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Does air pollution influence music sentiment? Measuring music sentiment by machine learning☆

Feng Guo [a], Zhiyuan Lin [b], Xiaoliang Lyu [c], Qingling Shi [d,*]

[a] School of Public Economics and Administration, Shanghai University of Finance and Economics, China
[b] School of Statistics, University of Minnesota, Twin Cities, China
[c] School of Accountancy, Shanghai University of Finance and Economics, China
[d] The Center for Modern Chinese City Studies/Institute of Urban Development, East China Normal University, China

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ABSTRACT

Air pollution has imposed significant negative effects on individuals' well-being, including citizens' sentiment levels. To test this claim, we investigate the impact of air pollution on Chinese urbanites' music sentiments. The analysis is based on a unique dataset of high-frequency music consumption records from a music platform in China from October 13th, 2019 to January 7th, 2020. Using machine learning algorithms, songs on this platform are divided into cheerful songs, melancholy songs and other categories, by which a music sentiment index (MSI) is generated at city-daily level. By matching MSI and daily air quality, this study finds that the MSI declines during highly polluted days, indicating that: on highly polluted days, citizens tend to enjoy melancholy songs over cheerful ones. In addition, this effect becomes more remarkable when the Air Quality Index (AQI) score is above 200, a critical point for "heavily polluted" and "severely polluted" days.

1. Introduction

In addition to physiological damage (Beatty & Shimshack, 2014; Greenstone & Hanna, 2014), previous studies have also found that air pollution has a serious negative impact on the mental health of residents, including people's sentiment (Hirshleifer & Shumway, 2003; Goetzmann et al., 2015; Zheng et al., 2019). However, the sentiment, as an unobservable characteristic, is difficult to be measured accurately and must be estimated by proxy variables (Zhou, 2018). For instance, the sentiment could be estimated by market indicators (Baker & Wurgler, 2006), questionnaire survey (Ilut & Schneider, 2014), text analysis (Antweiler and Fran, 2004), or exogenous shocks (Edmans et al., 2007). In this study, we use citizens' music listening records, including dates, locations and song lists, to identify the audiences' sentiment, which are collected from a Chinese online music platform, and we further investigate the impact of air pollution on music sentiment. Based on research in the psychological literature, the proclivity of music genre reflects human sentiment. For example, the study of North and Hargreaves (1996) showed that participants' preferences for music is matching with their current sentimental state. Saarikallio & Erkkilä (2007) recorded that sad or angry persons tended to listen to sad music to express their emotions. Hunter et al. (2011) found that subjects' preference for optimistic music was eliminated after inducing pessimism. Moreover, another advantage of using music to measure sentiment is that the melody of music is beyond vocabulary and language. It

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* Correspondence to: The Institute of Urban Development, East China Normal University, Shanghai 200063, China.
E-mail address: qlshi@iud.ecnu.edu.cn (Q. Shi).

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can generate a generic and consistent measurement of sentiment across countries, nations, and even time (Edmans et al., 2022). Using machine learning algorithms, this study attempts to construct a music sentiment index (MSI) based on the analysis of music frequency spectrum. Then, merging this new sentiment measurement and the air quality data, this paper further investigates the impact of air pollution on people's sentiment.

China is the prime focus of our empirical study for its severity of air pollution. Air pollution is one of main health risk factors for Chinese residents (Yang et al., 2013). According to Chen et al. (2013), total suspended particulates (TSPs) is inducing a reduction by over five years of the life expectancies of North China residents, with the reason that residents in North China burn coal for heating in winter, causing serious air pollution. Air quality has become one of the greatest policy challenges in developing countries such as China. Thus, providing detailed orientation for policy makers with regard to both palpable and impalpable utility loss, perspicacious insights of detrimental effects from pollution is required by welfare evaluations of policy interventions. Moreover, in recent years, with rapid development of China's economy and surge of residents' income, growing spiritual and cultural demand results in continuous growth of cultural and entertainment consumption. For example, according to the data released by China's National Bureau of Statistics, per capita consumption expenditure on education, culture and entertainment in 2020 was ￥2032, accounting for 9.6% of per capita consumption expenditure in China. When one is in a bad mood, one will resort to some recreational means like music, movies and so on. Digital music, in particular, has benefited from the popularity of the Internet and favorable policies. The digital music industry has expanded rapidly and the scale of users has been growing. More than 600 million music platform users are creating a 66.4-billion-yuan business in 2019. The objective of this study is to identify a possible causal impact that air pollution has on the sentiments in the music urban residents enjoy.

Detailed and exhaustive data, including daily music consumption record, weather, and air quality aggregated at city level across China, enables the following analysis. The daily music consumption data is retrieved from NetEase Cloud Music, which is similar to Spotify and iTunes and it is one of the largest online music platforms in China. Through nearly three months of crawling in the middle of the night every day, from October 13th, 2019 to January 7th, 2020, we recorded the songs listening record of millions of listeners each day on NetEase Cloud Music. Using a machine learning algorithm, we classify music pieces into three categories: cheerful songs, melancholy songs, and others with obscure scores between cheerful songs and melancholy songs. A Music Sentiment Index (MSI) is calculated on a city-daily basis. Daily fluctuations of air quality index are used to reckon the marginal impact of air contamination on music preferences: more cheerful songs or more melancholy songs.

Nonetheless, one unneglectable problem is that some factors, like weather conditions, if not directly, may influence an individual's proclivity to enjoy certain types of music. Therefore, prospective weather independent of interest like humidity, precipitation, temperature, and wind speed are included. In addition, to control the influence of widespread geographical and meteorological differences, we also introduce city fixed effects and date fixed effects. With the control of these confounding factors and fixed effects, air quality's variation can be deemed as an exogenous variation. Moreover, to address potentially endogenous threats to identification, we also conduct a 2SLS method, using the ventilation coefficient as IV for air quality. An adverse impact of air pollution on the MSI with statistical significance is identified, which means that people enjoy more melancholy songs than cheerful ones on polluted days. Additionally, we discern nonlinear patterns in the estimated result, given that the negative effect becomes more apparent when air pollution level falls in the category of "heavily polluted" or "severely polluted" (Air Quality Index above 200). These results' robustness is subsequently corroborated by various specification tests.

Our research proffers contributions to several branches of literature. First, we have enriched the research on the harm of air pollution. In addition to physiological damage (Beatty & Shimshack, 2014; Greenstone & Hanna, 2014), previous studies have also found that air pollution has a serious negative impact on mental health of residents, for example, tension (Chattopadhyay et al., 1995), annoyance (Danuser, 2001; Rotko et al., 2002), depression (Evans & Cohen, 1987; Zeidner & Schechter, 1988; Lundberg, 1996), anxiety (Schiffman et al., 1995; Lundberg, 1996), sleeplessness (Heyes & Zhu, 2019), and reduced levels of subjective well-being (Gu et al., 2015; Zhang et al., 2017).

Second, by investigating the influence of air pollution on music sentiment, we provide a supplement to the literature of sentiment measure. At present, four major methods are used to measure sentiment in literature. The first method is using market-related indicators to represent market sentiment, such as the investor sentiment index constructed by Baker and Wurgler (2006). The second method is based on questionnaires and interviews. For example, the University of Michigan Consumer Confidence Index and the Gallup Investor Optimism Index (Ilut & Schneider, 2014; Bollerslev et al., 2018). The third method relies on text data, for example, social media posts (Antweiler & Frank, 2004; Zheng et al., 2019), newspapers (Tetlock, 2007; García, 2013), the companys' annual reports (Loughran & McDonald, 2011) and the Federal Open Market Commission (FOMC) statements (Bollerslev et al., 2018). The fourth method uses exogenous events as shocks of sentiment, such as terrorist attacks (Chen et al., 2020), sports events (Edmans et al., 2007), etc. The aforementioned measurement of sentiment is mainly based on specific groups (such as investors), specific markets (such as capital markets), specific language countries (such as English speaking countries) and specific time (such as event shocks). In addition, the music sentiment used in this paper has also been studied by other literatures, for example, Edmans et al. (2022) and Fernandez-Perez et al. (2020). The above two literatures have studied the economic consequences of music sentiment and find that music sentiment has a significant positive correlation with stock market return. Different from these studies, this paper uses machine learning algorithms and music score analysis technology to identify the causal effect of air pollution on music sentiment.

Third, we contribute to the exploitation of unconventional data from the internet to study behavioral responses to air pollution in developing countries where data availability is a major obstacle. Related studies in China include studies of e-commerce mask sales (Zhang & Mu, 2018), smartphone application-based exercise data (Hu et al., 2017), online search records (Liu et al., 2018; Qin & Zhu, 2018; Shi & Guo, 2019), social media posts (Zheng et al., 2019; Heyes & Zhu, 2019) and movie ticket sales (He et al., 2022).

The rest of this paper is organized as follows. Section 2 details data sources and the machine learning algorithm for determining

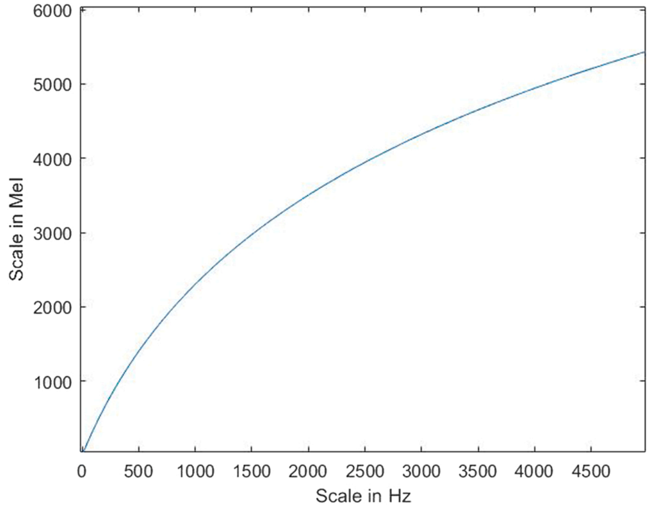

Fig. 1. The Relationship between the Frequency Scale in Hz and Mel. Note: It approximately fits a curve of $F_{mel} = 2595\log(1 + f/700)$.

music sentiment. Section 3 describes the empirical strategy. The main results and additional analyses are reported in Section 4. Section 5 concludes the paper.

2. Data

Our sample set of investigation contains 328 Chinese cities. To achieve the research objective, we develop a city-daily level measure of the music sentiment index derived from a Chinese music platform. Detailed meteorological data for controlling the prospective confounding impacts of weather on music preferences and constructing our instrumental variables is also included.

2.1. Music

The music data used in this study are collected from NetEase Cloud Music,[1] one of the largest online music platform in China via a distributed web crawler. Attributes such as location and the record of songs listened (presented as a percentage of the total) are listed on the 'user page' of each user. Because the record only reveals footprints for the last 7 days combined, we collect the data every day to speculate the everyday record. The time window starts from October 13th, 2019 and ends on January 7th, 2020. The collection started at 4:00 am(GMT+8) each day to create a more reasonable daily cutoff considering overnight listeners.

Over 2 million songs are included in listeners' records. Considering that processing a song is a herculean task compared to processing a text message in terms of time consumption, we filter out paid songs and less popular songs that are listened to fewer than 50,000 times during our study period among sample users to obtain a smaller subset that we are capable of handling. We thus reduce the song set to 53,000, while still covering 97% of listeners' records.

The indexing process needs to be constructed from scratch on the basis of existing machine learning algorithms. The very first step is to define the term 'sentiment' in a musical context. Unlike text data such as tweets that are usually difficult to extract emotion from, songs are created to convey emotion and are designated with written emotional annotations for better communication between composers and performers. These discrete annotations are ideal labels for any machine-learning-based algorithm. Another approach to extracting the emotion from a certain piece of music is to study its 'arousal value' and 'valence value' (also known as the V-A model). James (1980) proposed a simple model that projects human emotions onto a coordinate system with 'arousal value', or the intensity of human emotion, on the y-axis and 'valence value', or the degree of positivity (if it goes below zero, it becomes negative), on the x-axis. The V-A model is very popular in emotion analysis, especially in the field of music emotion, because a certain piece of music is both simple and stable in the sense that labelers can easily reach a consensus on the V-A value of a particular piece. A wide variety of music sentiment datasets adopt V-A values for their labels, such as Database for Emotional Analysis of Music (DEAM),[2] which provides 1802 songs with V-A labels for every 0.5 s slice and constitutes the training set for our machine learning algorithm, as well as the Mood-Swings Turk (MTurk)[3] dataset on pop music and the Emotion in Music Database (1000 songs).[4]

The second step is to identify proper method to connect songs to their labels. Mel spectrum is a practical method to extract pitch and volume from abstract song waves. A song wave is a combination of waves with different frequencies and volumes. We use the Fast

1 Homepage of NetEase Cloud Music, https://music.163.com/
2 http://cvml.unige.ch/databases/DEAM/
3 http://www.met-lab.org/emotion-recognition
4 http://cvml.unige.ch/databases/emoMusic/

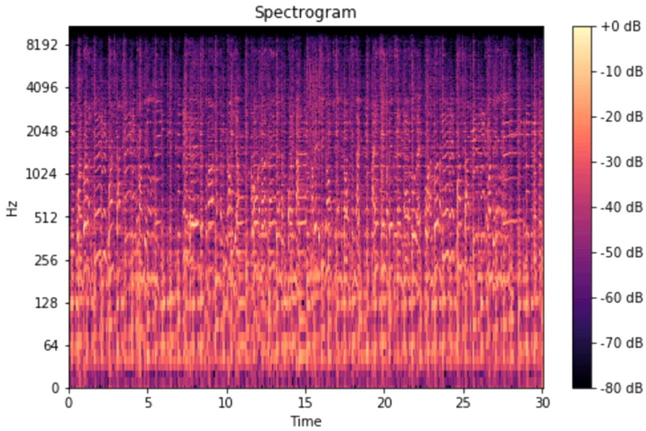

Fig. 2. An Example of a Spectrum Extracted from a Music Piece. Note: The X-axis represents the time of the song. The Y-axis represents the frequency at a certain time, while the color indicates the volume as measured in dB.

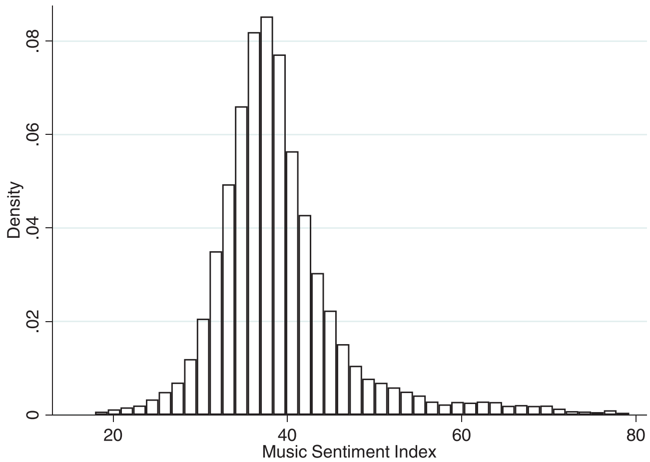

Fig. 3. The Distribution of the Music Sentiment Index.

Fourier Transform (FFT) to transform the time-domain waveform into a frequency-domain waveform to reveal underlying pitch and volume, that is, to extract exact wave frequency and volume from a compound song file. The next step is to transform the simple spectrum we get into Mel spectrum. A major problem of simple spectrum with a linear scale of frequencies is that it's not the way we perceive actually sound. For instance, the difference between 500 and 1000 Hz is much more salient than that between 10,000 and 10,500 Hz, even though the mathematical distance is the same. Thus, linear spectrums are rather difficult to analyze. Stevens et al. (1937) proposed Mel scale, a scale of pitch such that equal distances in pitch sound equally distant to the listener, which makes the image of the spectrum makes more sense. We apply the Mel filter, a mathematical operation to convert the frequencies to the Mel scale. Mao et al. (2014) and Anna et al. (2017) applied the Mel spectrum and transformation to process songs and showed that it performed better than simple, manually calculated attributes such as the mean of volume and/or frequency. Fig.s 1 and 2.

This spectrum is a perfect input for a Convolutional Neural Network (CNN), which is one of the most powerful tools for performing dimension reduction and classifying images and texts (Kim, 2014). Using CNN has been a basic tactic in music emotion classification tasks. For example, Dong et al. (2019) used a CNN and Recurrent Neural Network (RNN) to form a new setting named the Bidirectional Convolutional Recurrent Sparse Network (BCRSN), which achieved excellence in predicting V-A values in the DEAM dataset. We construct a CNN-based neural network via TensorFlow and Keras and train it with processed spectra and labels from the DEAM dataset. The trained model is used to predict the valence value, or sentiment index, in the songs we collect from NetEase Cloud Music.

All songs are categorized into 3 classifications: positive (cheerful songs), negative (melancholy songs), and neutral. Valence values in the DEAM are normalized and scaled between 1 and 0. The lower the value is, the melancholier it is. The upper bound for negative classification is set at 0.25, and the lower bound for positive classification is set at 0.55 given that the songs' valence in the study is not normally distributed. Between the two bounds is the neutral set. After that, a complete mapping of songs is created and is ready for further exploration.

We follow Antweiler and Frank (2004) to construct our indicators for music sentiment. To measure music sentiment, we calculate

Table 1
Summary Statistics.

	Obs	Mean	Std Dev	Min	Max
MSI1	25766	39.091	7.768	14.988	79.242
MSI2	25766	83.417	20.424	30.196	215.472
MSI3	25766	394.422	74.074	146.050	832.482
AQI	29170	71.139	41.695	9.031	500.000
PM2.5	29167	45.390	33.068	1.867	310.325
PM10	29170	77.368	51.998	5.000	853.986
SO_2	29170	13.061	9.930	1.021	145.167
CO	29169	0.888	0.444	0.117	6.375
NO_2	29170	34.720	16.943	2.467	121.219
O_3	28809	68.602	33.971	2.333	300.000
Temp	29170	8.061	9.829	-34.510	29.700
Precipitation	29169	0.868	3.330	-0.400	99.500
Humidity	29170	66.759	17.261	9.330	100.000
Wind	29170	2.653	1.525	0.050	18.620

Notes: The dataset contains daily data on 328 Chinese cities from Oct. 13th, 2019 to Jan. 7th, 2020.

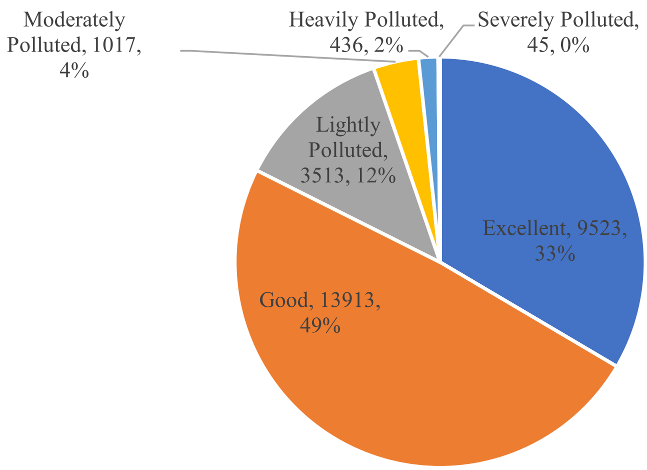

Fig. 4. The Proportion Composition of AQI Scores in 328 Cities in China, Oct. 13th, 2019 to Jan. 7th, 2020. Data Source: Ministry of Ecology and Environment of the People's Republic of China.

the Music Sentiment Index as (cheerful songs - melancholy songs)/(cheerful songs + melancholy songs), in which "cheerful songs" is the number of cheerful songs residents enjoyed in one day in a city, and "melancholy songs" is the number of melancholy songs residents enjoyed in one day in the same city. Higher MSI values indicate that residents enjoy more cheerful songs than melancholy songs. As robust checks, we also use the following two approaches to define music sentiment: ln((1 + cheerful songs)/(1 + melancholy songs)) and ln(1 + total songs)*MSI, in which total songs = cheerful songs + melancholy songs + other songs. The distribution of the Music Sentiment Index is shown in Fig. 3, from which we can see that the MSI is normally distributed.

2.2. *Air pollution*

The daily air quality is synthesized from hourly gauges collected at monitoring sites in each city. As it is revealed by Heyes and Zhu (2019), variations between different monitoring stations in the same city are neglectable. The same synthesis approach is also adopted by official air quality report[5] to calculate the Air Quality Index (AQI). According to the technical regulation, AQI is calculated based on hourly and daily concentration of six major pollutants (i.e. PM2.5, PM10, SO2, NO2, CO, and O3). The AQI score ranges from 0 to 500, where a larger score means worse pollution. Then the technical regulation divides air quality into six alert levels[6] according to AQI score. AQI data and concentrations of the six major pollutants are used in this study, and they are gathered from the site of the Ministry of Ecology and Environment (MEE) of the People's Republic of China.

Summary statistics for daily air quality in our whole sample are included in Table 1. During the sample period, the average AQI is

[5] http://kjs.mee.gov.cn/hjbhbz/bzwb/jcffbz/201203/t20120302_224166.shtml
[6] 'Excellent' for AQI located between 0 and 50, and 'good' between 51 and 100, 'lightly polluted' between 101 and 150, 'moderately polluted' between 151 and 200, 'heavily polluted' between 201 and 300, and 'severely polluted' between 301 and 500.

Table 2
Benchmark Results.

	(1)	(2)	(3)	(4)	(5)
Dependent variable	MSI1	MSI1	MSI1	MSI1	MSI1
AQI/100	-0.953	-0.051	-0.171***	-0.113**	-0.089 *
	(1.187)	(0.052)	(0.051)	(0.051)	(0.049)
temperature	-0.033	0.062***	0.043***	0.050***	
	(0.030)	(0.004)	(0.006)	(0.007)	
precipitation	-0.019	-0.012**	-0.006	-0.007*	
	(0.041)	(0.005)	(0.004)	(0.004)	
humidity	-0.070***	0.001	-0.000	-0.001	
	(0.025)	(0.001)	(0.001)	(0.001)	
wind speed	-0.168	-0.068***	-0.030***	-0.046***	
	(0.189)	(0.011)	(0.010)	(0.009)	
City FEs	NO	YES	YES	YES	YES
Month FEs	NO	NO	YES	NO	NO
Week FEs	NO	NO	YES	NO	NO
Day-of-Week FEs	NO	NO	YES	NO	NO
Date FEs	NO	NO	NO	YES	YES
N	25765	25764	25764	25764	25765
R^2	0.0309	0.931	0.945	0.949	0.948

Notes: 1. The dependent variable is the music sentiment index *MSI* at the city-daily level; 2. AQI/100 equals to the daily AQI ÷100; 3. Each column includes meteorological characteristics aforementioned: daily average temperature, daily precipitation, daily wind speed and daily air humidity; 4. Standard errors in the brackets are clustered at the city level; 5. *p < 0.1, * *p < 0.05, * **p < 0.01.

71.3, which falls in the "good" category. However, the information of average AQI fails to unveil the considerable variances of the air quality in Chinese cities, which can be found in both the huge standard deviation and the range of the major variables shown in Table 1. Fig. 4 shows the proportion of the different levels of AQI during our research period, during which the proportion of polluted days (including lightly polluted and more serious scenarios) is 17.2%, and approximately 1.6% of days reach the "heavily polluted" or "severely polluted" level, which means the AQI is over 200. PM10 and PM2.5 combined are the major pollutants on 95% of polluted days. Moreover, there are large variations in AQI across cities and within cities. The standard deviation of the mean AQI across cities is 24.87, and the average within-city standard deviation is 33.55.

2.3. Weather

Weather conditions can influence mood directly. Zhang et al. (2017) found that rainy days are more likely to trigger negative emotions than sunny days do. Gao et al. (2019) showed that rising temperature have a greater impact on both suicide and suicide attempts. Thus, it is a reasonable assumption that people are more likely to undergo depressed emotion when exposed to the polluted ambient.

The strong correlation between air pollution and some weather conditions is worth contemplating (Zhang et al., 2017; Qin & Zhu, 2018). Thus, in light of probability of biased estimations, we deem the meteorological readings as essential control variables. The weather variables involved in the study is comprised of daily average temperature (*Temp*), daily precipitation (*Precipitation)*, daily wind speed (*Wind*), and daily air humidity (*Humidity*). The meteorological readings are retrieved from more than 820 monitoring stations of the National Meteorological Information Center of China. The reading of a certain city comes from its closest station. In Table 2, the summary statistics of the weather data show that the weather conditions of different cities in China are quite different.

3. Empirical strategy

The major concern of our study is the correlation between a specific city and its music sentiment; that is, *if the air in Beijing is highly polluted on a certain day, does that mean residents in Beijing will enjoy more cheerful songs or more melancholy songs on that day?*

3.1. Ordinary least squares

The specification below is set in a straightforward panel fixed effects setting.

$$MSI_{it} = \alpha_0 + AQI_{it}\beta + W_{it}\gamma + \theta_i + \tau_t + \varepsilon_{it} \tag{1}$$

In Eq. (1), MSI_{it} is the music sentiment index in city$i$ on date t. AQI_{it} is the average daily air quality in city$i$ on date t, including AQI and the concentration of the six major pollutants, that is PM10, PM2.5, SO_2, NO_2, CO, and O_3. However, the variables we are most concerned about are the composite AQI score and the concentration of PM2.5.

As mentioned above, in assessing the impact of air quality on music sentiment, weather variables are very important confounding factors, so we include weather variables in equation (1) as the control variables, which have been described in detail in subsection 2.3. Some time-invariant characteristics of a city, such as cultural traditions and climatic characteristics, may also affect people's music

Table 3
Results for Other Pollutants.

	(1)	(2)	(3)	(4)	(5)	(6)
	PM2.5	PM10	SO_2	CO	NO_2	O_3
pollutant/100	-0.227***	-0.044	-1.016***	-17.322***	-0.223	-0.153**
	(0.067)	(0.039)	(0.242)	(4.050)	(0.148)	(0.076)
Weather	YES	YES	YES	YES	YES	YES
City FEs	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES
N	25760	25764	25764	25762	25764	25413
R^2	0.949	0.949	0.949	0.949	0.949	0.949

Notes: 1. The dependent variable is the music sentiment index *MSI* at the city-daily level; 2. The variable '*pollutant/100*' is the daily pollutant concentration divided by 100; 3. Each column includes meteorological characteristics aforementioned: daily average temperature, daily precipitation, daily wind speed and daily air humidity; 4. Standard errors in the brackets are clustered at the city level; 5. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

sentiment, so we also control the city fixed effects, which are θ_i in Eq. (1). In similar studies, city economic characteristics are often included as control variables, if the research period is relatively long. However, in our perspective, the lack of economic characteristics is not a serious problem. The study is conducted at the city-daily level, and the sample period is only three months, during which we could roughly regard the economic characteristics of different cities as constants. So after controlling the city fixed effects, the problem of missing variables can be alleviated. τ_t is date fixed effects, with which common time trends are absorbed. The error term is ε_{it}. β is the coefficient that we mainly focus on, and it represents the effect of air quality on music sentiment after controlling other confounding factors.

3.2. Instrumental variable estimation

We identify two major problems that would cause doubt on the validity of the fixed effect estimation. First, potential measurement errors in air pollution data, the independent variable in the equation, is involved, indicating a tenuous fixed effect estimates. Second, various controls for potential confounders are involved, but still we cannot get rid of the presence of omitted variables. For instance, an underlying link between local economic movement that positively correlates to AQI will cast bias to our estimates. In this scenario, we adopt the instrumental variable (IV) approach, a typical method to overcome potential endogeneity and corroborate our estimate of major concern.

Following Broner et al. (2012) and Hering and Poncet (2014), we use Ventilation Coefficient (VC) as the IV for air quality. This coefficient is defined as the product of wind speed and boundary layer height. It's apparent that one should ascribe the horizontal diffusion of pollutants to the motion of wind, making wind speed one of the relevant factors. And surely another factor is boundary layer height, which determines how high the pollutant can go. Thus, VC is calculated to reflect the meteorological conditions that determine the spreading speed of pollutants, drawing a salient link to air quality. At the same time, these coefficients are determined by complex meteorological conditions, fitting the criteria of "good" IV for being exogenous to the music enjoyment preferences.

The wind speed and boundary layer height data for calculating the VC come from the ERA5 hourly data on single levels from 1979 to present by European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 is the fifth generation ECMWF atmospheric reanalysis of the global climate that provides the boundary layer height, the u-component of neutral wind and v-component of neutral wind at a 10-m height for a global grid of 0.5°* 0.5° cells. The wind speed is the module of the wind vector that is described by the u-component and v-component. The VC of a city is represented by the data of its cells' closest air quality stations. Specification for 2SLS estimation is represented by the following equations:

$$AQI_{it} = \tau + VC_{it}\rho + W_{it}\sigma + \theta_i + \tau_t + \varepsilon_{it}(\text{First Stage}) \tag{2}$$

$$MSI_{it} = \tau + AQI_{it}\beta + W_{it}\gamma + \theta_i + \tau_t + \varepsilon_{it}(\text{Second Stage}) \tag{3}$$

4. Empirical results

4.1. Benchmark results

We run the main regression to measure the effect of air pollution on music sentiment. To get a more salient interpretation of the estimated coefficients, the original AQI values are divided by 100. Table 2 and Table 3 report the coefficients from Eq. (1) with the fixed effect regression model for the AQI (Table 2) and other pollutants (Table 3), where the dependent variable is the music sentiment index, and the independent variables of interest are the AQI and other pollutants. Column (1) of Table 2 is the most relaxed specification which involves only weather covariates, including average temperature, humidity, precipitation and wind speed, for the reason we've mentioned in subsection 2.3.

In Column (2) and Column (3), we add city fixed effects and several time related fixed effects, such as month fixed effects, week fixed effects, day of the week fixed effects, and holiday fixed effects. The reason for controlling these fixed effects is that music enjoying behavior may be different on working days from days of rest. As it is shown in the result of Column (3), the estimated coefficients become significant after the inclusion of these factors. In Column (4) in Table 2, date fixed effects are controlled for, which summarizes

Table 4
Robustness Results.

	(1) MSI2	(2) MSI3	(3) MSI4	(4) MSI2	(5) MSI3	(6) MSI4
pollutant/100	-0.256**	-1.257**	-0.070**	-0.550***	-2.585***	-0.141***
	(0.125)	(0.501)	(0.029)	(0.160)	(0.667)	(0.036)
Weather	YES	YES	YES	YES	YES	YES
City FEs	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES
N	25764	25764	25764	25760	25760	25760
R^2	0.956	0.940	0.943	0.956	0.940	0.943

Notes: 1. The dependent variable in Columns (1) and (4) is the music sentiment index *MSI2,* whose calculation formula is ln((1 + cheerful songs)/(1 + melancholy songs)); the dependent variable in Columns (2) and (5) is music sentiment index *MSI3,* whose calculation formula is ln(1 + total num) *MSI1, with total num = cheerful songs + melancholy songs + others; and the dependent variable in Columns (3) and (6) is the music sentiment index *MSI4,* whose calculation formula is as that of MSI1, but the music is only divided into two categories; 2. The '*pollutant/100*' is *AQI/100* in columns (1)–(3) and *PM2.5/100* in columns (4)–(6); 3. Each column includes meteorological characteristics aforementioned: daily average temperature, daily precipitation, daily wind speed and daily air humidity; 4. Standard errors in the brackets are clustered at the city level; 5. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

the preferred specification for the empirical analysis based on fixed effect. In Table 3, we investigate the impacts of other pollutants on the music sentiment index using the same settings as in Column (4) in Table 2.

From Table 2 and Table 3 in Table 2, we find negative coefficients of the AQI, PM2.5, and some other pollutants. The estimate of the average marginal effect of the AQI on the music sentiment index is approximately − 0.11 and statistically significant at the 5% level. This estimate implies that 100 points' growth in the AQI reduces the music sentiment index by 0.11 while other things are equal. Polluted days cause people to experience negative emotions, which has been widely confirmed by existing research. It also confirms another suspending question: how responsive are people facing adventitious emotional impact? If people had taken actions to countervail emotion effects, just as people took measures to protect themselves from the impact of air pollution on their health, they would have listened to more cheerful songs. But our results show that people listen to relatively more melancholy songs on polluted days, indicating that people are more likely to 'suffered' from it rather than be 'triggered' by it.

We also find that weather has an obvious impact on the music sentiment index according to Table 2, especially after including the fixed effects for city and date in Column (4) in Table 2. After the removal of the weather factors, the coefficient of the influence of AQI on the music sentiment index decreases, which is shown in Column (5) in Table 2. These results show that it is necessary to include weather factors in the regression. Specifically, according to the regression results in Table 2, the higher the temperature, the higher the music sentiment index. Our study period covers the cold autumn and winter in China; therefore, the higher the temperature, the better people's mood, which is in line with our intuition. The higher the rainfall and wind speed are, the lower the music sentiment index, which is also in line with the characteristics of autumn and winter. The relationship between weather and the music sentiment index is highly consistent with that between air pollution and the music sentiment index.

4.2. Robust checks

To verify the robustness of our empirical results, we also perform several robust checks. First, there are many other methods to calculate sentiment index, and we also use two other methods to conduct the same analysis (Antweiler & Frank, 2004). As shown in Columns (1) and (2) in Table 4, the increase in the AQI still has a significant negative impact on the music sentiment index by these two methods. In Column (3) of Table 4, the dependent variable is the music sentiment index MSI4, whose calculation formula is the same as that for MSI1 except that the music is divided into only two categories (i.e., melancholy songs and cheerful songs). In Columns (4) to (6) in Table 4, the independent variable is PM2.5, and the other specifications are consistent with Columns (1) to (3) in Table 4. The conclusion is also robust.

The veracity of air quality data in China has been seriously questioned in some empirical studies. Score 100 has been a categorical division for "blue sky" day, which means, it is a "blue sky" day if the AQI< 100, and it is a polluted day if the AQI> =100 (Chen et al., 2013; Ghanem & Zhang, 2014). While more "blue sky" days indicates local governments' good achievements in air pollution control, there are certain incentives for local government to rig the data towards "blue sky" when actual AQI is slightly higher than 100. Empirical evidence of adulterated data can be found: the number of days when AQI is between 96 and 100 was significantly higher than the number of days when AQI was between 101 and 105 in Beijing (Andrews, 2008). However, other studies defend the reliability and show such problem has been mitigated since 2013 (Stoerk, 2016).

Nevertheless, to be prudent, as other studies have done (He et al., 2022; Shi et al., 2020), we remove the sample with AQI values around 100, to offset potential problems caused by untruth. Specifically, we delete samples with AQI (or PM2.5) in 3 ranges, that is, between 95 and 105 (for PM2.5, between 70 and 80), between 90 and 110 (for PM2.5, between 65 and 85), and between 80 and 120 (for PM2.5, between 60 and 90), as we need to test our dataset by three different kind of removal specification to verify the assumption in robust test. The reason for different critical points for PM2.5 compared with the AQI is that the sub-index 100 for PM2.5 is 75. Then, using these censored samples, we conduct our regression again, and our basic conclusion is still significant, as it is shown in Table 5. It suggests that the potential concern of air pollution data manipulation is not a threat to our conclusion.

Table 5
Robustness Results without Easily Falsified AQI Data.

	(1)	(2)	(3)	(4)	(5)	(6)
	Drop AQI [95–105]	Drop AQI [90–110]	Drop AQI [80–120]	Drop PM2.5 [70–80]	Drop PM2.5 [65–85]	Drop PM2.5 [60–90]
pollutant/100	-0.120**	-0.123**	-0.133**	-0.231***	-0.243***	-0.249***
	(0.051)	(0.052)	(0.055)	(0.068)	(0.068)	(0.071)
Weather	YES	YES	YES	YES	YES	YES
City FEs	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES
N	24,508	23,164	20,353	24,504	23,197	21,859
R^2	0.949	0.950	0.950	0.949	0.949	0.949

Notes: 1. The dependent variable is the music sentiment index *MSI* at the city-daily level; 2. The '*pollutant/100*' is *AQI/100* in columns (1)-(3) and *PM2.5/100* in columns (4)-(6); 3. Each column includes meteorological characteristics aforementioned: daily average temperature, daily precipitation, daily wind speed and daily air humidity; 4. Standard errors in the brackets are clustered at the city level; 5. *$p < 0.1$, * *$p < 0.05$, * **$p < 0.01$.

Table 6
Nonlinear Effects.

	(1)	(2)
	AQI	PM2.5
Excellent (default)		
Good	-0.041	-0.021
	(0.039)	(0.035)
Lightly Polluted	-0.038	-0.053
	(0.056)	(0.059)
Moderately Polluted	-0.249***	-0.289***
	(0.079)	(0.081)
Heavily Polluted and Severely Polluted	-0.324**	-0.434***
	(0.134)	(0.138)
Weather	YES	YES
City FEs	YES	YES
Date FEs	YES	YES
N	25764	25764
R^2	0.949	0.949

Notes: 1. The dependent variable is the music sentiment index *MSI* at the city-daily level; 2. The explanatory variable in Column (1) is calculated based on the AQI and that in Column (2) is calculated based on PM2.5; 3. Each column includes meteorological characteristics aforementioned: daily average temperature, daily precipitation, daily wind speed and daily air humidity; 4. Standard errors in the brackets are clustered at the city level; 5. *$p < 0.1$, * *$p < 0.05$, * **$p < 0.01$.

Table 7
2SLS Results.

	(1)	(2)	(3)	(4)
	AQI First Stage	PM2.5	MSI Second Stage	MSI
pollutant/100	-0.282**	-0.219**	-2.104**	-2.835**
	(0.006)	(0.005)	(1.053)	(1.435)
Kleibergen-Paap rk Wald F statistic	28.699	21.697		
Stock-Yogo Weak IV test critical values: 10% maximal IV size	16.38	16.38		
Weather	YES	YES	YES	YES
City FEs	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES
N	25686	25682	25686	25682
R^2	0.496	0.518	0.942	0.942

Notes: 1. The first-stage in Columns (1) and (2) is a regression of the daily mean value of the pollutant with respect to the VC; 2. The second-stage in Columns (3) and (4) is a regression of MSI with respect to the instrumented daily pollution; 3. The '*pollutant/100*' is *AQI/100* in columns (1) and (3) and *PM2.5/100* in columns (2) and (4); 4. Each column includes meteorological characteristics aforementioned: daily average temperature, daily precipitation, daily wind speed and daily air humidity; 5. Standard errors in the brackets are clustered at the city level; 6. *$p < 0.1$, * *$p < 0.05$, * **$p < 0.01$.

4.3. Nonlinear results

Some recent studies have come to realize that nonlinearity of the effects of air pollution (Qin & Zhu, 2018; Zhang & Mu, 2018; Shi & Guo, 2019), showing that damage quickly escalated as the air pollution level rises. We use categorical pollution levels as categorical variables to scrutinize our concern. Following the official technical guidance mentioned above, we subsume our observations regarding the AQI and PM2.5 score in five categories, except that "Heavily Polluted" and "Severely Polluted" categories are merged into one category for their low ratio. "Excellent" group is appointed to the reference group to avoid the perfect multicollinearity. This specification allows us to identify the nonlinear effect of air pollution. The coefficients display more salient negative impacts at higher pollution levels, as it is shown in Table 6. As expected, we find that the MSI decreases nonlinearly as the AQI (PM2.5) reaches higher levels, while the coefficients are negative but statistically nonsignificant at the levels of "*Good*" and "*Lightly Polluted*" (AQI in the interval [50,150] and PM2.5 in the interval [35,115]).

4.4. Two-stage least squares method

The 2SLS results using the VC as IV for air quality are reported in Table 7, where the control variables and fixed effects are set as that in Column (4) of Table 2. We find the first stage generates reasonable result for that the significance is better than the 1% in each specification, and variations in the VC have a strong effect on the AQI and PM2.5. The Kleibergen-Paap Wald F statistic in each of the two first stages is higher than the critical values (10% maximal IV size) of Stock-Yogo weak-IV test, which is listed in Table 7. Therefore, weak instruments problem is ruled out. From the second stage results of Table 7, we can find that the conclusion is more remarkable than those in the fixed effect results.[7] After solving the possible endogeneity problems, the results support our conclusions in this study: people enjoy relatively more melancholy songs on polluted days.

5. Conclusions

Sentiment is an important manifestation of human well-being in modern context, and its subsequent economic implications has been shown by various studies. This research would imply a so-far unaccounted-for correlation between proclivity of city inhabitants' music consumption and air pollution. The thorough understanding of the ways through which air pollution affects music sentiment and, indirectly, the understanding of boons of clean sky, are an essential for the processing of building a welfare-maximizing society.

Basing on a unique dataset of high-frequency music consumption records from a music platform in China from October 13th, 2019 to January 7th, 2020. This study finds that the music sentiment index, which is generated using machine learning algorithms, declines during highly polluted days, which means that on highly polluted days, people tend to enjoy melancholy songs more than cheerful songs. In addition, this effect becomes more significant when the AQI score is above 200, a sign of "heavily polluted" and "severely polluted" days. We believe we have provided a pioneering empirical research that initially scrutinizes the impact on music sentiment from air pollution. The estimated effects are substantial and shown to be robust to various checks. The conclusion of this study is that the government should consider both the physical health and mental health consequences of air pollution when making policies.

Of course, there are still limitations in this study. The dearth of user information like age and occupation constrained our further heterogeneity analysis of different groups, with which would had drawn richer conclusions. For example, most user of the studied music platform are young people, so they may not be a good representative of the whole residents. Moreover, due to technical limitations of music platform on web crawlers, the time window of this study is only about 3 months, which also limits the scale of our data.

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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[7] Due to heterogeneity, the estimator coefficient of 2SLS is greater than that of OLS.

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