Air pollution, residents’ happiness, and environmental regulation: evidence from China

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Abstract
This study investigates the impact of air pollution on residents’ subjective happiness, using data from the China General Social Survey for 2013, 2015, and 2017, regional air pollution, and socioeconomic indicators. We find that air pollution has a negative effect on residents’ subjective happiness. Specifically, the average marginal effect of the logarithm of SO2 emissions on happiness is $-0.0099$ and significant at the 1% level; namely, a one-unit increase in lnSO2 will reduce the likelihood of residents feeling happy by 0.99%. This negative effect is greater for those who have children, are old, or have a higher level of education. We also empirically test two mechanisms by which air pollution affects subjective happiness—depressed mood and leisure activities outside the home—and demonstrate that environmental regulation can moderate the negative impact of air pollution on happiness, but the moderating effects are nonlinear. Environmental governance investments are more effective at the low level, pollutant discharge fees are more effective at the medium level, and complaints about environmental pollution are more effective at the high level. As well as enriching theoretical insights into the relationship between air pollution and happiness, this study provides a valuable reference for developing more suitable policies in relation to environmental management and national happiness.

Keywords Air pollution · Residents’ happiness · Depressed mood · Leisure activity · Environmental regulation

Introduction
Since the reform and opening-up in 1978, China’s rapid economic development has to a great extent satisfied people’s material needs, but it has also created serious air pollution (Li et al. 2016). In 2013, severe haze pollution was observed in more than 100 cities across the country (Huang et al. 2014). In 2015, China’s air quality score ranked second to last internationally, according to the Environmental Performance Index, a 2016 report published by Yale University. Serious air pollution may adversely affect people’s happiness, and a decrease in happiness is harmful to residents’ health (Diener and Chan 2011), social productivity (Oswald et al. 2015), and social harmony (Clark 2018), so the issue related to air pollution and happiness has aroused widespread concern. A growing body of literature has documented the negative effects of air pollution on residents’ happiness (Ferreira et al. 2013; Li et al. 2014; Zhang et al. 2017; Yuan et al. 2018; Song et al. 2020a, b; Liu and Hu 2021). However, research gaps remain. For example, what are the heterogeneous effects of air pollution on the happiness of different groups? What are the mechanisms by which air pollution affects happiness? Can environmental regulation alleviate the negative effect of air pollution on happiness? Existing studies do not provide adequate answers to these questions, a shortcoming that this study attempts to address. By matching individual data from the China General Social Survey (CGSS) with regional air pollution data, we explore the heterogeneous impact of air pollution on happiness. We address endogeneity problems and carry out a series of robustness tests. We also empirically test two
mechanisms by which air pollution affects happiness, and examine how environmental regulation can moderate the impact of air pollution on happiness.

This study makes three contributions to the literature. First, it enhances and enriches understanding of the relationship between air pollution and residents’ happiness by providing micro-level evidence from China. Despite the growing body of studies documenting the negative impact of air pollution on residents’ happiness (Ferreira et al. 2013; Li et al. 2014; Zhang et al. 2017; Yuan et al. 2018; Song et al. 2020a, b; Liu and Hu 2021), further research is needed to strengthen the generalizability of previous results, which is limited by a focus on early data analysis, reliance on one cross-sectional analysis, and use of only one kind of proxy variable for air pollution. Additionally, the robustness tests and heterogeneous analysis in previous studies are inadequate; in some cases, the results of the heterogeneous analysis are not even consistent. Accordingly, this study conducts a multi-period data analysis using 2013, 2015, and 2017 CGSS data, and performs a series of detailed robustness tests: addressing endogeneity problems, changing the measure of happiness, replacing air pollution indicators, and using alternative models and regional clustering standard errors. In addition to exploring the heterogeneous effects of air pollution on happiness in relation to age and education, we investigate the differences between those who have children and those who do not, a factor that has not been studied in previous research.

Second, this study empirically investigates two mechanisms by which air pollution affects happiness. Recent research has explored the mechanisms of physical health (Yuan et al. 2018), self-rated health (Li and Zhou 2020), residents’ perceptions of pollution (Chen et al. 2020), and quality of life (Ma et al. 2019) in the relationship between air pollution and happiness. However, these mechanisms are not sufficient. We address this gap by empirically testing two further mechanisms: depressed mood and leisure activities outside the home.

Third, this study investigates the moderating role of three types of environmental regulation in the relationship between air pollution and residents’ happiness. This is a novel point that has been neglected in previous studies. We find one related study, focusing on the alleviating effect of air pollution taxes on the relationship between air pollution and residents’ happiness (Liu et al. 2019), but other types of environmental regulations have to date been ignored. Accordingly, this study evaluates whether three common types of environmental regulation (command-and-control, market-based, and voluntary) can alleviate the impact of air pollution on happiness.

The remainder of the paper is organized as follows. “Literature review” reviews the relevant literature. “Theory and hypotheses” sets out the theoretical analysis and assumptions, and “Research design” describes the data, variables, and models. “Empirical results” presents the empirical results and “Conclusions” the conclusions.

Literature review

Since Easterlin (1974) formulated the Easterlin paradox, namely that happiness does not increase synchronously with rapid economic growth, researchers have acknowledged the many non-economic factors that play an important role in residents’ happiness, including demographic characteristics (MacKerron 2012), social relations and social structure (Hallier and Hadler 2006), the political and institutional environment (Alvarez-Diaz et al. 2010), and the natural environment (Zhang et al. 2017; Cuñado and De Gracia 2013). On this basis, more and more scholars have included environmental quality in their economic studies of happiness, and the impact of air pollution has received particularly extensive research attention at both the macro- and micro-levels. Here, we summarize three important aspects that have emerged from micro-level studies on the relationship between air pollution and residents’ happiness.

First, the effects of air pollution on happiness (or well-being) have been documented extensively. Many studies have verified the negative impact of air pollution on residents’ happiness in multiple countries, including American (Levinson 2012) and European countries (Welsch 2006; Ferreira et al. 2013) and China (Huang and He 2013; Yang and Zhang 2014; Li 2015; Yuan et al. 2018; Shi and Yu 2020; Song et al. 2020a, b; Ye and Zhang 2020; Liu and Hu 2021). However, there remain deficiencies in understanding of the relationship between air pollution and happiness in China, in particular, owing to a focus on early data analysis, reliance on one cross-sectional analysis, and limited use of proxy variables for air pollution. Robustness tests and heterogeneity effect analysis have also been inadequate, to the extent that the results are in some cases not even consistent.

Second, given the direct impact of air pollution on residents’ happiness, scholars are paying increasing attention to the mechanisms by which air pollution affects happiness. Multiple mechanisms have been investigated, including mental health (Zhang et al. 2017), physical health (Yuan et al. 2018), quality of life (Li 2015; Ma et al. 2019), self-rated health (Li and Zhou 2020), and perceptions of pollution (Chen et al. 2020). However, these studies do not take into account other potential mechanisms, such as depressed mood and leisure activities outside the home.

Third, few studies have considered environmental regulation in the context of air pollution and happiness. We find only two relevant studies. Liu et al. (2019) showed that environmental taxes can alleviate the negative impact of environmental pollution on residents’ happiness. However, it is
not clear from their results whether other types of regulation can have a similar effect. Guo et al. (2020) explored the direct impact of environmental regulation on happiness, and found that three types of regulations (command-and-control, market-based, and voluntary) can all effectively increase happiness through green technology innovation. However, they restricted their attention to direct effects, neglecting the indirect effects that may moderate the negative impact of air pollution on happiness. To address these research gaps, the present study explores the moderating effect of multiple types of environmental regulations on the relationship between air pollution and happiness.

Theory and hypotheses

This study uses the theory of needs (Maslow 1943) to clarify the impact of air pollution on residents’ subjective happiness. Subjective happiness is essentially an emotion or cognition, and one of its important sources is individual needs (Li and Shi 2017). Therefore, subjective happiness can be regarded as an emotional response to or cognitive evaluation of the satisfaction of needs. When needs are satisfied, happiness can increase directly. Human needs are multi-level and diverse, and Maslow (1943) categorized them into five levels, from low to high: physiological needs, safety needs, love and belonging needs, esteem needs, and self-actualization needs. Polluted air can cause serious physical harm or disease (Chen and Kan 2008; Matus et al. 2012), making it impossible to satisfy the need to maintain physical health and thereby resulting in unhappiness. In light of these considerations, we propose the following hypothesis:

**H1:** Air pollution may have a negative impact on happiness.

This study considers two mechanisms by which air pollution may affect residents’ subjective happiness. In the first mechanism, air pollution causes depressed mood. It has been suggested that exposure to ambient air pollution increases the risk of depressive symptoms. A study of women in the USA reported that both long- and short-term exposure to air pollution are related to symptoms of anxiety (Power et al. 2015), a condition that is often comorbid with depression (Lamers et al. 2011). Short-term studies in Korea have found that air pollution is associated with an increased risk of suicide (Kim et al. 2010a, b) and depressive symptoms (Lim et al. 2012). Increases in ambient air pollution have been associated with emergency department visits for depression in Korea (Cho et al. 2014) and in Canada (Szyszkowicz et al. 2009). These mental health risks are likely to reduce residents’ happiness.

In the second mechanism, air pollution decreases leisure activities outside the home. According to the stress reduction theory (Ulrich 1983) and attention restoration theory (Kaplan and Kaplan 1989), the visual features of natural environments relieve the tension, tiredness, and everyday stress that can lead to unhappiness (Chang et al. 2019). Adequate leisure activities outside the home facilitate fuller contact with the natural environment and thus may alleviate a reduction in residents’ happiness. However, leisure activities outside the home may also pose health risks through exposure to air pollution, and people may reduce their activities to avoid these risks (Noonan 2014). The resulting decrease in direct contact with the natural environment may lead to unhappiness.

On the basis of this analysis, we propose our second hypothesis:

**H2:** Depressed mood and decreased leisure activities outside the home are two mechanisms by which air pollution reduces residents’ happiness.

If hypothesis H1 holds (that is, if air pollution affects subjective happiness), then environmental regulation has an important role to play in the relationship between air pollution and subjective happiness. Environmental regulations are designed to achieve a balance between protecting the environment and encouraging the development of the economy. According to the means of governance used, environmental regulation can be categorized into three types: command-and-control, market-based, and voluntary (Liu et al. 2018; He 2019; Li and Ramanathan 2018; Guo et al. 2020). The different types of environmental regulation have different functions.

Moderate command-and-control environmental regulations, such as environmental laws and government investment in environmental governance, are conducive to reducing pollutant emissions and energy consumption and improving the quality of the environment (Song et al. 2020a, b). Market-based environmental regulations, such as pollution charges, can also help to reduce pollutant emissions and improve regional ecological efficiency (Ren et al. 2018). Thus, environmental regulations of these types may moderate the negative effects of air pollution on happiness by improving air quality. Clean air can also be regarded as an environmental public good that is closely associated with residents’ subjective happiness (Frey and Stutzer 2010).

Voluntary environmental regulations, which mainly take the form of public environmental awareness and participation (Wesselink et al. 2011), can strengthen the intensity and scope of the implementation of other measures. When members of the public are aware of environmental pollution, they begin to contribute spontaneously to environmental protection, steering society to pay
more attention to environmental problems and to strive to improve the quality of the environment in a range of ways. In particular, the public can urge enterprises and governments to implement and monitor environmental laws and regulations. As environmental problems and public awareness increase, public supervision has an increasingly strong impact on the quality of the environment (Zhang et al. 2008). When groups of people have positive expectations of improving the quality of the environment and participate actively in environmental protection, they are more likely to feel happy (Blinder and Blankenberg 2016; Suarez-Varela et al. 2016).

Although environmental regulations can help to alleviate the negative effect of air pollution on happiness, they may also have effects that are less beneficial. Strict environmental laws and regulations may slow economic growth to an unacceptable degree, significant investment in environmental governance may encroach on other public expenditures, and onerous environmental charges may reduce overall efficiency. Moreover, while participating in environmental protection supervision and management, the public is likely to experience dissatisfaction with environmental management (Shi and Guo 2019), as well as anxiety caused by paying too much attention to environmental problems (Kaida and Kaida 2016; Charfeddine et al. 2018). These factors may also affect people’s subjective happiness. In line with this analysis, we propose our final hypothesis:

**H3**: Environmental regulation can alleviate the negative effect of air pollution on happiness, and the moderating effect may be nonlinear.

The theoretical analysis framework of this study is shown in Fig. 1.

**Fig. 1** The theoretical analysis framework

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**Research design**

**Data**

The individual-level data are taken from the CGSS for 2013, 2015, and 2017. The CGSS is a nationwide authoritative survey conducted by the National Survey Research Center at Renmin University of China. The survey has a targeted sample of 12,000 respondents. It uses a multi-stage, stratified, and scale-proportional PPS (probability proportional to size) method to select the participating households, and its sampling frame covers all provinces in mainland China. The primary sampling units are 100 counties or districts and five metropolises, yielding a total of 480 village or neighborhood committees. The survey uses the equal probability method to select 30 households from each village or neighborhood committee, and then to select at random one member aged 18 or above from each of those households. Thus, the CGSS collects rich individual information and is suitable for the study of happiness-related issues.

The regional-level data have three components. First, the data related to provincial pollutant emissions and socioeconomic characteristics (SO2 emissions, economic development, medical conditions, and the unemployment rate) are taken from the China Statistical Yearbook for 2013, 2015, and 2017. Second, the data for the three types of environmental regulations at the provincial-level are taken from the
China Environmental Statistics Yearbook (for the command-and-control and market-based types) and the Ministry of Ecology and Environment of the People’s Republic of China (for the voluntary type).

Third, the data for air quality, as measured in air quality indicators (AQI) and PM$_{2.5}$ concentration levels, are taken from the Air Quality Online Monitoring and Analysis Platform, which provides historical monthly average air pollution data for 367 cities from 2013 onward and covers all cities in mainland China at prefecture level and above. We aggregate the city-level air quality records spatially to obtain provincial-level average values for AQI and PM$_{2.5}$ concentration levels.

For the purposes of this study, the individual-level data of CGSS and the regional-level data are matched by province name and year. Observations with missing or abnormal data are removed, and the final dataset consists of 30,745 observations.

**Variables**

The dependent variable in this study is residents’ subjective happiness, measured by the responses to item 36 of the CGSS questionnaire: “Overall, do you think your life is happy?” (permitted responses: “very unhappy,” “relatively unhappy,” “unclear,” “relatively happy,” and “very happy”). Following Chen et al. (2020), we categorize the responses using a binary variable that takes the value 1 if the respondent chose “relatively happy” or “very happy” and 0 otherwise.

The core independent variable is air pollution. PM$_{2.5}$ is a major contaminant that causes air pollution (Yue et al. 2021), has a small particle size, and can penetrate into the alveoli and fine bronchial tissue, causing serious damage to the human body in cases of long-term exposure at high levels (Tanaka 2015; Cesur et al. 2016; Zhang and Mu 2018). SO$_2$ emissions are the main cause of increases in PM$_{2.5}$ (Yang et al. 2019), and they cause greater irritation to human tissue (Jiang et al. 2019). Therefore, this study uses SO$_2$ emissions as a proxy for air pollution levels. A map of the spatial distribution of SO$_2$ emissions in 2017 is given in the Appendix (Fig. 2). Specifically, the SO$_2$ emissions in the Bohai Rim, provinces north of Shanxi, Jiangsu province on the eastern coast, and Guizhou province tend to be higher than in the rest of China.

Drawing on previous studies (Chen et al. 2020; Jin et al. 2020; Yuan et al. 2018; Li and Fan 2016), we control two categories of factors that influence happiness: individual-level characteristics and provincial-level socioeconomic characteristics. The individual-level characteristics are age, gender, self-rated health, having/not having children, marital status, social security, and income. The provincial-level socioeconomic characteristics are economic development, medical conditions, and the rate of unemployment. The proxy variables for these characteristics are given in Table 1.

The mechanisms tested in this study are depressed mood and leisure activities outside the home. Depressed mood is measured using responses to the questionnaire item in CGSS “How often did you feel depressed in the past four weeks?” Responses are given on a Likert scale ranging from 1 (always) to 5 (never), such that a higher value denotes less depressed mood. Three types of leisure activities outside the home (watching movies, shopping, and exercising) are measured using responses to the corresponding questionnaire item in CGSS: “In the past year, did you often engage in watching a movie, shopping or exercising in your spare time?” Responses are given on a Likert scale ranging from 1 (never) to 5 (every day), such that a higher value denotes a higher frequency of leisure activities.

This study includes three types of environmental regulations: command-and-control, market-based, and voluntary. In line with previous studies (He 2019; Li and Ramanathan 2018; Guo et al. 2020) and the availability of data, we take the proportion of government environmental investment in GDP, pollutant discharge fees, and the number of complaints about environmental pollution, respectively, to measure the intensity of each type of environmental regulation.

The descriptions of the variables are given in Table 1.

**Models**

**Baseline model**

To estimate the impact of air pollution on residents’ subjective happiness, we establish the following baseline model:

\[
\text{Happiness}_{ijt} = \alpha_0 + \beta_0 \cdot \ln \text{SO}_{2_{ijt}} + \gamma_0 \cdot X_{ijt} + \eta_0 \cdot YD_{it} + \varepsilon_{ijt} \quad (1)
\]

where Happiness$_{ijt}$ represents the happiness of resident i in province j in year t, lnSO$_{2_{ijt}}$ is the level of SO$_2$ emissions (reflecting the level of air pollution of a province), and X$_{ijt}$ is the vector of both the individual-level and provincial-level variables. The individual-level variables are Age, Age$^2$, Gender, Health, Children, Marriage, Socialsecurity, and lnIncome. The provincial-level variables are ln(GDP)$^3$, Hospitalbed, and Unemployment. All the variables in Eq. (1) are

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1 Ministry of Ecology and Environment of the People’s Republic of China: http://www.mee.gov.cn/hdj/.
2 Air Quality Online Monitoring and Analysis Platform: https://www.aqistudy.cn/historydata/.
3 There is a high correlation between ln(GDP) and lnSO$_2$. To avoid estimation bias caused by collinearity, we regress ln(GDP) on lnSO$_2$ and take the residual term as the proxy variable of economic development, according to Mei et al. (2020).
described in Table 1. $YD$ is a vector of 2-year dummy variables to control for time differences, and $\epsilon_{ijt}$ is the error term. As the dependent variable $Happiness_{ijt}$ is a binary dummy variable, we use a probit model to estimate Eq. (1).

**Mechanism analysis model**

To test the mechanisms (depressed mood and leisure activities outside the home) by which air pollution affects residents’ happiness, we use the following model:

$$\text{Mechanism}_{ijt} = \pi_1 + \pi_2 \cdot \ln SO_2 + \pi_3 \cdot X_{ijt} + \pi_4 YD_t + \epsilon_{ijt}$$  \hspace{1cm} (2)

where $\ln SO_2$, $X$, $YD_t$, and $\epsilon$ are as in Eq. (1). Mechanism represents depressed mood or three types of leisure activities outside the home (watching movie, shopping, and exercising). As the explained variable in Eq. (2) is multi-classified, we use an ordered probit model for regression estimation.

**Moderating effect model**

To explore the moderating effect of environmental regulations in alleviating the impact of air pollution on happiness, this study includes the interaction term for environmental regulation and air pollution in Eq. (1):

$$Happiness_{ijt} = \alpha_1 + \beta_1 \cdot \ln SO_2 + \gamma_2 \cdot X_{ijt} + \eta_2 YD_t + \phi \cdot \text{Mod}_{ijt} + \varphi \cdot \ln SO_2 \cdot \text{Mod}_{ijt} + \epsilon_{ijt}$$  \hspace{1cm} (3)

where $\text{Mod}$ denotes three types of environmental regulations (command-and-control, market-based, or voluntary); $\ln SO_2, X, YD_t$, and $\epsilon$ are as in Eq. (1). If the estimated value of $\varphi$ is positive and statistically significant, environmental regulation is shown to alleviate the impact of air pollution on happiness. As with Eq. (1), we use a probit model to estimate Eq. (3).

**Empirical results**

**Baseline analysis**

We use a probit model to estimate Eq. (1), and we give the estimated results in Table 2. We control for the individual-level, provincial-level, and year dummy variables stepwise, and we list the estimated coefficients in columns (1) to (3),

| Variable | Description | Mean | S.D. |
|----------|-------------|------|------|
| Dependent | $Happiness$ | Happiness status (1 = very happy or relatively happy, 0 = otherwise) | 0.76 | 0.42 |
| Independent | $\ln SO_2$ | Logarithm of SO$_2$ emissions of a province | 3.71 | 0.87 |
| Control | Individual-level | Age | Age | 55.26 | 16.47 |
| | | $Age^2$ | Square of age | 3324.55 | 1855.14 |
| | | Gender | 1 = male, 0 = female | 0.49 | 0.50 |
| | | Health | Self-rated health (1 = health, 0 = otherwise) | 0.88 | 0.33 |
| | | Children | 1 = has at least one child, otherwise = 0 | 0.78 | 0.41 |
| | | Marriage | 1 = married, otherwise = 0 | 0.94 | 0.23 |
| | | Socialsecurity | 1 = participates in at least one type of social security, otherwise = 0 | 0.94 | 0.23 |
| | lnIncome | Logarithm of income | 8.38 | 3.62 |
| Provincial-level | $\ln GDP$ | Logarithm of province’s GDP | 10.81 | 0.41 |
| | Hospitalbed | Number of hospital beds per 10,000 people in province | 51.61 | 7.51 |
| | Unemployment | Rate of unemployment | 3.25 | 0.65 |
| Mechanism | Depress | Range from 1 to 5, where a higher value denotes less depressed mood | 3.86 | 0.96 |
| | Movie | Range from 1 to 5, where a higher value denotes watching more movies | 1.45 | 0.73 |
| | Shopping | Range from 1 to 5, where a higher value denotes more shopping | 2.57 | 1.09 |
| | Exercising | Range from 1 to 5, where a higher value denotes more physical exercise | 2.35 | 1.53 |
| Moderator | Investment | Proportion of government environmental investment in province’s GDP | 1.39 | 0.65 |
| | lnFee | Logarithm of province’s pollutant discharge fees | 10.85 | 0.81 |
| | Complaint | Number of complaints about province’s environmental pollution$^1$ | 0.24 | 0.23 |

$^1$ In 2013, the complaint channel was the environmental protection report hotline. In 2015 a WeChat report option was added, and in 2017 an online report option was added. The statistics for the 3 years were not consistent or comparable, and therefore, the annual number of complaints was standardized.
respectively. We report the average marginal effects in columns (4) to (6). The regression coefficients on \( \text{lnSO}_2 \) are \(-0.0535, -0.0449, \) and \(-0.0330, \) respectively, significant at the 1% level. This shows that air pollution has a statistically significant negative effect on residents’ happiness, which is consistent with hypothesis H1 and with previous studies (Ferreira et al. 2013; Zhang et al. 2017; Li et al. 2014). This result also indicates that the negative effect of air pollution on happiness will be overestimated if provincial-level and time variables are not controlled for. We therefore focus on the coefficient on \( \text{lnSO}_2 \) in column (3) and its average marginal effect in column (6). The average marginal effect of \( \text{lnSO}_2 \) is \(-0.0099\), significant at the 1% level, which means that a one-unit increase in \( \text{lnSO}_2 \) will reduce the likelihood of residents feeling happy by 0.99%.

**Robustness tests**

**Endogeneity test**

Although we control for many factors in the baseline model, there remains a concern over potential endogeneity due to missing variables and measurement error. For example, people might have increased their expenditure on protective equipment, such as masks and air purifiers, to reduce their exposure to air pollution (Zhang and Mu 2018; Sun et al. 2017), and this could affect their happiness. It is highly likely that expenditure on protection from pollution is related to air pollution levels. However, due to lack of information, this expenditure is not included in the baseline model, which may therefore cause endogeneity and affect our estimation. In addition, as the provincial-level \( \text{SO}_2 \) emission levels are approximate, they may not accurately reflect residents’ perceptions of air pollution. Such measurement errors in air pollution level may lead to estimation bias.

To reduce any resulting bias caused by endogeneity, we use an instrumental variable (IV) and adopt a two-stage IV-probit model as follows:

\[
\text{lnSO}_{2it} = \theta_1 + \theta_2 \cdot \text{IV}_{it} + \theta_3 \cdot X_{it} + \theta_4 \cdot YD_t + \epsilon_{it} \quad (4)
\]

Happiness\(_{it} = \alpha_2 + \beta_2 \cdot \hat{\text{lnSO}}_{2it} + \gamma_2 \cdot X_{it} + \eta_2 \cdot YD_t + \epsilon_{it} \quad (5)
\]

where IV represents the instrumental variable. \( \hat{\text{lnSO}}_2 \) is the predicted value of \( \text{lnSO}_2 \) obtained in Eq. (4) and is used in the second stage as the core explanatory variable. Other variables are as in Eq. (1).

We use the logarithm of the average \( \text{SO}_2 \) emissions of the surrounding provinces, denoted by \( \text{ln}(\text{around}_\text{SO}_2) \), as the instrumental variable for a province’s \( \text{SO}_2 \) emissions. On the one hand, the \( \text{SO}_2 \) emissions of the surrounding provinces are determined mainly by the level of local industrial development, which implies a certain degree of exogeneity. On the other hand, according to the first law of geography (Tobler 1970), geographical items are related to each other in spatial distribution; owing to industrial agglomeration, the \( \text{SO}_2 \) emissions of a province may relate to the \( \text{SO}_2 \) emissions of its surrounding provinces. In short, the average \( \text{SO}_2 \) emission of the surrounding provinces is a valid instrumental variable that satisfies both the exogeneity and correlation assumptions. Accordingly, we use it to run a two-stage IV-probit model, and the estimated results for Eqs. (4) and (5) are given in Table 3. According to the Wald test results for exogeneity, \( \text{lnSO}_2 \) can be considered an endogenous variable at the 5% level. The estimated coefficient on \( \text{ln}(\text{around}_\text{SO}_2) \) at the first stage is 1.4548, significant at the 1% level, and the \( F \)-value is greater than 10. Therefore, \( \text{ln}(\text{around}_\text{SO}_2) \) is a valid instrumental variable and there are no weak instrumental problems. In column (2), the regression coefficient for predicted \( \text{lnSO}_2 \) at the second stage is \(-0.0794\), significant at the 1% level, which shows that the effect of air pollution on happiness is robust for a two-stage IV-probit model.

**Redefinition of the dependent variable**

In line with existing practice (Chen et al. 2020), we treat happiness as a binary variable that takes the value 1 if the respondent felt very happy or relatively happy and 0 otherwise. Respondents who reported feeling unclear are regarded as unhappy. This could cause estimate bias. To mitigate this concern, we redefine happiness using a tri-classified and a five-classified variable. The tri-classified happiness variable takes the value 1 for very unhappy or relatively unhappy, 2 for unclear, and 3 for relatively happy or very happy. The five-classified happiness variable takes the value 1 for very unhappy, 2 for relatively unhappy, 3 for unclear, 4 for relatively happy, and 5 for very happy. We introduce the tri-classified and five-classified variables into the baseline model, and we use an ordered probit model to re-estimate Eq. (1). The estimated results are given in Table 4. In columns (1) and (2), the regression coefficients for \( \text{lnSO}_2 \) are \(-0.0447 \) and \(-0.0437\), respectively, significant at the 1% levels. The results show no substantial change in either the sign or magnitude of the effect of \( \text{lnSO}_2 \).

**Replacement of the core independent variable**

Although \( \text{SO}_2 \) emissions are one of the main sources of air pollution pollutants, they may not accurately reflect \( \text{SO}_2 \) concentration levels in the air, which can also be affected by meteorological and geographical conditions (such as wind speed, wind direction, and the height of the atmospheric boundary layer). Thus, it may be impossible to capture
residents’ perceptions of air pollution fully. Therefore, to alleviate the estimation bias caused by this discrepancy, we conduct robustness tests, replacing the core independent variable of SO2 emissions with AQI and PM2.5 concentration levels, respectively. AQI is the air quality evaluation standard introduced in China in March 2012. According to the Technical Regulation on Ambient Air Quality Index (on trial),4 AQI is calculated from the concentrations of six pollutants (PM2.5, PM10, SO2, NO2, CO, and O3) and is widely used to monitor air quality in Chinese cities. PM2.5 is a major contaminant that causes air pollution (Yue et al. 2021), has a small particle size, and can penetrate into the fine bronchial tissues and alveoli, causing serious damage to the human body in case of long-term exposure at

Table 2 Effect of air pollution on residents’ happiness

| Variable    | Coefficient (1) | Coefficient (2) | Coefficient (3) | Marginal effect (4) | Marginal effect (5) | Marginal effect (6) |
|-------------|-----------------|-----------------|-----------------|--------------------|--------------------|--------------------|
| lnSO2       | -0.0535***      | -0.0449***      | -0.0330***      | -0.0160***         | -0.0134***         | -0.0099***         |
|             | (0.0080)        | (0.0086)        | (0.0101)        | (0.0024)           | (0.0026)           | (0.0030)           |
| Age         | -0.0528***      | -0.0526***      | -0.0519***      | -0.0158***         | -0.0158***         | -0.0155***         |
|             | (0.0039)        | (0.0039)        | (0.0039)        | (0.0012)           | (0.0012)           | (0.0012)           |
| Age^2       | 0.0005***       | 0.0005***       | 0.0005***       | 0.0002***          | 0.0002***          | 0.0001***          |
|             | (0.0000)        | (0.0000)        | (0.0000)        | (0.0000)           | (0.0000)           | (0.0000)           |
| Gender      | -0.1189***      | -0.1219***      | -0.1197***      | -0.0356***         | -0.0365***         | -0.0358***         |
|             | (0.0167)        | (0.0168)        | (0.0168)        | (0.0050)           | (0.0050)           | (0.0050)           |
| Health      | 0.5174***       | 0.5316***       | 0.5380***       | 0.1551***          | 0.1591***          | 0.1608***          |
|             | (0.0173)        | (0.0174)        | (0.0175)        | (0.0052)           | (0.0052)           | (0.0052)           |
| Children    | 0.1050***       | 0.0910**        | 0.0857**        | 0.0315***          | 0.0272**           | 0.0256**           |
|             | (0.0356)        | (0.0358)        | (0.0359)        | (0.0107)           | (0.0107)           | (0.0107)           |
| Marriage    | 0.3651***       | 0.3714***       | 0.3743***       | 0.1094***          | 0.1111***          | 0.1119***          |
|             | (0.0239)        | (0.0240)        | (0.0240)        | (0.0072)           | (0.0072)           | (0.0072)           |
| Socialsecurity | 0.2672***   | 0.2680***       | 0.2629***       | 0.0801***          | 0.0802***          | 0.0786***          |
|             | (0.0332)        | (0.0332)        | (0.0332)        | (0.0099)           | (0.0099)           | (0.0099)           |
| lnIncome    | 0.0098***       | 0.0113***       | 0.0119***       | 0.0029***          | 0.0034***          | 0.0036***          |
|             | (0.0023)        | (0.0023)        | (0.0223)        | (0.0007)           | (0.0007)           | (0.0007)           |
| lnGDP       | 0.0185          | 0.0148          | 0.0148          | 0.0056             | 0.0044             | 0.0044             |
|             | (0.0137)        | (0.0138)        | (0.0138)        | (0.0041)           | (0.0041)           | (0.0041)           |
| Hospitalbed | 0.0099***       | 0.0053***       | 0.0053***       | 0.0030***          | 0.0016***          | 0.0004***          |
|             | (0.0012)        | (0.0015)        | (0.0015)        | (0.0003)           | (0.0003)           | (0.0004)           |
| Unemployment| 0.0140          | 0.0248*         | 0.0248*         | 0.0042             | 0.0074*            | 0.0038*            |
|             | (0.0127)        | (0.0128)        | (0.0128)        | (0.0038)           | (0.0038)           | (0.0038)           |
| YD          | No              | No              | Yes             | No                 | No                 | Yes                |
| Cons        | 1.2352***       | 0.6175***       | 0.6492***       | 0.0176             | 0.0176             | 0.0176             |
|             | (0.1003)        | (0.1218)        | (0.1223)        | (0.0182)           | (0.0182)           | (0.0182)           |
| Pseudo R-squared | 0.0472    | 0.0497          | 0.0514          | 0.3550             | 0.3550             | 0.3550             |
| Observations| 30,745          | 30,745          | 30,745          | 30,745             | 30,745             | 30,745             |

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; robust standard errors in parentheses.

Table 3 Test of endogeneity and two-stage IV-probit model

| Variable          | First stage (1) lnSO2 | Second stage (2) Happiness |
|-------------------|-----------------------|---------------------------|
| ln(around SO2)    | 1.4548***             | -0.0794***                |
|                   | (0.0176)              | (0.0182)                  |
| lnSO2             |                       |                           |
| Control variables | Yes                   | Yes                       |
| Wald test of exogeneity | 4.65**            |                           |
| F                 | 1248.03               |                           |
| R-squared         | 0.3550                |                           |
| Observations      | 30,745                | 30,745                    |

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; robust standard errors in parentheses.

4 http://www.mee.gov.cn/yw.gz/jgbz/bzw/jcflbz/201203/t2012 0302_224166.shtml.
Given that the assumption of normal distribution may not hold, we use a logistic model to carry out a robustness test. The multi-level model also addresses the intra-class correlation when the individual-level and province-level variables are both included in the model. We therefore re-estimate Eq. (1) using a logistic model and a two-level mixed-effect probit model, respectively. The estimated results, given in Table 6, again demonstrate that the main findings for the effect of air pollution on happiness are robust to using the provincial clustering standard errors.

### Heterogeneous effect analysis

In order to capture the heterogeneous effects of air pollution on the happiness of different groups and to carry out more targeted environmental policies related to improving residents’ happiness, we conduct grouping regression from multiple perspectives. The groupings are based on three aspects: having/not having children, age, and education level. The regression results for Eq. (1) are shown in Table 8.

Children generally have poor resistance to dirty air (Kim et al. 2010a, b). Accordingly, we examine whether the groups who have children are more influenced by air pollution than the groups who do not have children. In row (1), the regression coefficient on lnSO$_2$ for the groups who have children is $-0.0519$, significant at the 5% level. The coefficient on lnSO$_2$ for those without children is $-0.0438$, significant at the 1% level. These results indicate that the negative effect of air pollution on happiness is greater for people with children. When facing air pollution, they consider not only themselves but also their children, and thus, they are more sensitive to the risks.

### Use of logistic and multi-level models

Given that the core explanatory variable used in this study is at provincial-level, so there may be heteroscedasticity in the baseline model. We thus carry out the LR test, and the result rejects the homoscedasticity null hypothesis. Therefore, we use provincial clustering standard errors to overcome the potential bias caused by the heteroscedasticity. Controlling for the individual-level, provincial-level, and year dummy variables stepwise, we re-estimate Eq. (1). The estimated results are given in Table 7, and the provincial clustering standard errors are in parentheses. Although the provincial clustering standard errors are larger than the robust standard errors in Table 2, the coefficients of lnSO$_2$ in columns (1)–(3) are still significantly negative, consistent with the baseline result. This shows that the main findings are still robust to using the provincial clustering standard errors.

### Use of provincial clustering standard errors

Although the provincial clustering standard errors are larger than the robust standard errors in Table 2, the coefficients of lnSO$_2$ in columns (1)–(3) are still significantly negative, consistent with the baseline result. This shows that the main findings are still robust to using the provincial clustering standard errors.
Although anxiety about the hazards of air pollution is widespread, elderly people may be disproportionately affected (Dons et al. 2018). We therefore anticipate that the effects of air pollution on the happiness of residents may vary according to age. China’s National Bureau of Statistics categorizes people over 65 as elderly. Therefore, we divide people into two groups, below and above the age of 65, and we consider the relationship between air pollution and happiness separately for each group. In row (2), the coefficient on $\ln SO_2$ for those above 65 is $-0.0481$, significant at the 1% level. The regression coefficient on $\ln SO_2$ for the group below 65 is $-0.0308$, significant at the 10% level. These results indicate that air pollution has a greater negative impact on elderly people, which is consistent with previous findings (Song et al. 2020a, b). The main explanation may be that elderly people are more likely to be in poor health and to have relatively low resistance to dirty air; accordingly, they are more likely to feel threatened by air pollution and to feel unhappy when facing it.

The health risks posed by air pollution can be modified by a person’s environmental perception and awareness (Badland and Duncan 2009; Hodgson and Hitchings 2018), which are driven by individual levels of preparedness and knowledge. As education can increase knowledge, we suppose that there may be differences in the impact of air pollution on residents’ happiness under different levels of education. We therefore divide the sample into two groups: those who have received education at college level or above, and those who have not. The grouping regression results listed in row (3) show that the coefficient on $\ln SO_2$ for the groups who have received higher level education is $-0.0371$ (significant at the 5% level) and that the coefficient for the groups who have not received higher level education is $-0.0293$ (significant at the 1% level). This supports the supposition that people who have received higher education are more influenced by air pollution than those who have not. There are two possible explanations. On the one hand, people with a higher level of education tend to have higher incomes (Griliches and Mason 1972); our data show that the average annual income of the groups who have received higher education is 68,592.69 RMB, far more than that of the groups who have not, at 22,169.75 RMB. It is therefore likely that the material needs of the groups who have received higher education are better satisfied, allowing them to pursue higher needs (Maslow 1943), such as the coordinated development of the economy, society, and environment (Song et al. 2020a, b). On the other hand, people with higher education may have better levels of preparedness and knowledge, which will increase their environmental perception and awareness. Thus, they have more stringent requirements for air quality, which may cause them to be more sensitive to air pollution and, in turn, more likely to feel unhappy.

| Variable | Group | $\ln SO_2$ | S.E. | Control variables/YD | Observations |
|----------|-------|------------|------|----------------------|--------------|
| $\ln SO_2$ | (1) Children Have | $-0.0519^{**}$ | (0.0222) | Yes | 26,971 |
|         | Have not | $-0.0438^{***}$ | (0.0094) | Yes | 3774 |
| (2) Age Above 65 | $-0.0481^{***}$ | (0.0104) | Yes | 9136 |
|         | Below 65 | $-0.0308^{*}$ | (0.0158) | Yes | 21609 |
| (3) Education High | $-0.0371^{**}$ | (0.0183) | Yes | 5295 |
|         | Low | $-0.0293^{***}$ | (0.0100) | Yes | 25,450 |

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; robust standard errors in parentheses
Mechanism analysis

To confirm that depressed mood and leisure activities outside the home are mechanisms by which air pollution affects happiness, we conduct mechanism analysis. We introduce the variables Depress, Movie, Shopping, and Exercising, and we use an ordered probit model to estimate Eq. (2). The results are given in Table 9. Column (1) shows that the estimated effect of lnSO2 on Depress is −0.1434, significant at the 1% level; that is, air pollution can affect happiness through the channel of causing depressed mood, which verifies the first mechanism proposed in the “Theory and hypotheses” section. Similarly, the estimated results of Eq. (2) in columns (2) to (4) show that air pollution can decrease residents’ leisure activities outside the home, such as watching movies, shopping, and exercising, thereby reducing their happiness; that is, the second mechanism in “Theory and hypotheses” is also verified. Therefore, hypothesis H2 is supported.

Table 9 Mechanism analysis

| Variable         | (1)       | (2)       | (3)       | (4)       |
|------------------|-----------|-----------|-----------|-----------|
| lnSO2            | −0.1434***| −0.0531***| −0.0255***| −0.0269** |
|                  | (0.0085)  | (0.0081)  | (0.0066)  | (0.013)   |
| Control variables/YD | Yes       | Yes       | Yes       | Yes       |
| Observations     | 30,602    | 30,602    | 30,602    | 30,602    |

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; robust standard errors in parentheses

Moderating effect of environmental regulation

We also explore empirically whether the three types of environmental regulations (command-and-control, market-based, and voluntary) can moderate the negative impact of air pollution on residents’ subjective happiness. In the “Variables” subsection, we established a moderating effect model by introducing proxy variables: the proportion of government environmental investment in GDP (InVestment), pollutant discharge fees (lnFee), and the number of complaints about environmental pollution (Complaint). The estimated results for Eq. (3) are shown in Table 10. In column (1), the regression coefficients on lnSO2 and lnVestment*lnSO2 are −0.1079 and 0.0543, respectively, significant at the 1% level. This indicates that command-and-control environmental regulations can offset the negative effect of air pollution on subjective happiness. Similarly, the results in columns (2) and (3) show that both market-based and voluntary environmental regulations can also moderate the relationship between air pollution and happiness.

To capture this nonlinearity, proposed in hypothesis H3, we rank environmental regulations at three levels from low to high, defining the lowest 25% as low regulation, the highest 25% as high regulation, and the remainder as medium regulation. We re-estimate Eq. (3) at each level, with the results shown in Table 11. Columns (1) to (3) indicate that the regression coefficients on lnSO2 and lnVestment*lnSO2 are significant, and the coefficient of interaction terms is the smallest at the high level. This demonstrates that the moderating effect of environmental governance investment is nonlinear. Similarly, the results in columns (4) to (6) and (7) to (9) indicate that the moderating effects of pollutant discharge fees and number of complaints about environmental pollution are also nonlinear.

To summarize, three types of environmental regulations can all moderate the negative impact of air pollution on residents’ subjective happiness, but the overall moderating effects are nonlinear. In particular, environmental governance investments are more effective at the low level, pollutant discharge fees are more effective at the medium level, and complaints about environmental pollution are more effective at the high level. Therefore, hypothesis H3 is supported.

Conclusions

In recent years, the issue of air pollution and happiness has attracted widespread attention. This study combines data on individual-level characteristics from the CGSS for 2013, 2015, and 2017 with provincial-level data on air pollution and socioeconomic characteristics, and we use a probit model to investigate the heterogeneous effect of air pollution on residents’ subjective happiness. We also empirically test two mechanisms by which air pollution affects subjective happiness, and explore whether environmental regulations can moderate the effect of air pollution on happiness. Our findings support the following conclusions. Air pollution reduces residents’ subjective happiness, a finding that is robust to various alternative empirical specifications. This negative effect is greater for those who have children, are old, or have a higher level of education. The causal mechanisms of depressed mood and leisure activities outside the home are supported. Specifically, air pollution can reduce residents’ subjective happiness through the channels of depressed mood and fewer leisure activities outside the home. Finally, environmental regulations can moderate the negative impact of air pollution on happiness, but the
moderating effects are nonlinear. Environmental governance investments are more effective at the low level, pollutant discharge fees are more effective at the medium level, and complaints about environmental pollution are more effective at the high level.

The findings of this study have important policy implications for environment-related measures designed to increase national happiness. First, the government should focus on improving air quality, as our findings show that air pollution reduces residents’ subjective happiness. To avoid the risk of loss of happiness, development models in which the environment is sacrificed should be abandoned. Instead, local governments should commit themselves to achieving an equilibrium between economic development and the quality of the environment. Feasible strategies for improving air pollution may include controlling pollutant emissions, encouraging people to choose greener forms of travel, and strengthening monitoring, early warning, and timely response systems in relation to serious air pollution events.

Second, special attention should be paid to people who have children, are old, or have a higher level of education. These groups are more sensitive to the risks of air pollution, and therefore more targeted anti-haze health education should be made available for them to alleviate the depressed mood caused by air pollution. This education could include guidance on how to take appropriate protective measures, how to treat the harm of air pollution objectively, and how to maintain good mood and life satisfaction when faced with serious air pollution. Alternative leisure activities should also be explored to offset the lack of contact with the environment outside the home when air pollution is serious.

Finally, the government could adjust the intensity of environmental regulation to alleviate the impact of air pollution on happiness. The results of our moderating effect analysis indicate that environmental governance investments are more effective at the low level, pollutant discharge fees are more effective at the medium level, and complaints about environmental pollution are more effective at the high level. Therefore, local government could consider controlling environmental governance investment to avoid excessively encroaching on other public expenditures. Public environmental awareness, participation, and supervision should also be strongly encouraged. And, to maintain higher regional ecological efficiency, pollutant discharge fees should be kept at a moderate level.

This study has a number of limitations. Although we use multi-period data in order to address the endogeneity concerns associated with cross-sectional analysis, we believe that a panel data analysis over a greater number of years would provide more convincing evidence. It also remains unclear whether residents’ perceptions of air pollution are consistent with SO2 emissions and air quality records, given the spatial and temporal aggregation of those records. Further empirical study of individual perceptions of air pollution would be valuable in this connection. Finally, owing to data restrictions, the number of mechanisms we have been able to verify empirically and the number of environmental regulations we have been able to analyze are limited.

### Table 10 Overall moderating effect

| Variable          | (1)          | (2)          | (3)          |
|-------------------|--------------|--------------|--------------|
| $\ln SO_2$        | $-0.1079^{***}$ | $-0.9534^{***}$ | $-0.0733^{***}$ |
|                   | (0.0205)     | (0.1547)     | (0.0198)     |
| $\text{lnInvestment} \times \ln SO_2$ | 0.0543***   |              |              |
|                   | (0.0129)     |              |              |
| $\ln Fee \times \ln SO_2$ | 0.0755***   |              |              |
|                   | (0.0139)     |              |              |
| $\text{Complaint} \times \ln SO_2$ |              | 0.0448       |              |
|                   |              | (0.0524)     |              |
| Control variables/YD | Yes         | Yes          | Yes          |
| Observation       | 30,475       | 30,475       | 30,475       |

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; robust standard errors in parentheses

### Table 11 Nonlinearity of the moderating effect

| Variable          | Command-and-control regulation | Market-based regulation | Voluntary regulation |
|-------------------|-------------------------------|------------------------|---------------------|
|                   | (1) Low | (2) Medium | (3) High | (4) Low | (5) Medium | (6) High | (7) Low | (8) Medium | (9) High |
| $\ln SO_2$        | $-0.3508^{***}$ | $-0.1368^{*}$ | $-0.3771^{***}$ | 2.9936*** | $-4.2276^{***}$ | 1.0936 | $-0.0939^{*}$ | 3.6176*** | $-0.3552^{***}$ |
|                   | (0.0834) | (0.0828) | (0.1294) | (0.6968) | (1.0389) | (1.2477) | (0.0533) | (0.0753) | (0.0523) |
| $\text{lnInvestment} \times \ln SO_2$ | 0.4837*** | 0.1769** | 0.1233** | 0.4837*** | 0.1769** | 0.1233** | 0.4837*** | 0.1769** | 0.1233** |
|                   | (0.1517) | (0.0692) | (0.0547) | (0.1517) | (0.0692) | (0.0547) | (0.1517) | (0.0692) | (0.0547) |
| $\ln Fee \times \ln SO_2$ | $-0.2989^{***}$ | 0.3716*** | $-0.0855$ | $-1.3743^{*}$ | $-1.4177^{***}$ | 0.8485*** |
|                   | (0.0676) | (0.0942) | (0.1081) | (0.7913) | (0.2641) | (0.1331) |
| $\text{Complaint} \times \ln SO_2$ |              |              |              |              |              |              |
|                   |              |              |              |              |              |              |
| Control variables/YD | Yes         | Yes          | Yes          | Yes         | Yes          | Yes          |
| Observation       | 7849       | 15,829       | 7067         | 8122       | 14,908       | 7715         | 8031       | 14,738       | 7976       |

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; robust standard errors in parentheses
Appendix A

Fig. 2 Spatial distribution of SO₂ emissions, 2017

Author contribution Conceptualization, F.X. and D.Z.; data curation, X.-L.L.; formal analysis, F.X. and D.Z.; methodology, F.X. and X.-L.L.; supervision, F.X., D.Z., and X.-L.L.; visualization, X.-L.L.; writing original draft, X.-L.L., F.X., and D.Z.; writing review and editing, F.X. and X.-L.L.

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Data availability Not applicable

Declarations

Ethics approval This study does not involve ethical issues.

Consent to participate Not applicable

Consent for publication The authors agree to the publication in the journal.

Conflicts of interest The authors declare no competing interests.

References

Alvarez-Diaz A, Gonzalez L, Radcliff B (2010) The politics of happiness: on the political determinants of quality of life in the American States. J Polic 72(3):894–905

Badland HM, Duncan MJ (2009) Perceptions of air pollution during the work-related commute by adults in Queensland, Australia. Atmos Environ 43(36):5791–5795

Blinder M, Blankenberg AK (2016) Environmental concerns, volunteering and subjective well-being: antecedents and outcomes of environmental activism in Germany. Ecol Econ 124:1–16

Cesur R, Tekin E, Ulker A (2016) Air pollution and infant mortality: evidence from the expansion of natural gas infrastructure. Econ J 127(600):330–362

Chang PJ, Song R, Lin Y (2019) Air pollution as a moderator in the association between leisure activities and well-being in urban China. J Happiness Stud 20(8):2401–2430

Charfeddine L, Al-Malk AY, Al Korbi K (2018) Is it possible to improve environmental quality without reducing economic growth? Evidence from the Qatar economy. Renew Sustain Energy Rev 82:25–39

Chen B, Kan H (2008) Air pollution and population health: a global challenge. Environ Health Prev Med 13(2):94–101

Chen L, Zhang J, You Y (2020) Air pollution, environmental perceptions, and citizen satisfaction: a mediation analysis. Environ Res 184:109287

Cho J, Choi YJ, Suh M et al (2014) Air pollution as a risk factor for depressive episode in patients with cardiovascular disease, diabetes mellitus, or asthma. J Affect Disord 157:45–51
Clark AE (2018) Four decades of the economics of happiness: where next? Rev Income Wealth 64(2):245–269
Cuñado J, De Gracia FP (2013) Environment and happiness: new evidence for Spain. Soc Indic Res 112(3):549–567
Diener E, Chan MY (2011) Happy people live longer: subjective well-being contributes to health and longevity. Appl Psychol Health Well-Being 3(1):1–43
Doms E, Laeremans M, Anaya-Boig E, Avila-Palencia I, Brand C, De Nazelle A et al (2018) Concern over health effects of air pollution is associated to NO2 in seven European cities. Air Qual Atmos Health 11(5):591–599
Easterlin RA (1974) Does economic growth improve the human lot? Some empirical evidence. In: David PA, Reder MN (eds) Nations and households in economic growth. Academic Press, New York, pp 89–125
Ferreira S, Akay A, Brereton F, Cuñado J, Martinsson P, Moro M, Ningal TF (2013) Life satisfaction and air quality in Europe. Ecol Econ 88:1–10
Frey BS, Stutzer A (2010) Happiness: a new approach in economics. CESifo DICE Rep 8(4):3–7
Griliches Z, Mason WM (1972) Education, income, and ability. J Polit Econ 80(3, Part 2):S74–S103
Guo S, Wang W, Zhang M (2020) Exploring the impact of environmental regulations on happiness: new evidence from China. Environ Sci Pollut Res 27(16):1–18
Haller M, Hadler M (2006) How social relations and structures can produce happiness and unhappiness: an international comparative analysis. Soc Indic Res 75(2):169–216
He XB (2019) Investigating environmental regulation and income inequality of urban residents: the perspective of idiosyncratic regulatory tools. Collected Essays Finance Econ 247(6):104–112
Hodgson A, Hitchings R (2018) Urban air pollution perception through the experience of social practices: talking about breathing with recreational runners in London. Health Place 53:26–33
Huang YM, He LY (2013) Urbanization, environmental pollution and subjective well-being: an empirical study on China. China Soft Sci 12:82–93
Jiang BF, Xie YL, Xia DH, Liu XJ (2019) A potential source for PM2.5: analysis of fine particle generation mechanism in Wet Flue Gas Desulfurization System by modeling drying and breakup of shurry droplet. Environ Pollut 246:249–256
Jin Z, Zeng S, Cao C, Ma H, Sun D (2020) Impacts of pollution abatement projects on happiness: an exploratory study in China. J Clean Prod 274:122869
Kaido N, Kaida K (2016) Pro-environmental behavior correlates with present and future subjective well-being. Environ Dev Sustain 18(1):111–127
Kaplan R, Kaplan S (1989) The experience of nature: a psychological perspective. Cambridge University Press, Cambridge
Kim C, Jung SH, Kang DR et al (2010) Ambient particulate matter as a risk factor for suicide. Am J Psychiatry 167(9):1100–1107
Kim SG, Cho SH, Lambert DM, Roberts RK (2010) Measuring the value of air quality: application of the spatial hedonic model. Air Qual Atmos Health 3(1):41–51
Lamers F, van Oppen P, Comijs HC et al (2011) Comorbidity patterns of anxiety and depressive disorders in a large cohort study: the Netherlands Study of Depression and Anxiety (NESDA). J Clin Psychiatry 72(3):341–348
Levinson A (2012) Valuing public goods using happiness data: the case of air quality. J Public Econ 96(9–10):869–880
Li F, Zhou T (2020) Effects of objective and subjective environmental pollution on well-being in urban China: a structural equation model approach. Soc Sci Med 249:112859
Li G, Fang C, Wang S, Sun S (2016) The effect of economic growth, urbanization, and industrialization on fine particulate matter (PM2.5) concentrations in China. Environ Sci Technol 50(21):11452–11459
Li LL, Shi L (2017) Economic growth and subjective well-being: analyzing the formative mechanism of the Easterlin paradox. Sociol Stud 32(3):95–120+244
Li M, Zhang YR (2019) The effect of air pollution on migration: a study based on the choice of university city by international students in China. Econ Res J 54(6):168–182
Li MJ (2015) Environmental pollution, governmental regulation and the happiness sense of residents: an empirical analysis based on CGSS (2008) micro-survey data. Mod Econ Sci 37(5):59–68+126
Li R, Ramanathan R (2018) Exploring the relationships between different types of environmental regulations and environmental performance: evidence from China. J Clean Prod 196:1329–1340
Li T, Fan WT (2016) Parenthood and subjective well-being: a life-cycle and life-course perspective. Popul Res 40(5):6–19
Li Z, Folmer H, Xue J (2014) To what extent does air pollution affect happiness? The case of the Jinchuan mining area, China. Ecol Econ 99:88–99
Li ZJ, Hu MJ, Zhang AP, Zhou NX (2021) Influence and spillover effect of industrial eco-efficiency on PM2.5 pollution. Earth Sci 36(3):737–751
Lim YH, Kim H, Kim JH et al (2012) Air pollution and symptoms of depression in elderly adults. Environ Health Perspect 120(7):1023–1028
Liu H, Hu T (2021) How does air quality affect residents’ life satisfaction? Evidence based on multi-period follow-up survey data of 122 cities in China. Environ Sci Pollut Res 28(43):61047–61060
Liu Y, Li RL, Song Y, Zhang ZJ (2019) The role of environmental tax in alleviating the impact of environmental pollution on residents’ happiness in China. Int J Environ Res Public Health 16(22):4574
Liu Y, Li Z, Yin X (2018) The effects of three types of environmental regulation on energy consumption: evidence from China. Environ Sci Pollut Res 25(27):27334–27351
Liu Z, Yu L (2020) Stay or leave? The role of air pollution in urban migration choices. Ecol Econ 177:106780
Ma XJ, Wang CX, Zhang ZY (2019) Quantitative study of residents’ wellbeing from the perspective of a “two-dimensional” environment: new evidence from China CGSS data. Stat Res 36(9):56–67
MacKenzie G (2012) Happiness economics from 35,000 feet. J Econ Perspect 26(4):705–735
Maslow AH (1943) A theory of human motivation. Psychol Rev 50(4):370–396
Matus K, Nam KM, Selin NE, Lamsal LN, Reilly JM, Paltsev S (2012) Health damages from air pollution in China. Glob Environ Change 22(1):55–66
Mei DZ, Wu MT, Qian TF, Tan ST (2020) Income inequality, government expenditure, and real exchange rate: a study based on cross-country panel data. J Finan Res 4:31–47
Noonan DS (2014) Smoggy with a chance of altruism: the effects of ozone alerts on outdoor recreation and driving in Atlanta. Policy Stud J 42(1):122–145
Oswald AJ, Proto E, Sgroi D (2015) Happiness and productivity. J Labor Econ 33(4):789–822
Power MC, Kioumourtzoglou MA, Hart JE et al (2015) The relation between past exposure to fine particulate air pollution and prevalent anxiety: observational cohort study. Br Med J 350:h11111
Ren S, Li X, Yuan B, Li D, Chen X (2018) The effects of three types of environmental regulation on eco-efficiency: a cross-region analysis in China. J Clean Prod 173:245–255
Shi D, Yu H (2020) Reevaluating the subjective welfare loss of air pollution. J Clean Prod 257:120445
Shi Q, Guo F (2019) Do people have a negative impression of government on polluted days? Evidence from Chinese cities. J Environ Plann Man 62(5):797–817
Song Y, Yang T, Li Z, Zhang X, Zhang M (2020) Research on the direct and indirect effects of environmental regulation on environmental pollution: empirical evidence from 253 prefecture-level cities in China. J Clean Prod 269:122425
Song Y, Zhou A, Zhang M (2020) Exploring the effect of subjective air pollution on happiness in China. Environ Sci Pollut Res 27(34):43299–43311
Suarez-Varela M, Guardiola J, Gonzalez-Gomez F (2016) Do pro-environmental behaviors and awareness contribute to improve subjective well-being? Appl Res Qual Life 11(2):429–444
Sun C, Kahn ME, Zheng S (2017) Self-protection investment exacerbates air pollution exposure inequality in urban China. Ecol Econ 131:468–474
Szyszkoowicz M, Rowe BH, Colman I (2009) Air pollution and daily emergency department visits for depression. Int J Occup Med Environ Health 22(4):355–362
Tanaka S (2015) Environmental regulations on air pollution in China and their impact on infant mortality. J Health Econ 42:90–103
Tobler WR (1970) A computer movie simulating urban growth in the Detroit region. Econ Geogr 46(2):234–240
Ulrich RS (1983) Aesthetic and affective response to natural environment. In: Altman I, Wohlwill JF (eds) Behavior and the natural environment. Springer, Cham, pp 85–125
Welsch H (2006) Environment and happiness: valuation of air pollution using life satisfaction data. Ecol Econ 58(4):801–813

Wesselink A, Paavola J, Fritsch O, Renn O (2011) Rationales for public participation in environmental policy and governance: practitioners’ perspectives. J Environ Plann Manag 43(11):2688–2704
Yang JD, Zhang YR (2014) Pricing air pollution: an analysis based on happiness data. J World Econ 37(12):162–188
Yang JH, Kang SC, Ji ZM, Yang SX, Li CL, Tripathee L (2019) Vital contribution of residential emissions to atmospheric fine particles (PM2.5) during the severe wintertime pollution episodes in Western China. Environ Pollut 245:519–530
Ye LX, Zhang W (2020) Perceived air pollution, income and happiness. J Financ Econ 46(1):126–140
Yuan L, Shin K, Managi S (2018) Subjective well-being and environmental quality: the impact of air pollution and green coverage in China. Ecol Econ 153:124–138
Yue Q, Song Y, Zhu J, Li Z, Zhang M (2021) Exploring the effect of air pollution on settlement intentions from migrants: evidence from China. Environ Impact Assess Rev 91:106671
Zhang B, Bi J, Yuan Z, Ge J, Liu B, Bu M (2008) Why do firms engage in environmental management? An empirical study in China. J Clean Prod 16(10):1036–1045
Zhang J, Mu Q (2018) Air pollution and defensive expenditures: evidence from particulate-filtering facemasks. J Environ Econ Manag 92:517–536
Zhang X, Zhang X, Chen X (2017) Happiness in the air: how does a dirty sky affect mental health and subjective well-being? J Environ Econ Manag 85:81–94

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