Air pollution, heterogeneity, and subjective well-being: Evidence from China's micro survey data

Yunjiang Yu

Shanghai Lixin University of Accounting and Finance

Xing Shu (✉ frankluck666@126.com)

Shanghai Lixin University of Accounting and Finance <https://orcid.org/0000-0003-2039-2243>

Sajid Anwar

University of the Sunshine Coast

Sibo Yang

Shanghai Lixin University of Accounting and Finance

Research Article

Keywords: Air pollution, PM2.5, Subjective well-being, China, Heterogeneity

Posted Date: February 15th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1264835/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License. [Read Full License](#)

Abstract

Previous studies have not paid much attention to the heterogeneous effects of air pollution on subjective well-being. By matching the 2018 China Labour-Force Dynamics Survey data (CLDS2018) with urban air pollution data, we empirically examine the impact of air pollution on subjective well-being across pollution levels, income levels, gender, age, education as well as city size and region. Empirical analysis shows that an increase in air pollution has a negative and statistically significant impact on the well-being and the effect varies considerably across pollution levels, income levels, age, gender, education level, city size and region. Re-estimation using air pollution data released by the U.S. embassy in China shows that the empirical results presented in this paper are robust. After accounting for potential endogeneity and selection bias, PM2.5 continues to have a significant negative impact on the well-being of residents. Our analysis shows that air pollution is an important contributor to the Easterlin paradox, and (in the process of air pollution control) attention needs to be paid to both individual heterogeneity and urban differences.

1. Introduction

Since the reform and opening up of the economy in late 1970s, the average living standard of the Chinese population, as measured by per capita GDP, has significantly improved. Chinese per capita GDP increased from US\$294.46 in 1985 to US\$10,216.63 in 2019 (World Bank, 2021). However, at the same time, the level of air pollution in China has also significantly increased, which has adversely affected the well-being and living standard of the residents. The Chinese government has taken steps to reduce the level of air pollution. In recent years, the particulate matter 2.5 (PM2.5) pollution in China has decreased. In 2007, 91.7% of the population was exposed to PM2.5 pollution exceeding the World Health Organization's (WHO) target, but this proportion dropped to 81.2% in 2017 (World Bank, 2021). The Report on the State of the Ecology and Environment in China (RSEE, 2020) shows that, despite improvement in air quality over the previous year, 217 Chinese cities out of 338 failed to meet the air quality standards in 2019. The PM2.5 as the primary pollutant was found to be severe during 60.0% of the days in 2019. This situation not only poses a threat to the health and well-being of the residents but has the potential to also affect the Chinese economic growth rate adversely. As air pollution is an important contributor to the well-being, in this paper, we examine the impact of PM2.5 air pollution on subjective well-being in China.

The existing research on subjective well-being mainly focuses on households and/or the macro economy (Easterlin, 2005; Stutzer, 2002). It is generally believed that steady job (Knabe et al., 2011), higher income (Diener et al., 2006), family satisfaction (Tella et al., 2003), power and good health (Steptoe et al., 2005) are sources of subjective well-being, and the better the economy, the higher the employment rate, and the happier the people. However, with increasing concern over environmental degradation, more attention is being paid to the relationship between economic well-being and environment. Air pollution can affect not only the mood of public but also the health and thus the well-being (Li et al., 2014; Li et al., 2019; Liu Jun et al., 2021).

The main aim of this paper is to measure the impact of air pollution on subjective well-being of the population. We also consider whether the impact is heterogeneous across income levels, age and gender. While focusing on the differences, we also examine the mechanism through which the air pollution level affects the subjective well-being of the population.

We make some important contributions to the existing literature. First, we use a more comprehensive and nationally representative city-level air quality data. Second, unlike the previous studies, we pay more attention to the heterogeneity in the impact of environmental pollution on individual well-being, which allows one to develop a better understanding of the effect of environmental pollution on subjective well-being in China. Third, we also examine the mechanism behind the effect of environmental pollution on subjective well-being. Specifically, we further explore and identify the path that environmental pollution affects well-being.

The remainder of the paper is organised as follows. Section 2 summarises and evaluates the relevant literature on the effect of environmental pollution on subjective well-being of the residents. Section 3 describes the data and basic characteristics of the main variables. Section 4 explains the empirical strategy and the main findings. Section 5 discusses the mechanism through which air pollution affects the subjective well-being. Section 6 concludes the paper and also offers some recommendations.

2. Literature Review

Early studies, such as Easterlin (1974), argue that increase in income does not necessarily imply subjective well-being, and well-being also depends on other non-income factors. Well-being is a feeling when the basic needs of people have been satisfied, whereas subjective well-being involves self-evaluation of satisfaction and reflection on life (Diener et al., 2006; OECD publishing, 2013), which is more likely to be influenced by subjective perceptions of air pollution.

Existing studies that deal with the impact of air pollution on subjective well-being mainly includes three dimensions: (i) the link between air pollution and subjective well-being in different countries or within the same region (Liu et al., 2018; Smyth et al., 2008); (ii) heterogeneity of the explanatory variables such as income, climate, population and age (Song et al., 2019; Zhang et al., 2017; Zheng Junjun et al., 2015); and (iii) the monetary cost of air pollution control (Welsch, 2002; Welsch, 2003; Yin et al., 2018; Yuan et al., 2018; Zhang et al., 2017).

Using daily air quality data collected from thousands of monitoring stations provided by the U.S. Environmental Protection Agency and daily temperature and rainfall information from the National Climatic Data Center, Levinson (2012) find a statistically significant negative relationship between happiness levels and PM10 concentrations in the U.S. They also reported that air pollution can have a negative impact on health. Using data from regions of Spain and considering the climate effects such as the temperature and precipitation, Cuñado and de Gracia (2013) find that to achieve a 1% decrease in pollution, consumers will be willing to pay an average of 1.4% of their income in taxes.

Using data from Queensland, Australia, Ambrey et al. (2014) find (i) a negative relationship between PM10 pollution and satisfaction level and (ii) the resident the respondent surveyed indicated a strong willingness to pay to reduce the level of air pollution. MacKerron and Mourato (2009) used data from London to examine the relationship between air pollution and life satisfaction. They find that a 10 μ g/m³ increase in annual average NO₂ concentrations can decrease life satisfaction by 0.5 percentage points (they used an 11-point scale to measure life satisfaction).

Xu et al. (2018) used the 2013 data from the China General Social Survey to examine the impact of nitrogen oxide (NO₂) concentration and subjective well-being. Empirical analysis based on probit regression shows that on average the residents are willing to pay 3,239.20 RMB (approx. US\$496.75) for every 1ug/m³ decrease in NO₂ concentrations.

Ahumada and Iturra (2021) assessed the impact of particulate matter on individual subjective well-being of 305 Chilean cities in 2013. The main findings indicate that air pollution decreases people's well-being and its negative effect is robust to several specifications. On average, Chileans are willing to pay 7.46–11.98 USD per month to improve their air quality.

Xu Fang et al. (2021) used data from the China General Social Survey and data on air pollution to explore the impact and the critical path of air pollution on residents' happiness in China and evaluates whether environmental regulations can alleviate these effects. They find that air pollution can significantly impair residents' happiness, especially those who have children, are younger, are in poor health, have a lower education level, have lower income and live in a rural area. In addition, environmental regulations can effectively alleviate the impact of air pollution on residents' happiness.

Some existing studies have examined the heterogeneity in the impact of environmental pollution on well-being. For example, using the World Happiness Report data on 25 OECD countries over the 1994-2004 period, Menz and Welsch (2010) found that the negative effect of air pollution on life satisfaction of the elderly was higher than that of the middle-aged group. Their work supports the idea that preferences for air quality are U-shaped across the age of the residents. Using the information gleaned from 210 million microblogs, Zheng (2019) considered the emotional impact of air pollution on people who breathe in polluted air but do not end up in hospitals in China. They concluded that the well-being of the residents was relatively more adversely affected by pollution in weekdays. Furthermore, the severity of the weather moderates the emotional impact of air pollution and women were more sensitive than men to the negative impact of air pollution. However, in an earlier study, Huang Yongming and He Lingyun (2013) concluded that the impact of environmental pollution on the well-being of residents does not vary significantly across income, education and living environment, which is consistent with the conclusions of Levinson (2012). Using data from the 2016 China Labor-Force Dynamics Survey, the 2016 China City Statistical Yearbook and the 3rd-Quarter 2016 air pollution index, Guo Wei et al., (2021) found that increased CO emissions compromise the happiness of working adults, and this negative effect is substantially ameliorated among older working adults, but is significantly stronger in medium-density and high-density cities for happiness.

Based on the existing studies, the effect of air pollution on well-being can be attributed to two main channels: the health and subjective perceptions of the residents. Exposure to polluted air can lead to health risks, such as respiratory diseases, cardiovascular diseases, cancer and impaired cognitive function (Brunekreef and Holgate, 2002; Mills et al., 2009). Prolonged exposure to air pollutants is also likely to cause anxiety and depression (Guxens and Sunyer, 2012; Gu Hejun et al., 2020; Yang et al., 2021). On the other hand, haze and dust also effects people while they are travelling to and from work. It is well-known that environmental degradation can lower the quality of life (Qin and Zhu, 2018; Zheng et al., 2019). Of course, avoiding environmental degradation can involve significant monetary cost and some residents may choose to move out of heavily polluted regions or even emigrate to less polluted countries. Economic growth, which is often associated with environmental

degradation in developing countries, does improve the quality of life thereby enhancing the happiness of the residents. The overall effect of pollution on happiness depends on relative strength of the health and subjective perceptions of the residents (Ma Xiaojun et al., 2019; Zheng Junjun et al., 2015).

3. Data And Model

3.1 Data

We utilise measures of well-being from 2018 China Labour-force Dynamics Survey data (CLDS2018) maintained by Sun Yat-sen University, which is the latest published data. The data is based on comprehensive surveys conducted every two years starting from 2012. The survey includes data on the well-being of the residents and other characteristics such as the gender, age, income, and education. The respondents are the labour force ranging from 15-64 years old, and the sample covers 29 mainland Chinese provinces. Using the sample rotating and tracking approaches and after excluding the questionnaires with missing data, we were left with 4071 valid questionnaires. The PM2.5 data comes from the China National Environmental Monitoring Centre, and the PM2.5 data used in the robustness test comes from the U.S. Embassy in China. Other city-level data are obtained from the 2018 statistical yearbooks of various cities.

The CLDS 2018 questionnaire includes questions such as “In general, do you think that you have a happy life?” The response can be recorded on a 5-point Likert scale, where 1 means “very unhappy” and 5 means “very happy”. Nearly 27% of the residents rated themselves as “very happy”, slightly more than 40% rated themselves as “happy”. A summary of the responses are shown in Table 1.

Table 1: Key statistics of the well-being ratings

Happiness level	Number of ratings	Proportion
very Unhappy	58	1.42%
unhappy	177	4.35%
general	1096	26.92%
happy	1643	40.36%
very happy	1097	26.95%

3.2 Model specification

In order to examine the impact of air pollution on subjective well-being, based on related studies (e.g., Rehdanz and Maddison, 2008, Liu et al., 2018; and Zhu et al., 2019), we specify a regression equation as follows:

where y_{ic} is the subjective well-being of resident i in city c . $PM2.5_c$ is the annual average concentrations of PM2.5 in city c , which is measured by micrograms per cubic meter ($\mu\text{g}/\text{m}^3$). $\ln Income_{ic}$ is the annual household income of resident i in city c . X_{ic} is a vector of city and individual level control variables. ε_{ic} is the usual error term.

The city level control variables include urban population size, urban GDP, urban housing prices. The individual level variables include the age, gender, marital status, health status, political status, education level, home ownership, unemployment status, and whether the individual works in the state-owned enterprise (see Table 2).

The well-being indicator is a discrete ordered variable which is measured on a 5-point Likert scale. Previous studies on determinants of well-being mostly use the probit model but Ferrer-i-Carbonell et al. (2014) point out that OLS estimation produces results that are consistent with the results of ordered logit or probit models, which is also confirmed by several studies (e.g., see MacKerron and Mourato, 2009; Song et al., 2019; and Yuan et al., 2018).

3.3 Air pollution measures

Air pollution is the explanatory variables in this paper, which is measured by concentrations of PM2.5. We use PM2.5 for three reasons. First, PM10 and other harmful air pollutants are abundant in developing countries (Diao et al., 2018; Welsch, 2003), while PM2.5 contributes to haze (Zhang et al., 2017), which is more likely to affect the social well-being of the residents. Second, due to its extremely small size, PM2.5 can reach the lungs and also enter the bloodstream after inhalation, which can result in chronic diseases (Darçın, 2017). Third, blocking PM2.5 requires better quality face masks and hence it is harder to avoid it.

We use three types of control variables (i.e., individual, city, and the economy). The city level variables include the urban population size, urban GDP and the urban house price. The individual level variables cover the age, gender, marital status, health, political status, and education level. The economy level variables involve the income, housing, employment and whether work in the state-owned enterprise.

Table 2: Descriptive statistics of the key variables

Variable	Definition	Number	Mean	SD
Well-being	very unhappy =1☐unhappy = 2☐general =3☐happy =4☐ very happy =5	4071	3.87	0.91
Urban population size	urban permanent population (Million)	4071	5.30	4.98
PM2.5	urban average concentrations of PM2.5 in 2018 (μg /m ³)	4071	35.43	15.56
Urban GDP	urban GDP in 2018 (100 billion RMB)	4071	8.19	1.15
Urban housing price	natural logarithm of average urban housing price	4071	8.83	0.60
Age	age	4071	42.95	13.66
Gender	female = 0☐male = 1	4071	0.54	0.16
Marital status	single =0☐non-single = 1	4071	0.78	0.42
Health status	very unhealthy or unhealthy = 0☐generally healthy or very healthy = 1	4071	0.92	0.27
Political status	not a communist party member = 0☐communist party member =1	4071	0.13	0.34
Education level	college and above = 1, 0 otherwise	4071	0.46	3.79
Income	per capita household income in 2018 (10 thousand RMB)	4071	3.03	7.20
Home ownership	yes = 0☐no = 1	4071	0.17	0.35
Employment status	employed = 1☐unemployed or student = 0	4071	0.86	0.35
Whether work in the state-owned enterprise	Work in the state-owned enterprise=1, 0 otherwise	4071	0.14	0.35

4. Empirical Analysis

Table 3 shows the baseline regression estimation results. The estimated results show that the effect of air pollution on subjective well-being of the residents is negative and statistically significant. Model 1 examines the effect of city-level factors on well-being. We find that PM2.5 concentrations and housing prices adversely affect the well-being, while urban population size and urban GDP have a positive effect on well-being. The estimated coefficient of PM2.5 shows that a 1μg/m³ increase in PM2.5 concentrations lower the well-being by about 0.05 units. The estimated effects of other control variables are consistent with expectations. In cities with high GDP and large population. The residents tend to feel happier because of, among other things, superior medical care and better education opportunities. High housing prices put pressure on home buyers with loans and reduce their happiness.

Table 3: The effect of air pollution on well-being

	Model 1: Ordered Logit	Model 2: Ordered Logit	Model 3: Ordered Logit	Model 4: OLS
Urban population	0.013*** (3.26)	-0.016*** (3.23)	-0.014*** (3.21)	-0.018*** (3.20)
PM2.5	-0.051*** (4.95)	-0.031*** (5.4)	-0.035*** (4.43)	-0.038*** (4.61)
Urban GDP	0.113*** (5.25)	0.177*** (5.46)	0.130*** (5.57)	0.113*** (5.52)
Urban housing price	-0.120* (1.66)	-0.170* (1.67)	-0.140* (1.65)	-0.164** (2.28)
Age		-0.018*** (6.71)	-0.018*** (6.05)	-0.081*** (5.91)
Gender		-0.015*** (3.60)	-0.019*** (4.29)	-0.011*** (3.86)
Marital status		0.459*** (5.48)	0.586*** (6.71)	0.273*** (6.58)
Health		0.300*** (6.01)	0.390*** (5.89)	0.310*** (6.43)
Political status		0.190*** (4.53)	0.160*** (4.03)	0.160*** (3.93)
Education level		0.042*** (4.97)	0.036*** (3.87)	0.019*** (4.39)
Income			0.320*** (3.36)	0.307*** (3.77)
Home ownership			-0.195*** (4.62)	-0.186*** (4.63)
Employment status			-0.473*** (4.87)	-0.223*** (4.85)
Whether work in the state-owned enterprise			0.149 (1.60)	0.064* (1.86)

Constant	3.509***	2.503***	3.067***	2.988***
	[-6.03]	[-5.09]	[-8.18]	(9.19)
N	4186	4179	4072	4072
R ²	0.537	0.629	0.785	0.809

In model 2, both city and individual-level variables are included in the regression model. The estimated effect of PM2.5 concentration on well-being decreases, but the coefficient (-0.031) remains significantly negative. Among the individual-level variables, the being married and in good health increase the well-being of the residents. Specifically, the well-being of married residents is 0.459 units higher than single residents. The well-being of generally healthy or very healthy residents is 0.3 units higher than unhealthy or very unhealthy residents. The well-being of older residents and men is lower than younger and female residents. Being a member of the Communist Party of China and having more education are associated with higher levels of well-being in China. In model 3 in Table 3, the family and economic factors are included. The estimated results presented in Table 3 show that increase in household income increases the well-being, while employment and house renting reduces the well-being. In model 4, estimated by OLS, all control variables are included and the effect of PM2.5 on well-being continues to be negative and statistically significant (see Table 3).

4.1 Does the adverse effect of air pollution on well-being vary across pollutions levels?

We now focus on the impact of PM2.5 air pollution on well-being across pollution levels. We want to know, whether PM2.5 affects the well-being of the residents when pollution level is not very heavy? Based on China's Technical Regulation on Ambient Air Quality Index (AQI), we use the PM2.5 concentrations ranges to classify air pollution into four levels. The empirical results based on these four levels of pollution are presented in Table 4. The results show that when pollution is more serious, the adverse effect of PM2.5 on well-being of the residents in China is also stronger. This result is consistent with existing studies (e.g., Levinson, 2012; Menz and Welsch, 2010; and Zhang et al., 2017).

Table 4: The effect of air pollution on well-being across pollution levels

	0~35	35~75	75~115	>115
Urban population	-0.015***	-0.017***	0.045***	-0.059***
	(3.20)	(3.73)	(3.09)	(3.56)
PM2.5	-0.014***	-0.032***	-0.084***	-0.108***
	(4.34)	(4.27)	(4.59)	(4.17)
Urban GDP	0.103***	0.112***	0.108*	0.085**
	(5.52)	(5.81)	(1.79)	(2.22)
Urban housing price	-0.104**	-0.059	-0.185*	-0.632**
	(2.20)	(1.41)	(1.70)	(2.17)
Age	-0.079*	-0.029*	-0.011*	-0.014*
	(1.83)	(1.73)	(1.72)	(1.89)
Gender	-0.011***	-0.013***	-0.018***	-0.010***
	(3.60)	(3.63)	(3.66)	(3.62)
Marital status	0.174***	0.150**	0.161***	0.156***
	(6.61)	(2.29)	(4.15)	(4.69)
Health	0.467***	0.560**	0.882***	0.739**
	(6.43)	(2.26)	(3.49)	(2.01)
Political status	0.075*	0.051**	0.085*	0.066*
	(1.93)	(2.33)	(1.66)	(1.72)
Education level	0.056***	0.063	0.068***	0.032*
	(4.32)	(0.44)	(2.64)	(1.94)
Income	0.218***	0.260**	0.264***	0.223***
	(2.80)	(2.52)	(2.78)	(2.70)
Home ownership	-0.181***	-0.161	-0.110**	-0.123*
	(2.63)	(1.56)	(2.02)	(1.66)
Employment status	-0.209***	-0.295***	-0.224***	-0.237
	(4.03)	(4.09)	(2.86)	(1.38)
Whether work in the state-owned enterprise	0.061	0.013**	-0.061	0.078
	(1.58)	(2.06)	(0.31)	(1.57)
N	857	963	1111	1141

R² 0.749 0.767 0.786 0.792

Note: Normally, values of PM2.5 in the range 0~35µg/m³ represent excellent air quality, 35~75µg/m³ represents good, 75~115µg/m³ represents light pollution, 115~150µg/m³ represent moderate pollution, 150~250µg/m³ represent heavy pollution, and 250µg/m³ or above represents serious pollution.

4.2 Does the adverse effect of air pollution on well-being vary across income levels?

Economic factors are particularly critical for the well-being. It is generally believed that people with higher income improves the well-being. The estimated results presented in Tables 3 and 4 support this view. A question that arises is do people with high income avoid the adverse impact of pollution? To investigate this issue, we re-estimate our regression equation for three income levels (high-income, medium-income and low income). We rank income from low to high. The top 1/3 residents are defined as “low-income group”, the bottom 1/3 are “high income group” and the rest defined fall in “medium income group”. Income level estimation results presented in Table 5 show that the impact of air pollution on well-being is negative for all three income groups, but the estimated effect decreases across income groups. Specifically, the estimated effect is the highest for low-income groups and lowest for the highest income group. This result could be attributed to the fact that high-income people have more choices than medium and low-income people. For example, high-income people can buy houses in less polluted areas (Chen Yongwei et al., 2012) or buy air purifiers to improve the environment at home. However, low-income people do not have the ability to avoid PM2.5.

Table 5: The effect of air pollution on well-being across income levels

Variable	Model1 low-income	Model2 medium-income	Model3 high-income	Model4 interaction
PM2.5	-0.187*** (3.56)	-0.084*** (3.41)	-0.011*** (4.60)	-0.057*** (3.94)
PM2.5*income	NO	NO	NO	-0.013** (2.29)
Other control variables	YES	YES	YES	YES
R ²	0.792	0.759	0.788	0.792
N	1114	1914	1044	4072

In the last column of Table 5 (see model 4), we also estimate the interaction effect of air pollution and income on well-being using the full sample. Model 4 estimation results show that the interaction of income and PM2.5 has a negative and statistically significant effect, which implies that the adverse effect of pollution on well-being declines as household income increases.

4.3 The role of gender and age

We now consider whether the impact of pollution on well-being varies across household gender and age. The estimated results are shown in Table 6. Model 1 in Table 6 implies that PM2.5 has a significant negative effect on female's well-being. The estimated coefficient shows that a $1\mu\text{g}/\text{m}^3$ increase in PM2.5 concentration lowers the well-being of females by 0.072 units. Model 2 shows that PM2.5 also has a significant negative influence on male's well-being, with well-being decreased by 0.017 units for every $1\mu\text{g}/\text{m}^3$ increase in PM2.5 concentrations. Compared with males, females are more sensitive to PM2.5. The coefficient of interaction term, using the full sample, in model 3 is negative, which shows that PM2.5 has a higher adverse effect on the well-being of females.

Table 6: The effect of air pollution on well-being across gender and age

Variable	Model 1: females	Model 2: males	Model 3: interaction	Model 4: middle- aged and elderly	Model 5: the young	Model 6: interaction
PM2.5	-0.072** (2.28)	-0.017*** (3.97)	-0.036*** (5.19)	-0.071*** (3.98)	-0.011*** (4.41)	-0.009*** (3.60)
PM2.5*gender	NO	NO	-0.041*** (3.13)	NO	NO	NO
PM2.5*age	NO	NO	NO	NO	NO	0.048*** (3.68)
Other control variables	YES	YES	YES	YES	YES	YES
R2	0.794	0.785	0.807	0.801	0.770	0.766
N	1872	2200	4072	1544	2528	4072

The estimated results presented under model 4 in Table 6 show that PM2.5 concentration has a negative and statistically significant impact on the well-being of middle-aged and elderly people. For every $1\mu\text{g}/\text{m}^3$ increase in PM2.5 concentration, the well-being of middle-aged and elderly people decreases by 0.071 units on average. The same is true for young people in model 5, which suggests that a $1\mu\text{g}/\text{m}^3$ increase in PM2.5 concentration lowers the well-being of the residents by 0.011 units. The middle-aged and elderly are relatively more seriously affected by PM2.5 pollution than the young. The estimated coefficient of the interaction term, using the full sample, in model 6 is negative and statistically significant, which re-confirms that PM2.5 pollution has a relatively high impact on the well-being of middle-aged and elderly people compared to the young people.

4.4 The role of education

We now focus on the impact of air pollution on well-being of the Chinese residents across education levels. The full sample is divided into three groups: high school or below, undergraduate, postgraduate or above. The estimated results corresponding to these three educational groups, respectively, are shown under models 1, 2 and 3 in Table 7. The empirical results show that, the adverse effect of air pollution on well-being declines with educational attainment. On average, every $1\mu\text{g}/\text{m}^3$ increase in PM2.5 concentration decreases the well-being of the residents with high school or below, undergraduate and postgraduate or above education levels decreases,

respectively, by 0.094, 0.028 and 0.013 units. The coefficient of the interaction term using the full sample, in model 4, is negative, which shows that the higher the educational attainment, the lower is the impact of air pollution on well-being of the residents. The result could be attributed to the fact that lower-income residents in highly educated group are willing to pay more to reduce the adverse impact of environment on health and have a strong awareness of avoiding pollution.

Table 7: The effect of air pollution on well-being across education levels

Variable	Model 1: high school or below	Model 2: undergraduate	Model 3: postgraduate or above	Model 4: interaction
PM2.5	-0.094*** (3.71)	-0.028*** (3.65)	-0.013* (1.85)	-0.032*** (3.24)
PM2.5*education level	NO	NO	NO	-0.027*** (3.62)
Other control variables	YES	YES	YES	YES
R2	0.765	0.771	0.787	0.799
N	2895	2337	62	4072

4.5 Regional-level analysis

China is a large country in terms of both the population and land area. Some cities are very large, but many are not so large. In this section, we investigate the effect of PM2.5 on well-being of residents across Chinese regions. This will allow us to identify the spatial differences. Existing studies have shown that pollution is more serious in the north of China (due to central heating using coal) and hence the well-being of the residents is more seriously affected by PM2.5 and hence there is a strong willingness to pay for cleaner air (Ebenstein et al., 2017). To examine the spatial difference, the sample was split into (i) large, and medium and small cities and (ii) East and mid-Western regions. The estimated results are shown in columns labelled model 1 and 2 in Table 8. The results show that for every $1\mu\text{g}/\text{m}^3$ increase in PM2.5 concentration in large, and small and medium-sized cities, the well-being of the residents, respectively, decreases by 0.124 and 0.025 units on average. The results presented in columns labelled model 4 and model 5, respectively, indicate that the well-being of the residents in east, and mid-Western cities decreases by 0.193 and 0.042 units on average for every $1\mu\text{g}/\text{m}^3$ increase in PM2.5 concentration. The coefficient of the interaction term in model 3 is positive, and the coefficient of the interaction in model 6 is negative, which suggests that large cities and the Eastern regions are more adversely affected by air pollution in China (see Table 8).

Table 8: The effect of air pollution on well-being by city size and region

Variable	Model 1: large cities	Model 2: medium & small cities	Model 3: interaction	Model 4: East	Model 5: Mid- western	Model 6: interaction
PM2.5	-0.124***	-0.025**	-0.036***	-0.193***	-0.042***	-0.070**
	(3.53)	(2.39)	(3.08)	(4.76)	(4.86)	(2.11)
PM2.5*city size	NO	NO	0.017***	NO	NO	NO
			(2.77)			
PM2.5*east or mid- west	NO	NO	NO	NO	NO	-0.053***
						(3.40)
Other control variables	YES	YES	YES	YES	YES	YES
R2	0.786	0.787	0.788	0.790	0.792	0.814
N	2746	1326	4072	2387	1685	4072

4.6 Robustness checks

China's official data on air pollution concentrations are sometimes prone to being tweaked and/or the data does not cover some important aspects. For example, detection points are set far away from the road or water is frequently sprinkled around detection points, which may lead to data distortion to a certain degree and fail to reflect the real situation that residents of a region might be facing (Ebenstein et al., 2017).

In this Section, we discuss the estimation results using the PM2.5 level detected and published by the U.S. Embassy in China. This allows us to check the robustness our main results. The estimation results using the data on PM2.5 by the U.S. embassy and consulates in China are presented in Table 9. The results presented in Table 9 are qualitatively similar to the results presented in Tables 3 and 4 and hence our empirical results are reasonably robust.

Table 9: The effect of air pollution on well-being using the air pollution data released by the U.S. embassy in China

	Full sample	0~35	35~75	75~115	>115
Urban population size	-0.014***	-0.009***	-0.015***	0.029***	-0.086***
	(3.31)	(3.18)	(3.60)	(3.54)	(3.29)
PM2.5	-0.033***	-0.015***	-0.022***	-0.079***	-0.132***
	(4.25)	(4.34)	(4.29)	(4.62)	(4.58)
Urban GDP	0.106***	0.115***	0.122***	0.139*	0.053**
	(5.39)	(5.09)	(5.53)	(1.67)	(2.05)
Urban housing price	-0.168**	-0.129***	-0.067	-0.109	-0.638
	(2.28)	(3.60)	(1.41)	(1.36)	(1.07)
Age	-0.079***	-0.065*	-0.038*	-0.013	-0.017
	(5.83)	(1.71)	(1.74)	(1.43)	(1.29)
Gender	-0.016***	-0.015***	-0.013***	-0.016***	-0.017***
	(3.79)	(3.61)	(3.60)	(3.62)	(3.53)
Marital status	0.198***	0.178***	0.160**	0.163***	0.151***
	(6.79)	(6.86)	(2.18)	(4.31)	(4.59)
Health	0.312***	0.454***	0.568**	0.874***	0.716**
	(6.57)	(5.45)	(2.18)	(4.59)	(2.16)
Political status	0.157***	0.087*	0.063**	0.068	0.079
	(3.97)	(1.92)	(2.25)	(1.34)	(1.48)
Education level	0.028***	0.055***	0.055	0.070***	0.037*
	(4.65)	(4.93)	(0.56)	(2.98)	(1.82)
Income	0.384***	0.267***	0.243**	0.289***	0.255***
	(3.46)	(2.92)	(2.76)	(2.80)	(2.98)
Home ownership	-0.183***	-0.189***	-0.157	-0.129**	-0.176*
	(4.57)	(2.90)	(1.47)	(2.21)	(1.69)
Employment status	-0.227**	-0.210***	-0.245***	-0.273***	-0.258
	(2.06)	(4.68)	(4.43)	(2.79)	(1.49)
Whether work in the state-owned enterprise	0.064*	0.069	0.029**	-0.058	0.093
	(1.66)	(1.58)	(2.08)	(1.28)	(1.32)
N	4072	857	963	1111	1141

R2	0.865	0.870	0.849	0.863	0.875
----	-------	-------	-------	-------	-------

There may be reverse causality between PM2.5 and the well-being of residents, thus we use propensity score matching and Heckman two-step method to analyse the difference of well-being in cities with high PM2.5 and cities with low PM2.5.

As to PSM method, we first use the Probit model to calculate the propensity score of cities with larger PM2.5 (greater than the average 35.43), and the propensity score was incorporated into the regression model as a new variable. We focus on the average treatment effect (ATT) of the experimental group, and the basic model is as follows:

In the above equation, E represents the effect, and D and D^2 in this paper respectively represent the happiness obtained by choosing cities with larger PM2.5 and cities with smaller PM2.5. The difference between D and D^2 indicates the difference of well-being score between cities with larger PM2.5 and cities with smaller PM2.5. D is an indicative function, that is, if the city with larger PM2.5 is selected, a value of 1 is assigned; 0 otherwise.

Models 1 and 2, respectively, represent the regression results of nearest-neighbor matching and kernel matching, and the propensity score is less than 0, indicating that both models show the presence of the selection bias, and PM2.5 has a significant negative impact on well-being. After controlling for the selection bias, cities with higher PM2.5 report lower well-being than cities with lower PM2.5. PSM results show that PM2.5 continues to have a significant negative effect on residents' well-being, but the effect has decreased significantly.

We also use the Heckman two-step method to solve the problem of sample selection bias. In step one, we estimate the probability of choosing cities with high PM2.5, which is defined as 1. In step two, we estimate the well-being level of cities with high PM2.5. Model 3 estimation results show that the lambda coefficient is positive and statistically significant, indicating that there is an obvious selective bias problem. After controlling for the selection bias, Heckman's two-step method shows that PM2.5 continues to have a statistically significant impact on residents' well-being.

Table 10: Accounting for Endogeneity and Selection Bias

Variable	Model 1	Model 2	Model 3
	Nearest-neighbor matching	Kernel matching	Heckman
Urban population	-0.014***	-0.022***	-0.017***
	(3.29)	(3.32)	(3.68)
PM2.5	-0.008***	-0.009***	-0.108***
	(4.26)	(4.04)	(4.08)
Urban GDP	0.105***	0.123***	0.126***
	(5.45)	(5.36)	(5.57)
Urban housing price	-0.168**	-0.128***	-0.061
	(2.27)	(3.48)	(1.02)
Age	-0.065***	-0.056*	-0.049*
	(5.86)	(1.82)	(1.83)
Gender	-0.019***	-0.021***	-0.018***
	(3.56)	(3.57)	(3.59)
Marital status	0.191***	0.173***	0.165**
	(6.83)	(6.58)	(2.99)
Health	0.302***	0.404***	0.538**
	(6.75)	(5.89)	(2.17)
Political status	0.156***	0.085*	0.063**
	(3.92)	(1.85)	(2.26)
Education level	0.029***	0.054***	0.052
	(4.71)	(4.95)	(0.54)
Income	0.382***	0.266***	0.247**
	(3.49)	(2.98)	(2.55)
Home ownership	-0.189***	-0.188***	-0.156
	(4.58)	(2.92)	(1.49)
Employment status	-0.229**	-0.217***	-0.249***
	(2.66)	(4.34)	(4.68)
Whether work in the state-owned enterprise	0.068*	0.061	0.028**
	(1.78)	(1.03)	(2.01)
PSM Score	-2.346***	-0.932***	

3.98

3.85

lambda			0.203***
			4.05
N	4058	4058	4011
R2	0.658	0.674	0.655

5. Mechanism Analysis

Chen et al. (2013) find that long-term exposure to polluted air can shorten the life span of people by 3 years, when the total suspended PM2.5 increases by 100 $\mu\text{g}/\text{m}^3$. Existing studies, such as Chen et al. (2013), Yang Jidong and Zhang Yiran (2014), Mills et al. (2009), Zheng et al. (2019), Tsurumi and Managi (2020), argue that PM2.5 affects the well-being through the health and mood of the residents. To investigate the mechanism through which PM2.5 affects the well-being, we first divide the mechanism of PM2.5 on well-being into health and mood effects. These two variables are from the CLDS 2018 questionnaire. Health is measured by the health status of the respondents, where 1 means generally healthy of very healthy and 0 means very unhealthy or unhealthy. Mood is recorded on a 5-point Likert scale, where 1 means "very unhappy" and 5 means "very happy". We then examine the effect of PM2.5 on well-being in the full sample as well as across income levels and regions. The analytical approach involves replacing the explained variables with health and mood and keep other control variables unchanged.

The estimation results are presented in Table 10, which implies that PM2.5 is more likely to affect the health and mood of low-income groups. Therefore, compared with high-income groups, the higher the PM2.5, the lower the happiness of low-income groups is. Similarly, compared with small and medium-sized cities, PM2.5 has a greater impact on the health and mood of residents in large cities. Therefore, PM2.5 are prone to affect residents' well-being of large ones. In addition, there is no consideration of endogeneity in the paper because there is no inverse causality between air pollution and subjective well-being. Well-being of the residents does not lead to changes in air pollution.

Table 10: Mechanism analysis

Health status is the dependent variable						
Variable	Full sample	Low income	Medium income	High income	Large cities or above	Small and medium-sized cities
PM2.5	-0.209***	-0.487***	-0.232**	-0.077*	-0.368***	-0.159***
	(4.09)	(2.36)	(2.28)	(1.83)	(11.45)	(4.90)
Other control variables	YES	YES	YES	YES	YES	YES
R2	0.890	0.867	0.865	0.834	0.895	0.882
N	4071	1114	1913	1044	1325	2746

Mood is the dependent variable

Variable	Full sample	Low income	Medium income	High income	Large cities or above	Small and medium-sized cities
PM2.5	-0.074*** (5.32)	-0.138*** (3.21)	-0.056*** (2.97)	-0.020** (2.21)	-0.133*** (6.67)	-0.046*** (5.59)
Other control variables	YES	YES	YES	YES	YES	YES
R2	0.707	0.754	0.730	0.792	0.726	0.737
N	4071	1114	1913	1044	1325	2746

6. Conclusions And Policy Recommendations

This paper matches the 2018 China Labour-force Dynamics Survey data (CLDS2018) with urban air pollution data to empirically evaluate the impact of air pollution on subjective well-being of Chinese residents. We find that air pollution decreases the subjective well-being. Further analysis shows that the adverse effect of air pollution on well-being increases with the level of pollution. We find that people earning higher income are able to avoid some the adverse impact, which supports the view that household income moderates the relationship between air pollution and well-being in China. Females and elderly suffer more from air pollution in that the negative effect on well-being is higher than other groups.

Empirical analysis also supports the moderating role of education. Specifically, residents with higher education level experience a relatively smaller negative impact on well-being due to air pollution. We also find evidence of heterogeneity in the effect of air pollution on well-being of residents in China across cities and regions. The adverse impact of air pollution on well-being in large cities is more than 5 times higher than the effect in medium or small cities. An increase in air pollution decreases the well-being in all regions but the adverse effect in Eastern China is more than 4 times stronger than the effect in mid-Western region. The model was also re-estimated using air pollution data released by the U.S. embassy in China and the main results were found to be robust.

The results presented in this paper provide a good explanation for the “Easterlin Paradox” that economic growth may not increase the level of happiness in a country or region happiness. Our results suggest that air pollution can explain the paradox. From policy point of view, our results imply that when considering the cost of air pollution control, the subjective well-being of the residents should also be considered. Second, in the process of air pollution control, regional differences and differences in city size should also be taken into account. In particular, the subjective well-being of the residents of Eastern China and large cities may be more adversely affected by PM2.5 and hence more aggressive and targeted policies are needed to control air pollution. The policy choices may include transfer payments and financial subsidies to improve the governance capacity of the regional governments. Third, considering the heterogeneous effects of air pollution on social well-being of different groups (females, the older population, and less educated groups), policies (e.g., subsidies and low interest loans for education) that target the more vulnerable groups are highly desirable.

Declarations

Ethical: Approval: Not applicable.

Consent to Participate: Manuscript is approved by all authors for participation.

Consent to Publish: Manuscript is approved by all authors for publication.

Authors Contributions: Yunjiang Yu is responsible for conceptualization, methodology and original draft writing. Xing Shu is responsible for original draft writing and visualization. Sibao Yang is responsible for data curation and software. Sajid Anwar is responsible for review and editing writing.

Funding: The National Social Science Fund of China, Grant Number: 19CRK021; Shanghai Philosophy and Social Science Planning Project, Grant Number: 2018BSH006.

Competing Interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and materials: The data used or analyzed during the manuscript are available from the corresponding author on reasonable request.

References

1. Ambrey CL, Fleming CM, Chan YC (2014) Estimating the cost of air pollution in South East Queensland: An application of the life satisfaction non-market valuation approach. *Ecol Econ* 97(1):172–181
2. Ahumada G, Iturra V (2021) If the air was cleaner, would we be happier? An economic assessment of the effects of air pollution on individual subjective well-being in Chile. *J Clean Prod* 289:125–152
3. Brunekreef B, Holgate ST (2002) Air pollution and health. *Lancet* 360(9341):1233–1242
4. Chen Y, Ebenstein A, Greenstone M, Li H (2013) Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China's Huai River Policy. *PNAS Early Edition* 110(32):12936–12941
5. Cuñado J, Pérez de Gracia F (2013) Environment and happiness: new evidence for Spain. *Soc Indic Res* 112(3):549–567
6. Chen YW, Chen LZ (2012) Pricing clean air: Empirical evidence from Qingdao of China. *World Econ* 35(4):140–160
7. Diao B, Ding L, Cheng J (2018) The Spatial-Temporal Characteristics and Influential Factors of NO_x Emissions in China: A Spatial Econometric Analysis. *Int J Environ Res Public Health* 15(7):1405
8. Ed D, Lucas RE, Scollon NC (2006) Beyond the hedonic treadmill: revising the adaptation theory of well-being. *Am Psychol* 61(4):305–314
9. Di Tella R, MacCulloch R, Oswald A (2003) The Macroeconomics of Happiness. *Rev Econ Stat* 85:809–827
10. Easterlin RA (1974) Does Economic Growth Improve the Human Lot? Some Empirical Evidence. Academic Press, New York
11. Easterlin RA (2005) A puzzle for adaptive theory. *J Econ Behav Organ* 56(4):513–521
12. Ebenstein A, Fan M, Greenstone M et al (2017) New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy, *Proceedings of the National Academy of Sciences*, 114(39), 10384-10389

13. Ferrer-i-Carbonell A, Frijters P (2004) How important is methodology for the estimates of the determinants of happiness? *Econ J* 114(497):641–659
14. Frey B, Stutzer A (2002) What can economists learn from happiness research? *J Econ Lit* 40(2):402–435
15. Guxens M, Sunyer J (2012) A review of epidemiological studies on neuropsychological effects of air pollution. *Swiss Med Wkly* 141:w13322
16. Gu H et al (2020) Air pollution risks human mental health: an implication of two-stages least squares estimation of interaction effects. *Environ Sci Pollut Res* 27:2036–2043
17. Guo W, Chen LJ, Fan YQ, Liu MM, Jiang F (2021) Effect of ambient air quality on subjective well-being among Chinese working adults. *J Clean Prod* 296(2):126509
18. Huang YM, He LY (2013) Urbanization, environmental pollution and subjective well-being: An empirical study on China, *China Soft Science*, (12),82–93
19. Knabe A, Ratzel S (2011) Quantifying the psychological costs of unemployment: the role of permanent income. *Appl Econ* 43(21):2751–2763
20. Levinson A (2012) Valuing public goods using happiness data: The case of air quality. *J Public Econ* 96(9–10):869–880
21. Yunjiang Yu^{1,a}, Xing Shu^{3,*}, Sajid Anwar^{2,b}, Sibbo Yang^{1,c}
22. ¹School of International Economics and Trade, Shanghai Lixin University of Accounting and Finance, 201209, Shanghai, China
23. ²School of Business, University of the Sunshine Coast, Australia
24. ³Correspondence, School of International Economics and Trade, Shanghai Lixin University of Accounting and Finance, 201209, Shanghai, China
25. *frankluck666@126.com
26. ^a20159016@lixin.edu.cn
27. ^bSAnwar@usc.edu.au
28. ^c3314681@163.com
29. Li Y, Guan D, Yu Y, Westland S, Wang D, Meng J, Wang X, He K, Tao S (2019) A psychophysical measurement on subjective well-being and air pollution. *Nat Commun* 10(1):1–8
30. 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
31. Liu W, Xu Z, Yang T (2018) Health Effects of Air Pollution in China. *Int J Environ Res Public Health* 15(7):1471
32. Liu J et al (2021) Transition in air pollution, disease burden and health cost in China: A comparative study of long-term and short-term exposure. *Environ Pollut* 277:116770
33. MacKerron G, Mourato S (2009) Life satisfaction and air quality in London. *Ecol Econ* 68(5):1441–1453
34. 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
35. Menz T, Welsch H (2010) Population aging and environmental preferences in OECD countries: The case of air pollution. *Ecol Econ* 69(12):2582–2589

36. Mills NL, Donaldson K, Hadoke PW et al (2009) Adverse cardiovascular effects of air pollution. *Nat Clin Pract Cardiovasc Med* 6(1):36–44
37. OECD (2013) OECD Guidelines on Measuring Subjective Well-being[DB/OL]. OECD Publishing, Paris. <https://doi.org/10.1787/9789264191655-en>
38. Pan Y, Du XM (2010) Labor mobility, industrialization process and regional economic growth: An empirical study based on a nonparametric additive model. *J Quant Tech Econ* 27(5):34–48
39. Qin Y, Zhu H (2018) Run away? Air pollution and emigration interests in China. *J Popul Econ* 31(1):1–32
40. Rehdanz K, Maddison D (2008) Local environmental quality and life-satisfaction in Germany. *Ecol Econ* 64(4):787–797
41. RSSEE, The 2019 Report on the State of the Ecology and Environment in China, <http://english.mee.gov.cn/Resources/Reports/soe/SOEE2019/202012/P020201215587453898053.pdf>
42. Smyth R, Mishra V, Qian X (2008) The Environment and Well-Being in Urban China. *Ecol Econ* 68(1–2):547–555
43. Song Y, Li M, Zhang M, Sun X (2019) Study on the impact of air pollution control on urban residents' happiness from microscopic perspective. *J Clean Prod* 229:1307–1318
44. Song LJ, Yang L (2020) The trajectory of health expectancy among elderly and its influencing factors: An empirical study based on CLHLS, *Population and Economy*, (3),57–74
45. Steptoe A, Wardle J, Marmot M (2005) Positive affect and health-related neuroendocrine, cardiovascular, and inflammatory processes. *Proc Natl Acad Sci USA* 102(18):6508–6512
46. Tsurumi T, Managi S (2020) Health-related and non-health-related effects of PM2.5 on life satisfaction: Evidence from India, China and Japan. *Econ Anal Policy* 67:114–123
47. Welsch H (2002) Preferences over Prosperity and Pollution: Environmental Valuation based on Happiness Surveys. *Kyklos* 55(4):473–494
48. Xu F et al (2021) Air pollution, Residents' Happiness and Environmental Regulation: Evidence from China. *Research Square*
49. Yin H, Pizzol M, Jacobsen JB, Xu L (2018) Contingent valuation of health and mood impacts of PM2.5 in Beijing, China. *Sci Total Environ* 630:1269–1282
50. 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
51. Yang JD, Zhang YR (2014) Pricing of air pollution: Based on the analysis of Well-being data. *World Econ* 37(12):162–188
52. Yang Z et al (2021) Air pollution and mental health: the moderator effect of health behaviors. *Environ Res Lett* 16(4):1–13
53. 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
54. Zhang X, Zhang X, Chen X (2017) Valuing Air Quality Using Happiness Data: The Case of China, *Ecological Economics*, 137, 29-36
55. Zheng S, Wang J, Sun C, Zhang X, Kahn ME (2019) Air pollution lowers Chinese urbanites' expressed happiness on social media. *Nat Hum Behav* 3(3):237–243

56. Zhu Z, Li Z, Chen H, Liu Y, Zeng J (2019) Subjective well-being in China: how much does commuting matter? *Transportation* 46(4):1505–1524
57. Zheng JJ, Liu C, L, C.Z (2015) The impact of environmental pollution on happiness of Chinese: Based on the CGSS empirical research. *Wuhan Univ J Philos Social Sci* 68(4):66–73