Article

Association of PM$_{2.5}$ and Its Chemical Compositions with Metabolic Syndrome: A Nationwide Study in Middle-Aged and Older Chinese Adults

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Abstract: Studies on the association of PM$_{2.5}$ and its compositions with metabolic syndrome (MetS) were limited, and it was unclear which was the most hazardous composition. In this study, we aimed to investigate the association between PM$_{2.5}$ and its compositions with MetS and identified the most hazardous composition. In this study, we included 13,418 adults over 45 years across 446 communities from 150 counties of 28 provinces in nationwide China in 2015. MetS was defined based on the five indicators of the Joint Interim Societies, including: blood pressure (SBP (systolic blood pressure) and DBP (diastolic blood pressure)); fasting blood glucose (FBG); fasting triglyceride (FTG); high density lipoprotein cholesterol (HDL-C); and waist circumference (WC). We used chemical transport models to estimate the concentration of PM$_{2.5}$ and its compositions, including black carbon, ammonium, nitrate, organic matter, and sulfate. We used a generalized linear regression model to examine the association of PM$_{2.5}$ and its compositions with MetS. In this study, we observed that the average age was 61.40 (standard deviation (SD): 9.59). Each IQR (29.76 μg/m^3) increase in PM$_{2.5}$ was associated with a 1.27 (95% CI: 1.17, 1.37) increase in the odds for MetS. We indicated that black carbon showed stronger associations than other compositions. The higher associations were observed among women, participants aged less than 60 years, who lived in urban areas and in the Northeast, smokers, drinkers, and the obese populations. In conclusion, our findings identified the most harmful composition and sensitive populations and regions that required attention, which would be helpful for policymakers.

Keywords: particulate matter; metabolic syndrome; adults; composition; cross-sectional

1. Introduction

Metabolic syndrome (MetS) is an indicator combined with increased blood pressure, high blood glucose and triglyceride, excess waist circumference (WC), and low levels of cholesterol [1]. The prevalence of MetS is increasing globally, estimated to be 20–25% in the adult population [2,3]. In China, there was 24.5% of the population suffering from MetS in 2016 [4].

MetS is a global public health issue, which may lead to cardiovascular disease, diabetes, stroke, asthma, cancer, and related mortality [5,6], leading to the heavy burden of disease. The prevalence of MetS also increased with age due to the commonalities in biochemical changes in aging process and MetS [7]. Therefore, it is urgent to identify the risk factors of MetS, especially among the aging population. Previous studies indicated that MetS would be attributable to genetic factors, unhealthy diet, unhealthy lifestyle (smoking, drinking, and sedentary), and inadequate sleep [8].

A growing number of epidemiological studies suggested air pollution was a risk factor for MetS [9–11]. Some studies showed air pollutants might induce MetS risk [12,13]. However, the evidence that investigated the associations of air pollution with MetS was still limited and inconsistent, especially among developed countries with higher air pollution. Up to now, only several studies have examined the associations of air pollution with MetS among Chinese adults [10,14,15].

The inconsistencies in results may be due to the difference in the study population, region, sample, period, and level of air pollution. Another explanation was that fine particulate matter ($PM_{2.5}$) was a complex mixture including a series of components with various toxicities [16,17], which may lead to inconsistent results across different regions. However, most epidemiological studies only focused on the mass concentration of $PM_{2.5}$ [9–11,18].

In recent years, some researchers have started to focus on the compositions of $PM_{2.5}$ and explore the health outcomes attributed to various compositions, such as mortality, birth weight, and respiratory health [19–21]. To our knowledge, there were only a few studies that explored the association of $PM_{2.5}$ compositions with indicators of MetS, such as blood pressure [22], blood glucose [23], and blood lipids [24]. However, there has been no study to explore the associations of $PM_{2.5}$ compositions with MetS up to now. Hence, it is essential to examine the association between compositions of $PM_{2.5}$ and MetS, and identify the most harmful composition, which would be helpful to policy-makers in carrying out the control of air pollution.

This study provided the first chance to explore the association of $PM_{2.5}$ and its compositions with MetS among middle-aged and older adults based on the China Health and Retirement Longitudinal Study (CHARLS). We also aimed to identify the most hazardous components across regions and determine the most vulnerable region which should be focused on.

2. Materials and Methods

2.1. Study Participants

The dataset was taken from wave 3 of the China Health and Retirement Longitudinal Study (CHARLS) in 2015, which covered 150 counties/districts, 450 villages/urban communities across the country, involving 13,418 middle-aged and older adults above 45 years old in nationwide China by a multistage probability sampling strategy. The previous study described the details of the study population selection [25]. CHARLS collected the sociodemographic variables, health status, and household information using trained interviewers according to a standard protocol. The data of CHARLS can be obtained at http://opendata.pku.edu.cn publicly (accessed on 8 June 2022). All participants signed the written informed consent. The Ethical Review Committee of Peking University approved the study (IRB00001052-11015).

2.2. Estimation of $PM_{2.5}$ and Its Composition

We estimated the concentration of $PM_{2.5}$ and its compositions using aerosol optical depth (AOD) and conversion factors derived from the chemical transport models and evaluated against the ground observations [26]. In this study, the compositions included black carbon (BC), ammonium (NH_4^+), nitrate (NO_3^-), organic matter (OM), and sulfate (SO_4^{2-}). The data of $PM_{2.5}$ and its composition were publicly available from the Tracking Air Pollution in China (TAP) (http://tapdata.org/, last access: 20 May 2022). The spatial resolution of $PM_{2.5}$ and its composition were at $0.1° \times 0.1°$ grid. The concentration of each composition was calculated as follows (Equation (1)):

$$\text{Composition}^k_{\text{satellite}} = \text{AOD}_{\text{satellite}} \times \frac{\text{Composition}^k_{\text{CTM}}}{\text{AOD}_{\text{CTM}}} \tag{1}$$

In Equation (1), "satellite" and "CTM" refer to the data from the satellite and model, respectively; k refers to the different compositions of $PM_{2.5}$; the conversion factors between $PM_{2.5}$ compositions and AOD were estimated from the emission inventory over China [27].

In this study, the concentration of air pollutants was available at the city level because of confidentiality. We estimated the concentrations of $PM_{2.5}$ and its compositions according to the spatiotemporal coordinates and the date of the interview on the monthly average. We calculated the average concentration of $PM_{2.5}$ and its composition during the 1-year preceding the survey month as a surrogate for the long-term exposure concentration (Lag 1). We also simultaneously estimated the annual concentrations of $PM_{2.5}$ and its components at different exposure windows (from Lag 2 to Lag 5).

2.3. Definition of MetS

Metabolic syndrome (MetS) was jointly defined by five indicators, including blood pressure (SBP (systolic blood pressure) and DBP (diastolic blood pressure)); fasting blood glucose (FBG); fasting triglyceride (FTG); high density lipoprotein cholesterol (HDL-C); and waist circumference (WC). We determined that participants had MetS if they presented with three or more of the abovementioned factors. In this study, we chose the definition of MetS according to the joint definitions from different organizations and used the cut-off points of WC from China [28]. Specifically, (1) SBP $\geq$ 130 mmHg or DBP $\geq$ 85 mmHg; (2) WC > 85 cm for men and 80 cm for women, respectively; (3) FBG > 100 mg/dL; (4) FTG > 150 mg/dL; (5) HDL-C < 40 mg/dL for men and 50 mg/dL for women, respectively. Different organizations define MetS differently, and the detailed criteria for these definitions are shown in Table S1 (Supplementary Materials).

2.4. Covariates

Potential confounders were collected via a questionnaire by well-trained technicians. We obtained covariates including socioeconomic variables sex, age, urbanicity, marital status, educational level, the status of drinking and smoking, and the fuel type of household cooking/heating. The specific classification of each variable was presented in previous studies [29]. The fuel was classified into clean fuel (marsh gas, solar energy, natural gas, natural gas, liquefied petroleum gas, electricity, or municipal heating) and solid fuel (crop residue, coal, wood, or solid charcoal).

2.5. Statistical Analysis

The generalized linear model was used to explore the association of $PM_{2.5}$ and its compositions with MetS adjusted for age, sex, urbanicity, educational level, marriage status, smoking, drinking, fuel type of cooking and heating, and physical activity. We described the results as odds ratios (OR) of MetS per IQR increment of $PM_{2.5}$ and its compositions. We also conducted region-stratified analyses. We divided the whole of China into four districts: East; Middle; West; and Northeast.

We conducted a series of sensitivity analyses: (1) First, we investigated the association at different exposure windows (Lag 2, Lag 3, Lag 4, and Lag 5); (2) Second, we developed the analyses in different model-adjusted confounders; (3) We conducted the stratified analyses by sex, age group, urbanicity, smoking status, drinking status, and obese or not; (4) We also repeated the analyses to explore the association using the different definition of MetS from other organizations. All data processes were performed using R 4.1.1 (R Foundation for Statistical Computing, Vienna, Austria). The two-tailed *p* value < 0.05 was seen as statistical significance.

3. Results

3.1. The Basic Description

The characteristics of participants are depicted in Table 1. There were 4044 (30.14%) participants who had MetS in the population of 13,418. Participants were 61.40 (standard deviation (SD): 9.59) years old. We compared the differences in characteristics between

participants with or without MetS and found a significant difference between the two groups. We also observed that the participants with MetS had a higher body mass index (BMI), undertook less physical activity, were more likely to be women, living in a rural area, married, and to be from the population with a lower educational level.

Table 1. Characteristic of the participants.

	Non-MetS (n = 9374)	MetS (n = 4044)	p Value
Age, mean (SD), year	61.6 (9.79)	60.8 (9.07)	<0.001
Height, mean (SD), cm	158 (8.35)	158 (8.56)	0.392
Weight, mean (SD), kg	57.5 (10.5)	65.8 (11.3)	<0.001
Physical activity amount, mean (SD), MET min/week	119 (113)	95.5 (101)	<0.001
Sex (No. (%))			<0.001
Men	4681 (49.9%)	1492 (36.9%)	
Women	4691 (50.0%)	2552 (63.1%)	
Missing	2 (0.0%)	0 (0%)	
Urban or rural (No. (%))			<0.001
Urban	3227 (34.4%)	1869 (46.2%)	
Rural	6147 (65.6%)	2175 (53.8%)	
Marriage or not (No. (%))			0.28
Single	1217 (13.0%)	497 (12.3%)	
Married	8155 (87.0%)	3547 (87.7%)	
Missing	2 (0.0%)	0 (0%)	
Educational level (No. (%))			0.002
Primary or below	3952 (42.2%)	1609 (39.8%)	
Middle school	1721 (18.4%)	815 (20.2%)	
High school	705 (7.5%)	348 (8.6%)	
Collage or above	134 (1.4%)	72 (1.8%)	
Missing	2862 (30.5%)	1200 (29.7%)	
Heating fuel [1] (No. (%))			<0.001
Solid	5445 (58.1%)	2139 (52.9%)	
Clean	1516 (16.2%)	732 (18.1%)	
Missing	2413 (25.7%)	1173 (29.0%)	
Cooking fuel [1] (No. (%))			<0.001
Solid	4277 (45.6%)	1514 (37.4%)	
Clean	5081 (54.2%)	2520 (62.3%)	
Missing	16 (0.2%)	10 (0.2%)	
Smoke or not (No. (%))			<0.001
Smoke	2635 (28.1%)	767 (19.0%)	
No-smoke	5336 (56.9%)	2708 (67.0%)	
Missing	1403 (15.0%)	569 (14.1%)	
Drinking or not (No. (%))			<0.001
Drink	3480 (37.1%)	1184 (29.3%)	
Ever-drink	1015 (10.8%)	442 (10.9%)	
No-drink	4860 (51.8%)	2411 (59.6%)	
Missing	19 (0.2%)	7 (0.2%)	

Abbreviations: MetS, metabolic syndrome; SD, standard deviation. Notes: [1] Cooking fuel was classified into clean fuel (marsh gas, natural gas, liquefied petroleum gas, or electricity) and solid fuel (crop residue, coal, wood, or solid charcoal). Heating fuel was categorized as solid fuel (coal, crop residue, wood, or solid charcoal) and clean fuel (natural gas, solar energy, liquefied petroleum gas, electric, or municipal heating).

Table 2 shows the description of $PM_{2.5}$ and its compositions. The mean $\pm$ SD concentration was 49.31 $\pm$ 19.63 $\mu g/m^3$, 2.36 $\pm$ 0.70 $\mu g/m^3$, 7.45 $\pm$ 3.11 $\mu g/m^3$, 10.74 $\pm$ 5.11 $\mu g/m^3$, 11.93 $\pm$ 4.23 $\mu g/m^3$, 9.24 $\pm$ 3.34 $\mu g/m^3$ for $PM_{2.5}$, BC, NH_4^+, NO_3^-, OM, and SO_4^{2-}, respectively. The concentration of $PM_{2.5}$ and its compositions at different exposure windows did not differ significantly (Table S2). Table S3 shows the concentrations of $PM_{2.5}$ and its compositions in different regions. Most compositions had the highest concentration in the East, while the lowest concentration was observed in the West

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(Table S3). We also observed that the concentrations of all constituents in the East and middle regions exceeded the national average, while the concentrations in the West and Northeast regions were lower than the national average.

Table 2. The 1-year average concentration of the PM2.5 and its chemical constituent.

Air Pollutants	Mean	SD	Min	P_5	P_{25}	Median	P_{75}	P_{95}	Max
$PM_{2.5}$	49.31	19.63	19.84	22.14	32.25	45.87	61.89	84.98	93.27
BC	2.36	0.70	0.98	1.37	1.82	2.21	2.88	3.63	3.99
NH_4^+	7.45	3.11	2.76	3.04	4.83	7.43	9.57	12.92	14.03
NO_3^-	10.74	5.11	3.07	3.56	6.27	10.28	14.26	19.56	21.38
OM	11.93	4.23	4.95	6.00	8.56	11.46	14.77	20.12	21.70
SO_4^{2-}	9.24	3.34	3.07	4.78	6.35	8.64	11.77	15.27	16.61

Abbreviations: BC: Black Carbon; NH_4^+: Ammonium; NO_3^-: Nitrate; OM: organic matter; SO_4^{2-}: Sulfate.

3.2. Association between $PM_{2.5}$ and Its Compositions on MetS

Our study indicated significant positive associations of $PM_{2.5}$ and its compositions with the risk of MetS (Figure 1). The adjusted OR of MetS was 1.27 (95% CI: 1.17, 1.37) with an IQR (29.76 µg/m^3) increment in $PM_{2.5}$. In this study, we observed that BC was the most harmful composition because BC showed the strongest associations among all compositions. In the main model, per IQR (1.06 µg/m^3) the increment in BC was associated with a 1.25 (95% CI: 1.16, 1.36) increase in the risk of MetS. To identify the most vulnerable regions, we conducted region-stratified analyses and found that associations varied significantly in different regions. We also observed that $PM_{2.5}$ and all the compositions showed the greatest effects on MetS in the Northeast region, while the weakest effects were observed in the Western region. Take BC as an example, in the fully adjusted models, an IQR (1.06 µg/m^3) increase in BC was associated with a 65% (95% CI: 1.39, 1.96) and 19% (95% CI: 1.06, 1.34) increase in the risk of MetS in the Northeast and Western region, respectively.
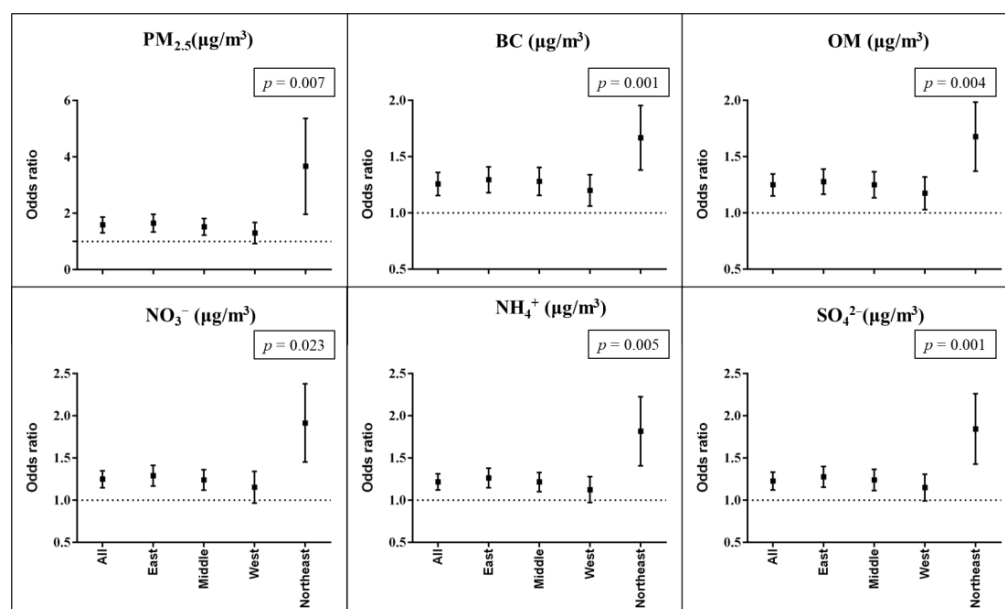

Figure 1. The association of metabolic syndrome (MetS) with an IQR incremental change in 1-year average $PM_{2.5}$ and its constitution, stratified by different regions. The bars show main effect estimates and 95% confidence intervals. The model was adjusted for age, sex, urbanicity, educational level, marriage status, smoking, drinking, cooking fuel type, heating fuel type, and physical activity. Abbreviations: BC: Black Carbon; NH_4^+: Ammonium; NO_3^-: Nitrate; OM: organic matter; SO_4^{2-}: Sulfate. *p* value refers to the difference of the estimations between different regions.

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We also conducted a set of sensitivity analyses. We explored the association of $PM_{2.5}$ and its compositions with MetS by different models after adjustments for various covariates (Table S4). We found that $PM_{2.5}$ and its compositions retained significant positive associations across different models. We also repeated the analyses using the concentration at different exposure windows, and observed that the positive associations of $PM_{2.5}$ and its chemical compositions with MetS remained stable (Table S5). Finally, the repeated analyses using the different definition of MetS also showed the positive associations (Figure S1). The above-mentioned series of sensitivity analyses indicated the robustness of our findings.

3.3. Stratified Analyses by Subgroups

Stratified analyses were performed on sex, age group, urbanicity, smoking status, drinking status, and obese or not (Figure 2). Although there were no significant differences in different subgroups, we still observed a consistent trend. It was noted that a greater association of $PM_{2.5}$ and its compositions with MetS was observed among women, participants aged less than 60 years, who lived in urban areas, were smokers, drinkers, and obese.
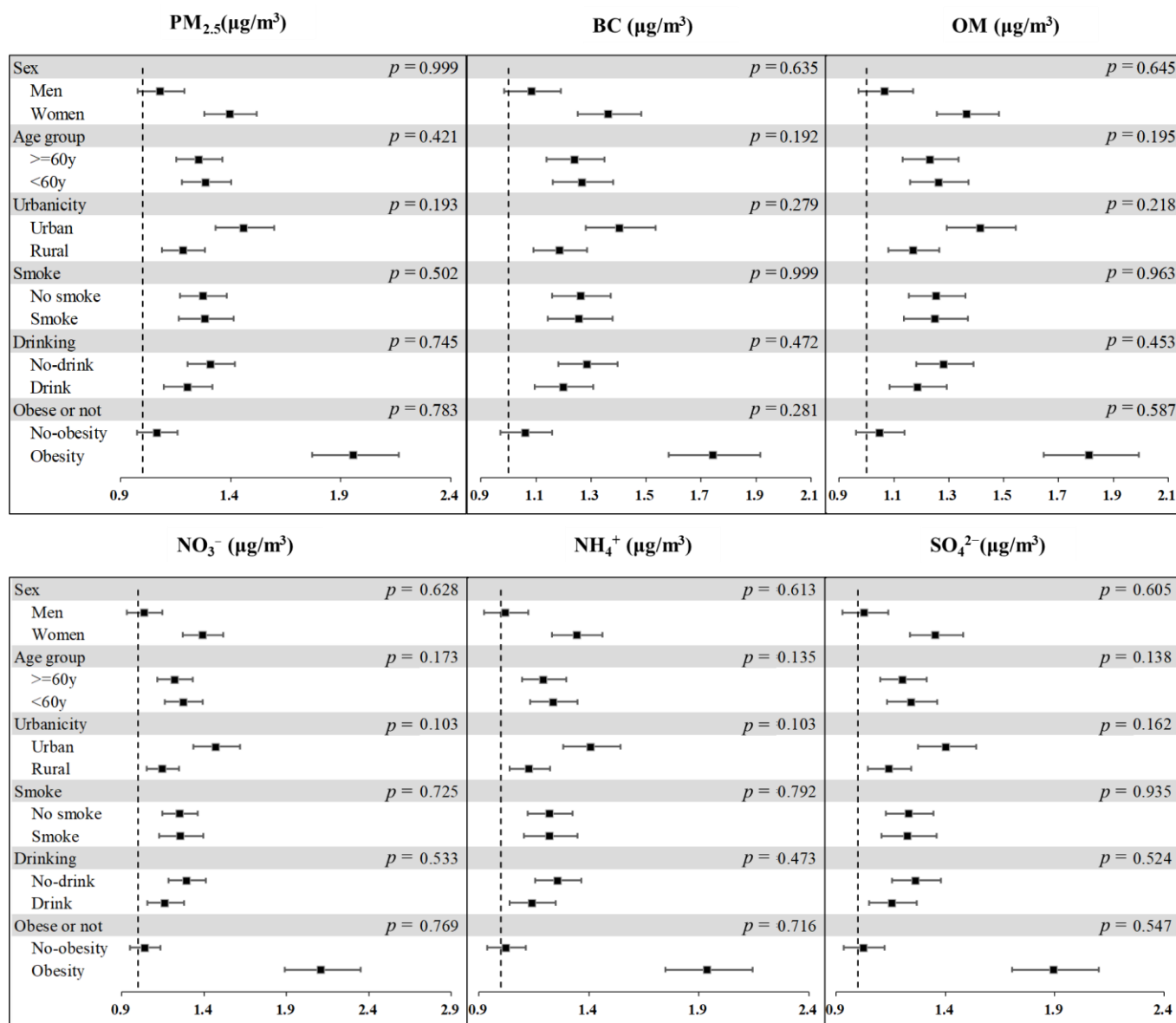

Figure 2. Odds ratios of metabolic syndrome (MetS) associated with an IQR incremental change in

1-year average $PM_{2.5}$ and its constitution, classified by different subgroups. The bars show main effect estimates and 95% confidence intervals. The model was the fully adjusted model adjusted for age, sex, urbanicity, educational level, marriage status, smoking, drinking, cooking fuel type, heating fuel type, and physical activity. Abbreviations: BC: Black Carbon; NH_4^+: Ammonium; NO_3^-: Nitrate; OM: organic matter; SO_4^{2-}: Sulfate. *p* value refers to the difference of the estimations between different subgroups.

4. Discussion

In this large nationwide epidemiology study, we observed $PM_{2.5}$ and its chemical composition associated with the increase in the risk of MetS for the first time. BC showed the strongest associations. The population living in the Northeast region showed the greatest effects. Generally, stronger associations were observed in women, participants aged less than 60 years, who lived in urban areas, were smokers, drinkers, and obese. This study provided further evidence on the association between $PM_{2.5}$ and MetS, and filled the gap on the topic of the association between $PM_{2.5}$ compositions and MetS. This study provided the first chance to identify the most harmful composition, vulnerable region, and population that required attention, which would help influence policy-making decisions.

Some studies have investigated the association of $PM_{2.5}$ with MetS, which was in line with our findings. The Normative Aging Study conducted in Boston found that each 1-$\mu g/m^3$ increment in $PM_{2.5}$ increased by 27% (95% CI: 6%, 52%) the risk of MetS. Another study in Korea indicated that each 10-$\mu g/m^3$ increment in $PM_{2.5}$ increased by 7% the risk of MetS [30]. However, most existing studies were found among developed countries, and limited studies were performed in the highly polluted areas. Up to now, only several studies were conducted among Chinese adults [10,14,15]. All the studies conducted in China found that $PM_{2.5}$ increased the risk of MetS, which was in line with our findings.

In this study, BC showed the strongest associations of $PM_{2.5}$ and its chemical compositions with MetS. BC was mainly derived from the incomplete burning of fossil fuels and biomass, and may play the most hazardous effect due to its tiny size [31,32]. Moreover, incomplete combustion may generate organic pollutants with greater toxicity carried on BC [33]. For other compositions, we also found a significant positive association with MetS. The OM was primarily from burning unclean fuel (biomass or coal), which may induce lipid metabolic disturbances [34,35]. The acidification and oxidation processes of sulfate dioxide (SO_2) or nitrogen oxides (NO_x) may generate inorganic water ions, such as NH_4^+, SO_4^{2-}, and NO_3^- [36,37]. Lipid metabolism was a possible mechanism by which the inorganic water ions affect MetS [38,39].

It is essential to identify the vulnerable population attributed to air pollution. In the stratified analyses, we observed stronger associations among women, subjects aged less than 60 years, who lived in urban areas, who were smokers, drinkers, and obese. We observed a greater association in women, which could be attributed to their smaller airways [40]. Prior evidence had reported greater associations in the elderly. However, we observed stronger associations among the younger population, consistent with some other studies [10,41]. A possible explanation is that the older population have a reduced response to nervous system stimuli, which may be more resistant than the younger population [10,42]. The participants who lived in urban areas were more sensitive and showed greater associations due to higher level of air pollution [43]. Our study also found that smokers, drinkers, and the obese population may have greater associations, which suggested unhealthy lifestyles may aggravate the harmful effects of air pollutants. The potential explanation is that unhealthy lifestyles can induce insulin resistance, leading to systemic inflammation and oxidative stress [44,45]. This study found the greatest associations of $PM_{2.5}$ and all the compositions on MetS in the Northeast region. The level of $PM_{2.5}$ and its compositions were higher in the northeast area due to more emissions from the burning of fossil fuels [46,47]. Meanwhile, the Western region showed the weakest associations due to the low population density and low level of air pollution [48].

Although the underlining mechanisms between air pollution and MetS were still unclear, some studies suggested several potential biological pathways. First, air pollutants

would enter the human body and induce oxidative stress and inflammation, which would contribute to developing MetS [49,50]. Second, air pollution might disrupt insulin signaling and cause insulin resistance via inducing the production of endogenous pro-inflammatory mediators and vasoactive molecules [51,52]. Third, air pollution might activate the pathways of development of MetS by interfering with DNA methylation levels [12,53].

The present study has notable strengths. First, this is the first epidemiological study to investigate the association of $PM_{2.5}$ chemical compositions with MetS among adults. This study also provided new evidence on the association between $PM_{2.5}$ and MetS based on the nationwide sample. Second, this study collected a set of potential confounders using the standard questionnaire. Third, this study covered national spatial data and included a large sample, which provided a chance to obtain the results across the nation.

This study has several limitations that require attention. First, the characteristics of the cross-sectional study design did not allow us to obtain causal inferences. Second, considering participants' confidentiality, the geographic information was only available at the city level, which may induce the misclassification of exposure. Third, although we have investigated many confounders, there were still unmeasured factors, including genes and other gaseous pollutants. Last, we did not include the gaseous components of $PM_{2.5}$ because of the lack of data. Further studies are needed to confirm our findings and add more evidence on the association of $PM_{2.5}$ and its compositions with MetS.

5. Conclusions

In this national sample of Chinese adults above 45 years old, 30.14% had MetS. This is the first study that observed that the $PM_{2.5}$ chemical compositions increased the risk of MetS among Chinese adults. We also found that BC showed the most hazard effects on the risk of MetS, which revealed that reducing BC emissions is an effective measure to reduce the risk of obesity. Women, participants aged less than 60 years, who lived in an urban area and the Northeast region, smokers, drinkers, and the obese population were more susceptible to $PM_{2.5}$ and its compositions, and needed more attention. More epidemiological and toxicological studies were required to confirm our findings further and add new evidence.

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References

1. Rochlani, Y.; Pothineni, N.V.; Kovelamudi, S.; Mehta, J.L. Metabolic syndrome: Pathophysiology, management, and modulation by natural compounds. *Ther. Adv. Cardiovasc. Dis.* **2017**, *11*, 215–225. [CrossRef] [PubMed]
2. Ranasinghe, P.; Mathangasinghe, Y.; Jayawardena, R.; Hills, A.P.; Misra, A. Prevalence and trends of metabolic syndrome among adults in the asia-pacific region: A systematic review. *BMC Public Health* **2017**, *17*, 101. [CrossRef] [PubMed]
3. International Diabetes Federation. The IDF Consensus Worldwide Definition of the Metabolic Syndrome. Available online: http://www.idf.org/metabolic-syndrome (accessed on 20 July 2022).
4. Li, R.; Li, W.; Lun, Z.; Zhang, H.; Sun, Z.; Kanu, J.S.; Qiu, S.; Cheng, Y.; Liu, Y. Prevalence of metabolic syndrome in Mainland China: A meta-analysis of published studies. *BMC Public Health* **2016**, *16*, 296. [CrossRef] [PubMed]
5. Huang, P.L. A comprehensive definition for metabolic syndrome. *Dis. Models Mech.* **2009**, *2*, 231–237. [CrossRef] [PubMed]
6. Lee, J.A.; Yoo, J.E.; Park, H.S. Metabolic syndrome and incidence of breast cancer in middle-aged Korean women: A nationwide cohort study. *Breast Cancer Res. Treat.* **2017**, *162*, 389–393. [CrossRef] [PubMed]
7. Guo, H.; Gao, X.; Ma, R.; Liu, J.; Ding, Y.; Zhang, M.; Zhang, J.; Mu, L.; He, J.; Yan, Y.; et al. Prevalence of Metabolic Syndrome and its Associated Factors among Multi-ethnic Adults in Rural Areas in Xinjiang, China. *Sci. Rep.* **2017**, *7*, 17643. [CrossRef] [PubMed]
8. Kaur, J. Assessment and screening of the risk factors in metabolic syndrome. *Med. Sci.* **2014**, *2*, 140–152. [CrossRef]
9. Zhang, J.-S.; Gui, Z.-H.; Zou, Z.-Y.; Yang, B.-Y.; Ma, J.; Jing, J.; Wang, H.-J.; Luo, J.-Y.; Zhang, X.; Luo, C.-Y. Long-term exposure to ambient air pollution and metabolic syndrome in children and adolescents: A national cross-sectional study in China. *Environ. Int.* **2021**, *148*, 106383. [CrossRef]
10. Yang, B.-Y.; Qian, Z.M.; Li, S.; Fan, S.; Chen, G.; Syberg, K.M.; Xian, H.; Wang, S.-Q.; Ma, H.; Chen, D.-H. Long-term exposure to ambient air pollution (including PM1) and metabolic syndrome: The 33 Communities Chinese Health Study (33CCHS). *Environ. Res.* **2018**, *164*, 204–211. [CrossRef]
11. Yu, Y.; Paul, K.; Arah, O.A.; Mayeda, E.R.; Wu, J.; Lee, E.; Shih, I.-F.; Su, J.; Jerrett, M.; Haan, M. Air pollution, noise exposure, and metabolic syndrome–a cohort study in elderly Mexican-Americans in Sacramento area. *Environ. Int.* **2020**, *134*, 105269. [CrossRef]
12. Peng, C.; Bind, M.-A.C.; Colicino, E.; Kloog, I.; Byun, H.-M.; Cantone, L.; Trevisi, L.; Zhong, J.; Brennan, K.; Dereix, A.E. Particulate air pollution and fasting blood glucose in nondiabetic individuals: Associations and epigenetic mediation in the normative aging study, 2000–2011. *Environ. Health Perspect.* **2016**, *124*, 1715–1721. [CrossRef] [PubMed]
13. Rajagopalan, S.; Brook, R.D. Air pollution and type 2 diabetes: Mechanistic insights. *Diabetes* **2012**, *61*, 3037–3045. [CrossRef] [PubMed]
14. Wang, Y.; Liu, F.; Yao, Y.; Chen, M.; Wu, C.; Yan, Y.; Xiang, H. Associations of long-term exposure to ambient air pollutants with metabolic syndrome: The Wuhan Chronic Disease Cohort Study (WCDCS). *Environ. Res.* **2022**, *206*, 112549. [CrossRef] [PubMed]
15. Hou, J.; Liu, X.; Tu, R.; Dong, X.; Zhai, Z.; Mao, Z.; Huo, W.; Chen, G.; Xiang, H.; Guo, Y. Long-term exposure to ambient air pollution attenuated the association of physical activity with metabolic syndrome in rural Chinese adults: A cross-sectional study. *Environ. Int.* **2020**, *136*, 105459. [CrossRef] [PubMed]
16. Fong, K.C.; Di, Q.; Kloog, I.; Laden, F.; Coull, B.A.; Koutrakis, P.; Schwartz, J.D. Relative toxicities of major particulate matter constituents on birthweight in Massachusetts. *Environ. Epidemiol.* **2019**, *3*, e047. [CrossRef]
17. Cheung, K.; Daher, N.; Kam, W.; Shafer, M.M.; Ning, Z.; Schauer, J.J.; Sioutas, C. Spatial and temporal variation of chemical composition and mass closure of ambient coarse particulate matter (PM10–2.5) in the Los Angeles area. *Atmos. Environ.* **2011**, *45*, 2651–2662. [CrossRef]
18. Zang, S.-T.; Luan, J.; Li, L.; Wu, Q.-J.; Chang, Q.; Dai, H.-X.; Zhao, Y.-H. Air pollution and metabolic syndrome risk: Evidence from nine observational studies. *Environ. Res.* **2021**, *202*, 111546. [CrossRef]
19. Zhao, Y.; Hu, Y.; Smith, J.P.; Strauss, J.; Yang, G. Cohort profile: The China Health and Retirement Longitudinal Study (CHARLS). *Int. J. Epidemiol.* **2014**, *43*, 61–68. [CrossRef]
20. Geng, G.; Zhang, Q.; Tong, D.; Li, M.; Zheng, Y.; Wang, S.; He, K. Chemical composition of ambient PM2.5 over China and relationship to precursor emissions during 2005–2012. *Atmos. Chem. Phys.* **2017**, *17*, 9187–9203. [CrossRef]
21. Bey, I.; Jacob, D.J.; Yantosca, R.M.; Logan, J.A.; Field, B.D.; Fiore, A.M.; Li, Q.; Liu, H.Y.; Mickley, L.J.; Schultz, M.G. Global modeling of tropospheric chemistry with assimilated meteorology: Model description and evaluation. *J. Geophys. Res.* **2001**, *106*, 23073–23095. [CrossRef]
22. Alberti, K.G.; Eckel, R.H.; Grundy, S.M.; Zimmet, P.Z.; Cleeman, J.I.; Donato, K.A.; Fruchart, J.C.; James, W.P.; Loria, C.M.; Smith, S.C., Jr. Harmonizing the metabolic syndrome: A joint interim statement of the International Diabetes Federation Task Force on Epidemiology and Prevention; National Heart, Lung, and Blood Institute; American Heart Association; World Heart Federation; International Atherosclerosis Society; and International Association for the Study of Obesity. *Circulation* **2009**, *120*, 1640–1645. [CrossRef] [PubMed]
23. Guo, Q.; Zhao, Y.; Zhao, J.; Qian, L.; Bian, M.; Xue, T.; Zhang, J.; Duan, X. Identifying the threshold of outdoor PM2.5 reversing the beneficial association between physical activity and lung function: A national longitudinal study in China. *Sci. Total Environ.* **2022**, *839*, 156138. [CrossRef] [PubMed]
24. Lee, S.; Park, H.; Kim, S.; Lee, E.-K.; Lee, J.; Hong, Y.S.; Ha, E. Fine particulate matter and incidence of metabolic syndrome in non-CVD patients: A nationwide population-based cohort study. *Int. J. Hyg. Environ. Health* **2019**, *222*, 533–540. [CrossRef] [PubMed]

25. Yang, Y.; Ruan, Z.; Wang, X.; Yang, Y.; Mason, T.G.; Lin, H.; Tian, L. Short-term and long-term exposures to fine particulate matter constituents and health: A systematic review and meta-analysis. *Environ. Pollut.* **2019**, *247*, 874–882. [CrossRef]
26. Wu, Y.; Li, H.; Xu, D.; Li, H.; Chen, Z.; Cheng, Y.; Yin, G.; Niu, Y.; Liu, C.; Kan, H.; et al. Associations of fine particulate matter and its constituents with airway inflammation, lung function, and buccal mucosa microbiota in children. *Sci. Total Environ.* **2021**, *773*, 145619. [CrossRef]
27. Sun, X.; Luo, X.; Zhao, C.; Zhang, B.; Tao, J.; Yang, Z.; Ma, W.; Liu, T. The associations between birth weight and exposure to fine particulate matter (PM2.5) and its chemical constituents during pregnancy: A meta-analysis. *Environ. Pollut.* **2016**, *211*, 38–47. [CrossRef]
28. Li, J.; Dong, Y.; Song, Y.; Dong, B.; van Donkelaar, A.; Martin, R.V.; Shi, L.; Ma, Y.; Zou, Z.; Ma, J. Long-term effects of PM2.5 components on blood pressure and hypertension in Chinese children and adolescents. *Environ. Int.* **2022**, *161*, 107134. [CrossRef]
29. Zheng, Y.; Wen, X.; Bian, J.; Lipkind, H.; Hu, H. Associations between the chemical composition of PM2.5 and gestational diabetes mellitus. *Environ. Res.* **2021**, *198*, 110470. [CrossRef]
30. He, Z.-Z.; Guo, P.-Y.; Xu, S.-L.; Zhou, Y.; Jalaludin, B.; Leskinen, A.; Knibbs, L.D.; Heinrich, J.; Morawska, L.; Yim, S.H.-L. Associations of Particulate Matter Sizes and Chemical Constituents with Blood Lipids: A Panel Study in Guangzhou, China. *Environ. Sci. Technol.* **2021**, *55*, 5065–5075. [CrossRef]
31. Jiang, P.; Zhong, X.; Li, L. On-road vehicle emission inventory and its spatio-temporal variations in North China Plain. *Environ. Pollut.* **2020**, *267*, 115639. [CrossRef]
32. Yang, J.; Sakhvidi, M.J.Z.; de Hoogh, K.; Vienneau, D.; Siemiatyck, J.; Zins, M.; Goldberg, M.; Chen, J.; Lequy, E.; Jacquemin, B. Long-term exposure to black carbon and mortality: A 28-year follow-up of the GAZEL cohort. *Environ. Int.* **2021**, *157*, 106805. [CrossRef] [PubMed]
33. Hopkins, L.E.; Laing, E.A.; Peake, J.L.; Uyeminami, D.; Mack, S.M.; Li, X.; Smiley-Jewell, S.; Pinkerton, K.E. Repeated iron–soot exposure and nose-to-brain transport of inhaled ultrafine particles. *Toxicol. Pathol.* **2018**, *46*, 75–84. [CrossRef] [PubMed]
34. Guo, S.; Hu, M.; Guo, Q.; Zhang, X.; Zheng, M.; Zheng, J.; Chang, C.C.; Schauer, J.J.; Zhang, R. Primary sources and secondary formation of organic aerosols in Beijing, China. *Environ. Sci. Technol.* **2012**, *46*, 9846–9853. [CrossRef] [PubMed]
35. Peng, X.; Hao, Q.; Wen, T.; Ji, D.; Liu, Z.; Wang, Y.; He, X.; Li, X.; Jiang, C. Characteristics of organic carbon and elemental carbon in atmospheric aerosols in the urban area in Beibei, a suburb of Chongqing. *Aerosol Air Qual. Res.* **2018**, *18*, 2764–2774. [CrossRef]
36. Huang, R.-J.; Zhang, Y.; Bozzetti, C.; Ho, K.-F.; Cao, J.-J.; Han, Y.; Daellenbach, K.R.; Slowik, J.G.; Platt, S.M.; Canonaco, F. High secondary aerosol contribution to particulate pollution during haze events in China. *Nature* **2014**, *514*, 218–222. [CrossRef] [PubMed]
37. Liu, S.; Zhang, K. Fine particulate matter components and mortality in Greater Houston: Did the risk reduce from 2000 to 2011? *Sci. Total Environ.* **2015**, *538*, 162–168. [CrossRef]
38. Park, S.; Ku, J.; Lee, S.-M.; Hwang, H.; Lee, N.; Kim, H.; Yoon, K.-J.; Kim, Y.; Choi, S.Q. Potential toxicity of inorganic ions in particulate matter: Ion permeation in lung and disruption of cell metabolism. *Sci. Total Environ.* **2022**, *824*, 153818. [CrossRef]
39. Tang, S.; Xie, J.; Wu, W.; Yi, B.; Liu, L.; Zhang, H. High ammonia exposure regulates lipid metabolism in the pig skeletal muscle via mTOR pathway. *Sci. Total Environ.* **2020**, *740*, 139917. [CrossRef]
40. Clougherty, J.E. A growing role for gender analysis in air pollution epidemiology. *Cienc. Saude Coletiva* **2011**, *16*, 2221–2238. [CrossRef]
41. Eze, I.C.; Schaffner, E.; Foraster, M.; Imboden, M.; von Eckardstein, A.; Gerbase, M.W.; Rothe, T.; Rochat, T.; Künzli, N.; Schindler, C.; et al. Long-Term Exposure to Ambient Air Pollution and Metabolic Syndrome in Adults. *PLoS ONE* **2015**, *10*, e0130337. [CrossRef]
42. Cohen, L.; Curhan, G.C.; Forman, J.P. Influence of age on the association between lifestyle factors and risk of hypertension. *J. Am. Soc. Hypertens.* **2012**, *6*, 284–290. [CrossRef] [PubMed]
43. Yang, J.; Shi, B.; Shi, Y.; Marvin, S.; Zheng, Y.; Xia, G. Air pollution dispersal in high density urban areas: Research on the triadic relation of wind, air pollution, and urban form. *Sustain. Cities Soc.* **2020**, *54*, 101941. [CrossRef]
44. Cena, H.; Fonte, M.L.; Turconi, G. Relationship between smoking and metabolic syndrome. *Nutr. Rev.* **2011**, *69*, 745–753. [CrossRef] [PubMed]
45. Baik, I.; Shin, C. Prospective study of alcohol consumption and metabolic syndrome. *Am. J. Clin. Nutr.* **2008**, *87*, 1455–1463. [CrossRef]
46. Song, C.; Wu, L.; Xie, Y.; He, J.; Chen, X.; Wang, T.; Lin, Y.; Jin, T.; Wang, A.; Liu, Y.; et al. Air pollution in China: Status and spatiotemporal variations. *Environ. Pollut.* **2017**, *227*, 334–347. [CrossRef]
47. Zhao, S.; Yu, Y.; Yin, D.; He, J.; Liu, N.; Qu, J.; Xiao, J. Annual and diurnal variations of gaseous and particulate pollutants in 31 provincial capital cities based on in situ air quality monitoring data from China National Environmental Monitoring Center. *Environ. Int.* **2016**, *86*, 92–106. [CrossRef]
48. Liang, D.; Wang, Y.-q.; Wang, Y.-j.; Ma, C. National air pollution distribution in China and related geographic, gaseous pollutant, and socio-economic factors. *Environ. Pollut.* **2019**, *250*, 998–1009. [CrossRef]
49. Fiorito, G.; Vlaanderen, J.; Polidoro, S.; Gulliver, J.; Galassi, C.; Ranzi, A.; Krogh, V.; Grioni, S.; Agnoli, C.; Sacerdote, C.; et al. Oxidative stress and inflammation mediate the effect of air pollution on cardio- and cerebrovascular disease: A prospective study in nonsmokers. *Environ. Mol. Mutagenesis* **2018**, *59*, 234–246. [CrossRef]

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50.   Haberzettl, P.; O'Toole, T.E.; Bhatnagar, A.; Conklin, D.J. Exposure to Fine Particulate Air Pollution Causes Vascular Insulin Resistance by Inducing Pulmonary Oxidative Stress. *Environ. Health Perspect.* **2016**, *124*, 1830–1839. [CrossRef]

51.   Miller, M.R. The role of oxidative stress in the cardiovascular actions of particulate air pollution. *Biochem. Soc. Trans.* **2014**, *42*, 1006–1011. [CrossRef]

52.   Wolf, K.; Popp, A.; Schneider, A.; Breitner, S.; Hampel, R.; Rathmann, W.; Herder, C.; Roden, M.; Koenig, W.; Meisinger, C. Association between long-term exposure to air pollution and biomarkers related to insulin resistance, subclinical inflammation, and adipokines. *Diabetes* **2016**, *65*, 3314–3326. [CrossRef] [PubMed]

53.   Wang, C.; Chen, R.; Cai, J.; Shi, J.; Yang, C.; Tse, L.A.; Li, H.; Lin, Z.; Meng, X.; Liu, C.; et al. Personal exposure to fine particulate matter and blood pressure: A role of angiotensin converting enzyme and its DNA methylation. *Environ. Int.* **2016**, *94*, 661–666. [CrossRef] [PubMed]