8,612	9,751	13,733	6,076
Time FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Weather Controls	YES	YES	YES	YES
Demographic and Socioeconomic Controls	YES	YES	YES	YES

Note 1. *** p<0.01, ** p<0.05, * p<0.1, and robust standard errors are included in parentheses

Table B. 3 Heterogeneous Effects of Pollution Duration on SWB by Age

Age	Hedonic Happiness			Life Satisfaction		
	(1) Young (16-39)	(2) Middle (40-59)	(3) Old (60 or above)	(1) Young (16-39)	(2) Middle (40-59)	(3) Old (60 or above)
D1ijt	-0.102	-0.406***	-0.210	-0.122	-0.0970	1.522***
	(0.127)	(0.150)	(0.954)	(0.135)	(0.212)	(0.556)
D2ijt	0.295**	-0.0971	0.478	-0.00766	0.237*	-0.385
	(0.125)	(0.136)	(0.409)	(0.138)	(0.126)	(0.430)
D3ijt	-0.0548	-0.0153	-0.413*	-0.0825	0.0309	-0.321
	(0.0842)	(0.0905)	(0.223)	(0.0974)	(0.0931)	(0.258)
D1+2ijt	0.190	0.484*		0.358	0.00204	
	(0.174)	(0.257)		(0.255)	(0.241)	
D1+3ijt	0.321	-0.432	0.760	0.205	-0.0211	2.159***
	(0.355)	(0.331)	(0.528)	(0.342)	(0.466)	(0.452)
D2+3ijt	-0.0212	-0.121	0.374	-0.214**	-0.160	0.210
	(0.113)	(0.115)	(0.423)	(0.107)	(0.122)	(0.257)
D1+2+3ijt	0.0321	-0.0669	0.147	0.0689	0.0339	0.128
	(0.0650)	(0.0648)	(0.186)	(0.0740)	(0.0690)	(0.208)
Constant	0.134	7.056*	-0.185	0.330	1.645	44.39***
	(2.343)	(4.145)	(22.78)	(2.658)	(4.938)	(15.72)
Observations	10,002	10,687	2,913	10,005	10,688	2,923
R-squared	0.128	0.136	0.229	0.167	0.133	0.217
Number of Individual	7,576	8,317	2,594	7,578	8,319	2,601
Individual FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Note 1. *** p<0.01, ** p<0.05, * p<0.1, and robust standard errors are included in parentheses

Table B. 4 Heterogeneous Effects of Pollution Duration on SWB by Gender

	Male		Female	
	Hedonic Happiness	Life Satisfaction	Hedonic Happiness	Life Satisfaction
D1ijt	-0.163	-0.00195	-0.217	-0.167
	(0.178)	(0.141)	(0.148)	(0.121)
D2ijt	0.245*	-0.0535	0.0755	0.0330
	(0.144)	(0.112)	(0.148)	(0.108)
D3ijt	0.0863	-0.102	-0.0273	-0.0229
	(0.0944)	(0.0776)	(0.0900)	(0.0725)
D1+2ijt	0.0988	0.266	0.511***	0.210
	(0.213)	(0.232)	(0.180)	(0.187)
D1+3ijt	0.0533	0.0495	0.411	-0.0706
	(0.703)	(0.360)	(0.464)	(0.285)
D2+3ijt	-0.122	-0.199**	0.108	-0.0878
	(0.121)	(0.0905)	(0.138)	(0.0890)
D1+2+3ijt	0.0544	0.0230	0.0392	-0.0268
	(0.0711)	(0.0597)	(0.0648)	(0.0548)
Constant	3.850**	0.878	2.792	3.250***
	(1.913)	(2.218)	(1.931)	(1.195)
Observations	10,420	13,254	10,407	13,253
R-squared	0.122	0.158	0.125	0.133
Number of Individual	8,139	9,860	8,128	9,861
Time FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Weather Controls	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES

Note 1. *** p<0.01, ** p<0.05, * p<0.1, and robust standard errors are included in parentheses

Table B. 5 Heterogeneous Effects of Pollution Duration on SWB by Education Level

	Male		Female	
	Hedonic Happiness	Life Satisfaction	Hedonic Happiness	Life Satisfaction
D1ijt	-0.216	0.0317	-0.370	-0.139
	(0.281)	(0.123)	(0.263)	(0.105)
D2ijt	-0.0278	0.112	-0.188	0.156
	(0.193)	(0.0975)	(0.163)	(0.103)
D3ijt	-0.162	0.0213	-0.0477	-0.0585
	(0.129)	(0.0679)	(0.119)	(0.0660)
D1+2ijt	0.174	0.246	0.434	0.366**
	(0.348)	(0.193)	(0.362)	(0.156)
D1+3ijt	0.515	-0.0326	1.155***	-0.163
	(0.789)	(0.355)	(0.296)	(0.235)
D2+3ijt	-0.397***	-0.0649	0.210	-0.0703
	(0.151)	(0.0772)	(0.172)	(0.0801)
D1+2+3ijt	-0.0411	0.0669	-0.0363	-0.00230
	(0.0941)	(0.0530)	(0.0832)	(0.0490)
Constant	2.648	2.279**	-2.536	2.772***
	(6.046)	(0.947)	(5.117)	(1.035)
Observations	8,322	15,352	8,313	15,347
R-squared	0.149	0.140	0.163	0.118
Number of Individual	6,871	11,244	6,863	11,242
Time FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Weather Controls	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES

Note 1. *** p<0.01, ** p<0.05, * p<0.1, and robust standard errors are included in parentheses

2. Government pay for the first 9 years of public-school education. It is referred as 九年义务教育, which translate to “9 years of mandatory education”.