Happiness in the Air:

How Does a Dirty Sky Affect Subjective Well-being?

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Abstract

Studies evaluating the welfare cost of air pollution understate its potential effect on our subjective well-being (SWB). This paper attempts to fill the gap via investigating the impact of air pollution on key dimensions of SWB, including moment-to-moment happiness, evaluative happiness, and mental health. We match a nationwide longitudinal survey in China with local air quality and rich weather conditions according to the exact time and place respondents were surveyed. Making use of variations in exposure to air pollution for the same individuals over time, we show that air pollution reduces hedonic happiness and increases the rate of depressive symptoms. However, life satisfaction is largely immune from the immediate air quality.

Keywords: hedonic happiness, life satisfaction, mental health, air pollution, Easterlin paradox

JEL Codes: I31, Q53, Q51

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1. Introduction

It has been well documented that exposure to air pollution increases health risks, such as cardiovascular diseases (Gallagher et al. 2010), respiratory diseases (Beatty and Shimshack 2014), and mortality (Chen et al. 2013). However, less is known about the impact of air pollution on our stated well-being. Studies on the psychological channel through which impacts of air pollution may operate have the potential to improve happiness, arguably the ultimate goal of human beings.

Among the few studies on the link between air pollution and happiness, most rely on either aggregate pollution and happiness data (Menz 2011) or individual-level 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. Studies at the individual level on the basis of cross-sectional data, on the other hand, are prone to estimation biases because not all time-invariant factors can be taken into account.

Moreover, none of the studies use well-matched air pollution and survey data. For example, monitoring stations often only record ambient concentrations every few days (Levinson 2012), and studies often average air pollution over a rather long period, such as one year (Ferreira et al. 2013). Consequently, the matched air pollution differs from the actual exposure, bringing measurement errors that may result in biased estimates.

Further, the literature often makes no explicit distinction between the impact of air pollution on hedonic and evaluative measures of happiness (Levinson 2012). Hedonic happiness refers to moment-to-moment experienced utility and directly links to immediate emotions and affection, while evaluative happiness reflects an overall assessment of life. 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.

To overcome these problems, we employ a novel national longitudinal survey with rich measures of both hedonic and evaluative happiness in combination with contemporaneous air quality and weather conditions at the time and place of each

interview. The well-matched air quality more precisely reflects environmental amenities facing interviewees than the heretofore often used measure of average air quality over a certain period. Air quality varies daily within each location for reasons less likely to be connected to any particular characteristics of respondents, therefore less likely to suffer from omitted variable bias. The longitudinal feature of the survey enables us to further account for correlated unobservables at multiple levels and location-specific seasonal variations. Our identifying assumption is that air pollution exposures are as good as random after accounting for these factors.

Modeling the relationship between air pollution and SWB in very flexible forms, we provide strong evidence that losses in amenity value of air quality are an important component of the overall costs of ambient air pollution. Specifically, 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. A decrease of one standard deviation (*SD*) in API boosts hedonic happiness (scaled from 0 to 4) by 0.05, which is larger than the impact of relative income status (0.04), one of the most important determinants of happiness in the literature. A back-of-the-envelope analysis indicates that the increase in API accounts for 33.7 percent of the actual decline in happiness from 2007 to 2014.

Valuing air quality as a time-varying local public good, people on average are willing to pay 4.67 CNY per day per person (266.87 USD per year per person) for a 0.1 *SD* improvement in air quality. To convert the changes in hedonic happiness into monetary damages, this means that a 0.1 SD worsening of air quality corresponds to 4.67 CNY per day per person worth of hedonic happiness.

To the best of our knowledge, this is the first study examining the impact of air quality on SWB in the developing setting where air pollution is generally more serious than its developed counterpart (Tanaka 2015; Chen et al. 2013; Greenstone and Hanna 2014). There is thus a need for more empirical evidence from the developing contexts.

Our study is also related to a few strands of literature. It contributes to the debate about the Easterlin paradox, that is, the observation that over time happiness is not promoted despite income growth. Few studies have explained the puzzle from the

viewpoint that worsening air quality accompanying economic growth in less-developed countries might reduce people's happiness, which is the focus of our paper. It also adds to the burgeoning body of literature on the impact of air pollution on various outcomes, such as standardized test scores, human capital formation, labor market outcomes (Lavy et al. 2014a, 2014b), and the productivity of indoor workers (Chang et al. 2014; Li, Liu, and Salvo 2015). Long-term exposure to air pollution may even change the structure and function of brains (Weir 2012). Both the short-term and the long-term consequences and the sizable willingness-to-pay (WTP) to improve air quality warn us that careful evaluations of the impact of air pollution on SWB are necessary.

The reminder 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 gauges the monetary cost of air pollution on happiness. Finally, section 6 concludes.

2. Data

2.1. Subjective Well-being

We utilize rich measures of happiness 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.

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 happiness measures in the survey with external air quality data. Second, rich measures of happiness 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 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 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 unsatisfaction that is more comparable with other SWB measures.

The second 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).[1]

The third SWB measure gauges short-term hedonic unhappiness. Respondents in

[1] 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.

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).[2]

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; Lavy et al. 2014a, 2014b) and is of high concentration in China (Li, Liu, and Salvo 2015).

Daily observations of API are collected from the air quality report published by the Ministry of Environmental Protection of China. The report, which started in 2000 and has covered 369 major cities by 2014, involves all the provincial municipalities and provincial capitals across all regions in China (Figure A1). Besides, short-term air pollution has been on the radar of the general population. For instance, keyword searches of "*wumai* (haze)" and "*kouzhao* (mask)" using China's major search engine *baidu.com* indicate that public awareness spiked in early 2013 when a major crisis of thick haze struck much of eastern China (Figure A2).

Rich weather data helps isolate the impact of air pollution from weather patterns and therefore mitigates potential estimation biases. 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 air visibility,[3] temperature, precipitation, wind speed, and

[2] 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.

[3] While air visibility is often driven by non-pollution factors, such as humidity, some atmospheric studies find visibility a noisy predictor of main air pollutant concentrations (Lee and Sequeira 2001; Qiu and

indicators for bad weather,[4] on consecutive days from 402 monitor stations in China. Besides, the sunshine duration data are obtained from the 194 monitor stations of the 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.[5] Meanwhile, we take a weighted average of rich 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. Whenever there are no stations within a radius of 60 km, the measure from the nearest station outside this radius but within 100 kilometers is used.[6] Figure 1 shows the matching of CFPS counties with API report cities and weather stations.[7] Both the binary indicator for bad weather and the sunshine duration are obtained from the nearest monitor station.

[Insert Figure 1]

The CFPS surveyed an unbalanced panel of 33,612 individual respondents (or 88,263 observations) in 2010, 2012 and 2014,[8] of which 55,941 observations could be matched to API and weather data within 100 kilometers.[9] Among the 55,941 observations, 4,706 are missing self-rated relative income status, and another 3,479 observations are missing life unsatisfaction. Since the six-item CES-D scale is only available in CFPS 2010 and 2014, the final dataset for analyses includes 47,756 observations for life unsatisfaction, 25,002 observations for hedonic unhappiness, and

Yang 2000; Cheung et al. 2005; Deng et al. 2008). Figure A3 shows consistent overall trend between API and air visibility in our sampled areas, mitigating the concern that API reports by the Chinese government are manipulated to achieve "blue-sky day" (Chen et al. 2012; Ghanem and Zhang 2014).

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

[5] 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.

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

[7] Our baseline results are robust to matching using narrower radiuses (but results for 100 kilometers are reported to retain more observations in the analysis) and alternative weights (e.g., inverse of the square root distance or squared distance between the monitor stations and the county centroids).

[8] The attrition rates for consecutive waves, i.e., 2010-2012 and 2012-2014, are 21.4% and 15.6%, respectively.

[9] Counties unmatched to any API report cities or weather stations within 100 kilometers are dropped. The matching rate 63.4% (=55941/88263) 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.

24,924 observations for mental well-being.[10]

3. Empirical Strategy

Our baseline econometric specification is as follows:

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

The dependent variable H_{ijt} is the self-reported happiness of respondent *i* in county *j* at date *t*. The key variable $\ln P_{jt}$ is the log form of air quality measure in county *j* at date *t*. For income variables, we include both the log form of household per capita income $\ln Y_{ijt}$ and the self-rated relative income status R_{ijt} ranging from 1 (*lowest*) to 5 (*highest*). 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 (Oswald 1997; Knight, Song, and Gunatilaka 2009; Knight and Gunatilaka 2010, 2011; Easterlin et al. 2012). We also control for sunshine duration $sunshine_{jt}$ in county *j* at date *t* and a vector of rich weather conditions W_{jt}, involving 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 SWB and air quality and therefore bias our estimations. λ_i denotes individual fixed effect; δ_j represents county fixed effect; η_t indicates month, year, and day-of-week fixed effects; $f(t)$ is the quadratic monthly trend that ranges from 1 (January, 2010) to 60 (December, 2014) or county-by-year fixed effects. 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 A4 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

[10] A balance test shows that there are no significant differences in observed characteristics between the matched and unmatched samples, mitigating the concern for selection bias in our matching process.

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 SWB measures (Figure 2). We first calculate deviations from the within-individual means for API and SWB measures and then plot the deviation of API against that of life unsatisfaction, CES-D score, and hedonic unhappiness. As shown in Figure 2, in accordance with our expectation, CES-D score and hedonic unhappiness demonstrate a positive relationship with API. However, no such relationship is found between API and life unsatisfaction. While these bivariate plots provide suggestive evidence, more rigorous analyses are presented in the next section to distinguish the real relationship between air pollution and SWB from confounded factors.

[Insert Figure 2]

4. Results

4.1. Baseline Results

We report baseline results of air pollution on various 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. In each panel, column (1) estimates a cross-sectional specification used in 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 unsatisfaction. 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 unsatisfaction. Both the absolute income and relative

income are negatively correlated with life unsatisfaction. 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 tend to have lower life satisfaction. The coefficient of API remains insignificant in the longitudinal specification in column (2). Results from our longitudinal estimations stay robust when day-of-week fixed effects, quadratic time trend, rich weather conditions, and county-by-year fixed effects are further added in columns (3) - (5).

Overall, life satisfaction is immune from short-term air pollution. It is interesting to examine to what extent they are susceptible to more extreme air pollution as measured by greater deviations of current air pollution from its trends. Table A3 tests weekly, monthly, quarterly, and half-year time trends, respectively. Life satisfaction remains insensitive to deviations from these trends. This muted impact might be explained by *hedonic adaptation,* processes that attenuate the long-term emotional impact of unfavorable circumstances. *Hedonic adaptation* is often evolutionarily optimal in protecting people from adverse mental reactions, preventing the continued expenditure of energy on futile attempts to change the unchangeable and redirecting motivation to changes that can be made (Frederick and Loewenstein 1999). For example, the level of air pollution that was previously very hedonically negative may become hedonically neutral over time as people transition the neutral reference point from lower to higher levels of pollution. *Hedonic adaptation* may be further strengthened through options to avoid exposure to air pollution in the longer term, such as the recent diffusion of air filters to the public.

Panel B of Table 2 examines air pollution on hedonic unhappiness. Higher API significantly increases hedonic unhappiness in column (1). Married men who receive more education and are healthier tend to be happier. Party membership is associated with being happier, presumably because it symbolizes higher social status and social recognition. Moreover, the effect of API is larger and becomes more significant when individual fixed effects are controlled for. Under this longitudinal specification, relative income imposes a highly significant effect on hedonic unhappiness, while there is no

significant effect for absolute income. Columns (3) and (4) 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 4) 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 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 A5 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 0.337 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 SWB elicited on the day of interview. Forwarding API by 1-7 days, placebo tests indeed suggest that unobserved factors unlikely drive the link between air pollution and SWB (Table A4).

4.2. Heterogeneity of the Effect

This section examines potential pathways between air pollution and happiness. First, the young generation may be more sensitive to air pollution due to their better access to air quality information and lower level adaptation to air pollution compared with older cohorts. Air pollution may also affect males and females differently (Lavy et al. 2014a). 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, while older persons are more accustomed to living in the dirty air. However, the impact by gender is mixed. Men's hedonic happiness is more sensitive to air pollution, while women's mental health is more saliently affected.

Second, we test the hypothesis that families with young children are more sensitive to air pollution via separating the sample into those who have children (younger than age 16 in 2014) and those who do not. Results in columns (6)-(7) of Table 4 confirm this pattern.

[Insert Table 4]

Third, the negative impact of air pollution may decrease with income as the rich may care more about health and are more able to take actions to avoid harmful effects. We divide the respondents into quintiles by household per capita income. Results in Columns (1) through (4) of Table 5 show that the poor are more affected by air pollution, meaning that air pollution may enlarge the happiness and mental health inequality between the rich and the poor.

Fourth, the relationship between air pollution and SWB by education may be less clear. On the one hand, lower education may restrict the ability to acquire information about air quality through, for example, smart phones and the internet (Levinson 2012; Greenstone and Hanna 2014). On the other hand, the more educated tend to be more knowledgeable about avoiding the harmful effects. We test this hypothesis via dividing the whole sample by education received. Columns (5) through (7) in Table 5 indicate that neither the illiterate nor the more educated are sensitive to bad air quality, while those in between react significantly to air pollution.

[Insert Table 5]

Fifth, attitude toward pollution may also affect reaction to air quality. CFPS 2014 includes a host of questions to elicit people's attitudes toward major social issues in China, including environmental quality.[11] The first two columns of Table 6 divide the

[11] The question for environmental issues is framed as "How severe do you think is the environmental problem in China?" The answer ranges from 0 (*not severe at all*) to 10 (*very severe*). To mitigate the concern that some respondents may overstate or understate their general attitudes toward social issues, we calculate a normalized attitude score toward pollution by dividing the pollution assessment score by

sample by attitude toward pollution. Results, however, suggest that being critical about environmental issues does not seem to mediate the impact of air pollution on SWB.

Further, workplace may play an important role in affecting people's response to air quality. An increase in particulate matter outdoors even leads to declined indoor worker productivity (Chang et al. 2014; Li, Liu, and Salvo 2015). We test whether air pollution imposes larger impact on people working outdoors than indoors. Results presented in columns (3)-(4) of Table 6 show that people working outdoors are much more sensitive to bad air quality.

Lastly, people living in more polluted areas may respond differently to air pollution than those in less polluted areas. On the one hand, the dose-response relationship determines that heavier air pollution may generate more negative impact on SWB. On the other hand, people in more polluted areas could be less sensitive to air pollution either because they are habituated to poor air quality or because people who are less concerned about air pollution sort into more polluted areas *ex ante*. We divide the whole sample by the median level of yearly average API. Results in the last two columns of Table 6 show that the effects of air pollution are more pronounced in less polluted areas, indicating that habituation and potential self-selection may dominate the dose-response relationship between air pollution and SWB.

[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, that income growth does not necessarily improve (hedonic) happiness.[12] Concern for relative income has been regarded as the most plausible explanation for the paradox

the average ratings of all eight questions. We divide our sample into two groups by the median of the normalized score.

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

(Luttmer 2005; Clark, Frijters, and Shields 2008; Chen 2015b).[13] We are 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. Our results suggest air pollution as an important contributor to the Easterlin paradox.

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 A6).

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 that time. 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 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

[13] 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).

new rural pension program has been rolled out since 2009 (Chen 2015a). The evidence suggests additional factors are at play.

We echo Easterlin (1974) by finding 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 over time (Column (2) of Panel B in Table 2). However, relative income affects hedonic well-being both at a point of time and over time, confirming relative income as a plausible explanation to the Easterlin paradox.

More interestingly, our results lend support to 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.[14] 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.[15] As revealed in Figure A7, API increased markedly from 2005 to 2014 in China, while air visibility declined sharply from 1997 to 2014.

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 0.050 (equivalent to 0.054 *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 *SD*s).[16] In the CCTV Postcard Survey, self-reported happiness declined by 0.326 *SD*s (measured by the *SD* in 2014) from 2007 to 2014. Seen from Figure A6, the 37.132 or 2.036-standard-deviation (measured by the *SD* in 2014) increase in API during the same period accounts for 33.7 percent of the actual decrease in happiness.

Finally, we assess the money metric value of air quality, which informs us the monetary cost of air pollution on happiness. By totally differentiating equation 1 and holding hedonic happiness constant (i.e., setting $dH = 0$), we calculate the average

[14] 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).
[15] See www.zhb.gov.cn/gkml/hbb/qt/201306/t20130604_253201.htm.
[16] All the summary statistics are calculated using the matched balanced panel of CFPS 2010 and 2014, i.e. Mean (hedonic unhappiness) = 0.715, SD (hedonic unhappiness) = 0.929; Mean (API) = 77.077, SD (API) = 36.564; Mean (relative income) = 2.377, SD (relative income) = 0.981.

marginal rate of substitution between air quality and absolute income $\partial Y/\partial P\big|_{dH=0} = -Y\hat{\alpha}/P\hat{\beta}_1$, also known as WTP. Plugging in 0.045 for $\hat{\alpha}$, -0.016 for $\hat{\beta}_1$ in Panel B of Table 2, 12781.16 CNY for the mean income, and 77.077 for the mean API, WTP amounts to 466.38 CNY, revealing that a 0.1 *SD* improvement in air quality raises an average person's happiness by an amount worth 1,705.27 CNY (466.38 × 36.564 × 0.1) per year.[17] This means people are willing to pay 4.67 CNY per day per person (or 266.87 USD per year per person) for a 0.1 *SD* improvement in air quality. Our estimated absolute level of WTP for the Chinese population is much smaller than that for the U.S. population, such as 1.80 USD (or 11.50 CNY) per day per person (Levinson 2012). However, if measured as the share of WTP in gross domestic product (GDP) per capita, Chinese are willing to pay a larger share of their income (3.7 percent = 4.67 CNY × 365 / 46,652 CNY) to reduce air pollution than their U.S. counterparts (1.2 percent = 1.80 USD × 365 / 54,629 USD).[18]

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 SWB measures in CFPS, a nationally representative survey, with air quality data according to the exact date of the interview. Our results show muted effects of daily air quality on overall life satisfaction, but bad air quality 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 as a result of declined happiness. The impact of air quality on happiness is even more than that of relative income, the currently accepted key contributor to the paradox. The findings suggest that the GDP-obsessed

[17] One standard deviation of API is 36.564.

[18] According to the World Development Indicators released by the World Bank, in 2014 gross domestic product per capita in China and the United States are 46,652 CNY and 54,629 USD, respectively.

development strategy in China has not brought about more happiness. The government should go beyond GDP and include environmental quality indicators in cadres' evaluation packages.

Furthermore, evaluating a wider spectrum of the impact of air pollution is valuable to public policies. Our results indicate that the current emphasis on health-related costs understates the costs of pollution and therefore the benefits of reducing pollution. More scientific evidence is expected in the aspects of cognition, labor productivity, and SWB.

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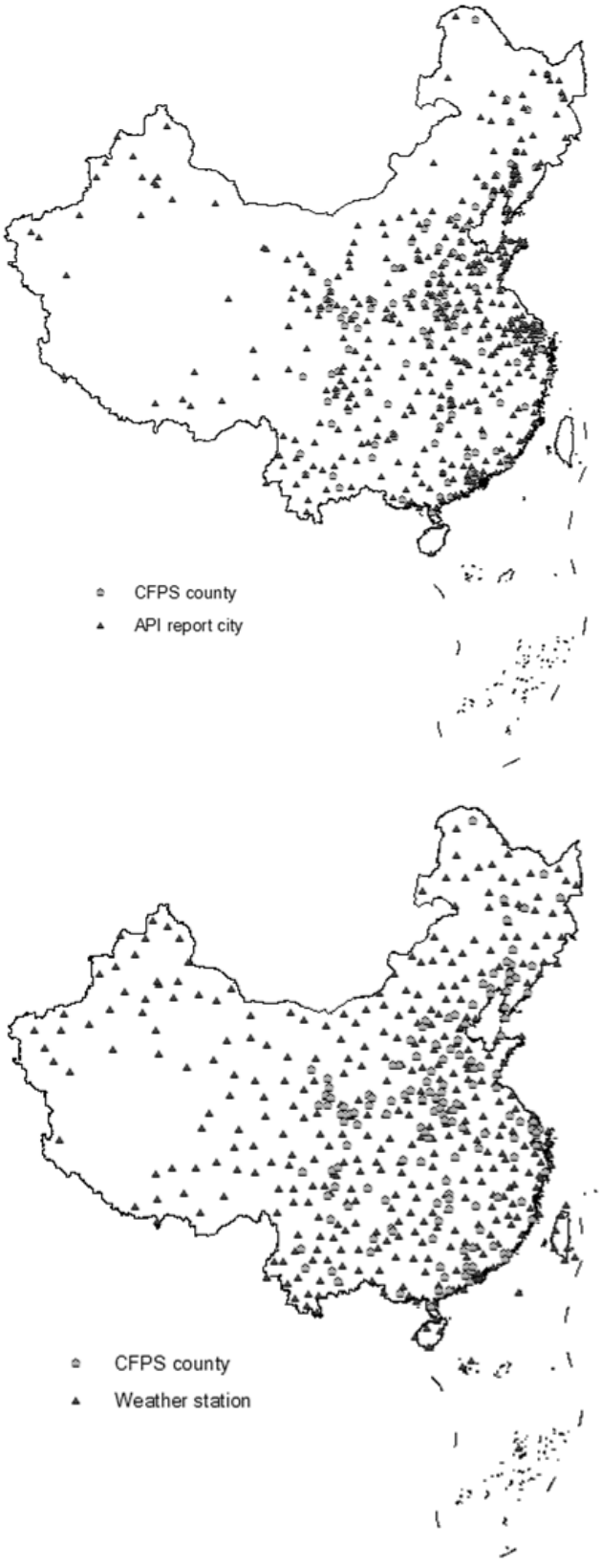
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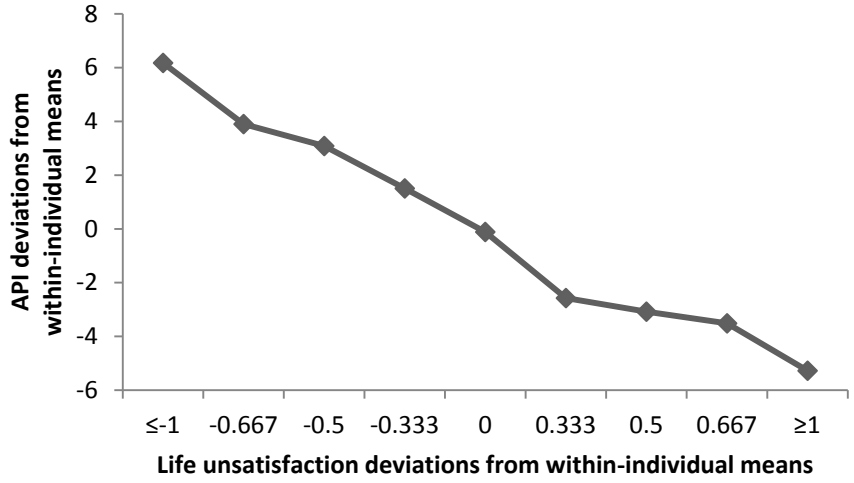
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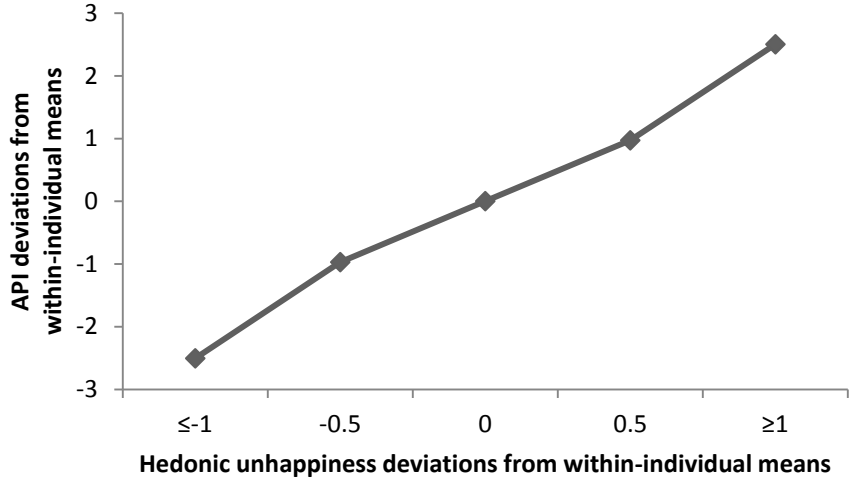
Figure 1: Distribution of CFPS counties and API report cities/weather stations

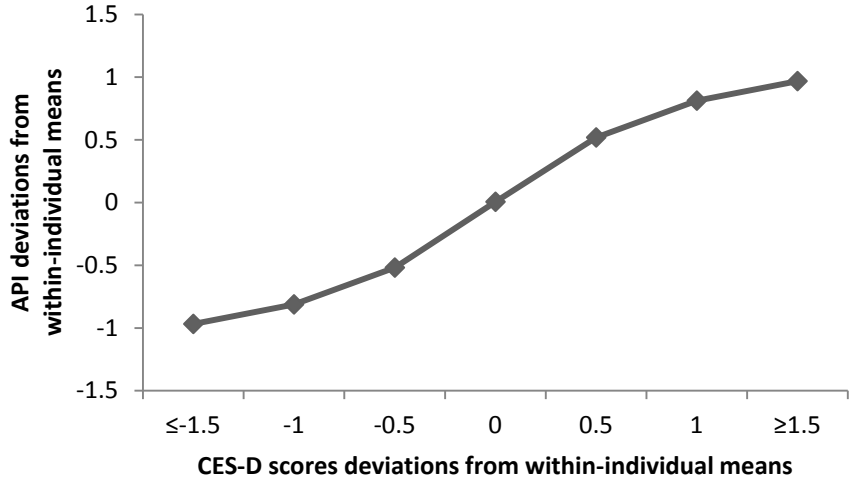


Source: China Family Panel Studies; the Ministry of Environmental Protection of China; National Climatic Data Center, National Oceanic and Atmospheric Administration.
Note: This figure is plotted using ArcMap 10.3.1. API = air pollution index. CFPS = China Family Panel Studies.

Figure 2: Relationship between subjective well-being and API







Source: China Family Panel Studies 2010, 2012 and 2014; the Ministry of Environmental Protection of China.
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 unsatisfaction	life unsatisfaction, 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 the first item in CES-D, ranging from 0 to 4, the lower the better	0.692	0.929	--	--	0.741	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	20.875	89.491	36.142
Per capita income	log form of household per capita income (Chinese 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	5.730	4.389	6.498	4.190
Temperature	weighted mean temperature (10 °F)	7.347	1.116	6.749	2.169	7.512	1.288
Temp. squared	weighted mean temperature (10 °F) squared	55.229	14.660	50.247	23.134	58.087	16.585
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)	4.659	1.510	4.777	1.524	4.864	1.546
Age squared	age (÷10) squared	23.981	14.606	25.146	15.039	26.049	15.400
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	4.666	7.468	4.679
Unemployed	indicator for unemployed 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 subjective well-being

A. Life unsatisfaction					
Dependent variable: life unsatisfaction (1-5)	(1)	(2)	(3)	(4)	(5)
API	0.008	0.021	0.022	0.024	0.003
	(0.020)	(0.021)	(0.021)	(0.022)	(0.022)
Household per capita income	-0.048***	-0.015*	-0.015*	-0.015*	-0.015*
	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Relative income	-0.251***	-0.188***	-0.188***	-0.188***	-0.186***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Individual fixed effect	No	Yes	Yes	Yes	Yes
County, year and month fixed effects	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects, quadratic time trend	Yes	No	Yes	Yes	Yes
County-by-year fixed effects	No	No	No	No	Yes
Weather controls	Yes	No	No	Yes	Yes
Observations	47,756	47,756	47,756	47,756	47,756
Adjusted (within) *R*-squared	0.152	0.116	0.116	0.117	0.135
B. Hedonic unhappiness					
Dependent variable: hedonic unhappiness (0-4)	(1)	(2)	(3)	(4)	(5)
API	0.045**	0.100***	0.100***	0.106***	0.096***
	(0.022)	(0.029)	(0.030)	(0.031)	(0.032)
Household per capita income	-0.016**	0.002	0.002	0.002	-0.001
	(0.008)	(0.012)	(0.012)	(0.012)	(0.011)
Relative income	-0.079***	-0.041***	-0.041***	-0.041***	-0.048***
	(0.007)	(0.014)	(0.014)	(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, quadratic time trend	Yes	No	Yes	Yes	Yes
County-by-year fixed effects	No	No	No	No	Yes
Weather controls	Yes	No	No	Yes	Yes
Observations	25,002	25,002	25,002	25,002	25,002
Adjusted (within) *R*-squared	0.074	0.018	0.018	0.018	0.051
C. Mental well-being					
Dependent variable: CES-D score (0-24)	(1)	(2)	(3)	(4)	(5)
API	0.199*	0.262**	0.254**	0.328**	0.218*
	(0.101)	(0.123)	(0.124)	(0.128)	(0.130)
Household per capita income	-0.155***	-0.048	-0.047	-0.046	-0.054
	(0.032)	(0.049)	(0.049)	(0.048)	(0.049)
Relative income	-0.436***	-0.214***	-0.215***	-0.214***	-0.241***
	(0.033)	(0.058)	(0.058)	(0.058)	(0.052)
Individual fixed effect	No	Yes	Yes	Yes	Yes
County, year and month fixed effects	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects, quadratic time trend	Yes	No	Yes	Yes	Yes
County-by-year fixed effects	No	No	No	No	Yes
Weather controls	Yes	No	No	Yes	Yes
Observations	24,924	24,924	24,924	24,924	24,924
Adjusted (within) *R*-squared	0.110	0.020	0.020	0.021	0.061
D. Depressive symptoms					
Dependent variable: depressive symptoms (0-1)	(1)	(2)	(3)	(4)	(5)
API	0.033**	0.039**	0.038**	0.046***	0.031*
	(0.013)	(0.016)	(0.017)	(0.017)	(0.016)
Household per capita income	-0.017***	-0.003	-0.004	-0.004	-0.004
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Relative income	-0.045***	-0.024***	-0.024***	-0.024***	-0.027***
	(0.004)	(0.007)	(0.007)	(0.007)	(0.006)
Individual fixed effect	No	Yes	Yes	Yes	Yes
County, year and month fixed effects	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects, quadratic time trend	Yes	No	Yes	Yes	Yes
County-by-year fixed effects	No	No	No	No	Yes
Weather controls	Yes	No	No	Yes	Yes
Observations	24,924	24,924	24,924	24,924	24,924
Adjusted (within) *R*-squared	0.089	0.009	0.010	0.011	0.050

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

Note: The weather controls include mean temperature and its square, total precipitation, mean wind speed, and a dummy for bad weather. 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 subjective well-being, by API level

Dependent variable	Life unsatisfaction	Hedonic unhappiness	Mental well-being	Depressive symptoms
	(1)	(2)	(3)	(4)
API51_100	0.010	0.061	0.215	0.021
	(0.018)	(0.037)	(0.174)	(0.023)
API101_150	0.003	0.101**	0.432**	0.058**
	(0.029)	(0.044)	(0.203)	(0.026)
API151_200	0.022	0.227**	0.834***	0.107**
	(0.069)	(0.089)	(0.314)	(0.044)
API201_300	0.064	0.104	-0.345	0.033
	(0.085)	(0.110)	(0.534)	(0.059)
API301_500	-0.077	0.337***	1.377***	0.183**
	(0.284)	(0.122)	(0.446)	(0.084)
Household per capita income	-0.016*	0.002	-0.043	-0.004
	(0.008)	(0.012)	(0.049)	(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
Observations	47,756	25,002	24,924	24,924
Adjusted (within) R-squared	0.117	0.018	0.022	0.011

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

Note: The weather controls include mean temperature and its square, total precipitation, mean wind speed, and a dummy for bad weather. 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, age and children

A. Hedonic unhappiness							
Dependent variable	Gender		Age			Having children younger than 16	
Hedonic unhappiness	Male	Female	Young (16–39)	Middle (40–59)	Old (60 or above)	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable mean	*0.641*	*0.784*	*0.735*	*0.731*	*0.673*	*0.733*	*0.707*
API	0.129***	0.090**	0.102*	0.107**	0.102*	0.136***	0.097***
	(0.044)	(0.044)	(0.054)	(0.044)	(0.055)	(0.048)	(0.036)
Observations	12,130	12,872	5,746	11,841	7,415	7,182	17,820
Adjusted (within) *R*-squared	0.018	0.021	0.038	0.019	0.022	0.033	0.015
B. Mental well-being							
Dependent variable	Gender		Age			Having children younger than 16	
CES-D scores	Male	Female	Young (16–39)	Middle (40–59)	Old (60 or above)	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable mean	*2.542*	*3.217*	*2.659*	*2.939*	*2.988*	*2.745*	*2.947*
API	0.256	0.410**	0.617***	0.319*	0.089	0.780***	0.162
	(0.156)	(0.172)	(0.198)	(0.177)	(0.220)	(0.168)	(0.150)
Observations	12,105	12,819	5,744	11,808	7,372	7,175	17,749
Adjusted (within) *R*-squared	0.019	0.025	0.044	0.023	0.033	0.035	0.022
C. Depressive symptoms							
Dependent variable	Gender		Age			Having children younger than 16	
Depressive symptoms	Male	Female	Young (16–39)	Middle (40–59)	Old (60 or above)	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable mean	*0.275*	*0.347*	*0.301*	*0.315*	*0.317*	*0.303*	*0.316*
API	0.045**	0.050**	0.099***	0.036	0.025	0.099***	0.027
	(0.022)	(0.021)	(0.032)	(0.022)	(0.027)	(0.025)	(0.019)
Observations	12,105	12,819	5,744	11,808	7,372	7,175	17,749
Adjusted (within) *R*-squared	0.012	0.014	0.028	0.011	0.022	0.019	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 3. 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 years		
Hedonic unhappiness	0–25%	25–50%	50–75%	75–100%	Illiterate	Less educated (education<9)	More educated (education≥9)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable mean	*0.793*	*0.764*	*0.715*	*0.629*	*0.817*	*0.709*	*0.680*
API	0.264***	0.159**	0.053	0.023	0.066	0.193***	0.077**
	(0.069)	(0.074)	(0.050)	(0.037)	(0.056)	(0.048)	(0.037)
Observations	5,071	5,424	6,224	7,677	4,907	7,058	13,037
Adjusted (within) *R*-squared	0.042	0.023	0.026	0.022	0.020	0.039	0.025

B. Mental well-being

Dependent variable	Income level				Education years		
CES-D scores	0–25%	25–50%	50–75%	75–100%	Illiterate	Less educated (education<9)	More educated (education≥9)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable mean	*3.455*	*3.227*	*2.796*	*2.357*	*3.821*	*2.912*	*2.528*
API	0.989***	0.689**	-0.125	0.112	0.225	0.693***	0.146
	(0.229)	(0.274)	(0.174)	(0.179)	(0.223)	(0.212)	(0.139)
Observations	5,048	5,409	6,201	7,663	4,872	7,033	13,019
Adjusted (within) *R*-squared	0.045	0.024	0.035	0.028	0.035	0.036	0.025

C. Depressive symptoms

Dependent variable	Income level				Education years		
Depressive symptoms	0–25%	25–50%	50–75%	75–100%	Illiterate	Less educated (education<9)	More educated (education≥9)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable mean	*0.376*	*0.351*	*0.300*	*0.253*	*0.407*	*0.318*	*0.274*
API	0.108***	0.111***	-0.004	0.011	0.051*	0.098***	0.016
	(0.024)	(0.037)	(0.028)	(0.022)	(0.030)	(0.027)	(0.021)
Observations	5,048	5,409	6,201	7,663	4,872	7,033	13,019
Adjusted (within) *R*-squared	0.033	0.018	0.020	0.013	0.036	0.020	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 3. 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 pollution attitude, workplace and pollution level

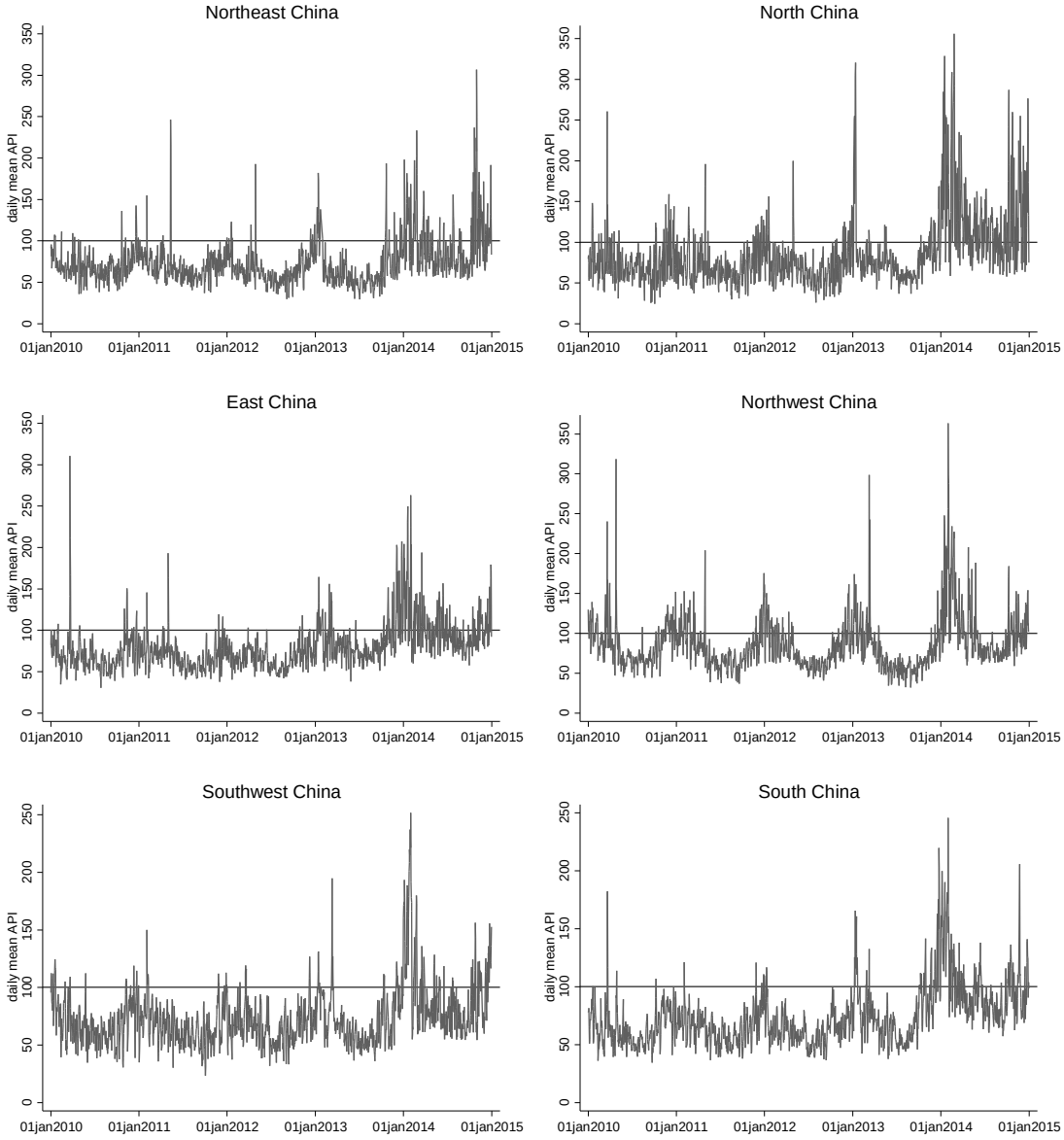
A. Hedonic unhappiness						
Dependent variable	Pollution attitude		Workplace		Local yearly pollution	
Hedonic unhappiness	Careless	Critical	Indoors	Outdoors	Polluted	Less polluted
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable mean	*0.738*	*0.689*	*0.702*	*0.733*	*0.707*	*0.725*
API	0.102**	0.111***	0.057	0.168***	0.075*	0.146***
	(0.047)	(0.035)	(0.055)	(0.048)	(0.043)	(0.050)
Observations	12,253	12,470	6,033	11,849	13,126	11,084
Adjusted (within) *R*-squared	0.022	0.020	0.031	0.020	0.023	0.019
B. Mental well-being						
Dependent variable	Pollution attitude		Workplace		Local yearly pollution	
CES-D scores	Careless	Critical	Indoors	Outdoors	Polluted	Less polluted
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable mean	*3.068*	*2.695*	*2.567*	*3.062*	*2.891*	*2.882*
API	0.348*	0.330**	0.408*	0.493**	0.273*	0.407*
	(0.189)	(0.134)	(0.207)	(0.196)	(0.157)	(0.207)
Observations	12,213	12,442	6,023	11,816	13,098	11,043
Adjusted (within) *R*-squared	0.023	0.027	0.029	0.025	0.034	0.014
C. Depressive symptoms						
Dependent variable	Pollution attitude		Workplace		Local yearly pollution	
Depressive symptoms	Careless	Critical	Indoors	Outdoors	Polluted	Less polluted
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable mean	*0.334*	*0.289*	*0.283*	*0.333*	*0.311*	*0.312*
API	0.051**	0.046**	0.041	0.069***	0.044*	0.050**
	(0.023)	(0.021)	(0.025)	(0.024)	(0.023)	(0.024)
Observations	12,213	12,442	6,023	11,816	13,098	11,043
Adjusted (within) *R*-squared	0.014	0.014	0.018	0.019	0.017	0.008

Source: China Family Panel Studies 2010 and 2014.

Note: Other covariates and fixed effects are the same as those in column (4) of Table 3. 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.

Online Appendix A: Supplementary Figures and Tables

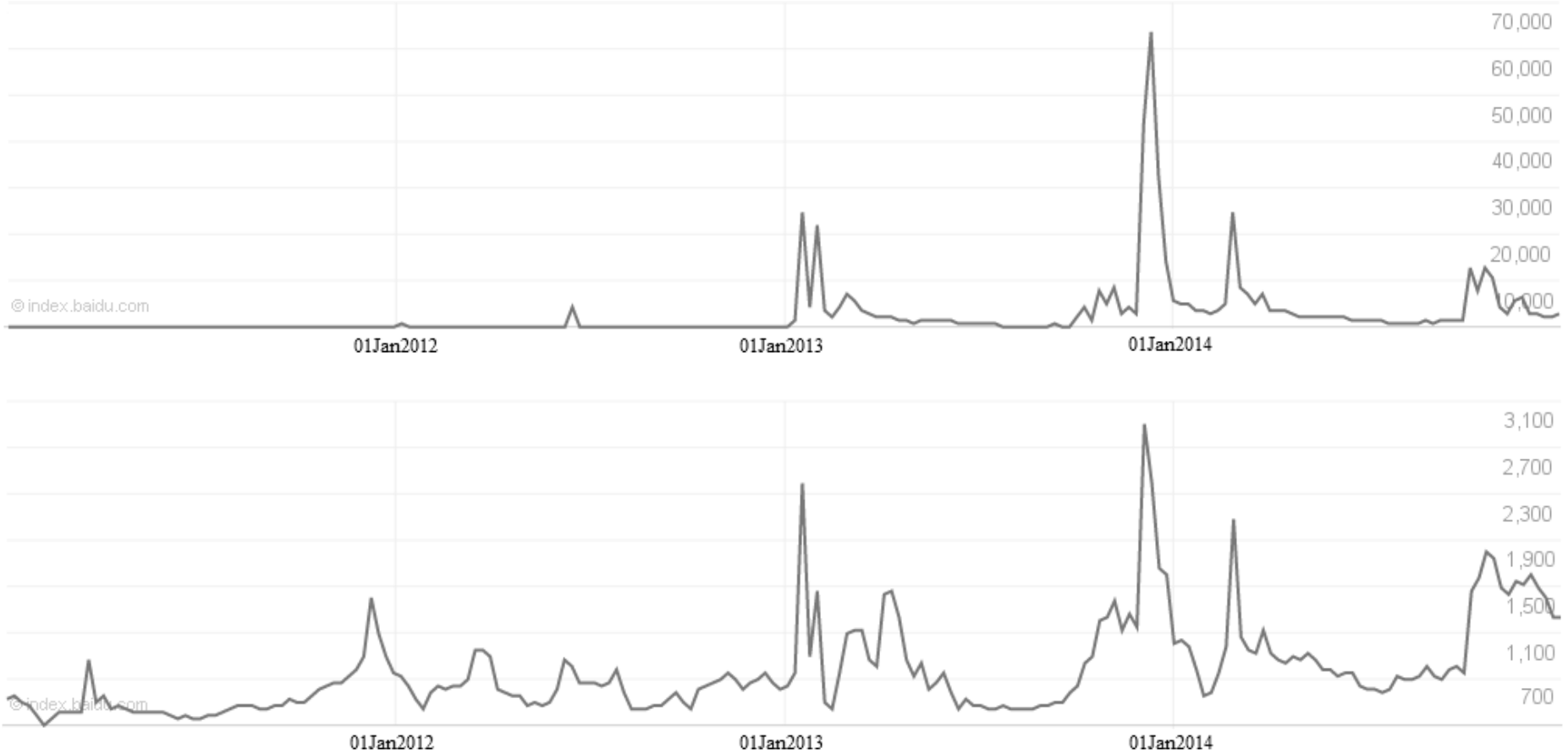
Figure A1: Daily air pollution index (API) in China, 2010–2014



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

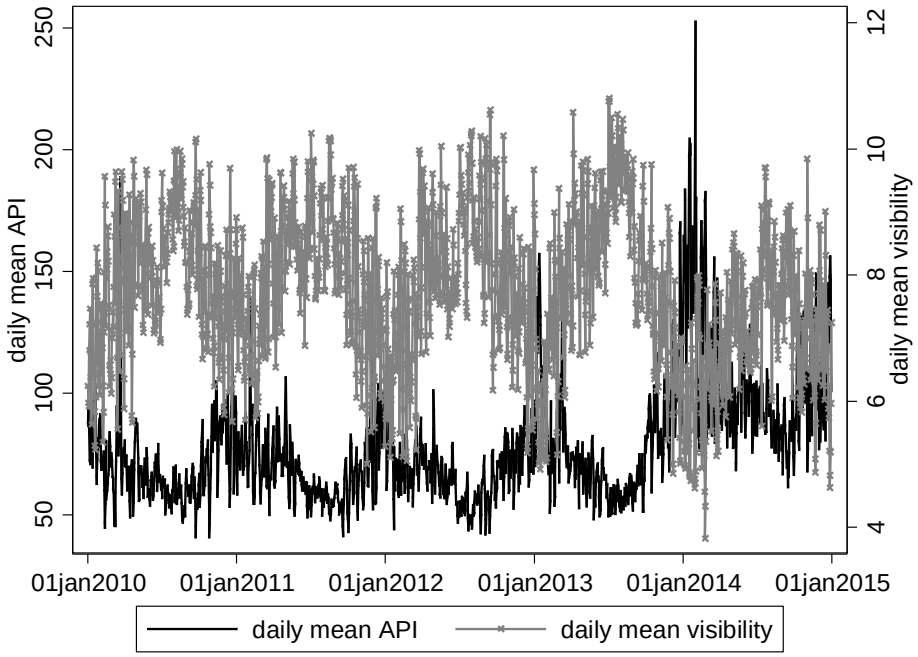
Note: The daily mean API is calculated by the weighted average values of all the API report cities within the region, where the weights are the yearly population in each city. The US National Ambient Air Quality Standards of fine particulate matter smaller than 10 micrometers is 0.15 mg/m^3, which corresponds 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: The Baidu Index of "wumai (haze)" and "kouzhao (mask)", 2011–2014



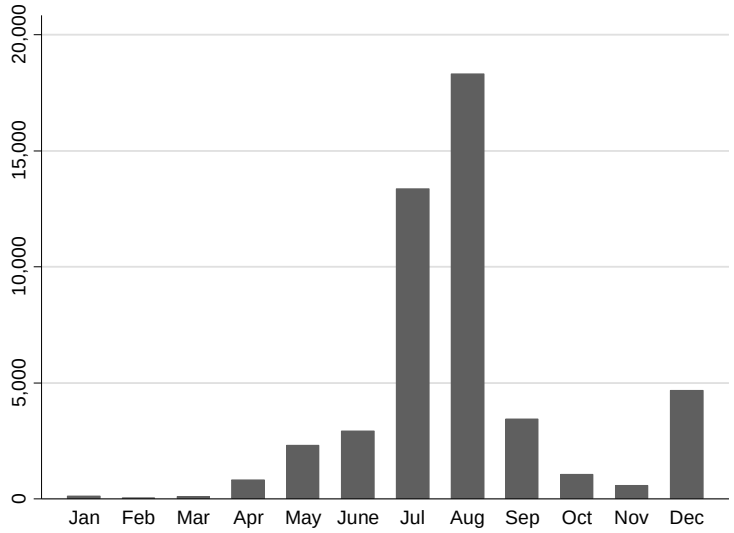
Source: http://index.baidu.com/.
Note: Jan=January.

Figure A3: Daily air pollution index (API) and air visibility in China, 2010–2014



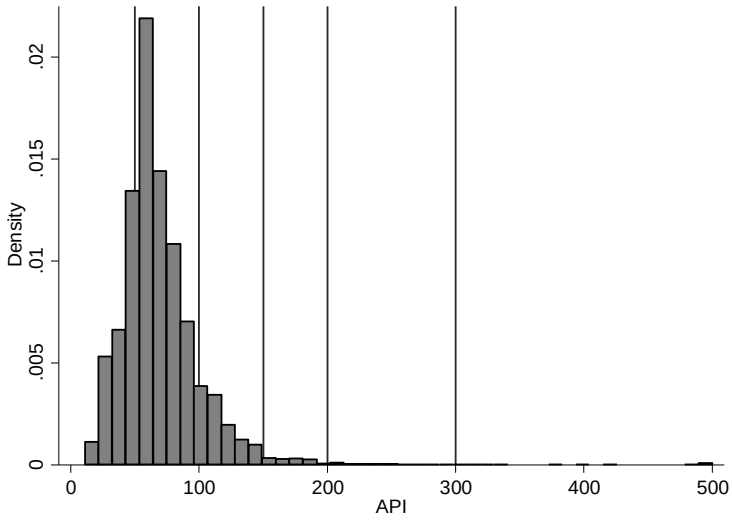
Source: API data is from Air quality daily report published by the Ministry of Environmental Protection of the People's Republic of China. Visibility data is from National Climatic Data Center under the National Oceanic and Atmospheric Administration.
Note: The daily mean API is calculated by the weighted average values of all the API report cities in China, where the weights are the yearly population in each city. The daily mean visibility is calculated by the weighted average values of all the monitor stations in China, where the weights are equal to the yearly population at the county level.

Figure A4: Interview date distribution, 2010, 2012 and 2014



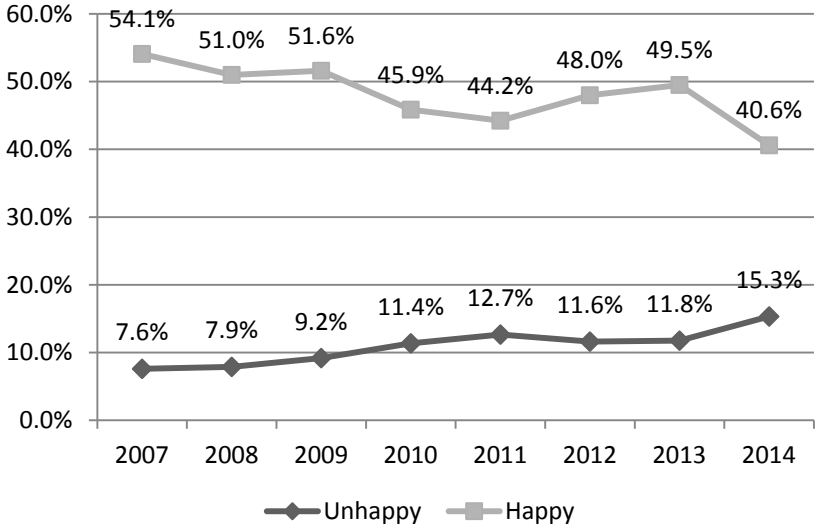
Source: China Family Panel Studies 2010, 2012 and 2014.
Note: Apr = April; Aug = August; Dec = December; Feb = February; Jan = January; Jul = July; Mar = March; Nov = November; Oct = October; Sep = September.

Figure A5: Distribution of API, 2010, 2012 and 2014



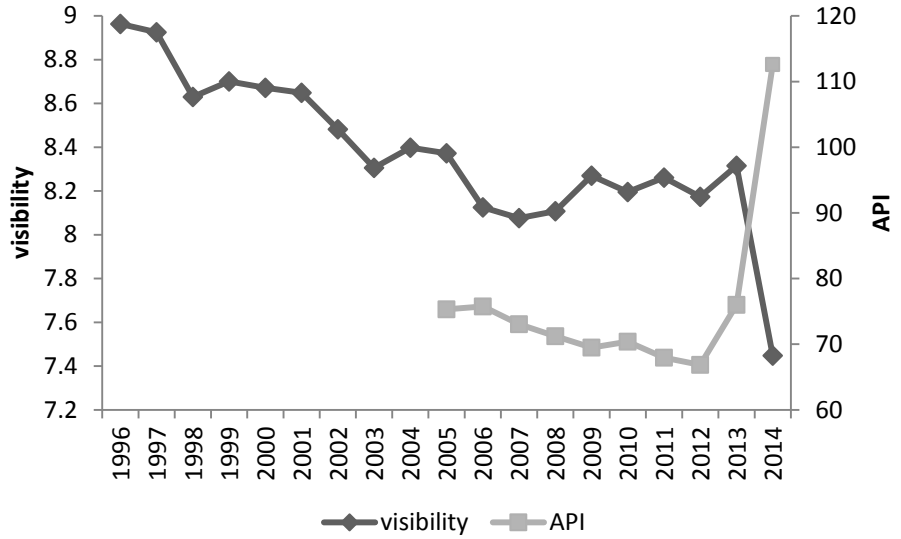
Source: Air quality daily report published by the Ministry of Environmental Protection of the People's Republic of China.

Figure A6: Happiness Trend in CCTV Postcard Survey, 2007–2014



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

Figure A7: API/Visibility Trend in China, 1996–2014



Source: API data is from Air quality daily report published by the Ministry of Environmental Protection of the People's Republic of China. Visibility data is from National Climatic Data Center under the National Oceanic and Atmospheric Administration.

Note: The yearly mean API is calculated by the weighted average values of all the API report cities in China, where the weights are the population in each city. The yearly mean visibility is calculated by the weighted average values of all the monitor stations in China where the weights are equal to the population at the county level.

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

Dependent variable	Life unsatisfaction					Hedonic unhappiness				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
API	0.008	0.021	0.022	0.024	0.003	0.045**	0.100***	0.100***	0.106***	0.096***
	(0.020)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.029)	(0.030)	(0.031)	(0.032)
Household per capita income	-0.048***	-0.015*	-0.015*	-0.015*	-0.015*	-0.016**	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	-0.251***	-0.188***	-0.188***	-0.188***	-0.186***	-0.079***	-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)	(0.014)
Sunshine Duration	-0.002	-0.002	-0.002	-0.001	-0.001	0.001	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Gender	0.100***					-0.102***				
	(0.010)					(0.014)				
Age (÷10)	0.284***					0.066**				
	(0.022)					(0.032)				
Age (÷10) squared	-0.035***	0.009	0.009	0.009	0.011	-0.010***	-0.016	-0.016	-0.016	-0.017
	(0.002)	(0.011)	(0.011)	(0.011)	(0.011)	(0.003)	(0.013)	(0.013)	(0.013)	(0.013)
Married	-0.183***	-0.145***	-0.145***	-0.144***	-0.145***	-0.129***	-0.021	-0.024	-0.023	-0.029
	(0.016)	(0.037)	(0.037)	(0.037)	(0.037)	(0.022)	(0.061)	(0.060)	(0.060)	(0.061)
Education	-0.001	-0.005	-0.005	-0.005	-0.007	-0.006***	-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	0.095**	-0.001	0.000	0.003	0.020	0.075*	0.037	0.038	0.037	0.057
	(0.038)	(0.049)	(0.049)	(0.049)	(0.043)	(0.039)	(0.050)	(0.050)	(0.049)	(0.054)
Party	-0.127***	-0.075	-0.074	-0.075	-0.085	-0.038*	-0.047	-0.046	-0.046	-0.098
	(0.018)	(0.066)	(0.065)	(0.066)	(0.063)	(0.022)	(0.077)	(0.076)	(0.076)	(0.078)
Chronic disease	0.125***	0.052***	0.052***	0.052***	0.054***	0.310***	0.201***	0.201***	0.201***	0.202***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.020)	(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, quadratic time trend	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
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	47,756	47,756	47,756	47,756	47,756	25,002	25,002	25,002	25,002	25,002
Adjusted (within) *R*-squared	0.152	0.116	0.116	0.117	0.135	0.074	0.018	0.018	0.018	0.051

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

Note: The weather controls include mean temperature and its square, total precipitation, mean wind speed, and a dummy for bad weather. 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 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	0.199*	0.262**	0.254**	0.328**	0.218*	0.033**	0.039**	0.038**	0.046***	0.031*
	(0.101)	(0.123)	(0.124)	(0.128)	(0.130)	(0.013)	(0.016)	(0.017)	(0.017)	(0.016)
Household per capita income	-0.155***	-0.048	-0.047	-0.046	-0.054	-0.017***	-0.003	-0.004	-0.004	-0.004
	(0.032)	(0.049)	(0.049)	(0.048)	(0.049)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Relative income	-0.436***	-0.214***	-0.215***	-0.214***	-0.241***	-0.045***	-0.024***	-0.024***	-0.024***	-0.027***
	(0.033)	(0.058)	(0.058)	(0.058)	(0.052)	(0.004)	(0.007)	(0.007)	(0.007)	(0.006)
Sunshine Duration	-0.004	-0.005	-0.005	0.002	-0.001	-0.000	-0.001	-0.001	0.001	-0.000
	(0.009)	(0.010)	(0.010)	(0.013)	(0.012)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Gender	-0.433***					-0.048***				
	(0.053)					(0.006)				
Age (÷10)	0.418***					0.018				
	(0.140)					(0.017)				
Age (÷10) squared	-0.047***	-0.060	-0.061	-0.061	-0.058	-0.003*	-0.004	-0.004	-0.004	-0.004
	(0.014)	(0.052)	(0.052)	(0.052)	(0.050)	(0.002)	(0.007)	(0.007)	(0.007)	(0.007)
Married	-0.848***	-0.387	-0.392*	-0.394*	-0.432*	-0.091***	-0.008	-0.010	-0.010	-0.014
	(0.106)	(0.234)	(0.233)	(0.235)	(0.239)	(0.011)	(0.027)	(0.027)	(0.027)	(0.028)
Education	-0.058***	-0.030	-0.030	-0.031	-0.031	-0.007***	0.001	0.001	0.001	0.001
	(0.009)	(0.024)	(0.023)	(0.023)	(0.021)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Unemployed	0.260*	0.225	0.225	0.230	0.416**	0.055**	0.038	0.038	0.037	0.055**
	(0.150)	(0.200)	(0.200)	(0.198)	(0.167)	(0.022)	(0.033)	(0.033)	(0.032)	(0.023)
Party	-0.162*	-0.127	-0.126	-0.118	-0.326	-0.011	0.023	0.023	0.023	-0.001
	(0.089)	(0.313)	(0.311)	(0.307)	(0.316)	(0.012)	(0.048)	(0.048)	(0.048)	(0.048)
Chronic disease	1.440***	0.722***	0.721***	0.726***	0.723***	0.136***	0.049***	0.049***	0.049***	0.051***
	(0.086)	(0.129)	(0.128)	(0.127)	(0.118)	(0.010)	(0.017)	(0.017)	(0.017)	(0.015)
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, quadratic time trend	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
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	24,924	24,924	24,924	24,924	24,924	24,924	24,924	24,924	24,924	24,924
Adjusted (within) *R*-squared	0.110	0.020	0.020	0.021	0.061	0.089	0.009	0.010	0.011	0.050

Source: China Family Panel Studies 2010 and 2014.

Note: The weather controls include mean temperature and its square, total precipitation, mean wind speed, and a dummy for bad weather. 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 A3: Deviation-from-the-mean effects of air quality on life unsatisfaction

Dependent variable	7-day deviation	30-day deviation	90-day deviation	180-day deviation
Life unsatisfaction	(1)	(2)	(3)	(4)
$\ln API_t - \ln(\frac{1}{k}\sum_{i=0}^{k-1} API_{t-i})$	0.015	-0.002	0.006	0.019
	(0.024)	(0.024)	(0.022)	(0.021)
Household per capita income	-0.015*	-0.015*	-0.015*	-0.015*
	(0.008)	(0.008)	(0.008)	(0.008)
Relative income	-0.188***	-0.188***	-0.188***	-0.188***
	(0.008)	(0.008)	(0.008)	(0.008)
Observations	47,756	47,756	47,756	47,756
Adjusted (within) *R*-squared	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, respectively. Other covariates and fixed effects are the same as those in column (4) of Table 3. 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 test—Forwarding API by 1-7 days

Dependent variable	Life unsatisfaction	Hedonic unhappiness	Mental well-being	Depressive symptoms
	(1)	(2)	(3)	(4)
API	0.016	0.096***	0.203*	0.035**
	(0.024)	(0.030)	(0.113)	(0.015)
API_F1	0.012	0.028	0.201	0.025
	(0.022)	(0.037)	(0.160)	(0.020)
Adj. (within) *R*-squared	0.117	0.019	0.021	0.011
API	0.013	0.108***	0.311**	0.049***
	(0.021)	(0.033)	(0.121)	(0.016)
API_F2	0.034	0.019	0.059	0.001
	(0.023)	(0.032)	(0.156)	(0.021)
Adj. (within) *R*-squared	0.116	0.019	0.021	0.010
API	0.007	0.106***	0.305**	0.043**
	(0.022)	(0.035)	(0.130)	(0.018)
API_F3	0.036*	-0.024	-0.090	0.000
	(0.022)	(0.032)	(0.125)	(0.017)
Adj. (within) *R*-squared	0.117	0.019	0.020	0.010
API	0.023	0.106***	0.287**	0.040**
	(0.023)	(0.036)	(0.130)	(0.017)
API_F4	-0.015	-0.007	0.157	0.027
	(0.023)	(0.034)	(0.135)	(0.018)
Adj. (within) *R*-squared	0.116	0.019	0.021	0.011
API	0.022	0.098***	0.295**	0.038**
	(0.022)	(0.032)	(0.126)	(0.016)
API_F5	0.008	0.003	-0.016	0.012
	(0.017)	(0.028)	(0.125)	(0.015)
Adj. (within) *R*-squared	0.117	0.017	0.021	0.011
API	0.020	0.107***	0.311**	0.041**
	(0.022)	(0.032)	(0.131)	(0.016)
API_F6	0.009	-0.050	-0.045	0.015
	(0.018)	(0.033)	(0.125)	(0.016)
Adj. (within) *R*-squared	0.118	0.019	0.022	0.011
API	0.020	0.101***	0.313**	0.038**
	(0.022)	(0.031)	(0.124)	(0.016)
API_F7	0.023	-0.014	0.014	0.029*
	(0.019)	(0.028)	(0.117)	(0.015)
Adj. (within) *R*-squared	0.117	0.019	0.022	0.012

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. Robust standard errors, clustered at the county level, are presented in parentheses. API = air pollution index. Adj. = Adjusted. *10% significance level. **5% significance level. ***1% 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	0.127*	0.110**	0.154**	0.073	0.110*	0.045
	(0.068)	(0.055)	(0.074)	(0.079)	(0.061)	(0.077)
Observations	2,744	5,564	3,822	3,002	6,277	3,593
Adj. (within) *R*-squared	0.047	0.021	0.028	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	0.555**	0.185	0.135	0.666**	0.462*	-0.015
	(0.242)	(0.190)	(0.311)	(0.265)	(0.241)	(0.317)
Observations	2,743	5,551	3,811	3,001	6,257	3,561
Adj. (within) *R*-squared	0.032	0.024	0.043	0.067	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	0.110**	0.034	0.018	0.090**	0.037	0.035
	(0.042)	(0.028)	(0.035)	(0.043)	(0.029)	(0.036)
Observations	2,743	5,551	3,811	3,001	6,257	3,561
Adj. (within) *R*-squared	0.040	0.015	0.030	0.047	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 3. 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.

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

	World Values Survey				CCTV Postcard Survey	
	Life Satisfaction (1–10)		Hedonic happiness (1–4)		Happiness (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).

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.