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Long-term effect of submicronic particulate matter (PM_1) and intermodal particulate matter ($PM_{1-2.5}$) on incident dyslipidemia in China: A nationwide 5-year cohort study

Meiling Hu[a,b,1], Jing Wei[c,1], Yaoyu Hu[a,b], Xiuhua Guo[a,b,d,e], Zhiwei Li[a,b], Yuhong Liu[a,b], Shuting Li[a,b], Yongxi Xue[a,b], Yuan Li[a,b], Mengmeng Liu[a,b], Lei Wang[f], Xiangtong Liu[a,b,*]

[a] School of Public Health, Capital Medical University, Beijing, 100069, China
[b] Beijing Municipal Key Laboratory of Clinical Epidemiology, Beijing, 100069, China
[c] Department of Atmospheric and Oceanic Science, Earth System Science Interdisciplinary Center, University of Maryland, College Park, USA
[d] National Institute for Data Science in Health and Medicine, Capital Medical University, China
[e] Centre for Precision Health, School of Medical and Health Sciences, Edith Cowan University, Australia
[f] Department of Food and Nutritional Hygiene, School of Public Health, Capital Medical University, China

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ABSTRACT

Background: There is insufficient evidence of associations between incident dyslipidemia with PM_1 (submicronic particulate matter) and $PM_{1-2.5}$ (intermodal particulate matter) in the middle-aged and elderly. We aimed to determine the long-term effects of PM_1 and $PM_{1-2.5}$ on incident dyslipidemia respectively.
Methods: We studied 6976 individuals aged ≥45 from the China Health and Retirement Longitudinal Study from 2013 to 2018. The concentrations of particular matter (PM) for every individual's address were evaluated using a satellite-based spatiotemporal model. Dyslipidemia was evaluated by self-reported. The generalized linear mixed model was applied to quantify the correlations between PM and incident dyslipidemia.
Results: After a 5-year follow-up, 333 (4.77%) participants developed dyslipidemia. Per 10 μg/m^3 uptick in four-year average concentrations of PMs (PM_1 and $PM_{1-2.5}$) corresponded to 1.11 [95% confidence interval (CI): 1.01–1.23)] and 1.23 (95% CI: 1.06–1.43) fold risks of incident dyslipidemia. Nonlinear exposure-response curves were observed between PM and incident dyslipidemia. The effect size of PM_1 on incident dyslipidemia was slightly higher in males [1.14 (95% CI: 0.98–1.32) vs. 1.04 (95% CI: 0.89–1.21)], the elderly [1.23 (95% CI: 1.04–1.45) vs. 1.03 (95% CI: 0.91–1.17)], people with less than primary school education [1.12 (95% CI: 0.94–1.33) vs. 1.08 (95% CI: 0.94–1.23)], and solid cooking fuel users [1.17 (95% CI: 1.00–1.36) vs. 1.06 (95% CI: 0.93–1.21)], however, the difference was not statistically significant ($Z = -0.82$, $P = 0.413$; $Z = -1.66$, $P = 0.097$; $Z = 0.32$, $P = 0.752$; $Z = -0.89$, $P = 0.372$).
Conclusions: Long-term exposure to PM_1 and $PM_{1-2.5}$ were linked with an increased morbidity of dyslipidemia in the middle-aged and elderly population. Males, the elderly, and solid cooking fuel users had higher risk. Further studies would be warranted to establish an accurate reference value of PM to mitigate growing dyslipidemia.

Abbreviations: PM, particular matters; PM_1, submicronic particulate matter; $PM_{1-2.5}$, intermodal particulate matter; $PM_{2.5}$, fine particulate matter; $PM_{2.5-10}$, coarse particulate matter; PM_{10}, inhalable particulate matter with a diameter <10 μm; CHARLS, the China Health and Retirement Longitudinal Study; OR, odds ratio; CI, confidence interval; O_3, ozone; NO_2, nitrogen dioxide; SO_2, sulfur dioxide; CO, carbon oxide; BMI, body mass index; CES-D, Center for Epidemiology Study depression; GLMM, Generalized linear mixed model; GEE, Generalized estimating equation model; DAG, directed acyclic graph; HR, hazards ratio; SD, standard deviation; IQR, interquartile range; AQG, air quality guideline.

* Corresponding author. School of Public Health, Capital Medical University, No.10 Xitoutiao, You'anmenWai, Fengtai District, Beijing, 100069, China.
E-mail addresses: 1818025@ccmu.edu.cn (M. Hu), weijing_rs@163.com (J. Wei), huyaoyu499@163.com (Y. Hu), statguo@ccmu.edu.cn (X. Guo), 15128472546@163.com (Z. Li), liuyho0@163.com (Y. Liu), 1818019@mail.ccmu.edu.cn (S. Li), xueyongxi@mail.ccmu.edu.cn (Y. Xue), liyuansue@163.com (Y. Li), liumengmeng@ccmu.edu.cn (M. Liu), lei.wang2@ccmu.edu.cn (L. Wang), xiangtongl@ccmu.edu.cn (X. Liu).
[1] Meiling Hu and Jing Wei contributed equally to the work.

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1. Introduction

As one of the major causes of cardiovascular disease, dyslipidemia contributes to 4.40 million premature deaths worldwide (Pirillo et al., 2021). The past few decades have witnessed a marked rise in dyslipidemia prevalence, especially in the middle-aged and elderly population (Peiris et al., 2021; Wang et al., 2022a). To reduce the prevalence and disease burden of dyslipidemia, it is pivotal to recognize modifiable factors of dyslipidemia to provide evidence for prevention.

Ambient air pollutants are modifiable risk factors for dyslipidemia (Wang et al., 2021b; Yusuf et al., 2020; Zhang et al., 2021b, 2021c). Air pollution leads to 6.9% of disability-adjusted life years and 19.5% of cardiovascular disease in China (Roth et al., 2020; Tian et al., 2022; Yin et al., 2020). Epidemiological researches have indicated that short-term exposure to particular matters (PM) can be an essential determinant of dyslipidemia (Chen et al., 2022; Ma et al., 2021; Zhang et al., 2022b). Recently, the long-term effect of PM on dyslipidemia has attracted much attention (Mao et al., 2020a, 2020b; Wang et al., 2021b). For example, children growing up in environments with prolonged PM pollution are linked to an upward incidence of hypercholesterolemia (Gui et al., 2020). *Wang* et al. reported that 3-year mean concentration of fine PM ($PM_{2.5}$) was related to increased lipids levels in ethnic minorities in southwest China (Wang et al., 2021b). Different-sized particles may have differential effects on lipids (Guo et al., 2022). However, evidence of prolonged exposure to submicronic PM (PM_1) and intermodal PM ($PM_{1\text{-}2.5}$) on dyslipidemia has been limited, especially in middle-aged and elder population in China.

Based on the China Health and Retirement Longitudinal Study (CHARLS), our analysis aimed to determine the long-term effects of both PM_1, $PM_{1\text{-}2.5}$, $PM_{2.5}$, coarse PM ($PM_{2.5\text{-}10}$), and inhalable PM with a diameter <10 μm (PM_{10}) on incident dyslipidemia respectively.

2. Material and methods

2.1. Participants

Covering individuals aged 45 and above in China to promote research on aging, CHARLS is a nationwide cohort study whose baseline investigation was in 2011 (Wave 1) (Zhao et al., 2014). The final 150 country-level unit samples fell within 28 provinces through multi-stage probability sampling. In this study, we utilized cohort data of CHARLS between 2013 (Wave 2) and 2018 (Wave 4). All respondents aged ≥45 at baseline were included. Participants with missing data on the questionnaire or air pollution exposure were excluded. After participants with dyslipidemia in 2013 were excluded, finally, 6976 participants were enrolled in our analysis (Fig. S1).

Ethics approval for the CHARLS project was obtained from the Ethics Review Committee of Peking University (IRB00001052-11015).

2.2. Exposure assessment

In our study, four-year annual concentrations of five different sizes of PMs and four gaseous pollutants (i.e., nitrogen dioxide [NO_2], sulfur dioxide [SO_2], ozone [O_3], and carbon oxide [CO]) were used as indicators of long-term exposure which was similar in the previous studies (Zhang et al., 2022a). The daily mean concentration of air pollutants at 1-km spatial resolution was collected from the China High Air Pollutants (CHAP) dataset (https://weijing-rs.github.io/product.html), which was generated using big data and artificial intelligence technology, and the predictions are reliable compared to ground measurements via cross-validated (Wei et al., 2019, 2021a, 2021b, 2022). Additionally, we deducted the concentrations of PM_1 from $PM_{2.5}$ to estimate concentrations of $PM_{1\text{-}2.5}$ and subtracted the concentrations of $PM_{2.5}$ from PM_{10} to estimate concentrations of $PM_{2.5\text{-}10}$.

We obtained the meteorological data, such as average day-to-day wind speed, solar radiation and temperature, from the National Meteorological Information Center of China (https://data.cma.cn/en). Annual average meteorological factors exposure for each participant was estimated by matching the geocoded residential addresses given at baseline in CHARLS at the province level. More detailed information can be found in the Supplementary Material.

2.3. Outcomes

In CHARLS, dyslipidemia was evaluated by self-reported based on the question: “Have you ever been diagnosed with dyslipidemia?“.

2.4. Covariates

Directed Acyclic Graph (DAG) was applied to show the causal relationship between PM and dyslipidemia with covariates (Fig. S2). In this study, there were five types of covariates adjusted to estimate the independent effect of PM on incident dyslipidemia: a) sociodemographic status, including age, sex, marital status, and education qualifications; b) lifestyle behavior variables, including daytime nap, depression status, type of cooking fuel, smoking status, and physical activity; c) anthropometric measurement includes height and weight, further to calculate body mass index (BMI); d) meteorological factors, i.e., wind speed, solar radiation, and temperature; e) gaseous pollutants, i.e., NO_2, SO_2, O_3, and CO.

Depression status was evaluated on a 10-question scale of the Center for Epidemiology Study depression (CES-D), with a higher score indicating worse depression status. Liquefied petroleum gas, natural gas, marsh gas, and electricity belong to clean energy. Coal and crop residue are solid fuels. Physical activity was the dichotomous variable. Participating in physical activity was considered if they had at least 10 min exercise continuously during a usual week.

2.5. Statistical analysis

The covariates listed above were adjusted in generalized linear mixed models (GLMM) to estimate independent long-term effect of PMs on incident dyslipidemia. The equation was as follows:

$$Logit\left[P\left(Y_{ij}\right)\right] = \left(\alpha + \gamma_i Z_j + \beta_1 X_{1ij} + \ldots + \beta_k X_{kij}\right) + \left(u_j + e_{ij}\right) \tag{1}$$

In details, $Logit\left[P\left(Y_{ij}\right)\right]$ is the logit of probability of dyslipidemia. We incorporated community level as random effects and covariates as fixed effects. In equation (1), $(\alpha + \gamma_i Z_j + \beta_1 X_{1ij} + \ldots + \beta_k X_{kij})$ represents the fixed effect, and $(u_j + e_{ij})$ represents the random effect. More detailed information on GLMM is described in the Supplementary Material (Supplemental methods).

We added covariates step by step in the following models. Model 1 was the crude model, only adjusting for one specific PM, and then Model 2 was additionally adjusted for CO. Model 3 was further adjusted for sociodemographic status (age, sex, marital status, and education qualifications), and BMI; Based on Model 3, Model 4 was further adjusted for lifestyle behavior variables (type of cooking fuel, depression status, and day sleeping status), and then Model 5 was further adjusted for meteorological factors (wind velocity and solar radiation), and Model 6 plus an adjustment for smoking status. Model 7 was further adjusted for temperature. Finally, Model 8 was adjusted for CO, sociodemographic status (age, sex, marital status, and education qualifications), BMI, lifestyle behavior variables (type of cooking fuel, depression status, day sleeping status, smoking status, and physical activity), and meteorological factors (wind velocity, solar radiation and temperature). Each model included a specific size of PM.

Odds ratio (OR) with 95% confidence interval (CI) was calculated to quantify the risk of incident dyslipidemia associated with per 10 μg/m^3 uptick in the concentrations of five sizes of PMs. To evaluate the conceivable role of specific size of PM, we used multi-pollutant models that were adjusted for various gaseous pollutants.

In order to evaluate potential effect modifiers, we conducted stratification analyses by sex, age [younger adults (age <60) vs. the elderly (age ≥60)], marital status (married and lived with spouse vs. other status), education qualifications (< primary school education vs. ≥ primary school education), the main source of cooking fuel (clean vs. solid), and daytime nap (nap vs. no-nap). In light of the age of the participants, we conducted stratification analyses by menopause status among all female participants.

The robustness of the associations between PM and incident dyslipidemia was evaluated by a series of sensitivity analyses. Considering that some variables vary over time, we included the time-dependent covariates in the generalized estimating equation (GEE) model. The adverse effects on incident dyslipidemia of different lag structure of PM were also included and compared. We added a sensitivity analysis using the minimally adjusted model, determined by a DAG. Cox proportional hazards model with time-varying exposures of PM, CO and meteorologic factors was also utilized to assess the correlation between dyslipidemia and PM.

The exposure-response curves for PM and dyslipidemia morbidity were portrayed using restricted cubic splines, of which three knots were chosen based on the Akaike information criterion according to previous studies (Inoue et al., 2020; Johannesen et al., 2020).

All the statistical analyses were conducted using R software (Version 4.2.0) with packages *lme 4*, *rms*, *survival* and *gee*. An α of 0.05 was set as the test level for two-tailed tests.

3. Results

3.1. Descriptive results

Finally, 6976 participants were enrolled of the CHARLS in our study, of whom 333 (4.77%) developed dyslipidemia after a five-year follow-up. Table 1 summarizes the baseline characteristics distribution between non-dyslipidemia and incident dyslipidemia groups. The median age was 58.0 years for the study population, and males accounted for 48.7%. Statistically significant differences were found between non-dyslipidemia and incident dyslipidemia groups in marital status, BMI, depression status (CES-D scores), and daytime nap ($P < 0.05$). Participants who were married and lived with a spouse ($\chi^2 = 10.41$, $P = 0.001$), had high BMI ($Z = -4.29$, $P < 0.001$), had depression status ($Z = -2.14$, $P = 0.032$), and napped in the daytime ($\chi^2 = 7.29$, $P = 0.007$) at baseline tended to have dyslipidemia conditions.

During the study period, average concentrations of PM_1, $PM_{2.5}$, and PM_{10} were 34.45 μg/m^3, 50.22 μg/m^3, and 82.87 μg/m^3, respectively, which were 3.35 times and 1.84 times the Chinese Ambient Air Quality Standards limit (15 μg/m^3 and 45 μg/m^3 for $PM_{2.5}$ and PM_{10}) (Table S1). Four-year average concentrations of PM_1 varied extremely among participants from 3.97 μg/m^3 to 122.98 μg/m^3, with a median of 34.45 μg/m^3. Spearman rank correlation coefficients between concentrations of air pollutants and meteorological factors were described in Table S2 and Fig. S3. There were high correlations among PM (Spearman rank correlation coefficients ranged from 0.55 to 0.91).

3.2. Main analyses of the associations between ambient PM and dyslipidemia

All five sizes of PM were significantly related to an incremental risk of incident dyslipidemia (Table 2 and Table S3). Per 10 μg/m^3 uptick in PM_1, $PM_{1\text{-}2.5}$, $PM_{2.5}$, $PM_{2.5\text{-}10}$ and PM_{10} concentrations was associated with 1.03 (95% CI: 0.96–1.11), 1.24 (95% CI: 1.08–1.43), 1.08 (95%CI: 1.02–1.15), 1.14 (95% CI: 1.05–1.23) and 1.06 (95% CI: 1.03–1.10) fold risks of incident dyslipidemia, respectively. The associations remained robust after adjustment for all five types of covariates, with OR of 1.11 (95% CI: 1.01–1.23), 1.23 (95% CI: 1.06–1.43), 1.09 (95% CI: 1.02–1.16), 1.09 (95% CI: 1.00–1.20) and 1.05 (95% CI: 1.01–1.10), respectively.

Table 1
Baseline characteristics of participants included in the study (n = 6976).

Variables	Total	Non-dyslipidemia	Dyslipidemia	*P*
Age (years), median (IQR)	58.0 (13.0)	58.0 (13.0)	59.0 (14.0)	0.311
Sex, *n* (%)				0.306
Female	3580 (51.3)	3400 (51.2)	180 (54.1)	
Male	3396 (48.7)	3243 (48.8)	153 (45.9)	
Marital status, *n* (%)				***0.001***
Married and lived with spouse	5848 (83.8)	5590 (84.1)	258 (77.5)	
Other[a]	1128 (16.2)	1053 (15.9)	75 (22.5)	
Education qualifications, *n* (%)				0.493
< primary school	3144 (45.1)	3000 (45.2)	144 (43.2)	
≥ Primary school	3832 (54.9)	3643 (54.8)	189 (56.8)	
BMI, median (IQR)	23.3 (4.8)	23.3 (4.8)	24.0 (4.8)	< ***0.001***
The main source of cooking fuel, *n* (%)				0.683
Clean fuel	3386 (48.5)	3228 (48.6)	158 (47.4)	
Solid fuel	3590 (51.5)	3415 (51.4)	175 (52.6)	
CES-D scores, median (IQR)	6.0 (8.0)	6.0 (8.0)	7.0 (8.0)	***0.032***
Daytime nap, *n* (%)				***0.007***
Yes	2884 (41.3)	2770 (41.7)	114 (34.2)	
No	4092 (58.7)	3873 (58.3)	219 (65.8)	
Smoking status, *n* (%)				0.385
Never smoke	3994 (57.3)	3798 (57.2)	196 (58.9)	
Quit smoking	735 (10.5)	695 (10.5)	40 (12.0)	
Current smoking	2247 (32.2)	2150 (30.8)	97 (29.1)	
Physical activity, *n* (%)				0.059
Yes	978 (14.0)	943 (14.2)	35 (10.5)	
No	5998 (86.0)	5700 (85.8)	298 (89.5)	

Abbreviations: *n*, number; IQR, interquartile range; BMI, body mass index; CES-D, the Center of Epidemiology Study depression.
Note:
[a] Married but do not live with spouse temporarily for reasons such as work, separation, not living together as a couple anymore, divorced, widowed, and never married.

3.3. Multi-pollutant models of associations between ambient PM and morbidity of dyslipidemia

Table S4 and Fig. 1 show the associations between PM and morbidity of dyslipidemia using multi-pollutant models after adjustment for covariates. After adjusted for CO, per 10 μg/m^3 uptick in four-year moving average concentration of PM_1, $PM_{1\text{-}2.5}$, $PM_{2.5}$, $PM_{2.5\text{-}10}$, and PM_{10} corresponded to 1.11 (95% CI:1.00–1.23), 1.23 (95% CI:1.06–1.42), 1.09 (95% CI:1.02–1.16), 1.09 (95% CI:1.00–1.19), and 1.05 (95% CI:1.01–1.09) fold risk of dyslipidemia morbidity, respectively. The associations of PM with incident dyslipidemia generally remained consistent in multi-pollutant models, which showed the robustness of our models.

Table 2
Odds ratio (95% confidence interval) of risk of incident dyslipidemia associated with per 10 μg/m^3 increment in 4-year average concentrations of particular matter (n = 6976).

Particular matters	OR (95% CI)	
	Model 1[a]	Model 5[b]
PM_1	1.03 (0.96, 1.11)	1.11 (1.01,1.23) *
$PM_{1-2.5}$	1.24 (1.08, 1.43) *	1.23 (1.06, 1.43) *
$PM_{2.5}$	1.08 (1.02, 1.15) *	1.09 (1.02, 1.16) *
$PM_{2.5-10}$	1.14 (1.05, 1.23) *	1.09 (1.00, 1.20)
PM_{10}	1.06 (1.03, 1.10) **	1.05 (1.01, 1.10) *

Note: *P-value < 0.05; **P-value < 0.001.
Abbreviations: PM_1, submicronic particulate matter; $PM_{1-2.5}$, intermodal particulate matter; $PM_{2.5}$, fine particulate matter; $PM_{2.5-10}$, coarse particulate matter; PM_{10}, inhalable particulate matter with a diameter <10 μm; OR, odds ratio; CI, confidence interval.
[a] Model 1 was the crude model.
[b] Model 5 was adjusted for carbon oxide, age, sex, marital status, education qualifications, body mass index, cooking fuel, depression status, day sleeping status, wind velocity, and solar radiation.

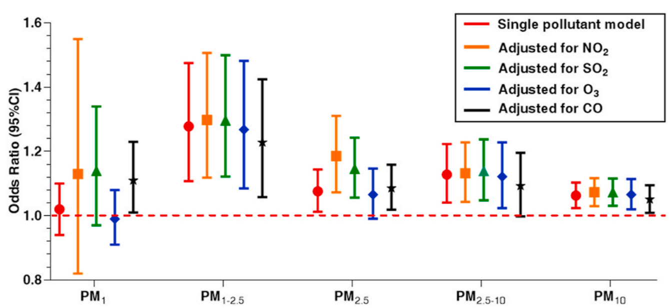

Fig. 1. Associations between per 10 μg/m^3 uptick in PM with morbidity of dyslipidemia in multi-pollutant models.
Abbreviations: PM_1, submicronic particulate matter; $PM_{1-2.5}$, intermodal particulate matter; $PM_{2.5}$, fine particulate matter; $PM_{2.5-10}$, coarse particulate matter; PM_{10}, inhalable particulate matter with a diameter <10 μm; NO_2, nitrogen dioxide; SO_2, sulfur dioxide; O_3, ozone; CO, carbon oxide; CI, confidence interval.

3.4. Dose-response curves of associations between PM and incident dyslipidemia

We found a nonlinear, reverse V-shaped dose-response association between exposure to PM and incident dyslipidemia, except for $PM_{1-2.5}$ (Fig. 2). With the increase of the concentration of PM, the OR value continued to increase sharply, leveling out at a concentration which is higher than the median. For example, with the increase of $PM_{2.5}$ concentration, OR value continued to rise until the concentration reached about 55 μg/m^3. When the concentrations of $PM_{2.5}$ reached a specific level, the OR value reached its maximum and began to decrease due to marginal utility slowly. An approximately linear relationship was observed between $PM_{1-2.5}$ and dyslipidemia in the range from 0 to 35 μg/m^3.

3.5. Stratified analyses

The associations between ambient PM and incident dyslipidemia stratified by sex, age, marital status, education qualifications, type of cooking fuel, and daytime nap status are shown in Fig. 3 and Table S5. The effect size of PM_1 on incident dyslipidemia was slightly higher in males [1.14 (95% CI: 0.98–1.32) vs. 1.04 (95% CI: 0.89–1.21)], the elderly [1.23 (95% CI: 1.04–1.45) vs. 1.03 (95% CI: 0.91–1.17)], participants who did not married or lived with a spouse [1.14 (95% CI: 0.87–1.50) vs. 1.09 (95% CI: 0.98–1.22)], people with less than primary school education [1.12 (95% CI: 0.94–1.33) vs. 1.08 (95% CI: 0.94–1.23)], solid cooking fuel users [1.17 (95% CI: 1.00–1.36) vs. 1.06 (95% CI: 0.93–1.21)], and participants with napping in the daytime [1.08 (95% CI: 0.95–1.21) vs. 1.02 (95% CI: 0.81–1.30)], however, the difference was not statistically significant ($Z = -0.82$, $P = 0.413$; $Z = -1.66$, $P = 0.097$; $Z = 0.31$, $P = 0.759$; $Z = 0.32$, $P = 0.752$; $Z = -0.89$, $P = 0.372$; $Z = -0.36$, $P = 0.718$).

The effect size of $PM_{1-2.5}$ on incident dyslipidemia was statistically significantly higher in males than that in females [1.49 (95% CI: 1.18–1.89) vs. 1.04 (95% CI: 0.85–1.27), $Z = -2.27$, $P = 0.023$).

The effect size of PM on incident dyslipidemia was slightly higher in postmenopausal women [e.g., PM_1: 1.08 (95% CI: 0.09–1.31) vs. 0.69 (95% CI: 0.06–8.05), $Z = -0.36$, $P = 0.717$], although the difference was not statistically significant.

Overall, the effect size of PM on incident dyslipidemia was higher in males [e.g., $PM_{1-2.5}$: 1.49 (95% CI:1.18–1.89) vs. 1.04 (95% CI:0.85–1.27)], the elder [e.g., $PM_{1-2.5}$: 1.33 (95% CI: 1.05–1.68) vs. 1.13 (95% CI: 0.93–1.37)], people with less than primary school education [e.g., $PM_{1-2.5}$: 1.28 (95% CI: 1.02–1.59) vs. 1.16 (95% CI: 0.94–1.43)], solid cooking fuel users [e.g., $PM_{1-2.5}$: 1.37 (95% CI: 1.12–1.67) vs. 1.09 (95% CI: 0.88–1.35)], participants with napping in the daytime [e.g., $PM_{1-2.5}$: 1.30 (95% CI:1.07–1.57) vs. 1.03 (0.80–1.33)], and statistically significant difference was observed merely in sex groups ($Z = -2.27$, $P = 0.023$; $Z = -1.03$, $P = 0.303$; $Z = 0.63$, $P = 0.527$; $Z = -1.51$, $P = 0.132$; $Z = -1.40$, $P = 0.160$).

3.6. Sensitivity analysis

Overall, the sensitivity analysis results were consistent with the main analyses. The associations between PM and incident dyslipidemia remained significant using the GEE model (Table 3). We constructed Model 9 and Model 10 using GEE, where the covariates of model 9 were based on the Wave 2 survey in 2013, and the covariates of model 10 were time-dependent variables. The difference in the results of model 9 and model 10 was not statistically significant [e.g., PM_1: 1.11 (95% CI: 1.01–1.21) vs. 1.08 (95% CI: 1.03–1.14), $Z = 0.48$, $P = 0.636$].

Association between long-term exposure to PMs with different lag structure and incident dyslipidemia are shown in Fig. 4 and Table S6. The moving average 1-year, 2-year, and 3-year concentrations of PMs (PM_1, $PM_{1-2.5}$, $PM_{2.5}$, and PM_{10}) showed statistically significant positive associations with morbidity of dyslipidemia. The 1-year moving average $PM_{2.5-10}$ concentration showed a positive correlation with incident dyslipidemia (OR = 1.08, 95% CI: 1.01–1.15).

The results of the sensitivity analysis remain consistent with our main findings based on the minimally adjusted model using a DAG (Table S7). The minimally adjusted model was adjusted for solar radiation, carbon oxide, education qualification, age and gender, selected by the DAG (Fig. S2).

The results of Cox proportional hazards models remain consistent with our main findings. Hazards ratio (HR) with 95% CI of risk of incident dyslipidemia associated with PM are presented in Table S8. Per 10 μg/m^3 uptick in PM_1, $PM_{1-2.5}$, $PM_{2.5}$, $PM_{2.5-10}$, and PM_{10} concentrations was associated with 1.06 (95% CI: 1.04, 1.08), 1.03 (95% CI: 0.80, 1.34), 1.03 (95% CI: 1.01, 1.05), 1.03 (95% CI: 1.01, 1.04), and 1.02 (95%CI: 1.01, 1.03) fold risks of incident dyslipidemia, respectively.

4. Discussion

In our study, long-term exposure to PMs was linked with an increased morbidity of dyslipidemia in the middle-aged and elderly Chinese population. The associations remained consistent after adjusting for various covariates, including individual demographic, lifestyle behavior, meteorological factors, and gaseous contaminants variables. Nonlinear exposure-response curves were observed between PM and incident dyslipidemia. Stratified analysis showed that males, the elderly, and people with less than primary school education, and solid cooking

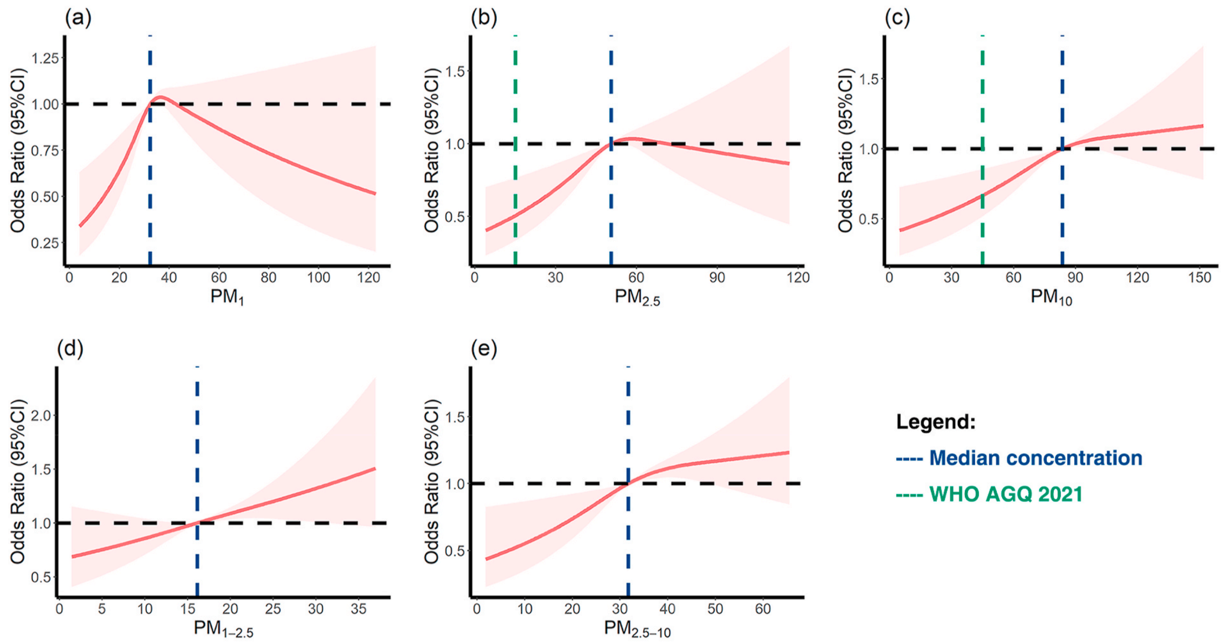

Fig. 2. Dose-response relationship between PM and incident dyslipidemia in China (2014)–2018.
Note: Shaded areas represent the 95% CI (95% confidence interval) of the OR (Odds ratio). The reference value of $PM_{2.5}$ (15 μg/m^3) and PM_{10} (45 μg/m^3) from WHO global air quality guidelines 2021 were marked as the green dotted line in (b) and (c).
Abbreviations: PM_1, submicronic particulate matter; $PM_{1\text{-}2.5}$, intermodal particulate matter; $PM_{2.5}$, fine particulate matter; $PM_{2.5\text{-}10}$, coarse particulate matter; PM_{10}, inhalable particulate matter with a diameter <10 μm; CI, confidence interval. . (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

fuel users were more vulnerable to adverse effects of PM on dyslipidemia. To the best of our knowledge, it is the broadest study investigating the correlation between long-term PM exposure and incident dyslipidemia in middle-aged and elderly Chinses population. Our study provided evidence for the chronic effects of PM pollution in the middle-aged and elderly population in developing countries.

In our study, long-term exposure to PMs was linked to dyslipidemia in the middle-aged and elderly Chinese population. Similarly, Wang et al. reported a positive association of PM_1 with hypertriglyceridemia and hypo-alpha-lipoproteinemia (Wang et al., 2021b). The correlation between PM and incident dyslipidemia has been extensively studied (Aryal et al., 2021; Fioravanti et al., 2018; Miyamura et al., 2021). However, few studies focused on PM_1 and $PM_{1\text{-}2.5}$ (Gui et al., 2020; Mao et al., 2020b).

Our study found that $PM_{1\text{-}2.5}$ could have more deleterious health effects than other PMs (PM_1, $PM_{2.5}$, $PM_{2.5\text{-}10}$, and PM_{10}). Different-sized particles may have differential effects on lipids (Gui et al., 2020; He et al., 2021; Shin et al., 2020; Yan et al., 2022). Some studies have also shown that smaller particles are more harmful to health since they can easily enter and get deposited in the human airway (Guo et al., 2022; Peng et al., 2020; Wang et al., 2021c). However, our result showed that the effect of PM_1 is less than $PM_{1\text{-}2.5}$. Manojkumar and colleagues have indicated that the deposition of $PM_{1\text{-}2.5}$ may differ from PM_1 in the head and pulmonary regions (Manojkumar et al., 2019). Previous research suggested that there are correlations between PM_1 and $PM_{1\text{-}2.5}$, and PM_1 may grow into $PM_{1\text{-}2.5}$ via complex processes, including stagnation of aerosols in high relative humidity conditions followed by advection during daytime hours (Geller et al., 2004). Besides, the toxic effects of size-specific PM may also be related to its composition and deposition fraction (Kelly and Fussell, 2012; Wang et al., 2022b). According to previous studies (Peralta et al., 2021), the specific PM components may contribute to different health effect (Nunez et al., 2022). Wang et al. reported that doses may be more related to the health influence due to PMs and they found that the total deposition fraction of PM_1 was about 72% lower than that of $PM_{1\text{-}2.5}$ (Wang et al., 2021a).

Exposure to $PM_{2.5}$ and PM_{10} has been connected with an increment in the level of blood lipids (Bo et al., 2019; McGuinn et al., 2019; Wu et al., 2019; Zhang et al., 2022b), although the results remain inconsistent (Li et al., 2021; Wang et al., 2021b; Zhang et al., 2021c). Several studies reported negative results (Fioravanti et al., 2018; Shanley et al., 2016; Yeatts et al., 2007). These discrepancies might be attributed to various causes, such as diversity in the samples, study geographies, or methodology. Our research focused on the population in China, where PM levels were higher than in developed countries. The comparison of research was hampered by geographic location, the health status of population, as well as covariables included in statistical models.

In our research, the estimate effects were majored contributed by a specific size of PM, since we didn't assess the potential effects of the co-exposure of PMs. Wang et al. reported that the estimated risk based on a specific size of PM was close to that based on total deposited PM (Wang et al., 2021a). A recently research showed that analysis of NO_2 without considering its collinearity with $PM_{2.5}$ may lead to overestimation (Ji et al., 2022). The collinearity of PMs and CO was not observed in our study. Thus, our models were robust when adjusted CO.

Stratified analysis showed that the elderly and male participants tended to have slightly larger effect of PM on incident dyslipidemia. Recent studies indicated that the elderly population are more easily influenced by air pollution-related blood lipid changes than younger adults (Wang et al., 2018a; Zhang et al., 2021a). *Yang* et al. reported that sex might modify the effects of air pollutants on blood lipid with mixed pattern (Wang et al., 2018a; Yang et al., 2018). Compared with women, men were more likely to engage in physical activity and thus had higher prevalence of dyslipidemia (Wang et al., 2018b). The trade-off between the benefits of physical activity and the potentially detrimental effects of augmented exposure to particular matter remains unclear.

We also find postmenopausal women were more susceptible to dyslipidemia. To the best of our knowledge, no previous study has reported the correlation between PM and dyslipidemia in women during menopause. Previous studies have shown that postmenopausal women often have dyslipidemia (Wooten et al., 2021). Postmenopausal women are

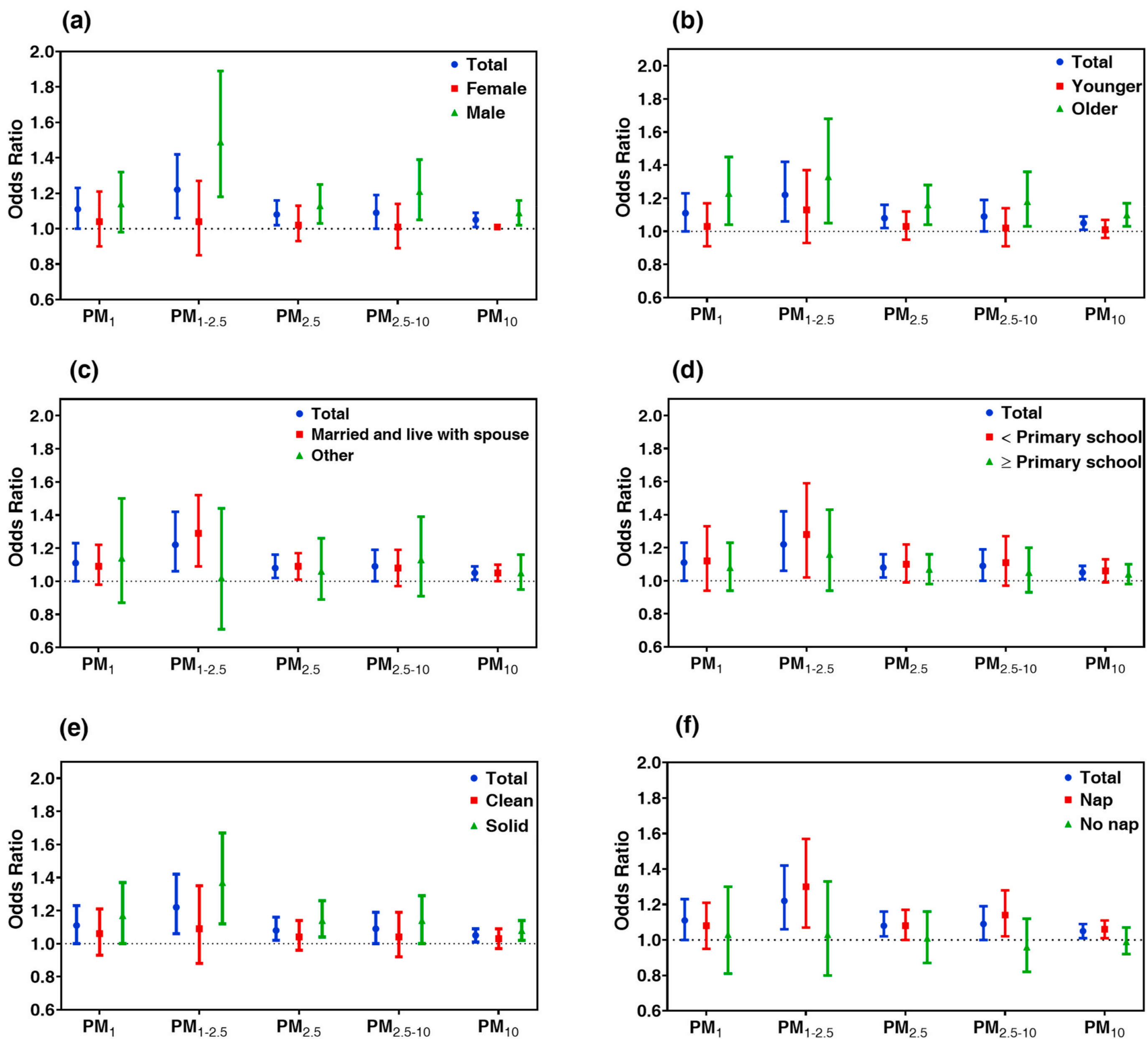

Fig. 3. Odds Ratio with 95% confidence intervals in dyslipidemia per 10 μg/m^3 increment in particular matter, stratified by (a) gender; (b) age (the younger group: age <60; the older group: age ≥60); (c) marital status; (d) education qualifications; (e) cooking fuel; (f) nap status.
Abbreviations: PM_1, submicronic particulate matter; $PM_{1\text{-}2.5}$, intermodal particulate matter; $PM_{2.5}$, fine particulate matter; $PM_{2.5\text{-}10}$, coarse particulate matter; PM_{10}, inhalable particulate matter with a diameter <10 μm.

more sensitive to PM (Niehoff et al., 2020). However, some studies have shown no significant difference in sensitivity to PM between premenopausal and postmenopausal women (White et al., 2019).

Our study observed nonlinear exposure-response curves were observed between PMs and incident dyslipidemia. Roughly consistent with a most recent study, we found a nonlinear, reverse V-shaped, dose-response association between exposure to PM and incident dyslipidemia, except for $PM_{1\text{-}2.5}$ (Zhou et al., 2022). Similarly, Li et al. reported nonlinear associations between $PM_{2.5}$ and blood lipids level (Li et al., 2021). According to the exposure-response curve of PM_1, we can reduce the incidence of dyslipidemia by reducing the concentration of PM_1 in the environment. The average concentrations of $PM_{2.5}$ and PM_{10} were substantially higher than the WHO global air quality reference value. Our next goal is to reduce the pollutant concentration to the reference value (Qi et al., 2021).

Although various pieces of evidence support positive association between PM and dyslipidemia, the potential mechanism by which PM affects lipid profile remains largely unknown. Some studies supposed that PM may contribute to higher lipid levels through oxidative stress processes and inflammatory (Ritz et al., 2022; Xu et al., 2019). An animal experiment demonstrated that PM pollution is characterized by elevated free fatty acid species and decreased phospholipid species, which may contribute to vascular inflammatory (Hill et al., 2021). It has been proved that exposure to $PM_{2.5}$ accelerates to deterioration of inflammation and oxidative stress in the circulation system of hyperlipidemic rats, causing hypercoagulability and cardiomyocyte apoptosis (Wang et al., 2019).

There are several advantages of our research. First, the study adds new evidence of the adverse effect of PMs, particularly PM_1, on blood lipids among the middle-aged and elderly based on the high-quality microdata in China. Second, the main source of cooking fuel was adjusted as indicator of the indoor pollution since indoor air pollution

Table 3
Associations between per 10 μg/m^3 uptick in particular matter and incident dyslipidemia using generalized estimating equations (GEE) model (n = 6976).

Particular matters	OR (95% CI)		Z-value	P-value
	Model 9[a]	Model 10[b]		
PM_1	1.11 (1.01, 1.21) *	1.08 (1.03, 1.14) *	0.48	0.636
$PM_{1\text{-}2.5}$	1.22 (1.06, 1.41) *	1.13 (1.04, 1.23) *	0.90	0.367
$PM_{2.5}$	1.08 (1.02, 1.15) *	1.07 (1.03, 1.11) **	0.34	0.737
$PM_{2.5\text{-}10}$	1.09 (1.00, 1.19)	1.10 (1.04, 1.16) **	−0.10	0.916
PM_{10}	1.05 (1.01, 1.09) *	1.05 (1.02, 1.07) **	0.15	0.878

Note: *P-value < 0.05; **P-value < 0.001.
Abbreviations: PM_1, submicronic particulate matter; $PM_{1\text{-}2.5}$, intermodal particulate matter; $PM_{2.5}$, fine particulate matter; $PM_{2.5\text{-}10}$, coarse particulate matter; PM_{10}, inhalable particulate matter with a diameter <10 μm; OR, odds ratio; CI, confidence intervals.
[a, b] Model 9 and Model 10 were adjusted for carbon oxide, age, sex, marital status, education qualifications, body mass index, cooking fuel, depression status, smoking status, day sleeping status, wind velocity, and solar radiation. Covariates in model 9 were based on the surveys in 2013 (Wave 2). Time-dependent covariates were included in model 10.

has drawn much attention due to the expansion of modern lifestyles featured with intensive urbanization and more time spent indoors (Deng et al., 2021; Qiu et al., 2022). Third, considering that variables may vary over time, we included the time-dependent covariates in the GEE model to test the robustness of our findings.

Limitations should also be addressed in this study. First, despite the high resolution (1 km^2), individual exposure to air pollution may be biased due to unevenly distributed emission sources, dilution, and physicochemical transformations. Second, information on diet pattern, family history of dyslipidemia, and occupational exposure were not included in our study, and further study would be warranted. Third, the incidence of dyslipidemia was based on self-reported, which may lead to misclassification and underestimation since many people in China, especially those in rural areas, may not have their blood lipid levels tested.

5. Conclusion

In conclusion, long-term exposure to PM_1 and $PM_{1\text{-}2.5}$ were linked with an increased morbidity of dyslipidemia in the middle-aged and elderly population. PM had a nonlinear exposure-response relationship with incident dyslipidemia. Males, the elderly, and people with less than primary school education, and solid cooking fuel users were more vulnerable to the detrimental effect of PM on dyslipidemia. Our study added new evidence of the adverse effect of PMs, particularly for PM_1 and $PM_{1\text{-}2.5}$, on the development of dyslipidemia. Further studies should be warranted to establish an accurate reference value of PM to mitigate growing dyslipidemia.

Credit author statement

Meiling Hu: Methodology, Software, Data curation, Writing- Original draft preparation, Visualization; **Jing Wei**: Data curation, Resources; **Yaoyu Hu**: Methodology, Software, Data curation, Visualization; **Xiuhua Guo**: Supervision, Writing- Reviewing and Editing. **Zhiwei Li**: Software, Data curation; **Yuhong Liu**: Software, Data curation; **Shuting Li**: Methodology, Software, Data curation; **Yongxi Xue**: Methodology, Software; **Yuan Li**: Methodology, Software; **Mengmeng Liu**: Methodology, Software, Data curation; **Lei Wang**: Methodology, Discussion; **Xiangtong Liu**: Conceptualization, Methodology, Data curation, Writing- Original draft preparation, Funding acquisition, Writing- Reviewing and Editing;

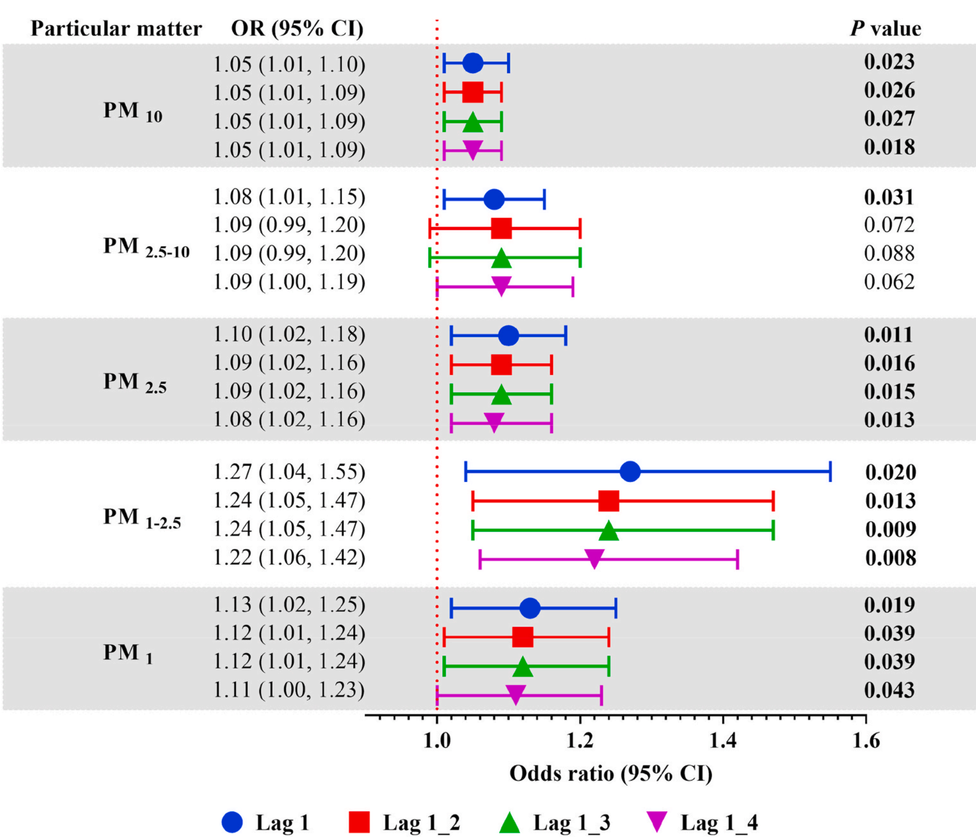

Fig. 4. Odds ratio (95% confidence interval) of risk of incident dyslipidemia associated with per 10 μg/m^3 increment in particular matters with different lag structure.
Abbreviations: PM_1, submicronic particulate matter; $PM_{1\text{-}2.5}$, intermodal particulate matter; $PM_{2.5}$, fine particulate matter; $PM_{2.5\text{-}10}$, coarse particulate matter; PM_{10}, inhalable particulate matter with a diameter <10 μm; OR, odds ratio; CI, confidence interval; Lag 1, the 1-year moving average concentrations of PM; Lag 1_2, the 2-year moving average concentrations of PM; Lag 1_3, the 3-year moving average concentration of PM; Lag 1_4, the 4-year moving average concentration of PM.

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Ethics approval

Ethics approval for the CHARLS project was obtained from the Ethics Review Committee of Peking University (IRB00001052-11015).

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

I have shared the link.

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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.2022.114860.

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