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Happiness in the Air: How Does a Dirty Sky Affect Subjective Well-being?

Xin Zhang
Xiaobo Zhang
Xi Chen

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Forschungsinstitut
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Xin Zhang
Peking University

Xiaobo Zhang
Peking University and IFPRI

Xi Chen
Yale University and IZA

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

Happiness in the Air: How Does a Dirty Sky Affect Subjective Well-being?*

Existing studies that evaluate the impact of pollution on human beings understate its negative effect on cognition, mental health, and happiness. This paper attempts to fill in the gap via investigating the impact of air quality on subjective well-being using China as an example. By matching a unique longitudinal dataset at the individual level, which includes self-reported happiness and mental well-being measures, with contemporaneous local air quality and weather information according to the exact date of interview, we show that worse air quality reduces shorter-term hedonic happiness and increases the rate of depressive symptoms. However, life satisfaction, an evaluative measure of happiness, is largely immune from immediate bad air quality.

JEL Classification: I31, Q51, Q53

Keywords: hedonic happiness, life satisfaction, mental well-being, air quality, China

Corresponding author:

Xi Chen
School of Public Health and Department of Economics
Yale University
New Haven, CT 06520
USA
E-mail: xi.chen@yale.edu

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1. Introduction

It has been well documented that exposure to air pollution increases more tangible health risks, such as cardiovascular diseases (Gallagher et al. 2010), respiratory diseases (Moretti and Neidell 2011; Beatty and Shimshack 2014), hospitalizations (Neidell 2009; Lleras-Muney 2010), and mortality (Jayachandran 2009; Chen et al. 2013). However, much less is known about how air pollution impairs less tangible outcomes like SWB and mental health, which complement the direct monetary measures of welfare (Graham 2005). The burgeoning literature on economics of happiness has promoted more and more countries to incorporate happiness as an important component in policy making and measuring economic and social well-being (Levinson 2013).

The few existing studies on the link between air pollution and happiness primarily rely on aggregate pollution and happiness data (Menz 2011) or individual-level repeated cross-sectional data (Levinson 2012). Studies based on aggregated data, however, are subject to the *ecological fallacy*. That is, the findings may differ or even contradict each other depending on the level of aggregation (Deaton and Lubotsky 2003). Studies at the individual level on the basis of cross-sectional data, on the other hand, are prone to estimation biases because of the difficulty in taking into account all time-invariant factors.

Moreover, few studies use well-matched air pollution and survey data. For example, monitoring stations often only record ambient concentrations every few days (Levinson 2012), and air pollution data tend to be aggregated over a rather long period, such as one year (Ferreira et al. 2013). Consequently, the matched air pollution may differ from the actual exposure and the resultant measurement errors may cause biased estimates.

Furthermore, the literature has not distinguished the impact of air pollution on hedonic and evaluative measures of happiness (Levinson 2012). As noted in Kahneman and Deaton (2010) and Deaton and Stone (2013), the two measures could yield drastically different results because they are often influenced by different factors. Hedonic happiness refers to moment-to-moment experienced utility and directly links to immediate emotions and affection, while evaluative happiness, such as life satisfaction, reflects an overall assessment of the entire life and therefore is less likely subject to short-term changes in external environment.

There has been little research examining the impact of air quality on mental health and SWB in the developing setting. Considering that air pollution in developing countries is generally more serious (Tanaka 2015; Chen et al. 2013; Greenstone and Hanna 2014), there is thus a need for more such empirical evidence.

To address these concerns, we employ a novel national longitudinal survey in China with rich measures of hedonic and evaluative happiness as well as mental health in combination with contemporaneous air quality and weather conditions at the time and place of each interview. The well-matched air quality measure more precisely reflects environmental amenities facing interviewees than the heretofore often used measure of average air quality over a certain period. Changes in air quality across days in a given location have little to do with the characteristics of individual respondents. Therefore, the longitudinal feature of the survey enables us to account for individual characteristics. Our identifying assumption is that air pollution exposures are as good as random after accounting for these factors.

We find that higher air pollution index (API) significantly reduces hedonic happiness and raises the rate of depressive symptoms. The impact on life satisfaction, however, is largely muted, possibly due to hedonic adaptation over time. Specifically, a one standard deviation (SD) improvement in a single-day air quality identified is associated with 0.03-0.04 SDs improvement in mental health. This identified impact is sizable when compared with other studies that also use standard clinic measures of mental health.[1] Meanwhile, a decrease of one SD in API boosts hedonic happiness (scaled from 0 to 4) by 0.036, which is a little smaller than the impact of relative income status (0.040), one of the most important determinants of happiness in the literature. The increase in API accounts for 24.4 percent of the actual decline in happiness from

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[1] Specifically, our identified effect is about one tenths in size to that of a divorce or being widowed in Britain (Gardner and Oswald 2006), one tenths in size to a medium size lottery win in Britain (Gardner and Oswald 2007), 1/30 in size to the immigration from Tonga to New Zealand (Stillman et al. 2009), and 1/5-2/5 in size to the re-employment after involuntary job loss in the U.S. (Mandal and Roe 2008).

2007 to 2014.

Our findings on hedonic happiness also contributes to the debate about the Easterlin paradox, that is, the observation that over time happiness does not display a strong correlation with income growth, while rich people are generally happier than the poor at any given time. While there is a large body of literature explaining the Easterlin paradox, few studies have explained the puzzle from the viewpoint that worsening air quality accompanying economic growth in less-developed countries might reduce happiness, which is the focus of our paper.[2]

We evaluate the willingness to pay (WTP) for better air quality, a time-varying local public good, in monetary value according to our estimates of air pollution on hedonic happiness.[3] The loss of the amenity value of air quality is sizable. Specifically, people on average are willing to pay ¥347 ($56, or 2.7% of annual household per capita income) for a one-unit reduction in API per year per person. In other words, a one SD improvement of air quality raises an average person's happiness by an amount worth ¥35 ($6) per day.

Given the growing number of days with bad air quality in the past decades, the strong association between contemporaneous air pollution and hedonic happiness means that the number of days that people experience bad mood must have gone up as well, which in turn may have a lasting economic impact. For example, recent studies show substantial loss of worker productivity and allocative inefficiency in the labor market due to contemporaneous air pollution.[4]

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[2] One exception is Di Tella and MacCulloch (2008), which shows that sulfur oxide emissions may serve as one plausible explanation to the paradox.

[3] This approach complements the direct survey method to solicit people's WTP for improvement in air quality with a few advantages (Levinson 2012).

[4] Specifically, a 10 ppb increase in ozone reduces farm worker productivity by 5.5 percent (or $700M/year) (Graff Zivin and Neidell 2012). A 10 $\mu g/m^3$ rise in PM2.5 inhibits manufacturing worker productivity by 6 percent (or $18B/year) (Chang et al. 2014a; Li, Liu, and Salvo 2015). A 10-unit spike in API reduces office worker productivity by 0.35 percent (or $2.2B/year) (Chang et al. 2014b). An additional 10 units of transitory PM2.5 exposure is associated with a 1.64 unit decline in a student's high-stake exam score, a 0.15 decline in years of college education, and a $30 decline in monthly salary (Ebenstein et al. 2016). Besides the more recognized physiological pathway, such as pulmonary and cardiovascular functioning, through which labor productivity may be harmed, air pollution may further affect labor productivity via the psychological pathway, such as psychiatric distress (Rotton and Frey 1984), depressive symptoms (Szyszkowicz 2007), and headache and eye irritations (Nattero and Enrico 1996). This psychological channel may operate through, for example, restricted outdoor activities.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 lays out the empirical strategy. Section 4 presents our main findings, including heterogeneous tests for potential mechanisms. Section 5 discusses implications for the Easterlin paradox and estimates the monetary cost of air pollution on happiness. Finally, section 6 concludes.

2. Data

2.1. Mental Health and Subjective Well-being Measures

We utilize rich measures of mental health and SWB in the China Family Panel Studies (CFPS), a nationally representative survey of Chinese communities, families, and individuals conducted in 2010, 2012, and 2014. The CFPS is funded by Peking University and carried out by the Institute of Social Science Survey of Peking University. The CFPS covers a wide range of domains for families and individuals from 162 counties in 25 provinces of China, including their economic activities, education outcomes, family dynamics and relationships, health, and SWB.[5]

There are four advantages of the CFPS for our purposes. First, information about geographic locations and dates of interviews for all respondents enables us to precisely match individual mental health and SWB measures in the survey with external air quality data. Second, rich measures ranging from moment-to-moment happiness and mental well-being to long-term life satisfaction allow us to compare the effects of air pollution in various time frames. Third, the longitudinal data allow us to remove unobserved individual factors that may bias the results. Fourth, the survey collected rich information at multiple levels, allowing us to control for a wide range of covariates.

We make use of three types of mental health and SWB measures. The first is life satisfaction (Welsch 2006, 2007; Rehdanz and Maddison 2008; MacKerron and Mourato 2009; Luechinger 2009, 2010; Menz 2011; Ferreira et al. 2013). All three

[5] The CFPS uses multistage probability proportional to size sampling with implicit stratification to better represent Chinese society. The sample for the 2010 CFPS baseline survey is drawn through three stages (county, village, and household) from 25 provinces. The randomly chosen 162 counties largely represent Chinese Society (Xie and Hu 2014).

waves of CFPS asked each respondent to answer the question, "Overall, how satisfied are you with your life?" on a scale from 1 (*not satisfied at all*) to 5 (*very satisfied*). With no specified time frame, life satisfaction, an evaluative measure of SWB, reflects the extent to which people's own experiences match their long-term aspirations and expectations about their lives as a whole (Stone and Mackie 2014). Life circumstances, such as income, education, and social status, are among the main determinants of life satisfaction. We reverse its response scale to indicate life dissatisfaction that is more comparable with other mental health and SWB measures.

The second mental health and SWB measure is the Center for Epidemiologic Studies Depression scale (CES-D) developed by Radloff (1977), a self-reported scale designed to measure the current level of depressive symptomatology in the general population. Compared to life satisfaction, the CES-D highlights multidimensional emotional experiences that affect people in a shorter period. The CFPS 2010 and 2014 use a 6-item scale (Appendix B), which is highly correlated with the standard 20-item CES-D scale and has adequate psychometric properties for sensitive and specific detection of depressive disorders (Aggarwal et al. 2008). The five options for each item scale from 0 (*never*) to 4 (*almost every day*). Therefore, the total CES-D score is valued between 0 and 24, with higher scores indicating more negative symptoms during the past month. Besides, we follow the Burnam screen to define a binary indicator for depressive symptoms with a cutoff of four (Burnam et al. 1988).[6]

The third SWB measure gauges short-term hedonic unhappiness. Respondents in the CFPS survey were asked to what extent they felt hard to cheer up in the past month, ranging from 0 (*never*) to 4 (*almost every day*). The higher the number, the unhappier the respondents were. Compared to life satisfaction, CES-D score and hedonic unhappiness are more directly related to the environment and people's affective state in day-to-day and moment-to-moment life (Stone and Mackie 2014).[7]

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[6] Note that each item in the standard CES-D scale ranges from 0 (never) to 3 (almost every day), rendering the standard binary depression indicator not perfectly comparable with that using CFPS given the same cut-off score. However, our findings are robust to using alternative CES-D cut-off scores. These results are available upon request.

[7] Hedonic well-being is closely related to the often-used terms "experienced well-being" and "emotional well-being." They are often used interchangeably in the literature.

2.2. Interpolation of Weather and Pollution Measures

We measure air quality using air pollution index (API) generated by a piecewise linear transformation from the concentrations of air pollutants, including sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and fine particulate matter smaller than 10 micrometers (PM10). API ranges from 0 to 500, and a larger API value indicates worse air quality. Evidence suggests that fine particulate matter is detrimental to health and human capital (Cohen et al. 2005; Ebenstein et al. 2016) and is of high concentration in China (Li, Liu, and Salvo 2015). Daily observations of API come from the air quality report published by the Ministry of Environmental Protection of China. The report started in 2000 and has covered 369 major cities by 2014, including all the provincial municipalities and provincial capitals across all regions in China (Figure A1).[8]

We also include rich weather data in our analysis to help isolate the impact of air pollution from weather patterns. The weather data come from the National Climatic Data Center under the National Oceanic and Atmospheric Administration of the United States. The dataset contains records of rich weather conditions, such as temperature, precipitation, wind speed, and indicators for bad weather,[9] on consecutive days from 402 monitoring stations in China. Besides, the sunshine duration data are obtained from the 194 monitoring stations of China National Meteorological Information Center. Sunshine may affect individuals' moods, social behavior, and health (Cunningham 1979; Wolfson 2013).

We match each CFPS county to the nearest city with an API report within 100 kilometers.[10] Meanwhile, we take a weighted average of weather data for each CFPS county with weights based on the inverse distance to all monitors within a radius of 60 km of the CFPS county centroid. In the absence of stations within a radius of 60 km, the measure from the nearest station outside this radius but within 100 kilometers is

[8] If the government indeed manipulates the API data when air quality is extremely bad as suggested by Chen et al. (2012) and Ghanem and Zhang (2014), using the official API data tends to underestimate the true impact of air pollution. Our estimates probably represent a lower bound.

[9] Bad weather includes fog, rain/drizzle, snow/ice pellets, hail, thunder, and tornadoes/funnel clouds.

[10] The distance is measured between the centroid of CFPS counties and the centroid of API report cities. We do not implement inverse distance weighting of air pollution index (API) as API depends nonlinearly on the level of local pollutants.

used.[11] Our baseline results are robust to matching API measures with narrower radiuses, including 60km.[12] We report the results based on the radius of 100 kilometers mainly to retain greater number of observations. Both the binary indicator for bad weather and the sunshine duration are obtained from the nearest monitoring station.

For life dissatisfaction, we take advantage of an unbalanced panel of 33,612 individual respondents (or 88,263 observations) in CFPS 2010, 2012 and 2014,[13] of which 55,941 observations could be matched to API and weather data within 100 kilometers.[14] Due to some missing values for life dissatisfaction and household demographics, the final dataset for analyses includes 47,758 observations (or 22,598 individuals). Because six-item CES-D scale is only available in the 2010 and 2014 waves, we use a balanced panel of 23,259 individual respondents (or 46,518 observations) in the two waves for hedonic unhappiness and mental well-being. Among the 46,518 observations, 29,619 observations could be matched to API and weather data within 100 kilometers. There are some missing values for household demographics. The resulting dataset has 25,003 observations (or 15,867 individuals) for hedonic unhappiness and 24,925 observations (or 15,838 individuals) for mental well-being.

3. Empirical Strategy

Our baseline econometric specification is as follows:

$$H_{ijt} = \alpha P_{jt} + \beta_1 \ln Y_{ijt} + \beta_2 R_{ijt} + X'_{ijt} r + W'_{jt}\phi + \lambda_i + \delta_j + \eta_t + f(t) + \varepsilon_{ijt} \quad (1)$$

The dependent variable H_{ijt} is mental health and SWB of respondent i in county j at date t. The key variable P_{jt} is the air quality measure in county j at date t. For income

[11] See Ziebarth et al. (2014) for an example of this interpolation approach.

[12] The results are available upon request.

[13] The attrition rates for consecutive waves, i.e., 2010-2012 and 2012-2014, are 19.3% and 13.9%, respectively. We compare the attrition rate of CFPS with UK Household Longitudinal Survey (UKHLS). The two surveys conducted during the same period and followed similar interview methods, so UKHLS serves as a good benchmark of CFPS. Compared to UKHLS, CFPS' attrition rate is reasonable. Besides, the CFPS office provides adjusted sample weights for differential response rates by observed covariates (Xie and Hu 2014). In order to address the concern for attrition, we have repeated the baseline results using weighted regressions. All the findings still hold. Results are presented in Table A7.

[14] Counties unmatched to any API report cities or weather stations within 100 kilometers are dropped. The matching rate 63.4% (=55,941/88,263) is higher than other studies. For example, one of the most comparable studies to us, Levinson (2012), was able to maintain 52.3% of the observations when matching the U.S. General Social Survey with PM10 readings from the EPA's Air Quality System.

variables, we include both the log form of annual household per capita income $\ln Y_{ijt}$ and the self-rated relative income status R_{ijt} ranging from 1 (*lowest*) to 5 (*highest*). Following the literature (Oswald 1997; Knight, Song, and Gunatilaka 2009; Knight and Gunatilaka 2010, 2011; Easterlin et al. 2012), we control for a set of demographic correlates of happiness X_{ijt}, including age and its square term, gender, marital status, years of education, unemployment status, party membership, and health status. We also control for a vector of rich weather conditions W_{jt}, involving sunshine duration, mean temperature and its square term, total precipitation, mean wind speed, and a dummy for bad weather on the day of interview, to mitigate the concern that they are correlated with both mental health/SWB and air quality and therefore bias our estimations. λ_i denotes individual fixed effect; δ_j represents county fixed effect; η_t indicate month, year, and day-of-week fixed effects; $f(t)$ is the quadratic monthly time trend that ranges from 1 (January, 2010) to 60 (December, 2014) or the county-by-year fixed effect. ε_{ijt} is the error term. Standard errors are clustered at the county level. Table 1 describes key variables and their summary statistics.

[Insert Table 1]

Figure A2 shows the distribution of interview dates for the three waves of the CFPS national sample, which span all months and seasons and thus enable us to isolate the impact of air pollution from seasonality. Overall, a majority of surveys were conducted in summer or winter as those seasons largely overlap with the summer vacation and winter break of the college students who implemented the CFPS. Variations for identification in our individual fixed effect model (equation 1) come from differential exposure to air pollution for the same respondent across the three waves. The average absolute change in API for each individual across waves amounts to 30.

Before undertaking quantitative analyses, we plot the relationships between API and main mental health and SWB measures (Figure 1). We first calculate deviations from the within-individual means for API and mental health/SWB measures and then graph the deviation of API against that of life dissatisfaction, CES-D score, and hedonic unhappiness. As shown in Figure 1, in accordance with our expectation, CES-D score and hedonic unhappiness demonstrate a positive relationship with API. However, the association between API and life dissatisfaction seems to be negative. Of course, these bivariate plots just provide suggestive evidence. More rigorous analyses are needed to control for other confounding factors.

[Insert Figure 1]

4. Results

4.1. Baseline Results

We report baseline results of air pollution on various mental health and SWB measures in Panel A through Panel D of Table 2, respectively. To save space, only key variables are reported. The corresponding full estimation results are presented in Table A1 and Table A2. We add fixed effects step by step, and test several alternative specifications. Column (1) estimates a repeated cross-sectional specification to facilitate direct comparison with previous studies (e.g., Levinson (2012)). Columns (2) through (5) present longitudinal evidence with individual fixed effects.

[Insert Table 2]

Panel A of Table 2 presents results on life dissatisfaction. Column (1) controls for demographic factors, weather, county fixed effects, quadratic time trend, and a full set of time fixed effects (i.e., year, month, and day-of-week). We do not find any significant relationship between API and life dissatisfaction. Both the absolute income and relative income are negatively correlated with life dissatisfaction. Consistent with the happiness literature, there is a U-shaped relationship between age and life satisfaction, and the trough of life satisfaction is around age 41 (Table A1). Men who are in poor health or divorced report lower life satisfaction. The coefficient for API remains insignificant in the longitudinal specification in column (2) when individual fixed effects are included. The pattern still holds when day-of-week fixed effects, quadratic time trend, rich weather conditions, and county-by-year fixed effects are further added in columns (3) through (5).

Overall, life satisfaction is immune from short-term air pollution. It is interesting to examine to what extent they are susceptible to long-term air pollution or more extreme air pollution as measured by greater deviations of current air pollution from its trends. Table A3 tests weekly, monthly, quarterly, half-year, one-year and two-year time trends, respectively. Life satisfaction remains insensitive to long-term air pollution and deviations from these trends. This muted impact might be explained by hedonic adaptation, a process that attenuates the long-term emotional impact of unfavorable circumstances. Hedonic adaptation may be evolutionarily optimal in protecting people from adverse mental reactions, saving energy on futile attempts to change the unchangeable and redirecting motivation to changes that can be made (Frederick and Loewenstein 1999). Over time, people may adjust their neutral reference point for the level of pollution upward. Future research is needed to directly test this hypothesis.

Panel B of Table 2 examines air pollution on hedonic unhappiness. Higher API significantly increases hedonic unhappiness as shown in column (1). Married, educated, and healthier men tend to be happier. Party membership is associated with high degree of happiness. Moreover, the effect of API is larger and becomes more significant when individual fixed effects are controlled for as indicated in column (2). Under this longitudinal specification, relative income plays a highly significant role in affecting hedonic happiness, while absolute income does not. Columns (3) through (5) further control for time trend and weather. Our main results remain robust to these additional controls.

In Panels C and D of Table 2, the CES-D scale and a binary measure of depressive symptoms (derived from the CES-D score greater than four) are employed to measure mental health, respectively. Similar to hedonic unhappiness, results from both cross-sectional and longitudinal specifications reveal that short-term air pollution worsens mental health and depressive symptoms.

In Table 3, we estimate the non-linear effect of air pollution on mental health and SWB. According to the air quality standard published by the U.S. Environmental Protection Agency (EPA), we divide API into six categories, i.e., “Good” (API<50), “Moderate” (API in 51-100), “Unhealthy for Sensitive Groups” (API in 101-150), “Unhealthy” (API in 151-200), “Very Healthy” (API in 201-300), and “Hazardous” (API>301). We assign each category a dummy variable and leave “Good” as the reference group. Figure A3 reveals the distribution of API with these cut-offs. The results in Table 3 show that the marginal effects increase significantly with the dose of exposure. Column (2) indicates that exposure to hazardous air pollution on the date of interview is associated with a 0.338 points increase in the hedonic unhappiness, more than triple the size of the effect for exposure to moderate air pollution.

If contemporary exposure to air pollution causes the decline in hedonic happiness and mental health, we should observe no effect of *future* air pollution on mental health and SWB elicited on the day of interview. As placebo tests, we control for the APIs in the forward 2-4 days simultaneously and repeat the previous analyses.[15] As shown in Table A4, almost all the coefficients for forward APIs are statistically insignificant, suggesting that unobservable factors unlikely drive the association between contemporaneous air pollution and SWB.

4.2. Heterogeneous Effect

We observe heterogeneous effect of air pollution on happiness and mental health. First, the effect may vary by gender and age. Columns (1) through (5) in Table 4 present the impact of air pollution by gender and age cohort, respectively. Table A5 further shows the impact by gender and age cohort combined. Results indeed suggest that young adults respond more strongly to air pollution than elderly. There are several possible explanations. First, older people are probably more accustomed to living in the dirty air. Second, young people spend more time outdoors than senior people. Third, young people are likely more informed of air quality thanks to wide access to smart phones and the Internet, therefore paying more attention to air pollution. In addition, we find that men and women respond to air pollution differently in accordance with the finding of Ebenstein et al. (2016). Interestingly, gender differences vary with the choice of outcome variables. Specifically, men's hedonic happiness is more sensitive to air pollution, while women's mental health is more saliently affected.[16]

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[15] Since air quality today can be highly correlated with air quality tomorrow, we exclude 1-day forward API to make sure we achieve clean identifications in these placebo tests.

[16] Following Menz and Welsch (2012), we have examined the life-cycle and birth-cohort effects by adding the interaction terms of age cohort or birth cohort with API in regressions. Regarding life-cycle

[Insert Table 4]

Furthermore, vulnerable populations, including those of lower income, less educated, working outdoors, living in more polluted areas, are more susceptible to air pollution. Grouping respondents by income quintile, results in Columns (1) through (4) of Table 5 show that the rich are less affected, presumably because they can take some preventive actions, such as installing air purifiers at home, to mitigate the harmful effects of air pollution. Columns (5) through (6) of Table 5 indicate that those who did not finish nine-year mandatory education are affected more. Results presented in Columns (1) through (2) of Table 6 confirm that air pollution imposes larger impact on people working outdoors, though recent evidence suggests that outdoor air pollution even reduce indoor worker productivity (Chang et al. 2014a, 2014b; Li, Liu, and Salvo 2015). People living in more polluted areas could be more (or less) sensitive to air pollution than those in less polluted areas, depending on whether the dose-response relationship (or habituation or self-selection into areas of poor air quality) dominates. Separating the sample by the median level of average API in the past four years, results in Columns (3) through (4) of Table 6 show that the effects of air pollution are graver in more polluted areas, indicating that the dose-response relationship may dominate.

[Insert Table 5]

Lastly, results in the last two columns of Table 6 show that families with young children (under age 16 in 2014) are more emotionally vulnerable to air pollution.

[Insert Table 6]

5. Implications for the Easterlin Paradox

Following the seminal work of Easterlin (1974, 1995), there has been a growing literature explaining the happiness puzzle, also known as the Easterlin paradox.[17]

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effects, there is not much difference across cohorts except for the age 55-64 cohort in regressions on mental well-being. Similarly, the difference across birth cohorts is generally not statistically different. The only exception is the oldest cohort born before 1930, who reported higher percentage of depressive symptoms. If including both life-cycle and birth-cohort effects, none of the coefficients for the interaction terms is significant. The results are available upon request.

[17] Several empirical studies (Hagerty and Veenhoven 2003; Stevenson and Wolfers 2008) based on cross-country data dismiss the paradox. Drawing an updated database of 37 countries, Easterlin et al. (2010) reconfirm the paradox. Despite the controversial cross-country evidence, the paradox has been observed

Concern for relative income has been regarded as the most plausible explanation for the paradox (Luttmer 2005; Clark, Frijters, and Shields 2008; Chen 2015b).[18] We are among the first to simultaneously evaluate the economic significance of air pollution, relative income, and other correlates in explaining the stagnant or even declining happiness trend. Following Di Tella and MacCulloch (2008), our results suggest air pollution as an additional important contributor to the Easterlin paradox, which has been largely ignored in the literature.

China provides an ideal case to study the Easterlin paradox. In spite of unprecedented income growth, China's average happiness measures did not improve from 1990 to 2010 (Easterlin et al. 2012). Life satisfaction (scaled from 1, *dissatisfied,* to 10, *satisfied*) and hedonic happiness (scaled from 1, *not at all happy,* to 4, *very happy*) from the World Value Survey, and happiness (scaled from 1, *very unhappy,* to 5, *very happy*) from the China Central Television (CCTV) Postcard Survey all reveal an obvious pattern of stagnant or even declined happiness in China during the past decades (Table A6). For example, the CCTV survey finds that the proportion of people feeling happy or very happy declined from 54.1 percent to 40.6 percent between 2007 and 2014, while the share of people reporting unhappy or very unhappy rose from 7.6 percent to 15.3 percent (Figure A4).

Easterlin et al. (2012) attribute the Chinese happiness puzzle to a high unemployment rate due to state-owned enterprise (SOE) reforms, the dissolution of the social safety net, and rising inequality throughout the 1990s and the early 2000s. These factors may explain the temporal pattern from 1990 through 2007, but they cannot account for the decline in happiness during 2007 through 2012, as all these indicators were improved in the period. The SOE reforms were finished by the late 1990s. Since 2004, the labor market has become tighter, resulting in lower unemployment rates and more rapid increases in real wages (Zhang, Yang, and Wang 2011; Zhang et al. 2014). Along with lower unemployment rates and rising wages, the Gini coefficient for China

in a number of major economies (Tella and MacCulloch 2006; Easterlin et al. 2012).

[18] Other plausible driving forces include the framing of happiness questions (Graham, Chattopadhyay, and Picon 2010), income measurement errors (Graham, Chattopadhyay, and Picon 2010), and omitted factors (for example, social trust and freedom) (Helliwell 2012; Inglehart et al. 2008).

as a whole has declined since 2008 (Xie et al. 2013). Moreover, more social safety nets have been put in place in the past decade. For example, the new rural cooperative medical scheme has been rolled out rapidly since 2003 (Li, Xia, and Yu 2014), and the new rural pension program has been rolled out since 2009 (Chen 2015a). The evidence suggests additional factors must be at play.

Same as Easterlin (1974), we also find a noticeable positive association between absolute income and happiness across individuals within a county at a given point of time (Column (1) of Panel B in Table 2), but the association disappears when individual fixed effects are controlled for to compare within each individual over waves of longitudinal survey (Column (4) of Panel B in Table 2). By comparison, relative income affects hedonic happiness both at a point of time and over time, confirming relative income as a plausible explanation to the Easterlin paradox.

More interestingly, our results also show worsening air quality as an additional driving force of the observed decline in happiness. According to the World Bank, 16 of the world's top 20 most polluted cities are in China.[19] The report published by China's Ministry of Environmental Protection in June 2013 shows that about 60 percent of 325 prefecture-level cities failed to meet the Ambient Air Quality Standards (GB3095-2012) in 2012.[20] Almost half of the Chinese population is exposed to PM2.5 at a level beyond the highest hazard threshold in the United States (*The Economist* 2015).

Based on a back-of-the-envelope calculation using results in Column (4) of Panel B in Table 2, a one SD decrease in API lifts happiness by 0.036 (equivalent to 0.039 *SD*s). The impact is rather sizable considering that a one SD increase in income status, one of the most important predictors of happiness, raises happiness by 0.040 (equivalent to 0.043 SDs).[21] In the CCTV Postcard Survey, self-reported happiness declined by 0.326 SDs (measured by the SD in 2014) from 2007 to 2014. The 37.132 units or 2.036-standard-deviation (measured by the SD in 2014) increase in population-weighted

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[19] See www.cbsnews.com/news/the-most-polluted-places-on-earth/, citing "The Little Green Data Book" (World Bank, May 2007, ISBN 0-8213-6967-9).
[20] See www.zhb.gov.cn/gkml/hbb/qt/201306/t20130604_253201.htm.
[21] All the summary statistics are calculated using the sample in Column (4) of Panel B in Table 2, i.e. Mean (hedonic unhappiness) = 0.715, SD (hedonic unhappiness) = 0.929; Mean (API) = 77.077, SD (API) = 36.563; Mean (relative income) = 2.377, SD (relative income) = 0.981.

annual mean API during the same period accounts for 24.4 percent of the actual decrease in happiness.[22]

Finally, we assess the money metric value of air quality based on the repeated cross-sectional results in Column (1) of Panel B in Table 2. The coefficient on API indicates that a one-unit increase in API leads to a decline in happiness by 0.048%, while the coefficient on log per capita income shows that a 1% increase in annual household per capita income raises happiness by 0.018%. According to a back-of-the-envelope calculation, people are on average willing to pay 2.7% of their annual income for a one-unit reduction in API on the day of the interview. By totally differentiating equation (1) and holding hedonic happiness constant (i.e., setting $dH = 0$), we calculate the average marginal rate of substitution between air quality and absolute income $\partial Y/\partial P\big|_{dH=0} = -Y\hat{\alpha}/\hat{\beta}_1$, also known as willingness to pay (WTP). Plugging in 0.048% for $\hat{\alpha}$, -0.018 for $\hat{\beta}$, 13029.06 for the mean annual household per capita income (in Chinese *yuan*), WTP corresponds to $\partial Y/\partial P$ =¥347, which indicates that a one-unit decline in API raises an average person's happiness by an amount worth ¥347 ($56.48) per year per person, or ¥0.95 per day per person.[23] To put this into context, note that the SD of API is 36.900. The WTP amounts to ¥35 (=36.900×¥0.95) for a one SD decline in API per day. In other words, people are on average willing to pay ¥35 ($5.70) per day for a one SD improvement in air quality.[24]

Our estimated absolute level of WTP for the Chinese population is much smaller than that for the U.S. population, such as $35 (or ¥215) for a one SD reduction per day per person (Levinson 2012). However, if measured as the share of annual household per capita income, Chinese are willing to pay a larger share of their annual income (2.7 percent) to reduce air pollution than their U.S. counterparts (2.1 percent).

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[22] The spike in API from 2012 to 2014 (as shown in Table 1) is probably more associated with the massive stimulus package by the Chinese government after the global financial crisis in the late 2000s. Most of the stimulus package went to the infrastructure and construction sector which has accelerated since 2010, mirroring the jump of API in the same period.

[23] ¥347 corresponds to $56.48 using the average 2014 exchange rate 1 USD = 6.1434 CNY.

[24] To address the potential endogeneity problem of the income variable, following Levinson (2012), we instrument household income by occupation-specific average income at the provincial level in the same year using 2SLS regression. The main finding still holds. The results are available upon request.

6. Conclusion

This paper estimates the impact of day-to-day air quality on long-term life satisfaction, short-term hedonic happiness, and mental well-being by matching self-reported mental and SWB measures in CFPS, a nationally representative survey, with air quality data according to the exact date and place of the interview. Although bad daily air quality does not affect much overall life satisfaction, it lowers hedonic happiness and raises the rate of depressive symptoms. In particular, people who are more concerned with environmental problems, work outdoors, earn lower incomes, reside in less polluted areas, or have young children are more sensitive to air pollution.

Our paper shows worsening air quality may contribute to the Easterlin paradox and render significant monetary cost associated with decline in happiness. The impact of air quality on happiness is only slightly smaller than that of relative income, the commonly regarded key contributor to the paradox. The findings suggest that the GDP-obsessed development strategy in China has not brought about improved happiness.

Furthermore, evaluating a wider spectrum of the impact of air pollution provides useful information for public policies. Our results indicate that the current emphasis on physical health related costs understates other hidden costs of pollution on mental health and SWB. If counting these additional costs, the benefits of reducing pollution would be higher.

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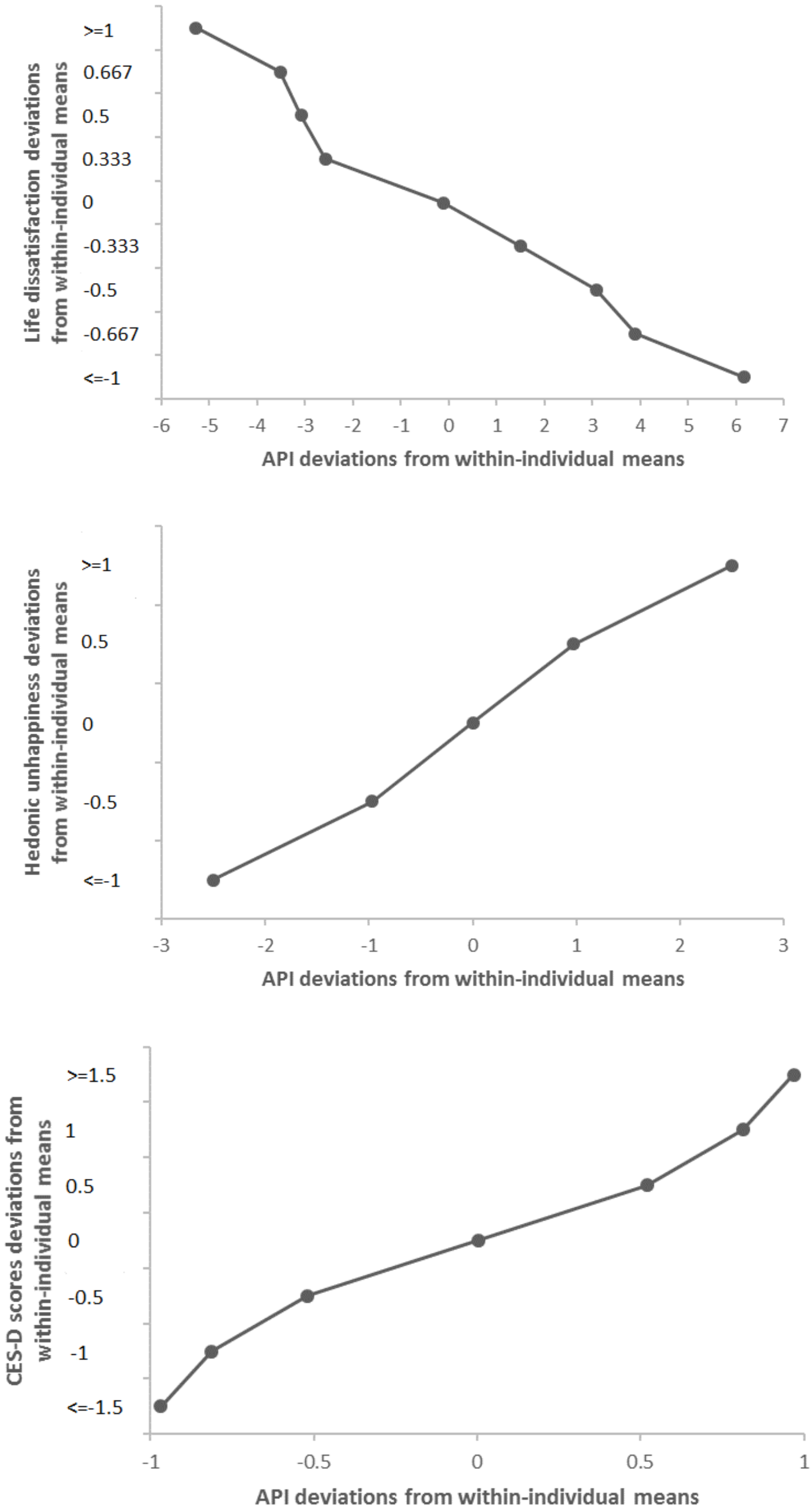
Figure 1: Relationship between API and mental health & subjective well-being



Source: China Family Panel Studies 2010, 2012 and 2014.
Note: API = air pollution index. CES-D = Center for Epidemiologic Studies Depression scale.

Table 1: Summary statistics of key variables

Variable	Definition	2010		2012		2014	
		Mean	SD	Mean	SD	Mean	SD
Life dissatisfaction	life dissatisfaction, ranging from 1 to 5, the lower the better	2.503	1.046	2.678	1.048	2.161	0.989
Hedonic unhappiness	answer to "To what extent did you feel hard to cheer up in the past month?", ranging from 0 (never) to 4 (almost every day), the lower the better	0.692	0.929	--	--	0.740	0.928
CES-D scores	the total score of the CES-D, 0–24, the lower the better	2.903	3.806	--	--	2.887	3.706
Depressive symptoms	indicator for depressive symptoms (= 1 if CES-D scores ≥ 4)	0.318	0.466	--	--	0.309	0.462
API	air pollution index	64.598	33.617	57.435	20.874	89.491	36.141
Per capita income	log form of annual household per capita income (yuan)	8.751	1.063	8.891	1.284	9.072	1.213
Relative income	self-rated relative income status, ranging from 1 to 5, the higher the better	2.220	0.965	2.242	0.967	2.534	0.970
Sunshine duration	sunshine duration (hours)	5.875	4.408	5.731	4.389	6.497	4.190
Temperature	weighted mean temperature (10 °F)	7.347	1.116	6.749	2.169	7.512	1.288
Precipitation	weighted total precipitation (inches)	0.157	0.455	0.136	0.436	0.122	0.409
Wind speed	weighted mean wind speed (knots)	4.761	2.279	5.382	3.008	4.909	2.191
Bad weather	indicator for bad weather (fog, rain or drizzle, snow or ice pellets, hail, thunder, tornadoes or funnel clouds)	0.456	0.498	0.447	0.497	0.318	0.466
Age	age (÷10)	4.657	1.509	4.777	1.524	4.864	1.546
Male	indicator for males	0.498	0.500	0.497	0.500	0.492	0.500
Married	indicator for married status	0.849	0.358	0.857	0.350	0.848	0.359
Education	years of education	6.522	4.876	7.310	4.665	7.468	4.679
Unemployed	indicator for unemployment status	0.069	0.253	0.011	0.102	0.009	0.093
Party	indicator for party membership	0.079	0.270	0.088	0.284	0.084	0.277
Chronic disease	indicator for suffering from chronic diseases	0.142	0.350	0.133	0.340	0.182	0.386

Source: China Family Panel Studies 2010, 2012 and 2014.

Note: API = air pollution index; CES-D = Center for Epidemiologic Studies Depression scale; SD = Standard deviation; Dashes indicate no data for the 2012 wave of survey.

Table 2: Effects of air quality on mental health and subjective well-being

	(1)	(2)	(3)	(4)	(5)
A. Dependent variable: Life dissatisfaction (valued 1-5)					
API (÷100)	-0.005	0.011	0.012	0.013	-0.003
	(0.030)	(0.034)	(0.034)	(0.035)	(0.033)
Household per capita income (log)	-0.047***	-0.015*	-0.015*	-0.016*	-0.016*
	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Relative income	-0.254***	-0.188***	-0.188***	-0.188***	-0.186***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	51,684	47,758	47,758	47,758	47,758
Adjusted (within) *R*-squared	0.151	0.116	0.116	0.117	0.135
B. Dependent variable: Hedonic unhappiness (valued 0-4)					
API (÷100)	0.048**	0.095***	0.095***	0.098***	0.089***
	(0.019)	(0.029)	(0.030)	(0.030)	(0.027)
Household per capita income (log)	-0.018**	0.002	0.002	0.002	-0.001
	(0.008)	(0.012)	(0.012)	(0.012)	(0.011)
Relative income	-0.077***	-0.041***	-0.041***	-0.041***	-0.048***
	(0.007)	(0.014)	(0.014)	(0.014)	(0.013)
Observations	32,655	25,003	25,003	25,003	25,003
Adjusted (within) *R*-squared	0.072	0.018	0.018	0.018	0.051
C. Dependent variable: CES-D score (valued 0-24)					
API (÷100)	0.249***	0.260**	0.252**	0.300**	0.288**
	(0.095)	(0.114)	(0.117)	(0.120)	(0.121)
Household per capita income (log)	-0.163***	-0.047	-0.046	-0.045	-0.041
	(0.032)	(0.049)	(0.049)	(0.048)	(0.048)
Relative income	-0.427***	-0.214***	-0.215***	-0.213***	-0.213***
	(0.035)	(0.058)	(0.058)	(0.058)	(0.057)
Observations	32,546	24,925	24,925	24,925	24,925
Adjusted (within) *R*-squared	0.111	0.020	0.020	0.021	0.022
D. Dependent variable: Depressive symptoms (valued 0-1)					
API (÷100)	0.037***	0.044***	0.043**	0.049***	0.047***
	(0.012)	(0.016)	(0.017)	(0.017)	(0.016)
Household per capita income (log)	-0.018***	-0.003	-0.004	-0.004	-0.003
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Relative income	-0.042***	-0.024***	-0.024***	-0.024***	-0.024***
	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	32,546	24,925	24,925	24,925	24,925
Adjusted (within) R-squared	0.087	0.010	0.010	0.011	0.013
Individual fixed effect	No	Yes	Yes	Yes	Yes
County, year and month fixed effects	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	No	Yes	Yes	Yes
Quadratic monthly time trend	Yes	No	Yes	Yes	No
County-by-year fixed effects	No	No	No	No	Yes
Weather controls	Yes	No	No	Yes	Yes

Source: China Family Panel Studies 2010, 2012 and 2014.

Note: Comparable hedonic happiness, CES-D score and depressive symptoms are only available in the waves of 2010 and 2014, while life dissatisfaction is available in all three waves. Therefore, the number of observation in Panels B through D is smaller than that in Panel A. Other demographic controls include gender, age and its square, married status, years of education, unemployment status, party membership, and an indicator for chronic diseases. The weather controls include sunshine duration, mean temperature and its square, total precipitation, mean wind speed, and a dummy for bad weather (fog, rain/drizzle, snow/ice pellets, hail, thunder, and tornadoes/funnel clouds). Robust standard errors, clustered at the county level, are presented in parentheses. API = air pollution index. *10% significance level. **5% significance level. ***1% significance level.

Table 3: Effects of air quality on mental health and subjective well-being, by API level

Dependent variable	Life dissatisfaction	Hedonic unhappiness	Mental well-being	Depressive symptoms
	(1)	(2)	(3)	(4)
API51_100	0.010	0.061	0.216	0.022
	(0.018)	(0.037)	(0.174)	(0.023)
API101_150	0.003	0.102**	0.433**	0.058**
	(0.029)	(0.044)	(0.203)	(0.026)
API151_200	0.022	0.227**	0.836***	0.107**
	(0.069)	(0.089)	(0.314)	(0.044)
API201_300	0.064	0.105	-0.342	0.033
	(0.085)	(0.110)	(0.533)	(0.059)
API301_500	-0.077	0.338***	1.381***	0.183**
	(0.284)	(0.122)	(0.446)	(0.084)
Household per capita income (log)	-0.016*	0.002	-0.043	-0.004
	(0.008)	(0.012)	(0.048)	(0.006)
Relative income	-0.188***	-0.042***	-0.217***	-0.024***
	(0.008)	(0.014)	(0.058)	(0.007)
Individual fixed effect	Yes	Yes	Yes	Yes
County, year and month fixed effects	Yes	Yes	Yes	Yes
Day-of-week fixed effects, quadratic time trend	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Number of observations	47,758	25,003	24,925	24,925
Adjusted (within) R-squared	0.117	0.018	0.022	0.011

Source: China Family Panel Studies 2010, 2012 and 2014.

Note: All other covariates follow Table 2. Robust standard errors, clustered at the county level, are presented in parentheses. API = air pollution index. *10% significance level. **5% significance level. ***1% significance level.

Table 4: Heterogeneous effects of air quality, by gender and age

A. Hedonic unhappiness

Dependent variable	Gender		Age		
Hedonic unhappiness	Male	Female	Young (16–39)	Middle (40–59)	Old (60 or above)
	(1)	(2)	(3)	(4)	(5)
Dependent Variable mean	*0.641*	*0.784*	*0.735*	*0.731*	*0.673*
API (÷100)	0.134***	0.074	0.092	0.088**	0.119*
	(0.050)	(0.045)	(0.059)	(0.038)	(0.063)
Observations	12,131	12,872	5,746	11,842	7,415
Adjusted (within) *R*-squared	0.018	0.020	0.038	0.019	0.023

B. Mental well-being

Dependent variable	Gender		Age		
CES-D scores	Male	Female	Young (16–39)	Middle (40–59)	Old (60 or above)
	(1)	(2)	(3)	(4)	(5)
Dependent Variable mean	*2.542*	*3.217*	*2.659*	*2.939*	*2.988*
API (÷100)	0.184	0.411**	0.597***	0.242	0.147
	(0.155)	(0.174)	(0.189)	(0.167)	(0.226)
Observations	12,106	12,819	5,744	11,809	7,372
Adjusted (within) *R*-squared	0.019	0.025	0.043	0.023	0.033

C. Depressive symptoms

Dependent variable	Gender		Age		
Depressive symptoms	Male	Female	Young (16–39)	Middle (40–59)	Old (60 or above)
	(1)	(2)	(3)	(4)	(5)
Dependent Variable mean	*0.275*	*0.347*	*0.301*	*0.315*	*0.317*
API (÷100)	0.041*	0.058***	0.110***	0.030	0.040
	(0.022)	(0.022)	(0.031)	(0.022)	(0.026)
Observations	12,106	12,819	5,744	11,809	7,372
Adjusted (within) *R*-squared	0.012	0.015	0.029	0.011	0.022

Source: China Family Panel Studies 2010 and 2014.

Note: Other covariates and fixed effects are the same as those in column (4) of Table 2. Robust standard errors, clustered at the county level, are presented in parentheses. CES-D = Center for Epidemiologic Studies Depression scale. *10% significance level. **5% significance level. ***1% significance level.

Table 5: Heterogeneous effects of air quality, by income level and education

A. Hedonic unhappiness

Dependent variable	Income level				Education	
Hedonic unhappiness	0–25%	25–50%	50–75%	75–100%	Less educated (education<9)	More educated (education≥9)
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable mean	*0.793*	*0.764*	*0.715*	*0.629*	*0.753*	*0.679*
API (÷100)	0.240***	0.147**	0.037	0.020	0.123***	0.075*
	(0.088)	(0.064)	(0.050)	(0.042)	(0.034)	(0.041)
Observations	5,071	5,424	6,225	7,677	11,965	13,038
Adjusted (within) *R*-squared	0.040	0.023	0.026	0.022	0.018	0.025

B. Mental well-being

Dependent variable	Income level				Education	
CES-D scores	0–25%	25–50%	50–75%	75–100%	Less educated (education<9)	More educated (education≥9)
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable mean	*3.455*	*3.227*	*2.795*	*2.357*	*3.284*	*2.528*
API (÷100)	0.933***	0.619**	-0.154	0.105	0.479***	0.090
	(0.276)	(0.265)	(0.146)	(0.183)	(0.162)	(0.144)
Observations	5,048	5,409	6,202	7,663	11,905	13,020
Adjusted (within) *R*-squared	0.044	0.024	0.035	0.028	0.024	0.025

C. Depressive symptoms

Dependent variable	Income level				Education	
Depressive symptoms	0–25%	25–50%	50–75%	75–100%	Less educated (education<9)	More educated (education≥9)
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable mean	*0.376*	*0.351*	*0.300*	*0.253*	*0.354*	*0.274*
API (÷100)	0.108***	0.108***	-0.015	0.025	0.074***	0.019
	(0.030)	(0.039)	(0.025)	(0.022)	(0.020)	(0.023)
Observations	5,048	5,409	6,202	7,663	11,905	13,020
Adjusted (within) *R*-squared	0.034	0.019	0.020	0.013	0.019	0.011

Source: China Family Panel Studies 2010 and 2014.

Note: Other covariates and fixed effects are the same as those in column (4) of Table 2. Robust standard errors, clustered at the county level, are presented in parentheses. CES-D = Center for Epidemiologic Studies Depression scale. *10% significance level. **5% significance level. ***1% significance level.

Table 6: Heterogeneous effects of air quality, by workplace, pollution level and children

A. Hedonic unhappiness

Dependent variable	Workplace		Local yearly pollution		Having children younger than 16	
Hedonic unhappiness	Indoors	Outdoors	Polluted	Less polluted	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable mean	*0.702*	*0.732*	*0.726*	*0.703*	*0.733*	*0.707*
API (÷100)	0.068	0.134***	0.103***	0.073	0.108***	0.096**
	(0.059)	(0.045)	(0.036)	(0.050)	(0.034)	(0.039)
Observations	6,033	11,850	12,641	11,570	7,182	17,821
Adjusted (within) *R*-squared	0.031	0.019	0.023	0.023	0.032	0.015

B. Mental well-being

Dependent variable	Workplace		Local yearly pollution		Having children younger than 16	
CES-D scores	Indoors	Outdoors	Polluted	Less polluted	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable mean	*2.567*	*3.062*	*2.975*	*2.789*	*2.745*	*2.947*
API (÷100)	0.385*	0.367**	0.365***	0.165	0.664***	0.127
	(0.220)	(0.175)	(0.133)	(0.209)	(0.121)	(0.158)
Observations	6,023	11,817	12,614	11,528	7,175	17,750
Adjusted (within) *R*-squared	0.028	0.024	0.035	0.014	0.033	0.022

C. Depressive symptoms

Dependent variable	Workplace		Local yearly pollution		Having children younger than 16	
Depressive symptoms	Indoors	Outdoors	Polluted	Less polluted	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable mean	*0.283*	*0.333*	*0.321*	*0.301*	*0.303*	*0.316*
API (÷100)	0.050*	0.060**	0.052**	0.032	0.092***	0.029
	(0.027)	(0.024)	(0.020)	(0.024)	(0.019)	(0.020)
Observations	6,023	11,817	12,614	11,528	7,175	17,750
Adjusted (within) *R*-squared	0.018	0.019	0.020	0.009	0.020	0.013

Source: China Family Panel Studies 2010 and 2014.

Note: Other covariates and fixed effects are the same as those in column (4) of Table 2. Robust standard errors, clustered at the county level, are presented in parentheses. CES-D = Center for Epidemiologic Studies Depression scale. *10% significance level. **5% significance level. ***1% significance level.

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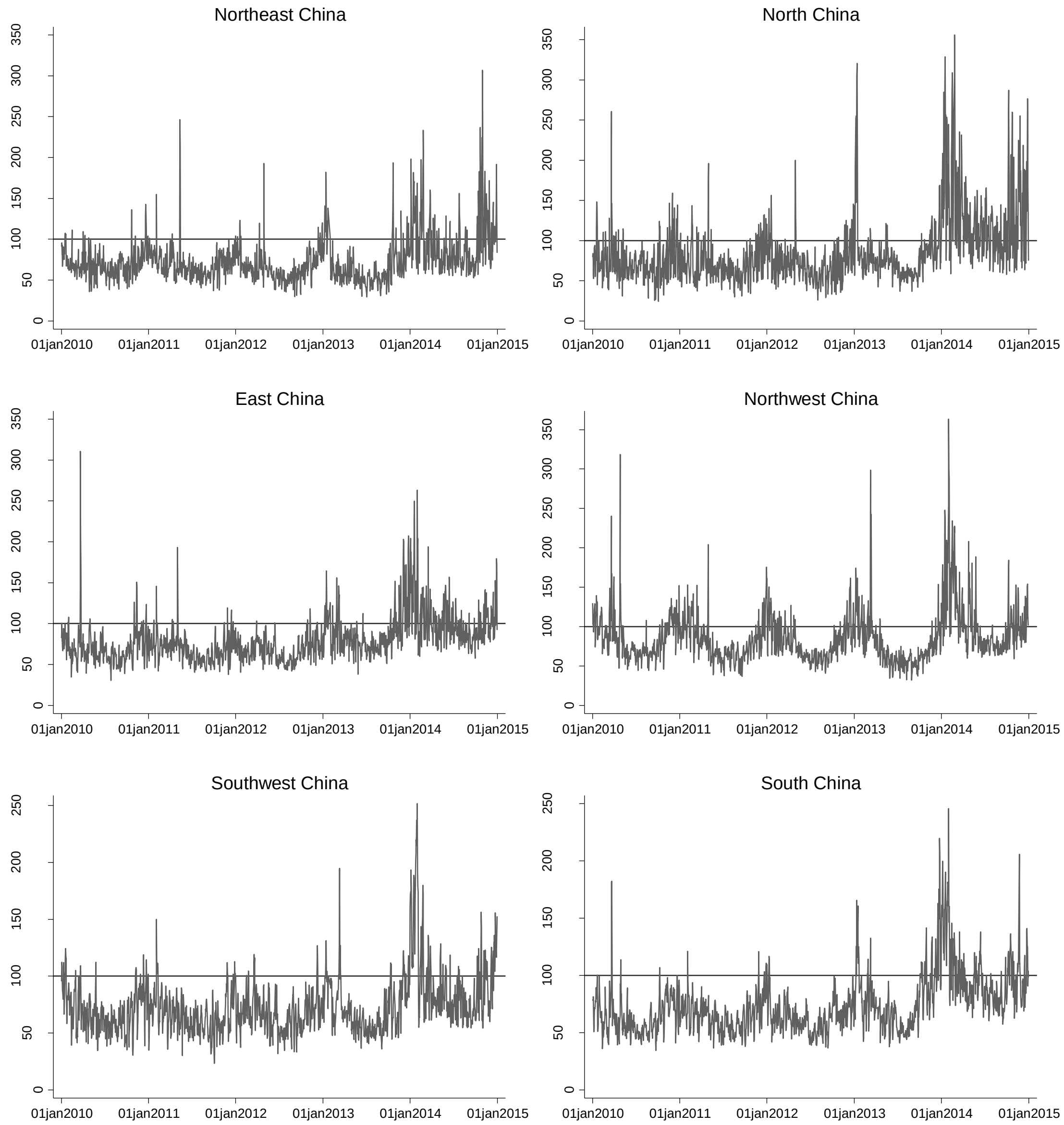
Online Appendix A: Supplementary Figures and Tables

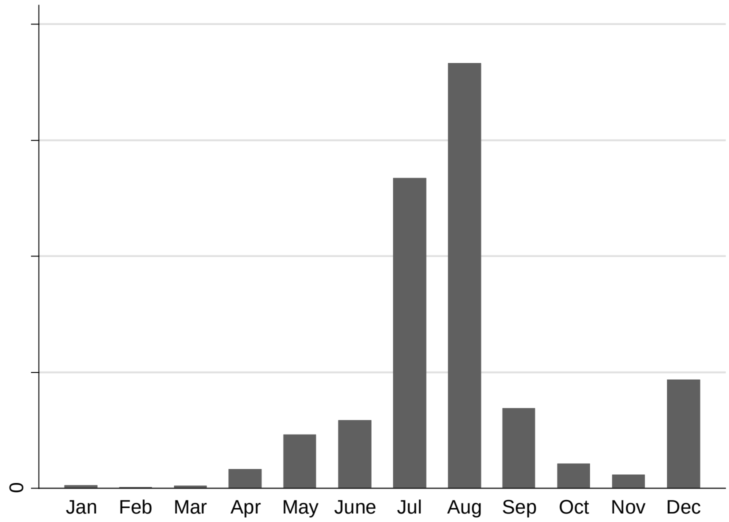
Figure A1: Daily air pollution index (API) in China, 2010–2014



Source: Air quality daily report published by the Ministry of Environmental Protection of the People's Republic of China.

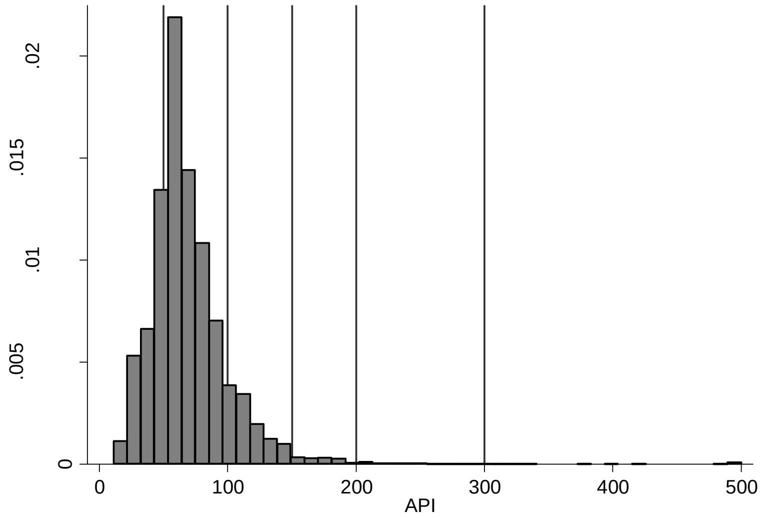
Note: The daily mean API is calculated by the weighted average values of all the API report cities within the region, where the weights are the yearly population in each city. The US National Ambient Air Quality Standards of fine particulate matter smaller than 10 micrometers is 0.15 mg/m^3, which corresponds to 100 of API in China. Northeast China includes Heilongjiang, Jilin, and Liaoning. North China includes Beijing, Hebei, Inner Mongolia, Shanxi, and Tianjin. East China includes Anhui, Fujian, Jiangsu, Jiangxi, Shandong, Shanghai, and Zhejiang. Northwest China includes Gansu, Ningxia, Qinghai, Shanxi, and Xinjiang. Southwest China includes Guizhou, Sichuan, Tibet, Yunnan, and Chongqing. South China includes Guangdong, Guangxi, Hainan, Henan, Hubei, and Hunan. jan = January.

Figure A2: Interview date distribution, 2010, 2012 and 2014



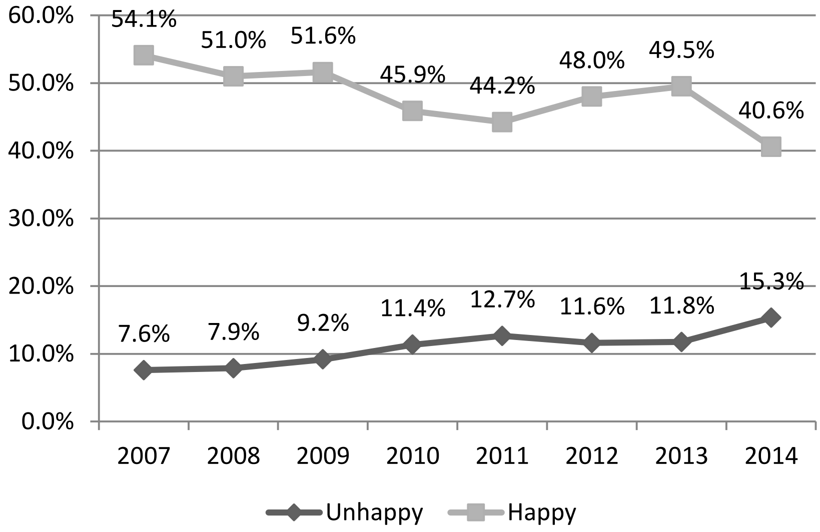
Source: China Family Panel Studies 2010, 2012 and 2014.
Note: Apr = April; Aug = August; Dec = December; Feb = February; Jan = January; Jul = July; Mar = March; Nov = November; Oct = October; Sep = September.

Figure A3: Distribution of API, 2010, 2012 and 2014



Source: Air quality daily report published by the Ministry of Environmental Protection of the People's Republic of China.

Figure A4: Happiness Trend in CCTV Postcard Survey, 2007–2014



Source: CCTV Postcard Survey.
Note: CCTV = China Central Television.

Table A1: Effects of air quality on life dissatisfaction and hedonic unhappiness

Dependent variable	Life dissatisfaction					Hedonic unhappiness				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
API (÷100)	-0.005	0.011	0.012	0.013	-0.003	0.048**	0.095***	0.095***	0.098***	0.089***
	(0.030)	(0.034)	(0.034)	(0.035)	(0.033)	(0.019)	(0.029)	(0.030)	(0.030)	(0.027)
Household per capita income	-0.047***	-0.015*	-0.015*	-0.016*	-0.016*	-0.018**	0.002	0.002	0.002	-0.001
	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)	(0.011)
Relative income	-0.254***	-0.188***	-0.188***	-0.188***	-0.186***	-0.077***	-0.041***	-0.041***	-0.041***	-0.048***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.014)	(0.014)	(0.014)	(0.013)
Gender	0.106***					-0.101***				
	(0.010)					(0.012)				
Age (÷10)	0.276***					0.020				
	(0.021)					(0.025)				
Age (÷10) squared	-0.034***	0.012	0.012	0.012	0.015	-0.005**	-0.017	-0.017	-0.017	-0.019
	(0.002)	(0.012)	(0.012)	(0.012)	(0.011)	(0.003)	(0.014)	(0.014)	(0.014)	(0.013)
Married	-0.178***	-0.142***	-0.142***	-0.141***	-0.141***	-0.125***	-0.023	-0.026	-0.025	-0.032
	(0.015)	(0.038)	(0.038)	(0.038)	(0.037)	(0.018)	(0.061)	(0.060)	(0.060)	(0.061)
Education	-0.001	-0.005	-0.005	-0.005	-0.007	-0.005***	-0.005	-0.005	-0.005	-0.007
	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)	(0.002)	(0.007)	(0.007)	(0.007)	(0.007)
Unemployed	0.121***	-0.002	-0.000	0.003	0.019	0.067*	0.041	0.042	0.041	0.059
	(0.035)	(0.049)	(0.049)	(0.049)	(0.043)	(0.034)	(0.050)	(0.050)	(0.050)	(0.054)
Party	-0.125***	-0.074	-0.074	-0.074	-0.084	-0.035*	-0.046	-0.046	-0.045	-0.098
	(0.017)	(0.066)	(0.065)	(0.065)	(0.063)	(0.019)	(0.077)	(0.077)	(0.076)	(0.078)
Chronic disease	0.124***	0.052***	0.052***	0.052***	0.054***	0.295***	0.201***	0.201***	0.201***	0.202***
	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.018)	(0.030)	(0.030)	(0.030)	(0.031)
Individual fixed effect	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
County, year and month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Quadratic monthly time trend	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes	No
County-by-year fixed effects	No	No	No	No	Yes	No	No	No	No	Yes
Weather controls	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes
Observations	51,684	47,758	47,758	47,758	47,758	32,655	25,003	25,003	25,003	25,003
Adjusted (within) *R*-squared	0.151	0.116	0.116	0.117	0.135	0.072	0.018	0.018	0.018	0.051

Source: China Family Panel Studies 2010, 2012 and 2014.

Note: To save space in Table 2, this appendix table presents the full set of results in Panels A and B of Table 2. API = air pollution index. *10% significance level. **5% significance level. ***1% significance level.

Table A2: Effects of air quality on mental well-being and depressive symptoms

Dependent variable	CES-D scores					Depressive symptoms				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
API (÷100)	0.249***	0.260**	0.252**	0.300**	0.288**	0.037***	0.044***	0.043**	0.049***	0.047***
	(0.095)	(0.114)	(0.117)	(0.120)	(0.121)	(0.012)	(0.016)	(0.017)	(0.017)	(0.016)
Household per capita income	-0.163***	-0.047	-0.046	-0.045	-0.041	-0.018***	-0.003	-0.004	-0.004	-0.003
	(0.032)	(0.049)	(0.049)	(0.048)	(0.048)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Relative income	-0.427***	-0.214***	-0.215***	-0.213***	-0.213***	-0.042***	-0.024***	-0.024***	-0.024***	-0.024***
	(0.035)	(0.058)	(0.058)	(0.058)	(0.057)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
Gender	-0.428***					-0.048***				
	(0.045)					(0.006)				
Age (÷10)	0.193*					0.006				
	(0.109)					(0.013)				
Age (÷10) squared	-0.022**	-0.068	-0.069	-0.070	-0.069	-0.001	-0.006	-0.006	-0.006	-0.006
	(0.011)	(0.057)	(0.057)	(0.057)	(0.056)	(0.001)	(0.008)	(0.008)	(0.007)	(0.008)
Married	-0.770***	-0.397*	-0.402*	-0.405*	-0.410*	-0.088***	-0.011	-0.013	-0.012	-0.013
	(0.079)	(0.238)	(0.237)	(0.239)	(0.239)	(0.009)	(0.028)	(0.027)	(0.028)	(0.028)
Education	-0.055***	-0.030	-0.030	-0.031	-0.032	-0.006***	0.001	0.001	0.001	0.001
	(0.008)	(0.023)	(0.023)	(0.023)	(0.023)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Unemployed	0.245*	0.237	0.237	0.245	0.236	0.046**	0.040	0.040	0.039	0.038
	(0.133)	(0.200)	(0.200)	(0.198)	(0.197)	(0.019)	(0.032)	(0.032)	(0.032)	(0.032)
Party	-0.178**	-0.126	-0.125	-0.118	-0.130	-0.013	0.023	0.023	0.023	0.021
	(0.072)	(0.313)	(0.311)	(0.308)	(0.312)	(0.009)	(0.048)	(0.048)	(0.048)	(0.049)
Chronic disease	1.431***	0.723***	0.722***	0.727***	0.718***	0.137***	0.049***	0.050***	0.050***	0.048***
	(0.089)	(0.129)	(0.129)	(0.127)	(0.126)	(0.009)	(0.017)	(0.017)	(0.017)	(0.017)
Individual fixed effect	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
County, year and month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Quadratic monthly time trend	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes	No
County-by-year fixed effects	No	No	No	No	Yes	No	No	No	No	Yes
Weather controls	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes
Observations	32,546	24,925	24,925	24,925	24,925	32,546	24,925	24,925	24,925	24,925
Adjusted (within) R-squared	0.111	0.020	0.020	0.021	0.022	0.087	0.010	0.010	0.011	0.013

Source: China Family Panel Studies 2010 and 2014.

Note: To save space in Table 2, this appendix table presents the full set of results in Panels C and D of Table 2. API = air pollution index. *10% significance level. **5% significance level. ***1% significance level.

Table A3: Long-term effects of air quality on life dissatisfaction

A. Mean effects of API						
Dependent variable	7-day mean	30-day mean	90-day mean	180-day mean	1-year mean	2-year mean
Life dissatisfaction	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	0.019	0.117*	0.115	-0.002	0.069	0.040
	(0.043)	(0.063)	(0.098)	(0.078)	(0.077)	(0.105)
Per capita income	-0.016*	-0.016*	-0.016*	-0.016*	-0.016*	-0.016*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Relative income	-0.188***	-0.189***	-0.188***	-0.188***	-0.188***	-0.188***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	47,758	47,758	47,758	47,758	47,758	47,758
Adjusted (within) *R*-squared	0.117	0.117	0.117	0.117	0.117	0.117
B. Deviation-from-the-mean effects of API						
Dependent variable	7-day deviation	30-day deviation	90-day deviation	180-day deviation	1-year deviation	2-year deviation
Life dissatisfaction	(1)	(2)	(3)	(4)	(5)	(6)
$API_t - \frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$	0.007	-0.008	0.002	0.013	0.006	0.011
	(0.040)	(0.037)	(0.035)	(0.034)	(0.034)	(0.035)
Per capita income	-0.016*	-0.016*	-0.016*	-0.016*	-0.016*	-0.016*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Relative income	-0.188***	-0.188***	-0.188***	-0.188***	-0.188***	-0.188***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	47,758	47,758	47,758	47,758	47,758	47,758
Adjusted (within) *R*-squared	0.117	0.117	0.117	0.117	0.117	0.117

Source: China Family Panel Studies 2010, 2012 and 2014.

Note: $\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i}$ indicates the mean of API in the past k days, where k equals 7, 30, 90, and 180, 365 and 730, respectively. Other covariates and fixed effects are the same as those in column (4) of Table 2. The coefficients on API are scaled by 100 to make them more readable. Robust standard errors, clustered at the county level, are presented in parentheses. API = air pollution index. *10% significance level. ***1% significance level.

Table A4: Placebo tests—API in the forward 2-4 days

Dependent variable	Life dissatisfaction	Hedonic unhappiness	Mental well-being	Depressive symptoms
	(1)	(2)	(3)	(4)
API_F2	0.034	0.046	0.114	0.009
	(0.027)	(0.042)	(0.203)	(0.023)
API_F3	0.053*	-0.024	-0.193	0.010
	(0.027)	(0.035)	(0.187)	(0.020)
API_F4	-0.053*	0.045	0.347*	0.031
	(0.028)	(0.040)	(0.181)	(0.020)
Observations	45,748	23,359	23,286	23,286
Adj. (within) R-squared	0.116	0.019	0.020	0.009

Source: China Family Panel Studies 2010, 2012 and 2014.

Note: Other covariates and fixed effects are the same as those in column (4) of Table 2. All the coefficients are scaled by 100 to make them more readable. Robust standard errors, clustered at the county level, are presented in parentheses. API = air pollution index. Adj. = Adjusted. *10% significance level.

Table A5: Heterogeneous effects of air quality, by gender and age

A. Hedonic unhappiness

Dependent variable	Male			Female		
Hedonic unhappiness	Young (16–39)	Middle (40–59)	Old (60 and older)	Young (16–39)	Middle (40–59)	Old (60 and older)
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable mean	*0.688*	*0.643*	*0.605*	*0.777*	*0.809*	*0.745*
API (÷100)	0.117	0.097*	0.205**	0.073	0.087	0.026
	(0.076)	(0.058)	(0.089)	(0.086)	(0.053)	(0.072)
Observations	2,744	5,565	3,822	3,002	6,277	3,593
Adj. (within) *R*-squared	0.046	0.019	0.030	0.053	0.022	0.028

B. Mental well-being

Dependent variable	Male			Female		
CES-D scores	Young (16–39)	Middle (40–59)	Old (60 and older)	Young (16–39)	Middle (40–59)	Old (60 and older)
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable mean	*2.537*	*2.522*	*2.575*	*2.770*	*3.309*	*3.431*
API (÷100)	0.437	0.003	0.258	0.756***	0.441*	-0.034
	(0.268)	(0.198)	(0.317)	(0.240)	(0.228)	(0.298)
Observations	2,743	5,552	3,811	3,001	6,257	3,561
Adj. (within) *R*-squared	0.030	0.023	0.043	0.069	0.028	0.034

C. Depressive symptoms

Dependent variable	Male			Female		
Depressive symptoms	Young (16–39)	Middle (40–59)	Old (60 and older)	Young (16–39)	Middle (40–59)	Old (60 and older)
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable mean	*0.292*	*0.269*	*0.271*	*0.310*	*0.355*	*0.366*
API (÷100)	0.106**	0.017	0.034	0.116***	0.040	0.046
	(0.044)	(0.030)	(0.037)	(0.037)	(0.029)	(0.034)
Observations	2,743	5,552	3,811	3,001	6,257	3,561
Adj. (within) *R*-squared	0.039	0.014	0.030	0.050	0.017	0.028

Source: China Family Panel Studies 2010 and 2014.

Note: Other covariates and fixed effects are the same as those in column (4) of Table 2. Robust standard errors, clustered at the county level, are presented in parentheses. CES-D = Center for Epidemiologic Studies Depression scale. Adj. = Adjusted; Dep. Var. = Dependent variable. *10% significance level. **5% significance level. ***1% significance level.

Table A6: Summary statistics of subjective well-being in China, 1990–2014

	World Values Survey				CCTV Postcard Survey	
	Life Satisfaction (valued 1–10)		Hedonic happiness (valued 1–4)		Happiness (valued 1–5)	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
1990	7.292	2.101	2.946	0.813		
1995	6.833	2.418	3.052	0.659		
1997						
1998						
1999						
2000						
2001	6.530	2.468	2.868	0.634		
2002						
2003						
2004						
2005						
2006						
2007	6.760	2.395	2.936	0.749	3.623	0.921
2008					3.623	0.973
2009					3.560	0.964
2010					3.477	1.008
2011					3.396	0.983
2012	6.858	1.985	3.006	0.585	3.477	1.001
2013					3.476	1.004
2014					3.298	0.997

Source: World Values Survey and CCTV Postcard Survey.
Note: World Values Survey (1990, 1995, 2001, 2007, 2012)—Life satisfaction: All things considered, how satisfied are you with your life as a whole these days? ([*dissatisfied*] 1 2 3 4 5 6 7 8 9 10 [*satisfied*]). Hedonic happiness: Taking all things together, would you say you are: *very happy, quite happy, not very happy,* or *not at all happy?* (coded 4, 3, 2, or 1). CCTV Postcard Survey (2007–2013) (in Chinese)—Happiness: How do you feel about your current life? (*very happy, fairly happy, just so-so, not happy,* or *very unhappy;* coded 5, 4, 3, 2, or 1).

Table A7: Baseline results – using weighted regressions

	(1)	(2)	(3)	(4)	(5)
A. Dependent variable: Life dissatisfaction (valued 1-5)					
API (÷100)	0.035	0.045	0.045	0.049	0.039
	(0.026)	(0.032)	(0.032)	(0.032)	(0.036)
Household per capita income (log)	-0.047***	-0.010	-0.010	-0.011	-0.008
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Relative income	-0.253***	-0.178***	-0.178***	-0.180***	-0.180***
	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	47,372	46,780	46,780	46,780	46,780
Adjusted (within) *R*-squared	0.163	0.119	0.119	0.122	0.147
B. Dependent variable: Hedonic unhappiness (valued 0-4)					
API (÷100)	0.031	0.070*	0.070*	0.067	0.069*
	(0.036)	(0.041)	(0.041)	(0.041)	(0.038)
Household per capita income (log)	-0.005	-0.001	-0.000	-0.001	-0.010
	(0.011)	(0.013)	(0.013)	(0.013)	(0.013)
Relative income	-0.071***	-0.037**	-0.038**	-0.037**	-0.040**
	(0.012)	(0.018)	(0.018)	(0.017)	(0.017)
Observations	27,977	24,997	24,997	24,997	24,997
Adjusted (within) *R*-squared	0.077	0.022	0.022	0.026	0.062
C. Dependent variable: CES-D score (valued 0-24)					
API (÷100)	0.097	0.246*	0.246*	0.277**	0.279**
	(0.130)	(0.128)	(0.128)	(0.138)	(0.137)
Household per capita income (log)	-0.100*	-0.072	-0.069	-0.073	-0.073
	(0.052)	(0.051)	(0.052)	(0.051)	(0.050)
Relative income	-0.382***	-0.166**	-0.166**	-0.163**	-0.163**
	(0.050)	(0.068)	(0.069)	(0.068)	(0.068)
Observations	27,889	24,919	24,919	24,919	24,919
Adjusted (within) *R*-squared	0.108	0.027	0.027	0.030	0.030
D. Dependent variable: Depressive symptoms (valued 0-1)					
API (÷100)	0.024	0.041**	0.041**	0.043**	0.044**
	(0.016)	(0.019)	(0.019)	(0.019)	(0.019)
Household per capita income (log)	-0.012**	-0.007	-0.007	-0.007	-0.007
	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)
Relative income	-0.040***	-0.021**	-0.021**	-0.020**	-0.020**
	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	27,889	24,919	24,919	24,919	24,919
Adjusted (within) R-squared	0.085	0.012	0.012	0.014	0.014
Individual fixed effect	No	Yes	Yes	Yes	Yes
County, year and month fixed effects	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	No	Yes	Yes	Yes
Quadratic monthly time trend	Yes	No	Yes	Yes	No
County-by-year fixed effects	No	No	No	No	Yes
Weather controls	Yes	No	No	Yes	Yes

Source: China Family Panel Studies 2010, 2012 and 2014.

Note: Other demographic controls include gender, age and its square, married status, years of education, unemployment status, party membership, and an indicator for chronic diseases. The weather controls include sunshine duration, mean temperature and its square, total precipitation, mean wind speed, and a dummy for bad weather (fog, rain/drizzle, snow/ice pellets, hail, thunder, and tornadoes/funnel clouds). All the regressions are weighted by the adjusted sample weights for differential response rates by observed covariates (Xie and Hu 2014). Robust standard errors, clustered at the county level, are presented in parentheses. API = air pollution index. *10% significance level. **5% significance level. ***1% significance level.

Online Appendix B: Center for Epidemiologic Studies Depression scale (CES-D) in China Family Panel Studies (CFPS)

Six-item CES-D in CFPS 2010 and 2014

Below is a list of the ways you might have felt or behaved. Please tell me how often you have felt this way during the past month.

0. Never

1. Sometimes

2. Half the Time

3. Often

4. Almost Every Day

During the past month:

1. I felt depressed and nothing can cheer me up.

2. I felt nervous.

3. I felt restless and hard to calm down.

4. I felt hopeless about the future.

5. I felt that everything I did was an effort.

6. My life was meaningless.