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RESEARCH ARTICLE

Air pollution, social engagement and subjective well-being: evidence from the Gallup World Poll

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Abstract
The link between air pollution and individual happiness is widely documented. However, the role of social engagement in pollution reduction is seldom considered in the nexus. As such, using large individual-level data from the Gallup World Poll of 151 countries for 2005–2018, this study applies a pooled cross-sectional data approach (controlling for country and year fixed effects) to examine the impact of air pollution on individual happiness and the role of social engagement in shaping the pollution-happiness relationship. The key findings of this study reveal that better air quality raises personal subjective well-being, given that the coefficient of individuals' perceived air quality is positive and statistically significant. More importantly, social engagement in pollution reduction is found to play an important moderating role in shaping the pollution-happiness relationship. Moreover, using a series of robustness checks, such as applying an alternative measure of happiness, an alternative measure of air quality (objective air quality), and using an instrumental variable estimation approach, confirms the positive effect of air quality (perceived or objective) on improving individuals' happiness and the moderating role of social engagement. Furthermore, this study reveals that different demographic characteristics (i.e., age, sex, income, marital status, and urban/rural residence) respond differently to the adverse effects of air pollution and the moderating role of social engagement in pollution reduction. Thus, some policies can be revised and proposed in light of the novel findings of social engagement. In particular, the government should take an active role in combating air pollution and improving air quality by increasing financial input and strengthening environmental protection publicity. The limitations of the study and directions for future research are discussed.

Keywords Air pollution · Subjective measurement · Objective measurement · Subjective well-being · Social engagement · Gallup World Poll

JEL Classification I18 · I31 · Q53 · D90 · C26

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Highlights
- We estimate the impact of measured and perceived air pollution on subjective well-being (current or expected).
- We explore the moderating role of social engagement in pollution reduction in shaping the impact.
- We identify the causal effect using an instrumental variable estimation approach.
- We examine whether the impact is heterogeneous across different demographic groups.
- We use individual observations from 151 countries for 2005–2018.

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Introduction

Air pollution is a global health threat, contributing to about 3–7 million deaths globally per year according to different sources (e.g., WHO (World Health Organization) 2014; Lelieveld et al. 2015; WB-IHME (World Bank and Institute for Health Metrics and Evaluation) 2016). Air pollution also incurs other economic and environmental consequences. As a result, various government policy tools have been jointly implemented in different countries to reduce air pollution. While the effects of air pollution on human health are well documented in economic, sociological, and especially epidemiological studies, there is relatively little empirical evidence on the impact of air pollution on individual happiness or well-being, which is an important policy issue regarding the health of society as a whole (Welsch 2006; Darçın 2017).

While the definition of happiness is not universally accepted, it is substantially similar worldwide. Furthermore, the terms quality of life, happiness, and life satisfaction are often used interchangeably with subjective well-being (SWB; Eger and Maridal 2015; Delle Fave et al. 2016). SWB is defined as individuals' overall evaluations of their lives and emotional experiences, but it is also an umbrella term that encompasses the concepts such as life satisfaction or happiness applied in numerous socioeconomic investigations (Diener et al. 2017). It builds on a notion of experienced utility, addressing the limitations of the rational choice model, for example, cognitive bias and information asymmetry (Kahneman and Krueger 2006; Rok 2020).

A body of studies has analyzed the relationship between air pollution and SWB (i) using different air pollutants such as particulate matter 2.5 (PM2.5; Liao et al. 2015), PM10 (Welsch 2006; Levinson 2012; Ferreira et al. 2013), SO_2 (Smyth et al. 2008; Luechinger 2009; Ferreira et al. 2013), and NO_2 (Welsch 2006; MacKerron and Mourato 2009; Petrowski et al. 2021); (ii) using perceived and/or objective pollution indicators (MacKerron and Mourato 2009; Liao et al. 2015); (iii) targeting different countries or regions (e.g., the UK and USA in Dolan and Laffan 2016; Germany in Rehdanz and Maddison 2008; Spain in Cuñado and Pérez de Gracia 2013; China in Zhang et al. 2017a, b; Turkey in Taşkaya 2018; London in MacKerron and Mourato 2009; Europe in Ferreira et al. 2013); (iv) employing different methods (e.g., ordinary least squares (OLS) in MacKerron and Mourato 2009; Liu et al. 2021; Emmerling et al. 2021; ordered-probit/logit in Ferrer-i-Carbonell and Gowdy 2007; Di Tella and MacCulloch 2008; Whiteley et al. 2010; or structural equation modeling in Li et al. 2014); and (v) applying different types of data sets (aggregated data used in Menz and Welsch 2010; individual-level cross-sectional data in Levinson 2012; or panel data in Zhang et al. 2017a, b and Ngoo et al. 2021). Despite a substantial increase in SWB research over the past decades, results are controversial (Liu et al. 2021) and several vital gaps remain.

The objective of this study is to investigate the impact of air pollution on individual happiness and the role of social engagement in pollution reduction in shaping the pollution-happiness relationship. The scope of this study is motivated by the following three aspects: (1) While the effects of air pollution on tangible health risks such as cardiovascular diseases, respiratory diseases, and mortality (Gallagher et al. 2010; Beatty and Shimshack 2014; Tanaka 2015) are well documented, how air pollution impairs less tangible outcomes like SWB remains to be studied (Graham 2005). (2) It is well known that air pollution already exists in a large number of the happiness-related literature, but most previous studies have not distinguished between measured and perceived air pollution. Furthermore, they are mainly concerned with the impact of measured air pollution (e.g., PM10, PM2.5, NO_2) on SWB. (3) It is commonly recognized that pollution (measured or perceived) significantly reduces SWB, but how is this reduction effect affected by social efforts in combating pollution? What signals are conveyed to residents? For instance, when a country is making efforts to improve air quality, it may on one hand send a positive signal, increasing some residents' satisfaction with the government or society and thus their sense of SWB. On the other hand, a country's efforts to control air pollution may send a negative signal to the public, causing residents who previously thought the air quality was acceptable to suddenly realize that it is poor because of government intervention. This will affect their SWB. In addition, the results of this study are expected to promote relevant policies that will combat air pollution and increase individual SWB.

This study adds to the existing literature as follows. First, though empirical studies examining the relationship between environmental pollution and SWB have emerged, this relationship has not been fully explored and these studies produced inconclusive results (see Table 6 in the Appendix for more detail). For instance, some scholars argued that objective air pollution caused by pollutants such as PM2.5, SO_2, NO_2, phosphorus, and suspended solids can significantly reduce people's SWB (Welsch 2006; Luechinger 2009; Dolan and Laffan 2016). Others further contended that people's subjective perceptions of environmental pollution affect their SWB (Ferrer-i-Carbonell and Gowdy 2007; Rehdanz and Maddison 2008; Sulemana et al. 2016). However, some scholars disagree, arguing that the relationship between air pollution and SWB is not significant or even positively correlated (Welsch 2006; Smyth et al. 2008; Ayres and Hurley 2010; Liao et al. 2015). This study provides additional evidence to the existing literature using individual-level data from the Gallup World Poll (GWP), which covers nearly 1 million observations from 151 countries worldwide, helping to broaden the geographical limitations of the existing literature.

Second, except for a genuine interest in examining how the environment affects people's SWB, there is an emerging interest in how government performance (e.g., government effectiveness, regulatory quality, or trustworthiness) affects people's SWB (Bjørnskov et al. 2007; Helliwell and Huang 2008; Whiteley et al. 2010; Liu et al. 2020). Inspired by this limited but growing literature, we investigate whether and how social engagement in pollution reduction plays a moderating or interactive effect on the pollution-happiness nexus, a direction unexplored before. The output of this study is expected to promote relevant policies in relation to social pollution–reduction engagement and the improvement of individuals' happiness.

Third, we apply a causal analysis, rather than correlation, in this study. As such, we attempt to estimate the causal impact of pollution on happiness using an instrumental variable (IV) approach, an endogeneity issue unexplored in previous studies. Moreover, to gain a more holistic understanding of how air pollution affects SWB, we compare the possibly different performances of two environmental indicators, one subjective (perceived air quality) and the other objective (PM2.5 concentration). PM2.5, an objective pollution indicator, is most strongly associated with increased risks of mortality or morbidity (Ayres and Hurley 2010), is conceptually different from subjective measurement (Mínguez et al. 2013), and has a different impact on individual happiness from subjective measures in empirical studies (MacKerron and Mourato 2009). There are no uniform findings on the effects of PM2.5 on SWB. While most literature concludes that PM2.5 threatens physical and mental health, some research based on country-specific studies concludes that PM2.5 does not significantly affect the SWB of residents in all countries (Tsurumi and Managi 2020). However, only a few studies have examined the influence of both subjective and objective pollution evaluations on SWB, and their results are not consistent. Thus, this study aims to explore and compare their roles in affecting happiness by considering both measurements. Furthermore, when facing air pollution, we expect that some groups of people may be more susceptible to the adverse effects thereof than others. We conduct further heterogeneous analysis using different demographic characteristics (age, sex, income, marital status, and urban/rural residence). This will enable policymakers to initiate viable policies aligned with each group's peculiarity.

The remainder of this study is structured as follows. "Data and variables" describes the data and variables used. "Empirical model" introduces the empirical models and estimation issues. "Results and discussion" reports the baseline regression results, which are further verified by various robustness checks. "Heterogeneity analysis" examines the extent to which the baseline results vary across different groups of respondents. Finally, "Conclusions" concludes with relevant policy implications.

Data and variables

The data used in this study are primarily from the GWP, a dynamic survey that tracks global hot topics including well-being, food access, employment, and leadership performance. Since 2005, the GWP has conducted randomly selected research on more than 160 countries each year, tracking ongoing issues with representative data. Each year, approximately 1000 participants aged 15 years or older in the participating country are contacted through landline and/or mobile phone or face-to-face interviews.[1] This study uses GWP survey results for 2005–2018 and restricts the sample to 151 countries that have all available data on individual demographic characteristics and other macroeconomic controls. This leaves us with 1249 country-year data points (or 1,466,109 individual observations). The list of countries is provided in Appendix Table 7.

Subjective well-being

The dependent variable used in this study is SWB. To measure respondents' well-being, the Cantril ladder (Cantril 1965) form of questions about respondents' SWB in the GWP questionnaire is used. These questions ask respondents to imagine an 11-level ladder from 0 (worst case scenario) to 10 (best case scenario), and then to rate where they are in their lives on the ladder. The dependent variable used in this study is question WP16 in the GWP:

> Happiness (current): *"Please imagine a ladder with steps numbered from 0 at the bottom to 10 at the top. Suppose we say that the top of the ladder represents the best possible life for you, and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time, assuming that the higher the step the better you feel about your life, and the lower the step the worse you feel about it? Which step comes closest to the way you feel?" (WP16)*

Figure 1 (panel A) shows that countries such as Canada, Ireland, the Netherlands, Poland, Congo, Benin, and the Dominican Republic have high SWB scores, which are generally distributed in North America, Europe, Oceania, and the west coast of Africa. In contrast, Brazil, Haiti, Albania, Madagascar, Portugal, and other countries have the lowest scores, which are concentrated in South America, Central Africa, and South Asia. Given that the subjective conception of happiness for a particular person in a more or less polluted place may not be instantaneous but rather emerges over time, in this study, we also use an alternative measurement of SWB by asking the respondents' view on their "feeling about life in the future" (question WP18). The question reads as follows:

> Happiness (future): *"Please imagine a ladder with steps numbered from 0 at the bottom to 10 at the top.*

[1] Refer to http://www.gallup.com/178667/gallup-world-poll-work.aspx for further methodological details.

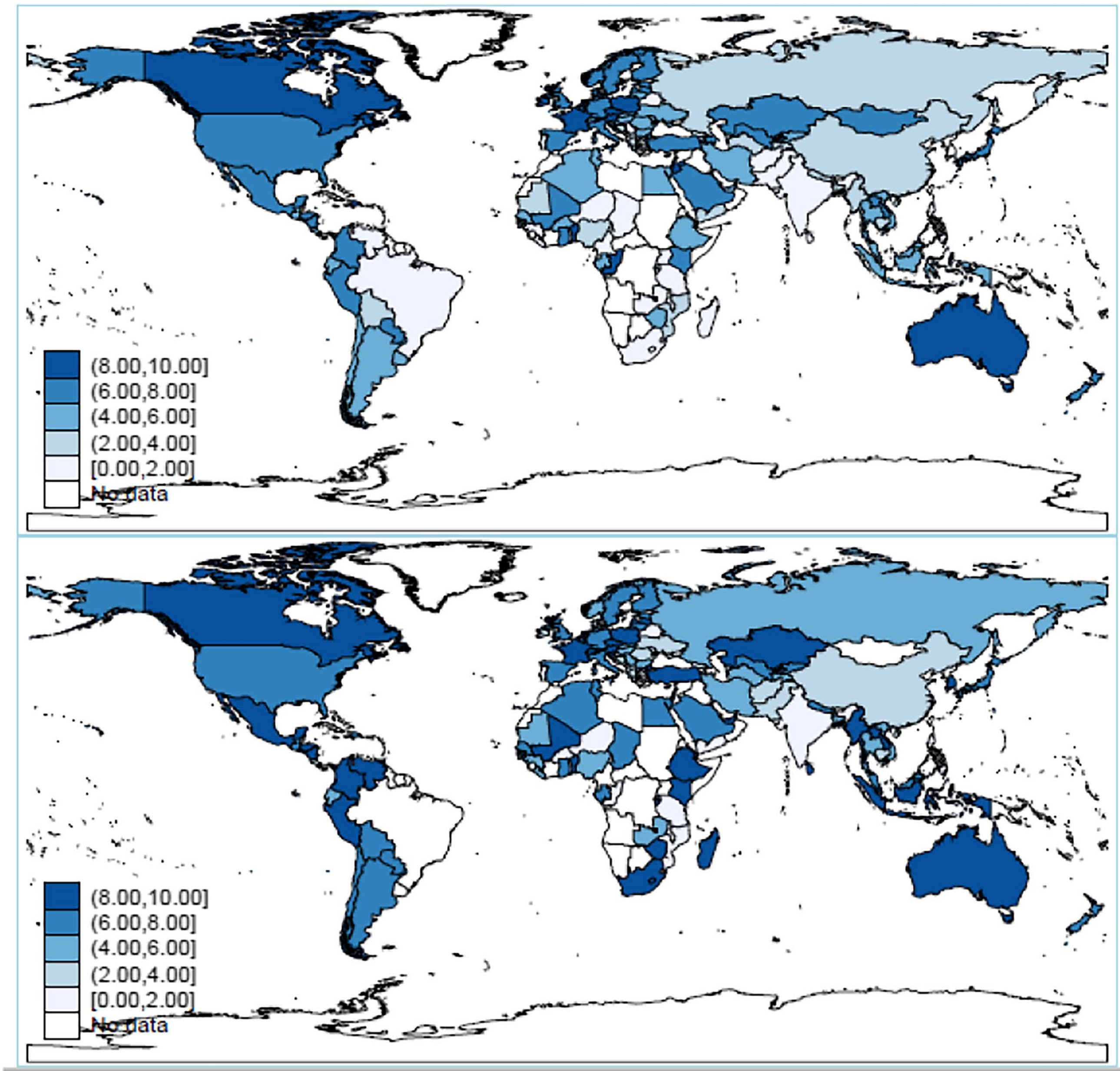


Fig. 1 Current and future expectations of SWB rating worldwide, 2018. **A**, **B** Individuals' SWB score

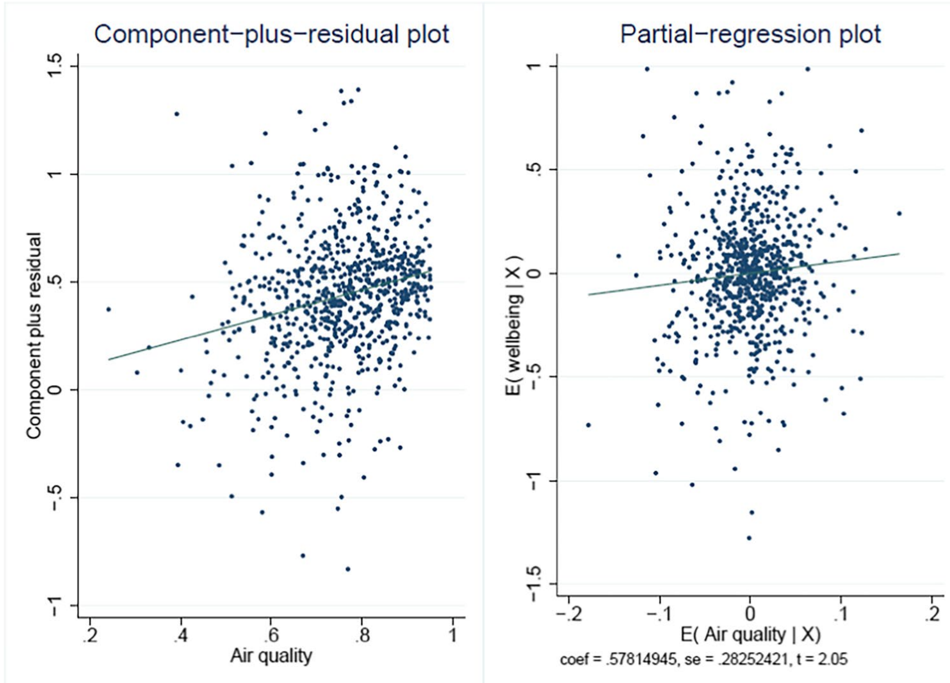
> *Suppose we say that the top of the ladder represents the best possible life for you, and the bottom of the ladder represents the worst possible life for you. Just your best guess, on which step do you think you will stand on in the future, say about five years from now?" (WP18)*

Compared with panel A of Fig. 1, panel B shows that individuals' SWB score has not changed much. In particular, Brazilian and Mongolian respondents have lower expectations of happiness in the next five years, while the Russians have higher expectations.

Air pollution

Air pollution is the key independent variable affecting SWB. European Environment Agency defines air pollution as "the presence of contaminant or pollutant substances in the air at a concentration that interferes with human health or welfare,

Fig. 2 Partial residual and partial-regression average plots



or produces other harmful environmental effects." Air pollutants can originate from manmade sources including emissions from internal combustion engines or the burning of fossil fuels such as coal, oil, petrol, or diesel. However, they can also come from natural sources such as forest fires, wind erosion, and volcanic eruptions (Darçın 2017).

In this subsection, we use two versions of air pollution indicators—one subjective and one objective.[2] There are several discrepancies between these two indicators. First, conceptually, subjective environmental pollution is a more general concept than objective environmental pollution, as the former "*includes not only the information provided by monitoring stations (i.e., the objective condition of the environment) and that communicated to citizens through the media, but also the way such information is communicated, exchanged, and perceived by all citizens*" (Mínguez et al. 2013, p. 171). Thus, it can be expected that even faced with the same objective air environment, different individuals will have a different sensitivity to objective air pollution, resulting in different subjective air pollution indexes and thus, different SWB. Second, empirically, the relationship between these two measures is complex and empirical results on their relationship are mixed (Brody et al. 2004). While some studies find these two measurements to be significantly correlated (Oglesby et al. 2000; Smyth et al. 2008; Atari et al. 2009; Liao et al. 2015), and both are important determinants of SWB (MacKerron and Mourato 2009; Liao et al. 2015), they are weakly related or even independent in others (e.g.,Forsberg et al. 1997; Kruize 2008; Semenza et al. 2008). Third, while subjective air pollution in Europe and other countries has a significantly adverse impact on local residents' happiness (Welsch 2006; MacKerron and Mourato 2009), it is found to be more harmful than objective air pollution (Ferrer-i-Carbonell and Gowdy 2007; MacKerron and Mourato 2009). Thus, one goal of this study is to compare the difference between objective and subjective measures of air quality and evaluate their relative importance on impacting SWB.

Perceived air quality (*Air*) is derived from question WP94 in the GWP: "*In this city or area you live, are you satisfied with the quality of air*?" Respondents can choose 1 for "satisfied" and 0 for "dissatisfied."[3] We

[2] The subjective measure, or perceived air pollution, refers to an individual's subjective judgment of air quality, which depends on many factors, such as individual physical condition, gender, educational background, and economic status. The objective measure reflects the air pollution data released by meteorological departments, which is considered an objective indicator.

[3] It is noteworthy that a similar question (WP3469) in the GWP states: "*In your opinion, how serious is the problem of air pollution where you live – very serious, somewhat serious, not very serious, not serious, or not at all serious?*" Despite this variable being capable of reflecting the depth of perceived air quality, the number of valid responses to this question is less than 10,000. The data used in this study covers more than 100 countries from 2005 – 2018. Thus, if we use the WP3469 data as an alternative measurement, the sample size of each country will be less than 10 people, which is extremely poor and unrepresentative. Thus, we did not use this measurement in this study.

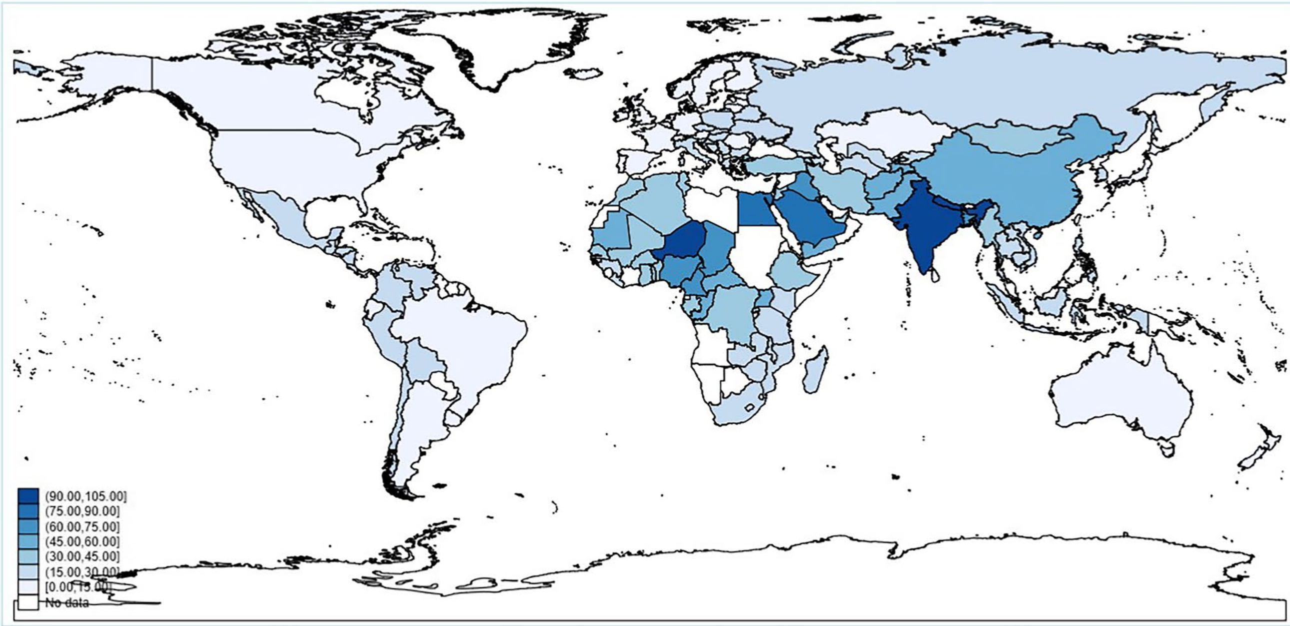


Fig. 3 PM2.5 worldwide, 2017

expect that respondents will be happier when they are satisfied with local air quality, i.e., β is expected to be positive in Eq. (1). Figure 2 shows two types of diagnostic plots after running a simple regression of SWB against perceived air quality, when both country and year fixed effects are controlled for: (i) the partial residual plot, also known as a component-plus-residual plot (Ezekiel 1924; Larsen and McCleary 1972); and (ii) partial-regression leverage plot or added-variable plot (Mosteller and Tukey 1977; Belsley et al. 2005). Both plots provide evidence of a positive association between perceived air quality and reported happiness. Measured air pollution (*PM2.5*), or the objective indicator, is proxied by PM2.5, which is considered the best proxy for the "ideal" measure of air pollution (OECD 2011). Exposure to concentrations of PM2.5 in both urban and rural areas is weighted by population and aggregated at the national level (Van Donkelaar et al. 2016). Data are retrieved from the World Bank database. This variable may suffer from some measurement error given that Gallup interviews about 1000 people in each country every year, and the average air quality of the places where these people live is not necessarily equal to the national weighted average of that year. Therefore, we use the rank of averaged air quality in this robustness check, as it is an ideal indicator that should be not be affected by measurement error. Thus, this study classifies the original PM2.5 concentration data into 10 deciles from small to large, and assigned values of 1–10. Figure 3 maps the PM2.5 concentration worldwide in 2017,[4] showing that the seriously polluted areas are concentrated in Africa and Asia, especially North Africa and South Asia.

Social engagement

What efforts can governments, business firms, and individuals make to battle pollution? Governments have developed a myriad of policies to reduce pollution, such as tax (e.g., carbon tax or environmental taxes for water pollution emissions or for increasing renewable energy consumption), subsidy (i.e., monetary awards for firms having developed renewable energy technology to reduce pollution), pollution permits, and regulations (e.g., the UK's 1956 Clean Air Act). Some of these policies are designed to change economic incentives and institutions so that individuals and business firms find it in their own interest to reduce pollution. Governments have been also taking actions to increase public awareness around air pollution, which includes working with broadcasters and social media companies to spread information on the topic.

From the firm side, industrial manufacturing and the construction industry are the two largest polluters. The most common airborne pollutants generated by these two sectors include volatile organic compounds, hazardous air pollutants, and solid PM. Some common measurements to reduce

[4] We only have access to data from 2010 to 2017.

air pollution emissions include optimizing the firm's operations by switching from coal and fossil fuels to renewable and clean energy sources (e.g., solar, wind, and biomass); using scrubbers, catalytic or recuperative thermal oxidizers, and other technologies to mitigate or eliminate pollution emissions at the source before it enters the atmosphere; and choosing cleaner and nontoxic raw materials.

For individuals, numerous efforts can be taken to reduce air pollution. These include conserving energy at home, work, or everywhere; decreasing waste; reducing toxins; carpooling or using public transportation, biking, or walking wherever possible.

Because no universal indicator exists for social engagement in pollution prevention and reduction, we use the share of renewable energy in the total final energy consumption of a country as an imperfect but reasonable proxy (*Social*). Empirical studies have shown that renewable energy affects people's well-being and human development index (Zhang et al. 2017a). As such, governments in some countries influence residents' acceptance of renewable energy through publicizing government reports related to renewable energy (Zobeidi et al. 2021) or by encouraging residents to participate in renewable energy generation in the form of "Renewable Energy Communities" and as "prosumers." De Crescenzo et al. (2020) and Pons-Seres de Brauwer and Cohen (2020) show that European residents do pay attention to their share of renewable energy generation and even invest in the construction of renewable energy projects. In addition, governments encourage businesses to use renewable energy through market-oriented approaches such as green power certificates or renewable energy certificates (Tu et al. 2020). Governments' behavior indicates that the "share of renewable energy generation" is a government-led goal that combines the willingness and behavior of various parties including the government, enterprises, and residents, and the process of implementing this goal will bring about changes in air quality. Thus, this proxy signals a fair degree of overlap of pollution-reducing involvement among governments, business firms, and individuals.

Control variables

To reduce omitted variable bias, we control for various socioeconomic and demographic characteristics (at the individual or national level) that may be important predictors of SWB. Based on the existing literature (e.g.,Easterlin 1974; Ferrer-i-Carbonell and Gowdy 2007; Knight et al. 2009; Menz and Welsch 2010; Mikucka et al. 2017; Lu et al. 2020; Ngoo et al. 2021), we control for age, sex, marital status, educational attainment, self-reported health, urban/rural residence status, income, networking, and national economic development:

Age (WP1220): Age of person *i*, in years.

Age2: The squared term of variable *Age*, used to capture the possible nonlinear effect of age (Ferrer-i-Carbonell and Gowdy 2007; Knight et al. 2009).

Gender (WP1219): 1 if male; 0 otherwise.

Marital (WP1223): 1 if the respondent is "married," or has a "domestic partner"; and 0 if "single," "never been married," "separated," "divorced," or "widowed."

Edu (WP3117): Gallup has harmonized the education variables and created a worldwide dataset with standardized individual-level education data. This variable measures a respondent's highest completed education level. The education variable is equal to 1 if the respondent has primary education or below, 2 for secondary education, and 3 for tertiary education or above.

Urban (WP14): 1 if the respondent lives in a large city or a suburb of a large city and 0 if the respondent lives in a rural area, farm, small town, or village.

Income (*INCOME*5): Per capita income quintiles: 1 if the respondent is in the poorest 20%, 2 for the second 20%, 3 for the middle 20%, 4 for the fourth 20%, and 5 for the richest 20%.

Internet (WP39): 1 if the respondent's home has access to the Internet; 0 otherwise.

Health (WP23): 1 if the respondent does not have any health problems that prevent him/her from doing any of the things people of his/her age normally can do; 0 otherwise.

GDP: defined as the natural log of gross domestic product in terms of purchasing power parity (at constant 2010 US dollars). Data are from the World Bank Development Indicators database.

Table 1 reports the summary statistics of the variables that are used in our analysis. Because of the large number of variables involved in this study, the presence of multicollinearity would render the estimation results unreliable; thus we performed a correlation analysis. The Spearman correlation coefficient matrix of the variables used is provided in Appendix Table 8. The correlation coefficients between the main variables do not exceed 0.5, implying that the correlation between the variables used in this study is not strong and there is no obvious problem of multicollinearity. Thus, a subsequent regression analysis can be performed.

Empirical model

Baseline specification

The baseline model used to examine the impact of air pollution on happiness is specified as follows:

Table 1 Summary statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Dependent variables					
Happiness (current)	1,862,096	5.507	2.309	0.000	10.000
Happiness (future)	1,717,098	6.786	2.405	0.000	10.000
Key covariates					
Air	1,682,645	0.748	0.434	0.000	1.000
PM2.5	1,260,524	32.000	21.950	5.861	100.800
Social	1,460,590	0.293	0.298	0.000	0.970
Individual variables and country					
Gender	1,896,082	0.466	0.499	0.000	1.000
Age	1,886,084	41.130	17.530	13.000	101.000
Age2	1,886,084	1,998.788	1,628.689	169.000	10,201.000
Marital	1,863,073	0.585	0.493	0.000	1.000
Urban	1,773,120	0.433	0.495	0.000	1.000
Edu	1,810,416	1.834	0.679	1.000	3.000
Income	1,497,446	3.220	1.420	1.000	5.000
Internet	1,402,419	0.376	0.484	0.000	1.000
Health	1,772,800	0.750	0.433	0.000	1.000
GDP	1,860,260	7.126	2.075	2.169	12.100

$$Happiness_{ijt} = \propto + \delta Air_{ijt} + X\beta + \mu_j + \nu_t + \varepsilon_{ijt} \quad (1)$$

where $Happiness_{ijt}$ is the self-reported happiness (Cantril ladder) of individual i from country j in year t. The key independent variable of interest, *Air*, is denoted by perceived air pollution (*Air*) and measured air pollution (*PM2.5*) for individual i from country j in the year t. X is a vector of covariates consisting of individual- or country-level control variables that could influence well-being, such as those for gender, age, marital status, level of education, income, and national GDP. μ_j and ν_t are country and year fixed effects, respectively, used in all specifications to control for the unobservable characteristics affecting an individual's well-being that vary only at the country level or over time. ε_{ijt} is the disturbance term, which is assumed to be correlated at the country-year level. Our coefficient of interest is δ, representing the estimated relationship between air pollution and happiness. Thus, $\delta > 0$ in the model using *Air* (or *PM2.5*) implies that self-reported happiness increases as perceived air quality rises (or as measured air pollution falls).

Moderating role of social engagement

To examine the moderating effect of social engagement on the relationship between air pollution and happiness, Eq. (1) is rewritten as follows:

$$Happiness_{ijt} = \alpha + \delta Air_{ijt} + \xi Air_{ijt} \times Social_{jt} + \gamma Social_{jt} + X\beta + \mu_j + \nu_t + \varepsilon_{ijt} \quad (2)$$

where $Social_{jt}$ denotes the social engagement in pollution reduction for country j in year t. $Air_{ijt} \times Social_{jt}$ is the interaction term between social engagement and air pollution.

The OLS method is used to estimate Eqs. (1) and (2), given that the response scale can be treated as cardinal.[5] One concern is the assumption of a normal distribution of the dependent variable in the baseline model, as the true data generating process might not follow a normal distribution as the dependent variable is a non-negative count number. For comparison purposes, we also use a Poisson model, which is common for count data (Cameron and Trivedi 2005).

Endogeneity issue

Adding the control variables (e.g., education, social networking, and income) and fixed effects may alleviate some

[5] Treating happiness as a continuous variable (i.e., cardinal instead of ordinal) is common in the literature (Haller and Hadler 2006; Knight et al. 2009; Oshio 2017; Lu et al. 2020). Indeed, the ordinal and cardinal treatments of happiness scores generate quantitatively similar results in microeconometric happiness functions (Frey and Stutzer 2000). This is less of a practical problem than a theoretical one (Kahneman et al. 1999)

Table 2 Baseline results

	(1) OLS	(2)	(3) Poisson	(4)
Air	0.273*** (0.019)	0.347*** (0.026)	0.050*** (0.003)	0.061*** (0.005)
Social		–0.103 (0.166)		–0.028 (0.031)
Air × social		–0.242*** (0.050)		–0.036*** (0.010)
Gender	–0.134*** (0.011)	–0.134*** (0.011)	–0.025*** (0.002)	–0.025*** (0.002)
Age	–0.046*** (0.003)	–0.046*** (0.003)	–0.009*** (0.000)	–0.009*** (0.000)
Age2	4.538e–04*** (1.601e–05)	4.525e–04*** (1.602e–05)	8.600e–05*** (2.768e–06)	8.640e–05*** (2.768e–06)
Marital	0.197*** (0.016)	0.200*** (0.016)	0.035*** (0.003)	0.036*** (0.003)
Urban	0.124*** (0.022)	0.118*** (0.022)	0.023*** (0.004)	0.022*** (0.004)
Edu	0.310*** (0.014)	0.305*** (0.014)	0.057*** (0.003)	0.056*** (0.003)
Income	0.200*** (0.006)	0.202*** (0.006)	0.037*** (0.001)	0.038*** (0.001)
Internet	0.815*** (0.030)	0.809*** (0.032)	0.142*** (0.006)	0.141*** (0.006)
Health	0.482*** (0.025)	0.481*** (0.025)	0.094*** (0.004)	0.094*** (0.004)
GDP	0.143*** (0.017)	0.132*** (0.017)	0.027*** (0.003)	0.025*** (0.003)
Constant	2.840*** (0.175)	2.929*** (0.191)	1.198*** (0.034)	1.218*** (0.037)
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Obs	810,943	810,384	810,943	810,384
R-squared	0.246	0.246		

Robust standard errors in parentheses are clustered at the country-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

of the concerns of bias due to omitted variables, such as religious belief (Helliwell 2003), degree of sensitivity to pollution (MacKerron and Mourato 2009), or respondents' experiences regarding the effects of environmental issues; measurement errors, such as inaccurate measurement of air pollution; or reverse causality, such as happier people will care more/less about perceived air quality (MacKerron and Mourato 2009). However, they cannot completely eliminate potential endogeneity.

To address these possible forms of endogeneity, we adopt the IV approach to make causal inferences about the impact of the air pollution indicator on happiness when the indicator is endogenous. Following Fisman and Svensson (2007) and Bucher-Koenen and Lusardi (2011), we construct the instrument variable (IV_{ij}) for Air_{ij} (i.e., perceived air pollution by respondent i in country j, ranging from 0 to 10) in two steps. First, we calculate the national average of the perceived air pollution of all respondents excluding respondent i himself/herself from country j ($\overline{Air_{ij}}$). Second, we let the IV_{ij} equal 1 if $\overline{Air_{ij}}$ is ranked in the 50th percentile, and 0 otherwise. Correspondingly, we use the interaction term of this variable with social engagement as another instrumental variable of the original interaction term. Consequently, the IV or two-stage least squares estimation (2SLS) is performed. IV_{ij} is likely to serve as a valid instrument. First, it is correlated with Air_{ij} because when the majority of the country's residents perceive the air to be poor or good, it is highly likely that the respondent will hold the same view. Second, the respondent's perception alone does not necessarily affect the nation's overall perception. Third, others' pollution perception on average is unlikely to have a direct effect on individual happiness.

Results and discussion

Baseline results

Table 2 reports our baseline estimates from Eqs. (1) and (2). The key explanatory variable is perceived air quality *Air*. All specifications control for country and year fixed effects. Standard errors are clustered at the country-year level to avoid the downward bias of the standard errors of the aggregated variables (Moulton 1986, 1990). Columns (1) and (2) present the results for the OLS, and columns (3) and (4) those for the Poisson estimation, in which columns (2) and (4) report the results on interaction effects (between perceived air quality and social engagement).

Column (1) of Table 2 shows that the coefficient of perceived air quality is positive and significant at the 1% level after controlling for demographic attributes, country and time fixed effects. Comparing column (3) with column (1), the estimation using the Poisson model does not vary fundamentally in terms of trend, as the estimated parameter bears the same negative sign and statistical significance. More importantly, the estimated well-being effect (0.275) is quite close in magnitude to that (0.273) in the OLS model.[6] Specifically, the coefficient ($\delta = 0.273$, $t = 14.15$) suggests that one standard deviation improvement in perceived air quality would increase happiness by 0.13 ($0.434 \times 0.273 = 0.13$). This result indicates that the estimated effect of happiness is substantial and an increase in perceived air quality significantly improves happiness. This is expected and consistent with studies such as Rehdanz and Maddison (2008), Di Tella and MacCulloch (2008), Levinson (2012), Weinhold (2013), Ferreira et al. (2013), García-Mainar et al. (2015), Orru et al. (2016), Chu et al. (2017), and Zhang et al. (2017a, b). Among these studies, two are closest to our findings, namely, García-Mainar et al. (2015), who used Spanish data and found a coefficient of 0.19 for subjective air quality, and Chu et al. (2017), who used Chinese data and found a coefficient of 0.25.

Column (2) of Table 2 shows the results of the interactive effect of social engagement. The interaction term ($\xi = -0.242$, $t = -4.81$) is negative and statistically significant at the 1% level. The coefficient of perceived air quality ($\gamma = 0.347$, $t = 13.59$) remains positive and statistically significant. This result suggests that (i) the marginal effect of perceived air quality on SWB is 0.276 ($0.347 - 0.242 \times 0.293 = 0.276$), which is similar to the coefficient of 0.273 in column (1) without the interaction term; (ii) social engagement in pollution reduction weakens the positive impact of perceived air quality on reported happiness. In other words, respondents' happiness is less affected by perceived air quality when they observe that the whole society is engaged in protecting the air. The moderating effect of social engagement is reasonable and can be explained by the "law of diminishing marginal utility" (Gossen 1983) in economics. When people observe that more social efforts are made to improve the air quality, they tend to believe that air quality will improve and will gradually shift their attention from air quality to other issues. Eventually, the positive effect of perceived air quality will weaken, that is, the marginal effect of an additional unit of improvement of air quality will not be stronger than that without social engagement.

Turning to the control variables, each covariate in these models has the same sign. Reported happiness increases with income, which is in line with a number of studies (e.g.,Graham and Pettinato 2001; Clark et al. 2005; Shields and Price 2005; Lelkes 2006; Stevenson and Wolfers 2008; Sacks et al. 2010; Diener et al. 2013; Veenhoven and Vergunst 2014) but inconsistent with others (e.g., Layard et al.

Table 3 PM2.5 and Happiness (current)

	(1)	(2)	(3a)	(3b): standardized beta coefficient)
PM2.5	–0.031 (0.034)	–0.112** (0.047)	–0.113** (0.049)	–0.140** (0.060)
Social		–1.307* (0.783)	–1.283 (0.787)	–0.155 (0.095)
PM2.5 × social		0.271* (0.162)	0.278*** (0.103)	0.262*** (0.097)
Air			0.311*** (0.016)	0.058*** (0.003)
Air × social			–0.272*** (0.042)	–0.034*** (0.005)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Obs	787,631	787,060	727,091	727,091
R-squared	0.289	0.289	0.290	0.290

Robust standard errors in parentheses are clustered at the country-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

[6] The marginal effect is simply computed as the coefficient estimate of perceived air quality in column (1) of Table 2 multiplied by the mean value of happiness in Table 1 (Hilbe 2011, p. 128).

2010; Clark et al. 2014).[7] In addition, women tend to be happier than men, implying a gender difference (Di Tella and MacCulloch 2008; Herbst 2011; Zweig 2015; Wang et al. 2021). Age exhibits a *U*-shaped relationship with happiness, which almost replicates the basic conclusion of existing studies (Clark et al. 2005; Shields and Price 2005; Knight et al. 2009; Whiteley et al. 2010; Ejrnæs and Greve 2017; Lu et al. 2020). There is a quadratic age effect, with a turning point in a range from the mid-30 s to approximately the late-40 s. Furthermore, individuals who are married, better educated, have access to the Internet, or live in urban areas or a wealthier country are happier than their counterparts.

Objective measure of air quality

Table 3 reports the result of OLS using the objective measure of pollution (*PM2.5*). Column (1) considers only the variable PM2.5 and shows that it is negative but statistically insignificant. This result is contrary to that of Welsch (2006), MacKerron and Mourato (2009), and Cuñado and Pérez de Gracia (2013), who found a statistically significant and negative coefficient for PM2.5. However, it is consistent with that of Welsch (2006), Smyth et al. (2008), Taşkaya (2018), and Tsurumi and Managi (2020), who found that an objective measure of pollution (PM10, SO_2, or NO_2) does not significantly impact individual happiness. One explanation is that compared to a subjective measure of air quality, the objective measure has a limited impact on individual happiness: Even if the PM2.5 index is as high as 200, if an individual thinks the air quality is not bad, it will not affect his or her happiness. Column (2) shows the results of the interactive effect of social engagement. The interaction term is statistically significant and positive, and the marginal effect of PM2.5 (evaluated at the mean of social engagement) is thus calculated as -0.0322 ($-0.112+0.271\times0.293=-0.0322$). These results suggest that social engagement in reducing pollution plays a role in moderating the impact of objective pollution on individual well-being, consistent with the conclusion we obtained in the baseline model using a subjective environmental measurement. Combining the result in column (1) when considering only the variable PM2.5 and that in column (2) when considering both PM2.5 and its interaction with social engagement, we conclude that PM2.5 per se has no impact on individual happiness (column (1)). This is consistent with the evidence from Turkey (Taşkaya 2018) and that from India and China (Tsurumi and Managi 2020). After adding the interaction term (column (2)), both PM2.5 and the interaction term are statistically significant. We interpret this result as indicating that social engagement in reducing pollution plays a moderating role in shaping the impact of objective pollution on individual happiness. The rationale is that government involvement conveys relevant pollution information to the public that reinforces public concern about pollution, which leads to the significant effect of PM2.5 on individual happiness, an effect reinforced by government involvement.

As the combination of objective and subjective approaches is gaining ground in the happiness literature (Chasco and Gallo 2013; Liao et al. 2015), column (3a) simultaneously adds perceived air quality, measured air quality, and their interactions with social engagement in the previous model. Both the subjective and objective measures are relevant in explaining individual happiness, and the moderating role of social engagement remains valid. More importantly, we can proceed to evaluate the relative contribution of these two pollution measurements to happiness. This can be done by obtaining the standardized beta coefficient estimates through running the same regression model in column (3a). These estimates are reported in column (3b). At the 1st quartile (0.06), median (0.29), and 3rd quartile (0.46) values of social engagement, the marginal effect of perceived air quality is calculated as follows: 0.06 ($0.058-0.034\times0.06=0.056$), 0.05, and 0.04, respectively. The value for PM2.5 at each percentile is -0.12, -0.06, and -0.02, respectively. Hence, a subjective evaluation appears more important in affecting individual happiness than the objective measure as the degree of social engagement rises, which is in general consistent with existing research (Ferrer-i-Carbonell and Gowdy 2007; MacKerron and Mourato 2009).

IV results

One potential concern is that the empirical analysis thus far is plagued with an endogeneity bias using either measurement of pollution indicators, even after including a variety of control variables and country and year fixed effects. Thus, we attempt to examine the causal impact of pollution on happiness using the IV approach with instruments constructed in subsection 3.3.

Column (1) of Table 4 reports the IV results. Because of the weak instruments concern, we also report an Anderson-Rubin (AR) test (Anderson and Rubin 1949), which is robust to the weakness of the instruments. This is a test of the null that the coefficients on the excluded instruments are jointly

[7] There are ongoing debates about the relationship between income and subjective well-being. During the last few decades, economic literature on happiness has grown rapidly on the Easterlin paradox (also known as income-happiness paradox), which refers to a contradictory finding on income-happiness relationship using time-series and cross-sectional data. In the long run (time-series), economic growth does not increase people's happiness, even when there is a positive association between the two variables in cross-sectional studies (Rojas 2019). Readers may refer to Clark et al. (2008) for a review of the literature on the relationship between income and subjective well-being.

Table 4 Other robustness checks

	(1)	(2)	(3)	(4)	(5a)	(5b)
	Using IV approach	Happiness (future)	Water quality	Removing extreme values	Using aggregated Gallup data	Using aggregated data + difference eq. model
Air	0.873*** (0.173)	0.317*** (0.017)		0.279*** (0.015)	1.184*** (0.212)	2.009*** (0.492)
Air × social	–0.018*** (0.004)	–0.300*** (0.048)		–0.241*** (0.037)	–1.596*** (0.546)	–2.194* (1.276)
Social	2.094*** (0.309)	–0.667 (0.502)	0.867** (0.425)	0.748 (0.430)	1.537*** (0.528)	0.732 (1.241)
Perceived water quality			0.309*** (0.020)			
Perceived water quality × Social			–0.134*** (0.041)			
Anderson-Rubin LR statistic	32.67[0.0000]					
Cragg-Donald *F* statistic	792.55					
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	No
Country FE	Yes	Yes	Yes	Yes	Yes	No
Obs	810,384	752,870	813,314	810,384	702	523

Robust standard errors in parentheses are clustered at the country-year level. The *p*-value is reported in bracket. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. †Notice that, variables are measured in changes and robust standard errors are clustered at the country level in the first-difference equation model

zero when they are included in place of the endogenous covariates in the outcome equation.

Several results can be summarized. First, it is reassuring that the IV coefficient estimate of perceived air quality and its interaction term are robust, and social engagement in reducing pollution continues to play a moderating role on perceived air quality. Second, the estimated association between the perceived indicator and happiness intensifies substantially when the perceived air quality variable is instrumented: The marginal effect of perceived environmental evaluation (evaluated at the mean of social engagement) is 0.82 ($0.873-0.18\times0.293=0.82$), while this number is 0.28 ($0.347-0.242\times0.293=0.28$) in the corresponding OLS model. Third, the following three facts lend some credence to the belief that the instruments chosen are appropriate: (i) the *p*-value of the Anderson-Rubin likelihood ratio (LR) test (critical value = 32.67, $p=0.0000$) implies that the null hypothesis can be rejected and the impact of perceived air quality is significant. (ii) The Cragg-Donald *F* values (792.55) lie well above the commonly used critical value of 10, suggesting that the instruments chosen are not weak. (iii) Though our estimation results may be challenged by weak instruments, in settings with weak instruments, it has been proven that IV estimates are "biased toward" the corresponding OLS estimates (for a discussion, see, e.g., Angrist and Pischke 2008, ch. 4). Given that the corresponding marginal impact from OLS is about one-third of that of the IV model, we expect that weak instruments only underestimate rather than overestimate the relationship between perceived air quality and happiness.

Other robustness checks

The remaining columns of Table 4 report a battery of robustness checks. In column (2), we use an alternative measurement of SWB (*Happiness*(*future*))—i.e., respondents' predictions about their well-being 5 years later—as the new dependent variable. This is considering that these two measurements can differ and that the subjective conception of happiness for a person in a more or less polluted place may not be instantaneous but emerges over time. Using this new dependent variable does not alter the marginal impact of perceived air quality (0.23, which is close in magnitude with the same sign) and the interactive effect of social engagement.

Column (3) shows an alternative subjective measure—respondent's perceived perception of water quality. We use question WP95 in the GWP: "In the city or area where you live, are you satisfied or dissatisfied with the quality of water?" As expected, both perceived air quality and water quality are equally weighted in decreasing residents' happiness (0.27 vs. 0.28 in terms of marginal effect).

In column (4), we delete possible outliers by removing respondents whose reported well-being score is below the 5^{th} percentile or above the 95^{th} percentile of the distribution.[8] Again, the coefficients of interest remain of the expected sign and significance. Together, columns (2)–(4) show that the baseline results, using individual micro-level data, are robust to an alternative measure of either the dependent or independent variable.

Columns (5a) and (5b) consider the aggregated Gallup data by averaging all data for all variables in Eq. (2) at the country level. This results in an unbalanced panel model of 702 observations with 117 countries, which is estimated using the Kmenta-type FGLS procedure allowing for heteroscedasticity and AR(1) autocorrelation (Kmenta 1986). The rationale for this approach is two-pronged. First, the number of respondents across countries is unevenly distributed (as shown in Appendix Table 7), and we are concerned that when using individual-level data, this may result in estimates being heavily dominated by observations from large countries. Second, because respondents vary between years, aggregating the country-level Gallup data allows comparing (average) happiness ratings (within a country) across years. Column (5a) shows that using aggregated Gallup data, the corresponding key coefficients are larger (in absolute terms) in magnitude with similar statistical significance. In addition, the calculated marginal effect (0.67) is three times larger than the baseline result (0.28) in column (2) of Table 2, implying that the positive impact of air quality on national happiness is generally stronger when using aggregated data at the country level.

Last, column (5b) uses the same aggregated Gallup data as above, but employs a first-difference (FD) equation model, which regresses the change in average happiness rating from 2008 to 2018 on the changes of perceived air quality and other control variables. Estimating an FD equation model has some desirable properties: (i) First-differencing eliminates the country fixed effects. (ii) The FD estimator is more efficient as it deals with the problem of serial correlation. (iii) The series will usually be stationary after first-differencing. Column (5b) reveals that the moderating role of social engagement still holds, confirming that our baseline OLS finding is not driven by the transient or irregular fluctuations present in the happiness data. However, the marginal impact of perceived air quality on happiness strengthens.

Heterogeneity analysis

Like some groups of people are more susceptible to the adverse effects of air pollution than others, some are more sensitive to the degree of how improving air quality might affect their own happiness.

Columns (1) and (2) of Table 5 show the results for men versus women, using the subjective measure (panel A) and objective measure (panel B), respectively. The last row of each panel shows the calculated marginal effect of each environmental measurement on happiness evaluated at the mean value of the interaction term (social engagement). Two conclusions can be summarized as follows: (i) The moderating role of social engagement in pollution reduction is similar in magnitude using either a subjective or objective measure, suggesting no evident difference between men and women, that is, social engagement in reducing pollution is equally important. (ii) The literature hypothesized that women are more concerned than men about local environmental problems because women have been socialized to be family nurturers and caregivers (Blocker and Eckberg 1989; Mohai 1992), resulting in different value systems (e.g., altruism, compassion). Several other explanations include perceptions of general risk and vulnerability, and feminist beliefs including commitment to the egalitarian values of fairness and social justice. However, empirical results are mixed.[9] Columns (1) and (2) reveal that women tend to be more concerned about air quality improvement, reflected by the larger (in absolute value) marginal effect estimate using the subjective measure. However, the effect is the opposite when using the objective measure. Note that the magnitudes in these two groups using either environmental measurement are close. Thus, overall, women appear to care slightly more than men about the environment, which is consistent with a large body of existing research that found a modest gender difference in environmental concern (Blocker and Eckberg 1989; Bord and O'Connor 1997; Finucane et al. 2000; Hamilton 2011; McCright and Dunlap 2013, 2013, Van der Linden 2015).

Columns (3)–(5) report results respectively for three age groups (15–18, 19–64, and ≥ 65 years). There appears to be some differentiation by age, although the differences are small. Older respondents are slightly more sensitive than younger ones to the relationship between air pollution (subjective or objective) and happiness, and the extent of social efforts to reduce air pollution. This suggests that awareness of air pollution among older adults is higher than among the youth. As older adults are more likely to be affected by air pollution, an additional improvement of air quality will offer them a higher level of life satisfaction. This

[8] Apart from this simple method to deal with outliers, there are several other approaches such as winsorization (Barnett and Lewis 1994), rank-based inverse normal transformation (Beasley et al. 2009), and robust regression using the M-estimator (Huber and Ronchetti 2009).

[9] Refer to Davidson and Freudenburg (1996) and Kahan et al. (2005) for reviews of gender effects on environmental-risk perceptions.

Table 5 Heterogeneity analysis

Panel A: subjective measure	(1) Male	(2) Female	(3) Age < 24	(4) Age: 24–65	(5) Age > 65	(6) Poorest 20%	(7) Middle income	(8) Richest 20%	(9) Urban	(10) Rural
Air	0.310***	0.291***	0.278***	0.298***	0.304***	0.325***	0.310***	0.262***	0.298***	0.258***
	(0.019)	(0.016)	(0.027)	(0.015)	(0.031)	(0.030)	(0.017)	(0.020)	(0.017)	(0.022)
Social	0.874*	0.835*	0.545	0.847*	1.09**	0.857	0.796*	0.831	0.754	0.819
	(0.497)	(0.447)	(0.665)	(0.448)	(0.449)	(0.571)	(0.474)	(0.558)	(0.493)	(0.512)
Air × social	–0.425***	–0.278***	–0.227***	–0.258***	–0.224**	–0.380***	–0.265***	–0.174***	–0.183***	–0.213**
	(0.078)	(0.044)	(0.059)	(0.039)	(0.104)	(0.011)	(0.043)	(0.051)	(0.053)	(0.048)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE and region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	373,233	437,151	146,611	810,384	85,165	129,383	471,631	209,370	328,635	481,749
R-squared	0.285	0.289	0.284	0.286	0.319	0.259	0.278	0.255	0.245	0.287
Marginal effect of perceived air quality	**0.1853**	**0.2094**	**0.2114**	**0.2223**	**0.2383**	**0.2135**	**0.2322**	**0.2109**	**0.2443**	**0.1955**
Panel B: objective measure										
PM2.5	–0.109**	–0.107**	–0.113*	–0.112**	–0.124**	–0.061	–0.160***	–0.031	–0.063	–0.152***
	(0.051)	(0.045)	(0.061)	(0.047)	(0.049)	(0.065)	(0.048)	(0.048)	(0.048)	(0.052)
Social	–1.248	–1.33*	–2.27**	–1.31*	–1.16	–0.864	–1.855**	–0.399	–1.041	–1.679**
	(0.849)	(0.782)	(1.118)	(0.784)	(0.768)	(1.016)	(0.824)	(0.814)	(0.846)	(0.870)
PM2.5 × social	0.259**	0.280***	0.323**	0.271***	0.401***	0.169	0.339**	0.176	0.286**	0.294***
	(0.112)	(0.100)	(0.130)	(0.102)	(0.120)	(0.128)	(0.109)	(0.112)	(0.121)	(0.109)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE and region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	362,873	424,187	139,085	787,060	85,372	125,959	457,898	203,213	322,044	465,016
R-squared	0.288	0.291	0.285	0.289	0.317	0.262	0.281	0.255	0.246	0.292
Marginal effect of PM2.5	**–0.0313**	**–0.0264**	**0.0011**	**–0.0325**	**–0.0339**	**–0.0127**	**–0.0645**	**0.0193**	**–0.0005**	**–0.0523**

Robust standard errors in parentheses are clustered at the country-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Control variables, country, and year fixed effects are omitted to conserve space finding is consistent with those of Kim et al. (2012) and Menz and Welsch (2010) who show that the negative association between air pollution and life satisfaction is stronger for older people than for middle-aged individuals. However, it differs from those of other studies such by as Turner and Struthers (2018), who showed that younger respondents are more concerned about or aware of air quality than older respondents, and Hopkins et al. (2001), who found that the youth have better awareness than older adults because they use more social and other electronic media to obtain information. It is noteworthy that some studies even found no association between age and perceptions of air quality (e.g., Egondi et al. 2013). Thus, the relationship seems controversial and the reasons for these differences, if any, are not clear-cut. More work on differences among age groups might be warranted.

Columns (6)–(8) present the results for respondents of three income groups: the bottom income group (poorest 20% of the population), top income group (richest 20% of the population), and middle income group. Compared to the poorest income group, the marginal impact of subjective air quality improvement (objective air pollution) on happiness is more pronounced in the middle or top income group, implying that rich residents suffer more from or are more sensitive to air pollution (à la Di Tella and MacCulloch 2008). The reasons for this difference can be attributed to Maslow's (1954) "Hierarchy of Needs Theory" or Kuznets' (1955) "Environmental Kuznets Curve Theory." The former argues that more basic, survival needs (e.g., food or shelter) must first be attended to and satisfied before people can focus on "higher order" needs (e.g., esthetics or the esthetic environment). In other words, poorer people have more pressing problems to attend to. The latter theory states that people will not value the environment much until they are at a higher income level. Another possible reason that the poor tend to be less concerned about air quality is fatalism and helplessness (Muindi et al. 2014): They simply cannot do anything about the environment or impose any influence over actions and decision makers; thus, they are accustomed to the poor environments wherein they live. For these reasons, among other possible ones, we expect that an additional unit increase of air quality will not provide the poor with much happiness.[10]

Furthermore, an interesting finding is that the poor group is more affected than the other income groups by the moderating role of social engagement, as evidenced by the larger (in absolute term) coefficient estimate of the interaction term with subjective air quality in column (6). This is presumably reasonable as the low-income group has little influence over actions against pollution and decision makers, or simply cannot prevent pollution by taking preventive actions (e.g., changing their place of residence or buying air purifiers); they can only hope that society and the government will actively attend to the problem. Therefore, social efforts play bigger roles for the poor in modifying the relationship between perceived air quality and individual happiness. We did not find such a moderating effect or a negative relationship between objective pollution and individual happiness for the poor, as the coefficient estimates in panel B of column (6) are statistically insignificant. This finding could imply that a subjective rather than objective evaluation of the environment matters more for poor people.

Columns (9)–(10) indicate that urban residents are more concerned with perceived air quality, a similar view to those of Althoff and Greig (1977) and Turner and Struthers (2018). All air pollutants including particulate matter and ground-level ozone are more concentrated in cities (Strosnider et al. 2017). As expected, people living in urban areas are most exposed to air pollution, and will thus be more sensitive to a change in air quality. Therefore, it is expected that urban residents would enjoy a higher level of life satisfaction than rural residents with the same increment in improved air quality.

In sum, urban, affluent, and older individuals are more concerned about air pollution. However, the variation in levels of concern across different demographic groups is relatively moderate. In addition, social engagement in pollution reduction plays a moderating role in modifying the relationship between air pollution and individual happiness.

Conclusions

Environmental pollution, a global issue of great concern, affects people's physical and psychological health. In this study, we analyzed the effects of subjective and objective air quality on people's SWB using individual data from 151 countries in the Gallup database from 2005 to 2018. Based on this, we used the IV estimation method to address the issue of endogeneity. In addition, we considered the effect of social engagement in pollution reduction on SWB. Through the base-model regression, robustness tests, and heterogeneity analysis, we derived the following key conclusions: (1) Subjective air quality has an impact on personal happiness, and the better the subjective air quality is, the higher is personal happiness. (2) When residents perceive the

[10] Despite the theories mentioned stating that the poor are concerned about air pollution, empirical studies have provided mixed results regarding the relationship between level of affluence and environmental concern, perception, and response. In addition, a meta-analysis by Vaughan and Nordenstam (1991) even shows that the response by the poor is heterogeneous.

government or society's efforts to improve air quality, the impact of air quality on residents' happiness will decrease. In other words, social engagement in pollution reduction weakens the positive impact of perceived air quality on reported happiness and the negative impact of objective air pollution on happiness. (3) When considering the effects of both subjective and objective air measurements, this study found that subjective evaluation seems more important in affecting individual happiness than the objective one as the degree of social engagement rises. (4) In the robustness checks section, this study verified the effect of subjective air quality on individual happiness using an IV estimation technique and the moderating effect of social engagement. Furthermore, in terms of other robustness checks, we tried to use alternative happiness data, water pollution data, to remove extreme values, and to use aggregated data. All these did not affect the fundamental conclusion of this study, namely that air pollution affects subjective air perception, and the increase of social engagement in reducing pollution weakens this effect. (5) In the heterogeneity analysis, we found that urban, affluent, and older individuals are more concerned about air pollution. We also found that the poor group is more affected than the other income groups by the moderating role of social engagement.

In light of these findings, this study offers the following policy implications. First, our analysis suggests that the government should be aware of the greater impact of the subjective evaluation of air quality on residents when addressing the sources of pollution (i.e., optimizing objective air quality). The government should make "improving residents' perceived air quality" part of its policy objectives and influence residents' subjective air quality perception from the publicity side, such as by publicizing the results of air quality improvement in the local media, producing and publishing regular reports on the progress of renewable energy development or carbon neutrality. This would enable achieving the two-pronged effect of "objectively combating air pollution" and "subjectively controlling the impact of air pollution on residents' happiness" in a timely manner.

Second, in the process of guiding all classes toward equality, the government should pay attention to the happiness of poor groups and implement economic measures such as reducing income disparity and encouraging transfer payments. This is because the poor are more vulnerable and mostly engaged in outdoor physical activities. As such, they cannot enjoy better air quality by purchasing air purifiers or relocating. The results of this study show that the happiness of the poor is most affected by air quality without considering the interaction term. However, after considering the moderating effect of social engagement, the poor are least affected. Thus, the government should change the consumption concepts and consumption patterns of low-income groups, advocate green consumption and minimum consumption of resources, and involve them in environmental improvement efforts to increase their sense of participation and well-being. Also, the government should vigorously develop renewable energy sources, and increase the proportion of renewable energy generation on the premise of ensuring power security and stability, so as to reduce the loss of happiness suffered by the poor because of bad weather, and to achieve equality in happiness for the poor and rich.

Third, the government should realize that the development of renewable energy will not only drive the development of related industries and achieve green and clean energy such as achieving the grid parity of wind power or solar PV power (Tu et al. 2020), but will also play a moderating/weakening role in the impact of air quality on individual well-being. In times of poor air quality, the government should incorporate the positive externalities brought by renewable energy development into the cost–benefit analysis when setting renewable energy related targets. In addition, the government should be aware that when objective air quality is improved, the corresponding increase in well-being will be limited because of the moderating role of social engagement. Thus, governments need to improve individuals' happiness through other channels. In short, each country should reasonably formulate its own policies in accordance with its own levels of air pollution and social engagement to achieve the policy goals of combating air pollution, improving national happiness, and promoting the economic and spiritual equality of different classes.

This study has some limitations. First, identifying the cause-and-effect relationship between pollution and happiness is extremely difficult for three major reasons (omitted variable, self-selection, and habituation; Levinson 2018) and others such as reverse causality or measurement errors. For instance, in relation to the omitted variable issue, common factors could exist that affect both air quality and personal well-being, such as the different institutional backgrounds of each country, noise pollution, light pollution, and other potential variables omitted from the model. Regarding the issue of self-selection, while most people in Europe and the USA may be able to receive and respond to questionnaires, the GWP may only survey people with a high income and education level in poorer countries, excluding those living at the bottom of the social ladder. This would lead to a potential survivorship/sample bias. Second, the proxy variable for social engagement among governments, business firms, and individuals is not perfect. Other proxies (e.g., environmental regulation intensity, corporate social responsibility) can be more reasonable in terms of the "social engagement" metric. These could be all possible avenues for future research.

Appendix

Please see Table 6
Please see Table 7
Please see Table 8

Table 6 Pollution-happiness-related studies

Author(s)	Target area	Sample period	SWB (data source)	Pollution	Method	Pollution-happiness nexus	Potential advantage	Potential disadvantage
Welsch (2006)	Worldwide	1995	Individual-level data (World Database of Happiness)	Measured pollution (SO_2, NO_2, Phosphorus, Suspended solids)	OLS	Insignificant	Several pollutants considered	1. Country- or region- fixed effects not controlled; 2. endogeneity issue ignored; 3. perceived air measure not considered
Welsch (2006)	10 European countries	1990–1997	Averaged happiness at the country level (World Database of Happiness)	Measured pollution (NO_2, TSP, lead concentration)	GLS; FE	Negative	1. Several pollutants considered; 2. panel data used to control for unobservable heterogeneity	1. Country level instead of individual-level happiness used; 2 endogeneity issue ignored; 3. perceived air measure not considered
Ferrer-i-Carbonell and Gowdy (2007)	UK	1996	Individual-level data (the British Individual Panel Survey)	Perceived pollution	OP	Negative	Environmental awareness (ozone pollution) considered	1. Targeting only on the UK; 2. country- or region- fixed effects not controlled; 3. endogeneity issue ignored; 4. measured air measure not considered
Di Tella and MacCulloch (2008)	Europe and USA	1975–1997	Individual-level data (Euro-Barometer Survey Series & the United States General Social Survey)	Measured pollution (SO_x emissions)	OP	Negative	1. Large sample size (350,000) used; 2. country- and year- fixed effects controlled	1. Perceived air measure not considered; 2. endogeneity due to reverse causality ignored
Rehdanz and Maddison (2008)	Germany	1994, 1999, 2004	Individual-level data (German Socio-Economic Panel survey)	Perceived pollution	OP	Negative	1. Repeated cross-sectional survey data used; 2. noise pollution considered	1. Targeting only on Germany; 2. endogeneity issue ignored; 3. perceived air measure not considered
Smyth et al. (2008)	30 cities in China	2003	Individual-level data (China Mainland Marketing Research Company (CMMRC))	Measured pollution (SO_2)	OP	Insignificant	Study restricted to a developing country like China	1. Targeting only on urban China; 2. endogeneity issue ignored; 3. perceived and objective air measure not distinguished
Luechinger (2009)	Germany	1985–2003	Individual-level data (German Socio-Economic Panel)	Measured pollution (SO_2)	OLS; FE; IV	Negative	1. IV method is applied to avoid the potential source of bias; 2. high-resolution pollution data used to minimize possible measurement errors; 3. panel data at the individual level used to control for individual heterogeneity	
MacKerron and Mourato (2009)	London	2007	Individual-level data (Web survey)	Perceived pollution; Measured pollution	OLS; OP/OL	Negative	1. Both perceived and measured air pollution considered; 2. several regression methods implemented	1 sample observations of only 400 Londoners; 2. endogeneity issue ignored
Menz and Welsch (2010)	25 OECD countries	1990, 1995, 2000–2004	Individual-level data (World Database of Happiness)	Measured pollution (PM10)	OLS; FE	Negative	1. How the preferences for air quality (PM10 concentrations) are affected by population aging is examined; 2. panel method used	1. Aggregation bias: using aggregated/national level pollution data; 2. endogeneity issue ignored

Table 6 (continued)

Author(s)	Target area	Sample period	SWB (data source)	Pollution	Method	Pollution-happiness nexus	Potential advantage	Potential disadvantage
Levinson (2012)	The USA	1984–1996	Individual-level data (General Social Survey)	Measured pollution	OLS; OP; FE	Negative	1. Estimated the economic benefit of a local public good by combining yearly survey data with air quality and weather information (hourly and daily data from monitors) to model individuals' self-reported levels of happiness, as a function of their demographic characteristics; 2. find evidence of a substantial trade-off between income and environmental quality	
Cuñado and Pérez de Gracia (2013)	Spain	2008	Individual-level data (European Social Survey)	Measured pollution (CO_2 NO_2 PM10)	OLS; OP	Negative	1. The first paper using Spanish regional data on self-reported happiness and climate and air pollution indicators; 2. estimated the monetary valuation of non-market goods such as climate or air pollution variables for the Spanish regions	1. Analysis is limited to Spain only; 2. the use of regional variables might be too aggregated; 3. it did not consider some possible interactions of air quality indicators with other variables like age (e.g., Menz and Welsch, 2010) or social engagements (e.g., this study)
Ferreira et al. (2013)	Europe	2002–2007	Individual-level data (European Social Survey)	Measured pollution (SO_2)	OLS; OL/OP	Negative	The first multi-country analysis that uses disaggregated/regional data on SO2 to explain individual SWB in Europe	1. Analysis only considers SO_2, it may not extend to other, more local, air pollutants; 2. endogeneity issue ignored
Li et al. (2014)	Jinchuan mining area in China	2012	Individual-level data (Survey in Jinchuan)	Perceived pollution	SEM	Negative	Both subjective and objective risks are considered as a determinant of happiness	1. A small sample of 759 Individuals surveyed; 2. considered only air pollution, while ignoring water pollution and solid waste in the Jinchuan mining area in China; 3. endogeneity issue ignored
Liao et al. (2015)	Taiwan	2010	Individual-level data (Taiwan Social Change Survey)	Perceived pollution (TSCS) Measured pollution (PSI: PM10, O_3, SO_2, NO_2, CO)	Probit	Negative (PP); Insignificant (MP)	1. Considered both subjective and objective measures of air quality; 2. considered the endogeneity issue of subjective air quality	1. Focusing only on Taiwan area; 2. using objective measure as instrument for subjective measure may not be proper as both measures are expected to directly affect SWB
Dolan and Laffan (2016)	UK	2012–2013	Individual-level data	Measured pollution (PM2.5)	OLS	Negative	1. Usage of a large sample (165,000 individuals in the UK); 2. consideration of different measures of SWB	1. Analysis only represents a snap shot at one time period of the nexus between local air pollution and SWB; 2. endogeneity issue ignored; 3. perceived and objective air measure not distinguished

Table 6 (continued)

Author(s)	Target area	Sample period	SWB (data source)	Pollution	Method	Pollution-happiness nexus	Potential advantage	Potential disadvantage
Zhang et al. (2017a, b)	China	2010, 2012, 2014	Individual-level data (CFPS panel survey)	Measured pollution (API: SO2, NO2, PM10)	FE	Negative	1. Panel data used; 2. examined the impact of air pollution on several key dimensions, including mental health status, depressive symptoms, moment-to-moment happiness, and evaluative happiness; 3. evaluated the willingness to pay for better air quality	
Taşkaya (2018)	Turkey	2015	Individual-level data	Measured pollution (PM10)	Hierarchical multiple regression model	Insignificant	Noise pollution considered	1. Using secondary, possible misleading data; 2. Suffering from omitted variable bias problem as important values such as clean water accessibility are not included; 3. endogeneity issue ignored
Rok (2020)	Targówek district, Warsaw, Poland	2019	Individual-level data (CATI panel survey)	Measured pollution (PM2.5); Perceived pollution	OL + IV	Negative	1. Various SWB measures used; 2. both subjective and objective air pollutions used; 3. examined the relationship between short-term perceived/objective air pollution on SWB	1. Used a small number of repetitions of the CATI survey (125 respondents over 3 rounds in April, 2019), which may undermine the validity of matching SWB with air pollution levels due to unobserved, time-variant confounding factors
Tsurumi and Managi (2020)	India, China, and Japan	2015, 2016	Individual-level data (Internet surveys)	Measured pollution (PM2.5)	SEM	Insignificant (India, China); Negative (Japan)	Made a comparison of countries with different levels of economic development in terms of the health-related effects and non-health-related effects of PM2.5 concentrations on life satisfaction	1. Only three countries considered, results may not be representative and generalizable; 2. subjective pollution measure ignored; 3. endogeneity ignored
Emmerling et al. (2021)	Worldwide	2005–2018	Individual-level data (Gallup World Poll)	Measured pollution (volatile organic compounds)	OLS; MLE; variance decomposition	Negative	1. Many determinants examined; 2. variance decomposition is done to explore the contribution of either cross-country differences or individual-specific factors to the variation of SWB	1. Analysis may suffer from omitted variable bias due to omissions of social factors and some part of the climate impacts; 2. endogeneity ignored
Liu et al. (2021)	Shandong province, China	2017	Individual-level data (Survey from Shandong University)	Measured pollution (PM2.5, PM10, SO_2)	OLS	Negative and heterogeneous effect	1. The effect of different duration of air pollution exposure on subjective well-being is investigated; 2. hourly updated air pollution data used. These are rarely seen in previous studies	1 Target at one province in China; 2. endogeneity issue such as sample selection bias (telephone-survey conducted during Nov. and Dec. of 2017) and reverse-causality bias
Petrowski et al. (2021)	Germany	2006	Individual-level data (USUMA, Berlin Polling Institute)	Measured pollution (PM10)	OLS	Negative	Large representative data collection, including subjective psychological parameters, which was matched with reliable pollution data (PM10)	1. Cross-sectional data, representing one moment in time, long term effects cannot be drawn; 2. perceived air pollution ignored; 3. endogeneity issue ignored

FE, fixed effects; *GLS*, generalized least squares; *IV*, instrumental variable; *MLE*, maximum likelihood estimation; *OL*, ordered logit; *OLS*, ordinary least squares; *OP*, ordered probit; *SEM*, structural equation model

Table 7 List of sample countries

Country	Obs	Country	Obs	Country	Obs	Country	Obs
AFG	13,010	DNK	13,780	KOR	15,116	PRY	13,001
AGO	4000	DOM	13,000	KWT	15,027	QAT	7060
ALB	12,069	DZA	9047	LAO	8505	ROU	12,033
ARE	19,652	ECU	13,135	LBN	17,053	RUS	30,021
ARG	13,000	EGY	22,924	LBR	10,000	RWA	11,504
ARM	13,000	ESP	15,031	LBY	5020	SAU	18,437
AUS	13,236	EST	11,234	LKA	13,461	SDN	7592
AUT	13,010	ETH	8004	LTU	12,029	SEN	13,000
AZE	13,000	FIN	11,766	LVA	11,097	SGP	13,652
BDI	5000	FRA	14,989	MAR	11,079	SLV	13,008
BEL	13,092	GAB	8016	MDA	13,000	SOM	3191
BEN	10,000	GBR	35,651	MDG	10,016	SRB	11,016
BFA	12,008	GEO	13,080	MDV	1000	SUR	504
BGD	15,248	GHA	13,008	MEX	14,088	SVK	10,048
BGR	11,010	GIN	8008	MKD	12,193	SVN	11,535
BHR	13,255	GMB	2000	MLI	12,000	SWE	13,763
BIH	13,038	GRC	12,005	MLT	10,064	SYR	11,452
BLR	13,701	GTM	13,050	MMR	7700	TCD	13,000
BLZ	1006	GUY	501	MNG	11,000	TGO	8000
BOL	13,003	HND	13,004	MOZ	7000	THA	14,473
BRA	14,235	HRV	12,068	MRT	14,992	TJK	15,000
BTN	3040	HTI	5537	MUS	5000	TKM	9000
CAN	15,491	HUN	12,091	MWI	11,000	TTO	2522
CAR	5000	IDN	15,390	MYS	12,266	TUN	13,290
CHE	8514	IND	50,434	NER	13,016	TUR	15,006
CHL	13,287	IRL	12,502	NGA	14,002	TZK	13,016
CHN	59,704	IRN	14,866	NIC	13,016	UGA	13,000
CMR	13,200	IRQ	16,024	NLD	12,760	UKR	13,323
COD	8000	ISL	3631	NOR	10,010	URY	13,022
COG	9000	ISR	13,014	NPL	14,107	USA	15,461
COL	13,000	ITA	15,039	NZL	11,800	UZB	12,000
COM	8000	JAM	2561	OMN	2016	VEN	13,000
CRI	13,010	JOR	17,053	PAK	19,751	VNM	14,135
CUB	1000	JPN	17,168	PAN	13,028	YEM	15,000
CYP	10,581	KAZ	13,000	PER	13,000	ZAF	14,001
CZE	12,169	KEN	14,200	PHL	14,200	ZMB	12,001
DEU	39,394	KGZ	13,000	POL	13,029	ZWE	13,000
DJI	5000	KHM	13,624	PRT	13,065		

Full name of each country is available at https://unstats.un.org/unsd/tradekb/Knowledgebase/Country-Code

Table 8 Correlation coefficients

	Air	PM2.5	Social	Gender	Age	Marital	Urban	Edu	Income	Internet	Health
Air	1										
PM2.5	–0.03	1									
Social	0.11	0.18	1								
Gender	0.02	0.07	0.02	1							
Age	0.02	–0.26	–0.12	–0.02	1						
Marital	0.02	0.06	–0.02	0.02	0.26	1					
Urban	–0.19	–0.09	–0.23	–0.01	0.02	–0.06	1				
Edu	–0.08	–0.26	–0.28	0.04	–0.05	–0.04	0.24	1			
Income	–0.04	0.01	0	0.06	0.02	–0.04	0.18	0.24	1		
Internet	–0.06	–0.38	–0.34	0.01	0.01	–0.01	0.25	0.43	0.16	1	
Health	0.02	0	–0.02	0.05	–0.27	–0.01	0.05	0.14	0.08	0.13	1

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Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare no competing interests.

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