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Recency and projection biases in air quality valuation by Chinese residents☆

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HIGHLIGHTS

- Examine how recency and projection biases affect air quality valuation using responses to subjective well-being questions
- Valuation is higher for one-day improvement compared to one-year improvement in air quality
- These biases call into question the appropriate temporal scale when conducting air quality valuation studies
- Policymakers could exploit these biases to introduce more stringent policies during periods of intense air pollution

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ABSTRACT

We combine survey responses to subjective well-being (SWB) questions with air pollution data to recover Chinese residents' valuation of air quality improvements. Motivated by theoretical models of 'projection bias' and 'recency bias', we posit that one's SWB (and valuation) is affected disproportionately by more recent experiences with air pollution, even though long-term air pollution is more detrimental to one's actual well-being. Towards this end, we find that valuation for a unit improvement in $PM_{2.5}$ is twice as large when air quality on the day of survey is used as the explanatory variable compared to air quality averaged over a year. Our findings have far-reaching research and policy implications as they call into question the appropriate temporal scale of air quality conditions when conducting valuation studies or policy evaluations. Furthermore, our results imply that policymakers could conceivably exploit this behavioral bias to introduce more stringent air quality management policies when air quality is extremely poor.

1. Introduction

Air pollution is fast becoming a major public health challenge especially across the developing world. It is estimated that in 2012, 3.2 million or one in nine premature deaths in low- and middle-income countries were attributable to outdoor air pollution (WHO, 2014). Unfortunately, this challenge is projected to intensify as policymakers struggle to keep air quality from worsening (OECD, 2012). Nowhere is the problem of air pollution most prominent in China where decades of sterling economic growth were accompanied by corresponding deterioration in the environment (Z. Chen et al., 2013; Diao et al., 2009; Ebenstein et al., 2015; Huang et al., 2012; Wu et al., 2017). The Chinese government has been taking the fight to air pollution, but with varying degrees of success as they seek to improve air quality without sacrificing economic growth (Xie et al., 2016; Q. Zhang et al., 2012). One of the key ingredients that will aid policymakers in this battle of 'trade-offs' is the accurate valuation for air quality improvements. Access to such valuation will help decision-makers better weigh the benefits of reducing air pollution against its costs. Perhaps recognizing the urgent need for accurate valuation of air quality improvements, research on air quality valuation in China has increased in recent years. These studies can be generally categorized by the techniques in which valuation was elicited:

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stated preference (Dong and Zeng, 2018; Du and Mendelsohn, 2011; Hammitt and Zhou, 2006; Lin and Tan, 2017; Chuanwang Sun et al., 2016a; Chuanwang Sun et al., 2016b; Tan and Zhao, 2014; Tang and Zhang, 2016; G. Wang et al., 2016; H. Wang and Mullahy, 2006; K. Wang et al., 2015; X. Wang et al., 2006; Y. Wang and Zhang, 2009; Wei and Wu, 2017; Yu and Abler, 2010); property hedonic (D. Chen and Chen, 2017; Zheng et al., 2014; Zheng and Kahn, 2008; Zheng et al., 2010); averting expenditures (Barwick et al., 2017; Ito and Zhang, 2016; J. Zhang and Mu, 2017); happiness (Liu et al., 2018; X. Zhang et al., 2017); and migration (S. Chen et al., 2017; Freeman et al., 2017).

This study departs from the usual valuation techniques and instead uses subjective well-being or self-reported happiness to value air quality improvements. In conducting this study, we expand upon earlier works in two ways. First, air pollution, while undesirable, is often correlated with desirable attributes such as economic opportunities. This is especially true in developing countries where access to jobs are highly valued (Tan-Soo, 2017). Hence, valuation for clean air would be biased downwards if this confounding relationship is not controlled for. Towards this end, we use a wind-based instrumental variable to verify the direction of the confounding relationship and recover causal interpretation of willingness-to-pay for clean air. Second, this is one of the first studies to investigate empirically if valuation of air quality improvement is susceptible to projection or recency biases. From a welfare standpoint, it is obvious that one is better off with year-round improvement in air quality rather than just a month or a day of improvements. However, evidence from behavioral economics and psychology provide fodder to believe that one could possibly place a higher value for the shorter improvement than the longer-term improvement.

Using a household-level representative sample from China, we first find that the relationship between one's self-reported happiness and air quality is indeed confounded. We deploy an instrumental variable strategy by using upwind transmission of pollution to break this confounding relationship and derive unbiased valuation for clean air. Second, we unearth a previously undiscovered relationship between valuation and temporal scale of air pollution. Specifically, we find that the valuation for air quality improvements systematically decreases as we move from daily measures of air quality to annual averaged air quality. This is to say that individuals' valuation for air quality is most strongly influenced by their most recent experiences with air pollution. This finding provides new directions for future work in air quality valuation and insights in air quality management policies.

1.1. Literature review

The logic behind using happiness or well-being data to value air quality improvements is hinged on the assumption that subjective well-being or self-reported happiness is correlated with one's 'utility' or welfare. If we accept this assumption, then we could conceivably estimate an indirect utility function to recover marginal utilities or preference parameters. This technique contains elements of both revealed and stated preference methods. First, the stated preference portion is reflected by respondents' self-reporting of their happiness or well-being level. Second, the revealed preference portion is inferred by the researcher as we obtain air quality measures based on the respondents' residential locations. There is increasing popularity in using subjective well-being to value air quality because self-rated happiness questions are included in most social surveys and air quality information are relatively easier to obtain than before. This method also confers empirical advantage as the recovered marginal willingness-to-pay is a more comprehensive valuation for air quality improvements rather than a lower-bound estimate as seen in many revealed preference studies (Barwick et al., 2017; Ito and Zhang, 2016). In one of the earliest applications of subjective well-being data to air quality valuation, Welsch (2002) used a country-level survey and found that respondents from more polluted countries reported lower levels of happiness. The global average marginal willingness to pay (MWTP) was computed to be US$70 per kiloton of nitrogen dioxide. With the same approach, Welsch (2006) again used a country-level dataset to estimate valuation. The dataset in his second iteration included repeated observations for each country and thus he was able to control for time and spatially invariant factors. Many latter studies, such as Luechinger (2009) and Ferreira et al. (2013), used individual-level panel datasets.[1] As such, they could introduce individual fixed-effects to control for respondent-level heterogeneity. Luechinger (2009) further addressed the endogeneity of air pollution by using pollution from upwind locations as instrumental variable. He found that the MWTP for air quality in Germany is higher after instrumenting, suggesting positive confounding factor (e.g. positive correlation between air pollution and economic opportunities) between air pollution and happiness. Lastly, Levinson (2012) and X. Zhang et al. (2017) applied this method to individual cross-sectional data from the United States and China respectively. However, a key difference between these two studies and the others is that they used air quality on the day of the survey as opposed to an annual average used in other studies.

2. Theoretical model and empirical strategy

This paper is, to the best of our knowledge, one of the first studies to examine if air quality valuation is subjected to projection or recency biases. There are at least two reasons why we believe such a relationship exists. First, from microeconomics theory, the behavioral anomaly of 'projection bias' is formalized in an individual decision-making model (Loewenstein et al., 2003). This gist of 'projection bias' is that individuals project current conditions to their future selves. The canonical example to demonstrate projection bias is excessive grocery purchases on an empty stomach. Similarly, it is also possible that one might 'over' purchase air purifiers (or any other protective equipment) or in other words, have exceedingly high valuation for clean air during periods of bad air quality due to projection bias. Such tendencies have been observed with respect to over-purchase of winter clothing during periods of frigid conditions (Conlin et al., 2007). Recent studies by J. Zhang and Mu (2017) and Cong Sun et al. (2017) provided some evidence to support this hypothesis with respect to air pollution as they found that e-commerce sales of face-masks and air purifiers in China increased by multiple folds during days of severe air pollution. Second, the behavioral economics and psychology literature suggest the existence of 'recency bias', i.e. one's overall experience is much more affected by recent events. For example, Garbinsky et al. (2014) found that end moments of a culinary experience are more influential than the beginning moments in affecting experimental subjects' memory of the entire experience. Similarly, Redelmeier and Kahneman (1996) found that even though all patients incurred similar amount of pain in a colonoscopy examination, those who experienced less pain at the end of the procedure had a more favorable view of the entire examination compared to patients who experienced more pain at the end. In the case of air pollution, this could mean that a respondent reports lower level of happiness if the interview happens to be conducted on a day when air pollution is particularly high.

2.1. Theoretical model

We use a standard microeconomic model to demonstrate how air quality of different time-windows may affect a utility maximizing individual's valuations of air quality improvements. Adapting from Champ et al. (2003), we assume that an individual's utility is given by:

$$U = U(X, L, S) \tag{1}$$

$$S = S(\alpha, Z) \tag{2}$$

[1] It should be noted that Ferreira et al. (2013) stopped after estimating an indirect utility function and did not extend the analysis to value air quality.

where X is consumption of a unitaire good, L is leisure time, and S is time spent sick. Furthermore, we assume in Eq. (2) that sickness is a function of air pollution, α and other exogenous factors Z, such as age and health endowment. Next, without loss of generality, we suppress mitigating and averting behaviors and write the budget constraint as:

$$I + w*(T-L-S) = X + M(S) \tag{3}$$

where I is the non-labor income, w is the wage rate, T is total time available, L is leisure time, and $M(S)$ is medical expenses. The left-hand-side in Eq. (3) refers to the individual's total earning, which consists of non-labor income and labor income. The right-hand-side refers to the individual's expenditure, which consists of the unitaire good and medical expenses.

We can substitute Eq. (2) into Eqs. (1) and (3) and solve for the utility maximization problem. In turn, we obtain the optimal amount of X^* and L^* in terms of I, w, and α.

The indirect utility can thus be written as:

$$V = V(I, w, M(S)) \tag{4}$$

The marginal willingness-to-pay (MWTP) for clean air is thus the marginal rate of substitution between the marginal utility of α to the marginal utility of I:

$$MWTP = -\frac{\left(\partial V/\partial M\right)\left(\partial M/\partial S\right)\left(\partial S/\partial \alpha\right)}{\partial V/\partial I} \tag{5}$$

$\partial V/\partial M$ is the marginal disutility of medical expenses, and assumed to be negative. $\partial S/\partial \alpha$ is the marginal effect of air pollution on sickness and assumed to be positive. $\partial M/\partial S$ is the marginal effect of sickness on medical expenses and assumed to positive. Lastly, $\partial V/\partial I$ is the marginal utility of income, and assumed to be positive.

In this simple and conventional setup, air pollution affects one's utility or well-being only through the health channel, denoted by S in the model.

First, we consider the case without projection or recency biases. Suppose there are two measures of air pollution α_1 and α_2 at different time-windows, say α_1 is measured at a shorter time scale compared to α_2. In this regard, one could conceivably argue that $MWTP_{|\alpha_1} \le MWTP_{|\alpha_2}$ as long-term air pollution has greater adverse impacts on health compared to short-term air pollution, i.e. $\partial S/\partial \alpha_1 \le \partial S/\partial \alpha_2$. There are several pieces of evidence to support this argument. First, Hoek et al. (2013) summarized results from various epidemiological studies on the health effects of air pollution and found that the relative risk of cardiovascular mortality per 10 μg/m^3 of annual $PM_{2.5}$ is at around 1.11 for long-term exposure (defined as annual or longer). On the other hand, Shah et al. (2015), also in a review paper, found that the relative risk of mortality for short-term exposure (defined as up to weekly-average) is at around 1.012 per 10 μg/m^3 of short-term exposure to $PM_{2.5}$. Second, the idea that air quality of longer time-window is of greater concern is also reflected in the World Health Organization's air pollutant standards where the standard for daily $PM_{2.5}$ is at 25 μg/m^3 while the yearly standard is markedly more stringent at 10 μg/m^3.

Second, we now consider a case where projection or recency bias is allowed to affect air quality valuation. To do so, we modify Eq. (1) to allow air pollution to directly cause disutility or unhappiness to the individual through recency or projection bias:

$$U = U(X, L, S, \alpha) \tag{1$'$}$$

Eq. (1′) is different from Eq. (1) by virtue of air pollution α, entering directly into the individual's utility function. While earlier models only assess disutility of air pollution through the health channel (i.e. through the S channel in our model), it is conceivable that air pollution may also confer disutility directly through hedonic experiences to exposed individuals. There are two explanations for this. First, earlier experiments showed that on top of their intrinsic effects, recent or latest experiences register more deeply in the respondents' mind – a phenomenon known as recency bias. While this phenomenon had been demonstrated in pain and culinary experiences, this is the first study to test if individuals respond similarly to air quality (Garbinsky et al., 2014; Redelmeier and Kahneman, 1996). Second, it is also possible that individuals attribute additional disutility to current air pollution due to projection bias. Loewenstein et al. (2003) made the case that individuals are susceptible to projection bias where they extrapolate current conditions onto their future selves.

Following Eq. (1′), we can rewrite Eqs. (4) and (5) as:

$$V = V(I, w, M(S), \alpha) \tag{4$'$}$$

$$MWTP = -\frac{\left(\partial V/\partial M\right)\left(\partial M/\partial S\right)\left(\partial S/\partial \alpha\right) + \partial V/\partial \alpha}{\partial V/\partial I} \tag{5$'$}$$

The main difference between Eqs. (5′) and (5) is that, other than the health channel, valuation for air quality improvement is now also directly affected through the recency and projection biases channels, $\partial V/\partial \alpha$. In contrast to the earlier case, we hypothesize that the direct marginal disutility of air pollution $\partial V/\partial \alpha$ is larger in magnitude as air quality is evaluated at a shorter timeframe. That is, $\partial V/\partial \alpha_1 \le \partial V/\partial \alpha_2$ if α_1 is air quality measured at a shorter time scale and α_2 is air quality measured at a longer time scale.[2] Consequently, in comparison to the case without projection or recency biases, this means that $MWTP_{|\alpha_1} \ge MWTP_{|\alpha_2}$ if:

$$-\frac{\left(\partial V/\partial M\right)\left(\partial M/\partial S\right)\left(\partial S/\partial \alpha_1\right) + \partial V/\partial \alpha_1}{\partial V/\partial I} > -\frac{\left(\partial V/\partial M\right)\left(\partial M/\partial S\right)\left(\partial S/\partial \alpha_2\right) + \partial V/\partial \alpha_2}{\partial V/\partial I} \tag{6}$$

After rearranging, Eq. (6) becomes:

$$-\frac{\left(\partial V/\partial M\right)\left(\partial M/\partial S\right)}{\partial V/\partial I}\left(\partial S/\partial \alpha_2 - \partial S/\partial \alpha_1\right) < \frac{1}{\partial V/\partial I}\left(\partial V/\partial \alpha_2 - \partial V/\partial \alpha_1\right) \tag{6$'$}$$

First, the terms on each side of the Eq. (6′) represent the change in marginal utility as we shift from long-term exposure to short-term exposure. Specifically, the L.H.S. expression shows the increase in marginal utility through health channels from long-term to short-term exposure. Similarly, the R.H.S. expression shows the decrease in marginal utility through increased projection and recency biases from long-term to short-term exposure. Hence, $MWTP_{|\alpha_1} \ge MWTP_{|\alpha_2}$ if the projection and recency biases overwhelm effects from the health channels.

2.2. Empirical model

Using the theoretical model we developed and empirical strategies from earlier happiness-based valuation studies (e.g. Levinson, 2012; Luechinger, 2009), we estimate a reduced-form indirect utility function:

$$Y_{irt} = \alpha_0 + \alpha_1 Poll_{r,t-lag} + \alpha_2 \ln(income_i) + W_{r,t-lag}\xi + Z_i\Omega + \lambda_t + \sigma_r + \varepsilon_{irt} \tag{7}$$

[2] Note that $\partial V/\partial \alpha$ is negative as increased air pollution decreases utility.

$$MWTP = -\frac{dY/dPoll}{dY/dincome} = -\frac{\alpha_1}{\alpha_2}\overline{income} \tag{8}$$

In Eq. (7), we regress self-reported well-being (used as a proxy for indirect utility) reported by respondent i, from county r, at time-of-interview t on a vector of weather characteristics W, and socioeconomic characteristics, Z. Time (specifically, month-by-week[3]) fixed effects, λ and county fixed effects, σ are included to control for any time- and county-invariant factors. The weather characteristics controls are included up to second-order polynomials and consist of temperature, precipitation, duration of sun, and wind speed. The socioeconomic characteristics controls are age and its squared counterpart, sex, residence type and size, marital status, ethnic group, and family size.

The main explanatory variables are income and air quality. The coefficient on income α_2, can be interpreted as the marginal utility of income. Similarly, the coefficient on air quality, α_1, can be interpreted as the marginal utility of air quality. α_1 and α_2 can thus be used to derive the average marginal rate of substitution between income and air quality, or also known as the marginal willingness-to-pay (Eq. 8).

Lastly, we test the hypothesis discussed in the theoretical model section by experimenting with different lags of air quality (denoted by the *t-lag* subscript). The variable *lag* ranges from no lags (i.e. air quality on the day of the interview) to one-week lag, two-week lag, three-week lag, one-month lag, two-month lag, six-month lag, and one-year lag.

2.3. Instrumental variable strategy

Air quality is likely to be endogenous given that places with more economic growth also tend to be more polluted (e.g. Chay and Greenstone, 2005; Tan-Soo, 2017). Hence, it is likely that a more polluted place may also be deemed as more 'attractive' because of its economic opportunities. If undealt with, the coefficient for air pollution would show up empirically with an upward-biased estimate. A wide range of empirical strategies have been developed to deal with the endogeneity issue in air quality. Chay and Greenstone (2005) in their application to the United States housing market used county's non-attainment status as an exogenous variation of air quality. In an application to Indonesia, Tan-Soo (2017) used number of fire hotspots in upwind directions as instruments for air quality. Luechinger (2009) used a combination of individual fixed-effects and whether German power stations in upwind counties had installed scrubbers as instruments. Lastly, S. Chen et al. (2017) used high-altitude temperature gradient as an instrumental variable for air quality in China. Towards this end, our instrumental variable strategy is similar to studies that used upwind air pollution to instrument for downwind county air quality (e.g. Bayer et al. (2009); Tan-Soo (2017)). The rationale behind this instrument is that while upwind air pollution has a strong relationship with its downwind location's air quality, it would not affect the 'attractiveness' of the downwind location through other channels.

The equations for constructing upwind pollution can be written as

$$UpwindPoll_{rt} = \sum_{r' \neq r} \frac{Poll_{r't} \times V_{r't}}{D^2_{r',r}} \times \cos\theta_{r',r,t} \tag{9}$$

where

$$\cos\theta_{r',r,t} = \max\left\{ \cos\left(\gamma_{r',t} - \beta_{r't}\right), 0\right\} \tag{10}$$

The instrumental variable is constructed in the following manner. First, using a climatic dataset, we know the dominant upwind direction

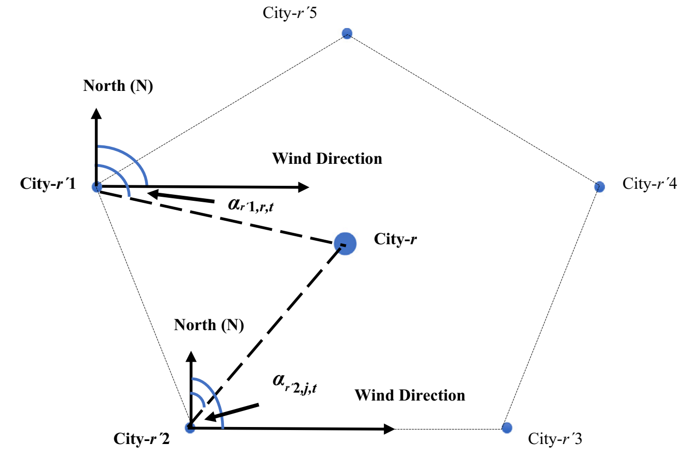

Fig. 1. Illustration of upwind instrumental variable strategy *Notes*: This figure illustrates examples of the regional transmission of air pollution from the upwind City-$r'1$ and City-$r'2$ to City-r. The black dash lines connecting City-r' and City-r represent the eventual transmission directions by wind *Cosine* decomposition.

for county r at time t (or any of its lags). Second, we can then pick out the counties in the upwind direction of county r. However, the amount of pollution that each upwind county (denoted as r') contribute to county r is dependent on its location with respect to the wind direction and distance. In the third step (refer to Fig. 1), we draw a straight-line from the centroid of upwind county $r'1$ to downwind county r and use cosine decomposition to calculate the proportion of pollution that will be carried over. For example, in Fig. 1, $r'1$ and $r'2$ are both upwind counties to county r. However, because of their location, compared to county $r'2$, county $r'1$ will obviously contribute a larger proportion of its pollution to r. The amount of contribution from each upwind county is thus apportioned by taking the cosine of the difference between the angle of the north direction of upwind county and straight-line to downwind county ($\gamma_{r',t}$) and the angle of the north direction of upwind county and wind direction ($\beta_{r't}$). As depicted in Fig. 1, the angular differences are $\theta_{r'1,r,t}$ and $\theta_{r'2,r,t}$ respectively for counties $r'1$ and $r'2$. It is possible for the angular difference to be less than zero, e.g., county $r'4$ in Fig. 1 which lies to the east of county r. As such, we bound the cosine decomposition in Eq. (9) to be non-negative since downwind counties will not contribute upwind county air pollution. Third and finally, we also weigh the amount of contributed pollution by wind speed, $V_{r't}$ and the squared-distance between each pair of city, $D^2_{r',r}$.

A central decision in constructing this instrument is the appropriate radius for selecting upwind counties. If the radius is too small, the exclusion restriction criteria may not be fulfilled, e.g. upwind county $r'1$ will affect downwind county r's attractiveness if both counties are very near to each other. On the other hand, the predictive power of this instrument will be diminished if the distance is too big. As such, we set a radius band of between 100 km to 300 km for upwind counties to be selected. This chosen radius band is roughly in-line with those used in other studies. For example, Bayer et al. (2009) used a distance of at least 80 km when instrumenting for air pollution in the United States. Similarly, Barwick et al. (2017) used a distance of at least 150 km for China.[4]

3. Data

The dataset for this study is assembled from three sources.

First, household- and individual-level data are from a sub-sample of the Chinese General Social Survey (CGSS) which was conducted from

[3] Month-by-week fixed effects means that all interviews conducted on say, the first week of July are assigned the value of one in a binary variable, and so on. Inclusion of this fixed effects control for any general factors occurring during that particular time-span.

[4] To further assess the suitability of this radius band, we implement robustness checks in Table 5 where we used larger and smaller radii.

July to October in 2015 (Fig. 2). The 2015 CGSS survey used a three-stage cluster strategy to select households that are collectively representative of the Chinese population. The first stage of the sampling process is at city or county level, followed by the neighborhood committee (or village committee in rural area) level, and finally, households are randomly selected to participate in the survey. Out of the full CGSS sample (which consists of 11,559 households from 478 neighborhood committees (or village committees in rural areas) across 28 provinces), 3640 households were randomly selected to receive additional survey modules with subjective well-being questions. Fig. 3 shows the distribution of this sample across 129 counties. As expected, most of the respondents were from the more populous Eastern provinces and cities. The CGSS survey contained information on households' socioeconomic status, educational level, and responses to self-reported well-being. More specifically, we use responses to two such questions to form our dependent variables. The first question is: "*How do you feel about your current health conditions*?". Respondents answer this question on a 5-point Likert scale ranging from very unhealthy to very healthy. The second question is: "*In general, do you feel happy with your life*?". Similarly, respondents answer on a 5-point Likert scale ranging from very unhappy to very happy. In this regard, we expect to observe similar patterns for both dependent variables as they are related measurements of subjective happiness, and especially since one's health condition is also a part of his/her well-being.

The second data source is from the China National Environmental Monitoring Centre (CNEMC) where we obtain hourly air quality information. Since 2013, the Chinese government has made air quality data publicly available, including air quality index (AQI) and six specific atmospheric pollutants: ground-level ozone (O_3), particle pollutants $PM_{2.5}$ and PM_{10}, carbon dioxide (CO), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2).[5] Our air quality measurements cover 1498 monitoring stations including geographical coordinates and altitude information for each station. Air pollution data is matched to the CGSS data using the following methods. First, we use the inverse-distance weighting (IDW) method to convert pollution data from station to county. The IDW method is widely used in the literature to impute either pollution or weather data (Currie and Neidell, 2005; Deschenes and Greenstone, 2007; Schlenker and Walker, 2015). The basic algorithm is to take the weighted average of all monitoring stations within the circle with certain radius for the centroid of each county. We choose 100 km as our radius (and our results are robust to different radius lengths). Second, we match pollution data to each respondent by their county code and averaged all pollution data and weather data to the week/month/year prior to the date of the interview, depending on the research design.

Lastly, meteorological data were obtained from the China Meteorological Data Service Center (CMDC), which is affiliated to the National Meteorological Information Center of China.[6] The CMDC records daily maximum, minimum, and average temperatures, precipitation, relative humidity, wind speed, and duration of sunshine for 820 weather stations in China. We convert weather data from station to county again using the IDW method. Similarly, we then assign weather data at various time frequencies to each respondent according to their county of residence.

3.1. Descriptive statistics

The descriptive statistics from the assembled dataset are collated in Table 1. On average, respondents mostly reported being healthy and happy as they registered 3.6 and 3.9 respectively on the Likert-scale (with 5 being most positive outcomes). We additionally defined two binary variables to reflect high levels of unhappiness or unhealthiness.

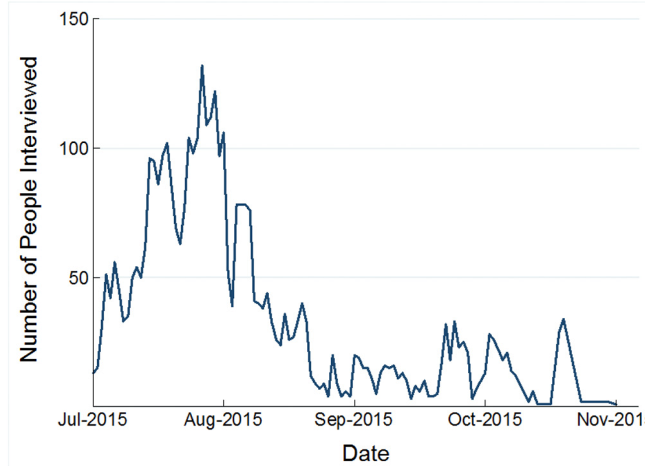

Fig. 2. Respondents' interviews distributed by month.

The variable "very unhealthy" is assigned a value of one if the respondent reported being very unhealthy or unhealthy in their self-rated health assessment. The variable "very unhappy" is constructed similarly. These two binary variables are used in the regression analyses in the same manner as the two other dependent variables. Similar to the Likert-scale response, only about 18% and 7% of respondents reported having high levels of unhealthiness and unhappiness respectively. The average respondent is around 50 years of age, has educational level of 4.97 – which corresponds to high school education, and makes around 36,000 CNY per year (equivalent to around US$5500).[7]

Next, we report average daily air quality indicators. AQI is a unitless composite air quality indicator that takes into account all major air pollutants. On average, the hourly AQI and $PM_{2.5}$ read at around 88 and 60 $\mu g/m^3$ respectively. In comparison, the hourly AQI and $PM_{2.5}$ for Beijing in 2016 are at around 102 and 73 $\mu g/m^3$ respectively. Reflecting China's wide geographical span and heterogenous conditions, there is wide variation for all air quality indicators. For example, while the lowest daily average $PM_{2.5}$ is around 25.8 $\mu g/m^3$ (which is near to the WHO recommended daily standard of 25 $\mu g/m^3$), the highest recorded $PM_{2.5}$ is at 121.4 $\mu g/m^3$.

4. Results

Results from estimation of Eq. (6) are collected in Table 2 where panel A contains results for self-rated health status and panel B contains results for subjective well-being. Column 1 shows the results from a fixed effects ordinary least squares model without instrumenting for air quality. The coefficients for daily $PM_{2.5}$ are mostly positive and statistically insignificant for the four dependent variables, suggesting that air pollution does not affect one's health status or well-being. This counter-intuitive result is most likely due to the confounding relationship between air pollution and economic opportunities. Next, using a two stage least squares linear model, we instrument for air quality using upwind pollution. The coefficients are now negative and statistically significant (Table 2, Column 2). The first stage Kleibergen-Paap Wald F-statistics is high at >20, indicating strong predictive power of upwind pollution on downwind air quality. For the next three models (Table 2, Columns 3–5), we incrementally add weather controls, socioeconomic characteristics controls, and survey weights to examine if the coefficient for air pollution is stable.[8] In the full specification in Column 5 (our preferred model), the marginal impact of $PM_{2.5}$ on self-rated health is

[5] Ghanem and Zhang (2014) showed that Chinese cities may manipulate air quality data around the cutoff point of 100 (AQI of less 100 is defined as 'blue skies' day in Chinese policies). We assess the veracity of our dataset by investigating for any anomalies corresponding to this cutoff point using probability density graphs (Fig. S1). We find no evidence of data manipulation in our dataset.

[6] The data can be obtained from http://data.cma.cn/.

[7] The remaining descriptive statistics for other household and individual characteristics are collected in Table A1.

[8] The survey weights are based on the number of respondents from a county in the sample vs. the population of the county.

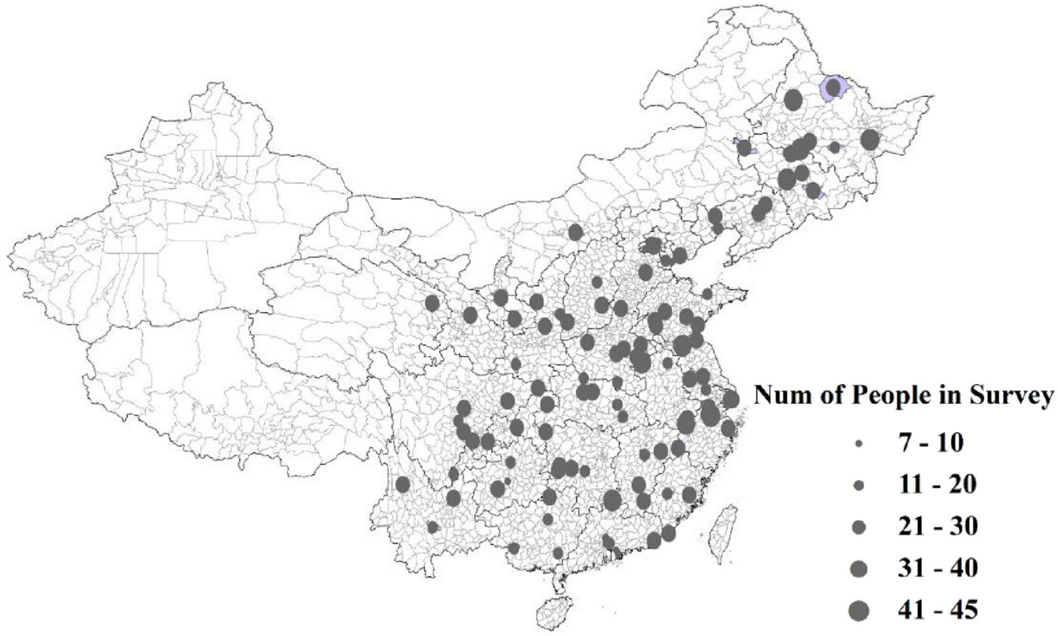

Fig. 3. Distribution of respondents from the CGSS survey ($N = 3863$ in 129 counties).

around −0.02 (self-rated health is reported on a Likert scale of one to five). Similarly, the marginal impact on subjective happiness is also at around −0.02. To allow for easier interpretation, we also estimate linear probability models by re-defining the dependent variables as binary outcomes where values of one and two in the self-reported happiness/health Likert scale are defined as very unhappy/unhealthy (takes the value of one now), and zero otherwise. Results from these linear probability models are collected in Columns 6 to 10 and they follow the same trend as their Likert-scale counterparts. Results from Column 10 can thus be interpreted as one additional unit of daily $PM_{2.5}$ would increase the probability of the average respondent reporting high level of unhappiness by 0.2% and poor health status by 1%. In this first round of analysis, we demonstrate that the relationship between air quality and well-being is confounded and instrumental variable strategy is needed to derive a causal relationship. As with earlier works in this literature, we have shown that air pollution negatively affects one's self-rated well-being.

Table 1
Descriptive statistics.

Variable	Definition (Unit)	Mean	Std.	Min	Max
Self-reported					
Self-rated health	1-Unhealthy, 5-healthy	3.60	1.07	1.00	5.00
Very unhealthy	0-No, 1-yes	0.18	0.38	0.00	1.00
Subjective well-being	1-Unhappy, 5-happy	3.87	0.82	1.00	5.00
Very unhappy	0-No, 1-yes	0.07	0.26	0.00	1.00
Air pollutants					
AQI	Index (0–500)	87.95	21.58	44.75	158.43
$PM_{2.5}$	μg/m^3	59.60	17.46	25.82	121.37
PM_{10}	μg/m^3	54.80	12.11	27.73	89.68
O_3	μg/m^3	97.28	29.12	47.94	193.96
SO_2	μg/m^3	29.17	20.27	6.96	147.56
NO_2	μg/m^3	35.97	13.46	11.54	64.07
CO	mg/m^3	1.15	0.40	0.50	2.21
Weather controls					
Temperature	0.1 °C (daily average)	146.56	49.08	19.00	248.26
Precipitation	0.1 mm (8–20 h accumu.)	28.68	16.18	6.85	82.70
Sunshine duration	0.1 h (daily total)	52.55	13.89	23.33	80.73
Relative humidity	% (daily average)	68.96	9.54	43.31	86.71
Wind-speed	0.1 m/s (hourly record)	21.69	8.15	8.20	64.68
Wind-direction	0–16 (daily average)	8.05	1.61	1.00	16.00

Notes: $N = 3640$. Research sample is 1/5 random subsample of CGSS. Survey period of CGSS 2015 lasts from Jul-2015 to Nov-2015. Please see Appendix A for personal characteristics and family information.

To calculate the MWTP for air quality improvement, log of income is added to the model (Table 3). Panel A shows the full specification model with income added. A quick comparison with the results in Table 2 shows that air quality coefficients are stable even after income is added. This suggests sufficient variation between income and air pollution exposure in the dataset. These results can thus be applied onto Eq. (7) to compute the marginal willingness-to-pay for air quality improvements (MWTP). Using subjective well-being as the dependent variable, the average MWTP for a 1 μg/m^3 improvement in daily level $PM_{2.5}$ is derived at around 6.2% of annual household income or around 4410 CNY. Similarly, the MWTP computed using self-rated health is at around 5.4% of annual household income. When considered either in terms of proportion or absolute amount, the MWTP computed in our study is larger than those recovered from other studies (e.g. Freeman et al., 2017; X. Zhang et al., 2017).[9]

4.1. Air pollution of varying temporal lengths

The air quality variable used in previous analyses was from the day at which the interview was conducted. A central investigation of this study is to examine how air quality valuation changes with air pollution of different temporal lengths. Table 4 contains the estimation results of using air quality averaged over different time lengths. First, we can see that the results exhibit projection or recency biases as the coefficient for air pollution steadily decreases in magnitude as the temporal length increases. In other words, a unit of $PM_{2.5}$ improvement on the day of the interview has a larger marginal impact on the respondent's subjective well-being compared to a unit of $PM_{2.5}$ improvement over the entire year. This monotonic relationship between time length of air pollution and coefficient of air pollution is observed for both self-rated health and subjective well-being.[10] However, these results will not be

[9] We have also conducted heterogeneity analysis by splitting the sample along the lines of sex of respondent, age group, educational level, and income level (see Tables A2 and A3 for results).

[10] Similar results are observed when the binary variables for self-rated health and subjective well-being are used as dependent variable.

Table 2
Regression results of air quality on subjective well-being.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	2SLS-1	2SLS-2	2SLS-3	2SLS-4	OLS	2SLS-1	2SLS-2	2SLS-3	2SLS-4
Panel A. Self-rated health	Self-rated health (1-unhealthy, 5-healthy)					Very unhealthy (1-unhealthy, 0-otherwise)				
$PM_{2.5}$	0.0001	−0.0121*	−0.0217**	−0.0171**	−0.0192**	0.0004	0.0055**	0.0091***	0.0082***	0.0098***
	(0.0016)	(0.0065)	(0.0089)	(0.0081)	(0.0091)	(0.0006)	(0.0022)	(0.0031)	(0.0030)	(0.0034)
Panel B. Subjective well-being	Subjective well-being (1-unhappy, 5-happy)					Very unhappy (1-unhappy, 0-otherwise)				
$PM_{2.5}$	−0.0041**	−0.0102*	−0.0158**	−0.0168**	−0.0200**	0.0003	0.0012**	0.0015*	0.0016**	0.0020**
	(0.0020)	(0.0056)	(0.0078)	(0.0079)	(0.0087)	(0.0002)	(0.0006)	(0.0008)	(0.0008)	(0.0009)
County *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-by-week *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Covariates	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes
Survey weights	Yes	No	No	No	Yes	Yes	No	No	No	Yes
KP *F*-statistics	NA	21.99	18.18	18.05	20.68	NA	21.99	18.18	18.05	20.68

Notes: $N = 3640$. Weather controls include the second order polynomial of temperature, precipitation, sunshine hours and wind force. We control the individual characters age, age squared, and gender, as well as the household characters residence, marriage status, ethnic group, family size and living space. The survey weights are based on the representativeness of the respondents in a county. Standard errors are clustered by date and listed in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

meaningful if there is a corresponding change in marginal utility of income such that valuation for air quality improvement remains the same. It is clear from Table 4 that coefficient for income remains largely consistent across the different models for each dependent variable. Hence, we can compute the MWTP using these results. For subjective well-being, MWTP decreases from around 6.2% of household income when current day air pollution is used to around 3.1% when annual-averaged air pollution is used – a one-fold increase. Similarly, the MWTP, when computed using self-rated health, decreases from 5.4% of household income to 1.9% when the air quality metric changes from daily to annual.[11,12]

4.2. Robustness checks

We conduct a series of robustness checks to ensure our results are stable under different empirical assumptions (Table 5). First, we cluster the standard errors by using different group definitions and find that the statistical significance level for $PM_{2.5}$ coefficients is unchanged across the four dependent variables (Table 5, Scenarios 1 and 2). Second, we shorten the IV boundary range from 100 km–300 km to 100 km–200 km. As a result, the $PM_{2.5}$ coefficients for all four dependent variables decreased in magnitude (Table 5, Scenario 3). This is to be expected as a nearer range means that the upwind pollution sources are closer to the cities they are instrumenting for and thus more likely to share more similar economic characteristics. As such, a near IV range will bias the results in the direction of OLS estimates. In contrast, the $PM_{2.5}$ coefficients are insignificant when a further IV range of 400 km–600 km is used (Table 5, Scenario 4). This is because the upwind pollution sources have little predictive power on downwind air quality as can be seen from the low first stage KP F statistics. Third, we alter the radius for climate monitoring stations from within 100 km to 50 km and 150 km respectively (Table 6, Scenarios 5 and 6). The $PM_{2.5}$ coefficients are slightly smaller for the self-rated health metrics, and largely similar for subjective well-being metrics.

[11] It is possible that respondents are answering the well-being questions with reference to their current conditions. However, this would not explain why there is a monotonic relationship between temporal lengths and valuation. Table S1 shows the pairwise correlations between air qualities and we see the correlation coefficients are not monotonic according to temporal lengths

[12] We also tested for simultaneity effects by examining the impact of air pollution on income and found no significant effects (Table S2).

4.3. Alternate air pollutants

Next, we re-run the baseline specification using different air pollutants (Table 6). First, judging by the KP F-statistics, upwind pollution sources are best at predicting pollutants such as AQI and PM_{10}. Hence, it is not surprising that the air pollutant coefficients are similar in magnitude to the $PM_{2.5}$s'. In comparison, the KP F-statistics is somewhat smaller for the SO_2, NO_2, O_3, and CO. As such, upwind pollution sources are not a good predictor for these pollutants and this is reflected in the air pollutants' coefficients in the second stage estimation.

4.4. Falsification test using lead-time air pollution

We conduct a falsification test by using lead-time pollution variables as we do not expect to see any relationship between one's well-being and future air quality. Even though the IV strategy was deployed to account for the confounding relationship between economic opportunities and self-report well-being, it is possible that our choice of instrument may not fully account for all endogeneity issues. Hence, this test will help detect other factors that are correlated with air quality, and also affect subjective well-being. Second, it is also possible that the monotonic relationship we observe between air pollution of lag temporal lengths is driven by seasonal patterns in air quality. Table 7 shows the coefficient for $PM_{2.5}$ and income at leads of 1-week, 2-week, 1-month, 2-month, 6-month, and 1-year. Unlike when using lagged air quality, there are no clear patterns in the results as most of the $PM_{2.5}$ coefficients are statistically insignificant. Hence, this falsification test confirms that our results are not driven by seasonal variation in air quality.

4.5. Other climate variables

As air quality is often correlated with other climate variables, we display the coefficients for these climate variables to demonstrate that there are no discernible patterns, as seen earlier for the $PM_{2.5}$ coefficients (Table 8).

4.6. Alternate model specifications

As the dependent variables are measured on ordinal scale, categorical-type regression models such as ordered logit or probit may be more suited for this analysis. However, we chose to rely on linear

Table 3
Regression results of air quality on subjective well-being with income added.

	Self-rated health		Subjective-wellbeing	
	Self-rated health (1-unhealthy, 5-healthy)	Very unhealthy (1-unhealthy, 0-otherwise)	Subjective well-being (1-unhappy, 5-happy)	Very unhappy (1-unhappy, 0-otherwise)
	(1)	(2)	(3)	(4)
Panel A. Add income				
$PM_{2.5}$	−0.0230**	0.0104***	−0.0206**	0.0025**
	(0.0091)	(0.0037)	(0.0100)	(0.0010)
ln (per capita household income)	0.1766***	−0.0634***	0.1380***	−0.0183***
	(0.0210)	(0.0078)	(0.0180)	(0.0032)
KP *F*-statistics	19.94*	19.91	19.75	19.91
Observations	3267	3270	3266	3270
Panel B. Willingness to pay				
Income (**1000 RMB**)				
Mean of per capita household income	29.4213	29.4213	29.4213	29.4213
Mean of household income	71.1130	71.1130	71.1130	71.1130
MWTP (%)				
% of Household income	−5.3883	−6.7867	−6.1759	−5.6520

Notes: Weather controls include the second order polynomial of temperature, precipitation, sunshine hours and wind force. We control the individual characters age, age squared, and gender, as well as the household characters residence, marriage status, ethnic group, family size and living space. Standard errors are clustered by date and listed in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

regressions for three main reasons. First, Angrist and Imbens (1995) showed that the two stage least squares estimator (2SLS) – which we used here – consistently estimates the "average causal response" even when the dependent variable is categorical. Second, unlike their linear counterparts, there are still no established models for ordered probit/logit model when instrumental variables are needed. However, IV-probit (i.e., with binary dependent variable) models had been developed. The IV-probit model (Table A4, Column 1) showed similar results in magnitude and statistical significance as those obtained from 2SLS. Third, when faced with a similar modeling situation, Anderson et al. (2016) used an 'informal' control function approach to circumvent the lack of an established ordered IV-probit model (Rivers and Vuong, 1988). In this application, a non-IV ordered probit is first estimated without the endogenous covariate (i.e., AQI). Both the residuals from this estimation and the endogenous covariate are then included as regressors in the second stage. Results of this estimation (Table A4, Columns 2 to 9) show that the coefficients are mostly similar in magnitude and size to their linear counterparts.

5. Discussions

In this study, we combine a social survey fielded in China with detailed air quality data to examine how responses to subjective well-being questions vary with exposure to air pollution. First, our results show that respondents reported being less happy and less healthy if they were exposed to more severe air pollution on the day of the survey.

Table 4
Regression results of air quality with temporal lags of various lengths on subjective well-being.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1-Year lag	6-Month lag	2-Month lag	1-Month lag	3-Week lag	2-Week lag	1-Week lag	Interview day
Explanatory Var.: $PM_{2.5}$								
Self-rated health (1-unhealthy, 5-healthy)	−0.0080**	−0.0095***	−0.0074*	−0.0109***	−0.0116***	−0.0100**	−0.0125***	−0.0230***
	(0.0034)	(0.0029)	(0.0042)	(0.0037)	(0.0039)	(0.0046)	(0.0045)	(0.0066)
Log income	0.1763***	0.1774***	0.1747***	0.1766***	0.1769***	0.1757***	0.1762***	0.1766***
	(0.0177)	(0.0182)	(0.0170)	(0.0176)	(0.0175)	(0.0184)	(0.0176)	(0.0181)
MWTP	−1.88	−2.22	−1.75	−2.55	−2.71	−2.35	−2.94	−5.39
(**% of household income**)								
Estimated coef.								
Subjective well-being (1-unhappy, 5-happy)	−0.0107**	−0.0111***	−0.0110**	−0.0110**	−0.0116**	−0.0124**	−0.0139**	−0.0206**
	(0.0043)	(0.0042)	(0.0045)	(0.0049)	(0.0052)	(0.0053)	(0.0059)	(0.0080)
Log income	0.1406***	0.1394***	0.1397***	0.1396***	0.1390***	0.1382***	0.1388***	0.1380***
	(0.0206)	(0.0196)	(0.0216)	(0.0207)	(0.0203)	(0.0204)	(0.0200)	(0.0198)
MWTP	−3.15	−3.29	−3.26	−3.26	−3.45	−3.71	−4.14	−6.18
(**% of household income**)								
Mean of $PM_{2.5}$	59.60	52.45	41.18	40.34	40.60	40.97	40.12	41.16
SD of $PM_{2.5}$	17.46	17.03	14.99	15.41	17.41	19.05	22.09	37.33

Notes: Weather controls include the second order polynomial of the same temporal length for temperature, precipitation, sunshine hours and wind force. We control the individual characters age, age squared, and gender, as well as the household characters residence, marriage status, ethnic group, family size and living space. Standard errors are clustered by date and listed in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 5
Robustness checks.

	(1) Self-rated health (1-unhealthy, 5-healthy)	(2) Very unhealthy (1-unhealthy, 0-otherwise)	(3) Subjective well-being (1-unhappy, 5-happy)	(4) Very unhappy (1-unhappy, 0-otherwise)
Baseline				
$PM_{2.5}$	−0.0192**	0.0098***	−0.0200**	0.0020**
	(0.0091)	(0.0034)	(0.0087)	(0.0009)
KP *F*-statistics	20.68	20.68	20.68	20.68
Scenario 1: Clustering by cohort				
$PM_{2.5}$	−0.0192***	0.0098***	−0.0200**	0.0020**
	(0.0065)	(0.0035)	(0.0081)	(0.0010)
KP *F*-statistics	59.36	59.36	59.36	59.36
Scenario 2: Two-way clustering by date and by cohort				
$PM_{2.5}$	−0.0192***	0.0098***	−0.0200**	0.0020***
	(0.0055)	(0.0026)	(0.0099)	(0.0005)
KP *F*-statistics	20.90	20.90	20.90	20.90
Scenario 3: IV range: 100–200 km				
$PM_{2.5}$	−0.0162*	0.0085**	−0.0193**	0.0014*
	(0.0091)	(0.0034)	(0.0086)	(0.0009)
KP *F*-statistics	20.59	20.59	20.59	20.59
Scenario 4: IV range: 400–600 km				
$PM_{2.5}$	−0.0977	0.0684	−0.0926	0.0222
	(0.2634)	(0.1671)	(0.2420)	(0.0505)
KP *F*-statistics	0.180	0.180	0.180	0.180
Scenario 5: IDW: ≤50 km				
$PM_{2.5}$	−0.0154**	0.0077***	−0.0193**	0.0019**
	(0.0078)	(0.0029)	(0.0078)	(0.0008)
KP *F*-statistics	22.65	22.65	22.65	22.65
Scenario 6: IDW: ≤150 km				
$PM_{2.5}$	−0.0138*	0.0070**	−0.0197**	0.0019**
	(0.0081)	(0.0030)	(0.0082)	(0.0009)
KP *F*-statistics	20.13	20.13	20.13	20.13

Notes: $N = 3640$. Weather controls include the second order polynomial of temperature, precipitation, sunshine hours and wind force. We control the individual characters age, age squared, and gender, as well as the household characters residence, marriage status, ethnic group, family size and living space. Unless stated otherwise, standard errors are clustered by date and listed in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 6
Robustness checks using alternate air pollutants.

	(1) Self-rated health (1-unhealthy, 5-healthy)	(2) Very unhealthy (1-unhealthy, 0-otherwise)	(3) Subjective well-being (1-unhappy, 5-happy)	(4) Very unhappy (1-unhappy, 0-otherwise)
AQI	−0.0162**	0.0083***	−0.0169**	0.0017**
	(0.0075)	(0.0028)	(0.0073)	(0.0008)
KP *F*-statistics	22.47	22.45	22.25	22.45
$PM_{2.5}$ (Baseline)	−0.0192**	0.0098***	−0.0200**	0.0020**
	(0.0091)	(0.0034)	(0.0087)	(0.0009)
KP *F*-statistics	20.68	20.65	20.46	20.65
PM_{10}	−0.0179**	0.0092***	−0.0186**	0.0018**
	(0.0083)	(0.0031)	(0.0083)	(0.0008)
KP *F*-statistics	21.93	21.91	21.83	21.91
O_3	−0.0773	0.0397*	−0.0797*	0.0079*
	(0.0492)	(0.0224)	(0.0478)	(0.0046)
KP *F*-statistics	3.859	3.843	3.925	3.843
SO_2	−0.1521***	0.0782***	−0.1576***	0.0156*
	(0.0508)	(0.0256)	(0.0535)	(0.0081)
KP *F*-statistics	19.00	18.97	19.05	18.97
NO_2	−0.0709**	0.0364***	−0.0739**	0.0073**
	(0.0355)	(0.0129)	(0.0348)	(0.0037)
KP *F*-statistics	15.51	15.51	15.24	15.51
CO	−1.8301**	0.9410***	−1.9009**	0.1877**
	(0.8941)	(0.3409)	(0.9370)	(0.0944)
KP *F*-statistics	17.34	17.20	17.15	17.20
Observations	3637	3640	3632	3640
County *FE*	Yes	Yes	Yes	Yes
Month-by-week *FE*	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Survey Weights	Yes	Yes	Yes	Yes

Notes: Weather controls include the second order polynomial of temperature, precipitation, sunshine hours and wind force. We control the individual characters age, age squared, and gender, as well as the household characters residence, marriage status, ethnic group, family size and living space. Standard errors are clustered by date and listed in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

This result is robust to the inclusion of a battery of socioeconomic and weather variables controls. To recover causal interpretation, we also deploy an instrumental variable (IV) strategy as air quality is known to be positively correlated with economic opportunities. This instrument, constructed using upwind pollution from counties 100–300 km away, worked as intended as the sign of the air pollution coefficient flipped from positive to negative after instrumenting. In all, we find that households are willing to pay around 5.4% to 6.2% of the household income for a unit improvement in air quality. Next, we extend the analysis to examine if valuation of air quality is affected by recency or projection bias. We find evidence of these biases as valuation of clean air systematically decreases when the temporal length of air pollution is gradually increased from daily to annual. The magnitude of these biases is non-trivial as valuation for a one-unit improvement in daily $PM_{2.5}$ is at 6.2% of household income and decreases to 3.1% of household income when improvement is considered in terms of annual $PM_{2.5}$. Alternatively, another way of framing these biases is that an average individual is willing to pay 3.1% of household income for a one-unit improvement for everyday over the year. On the other hand, the average individual is willing to pay 6.2% of household income for a one-unit improvement *only in tomorrow's* air quality. This is a counter-intuitive result as the health implications of exposure to long-term air pollution are more severe than short-term implications.

The implications of our findings are threefold. First, we have recovered a country-wide estimate of air quality improvement valuation for Chinese residents. Importantly, along with other studies in the air quality valuation literature (e.g. Freeman et al., 2017; Gonzalez et al., 2013; Tan-Soo, 2017), we show that air pollution is indeed correlated with factors that would increase one's utility (most likely economic opportunities). This confirms that a biased valuation for air quality improvements would have been estimated if these confounding factors are not dealt with. Second, to the authors' best knowledge, this is one of the first attempts to investigate recency and projection biases in air quality valuation. From a research viewpoint, our results provide fodder to conduct more empirical investigations to confirm if these valuation biases translate into 'excessive' purchases of protective equipment against air pollution. For example, Conlin et al. (2007) found that a much higher rate of returns for winter clothing if orders were made on a very cold day – suggesting excessive purchases at the onset. Also, our results call for a larger rethink on the valuation of air quality. For example, air quality valuation from contingent valuation studies – where data tend to be collected from respondents at the same location within a short time frame – could possibly be over or under-estimated, depending on the air quality on the day of the interview. This means that researchers

Table 7
Falsification test showing regression results of air quality with temporal leads of various lengths on subjective well-being.

Period $PM_{2.5}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1-Week lead	2-Week lead	3-Week lead	1-Month lead	2-Month lead	6-Month lead	1-Year lead
Self-rated health (1-unhealthy, 5-healthy)	−0.0044	−0.0096	0.1044	0.0077	−0.0224	−0.1344	0.2979
	(0.0069)	(0.0282)	(0.0774)	(0.0464)	(0.0585)	(0.1368)	(0.3913)
Log income	0.1807***	0.1795***	0.1626***	0.1792***	0.1775***	0.1791***	0.1804***
	(0.0161)	(0.0164)	(0.0186)	(0.0161)	(0.0168)	(0.0191)	(0.0178)
Very unhealthy (1-unhealthy, 0-otherwise)	0.0008	−0.0017	−0.0359	−0.0171	0.0105	0.0248	−0.0920
	(0.0017)	(0.0069)	(0.0270)	(0.0206)	(0.0262)	(0.0737)	(0.3093)
Log Income	−0.0648***	−0.0638***	−0.0584***	−0.0639***	−0.0641***	−0.0646***	−0.0641***
	(0.0085)	(0.0080)	(0.0071)	(0.0076)	(0.0073)	(0.0089)	(0.0088)
Subjective well-being (1-unhappy, 5-happy)	0.0104*	0.0165**	−0.0333	−0.1426***	−0.1590***	0.0158	−1.0518
	(0.0085)	(0.0261)	(0.0870)	(0.0317)	(0.0485)	(0.1242)	(0.9251)
Log income	0.1383***	0.1419***	0.1486***	0.1506***	0.1380***	0.1402***	0.1437***
	(0.0188)	(0.0201)	(0.0187)	(0.0217)	(0.0212)	(0.0205)	(0.0201)
Very unhappy (1-unhappy, 0-otherwise)	−0.0011	−0.0010	0.0022	−0.0066	0.0071	−0.0040	0.0511
	(0.0008)	(0.0013)	(0.0076)	(0.0044)	(0.0108)	(0.0126)	(0.0368)
Log income	−0.0185***	−0.0188***	−0.0191***	−0.0183***	−0.0185***	−0.0186***	−0.0186***
	(0.0019)	(0.0021)	(0.0019)	(0.0020)	(0.0026)	(0.0021)	(0.0022)
Mean of $PM_{2.5}$	39.48	38.30	38.10	38.15	41.03	60.92	53.29
SD of $PM_{2.5}$	21.88	18.02	17.34	15.66	17.17	21.22	15.90

Notes: Weather controls include the second order polynomial of temperature, precipitation, sunshine hours and wind force. We control the individual characters age, age squared, and gender, as well as the household characters residence, marriage status, ethnic group, family size and living space. Standard errors are clustered by date and listed in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 8
Coefficients from climatic variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1-Year lag	6-Month lag	2-Month lag	1-Month lag	3-Week lag	2-Week lag	1-Week lag	Interview day
Self-rated health (1-unhealthy, 5-healthy)								
Temperature	0.1895	−0.0039	0.0137	0.0160	0.0753	0.0062	0.0055*	0.0022
	(0.2087)	(0.0171)	(0.0173)	(0.0125)	(0.1073)	(0.0047)	(0.0031)	(0.0021)
Rainfall	0.0460	−0.0004	−0.0048	−0.0039	−0.0240	−0.0009	−0.0017***	0.0001
	(0.0760)	(0.0167)	(0.0089)	(0.0090)	(0.0356)	(0.0007)	(0.0006)	(0.0002)
Sunshine duration	−0.0387	−0.0016	0.0026	−0.0167	−0.0570	−0.0049	−0.0028	−0.0016**
	(0.4152)	(0.0398)	(0.0218)	(0.0120)	(0.0721)	(0.0048)	(0.0022)	(0.0008)
Subjective well-being (1-unhappy, 5-happy)								
Temperature	0.3212	−0.0194	0.0158	0.0141	0.0177	0.0061	0.0091***	0.0014
	(0.2011)	(0.0155)	(0.0101)	(0.0110)	(0.0219)	(0.0045)	(0.0030)	(0.0015)
Rainfall	−0.1015	−0.0204	−0.0013	0.0056	−0.0031	−0.0004	−0.0016***	−0.0002*
	(0.0714)	(0.0141)	(0.0054)	(0.0074)	(0.0071)	(0.0007)	(0.0006)	(0.0001)
Sunshine duration	−0.4229	0.0465*	−0.0128	0.0011	−0.0184	−0.0031	−0.0021	−0.0016**
	(0.4020)	(0.0282)	(0.0131)	(0.0104)	(0.0127)	(0.0039)	(0.0018)	(0.0006)

Notes: Weather controls include the second order polynomial of temperature, precipitation, sunshine hours and wind force. We control the individual characters age, age squared, and gender, as well as the household characters residence, marriage status, ethnic group, family size and living space. Standard errors are clustered by date and listed in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

need to start paying more attention on temporal scale of air quality when conducting valuation studies. Third, from a policy viewpoint, decision-makers could conceivably exploit this behavioral bias to engage the public more favorably with respect to air quality management policies immediately after a severe episode of air pollution. This is especially poignant for many developing cities in Asia as 'airpocalyse' events – short, but highly intense bouts of air pollution – have become more frequent in recent years.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.08.153.

Appendix A

Table A1
Summary statistics for personal characters and family information.

Variable	Definition (Unit)	Mean	Std.	Min	Max
Personal characteristics					
Gender	1-male, 0-female	0.47	0.50	0.00	1.00
Age	Years	50.64	16.78	18.00	93.00
Education	Level: 1 to13	4.97	3.15	1.00	13.00
Residence	1-urban, 0-rural	0.27	0.45	0.00	1.00

(continued on next page)

Table A1 (*continued*)

Variable	Definition (Unit)	Mean	Std.	Min	Max
Marriage	1-yes, 0-no	0.79	0.41	0.00	1.00
Minority	1-yes, 0-no	0.08	0.27	0.00	1.00
Religion	1-yes, 0-no	0.13	0.33	0.00	1.00
Per capita household income	1000 yuan per year	29.42	91.04	0.07	4000
Family information					
Living-space	m^2	116.40	86.61	0.00	1050.00
Family-size	Number	2.88	1.41	1.00	14.00

Notes: $N = 3640$. Research sample is 1/5 random subsample of CGSS. Survey period of CGSS 2015 lasts from Jul-2015 to Nov-2015.

Table A2
Regression results of air quality on subjective well-being: By gender and by age cohort.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male	Female	Workage	Retire (Age > 60)	Male	Female	Workage	Retire (Age > 60)
Panel A. Self-rated health	Self-rated health (1-unhealthy, 5-health)				Very unhealthy (1-unhealthy, 0-otherwise)			
$PM_{2.5}$	−0.0266**	−0.0382**	−0.0229**	−0.0279***	0.0100**	0.0160***	0.0078**	0.0191**
	(0.0121)	(0.0154)	(0.0097)	(0.0105)	(0.0042)	(0.0056)	(0.0034)	(0.0096)
Panel B. Subjective well-being	Subjective well-being (1-unhappy, 5-happy)				Very unhappy (1-unhappy, 0-otherwise)			
$PM_{2.5}$	−0.0094	−0.0280**	−0.0147	−0.0372*	0.0021	0.0024**	0.0012	0.0046***
	(0.0125)	(0.0130)	(0.0100)	(0.0205)	(0.0016)	(0.0011)	(0.0009)	(0.0012)
County *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-by-week *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1716	1921	2432	1205	1718	1922	2433	1207
KP *F*-statistics	18.12	20.50	20.19	17.42	18.10	20.42	20.20	16.47

Notes: $N = 3640$. Weather controls include the second order polynomial of temperature, precipitation, sunshine hours and wind force. We control the individual characters age, age squared, and gender, as well as the household characters residence, marriage status, ethnic group, family size and living space. Standard errors are clustered by date and listed in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table A3
Regression results of air quality on subjective well-being: By education and by income.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Below compulsory education	Above compulsory education	Below average income	Above average income	Below compulsory education	Above compulsory education	Below average income	Above average income
Panel A. Self-rated health	Self-rated health (1-unhealthy, 5-healthy)				Very unhealthy (1-unhealthy, 0-otherwise)			
$PM_{2.5}$	−0.0077	−0.0286***	−0.0141	−0.0720***	0.0013	0.0198***	0.0042*	0.0353**
	(0.0076)	(0.0106)	(0.0086)	(0.0067)	(0.0026)	(0.0069)	(0.0024)	(0.0148)
Panel B. Subjective well-being	Subjective well-being (1-unhappy, 5-happy)				Very unhappy (1-unhappy, 0-otherwise)			
$PM_{2.5}$	0.0031	−0.0504***	−0.0027	−0.0974**	−0.0001	0.0064***	0.0015	0.0082**
	(0.0092)	(0.0187)	(0.0091)	(0.0437)	(0.0004)	(0.0023)	(0.0011)	(0.0040)
County *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-by-week *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1267	2358	1538	1729	1268	2360	1540	1730
KP *F*-statistics	17.16	23.25	28.08	22.35	17.12	23.27	27.91	27.20

Notes: Weather controls include the second order polynomial of temperature, precipitation, sunshine hours and wind force. We control the individual characters age, age squared, and gender, as well as the household characters residence, marriage status, ethnic group, family size and living space. Standard errors are clustered by date and listed in parentheses.
*** $p < 0.01$.
** $p < 0.05$.

Table A4
IV-probit and IV-ordered probit regression results of air quality with temporal lags of various lengths on subjective well-being.

Period $PM_{2.5}$	(1)		(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Interview day		1-year lag	6-month lag	2-month lag	1-month lag	3-week lag	2-week lag	1-week lag	Interview day
Very unhealthy (1-unhealthy, 0-otherwise)		Self-rated health (1-unhealthy, 5-healthy)								
Mar. eff.	0.0088***	*Est. coef.*	−0.0085**	−0.0099**	−0.0078*	−0.0117**	−0.0121**	−0.0103*	−0.0129**	−0.0234***
	(0.0032)		'(0.0033)	(0.0046)	(0.0045)	(0.0052)	(0.0059)	(0.0053)	(0.0058)	(0.0082)
Log income	−0.0551***	Log Income	0.1962***	0.1979***	0.1929***	0.1973***	0.1972***	0.1949***	0.1954***	0.1974***
	(0.0093)		(0.0230)	(0.0229)	(0.0228)	(0.0229)	(0.0228)	(0.0230)	(0.0225)	(0.0231)
MWTP	−6.61	**MWTP**	−1.79	−2.07	−1.67	−2.45	−2.54	−2.19	−2.73	−4.90
Very unhappy (1-unhappy, 0-otherwise)		Subjective well-being (1-unhappy, 5-happy)								
Mar. eff.	0.0018**	*Est. coef.*	−0.0147**	−0.0150**	−0.0151**	−0.0152**	−0.0153*	−0.0168**	−0.0191**	−0.0279**
	(0.0009)		(0.0062)	(0.0059)	(0.0067)	(0.0072)	(0.0084)	(0.0084)	(0.0092)	(0.0123)
Log income	−0.0136***	Log Income	0.2044***	0.2026***	0.2014***	0.2030***	0.2013***	0.1997***	0.2003***	0.2003***
	(0.0032)		(0.0244)	(0.0242)	(0.0252)	(0.0244)	(0.0242)	(0.0244)	(0.0244)	(0.0246)
MWTP	−5.48	**MWTP**	−2.98	−3.06	−3.10	−3.09	−3.14	−3.48	−3.95	−5.76

Notes: Column (1) estimated using IV-probit, columns (2) to (9) estimated using IV-ordered probit. Weather controls include the second order polynomial of the same temporal length for temperature, precipitation, sunshine hours and wind force. We control the individual characters age, age squared, and gender, as well as the household characters residence, marriage status, ethnic group, family size and living space. Standard errors are clustered by date and listed in parentheses.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

* $p < 0.1$.

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