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Dirty skies lower subjective well-being

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ABSTRACT

Self-reported life satisfaction of China's population has not improved as much as expected during the economic boom, which was accompanied by a significant decline in environmental performance. Is environmental pollution the culprit for the lagging subjective well-being? To explore this issue, this paper adopts sentiment analysis to construct a real-time daily subjective well-being metric at the city level based on the big data of online search traces. Using daily data from 13 Chinese cities centred on Beijing between August 2014 and December 2019, we look at the corelation between subjective well-being and air pollution and the heterogeneity in this relationship based on two separate identification strategies. We find that air pollutants are negatively correlated with subjective well-being, and well-being tends to decline more from pollution during hot seasons. In addition, residents in wealthier regions tend to be more sensitive to air pollution. This result may be explained by the differences in the subjective perception of air pollution and personal preferences at different levels of income. These findings provide information about concerns of the public, thereby helping the government to take appropriate actions to respond to the dynamics of subjective well-being.

1. Introduction

As the by-product of industrialization, urbanization and motorization, air pollution has evolved into a global issue threatening human health, ranging from smog over cities to smoke inside homes. An estimated 4.2 million individuals die from ambient air pollution-related diseases annually, which is not surprising considering that approximately 91% of the world's population lives in places where air quality is worse than the recommended level of World Health Organization guidelines (World Health Organization, 2019). Copious research has been triggered on the high-visibility consequences of air pollution, such as hospitalization (Neidell, 2009; Gan et al., 2013) and mortality risks (Greenstone and Hanna, 2014). Nevertheless, little is known about low-visibility outcomes of airborne contamination shocks, such as subjective well-being and mental health.

Subjective well-being is an umbrella term that refers to various valuations and affective reactions that people have to life events, both negative and positive (Diener, 2006). Subjective well-being can be affected directly and indirectly by air pollution. On the one hand, air pollution could directly impact local conditions and thus human mood. Recent psychological studies indicate a plausible link between air pollution and psychological distress (Sass et al., 2017), such as anxiety (Pun et al., 2017) and mental disorders (Talbott et al., 2015). This effect is non-trivial, especially for vulnerable groups, especially children (Chen et al., 2018; Midouhas et al., 2018; Balietti et al., 2022) and older adults (Ailshire et al., 2017). On the other hand, through indirect channels, air pollution has significant impacts on people's physical health, social activities and quality of life, which are positively related to subjective well-being. Multiple scientific studies have shown correlations between short- and long-run exposure to air pollution and respiratory diseases (Guan et al., 2016), cardiovascular disease (Hamanaka and Mutely, 2018) and adverse birth outcomes (Bobak, 2000; Malmqvist et al., 2011). In addition, some studies examine the social context of air pollution such as criminal activities, indicating that increased levels of air pollution exposure are linked to a larger number of crimes committed (Bondy et al., 2020). Furthermore, there is convincing evidence of a link between severe air pollution and a reduced frequency of use of amenities, such as bike lanes and scenic spots (Chen et al., 2017); and fewer outdoor leisure activities tend to lead to lower levels of life satisfaction (Schmiedeberg and Schröder, 2017).

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The limited available research on the link between air pollution and subjective well-being mainly relies on the life satisfaction approach. In this approach, the responses to one or more self-rated questions in large-scale representative surveys are extracted to calculate aggregate happiness or individuals' stated well-being. Studies at the aggregate level can ignore interesting underlying differences especially in cases where air quality is determined by regional characteristics and thus creating differential effects on subjective well-being (Levinson, 2012). Moreover, air pollution data aggregated over a long period of time may deviate from actual exposure, and the consequent measurement errors based on unmatched air pollutant data may cause biased estimates (Zhang et al., 2017). Another issue further complicates most prior attempts to estimate the impact of air pollution on subjective well-being using the life satisfaction approach: both aggregated happiness and individuals' stated well-being are based on the assumption that respondents can correctly rate their emotional state. Nevertheless, it is difficult for respondents to distinguish between hedonic and evaluative measures of happiness (Kahneman and Krueger, 2006), which will yield markedly varying results for different factors exerting an influence (Kahneman and Deaton, 2010; Deaton and Stone, 2013). Hedonic happiness refers to real-time experienced utility and is likely subject to short-run shocks in external circumstances. By contrast, evaluative happiness reflects an overall evaluation of life as a whole. The conflation of the two will make the actual effect of air pollution difficult to assess.

Psychophysical procedures, such as judgement of photographs, have been adopted as another feasible method to improve people's understanding of the air pollution impact on subjective well-being in a visual sense. The assumption behind this method is that visual input can dominate complex information processing of the brain and integrated affective reactions. Although photograph judgements have been strongly recommended in terms of their cost-effectiveness, they are insufficient in describing the subjective well-being of a person, as they provide measures only based on visual stimuli (Li et al., 2018). Moreover, the accuracy of judging photographs depends on a high-resolution air quality image index, which can be obtained only in countries with a wide range of air quality from excellent to harmful (Li et al., 2018), so that the nuances can be discerned by the naked eye. Furthermore, the fact that observers' varying criteria for judging images hinge on the nature of their past experiences is another issue that needs to be addressed.

To go beyond the limitations of these methods, this paper adopts sentiment analysis (Kramer, 2010; Thelwall et al., 2012; Tov et al., 2013) to examine the air pollution impact on subjective well-being. Sentiment analysis focuses on systematically extracting users' emotional state from naturally produced text. In this approach, a cluster of words (reflecting positive or negative emotions) categorized by the Linguistic Inquiry and Word Count (LIWC) 2015 dictionary is defined to have some psychological meaning (positive or negative emotions) (Kramer, 2010). Users who utilize words from a particular category more frequently are considered to have a higher level of the psychological construct that the category is designed to measure (Kramer, 2010). For example, an individual will express his (her) strong negative emotions by using more words with pessimistic meaning. The high-quality design of the LIWC dictionary and the fine-grained classification of LIWC categories make it a favourite among psychologists conducting research on the psychological state of individuals (Balage Filho et al., 2013; Zhao et al., 2016), and the dictionary constitutes a trustworthy corpus for our analysis. This top-down approach has been proven to be effective in gauging the subjective feelings of individuals (Hancock et al., 2007; Kahn et al., 2007). On this basis, we take the Baidu Index for different search terms expressing certain emotions as a proxy to measure subjective well-being of individuals. The Baidu Index utilizes a weighted algorithm to calculate the daily search volume of keywords from online search traces based on the Baidu search engine. Baidu is the largest search platform in mainland China and the fourth largest search engine in the world (Statcounter, 2020), with 1.1 billion users worldwide. It covers nearly 90% of Chinese netizens and responds to 6 billion searches per day, and avoids the problem of unrepresentativeness caused by a small sample size.

To the best of knowledge, there is only a very limited number of papers employing the method of sentiment analysis to measure the impact of air pollution on happiness. For example, Zheng et al. (2019) established a daily city-level expressed happiness indicator grounded in Sina Weibo posts posted over the course of nine months in 2014 and found a negative relationship between airborne pollutant concentrations and the daily local happiness index. However, measuring happiness based on Weibo posts may underestimate the impact of air pollution on happiness due to the inherent bias in its user group. Although Weibo users account for a substantial group of the population, nearly 0.17 billion people in 2014, this group is not a representative sample of the Chinese population. People who post on social media to express their emotions tend to be younger and more educated. In contrast, Baidu search engine's market share in China has always been an absolute leader, which helps address the biased sample concern. The Baidu Index is captured from a total of 6 billion online search traces per day, which ensures the accuracy of this index in measuring the concerns of individuals. In addition, Zheng et al. (2019) cover only a nine-month sample (March 2014 to November 2014), failing to capture the influence of air pollution in winter, during which the vast majority of air pollutants reach the highest level, resulting in further underestimates of the impact of air pollution on subjective well-being. This paper contributes by extending the scope of the research subject and the length of the research period to comprehensively capture the social cost of air pollution that is borne by the silent majority, who are neither investigated nor hospitalized, and that is thus undetected by previous research (Zheng et al., 2019). In addition, our analysis based on sentiment analysis conducts a more refined assessment of the connection between air pollution and subjective well-being, as we extract happiness data from subjects' search behaviour, which is insusceptible to subjects' subjective judgements, providing information about the concerns of the public. Moreover, this paper contributes to research on the impact of air pollution on subjective well-being by exploring the seasonal co-movement between air pollution and subjective well-being, the distribution of environmental externalities across income groups and the persistent effect of air pollution on subjective well-being.

Based on high-frequency data on subjective well-being and air pollution, this paper conducts a sentiment analysis and big data analysis to address three main research questions. First, does air pollution exert an influence on residents' subjective well-being at the local level? Second, are there periodic patterns between air pollution and subjective well-being? Third, does the influence of air pollution on subjective well-being vary across income groups? The social cost of air pollution in 13 cities in the highly developed Beijing-Tianjin-Hebei (Jing-Jin-Ji) region in terms of subjective well-being is fully explored. The Jing-Jin-Ji urban agglomeration is one of the regions with the most severe air pollution, and its changing pollution patterns have benefited from acting as the key area of the Air Pollution Prevention and Control Action Plan (General Office of the State Council, 2013), allowing us to explore the dynamics of subjective well-being. Additionally, the varying levels of economic development among the cities in this region enable us to explore the potential uneven distribution of pollution-related life satisfaction change. Therefore, we take the Jing-Jin-Ji region as the case study area of this paper. Using daily data on 13 cities in the Jing-Jin-Ji region from August 2014 to December 2019, we look at the connection between air pollution and subjective well-being and the heterogeneity in this connection based on two separate identification strategies. In our first empirical approach, we estimate fixed effects models on the basis of the panel structure of the data. We then supplement our main estimation strategy with the instrumental variable approach to solve endogeneity concerns. Finally, we investigate whether our estimates vary across months and income groups.

2. Methods

To assess the effect of air pollution on city-level subjective well-being, equation (1) is constructed based on Welsch (2006), as follows:

$$SWB_{it} = \beta_0 + \beta_1 \ln P_{it} + \beta_2 \ln X_{it} + \gamma_i + \varphi_t + \delta_i t + \varepsilon_{it}. \quad (1)$$

The dependent variable, SWB_{it}, measures the subjective well-being level of city i on day t. P_{it} is the variable of interest in our equation, representing the daily mean $PM_{2.5}$ concentrations in city i on day t. We expect the coefficient β_1 to be negative – pessimistic emotions are more likely to develop when air quality is poor. In the following binned estimates, we use the ambient air quality standards published by the Ministry of Ecology and Environment of the People's Republic of China (Ministry of Ecology and Environment of the People's Republic of China, 2020) to partition this variable into three categories: good ($PM_{2.5} \leq 35$ μg/m^3), qualified (35 μg/m$^3 < PM_{2.5} \leq 75$ μg/m^3) and polluted ($PM_{2.5} > 75$ μg/m^3). X_{it} is a set of weather controls, including temperature deviation, humidity, wind speed, visibility, pressure and precipitation. $\delta_i t$ is the time trend item. φ_t and γ_i are time and city fixed effects, respectively. ε_{it} is the disturbance term.

Weather controls are incorporated, as multiple well-documented science studies have shown that meteorological factors can influence both pollution levels (Borge et al., 2015; Borge et al., 2019) and subjective well-being (Zhang et al., 2017). By incorporating city fixed effects, our identification leans upon the comparison of subjective well-being levels among days with varying air pollutant levels in the same city. This method eliminates any potential confusion caused by the time-invariant structural and geographical disparities between cities (Bondy et al., 2020). A final concern is the possible periodic co-movements between pollutant levels and subjective well-being. For instance, we may guess that busy school months and hedonic vacations will differ in both pollutant levels and subjective well-being. To take such systematic time-varying elements into account, we incorporate a set of time fixed effects, φ_t, represented by dummies for the month of the year, to account for any potential seasonal co-movement (Bondy et al., 2020). We also include day of the week dummies to account for the potential short-run co-movement. Furthermore, $\delta_i t$ is included to capture exogenous changes in subjective well-being that the variables above cannot explain, such as sociocultural factors.

As the levels of air pollution are not randomly assigned, it is probable that unobserved time-varying correlated factors may confound our estimates. Additionally, equation (1) may be sensitive to measurement errors, thereby generating biased results. Therefore, we employ the instrumental variable approach to supplement our main empirical strategy. In this approach, we adopt wind direction as an exogenous shock to local air pollutant levels. Specifically, we estimate the following equations:

$$\ln P_{it} = f_0 + f_1 \ln winddirection_{it} + f_2 \ln X_{it} + \omega_i + \vartheta_t + \pi_i t + \varepsilon_{it,} \quad (2)$$

$$SWB_{it} = \alpha_0 + \alpha_1 \ln \widehat{P}_{it} + \alpha_2 \ln X_{it} + \gamma_i + \varphi_t + \delta_i t + \varepsilon_{it}. \quad (3)$$

The $winddirection_{it}$ is defined as the average wind direction across the day. Wind direction has been successfully used as an instrumental variable for air pollution in previous analysis due to the fact that it significantly affects the levels of airborne pollutants (Anderson, 2020; Bondy et al., 2020; Herrnstadt et al., 2021). Fig. 1 indicates the basic mechanism of our instrumental variable approach, illustrating the average level of $PM_{2.5}$ across all sampled cities on days where the average wind direction is as shown. The figure shows that varying wind direction has differentiated effects on airborne pollutant concentrations. On average, $PM_{2.5}$ is significantly higher on days where wind blows from the south and southwest than days with northwest wind. This link between wind direction and air pollution, and the fact that wind direction is determined by large-scale weather systems that are insusceptible to local activities, ensures the validity of our instrumental variable. Our key identification hypothesis is that the mean wind direction in city i on day t is not associated with subjective well-being in city i on day t, apart from its impact on air pollution, after controlling for weather controls, fixed effects, and the time trend item.

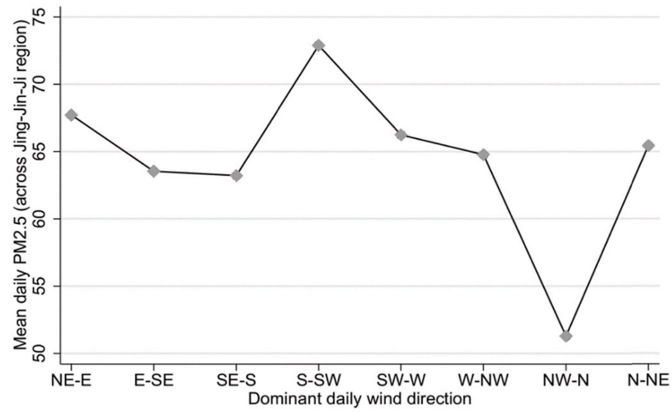

Fig. 1. The effect of wind direction on pollution.

3. Data

We employ the method proposed by Kramer, 2010, to measure the daily subjective well-being in each city. Considering the inequivalent use of positive and negative words in the LIWC 2015 dictionary, we used the following formula to generate a measure of subjective well-being that can be interpreted independently of language and dictionary:

$$SWB_{it} = \frac{\mu_{pit} - \mu_{pi}}{\sigma_{pi}} - \frac{\mu_{nit} - \mu_{ni}}{\sigma_{ni}}. \quad (4)$$

μ_{sit} ($s = p$ or n) represents the ratio of average searches per positive (negative) word to average searches for all sampled words (both positive words and negative words), searched by Baidu users within the city limits, for city i in day t. μ_{si} and σ_{si} indicate a "meta-average" and a standard deviation of these local daily averages across all sampled days. We standardized positive and negative words separately to ensure positivity and negativity are weighted equally in the analysis, which guarantees the effectiveness of out metric of subjective well-being. For example, even if an individual significantly overexpress his (her) negative emotions by using more words with pessimistic meaning in the search engine, daily relative negativity should still be informative as we argue that individuals that feel more negative will express less positivity. This paper used a total of 753 negative words and 545 positive words included in Baidu Index to construct the daily local subjective well-being indicator during August 2014 and December 2019, which constitutes an affluent corpora and a large-scale panel data to efficaciously reduce measurement errors and improve regression accuracy.

We obtain the air pollution data from China National Environmental Monitoring Centre (China National Environmental Monitoring Centre, 2020), which has publicly released hourly air pollutant concentrations ($PM_{2.5}$, PM_{10}, O_3, SO_2, CO and NO_2) of monitoring stations covering hundreds of prefecture cities since May 2014. As the missing data in July 2014 accounts for one-thirds, we start our research from August 2014 in view of the data quality and data accuracy. We collect these real-time records and then aggregating them to city/day level after filling the missing values according to Tang et al. (2020). The hourly air pollutants data obtained is high in data quality and continuity, with all the missing data lasting for no more than 4 hours and accounting for less than 1% in total records. We set the missing data as the arithmetic mean of the two closest valid values before and after. Airborne particulate matter has become the dominant air pollutant and health threat in urban areas (Zhang et al., 2015). With smaller particle size and longer residence time and transportation distance in the atmosphere, $PM_{2.5}$ poses greater impacts on human health, both psychological and physical, than other air pollutants. Thus, we first take $PM_{2.5}$ as the proxy of air pollution in the baseline empirical analysis. Apart from above mentioned six air pollutants, China National Environmental Monitoring Centre also reports a complex air quality metric – the Air Quality Index (AQI), which is calculated according to the local leading air pollutant on a daily basis. We use this indicator to replace $PM_{2.5}$ in the robustness test section to examine the credibility of baseline results.

Meteorological data on the daily basis for Chinese prefecture cities, including daily average temperature, humidity, wind speed, visibility, pressure and precipitation, are collected from China Meteorological Administration (China Meteorological Administration, 2020). Temperature deviation is defined as the absolute value of difference between daily average temperature and the optimal temperature range for humans (17–24 °C), defined by Asseng et al. (2021). Daily observations on the average direction of wind are collected from China Meteorological Administration (China Meteorological Administration, 2020), in which wind blows from one of the eight directions. Monthly average house price at the city level used in the heterogeneity analysis are collected from China Index Academy (China Index Academy, 2020), which has established a huge real estate information database, covering real estate projects of commercial housing, villas, affordable housing in 100 cities. Due to data availability, Cangzhou, Chengde, Xingtai and Zhangjiakou are not included in the heterogeneity analysis. Variables definition and summary statistics are presented in Table 1. Fig. 2 plots the distributions of subjective well-being and $PM_{2.5}$ of our sample.

This paper has three main limitations that we leave for future research to address. First, our subjective well-being indicator is derived from the Baidu Index, which covers the vast majority of Chinese search engine users. Although this paper significantly expands the scope of the research subject by adopting big data analysis, it still under-samples children and older adults. Future studies could further look into the impact of air pollution on subjective well-being of these vulnerable groups. Second, income and housing prices undoubtedly have a long-term cointegration relationship, and using housing prices as a proxy of the income level has been proven useful in previous studies. However, a housing price proxy cannot be seen as a perfect alternative. Future research could conduct large-scale surveys to obtain more accurate and complete income proxy data, such as the credit card expenditure data. Third, this paper takes 13 cities in the Jing-Jin-Ji region as the sampled cities to explore the air pollution impact on subjective well-being. Although valuable findings on the impact of temperature on subjective well-being are obtained, similar meteorological conditions of the sampled cities make it impossible to distinguish the differential impact that temperature has on subjective well-being across latitudes. Future studies could expand the sample to further explore the differential impact of temperature changes on subjective well-being.

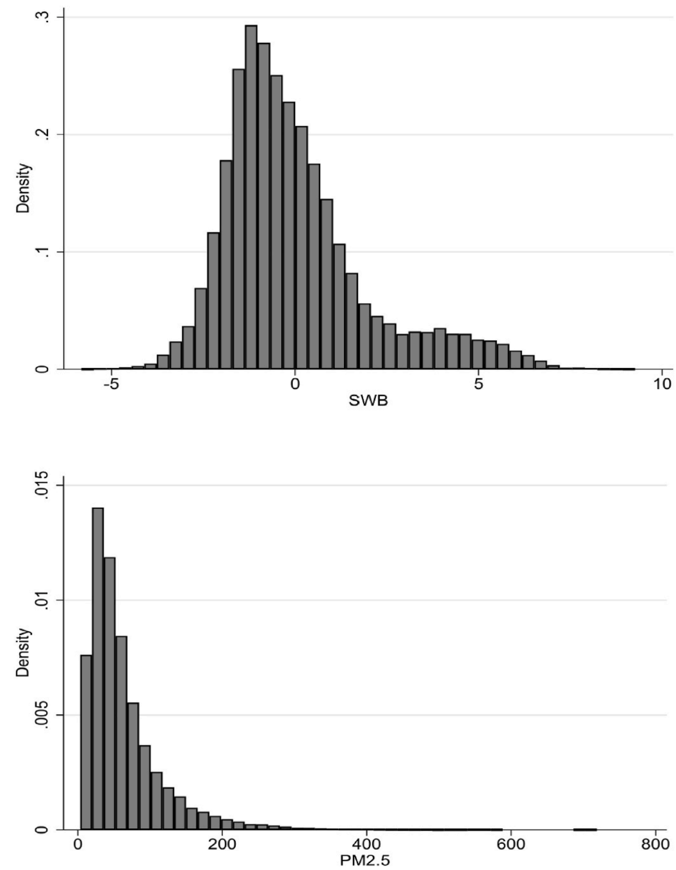

Fig. 2. The density plots of the subjective well-being and $PM_{2.5}$. Density plots of subjective well-being measurements (top) and $PM_{2.5}$ (bottom) by day and city.

Table 1
Variables definition and summary statistics.

Variables	Definition	Obs.	Mean	Std.
Subjective well-being index variables				
SWB	Normalized daily subjective well-being	25727	−5.56e-10	2.00
SWB-alternative	Daily subjective well-being	25727	0.19	0.07
Sources: Baidu website, http://index.baidu.com/v2/index.html#/.				
Pollution variables				
AQI	Daily air quality index	25727	100.56	62.19
$PM_{2.5}$	Daily mean $PM_{2.5}$ concentrations ($\mu g/m^3$)	25727	64.44	56.08
Sources: China National Environmental Monitoring Centre, http://www.cnemc.cn/.				
Instrumental variable				
WIND DIRECTION	Average wind direction (°)	25727	187.33	102.62
Sources: China Meteorological Administration, http://data.cma.cn/.				
Meteorological factors				
TEMPDEV	Daily temperature deviation from optimal temperature range (°C)	25727	7.62	7.79
WIND SPEED	Daily mean wind speed (m/s)	25727	2.16	1.12
VISIBILITY	Daily mean visibility (km)	25727	14.77	8.46
HUMIDITY	Relative humidity (%)	25727	56.80	20.02
PRESSURE	Average atmospheric pressure (hPa)	25727	1002.99	26.23
PRECIPITATION	Total amount of rainfall (mm)	25727	0.84	4.26
Sources: China Meteorological Administration, http://data.cma.cn/.				
Income variable				
INCOME	Monthly average income (Yuan)	585	11623.60	10217.38
Sources: China Index Academy, https://industry.fang.com/index/Research.				

4. Results

4.1. Baseline results

We first examine the association between air pollution and subjective well-being based on the baseline empirical model, which is shown in the Methods section. The estimates documented in Table 2 imply that higher levels of fine particulate matter concentrations are correlated to lower levels of subjective well-being. In column 1, we estimate models with the key explanatory variable, city and month of the year fixed effects based on the panel structure of the data. The coefficients estimated in column 1 indicate that 10-percent increase in $PM_{2.5}$ concentrations will decrease the happiness index by 0.016, an estimate significant at 1%. We add the day of the week dummies in column 2. The estimates remain unchanged

Table 2
Estimation of the impact of air pollution on subjective well-being by fixed effects models.

Dependent variable: SWB	(1)	(2)	(3)	(4)	(5)
$PM_{2.5}$ (log)	−0.161***	−0.164***		−0.105***	−0.100***
	(0.026)	(0.026)		(0.019)	(0.018)
$PM_{2.5}$ dummies ($PM_{2.5} \leq 20\mu g/m^3$ as default)					
$20\mu g/m^3 < PM_{2.5} \leq 35\mu g/m^3$			−0.250***		
			(0.042)		
$35\mu g/m^3 < PM_{2.5} \leq 75\mu g/m^3$			−0.396***		
			(0.062)		
$PM_{2.5} > 75\mu g/m^3$			−0.412***		
			(0.076)		
One-day lag (log)				−0.105***	−0.097***
				(0.017)	(0.016)
One-week lag (log)					−0.130***
					(0.022)
Constant	2.864***	2.806***	2.448***	3.021***	3.561***
	(0.145)	(0.150)	(0.104)	(0.174)	(0.247)
City fixed effects	YES	YES	YES	YES	YES
Time trend item	YES	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES	YES
Day of the week fixed effects	NO	YES	YES	YES	YES
Observations	25727	25727	25727	25714	25636
R-squared	0.352	0.356	0.357	0.357	0.359

Standard errors are in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

and are statistically significant at 1%. We also examine the possible non-linear relationship between air pollution and subjective well-being by replacing our continuous $PM_{2.5}$ measure with a binned estimate. Following Welsch and Kühling (2009), we replace the continuous $PM_{2.5}$ indicator with three $PM_{2.5}$ bins. We use the ambient air quality standards published by the Ministry of Ecology and Environment to rank the bins: good ($PM_{2.5} \leq 35$ μg/m^3), qualified (35 μg/m$^3 < PM_{2.5} \leq 75$ μg/m^3) and polluted ($PM_{2.5} > 75$ μg/m^3) (Ministry of Ecology and Environment of the People's Republic of China, 2020). The negative effect on subjective well-being increases non-linearly. Specifically, the coefficients are −0.250, −0.396 and −0.412 for good, qualified and polluted alerts, respectively. We then include the lagged terms of fine particulate matter to test whether $PM_{2.5}$ could have a persistent impact on subjective well-being. With the one-day lagged term added, apart from additional 10-percent increase in $PM_{2.5}$ concentrations leading to a 0.011 decrease in subjective well-being, adverse air conditions in the past significantly affect people's current subjective well-being. After adding a one-week lagged term, the magnitude at which air pollution affects individuals' present subjective well-being remains unchanged, while the two lagged terms are both statistically significant at the 1% level, suggesting that air pollution has a persistent impact on subjective well-being.

Although numerous studies have shown that material factors greatly shape happiness (Clark et al., 2008), it is well known that happiness hinges on a wider range of environmental factors, such as meteorological conditions, which has been demonstrated to be a crucial determinant of quality of life (Moro et al., 2008). We therefore incorporate a set of weather controls in Table 3 to capture the influence of meteorological factors. Inspired by the concept of the optimum temperature range for human performance (Asseng et al., 2021), we incorporate daily temperature deviation variable in column 1, we find that a 10-percent increase in daily temperature deviation will lower subjective well-being by 0.0003. We then further examine the possible non-linear relationship between temperature and subjective well-being by incorporating seven temperature bins. Column 2 suggests a non-linear link between daily average temperature and subjective well-being. People are sensitive to temperature changes away from the optimal temperature range for humans, and a slight deviation from optimal temperature range will lead to a substantial decline in subjective well-being. This finding implies that mitigating global warming will have differentiated impacts on subjective well-being across regions. The estimates for our preferred

Table 3
Estimation of the impact of air pollution on subjective well-being by a fixed effects model.

Dependent variable: SWB	(1)	(2)	(3)
$PM_{2.5}$ (log)	−0.164***	−0.140***	−0.330***
	(0.026)	(0.027)	(0.077)
Tempdev (log)	−0.003		−0.002
	(0.002)		(0.002)
Temperature dummies (tempdev∈[30 °C, +∞) as the default)			
Tempdev ∈[0 °C, 5 °C)		−1.150***	
		(0.274)	
Tempdev ∈[5 °C, 10 °C)		−1.305***	
		(0.285)	
Tempdev ∈[10 °C, 15 °C)		−1.100***	
		(0.269)	
Tempdev ∈[15 °C, 20 °C)		−0.876***	
		(0.245)	
Tempdev ∈[20 °C, 25 °C)		−0.729***	
		(0.224)	
Tempdev ∈[25 °C, 30 °C)		−0.571***	
		(0.157)	
Humidity (log)			0.233***
			(0.073)
Wind speed (log)			0.010
			(0.049)
Visibility (log)			−0.152
			(0.094)
Pressure (log)			5.947
			(4.504)
Precipitation (log)			−0.009**
			(0.004)
Trend	−0.002***	−0.002***	−0.002***
	(5.330e-05)	(5.400e-05)	(5.250e-05)
Constant	2.814***	3.497***	−38.284
	(0.148)	(0.216)	(31.076)
City fixed effects	YES	YES	YES
Time trend item	YES	YES	YES
Year-month fixed effects	YES	YES	YES
Day of the week fixed effects	YES	YES	YES
Observations	25727	25727	25727
R-squared	0.356	0.359	0.359

Standard errors are in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

specification with the full set of fixed effects and controls included are documented in column 3. In addition to temperature deviation, humidity and precipitation exert significant effects on subjective well-being. Specifically, 10-percent increase in humidity is related to an increase in subjective well-being of 0.023, while a 10-percent increase in precipitation will lower subjective well-being by 0.001. This estimate replicates the results of previous psychological studies showing that rainy days lower the happiness of subjects (Connolly, 2013).

Although we argue that our empirical strategy produces reliable evidence for the causal relationship between air pollution and subjective well-being, we cannot conclusively exclude the effects of time-varying omitted variables. Additionally, our baseline model may be sensitive to measurement errors, thereby generating biased results. Hence, we supplement our baseline model with the instrumental variable approach which adopts wind direction as an external shock to local air pollutant concentrations. The resultls are shown in Table 4. The first-stage F-test expressly shows that wind direction can serve as a good predictor of local air pollutant concentrations. Furthermore, wind direction is determined by large-scale weather systems, insusceptible to other socioeconomic and demographic factors affecting subjective well-being, ensuring the validity of our instrumental variable. We successively incorporate different groups of fixed effects and controls into the instrumental variable model in columns 1–5. By including city fixed effects, we can eliminate the potential confounding factors from the time-invariant structural and geographical disparities between cities. With the time fixed effects incorporated, concerns over the periodic co-movements between air pollutant concentrations and subjective well-being can be resolved. Our estimates from the instrumental variable model are highly negative and statistically significant across all specifications, supporting the findings from the baseline model that air pollution is negatively correlated with subjective well-being.

4.2. Robustness checks

To support the causal interpretation drawn from our analysis, we conduct several robustness tests. The estimates are shown in Table 5. We first consider robustness to the alternative subjective well-being specification and the air pollutant indicator. In column 1, we replace $PM_{2.5}$ with a composite air quality metric, the AQI, to comprehensively measure the impact of air pollutant concentrations on subjective well-being. Although the estimates replicate those of our previous analysis, the estimated coefficients become larger because the mean of the AQI is larger than the mean of $PM_{2.5}$. We replace the dependent variable with a non-normalized measure of subjective well-being in column 2. We find that these estimates are broadly in line with those of our previous analysis showing that airborne particulate matter concentrations vary negatively with subjective well-being. Columns 3 documents the estimates from models with additional controls (dummies for statutory holidays). The results support the estimates of our baseline specifications. In addition, holiday plays an important role in determining subjective well-being as it links to increased extent and quality of social connections that are positively connected with subjective well-being (Helliwell and Wang, 2014). The magnitude of the negative impact of $PM_{2.5}$ on subjective well-being increases after adding the dummies for statutory holidays (compared to Table 3 Column 3). Additional 10-percent increase in $PM_{2.5}$ concentrations is related to a decrease in subjective well-being of 0.034. People are much happier on statutory holidays than on normal days, which is in accordance with the findings of previous research (Nawijn, 2011). We incorporate city-month fixed effects in column (4) to capture the potential confusion caused by city-time-variant factors. The estimates replicate our previous analysis. In column 5 we use an alternative instrumental variable based on 16 wind directions. Again, the estimates are similar to the results documented in Table 4.

We next conduct the placebo test to further support the causal interpretation of our analysis. The results are documented in Table 6, in which we conduct several placebo exercises to test the relationship between subjective well-being and air pollution on irrelevant days. We look at air pollution levels in the later four and six months, respectively. Row 1 replicates estimates from baseline model (Table 3 column 3) and instrumental variable model (Table 4 column 5). The estimates verify that the link between subjective well-being and air pollution can only be seen on the same day, while there was no identifiable relationship between the placebo pollution levels and subjective well-being.

4.3. Heterogeneity tests

The significant and persistent impacts of air pollution on subjective well-being suggest that it is necessary to further investigate the connections between air pollution and subjective well-being. Many macroeconomic studies on air pollution argue that there are periodic movements in air pollutant levels resulting from changes in anthropogenic activities, atmospheric status and meteorological conditions (Cichowicz et al., 2017). For example, the levels of airborne pollutants are normally higher on weekends due to increased outings; and the concentrations of fine particulate matter are commonly higher in cold seasons in areas with more coal-fired heating activities. Therefore, we augment the baseline model by including the interaction terms between $PM_{2.5}$ concentrations and the dummies for each day of the week to explore any possible short periodic co-movements between air pollution and subjective well-being. We then incorporate the interaction terms between $PM_{2.5}$ concentrations and the dummies for each month of the year to explore potential seasonality co-movements.

Table 7 column 1 shows that there is distinct periodic pattern between air pollution and subjective well-being in the short run, and subjective well-being dropped more on weekends. This could be

Table 4
Estimation of the impact of air pollution on subjective well-being by instrumental variable models.

Dependent variable: SWB	(1)	(2)	(3)	(4)	(5)
$PM_{2.5}$ (instrumented)	−1.345***	−1.201***	−0.830***	−0.963***	−0.993***
	(0.202)	(0.160)	(0.147)	(0.144)	(0.144)
Constant	−37.715***	−25.222***	−66.283***	30.331	29.701
	(5.033)	(3.916)	(9.294)	(19.806)	(19.704)
Weather controls	YES	YES	YES	YES	YES
Time trend item	NO	YES	YES	YES	YES
City fixed effects	NO	NO	YES	YES	YES
Year-month fixed effects	NO	NO	NO	YES	YES
Day of the week fixed effects	NO	NO	NO	NO	YES
Observations	25727	25727	25727	25727	25727
First stage (F-test)	1504.580	1566.650	1061.230	1190.450	1020.340
R-squared	.	0.271	0.313	0.337	0.339

Standard errors are in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5
Robustness checks involving several different specifications.

	(1) Log-form AQI	(2) SWB-alternative	(3) Additional controls	(4) Additional fixed effects	(5) Alternative wind IV
$PM_{2.5}$ (log)	−0.483***	−0.010***	−0.338***	−0.348***	−0.965***
	(0.108)	(0.002)	(0.077)	(0.078)	(0.142)
Holiday			0.464***		
			(0.038)		
Constant	−26.535	−1.214	−38.810	−33.522	26.801
	(32.172)	(0.974)	(31.013)	(31.915)	(19.530)
Weather controls	YES	YES	YES	YES	YES
Time trend item	YES	YES	YES	YES	YES
City fixed effects	YES	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES	YES
Day of the week fixed effects	YES	YES	YES	YES	YES
City-month fixed effects	NO	NO	NO	YES	NO
Observations	25727	25727	25727	25727	25727
R-squared	0.360	0.357	0.362	0.368	0.341

Standard errors are in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table 6
Measuring the Relationship between subjective well-being and $PM_{2.5}$ on the Actual Day and Irrelevant Days.

Dependent variable: SWB	(1) (2) Without instruments		(3) (4) With instruments	
$PM_{2.5}$ (actual)	−0.330*** (0.077)		−0.993*** (0.144)	
4-month	−0.039		−0.494	
	(0.023)		(1.067)	
6-month		−0.029		−0.496
		(0.034)		(0.305)
Constant	−72.067*	−71.974*	−72.411***	−70.970***
	(33.681)	(33.656)	(12.552)	(12.636)
Weather controls	YES	YES	YES	YES
Time trend item	YES	YES	YES	YES
City fixed effects	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES
Day of the week fixed effects	YES	YES	YES	YES
Observations	25727	25727	25727	25727
R-squared	0.355	0.354	0.333	0.330

Standard errors are in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

attributed to more exposure to air pollution due to family or recreational activities on weekends. Seasonal co-movements between air pollution and subjective well-being are observed, with people suffering the most from air pollution during the hot season (i.e., July to September), instead of the polluted winter. Table 7 column 2 indicate that additional 10-percent increase in $PM_{2.5}$ concentrations during the hot season decreases subjective well-being by 0.040, an estimate significant at the 1% level. This seemingly counterintuitive outcome makes sense considering the existence of the thermo-sensitive physiological mechanism. Individuals' emotion well-being is reduced and mental states are instable when suffering from heat exposure (Keller et al., 2005; Ranson, 2014). In this case, additional external shocks, such as air pollution, are more likely to trigger negative emotions and further lower emotional well-being. The significant loss of subjective well-being in May and October can be attributed to both more pollution exposure during holidays (e.g. International Workers' Day and The National Day), and the extra efforts exerted to avoid such pollution, such as switching expected outdoor activities to indoor activities or being forced to change tourist destinations (He et al., 2020; Wang et al., 2020). In addition to $PM_{2.5}$ and the AQI, visibility has been widely used as a key parameter indicating air quality and an intuitive indicator of weather conditions (Molnár et al., 2008). Thus, we incorporate the interaction terms between $PM_{2.5}$ concentrations and visibility categories to look into the heterogeneous effects of air pollution on subjective well-being under different weather conditions. Visibility is divided into 6 categories: visibility type 1 (visibility<2 km), visibility type 2 (2 km ≤ visibility<4 km), visibility type 3 (4 km ≤ visibility<6 km), visibility type 4 (6 km ≤ visibility<8 km), visibility type 5 (8 km ≤ visibility<10 km) and visibility type 6 (visibility≥10 km). Table 7 column 3 show that the marginal decrease in subjective well-being caused by air pollution is greater on days with higher visibility. This finding also confirms our previous analysis showing that the link between air pollution and subjective well-being is non-linear.

Economists have long understood that environmental externalities are unevenly distributed among income groups, and as a result, certain groups of individuals bear a disproportionate burden of environmental damage. This heterogeneity is rooted in disparate levels of baseline exposure or vulnerability (Hsiang et al., 2019), for example, avoidance behaviours, such as purchasing face masks and air purification systems; alternatively, people who are sensitive to air pollution will migrate to less polluted locations (He et al., 2020). Here, we estimate the environmental burden across income groups from the perspective of subjective well-being. According to Bondy et al. (2020), we take the monthly average housing prices as a proxy for income.

Fig. 3 plot the estimates and corresponding 95% confidence interval for the heterogeneous effects of air pollution on subjective well-being across income levels. We stratify the income variable into six categories: income level 1 (monthly average income <5000 yuan), income level 2 (5000 yuan ≤ monthly average income <7000 yuan), income level 3 (7000 yuan ≤ monthly average income <9000 yuan), income level 4 (9000 yuan ≤ monthly average income <11000 yuan), income level 5 (11000 yuan ≤ monthly average income <13000 yuan), and income level 6 (monthly average income ≥13000 yuan). Fig. 3 indicates that the estimated effects of air pollution on subjective well-being are larger in wealthier regions. These results might be explained by the differences in the subjective perception of air pollution and the categories of personal needs can be reached among income groups. First, environmental knowledge will affect individuals' subjective judgements on environmental issues (Li et al., 2014). Specifically, only residents with corresponding environmental knowledge can accurately quantify the risk of environmental pollution, thereby increasing their attention to environmental issues. The more residents learn about the hazards of environmental issues, the more serious their subjective perception of the degree of air pollution will be (Li et al., 2014). In general, high-income groups tend to possess more environmental knowledge than low-income groups, as high-income earners generally have higher levels of education and a stronger ability to obtain information. Second, income levels affect the categories of personal needs that can be reached (Drakopoulos and Grimani, 2013). Subjective well-being essentially reflects a person's

Table 7
Heterogeneous effects of air pollution on subjective well-being.

Heterogeneity test of different days	(1)	Heterogeneity test of different months	(2)	Heterogeneity test of different weather conditions	(3)
	SWB		SWB		SWB
$PM_{2.5}$*Monday	−0.348***	$PM_{2.5}$*January	−0.283***	$PM_{2.5}$*visibility∈(0 km, 2 km)	−0.192
	(0.080)		(0.085)		(0.123)
$PM_{2.5}$*Tuesday	−0.349***	$PM_{2.5}$*February	−0.203**	$PM_{2.5}$*visibility∈[2 km, 4 km)	−0.256**
	(0.076)		(0.074)		(0.102)
$PM_{2.5}$*Wednesday	−0.340***	$PM_{2.5}$*March	−0.218**	$PM_{2.5}$*visibility∈[4 km, 6 km)	−0.302***
	(0.078)		(0.078)		(0.097)
$PM_{2.5}$*Thursday	−0.326***	$PM_{2.5}$*April	−0.323***	$PM_{2.5}$*visibility∈[6 km, 8 km)	−0.283**
	(0.078)		(0.074)		(0.095)
$PM_{2.5}$*Friday	−0.261***	$PM_{2.5}$*May	−0.423***	$PM_{2.5}$*visibility∈[8 km, 10 km)	−0.303***
	(0.075)		(0.068)		(0.087)
$PM_{2.5}$*Saturday	−0.336***	$PM_{2.5}$*June	−0.240***	$PM_{2.5}$*visibility∈[10 km, +∞)	−0.312***
	(0.077)		(0.072)		(0.077)
$PM_{2.5}$*Sunday	−0.351***	$PM_{2.5}$*July	−0.305***	Constant	−37.847
	(0.078)		(0.070)		(30.903)
Constant	−37.742	$PM_{2.5}$*August	−0.462***		
	(31.067)		(0.072)		
		$PM_{2.5}$*September	−0.407***		
			(0.070)		
$PM_{2.5}$*weekdays	−0.322***	$PM_{2.5}$*October	−0.482***		
	(0.077)		(0.076)		
$PM_{2.5}$*weekends	−0.341***	$PM_{2.5}$*November	−0.282***		
	(0.077)		(0.083)		
Constant	−34.297	$PM_{2.5}$*December	−0.232**		
	(30.845)		(0.085)		
		Constant	−50.152		
			(29.660)		
Weather controls	YES		YES		YES
Time trend item	YES		YES		YES
City fixed effects	YES		YES		YES
Year-month fixed effects	YES		YES		YES
Day of the week fixed effects	YES		YES		YES
Observations	25727		25727		25727
R-squared	0.356		0.361		0.361

Standard errors are in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Note: The first column shows estimates of two separate regressions, namely the heterogeneous effects of air pollution on subjective well-being across day of the week, and the heterogeneous effects of air pollution on subjective well-being across weekdays and weekends.

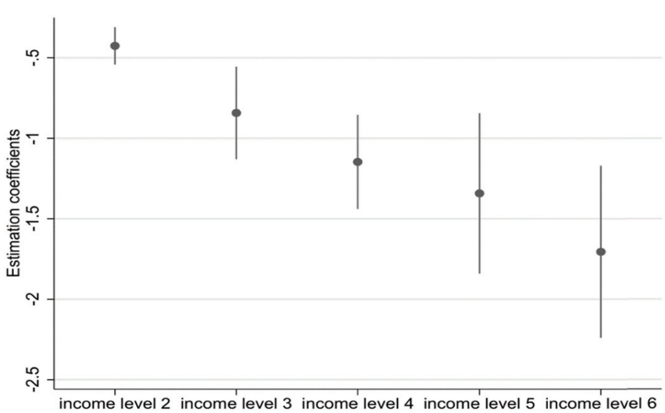

Fig. 3. The effect of air pollution on subjective well-being across income levels. *Note*: Income level 1 is considered the default group. The coefficients in the graph report the relative impact of the corresponding group compared to income level 1. Income level 1 has lowest income, while income level 6 has highest income.

cognitive and affective evaluations of his or her life (Diener et al., 2002), and the fulfillment of needs are one of its important sources (Tay and Diener, 2011). According to the central idea of Maslow's needs hierarchy theory, people will begin to pay more attention to satisfying secondary needs, such as health, after the primary needs are met, which mainly refer to the need for food, clothing and shelter (Drakopoulos and Grimani, 2013). For example, low-income earners tend to be more likely to accept working in a highly polluted environment, as they have no other choice, while high-income earners are willing and can afford to pay to improve the environment.

5. Conclusions

The impact of air pollution on subjective well-being is of particular interest considering serious environmental pollution and the thought-provoking phenomenon that the self-reported life satisfaction index of Chinese people has not increased as much as expected during the period of rapid economic development. This paper conducts sentiment analysis and big data analysis to explore this puzzle. Using daily data on 13 cities in the Jing-Jin-Ji region from August 2014 to December 2019, we find that higher levels of airborne pollutants are linked to lower levels of subjective well-being. Our findings concerning the impact of air pollution on subjective well-being remain after using alternative measure of air pollution, subjective well-being, and instrumental variables and so on. Additionally, this detrimental impact is persistent, which will last for at least one week. We also find that meteorological factors are closely associated with subjective well-being, which is in accordance with findings of previous psychological studies. This result suggests that in the context of irreversible global warming, more attention needs to be paid to the dynamics of subjective well-being. Finally, we examine whether our estimates vary across months and income groups. The findings show that greater adverse effects tend to occur in hot seasons and wealthier regions.

The findings of this paper show that the cost associated with air pollution should be re-considered to avoid the underestimation of such cost by simply considering the health cost of air pollution. In addition to health care expenditures, the loss of subjective well-being should also be included in the cost-benefit analysis framework of air pollution. This loss is likely to be substantial when considering its cumulative effects over time. Neglect or limited attention to this loss and its possible following outcomes, such as mental disorders, aggressive actions and substance abuse caused by negative emotions, may cause inadequate measures of air pollution control, thereby limiting governments' ability to create a better life for citizens.

To achieve ambitious pollution mitigation goals, in addition to government and industry efforts, individuals' abatement efforts are also crucial. It is considerable to propagate environmental knowledge to provide incentives for individuals to engage in activities that reduce emissions. Only residents with corresponding environmental knowledge can accurately quantify the risk of environmental pollution and consequently take appropriate adaptation and avoidance actions to minimize environmental burdens or exposure to environmental risks, such as using public transportation and energy-saving household appliances as much as possible, adjusting outdoor activities on highly polluted days, and purchasing face masks and air purification systems. Furthermore, policies need to pay attention to the diversity of needs and vulnerabilities of different groups for a better life to improve the overall happiness of residents across the country.

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CRediT authorship contribution statement

Lu Cheng: designed the study, drafted the first manuscript and performed the analyses. **Zhifu Mi:** designed the study, reviewed and commented on the manuscript. **Yi-Ming Wei:** reviewed and commented on the manuscript. **Shidong Wang:** reviewed and commented on the manuscript. **Klaus Hubacek:** reviewed and commented on the manuscript.

Declaration of competing interest

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.

Data availability

Data will be made available on request.

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