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Urban-rural differences in the association between long-term exposure to ambient air pollution and obesity in China

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A R T I C L E I N F O

Keywords:
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A B S T R A C T

Introduction: Ambient air pollution might increase the risk of obesity; however, the evidence regarding the relationship between air pollution and obesity in comparable urban and rural areas is limited. Therefore, our aim was to contrast the effect estimates of varying air pollution particulate matter on obesity between urban and rural areas.

Methods: Four obesity indicators were evaluated in this study, namely, body mass index (BMI), waist circumference (WC), waist-to-hip ratio (WHR), and waist-to-height ratio (WHtR). Exposure to ambient air pollution (e.g., particulate matter with aerodynamic diameters 1.0 μm [PM_1], $PM_{2.5}$, and PM_{10}) was estimated using satellite-based random forest models. Linear regression and logistic regression models were used to assess the associations between air pollution particulate matter and obesity. Furthermore, the effect estimates of different air pollution particulates were contrasted between urban and rural areas.

Results: A total of 36,998 participants in urban areas and 31, 256 in rural areas were included. We found positive associations between long-term exposure to PM_1, $PM_{2.5}$, and PM_{10} and obesity. Of these air pollutants, $PM_{2.5}$ had the strongest association. The results showed that the odds ratios (ORs) for general obesity were 1.8 (95% CI, 1.64 to 1.98) per interquartile range (IQR) μg/m^3 increase in PM_1, 1.89 (95% CI, 1.71 to 2.1) per IQR μg/m^3 increase in $PM_{2.5}$, and 1.74 (95% CI, 1.58 to 1.9) per IQR μg/m^3 increase in PM_{10}. The concentrations of air pollutants were lower in rural areas, but the effects of air pollution on obesity of rural residents were higher than those of urban residents.

Conclusion: Long-term (3 years average) exposure to ambient air pollution was associated with an increased risk of obesity. We observed regional disparities in the effects of particulate matter exposure from air pollution on the

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risk of obesity, with higher effect estimates found in rural areas. Air quality interventions should be prioritized not only in urban areas but also in rural areas to reduce the risk of obesity.

1. Introduction

Overweight and obesity have increased rapidly and reached epidemic proportions, with at least 2.8 million people dying from obesity-related conditions every year (WHO, 2018a). Nearly 2 billion adults are overweight or obese globally (WHO, 2020), and China has the largest obese population (Wang et al., 2019b). Obesity results from multiple factors at multiple levels, such as genetical and environmental factors (Franks and Atabaki-Pasdar, 2017; Wang et al., 2016). Accumulating evidence suggests that air pollution is an important risk factor for obesity (Deschenes et al., 2020; Jerrett et al., 2014; Kim and Yoon, 2020). Air pollution may induce a lack of physical activity and epigenetic modulation, promoting oxidative stress or inflammatory responses and subsequently influencing the risk of obesity (An and Xiang, 2015; Pardo et al., 2018; Shukla et al., 2019).

Studies have shown that the concentration of particulate matter with aerodynamic diameter 2.5 μm ($PM_{2.5}$) in rural areas was similar to that in urban areas (Aunan et al., 2019; Chafe et al., 2014; Du et al., 2018), indicating that air pollution levels are also high in rural areas. However, individuals in rural areas may be affected by low economic and educational levels, unhealthy living habits, and inadequate medical care levels, so they may be more vulnerable to air pollution's adverse effects (Ravishankara et al., 2020). Therefore, the relationship between air pollution and obesity in rural areas should be considered. However, few studies have addressed the relationship between air pollution and obesity in comparable urban and rural areas, and most studies on the relationship between air pollution and obesity are concentrated in urban areas (Kim et al., 2019; Li et al., 2016; Yang et al., 2019; Zhang et al., 2019).

Accumulating studies have explored the relationship between the $PM_{2.5}$ and particulate matter with aerodynamic diameters of 10 μm (PM_{10}) and obesity (Kim et al., 2019; Zhang et al., 2019, 2020). However, there is limited evidence on the relationship between particulate matter with aerodynamic diameters of 1 μm (PM_1) and obesity, although PM_1 may be more harmful due to its high surface-to-volume ratio, greater vascular penetration, and higher toxin content (Liu et al., 2021). Furthermore, these studies provided limited information on the association between air pollution particulate matter with different particle sizes and obesity.

To resolve these gaps, we aimed to explore the impacts of ambient air pollution (PM_1, $PM_{2.5}$, and PM_{10}) on obesity indicators (BMI, WC, WHR, and WHtR) in adults in Southwest China. In addition, we further contrasted the impacts of air pollution particulate matter with different particle sizes between urban and rural areas.

2. Materials and methods

2.1. Study population

A detailed cohort study and participant information were previously presented (Zhao et al., 2020). In brief, the China Multi-Ethnic Cohort (CMEC) study was initiated when 99,556 individuals aged 30–79 years old from five provinces of China were included. The CMEC was conducted in five provinces of Southwest China, and the baseline survey was performed from May 2018 to September 2019. In accordance with the ethnic characteristics and population estimates in Southwest China, seven ethnic groups were selected as participants, that is, the Han, Tibetan, Yi, Miao, Bai, Bouyei, and Dong ethnic groups. The detailed inclusion criteria of the CMEC were reported previously (Zhao et al., 2020).

The exclusion criteria of this study were as follows: 1) severe physical diseases that correlated with people's weight (e.g., stroke, tuberculosis, or bipolar disorder) and pregnancy; and 2) Tibetan herdsmen in Aba and Tibetan herdsmen in Lasa. First, Tibetan herdsmen in Aba have no fixed residence and move to the meadows in the summer, when the seasons change (Tibetannet, 2019). Second, Lhasa and Aba Tibetans live in high-altitude areas (altitude >3500 m). The environment is quite different from that of the other groups, and the primary risk factors are significantly different. Ultimately, a total of 68,254 participants were included in this study, with an enrolment rate of 68.6% (Figure S1).

2.2. Data collection

Baseline information on participant demographic characteristics (age, sex, ethnic group, education level, and average annual income), lifestyle habits (smoking and drinking status, secondary smoking and physical activity), indoor air pollution, and dietary intake was collected by using a standardized questionnaire. Smoking was defined as a total of more than 100 cigarettes smoked to date, and quitting smoking was defined as quitting for more than half a year. Secondary smoking was defined as whether one had a passive smoking history at home or in the workplace. The occasional drinking of alcohol was defined as drinking an average of 1–2 days per week or less in the past year, and regular drinking of alcohol was defined as drinking an average of 3–5 days per week or more in the past year. The physical activity parameter considered the participants' occupational, traffic, chores, and leisure time activities and was divided into low and high based on the median metabolic equivalent for task (MET) (Ainsworth et al., 2011). Indoor air pollution was classified as low, moderate, and high exposure to indoor air pollution. High exposure was defined as frequently cooking at home using one of the three fuels (firewood, carbon, and coal) for cooking without exhaust equipment. Moderate exposure was defined as frequently cooking at home using one of the three fuels (firewood, carbon, and coal) for cooking with exhaust equipment. Low exposure was defined as cooking occasionally or not at home using natural gas with exhaust equipment. The dietary intake over the past year was assessed using a food frequency questionnaire including nutritional supplement intake and personal history of severe food shortage. The residences were divided into urban and rural areas. Urban and rural areas are defined by the urban-rural classification code formulated by the National Bureau of Statistics of the People's Republic of China (2020). The urban and rural classification code consists of three digits, the first digit is 1 for the urban area, the first digit is 2 for the rural area.

The anthropometric measurements of obesity included participant height, waist circumference (WC), hip circumference, and weight. Height was measured to the nearest 0.1 cm with subjects' shoes off in an upright position against a calibrated wall. The weight with light clothing was measured to the nearest 0.1 kg using a weight measurement device. The WC was measured 1.0 cm above the navel and the hip circumference at the maximal width of the hip was measured to the nearest 0.1 cm with light clothing. The height, weight and WC were measured according to a standard protocol from the Working Group on Obesity (Chen et al., 2004).

2.3. Outcome assessment

The BMI was calculated as the body weight (kg) divided by the height squared (m^2). The WHR was calculated by dividing the WC (cm) by the hip circumference (cm), and the WHtR was calculated by dividing the WC (cm) by the height (cm). The BMI threshold for overweight was 25–30 kg/m^2 (WHO, 2020). The cut-off values for the BMI, WC, WHR, and WHtR for obesity were 30.0 kg/m^2 for both sexes, 90 cm for men and 85 cm for women, 90% for men and 85% for women, and 50% for both men and women, respectively (Hou et al., 2013; Srinivasan et al., 2009; WHO, 2018b; Yang et al., 2017).

2.4. Exposure

Ground-level PM_1, $PM_{2.5}$ and PM_{10} concentrations were estimated based on monitoring data, satellite remote sensing, meteorological factors (temperature and humidity) and land use information as well as other spatial and temporal predictors. The detailed data collection and process are described in previous studies (Wei et al., 2019a). Specifically, daily ground monitoring data on the PM_1 were collected from 153 stations covering most provinces across China in the China Atmosphere Watch Network (CAWNET) of the China Meteorological Administration and measured using a GRIMM Model 1.180 Aerosol Spectrometer (Wei et al., 2019b). Other pollutants ($PM_{2.5}$ and PM_{10}) were obtained from 1480 stations across China and acquired by the China National Environmental Monitoring Center (CNEMC) (http://www.cnemc.cn) (Wei et al., 2019a).

Daily 1-km MODIS MAIAC AOD data (MCD19A2) were used to estimate the PM_1, $PM_{2.5}$, and PM_{10} (https://weijing-rs.github.io/product.html). Space-time extremely randomized trees (STET) models were used for the estimation, which show a high predictive ability and are robust to noise (Pierre, 2006; Wei, 2021a). The 10-fold cross-validation R2 (root mean square error) of the estimated annual medians of PM_1, $PM_{2.5}$, and PM_{10} were 77% (14.6 μg/m3), 90% (10.09 μg/m^3), and 86% (24.8 μg/m^3), respectively (Wei, 2019b, 2020, 2021a,b). Details on the satellite-based estimation of air pollutants were presented in previous reports. The 3-year average concentration of individual air pollutant exposures was calculated based on the geocoded residential address.

2.5. Statistical analysis

We used linear regression models to assess the association between the PM_1, $PM_{2.5}$, and PM_{10} concentrations and the BMI, WHtR, WC, and WHR. The effect estimates were expressed as beta (β) and 95% confidence intervals (CIs). We used logistic regression models to assess the association between the PM_1, $PM_{2.5}$, and PM_{10} concentrations and the risk of overweight, obesity, and abdominal obesity by WHtR. The effect estimates were expressed as odds ratios (ORs) and 95% confidence intervals (CIs). The linear relationship between ambient air pollution and obesity was explored by using natural cubic spline analysis. We estimated the unadjusted models and the main models that were adjusted for the confounding variables including age, sex, ethnicity, residence, household income, educational level, physical activity level, smoking, secondary smoking, indoor air pollution, alcohol drinking, dietary intake, hypertension, and diabetes. All associations were reported per 10 μg/m^3 increase of air pollutant and per IQR μg/m^3 increase of air pollutant. An increase of 10 μg/m^3 of air pollutants helps us to compare the effect estimations with others. And an increase of IQR μg/m^3 of air pollutants can help us to compare the effect estimations of different particle sizes.

We performed analyses stratified by participant residence (rural areas vs urban areas), age (<60 vs≥ 60), sex, income (<6000 yuan vs $\geq$ 6000 yuan), drinking status (never vs occasionally or often), smoking status (never vs former or current), and physical activity (<27 MET-h/day vs≥ 27 MET-h/day) to examine whether the associations were consistent among different subpopulations. The differences between subgroups were examined using Z-test.

We also performed sensitivity analyses. To further compare the effects of different particle sizes, $PM_{1\text{-}2.5}$ and $PM_{2.5\text{-}10}$ were analyzed using the main model. Besides, we fitted the adjusted models using the one to four years average ambient air pollutant concentrations to test the robustness of the effect estimations. All the statistical analyses were performed using R 4.0.2 (R Foundation for Statistical Computing), and statistical significance was declared if $P < 0.05$.

3. Result

3.1. Demographic characteristics

Table 1 described the characteristics of 68,254 participants aged 30–79 years in this study. Among these participants, 36,998 people live in cities, and 31,256 live in rural areas. In brief, the mean age of these participants was 52.2 (SD = 11.4) years old. The prevalence of obesity was higher in rural areas (4.82%) than in urban areas (4.47%). However, the overweight rate (33.18%) in urban areas was slightly higher than that of rural areas (30.30%). Compared with rural people, urban people were more likely to be male, younger and Han, with higher family income, higher education level, lower indoor air pollution level, higher frequency of eating fruits, red meat and poultry meat, and greater possibility of diabetes. The people in rural areas were mainly non-smokers, non-drinkers, were more likely to have a higher level of physical activity, a higher frequency of eating pickled vegetables and hypertension. The obesity indicator of BMI of urban individuals was larger than rural individuals, but the indicators of WHtR and WHR of rural people were larger (Table 1).

Table 2 showed the three-year average concentrations of PM1, PM2.5, PM10. The interquartile range (IQR) of PM_1, $PM_{2.5}$, PM_{10} were 12.14 μg/m^3, 29.42 μg/m^3, and 40.3 μg/m^3, respectively. The concentrations of ambient air pollutants in urban areas were higher than those in rural areas.

3.2. Associations between ambient air pollutant exposure and obesity indicators

Table 3 showed the odds ratios (ORs) and 95% confidence intervals (CIs) for the association between the obesity measurements and a 10 μg/m^3 increase in average 3-year PM_1, $PM_{2.5}$, and PM_{10} exposure according to the adjusted models. In brief, significant changes statistically in BMI, WHtR, WC, WHR, overweight, general obesity, abdominal obesity by WHtR were observed per 10 increments in the PM_1, $PM_{2.5}$, and PM_{10} concentrations. For example, each 10 μg/m^3 increase in PM_1 was associated with an increased BMI of 0.86 kg/m^2 (95% confidence interval [CI], 0.81 to 0.91), WHtR of 1.71% (95%CI, 1.62 to 1.8), WC of 2.25 cm (95% CI, 2.11 to 2.39), WHR of 0.54% (95% CI, 0.44 to 0.64) and OR for general obesity of 1.63 (95% CI, 1.51 to 1.76).

Table 4 showed the ORs and 95% CIs for the association between the obesity indicators and per IQR μg/m^3 increase in average 3-year PM_1, $PM_{2.5}$, and PM_{10} exposure according to the adjusted models. In general, $PM_{2.5}$ was associated with the largest absolute changes in BMI, WHtR, WC, WHR, overweight, general obesity, and abdominal obesity by WHtR. The effect estimates of PM_{10} on the above indicators were the smallest among the three air pollutants. The results showed that the ORs for general obesity were 1.8 (95% CI, 1.64 to 1.98) per IQR μg/m^3 increase in PM_1, 1.89 (95% CI, 1.71 to 2.1) per IQR μg/m^3 increase in $PM_{2.5}$, and 1.74 (95% CI, 1.58 to 1.9) per IQR μg/m^3 increase in PM_{10}.

3.3. Stratified analyses

Fig. 1 and Fig. 2 depicted the results of the stratified residence analyses for exposure to PM_1, $PM_{2.5}$, and PM_{10}, respectively. In general, a greater effect of ambient air pollutants was observed in rural areas. For BMI, WHtR, WC, WHR, and abdominal obesity by WHtR, the associations were stronger in rural areas than those in urban areas. For example, the association between BMI and per 10 μg/m^3 increase in $PM_{2.5}$ was significantly higher among rural residents than urban residents. As for overweight and general obesity, the differences in effect estimations between the rural areas and urban areas were not significant, except PM_1.

Table S4 to S8 showed the results of the stratification analysis except for residence. In general, a greater effect of PM_1 on BMI, WHtR, overweight, and abdominal obesity by WHtR was observed in individuals

Table 1
Characteristics of the study participants.

Variables	Total (n = 68,254)	Urban area (n = 36,998)	Rural area (n = 31,256)	P value
Sex				
Male	26,725 (39.2%)	15,507 (41.9%)	11,218 (35.9%)	<0.001
Female	41,529 (60.8%)	21,491 (58.1%)	20,038 (64.1%)	
Age, years				
30-39	10,336 (15.1%)	6467 (17.5%)	10,336 (15.1%)	<0.001
40-49	21,047 (30.8%)	11,737 (31.7%)	21,047 (30.8%)	
50-59	18,488 (27.1%)	9277 (25.1%)	18,488 (27.1%)	
60-69	13,228 (19.4%)	6729 (18.2%)	13,228 (19.4%)	
≥70	5155 (7.6%)	2788 (7.5%)	5155 (7.6%)	
Ethnic				
Bai	5475 (8.0%)	80 (0.2%)	5395 (17.3%)	<0.001
Bouyei	4591 (6.7%)	1102 (3.0%)	3489 (11.2%)	
Dong	5678 (8.3%)	1164 (3.1%)	4514 (14.4%)	
Han	43,158 (63.2%)	32,482 (87.8%)	10,676 (34.2%)	
Miao	4180 (6.1%)	1654 (4.5%)	2526 (8.1%)	
Yi	5172 (7.6%)	516 (1.4%)	4656 (14.9%)	
Annual family income, Yuan/year				
<1,2000	12,016 (17.6%)	4076 (11.0%)	7940 (25.4%)	<0.001
12,000–19,999	11,863 (17.4%)	4898 (13.2%)	6965 (22.3%)	
20,000–59,999	24,695 (36.2%)	13,367 (36.1%)	11,328 (36.2%)	
60,000–99,999	10,348 (15.2%)	7355 (19.9%)	2993 (9.6%)	
≥100,000	9332 (13.7%)	7302 (19.7%)	2030 (6.5%)	
Education level				
Illiteracy	15,991 (23.4%)	4819 (13.0%)	11,172 (35.7%)	<0.001
Primary school	17,546 (25.7%)	7972 (21.5%)	9574 (30.6%)	
Junior high school	18,569 (27.2%)	10,932 (29.5%)	7637 (24.4%)	
High school	8362 (12.3%)	6482 (17.5%)	1880 (6.0%)	
Junior college	4859 (7.1%)	4180 (11.3%)	679 (2.2%)	
Bachelor's degree or above	2927 (4.3%)	2613 (7.1%)	314 (1.0%)	
Smoking status				
Never smoker	50,769 (74.4%)	26,949 (72.8%)	23,820 (76.2%)	<0.001
Quit smoking	3328 (4.9%)	2080 (5.6%)	1248 (4.0%)	
Smoker	14,157 (20.7%)	7969 (21.5%)	6188 (19.8%)	
Secondary smoke				
No	33,014 (48.4%)	17,279 (46.7%)	15,735 (50.3%)	<0.001
Yes	35,240 (51.6%)	19,719 (53.3%)	15,521 (49.7%)	
Indoor pollution				
1	10,752 (15.8%)	6008 (16.2%)	4744 (15.2%)	<0.001
2	54,044 (79.2%)	30,128 (81.4%)	23,916 (76.5%)	
3	3458 (5.1%)	862 (2.3%)	2596 (8.3%)	
Physical activity, MET-h/day				
Mean (SD)	27.0 (18.4)	24.3 (17.3)	30.1 (19.2)	<0.001
Alcohol drinking status				
Never	38,038 (55.7%)	18,540 (50.1%)	19,498 (62.4%)	<0.001
Occasionally	20,765 (30.4%)	13,061 (35.3%)	7704 (24.6%)	
Often	9451 (13.8%)	5397 (14.6%)	4054 (13.0%)	
Fruits				
Never or little	12,175 (17.8%)	4855 (13.1%)	7320 (23.4%)	<0.001
1–3 d/w	16,353 (24.0%)	7968 (21.5%)	8385 (26.8%)	
4–6 d/w	2702 (4.0%)	1520 (4.1%)	1182 (3.8%)	
Every day	37,024 (54.2%)	22,655 (61.2%)	14,369 (46.0%)	
Vegetables				
Never or little	415 (0.6%)	233 (0.6%)	182 (0.6%)	0.35
1–3 d/w	708 (1.0%)	405 (1.1%)	303 (1.0%)	
4–6 d/w	198 (0.3%)	109 (0.3%)	89 (0.3%)	
Every day	66,933 (98.1%)	36,251 (98.0%)	30,682 (98.2%)	
Red meat				
Never or little	6241 (9.1%)	2792 (7.5%)	3449 (11.0%)	<0.001
1–3 d/w	11,438 (16.8%)	6089 (16.5%)	5349 (17.1%)	
4–6 d/w	2019 (3.0%)	1077 (2.9%)	942 (3.0%)	
Every day	48,556 (71.1%)	27,040 (73.1%)	21,516 (68.8%)	
Poultry meat				
Never or little	48,115 (70.5%)	22,323 (60.3%)	25,792 (82.5%)	<0.001
1–3 d/w	18,933 (27.7%)	13,891 (37.5%)	5042 (16.1%)	
4–6 d/w	335 (0.5%)	246 (0.7%)	89 (0.3%)	
Every day	871 (1.3%)	538 (1.5%)	333 (1.1%)	
Milk				
Never or little	44,116 (64.6%)	20,090 (54.3%)	24,026 (76.9%)	<0.001
1–3 d/w	12,076 (17.7%)	7790 (21.1%)	4286 (13.7%)	
4–6 d/w	1375 (2.0%)	1012 (2.7%)	363 (1.2%)	
Every day	10,687 (15.7%)	8106 (21.9%)	2581 (8.3%)	
Pickled vegetables				
Never or little	40,536 (59.4%)	21,789 (58.9%)	18,747 (60.0%)	<0.001
1–3 d/w	18,656 (27.3%)	10,541 (28.5%)	8115 (26.0%)	
4–6 d/w	1139 (1.7%)	643 (1.7%)	496 (1.6%)	
Every day	7923 (11.6%)	4025 (10.9%)	3898 (12.5%)	
Hypertension				
Yes	23,091 (33.8%)	12,000 (32.4%)	11,091 (35.5%)	<0.001
No	45,163 (66.2%)	24,998 (67.6%)	20,165 (64.5%)	
Diabetes				
Yes	23,091 (33.8%)	4483 (12.1%)	3118 (10.0%)	<0.001
No	45,163 (66.2%)	32,515 (87.9%)	28,138 (90.0%)	
Obesity indicators				
BMI (kg/m^2)	24.0 (3.4)	24.1 (3.3)	23.9 (2.1)	<0.001
WC (cm)	81.9 (9.8)	81.9 (9.7)	81.9 (7.6)	0.47
WHtR (%)	52.0 (6.3)	51.7 (6.1)	52.4 (4.9)	<0.001
WHR (%)	88.3 (7.0)	87.9 (6.9)	88.8 (6.6)	<0.001

Note: $1.00 was equivalent to 6.75 yuan in 2009.
METs: metabolic equivalent tasks; BMI: body mass index; WC: waist circumference; WHtR: waist-to-height ratio; WHR: waist-to-hip ratio.

Table 2
Descriptive 3-year average concentrations of PM_1, $PM_{2.5}$, and PM_{10} by residence (μg/m^3).

Variables	Total			Urban area			Rural area		
	Minimum	Maximum	Median (25%, 75%)	Minimum	Maximum	Median (25%, 75%)	Minimum	Maximum	Median (25%, 75%)
PM_1	11.09	53.57	28.08 (21.59, 33.73)	11.09	53.57	32.54 (24.71, 35.68)	13.45	52.52	24.44 (21.29, 30.30)
$PM_{2.5}$	16.49	105.29	38.23 (26.34, 55.76)	16.49	105.29	52.91 (34.25, 59.72)	18.64	105.29	33.28 (23.97, 49.14)
PM_{10}	33.26	165.19	65.45 (52.18, 92.48)	34.69	165.19	87.14 (57.37, 98.09)	33.26	165.19	57.32 (48.27, 83.53)

PM_1, particulate matter with an aerodynamic diameter of 1.0 μm; $PM_{2.5}$, particulate matter with an aerodynamic diameter of 2.5 μm; and PM_{10}, particulate matter with an aerodynamic diameter of 10 μm.

Table 3
Associations between three-year exposure to ambient fine particulate matter and a risk of obesity of 10 μg/m^3.

	PM_1	PM2.5	PM_{10}
	β (95%CI)	β (95%CI)	β (95%CI)
Main analysis[a]			
BMI	0.86 (0.81, 0.91)	0.38 (0.36, 0.4)	0.24 (0.23, 0.26)
WHtR	1.71 (1.62, 1.8)	0.78 (0.74, 0.82)	0.51 (0.48, 0.53)
WC	2.25 (2.11, 2.39)	0.99 (0.93, 1.05)	0.63 (0.59, 0.67)
WHR	0.54 (0.44, 0.64)	0.28 (0.24, 0.33)	0.19 (0.16, 0.22)
	OR (95%CI)	OR (95%CI)	OR (95%CI)
Overweight[b]	1.42 (1.37, 1.47)	1.17 (1.15, 1.18)	1.1 (1.09, 1.11)
General obesity[c]	1.63 (1.51, 1.76)	1.24 (1.2, 1.28)	1.15 (1.12, 1.17)
Abdominal obesity by WHtR[d]	1.67 (1.62, 1.73)	1.26 (1.24, 1.28)	1.16 (1.15, 1.17)

BMI, body mass index; WHtR, waist-to-height ratio; WC, waist circumference; WHR, waist-to-hip ratio.
PM_1, particulate matter with an aerodynamic diameter of 1.0 μm; $PM_{2.5}$, particulate matter with an aerodynamic diameter of 2.5 μm; and PM_{10}, particulate matter with an aerodynamic diameter of 10 μm.
[a] Crude analysis: no adjustment.
[b] Overweight: 25 kg/m^2 ≤ BMI <30 kg/m.^{2}.
[c] General obesity: BMI ≥30 kg/m.^{2}.
[d] Abdominal obesity by WHtR: WHtR ≥0.50.

Table 4
Associations of risk of obesity indicators with per IQR μg/m^3 increase of ambient air pollution.

	PM_1	PM2.5	PM_{10}
	β (95%CI)	β (95%CI)	β (95%CI)
Main analysis[a]			
BMI	1.04 (0.98, 1.1)	1.13 (1.06, 1.19)	0.97 (0.92, 1.03)
WHtR	2.07 (1.96, 2.18)	2.32 (2.2, 2.43)	2.04 (1.94, 2.14)
WC	2.73 (2.56, 2.9)	2.96 (2.78, 3.14)	2.55 (2.39, 2.72)
WHR	0.66 (0.53, 0.78)	0.85 (0.72, 0.97)	0.76 (0.64, 0.87)
	OR (95%CI)	OR (95%CI)	OR (95%CI)
Overweight[b]	1.52 (1.46, 1.59)	1.58 (1.51, 1.66)	1.48 (1.42, 1.54)
General obesity[c]	1.8 (1.64, 1.98)	1.89 (1.71, 2.1)	1.74 (1.58, 1.9)
Abdominal obesity by WHtR[d]	1.86 (1.79, 1.94)	1.98 (1.89, 2.07)	1.83 (1.76, 1.9)

BMI, body mass index; WHtR, waist-to-height ratio; WC, waist circumference; WHR, waist-to-hip ratio.
PM_1, particulate matter with an aerodynamic diameter of 1.0 μm; $PM_{2.5}$, particulate matter with an aerodynamic diameter of 2.5 μm; and PM_{10}, particulate matter with an aerodynamic diameter of 10 μm.
[a] Crude analysis: no adjustment.
[b] Overweight: 25 kg/m^2 ≤ BMI <30 kg/m.^{2}.
[c] General obesity: BMI ≥30 kg/m.^{2}.
[d] Abdominal obesity by WHtR: WHtR ≥0.50.

who were older, had incomes below 6000 RMB, and those who were never drinking, ever smoking, and engaging in more physical activity (Table S4-S8). Similar effects also occurred in $PM_{2.5}$ and PM_{10}.

3.4. Sensitivity analyses

The sensitivity analyses showed the results of the association between obesity indictors and different air pollutant particle sizes (Table S9 & S10). The strongest association was observed in $PM_{2.5}$, followed by PM_1, $PM_{1\text{-}2.5}$, PM_{10}, and $PM_{2.5\text{-}10}$ (Table S10). Besides, Table S11 & S12 suggested comparable effect estimates for obesity measures when average ambient air pollution concentrations from different years before the survey were used as the exposure variable. For instance, increases of 10 μg/m^3 in PM_{10} over four years average concentration were associated with increases in the OR for overweight of 1.11 (95% CI, 1.1 to 1.12), the OR for general obesity of 2.2 (95% CI, 2.09 to 2.31), the OR for abdominal obesity by WHtR of 1.54 (95% CI, 1.48 to 1.61). The small difference in results over the four years indicated the robustness of the results. The relationships between long-term air pollution exposure and obesity measures were nonlinear in the adjusted model (Figure S2-S6).

4. Discussion

Strong positive associations were found between long-term (3 years average) air pollution particulates exposure and obesity, with a higher risk observed in rural areas. We also found that long-term exposure to $PM_{2.5}$ had the greatest effect on the risk of obesity among the three air pollutants. To our knowledge, this is the first to contrast urban-rural differences in the association of long-term exposure to PM_1, $PM_{2.5}$, and PM_{10} with obesity risk in China.

Our findings indicated long-term exposures to PM_1, $PM_{2.5}$ and PM_{10} were all positively associated with increased risk of obesity. The results were consistent with some previous studies (Cao et al., 2021; Deschenes et al., 2020; Furlong and Klimentidis, 2020; Liu et al., 2020). Nevertheless, the positive association between air pollution and obesity remains inconclusive. A review of air pollution effect on obesity including 66 studies, concluded only 29 studies with the positive association and 8 studies with the negative association (An et al., 2018). This inconsistency might be partly due to PM concentration and composition differences from different study regions, and partly due to population variation.

The effects of air pollution on obesity of urban residents were found to be smaller than those of rural residents, although the concentrations of air pollutants in urban areas were higher than those in rural areas. These findings were similar to previous studies in China (Li et al., 2018; Wang et al., 2019a; Zhao et al., 2021). In a national prospective cohort study, the concentration of $PM_{2.5}$ in rural areas is lower than that in urban areas, but the death risk of rural residents is higher than that of urban residents (Li et al., 2018). This rural/urban difference can be

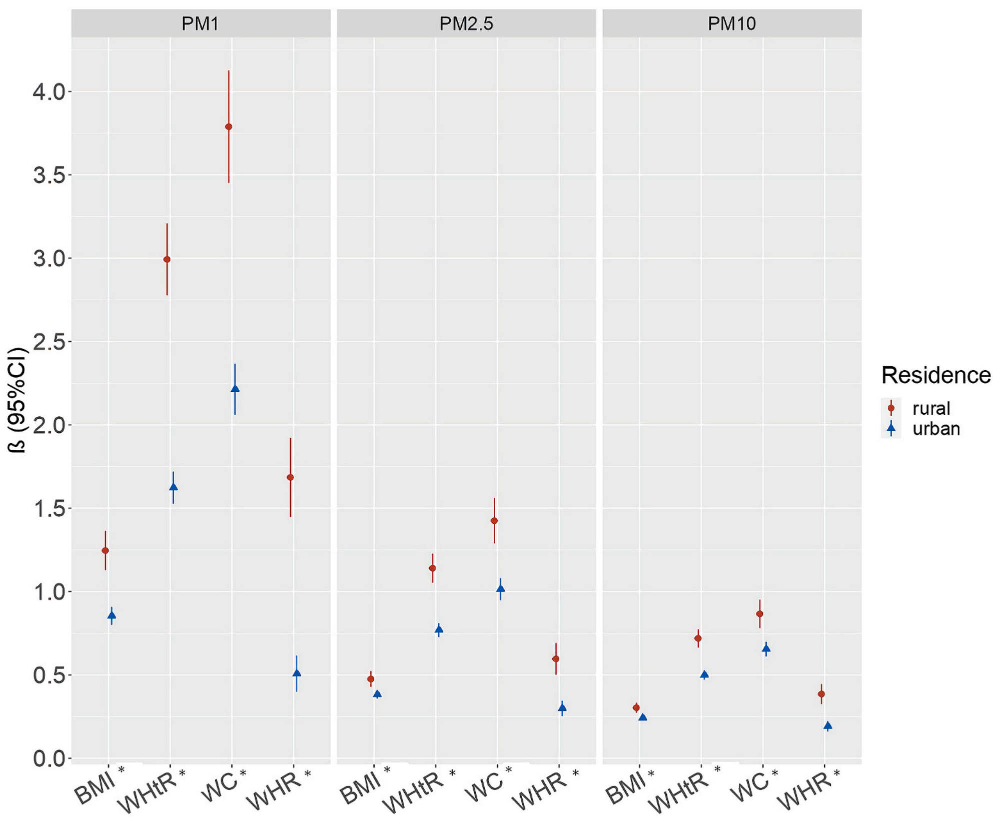

Fig. 1. Associations between PM_1, $PM_{2.5}$, and PM_{10} and continuous obesity indicators stratified by residence. BMI, body mass index; WC, waist circumference; WHR, waist-to-hip ratio; WHtR, waist-to-height ratio. PM_1, particulate matter with an aerodynamic diameter of 1.0 μm; $PM_{2.5}$, particulate matter with an aerodynamic diameter of 2.5 μm; and PM_{10}, particulate matter with an aerodynamic diameter of 10 μm. Adjusted model: Adjusted for age, sex, education level, average annual income, ethnicity, smoking, drinking, physical activity, fruit intake, vegetable intake, red meat intake, poultry intake, milk intake, pickled vegetable intake, hypertension, and diabetes. * : P value for difference <0.05. P value for difference: Z test was used to test for statistically significant difference in OR estimates across categories within subgroups. For example, in rural area vs urban area, we calculated: $Z = \frac{OR_{urban} - OR_{rural}}{\sqrt{se(OR_{urban})^2 + se(OR_{rural})^2}}$. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

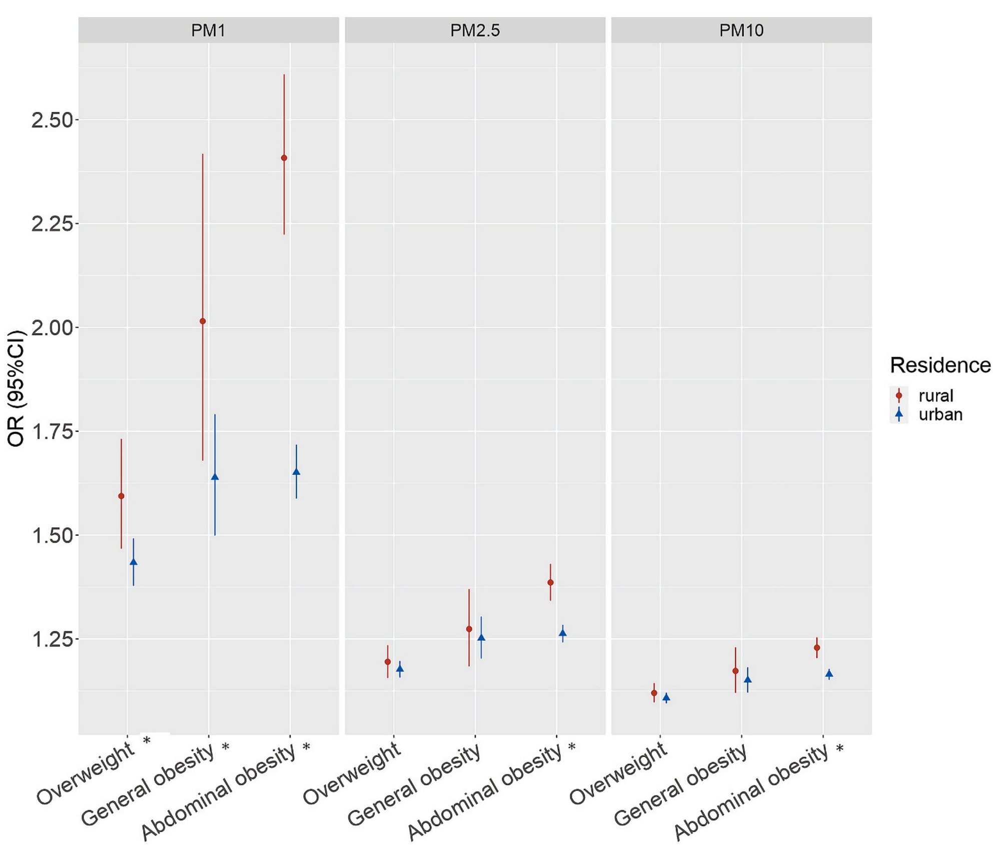

Fig. 2. Associations between PM_1, $PM_{2.5}$, and PM_{10} and categorical obesity indicators stratified by residence. BMI, body mass index; WC, waist circumference; WHR, waist-to-hip ratio; WHtR, waist-to-height ratio. PM_1, particulate matter with an aerodynamic diameter of 1.0 μm; $PM_{2.5}$, particulate matter with an aerodynamic diameter of 2.5 μm; and PM_{10}, particulate matter with an aerodynamic diameter of 10 μm. Adjusted model: Adjusted for age, sex, education level, average annual income, ethnicity, smoking, drinking, physical activity, fruit intake, vegetable intake, red meat intake, poultry intake, milk intake, pickled vegetable intake, hypertension, and diabetes. * : P value for difference <0.05. P value for difference: Z test was used to test for statistically significant difference in OR estimates across categories within subgroups. For example, in rural area vs urban area, we calculated: $Z = \frac{OR_{urban} - OR_{rural}}{\sqrt{se(OR_{urban})^2 + se(OR_{rural})^2}}$. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

explained as follows. Firstly, the PM concentrations and compositions between urban areas and rural areas were very different. For example, a larger proportion of $PM_{2.5}$ in rural areas came from biomass fuel consumption while the contribution of traffic exhausts source to $PM_{2.5}$ concentration was higher in urban areas (Saraga et al., 2021). This results in different components of PM between urban and rural areas, and different toxicities of specific components in the mixed composition, which in turn leads to different toxicities and health effects of PM (Lelieveld et al., 2015). Secondly, rural populations may be more vulnerable to air pollution, because they usually have low socioeconomic status, poor health in early life, less self-protection awareness, harsh living and working environments, insufficient health-care services, and staying outdoors for a long time and so on (Chen et al., 2017b; Chilunga et al., 2019; Tu et al., 2020). Finally, the primary causes of adiposity in urban areas are quite different from those in rural areas (Bowen et al., 2011; Carrillo-Larco et al., 2016; Sullivan et al., 2011; Unwin et al., 2010). For example, adiposity in urban areas was primarily caused by more fat and energy intake (Bowen et al., 2011; Unwin et al., 2010), lower levels of physical activity (Carrillo-Larco et al., 2016; Sullivan et al., 2011), and higher psychological pressure. Therefore, air pollution might account for less of the body weight of urban residents.

We found among the three PM fractions, $PM_{2.5}$ had the largest effect estimates. The results were consistent with the assumption in previous studies (Chen et al., 2017a; Liu et al., 2013) that smaller particles could reach the deep part of the respiratory tract, had a higher surface volume ratio, and carried more toxins, thus promoting more severe oxidative stress and inflammation. Hence the association of PM_{10} was the weakest. Compared with PM_1, $PM_{2.5}$ has a more complex mixture of fine particles (e.g., crustal matter), which may explain the greater effect of $PM_{2.5}$ (Buczynska et al., 2014). Similar result between $PM_{2.5}$ and PM_1 were found in the rural area of China (Liu et al., 2020).

The stratification analysis showed that the elderly, low-income groups and those who engaged in more physical activity were at higher risk of obesity affected by air pollution, which were consistent with previous studies (Li et al., 2015; Liu et al., 2020; Yang et al., 2019). The higher risk of the elderly may be due to their reduced self-cleaning ability and their tendency to accumulate particles, resulting in greater impact by air pollution (Liu et al., 2020; Yang et al., 2019). As for the low-income group, their social status is generally lower, intake more fat, and they are more likely to be obese (Volaco et al., 2018). People who are physically active have more outdoor sports and encounter more air pollutants, and the cumulative effect of air pollutants leads to an increase in the possibility of obesity (Weichenthal et al., 2014).

Our study has several strengths. First, we incorporated a rich set of covariates that have an important influence on the outcome to control for confounding issues in the analysis. Second, the range of air pollutants in this study was very large, including not only heavily polluted areas but also areas with less air pollution, so it could provide guidance for a wide range of areas where pollutants fall within this range.

Nevertheless, there were limitations to this current study. First, caution should be taken in making causal interpretations between air pollution exposures and obesity because our study outcomes were only collected at one time point. Second, due to limited data availability, it was impossible to adjust all the potential confounding factors, such as meteorological factors, noise, green space (Huang et al., 2020; Klompmaker et al., 2019), and the built environment (Wu et al., 2020). Finally, the information about passive smoking, diet, and physical activity was self-reported by the respondents, and there was no objective measurement method, which may lead to some recall bias.

5. Conclusion

Long-term exposure to PM_1, $PM_{2.5}$, and PM_{10} was associated with an increased risk of obesity, and $PM_{2.5}$ had the strongest association. In comparing urban and rural areas, we observed regional disparities in the effects of air pollution particulate matter exposure on the risk of obesity, with higher effect estimates found in rural areas. Sustained air pollution control measures are urgently needed not only in urban areas but also in rural areas.

Credit author statement

Meijing Liu: Data collection, Data analysis, Validation, and Writing-Original draft preparation and Editing. Wenge Tang: Data collection, Validation. Yan Zhang, Yanjiao Wang, Baima kangzhuo, Yajie Li and Xiang Liu: Data collection. Shuaiming Xu, Linjun Ao and Qinjian Wang: Data cleaning. Jing Wei: Data collection. Gongbo Chen, Shanshan Li, and Yumin Guo: Study design and Validation. Shujuan Yang: Study design, Data collection, and Writing-Reviewing and Editing. Delin Han: Study design, Data collection, and Writing-Reviewing and Editing. Xing Zhao: Study design, Methodology, Validation, Supervision, and Writing-Reviewing and Editing.

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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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2021.111597.

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