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Article

Socioeconomic and Demographic Associations with Wintertime Air Pollution Exposures at Household, Community, and District Scales in Rural Beijing, China

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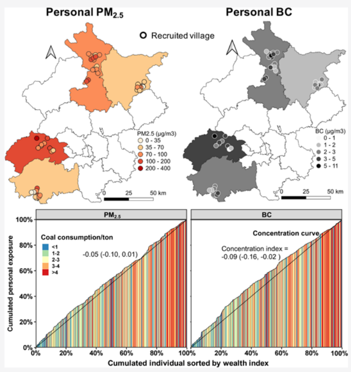
ABSTRACT: The Chinese government implemented a national household energy transition program that replaced residential coal heating stoves with electricity-powered heat pumps for space heating in northern China. As part of a baseline assessment of the program, this study investigated variability in personal air pollution exposures within villages and between villages and evaluated exposure patterns by sociodemographic factors. We randomly recruited 446 participants in 50 villages in four districts in rural Beijing and measured 24 h personal exposures to fine particulate matter ($PM_{2.5}$) and black carbon (BC). The geometric mean personal exposure to $PM_{2.5}$ and BC was 72 and 2.5 $\mu g/m^3$, respectively. The variability in $PM_{2.5}$ and BC exposures was greater within villages than between villages. Study participants who used traditional stoves as their dominant source of space heating were exposed to the highest levels of $PM_{2.5}$ and BC. Wealthier households tended to burn more coal for space heating, whereas less wealthy households used more biomass. $PM_{2.5}$ and BC exposures were almost uniformly distributed by socioeconomic status. Future work that combines these results with $PM_{2.5}$ chemical composition analysis will shed light on whether air pollution source contributors (e.g., industrial, traffic, and household solid fuel burning) follow similar distributions.



KEYWORDS: *air pollution, residential coal combustion, concentration curve, socioeconomic status (SES), household energy*

■ INTRODUCTION

Over 87% of the global population experiences ambient fine particulate matter ($PM_{2.5}$, aerodynamic diameter ≤ 2.5 μm) levels above 10 $\mu g/m^3$, the World Health Organization (WHO) recommended the annual interim target 4 of $PM_{2.5}$,[1] and is disproportionately represented by rapidly developing countries such as China (annual mean in 2013: 55 $\mu g/m^3$) and India (47 $\mu g/m^3$).[2] Air pollution contributed to almost five million premature deaths globally in 2017, including 1.2 million in China, which ranked in the top 10 countries with the highest mortality burden.[3] Reducing air pollution exposures is important for addressing global environmental health inequalities.[4,5]

Residential solid fuel combustion usually emits high concentrations of air pollutants and is a leading contributor to outdoor and indoor air pollution.[6−8] In China, household solid fuel combustion contributed 23, 71, and 68% to outdoor, indoor, and personal exposures of $PM_{2.5}$ in 2014, respectively.[8] Residential combustion of polluting fuels is a major source of anthropogenic $PM_{2.5}$ and carbonaceous PM.[9] The air pollutant emissions of solid fuel combustion depend on both stove types and fuel types.[10] To reduce household air pollution, interventions to replace polluting solid fuels and/or stoves with clean fuels and improved stoves have been conducted in diverse regions in China.[9,11−13]

Studies that evaluate air pollution interventions and policies can identify strategies to sustainably improve air quality at meaningful scales. To accurately attribute exposure reductions to targeted interventions and policies, it is important to understand how different factors, including indoor and outdoor sources, time−activity patterns, and household and individual demographics factors, can influence the patterns and levels of air pollution exposures.[14−16] $PM_{2.5}$ exposure distributions reported in the literature also suggest underlying socioeconomic patterning.[17−20] As the socioeconomic status (SES) increases, households tend to use less-polluting stoves, live and work in cleaner environments, and take more measures to protect themselves from exposure to $PM_{2.5}$.[19−22] Previous studies showed the negative associations between SES (income) and air pollutants—lower SES (income) population

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exposed to higher air pollution levels.[22,23,2429] Few studies have evaluated personal air pollution exposure patterning by SES, energy use, and housing conditions in China or, more broadly, in settings where households are transitioning away from solid fuels.[19,22,24] Such studies are critical to understanding where environmental exposure inequalities emerge and how to implement policies and strategies to address them.

As part of the baseline assessment for a longitudinal evaluation of a household energy transition program,[11,25] we evaluated air pollution exposure at individual, community (i.e., village), and district levels and its association with SES and household energy use in 50 rural villages within 4 districts in the Beijing Municipality Region. The Beijing Municipality Region comprises 16 administrative divisions (i.e., "districts") and located, along with 11 other provinces, in the region referred to as northern China. We recruited 977 participants; administered comprehensive questionnaires to assess the socioeconomic and demographic characteristics, housing conditions, and household energy practices, including stove and fuel use patterns; and measured 24 h integrated personal exposure in a random sub-sample of 446 participants. We aimed to (1) characterize the patterns of personal exposure to $PM_{2.5}$ and black carbon (BC) in rural Chinese settings; (2) investigate and compare the variation in personal exposures within and between villages; and (3) evaluate how air pollution exposures were distributed relative to the underlying socioeconomic and household energy use patterns. This study is one of the largest to investigate the personal exposure characteristics of residents in rural Beijing and one of the only studies to evaluate the almost entirely unexplored relationships between personal air pollution exposures and SES in the environmental inequality literature. Our study provides deeper insights into patterning of personal exposure to $PM_{2.5}$ and BC in rural Beijing and valuable baseline assessment prior to a large-scale household energy transition from coal-based heating to electric heating across northern China.

■ METHODS

Study Location. This study took place from December 2018 to January 2019 in 50 villages across 4 administrative divisions of peri-urban Beijing (i.e., the Beijing Municipality Region), including Mentougou (9 villages), Huairou (18 villages), Fangshan (11 villages), and Miyun (12 villages) (Text S1 and Figure S1). These villages were selected for study because, at baseline, their residents primarily used household coal and/or biomass stoves. At the time of enrollment in December 2018, none of these villages were involved in the Beijing municipal household energy transition program 北京市煤改清洁能源项目[11] Approximately half of these villages were anticipated to participate in the household energy transition program between 2019 and 2021 (during the longitudinal study, for which this baseline evaluation is the first set of measurements). Up through the winter of 2021, 20 of the 50 recruited villages took part in the program.

Study Design and Participant Recruitment. In each village, we obtained a village roaster, and a local guide helped us to first determine which households were currently in residence. We randomly selected households to approach for participation, and within each home, we randomly selected one eligible person from the household to participate in this study. In total, 977 households were recruited into this study, and most participants (827 of 977) reported on using coal stoves for heating, while the remaining participants used biomass and/or clean energy. Staff introduced the study and its measurements to an eligible person in each household and answered any questions related to the study. All participants provided written informed consent prior to joining the study. The study protocols were approved by research ethics boards at Peking University and McGill University. Detailed information about participant recruitment is stated in the Supporting Information (Text S2).

Personal Air Pollution Exposure Sample Collection. Among the 20 participants enrolled in each village, 10 were randomly selected to wear a personal exposure sampler to collect a filter-based, 24 h measurement of air pollution exposure. In total, we collected 494 filter samples. Due to the large number of samplers required for this project, two types of samplers were distributed to participants at random. Personal exposure monitors (PEMs, Apex Pro; Casella, UK) actively sampled air at a flow rate of 1.8 L/min. Ultrasonic personal aerosol samplers (UPAS, Access Sensor Technologies, Fort Collins, CO, USA) actively sampled air at 1.0 L/min.[26] Due to the higher flow rate of PEMs and to save battery power to ensure that PEMs can work for 24 h, PEMs were set to work on a duty cycle of 50%, wherein air was sampled for 1 min on, 1 min off. Both samplers housed 37 mm polytetrafluoroethylene (PTFE) filters (VWR, 2.0 μm pore size) and were equipped with a cyclone inlet with a 2.5 μm cutpoint. Following completion of the field sampling campaign, the samples and field blanks (8.3%) were transported to Colorado State University, where they were stored in a −20 °C freezer prior to $PM_{2.5}$ mass measurement and BC analysis. Details related to sample collection can be found in the Supporting Information (Text S3).

Filter Analysis. Filters were weighed on a microbalance (Mettler Toledo Inc., XS3DU, USA) with a 1 μg resolution in triplicate or more in the Automated Air Analysis Facility (AIRLIFT), until the differences among three weights were less than 3 μg.[31] The filter mass was blank-corrected using the median value of field blank filters [3 μg for UPAS-collected filters (53% of samples) and 27 μg for PEM-collected filters (47% of samples)], and $PM_{2.5}$ concentrations were calculated by dividing the mass by the sampled air volume.

The filters were analyzed for BC using an optical transmissometer data acquisition system (SootScan OT21 Optical Transmissometer; Magee Scientific, Berkeley, CA, USA). A classical Magee mass absorption cross section of 16.6 m^2/g for an 880 nm channel was used to convert the light attenuation of BC on PTFE filters to mass surface loadings.[27,28] BC concentrations were calculated by multiplying the surface loadings by the sampled surface area of the filters, correcting for the field blank, and finally dividing by the sampled air volume.

Additional details associated with filter collection and analysis are described in the Supporting Information (Text S3).

Outdoor Measurements of Real-Time and Gravimetric $PM_{2.5}$. We set up one to three commercially available $PM_{2.5}$ sensors (Plantower PMS7003 assembled with a data logger, an electronic screen, and a USB hub into a small metal box; Zefan, Inc., China) at different locations in each of 44 villages from December 14, 2018 to March 8, 2019 to measure time-resolved $PM_{2.5}$ mass concentrations at a frequency of 1 min. The Plantower is a laser-based particle sensor with a counting efficiency of 98% for particles of diameter larger than 0.5 μm,[30] which has been deployed in a wide range of settings and studies.[32−37]

Before the field season (December, 2018), all real-time $PM_{2.5}$ sensors were co-located with a reference instrument (Thermo Electron Synchronized Hybrid Ambient Real-Time Particulate Monitor, model 5030) on the rooftop of a building at Peking University campus for 7−10 days. The purpose was to check the performance of our $PM_{2.5}$ sensors before field deployment and provide assurance that these sensors can measure time-varying $PM_{2.5}$ concentrations and maintain a strong correlation with the reference instrument (Spearman $\rho > 0.7$). $PM_{2.5}$ concentrations monitored by our real-time $PM_{2.5}$ sensors were highly correlated with those measured by the reference instrument. All $PM_{2.5}$ sensors (n = 61) were of PMS7003 sensor type; however, because of the expected variability in performance as sensor age,[33] we evaluated the performance for two groups of sensors based on whether they had been previously used. One group (Sensor 1; n = 20) had been deployed in previous studies, while the other group (Sensor 2; n = 41) was deployed for the first time for our study. The Spearman correlation coefficients (ρ) were 0.89 ($p < 0.001$) and 0.81 ($p < 0.001$) for Sensor 1 and Sensor 2, respectively (Figure S2).

In the field, we co-located real-time $PM_{2.5}$ sensors with a gravimetric, filter-based sampler (UPAS) in each village. Linear regression was established between the filter-based $PM_{2.5}$ mass concentrations (i.e., the reference concentrations) and the sensor-based $PM_{2.5}$ concentrations averaged over the same time period as the sampling duration of each filter sample (Figure S3). We collected 1−6 filter-based samples per village, and in total, we evaluated 153 paired measurements. The slope of the linear regression model was used as the factor by which sensor-based $PM_{2.5}$ concentrations can be adjusted. The $PM_{2.5}$ adjustment factors did not differ significantly by district, with district-specific factors of 0.76, 0.83, 0.77, and 0.82 for Mentougou, Huairou, Fangshan, and Miyun, respectively. However, the $PM_{2.5}$ adjustment factors did differ by sensor age since sensors deployed in our study belonged to two groups that differed by 1 year. When evaluated separately, measurements made with Sensor 1 (older) and Sensor 2 yielded $PM_{2.5}$ adjustment factors of 0.82 and 1.03, respectively. Therefore, we applied the sensor-specific adjustment factors to calibrate the $PM_{2.5}$ concentrations obtained using the PMS7003 sensors.

Additional information related to outdoor $PM_{2.5}$ measurements and sensor calibration can be found in the Supporting Information (Text S4).

Questionnaires. The questionnaires were designed to assess household demographic information, household assets, house structure, stove and fuel use patterns, smoking status, occupation, and education. The design of our questionnaire on household energy use patterns is shown in Figure S4. The questionnaire and other study measurements were tested prior to the start of data collection for this study in 12 households located in Beijing. Further details about the questionnaires are shown in the Supporting Information (Text S5) and Open Science Framework at https://osf.io/gyh6d/.

Wealth Index Estimation. Literature studies have demonstrated that accurate measurement of income is a challenge,[38] and income is generally more variable than consumption.[39] Further, income is likely to change too rapidly to be a good indicator of household affluence.[40] On the contrary, a wealth index is generally viewed as a measure of long-term wealth or SES.[40] To measure the relative SES of each participant, we created a composite (wealth) index using principle component analysis (PCA) from owned household assets. The following assets were used as proxies of long-term household wealth:[41,42] car, motorbike, electric scooter, washer, refrigerator, freezer, TV, computer, air purifier, microwave, rice cooker, induction cooker, electric kettle, air conditioner, portable heater, electric blanket, fan, gas stove, coal stove, house area, number of rooms, agriculture land area, and forest land area owned by the participants and their households. Further details on wealth index estimation are provided in the Supporting Information (Text S6).

Concentration Curve and Concentration Index. We developed a series of concentration curves by plotting the cumulative $PM_{2.5}$ (or BC) exposures against cumulative distributions of the study population, ranked by wealth index (lowest to highest). Concentration curves were originally developed to assess the distributions of health inequality across regions and groups and are the bivariate analogue of the Lorenz curve, which is used to evaluate the inequality of population wealth distributions.[43,44] Some studies extended the concept of concentration curve and concentration index to examine the distributions of environmental pollutants.[45−47] In this study, we applied the concentration index to evaluate the extent to which personal $PM_{2.5}$ and BC exposures were uniformly or non-uniformly distributed in a rural Chinese population prior to a large-scale household energy transition.

A concentration curve above the 45° line (i.e., the line of equality) indicates that less wealthy households experience disproportionately higher air pollution exposures than wealthier households. Conversely, when the curve lies below the equality line, wealthier participants have higher exposures. The concentration index is defined as twice the area between the concentration curve and the line of equality and varies between −1 and 1, with the area counted as negative when the curve is above the equality line and positive when the curve is below the equality line.[43−46] We calculated the concentration index using the R package of "brechtdv/rineq" (https://rdrr.io/github/brechtdv/rineq/man/ci.html).

Statistical Analysis. We use descriptive statistical methods to examine the levels of exposures as well as the differences and variation between groups in our samples. Individual $PM_{2.5}$ and BC exposure distributions were described and summarized as district and village geometric means (GMs) and 95% confidence intervals (95% CI). We used Spearman correlation coefficients to evaluate the relationships between personal $PM_{2.5}$ and BC concentrations, personal $PM_{2.5}$ and outdoor $PM_{2.5}$. We applied Wilcoxon test to examine whether personal exposures differed by heating energy and smoking status, and analysis of variance (ANOVA) was conducted to compare the impact of different sampling days of a week (weekday and weekend) on personal exposures.

We excluded 48 out of 494 samples for the statistical analysis because the air sampler failed to record the sampling air volume (n = 4; 1%) (thus limiting our ability to verify the total sampled air volume) and because the sampling duration for some samples (n = 44; 9%) was < 80% of the target sampling duration (24 h for UPAS and 12 h for PEM) due to low battery power. Negative blank-corrected values ($PM_{2.5}$: n = 3 filters; BC: n = 4 filters) were randomly assigned a value between 0 and the limit of detection, which was 1.9 and 2.1 $\mu g/m^3$ for $PM_{2.5}$ collected with the UPASs and the PEMs,

Table 1. Sociodemographic and Household Characteristics of Study Participants (n = 446) with Personal Air Pollution Exposure Measurements in the Baseline Season of the Beijing Household Energy Transitions Study

	Total		Mentougou		Huairou		Fangshan		Miyun	
	n (%)	mean (SD)	n (%)	mean (SD)	n (%)	mean (SD)	n (%)	mean (SD)	n (%)	mean (SD)
Age										
All participants	446	60 (9)	69	62 (10)	163	60 (9)	102	60 (9)	112	59 (9)
Male	188 (42)	60 (9)	30 (43)	61 (9)	79 (48)	61 (9)	41 (40)	59 (8)	38 (44)	60 (9)
Female	258 (58)	60 (9)	39 (57)	63 (10)	84 (52)	59 (8)	61 (60)	60 (10)	74 (66)	59 (9)

	Total	Mentougou	Huairou	Fangshan	Miyun
	n (%)	n (%)	n (%)	n (%)	n (%)
Smoking Status					
Current smoker	124 (28)	22 (32)	55 (34)	24 (24)	23 (21)
Non-smokerliving with one or more smokers	140 (31)	23 (33)	48 (29)	34 (33)	35 (31)
Non-smoker	181 (41)	24 (35)	60 (37)	43 (42)	54 (48)
Occupation					
Agriculture and related workers	296 (66)	41 (59)	116 (71)	57 (56)	82 (73)
Non-agricultural employed workers	32 (7)	2 (3)	15 (9)	6 (6)	9 (8)
Does not work outside of the home	117 (26)	26 (38)	32 (20)	38 (37)	21 (19)
Farming Frequency[a]					
Everyday	57 (13)	16 (23)	9 (6)	10 (10)	22 (20)
Several days per week	188 (42)	18 (26)	71 (44)	47 (46)	52 (46)
Rarely	200 (45)	35 (51)	83 (51)	44 (43)	38 (34)
Exercising Frequency					
Everyday	248 (56)	44 (64)	85 (52)	57 (56)	62 (55)
Several days per week	78 (17)	10 (14)	34 (21)	18 (18)	16 (14)
Rarely	119 (27)	15 (22)	44 (27)	26 (25)	34 (30)
Heating System					
Clean energy and coal stove[b]	11 (2)	3 (4)	7 (4)	0 (0)	1 (1)
Coal stove with radiators	355 (80)	38 (55)	116 (71)	97 (95)	104 (93)
Traditional coal stove	43 (10)	20 (29)	17 (10)	4 (4)	2 (2)
Kang	37 (8)	8 (12)	23 (14)	1 (1)	5 (4)
Cooking Fuel					
Exclusive use of clean fuel[c]	277 (62)	50 (74)	74 (46)	93 (91)	60 (54)
Mixed use of solid fuel and clean energy[d]	157 (35)	12 (18)	85 (53)	9 (9)	51 (46)
Exclusive use of Solid fuel	9 (2)	6 (9)	2 (1)	0 (0)	1 (1)
Annual Income Quintile					
Lowest (20%)	89 (20)	18 (26)	33 (20)	15 (15)	23 (21)
Lower (20%)	90 (20)	11 (16)	35 (21)	18 (18)	26 (23)
Middle (20%)	89 (20)	12 (17)	36 (22)	15 (15)	26 (23)
Higher (20%)	89 (20)	14 (20)	32 (20)	23 (23)	20 (18)
Highest (20%)	89 (20)	14 (20)	27 (17)	31 (30)	17 (15)
Wealth Index Quintile					
Lowest (20%)	88 (20)	27 (40)	24 (15)	17 (17)	20 (18)
Lower (20%)	88 (20)	17 (25)	31 (19)	13 (13)	27 (25)
Middle (20%)	88 (20)	12 (18)	30 (18)	22 (22)	24 (22)
Higher (20%)	88 (20)	7 (10)	38 (23)	26 (25)	17 (15)
Highest (20%)	89 (20)	4 (6)	40 (25)	23 (23)	22 (20)

[a]Farming frequency indicated the averaged frequency that the participants did agriculture-related work in the last 6 months before the survey. [b]Clean energy and coal stove: in very few households (n = 11), participants installed clean energy heating devices alongside solid fuel stoves for heating. [c]Exclusive use of clean fuel (for cooking): in most households, participants relied exclusively on clean energy for cooking, including electricity and/or liquid petroleum gas (LPG). [d]Mixed use of solid fuel and clean energy: in some households, participants used both clean energy and solid fuel for cooking.

respectively, and 0.11 and 0.13 $\mu g/m^3$ for BC collected with the UPASs and the PEMs, respectively.

Since outdoor monitoring sites were set up in 44 of our study's 50 villages, for villages in which we did not deploy sensors (12% of sites) or in which the sensors were broken and did not record data (6% of sites), we used the outdoor data from the nearest neighboring villages. Time-averaged (24 h) outdoor $PM_{2.5}$ concentrations during personal exposure measurements were calculated from 10 am to 10 am on the next day. This time period aligned with the period when the personal exposure samples were collected in each village and facilitated the calculation of personal to outdoor (P/O) ratios of $PM_{2.5}$.

A series of mixed-effects regression models were developed to partition the total variance of personal exposures into its within-village and between-village components.[48] We started with the null (intercept-only) model

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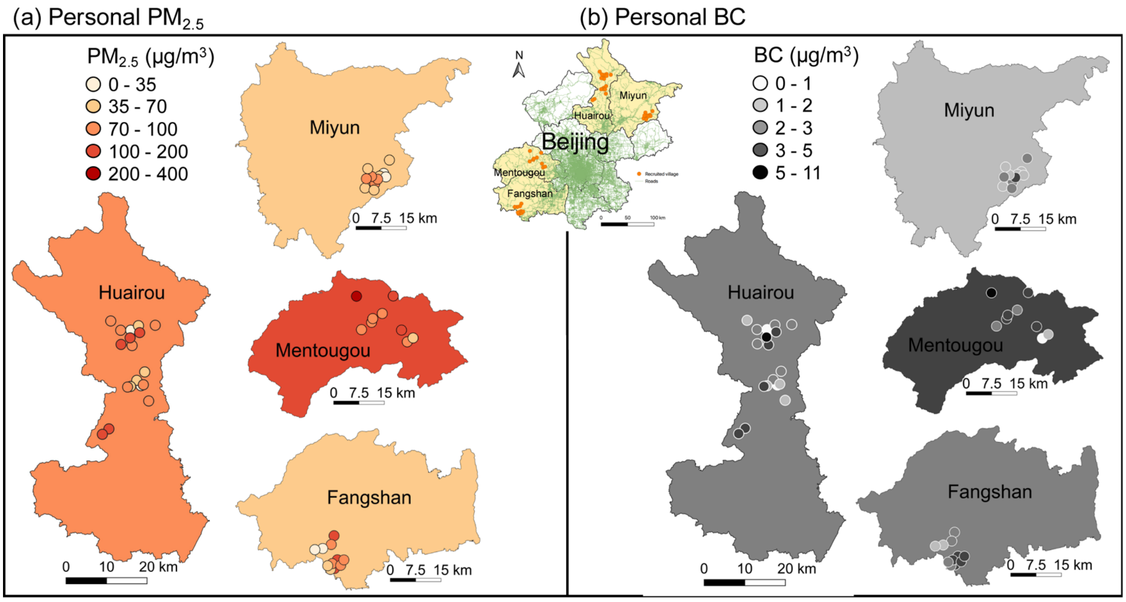

Figure 1. GMs of personal exposures to $PM_{2.5}$ (a) and BC (b) at the village and district levels. Village locations are indicated by dots with colors corresponding to village-level GMs of $PM_{2.5}$ and BC exposures (color darkens with increasing concentrations). District values represent GMs across respondents in our study villages.

$$\log(y_{ij}) = \beta_0 + b_i + \epsilon_{ij}$$

where $\log(y_{ij})$ is the log-transformed personal exposures of the jth participants from village i, b_i is the village random effect, and ϵ_{ij} is the remaining error with variance components for σ_b^2 and σ_ε^2, respectively, which can be roughly interpreted as the variance between-villages (σ_b^2) and within-villages (σ_ε^2). Assuming that b_i and ϵ_{ij} are independent and normally distributed with variances of σ_b^2 and σ_ε^2, respectively, and have a compound symmetry correlation structure, then intraclass correlation (ICC)[49] was calculated to present the proportion of total variability in exposure attributed to between-village differences by $\sigma_b^2/(\sigma_b^2 + \sigma_\varepsilon^2)$.

To evaluate the proportion of each variance component explained by different variables, we compared the null model with a set of models containing an increasing number of independent variables, including outdoor $PM_{2.5}$ and temperature, smoking status, heating fuel, and wealth index. The outdoor daily temperatures (24 h) were calculated for the same time period as the personal exposure assessment in each village. The outdoor temperature data were downloaded from the NOAA Integrated Surface Data database[50] and adjusted for altitude using an environmental lapse rate of −6.5 °C per 1000 m.[55]

All statistical analysis were performed using R version 3.5.2. All map plots were created by QGIS3.14.

RESULTS

Characteristics of Study Participants. We measured personal air pollution exposures of 446 participants in 50 villages from 4 districts, including Mentougou (n = 69), Huairou (n = 163), Fangshan (n = 102), and Miyun (n = 112) (Table 1). Our recruited villages are in the mountainous regions of Beijing, which are 35−100 km away from the city center. The altitude of all villages was below 700 m. The number of households in recruited villages varied from 47 to 1271, and the registered populations ranged from 99 to 2791 residents (Table S1).

The mean (± standard deviation: SD) age of participants with personal air pollution exposure measurements was 60 (± 9) years and 58% were female. As the China 2010 population census, half of the population in rural Beijing aged between 40 and 80 years (http://www.stats.gov.cn/tjsj/pcsj/rkpc/6rp/indexch.htm). Therefore, our participants are representative of rural populations in Beijing. Exposure to tobacco smoke was common for participants in this study: 28% of participants were current smokers, 31% were non-smokers who lived with one or more smokers, and the others (41%) were not exposed to tobacco smoke at home. Two-thirds of participants worked in agriculture or related fields (e.g., work outdoors involving physical activity), and fewer than 10% had a non-agricultural job (e.g., hired by government, factory worker, or self-employed). Over half (55%) of the participants reported on taking part in agricultural work in the previous 6 months, and over half (56%) of the participants reported on doing daily exercise (e.g., walking and dancing). Because the study villages are far from the city center and it is unlikely for our participants to travel regularly to the city and return on the same day, participants primarily resided indoors or nearby their homes during personal exposure sampling. As the participants reported, the mean (± SD) time they spent at home was 18 (± 4) h per day.

Characteristics of Housing and Household Energy Use. Participants lived in single-family homes with 1−3 levels. The mean (± SD) age of the homes was 19 (± 15) years. Participants used a range of stoves and fuel types for space heating (summarized in Table S2), which we classified into four categories (Table 1 and Text S7). Overall, among participants with a personal exposure measurement, 80% reported on using a centralized coal stove with radiators. Only 2% of participants reported on owning clean energy space heating devices. Forty-three participants (10%) reported on using traditional standalone coal stoves that were not connected to radiators. Thirty-seven participants (8%) did not have a dedicated coal stove and reported on exclusive use of a *kang*. Using clean energy, such as liquefied petroleum gas

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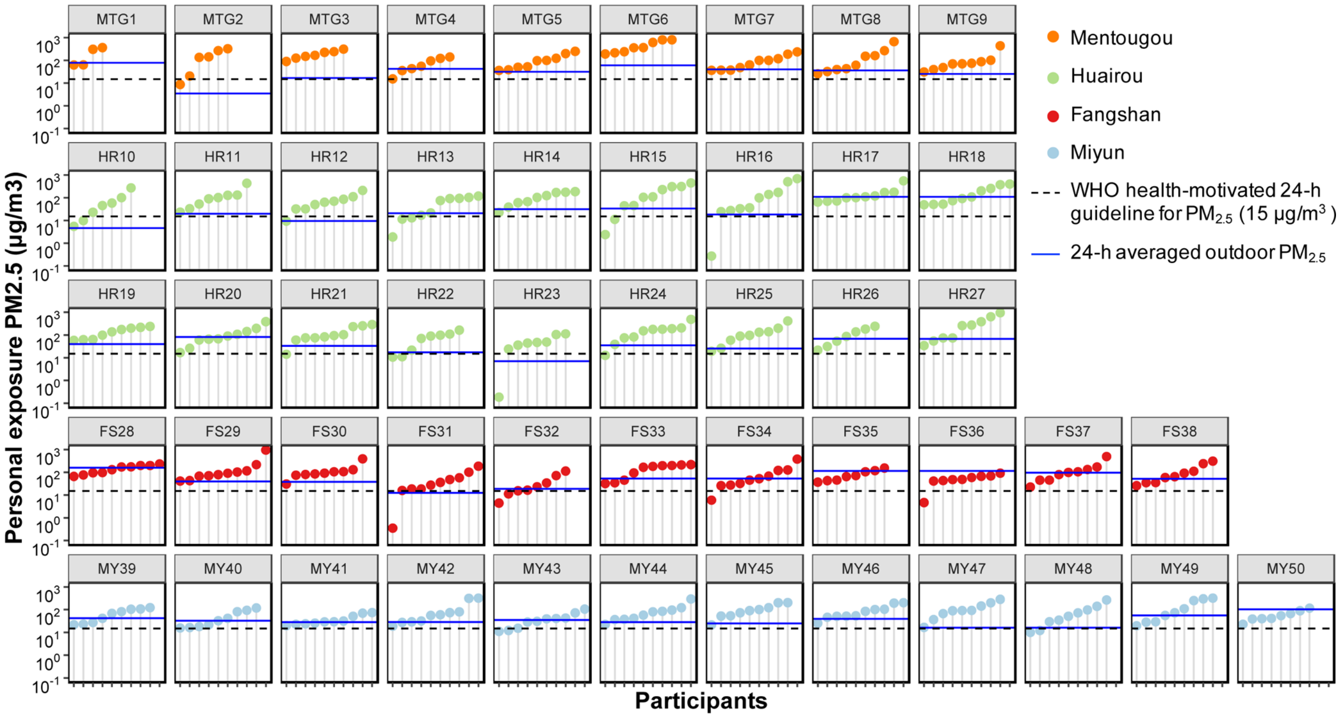

Figure 2. Participant personal $PM_{2.5}$ exposures. Each panel represents a different village, and each dot represents a participant in those villages. Districts are indicated by the color of the dots. The solid blue line in each panel shows the mean concentrations of outdoor $PM_{2.5}$ during the personal exposure measurements in the corresponding village. The dashed black line indicates the WHO 24 h guideline for $PM_{2.5}$ (15 $\mu g/m^3$). MTG = Mentougou; HR = Huairou; FS = Fangshan; and MY = Miyun.

(LPG), and/or electricity, was common for cooking, and only nine participants reported on exclusively cooking with solid fuels.

Wealth Index. The reported earned annual household income varied by households and districts (Table 1), ranging from 0 to ∼1,000,000 Chinese RMB. Log_{10}-transformed income generally follows a normal distribution (Figure S5). Participants in Fangshan reported on the highest income, with 30% reporting an annual income ranking in the highest quintile. Quintile distributions of household income in Mentougou and Huairou were similar. Fewer participants in Miyun (33%) ranked in the highest two quintiles of annual income compared to the other three districts (Huairou: 37%; Mentougou: 40%; and Fangshan: 53%).

The mean (95% CI) wealth index was 0.9 (0.3, 1.6), 0.5 (−0.3, 1.2), 0.1 (−0.6, 0.8), and −2.0 (−2.7, −1.2) in Huairou, Fangshan, Miyun, and Mentougou, respectively, indicating that participants in Huairou were the wealthiest and the least wealthy were in Mentougou. A larger proportion of participants were represented in the highest two quintile ranges of wealth index in Huairou (48%) and Fangshan (48%) compared to that in Miyun (35%) and Mentougou (16%) (Table 1). The wealth distribution among participants in Miyun was nearly uniform across all five quintiles, while in Mentougou, the two quintiles with the greatest representation were the first (40%) and second (25%) lowest quintiles.

Personal Air Pollution Exposure at the District Level. The GM exposure to $PM_{2.5}$ was 72 (95% CI: 65, 80) $\mu g/m^3$, much higher than the WHO health-motivated 24 h guideline for exposure to $PM_{2.5}$ (15 $\mu g/m^3$).[1] $PM_{2.5}$ exposures were highest in Mentougou [GM (95% CI): 105 (83, 133) $\mu g/m^3$] and lowest in Miyun [GM (95% CI): 56 (48, 66) $\mu g/m^3$] (Figure 1 and Table S3). Personal BC exposures [GM (95% CI): 2.5 (2.3, 2.8) $\mu g/m^3$] were also highest in Mentougou [GM (95% CI): 3.2 (2.4, 4.2) $\mu g/m^3$] and lowest in Miyun [GM (95% CI): 1.9 (1.6, 2.2) $\mu g/m^3$]. Personal $PM_{2.5}$ and BC exposures were strongly correlated (Spearman ρ: 0.80, $p < 0.001$) (Table S3), indicating that these exposures likely originated from similar emission sources. These correlations were stronger in Mentougou, Huairou, and Fangshan (Spearman ρ range: 0.80−0.86) compared with Miyun (Spearman ρ: 0.69).

The personal exposure to $PM_{2.5}$ (mean ± SD: 119 ± 138 $\mu g/m^3$ in weekdays and 107 ± 87 $\mu g/m^3$ in weekend days) and BC (4.0 ± 4.9 $\mu g/m^3$ in weekdays and 3.6 ± 3.4 $\mu g/m^3$ in weekend days) in weekdays was higher than in weekend days, but the differences were not statistically significant (ANOVA: $p > 0.1$).

Personal Air Pollution Exposure at the Village Level. The village-level GMs (95% CI) for exposure to $PM_{2.5}$ ranged from 23 (10, 55) $\mu g/m^3$ in Fangshan to 387 (238, 627) $\mu g/m^3$ in Mentougou (Figures 1 and 2 and Table S4). The 24h-mean concentrations of outdoor $PM_{2.5}$ at each village during the personal exposure measurements varied from 3.5 to 159 $\mu g/m^3$ (Figure 2). The seasonal mean of outdoor $PM_{2.5}$ concentrations by village and district are provided in the Supporting Information (Table S5). Village-level personal exposures to $PM_{2.5}$ were weakly correlated with those of outdoor $PM_{2.5}$ (Spearman $\rho = 0.28$, $p < 0.1$) measured on the same day. The ratios of personal exposure to outdoor (P/O) $PM_{2.5}$ can provide limited insights into the contribution of outdoor and non-outdoor sources to personal exposures. A P/O ratio greater than 1 is indicative of the presence of personal or indoor sources of $PM_{2.5}$.[51] The mean P/O ratios of $PM_{2.5}$ were greater than 1 in most villages, except 3 (of 11) villages in Fangshan and 1 (of 12) village in Miyun (Figure S6). Further,

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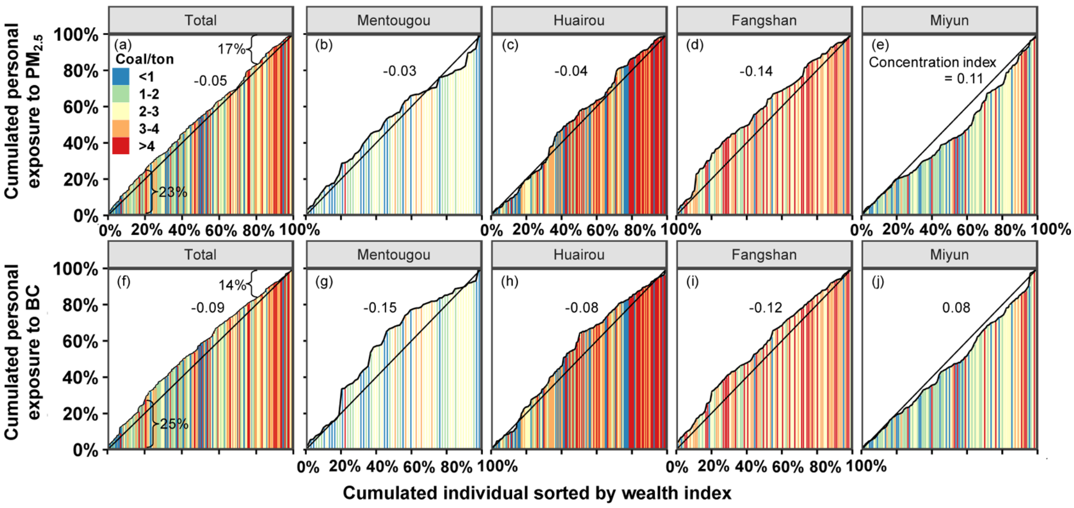

Figure 3. Concentration curves for personal exposure to $PM_{2.5}$ (a−e) and BC (f−j) sorted by wealth index. Panels (a,f) show the concentration curves for $PM_{2.5}$ and BC exposures of all participants. Panels (b−e, and g−j) show the concentration curves for $PM_{2.5}$ and BC exposures in Mentougou, Huairou, Fangshan, and Miyun, respectively. The horizontal axis in panels (a−j) shows the cumulative population sorted by wealth index from the lowest (on the left) to the highest (on the right). The decimals in each panel represent the concentration index. The color of the ribbon under the concentration curve represents household coal use (ton) for heating in the winter of 2018/2019. The diagonal is the line of equality.

the P/O ratios were negatively correlated with outdoor $PM_{2.5}$ (Spearman $\rho = -0.70$, $p < 0.001$) (Figure S6), suggesting that increases in outdoor $PM_{2.5}$ were not strongly associated with increasing personal $PM_{2.5}$ exposures.

Within villages, the personal exposure to $PM_{2.5}$ also varied from participant to participant (Figure 2), likely attributable to spatial and temporal differences in patterns of indoor emissions of $PM_{2.5}$, personal activity, and house ventilation, as participants spent more time indoors. Among 24 participants in Huairou and Fangshan, their personal exposures to $PM_{2.5}$ were lower than 15 $\mu g/m^3$, and the possible reasons were a lack of tobacco smoking among these participants, low outdoor $PM_{2.5}$ concentrations, and use of clean energy for cooking. However, 72 (16%) participants had $PM_{2.5}$ exposures over 200 $\mu g/m^3$, likely due to the high indoor emissions from solid fuel combustion and tobacco smoking.

The lowest village-level GM (95% CI) of BC exposures was 0.8 (0.4, 1.6) $\mu g/m^3$ in Huairou, while the highest was 11 (7.2, 16.9) $\mu g/m^3$ in Mentougou (Figure 1 and Table S4). The highest individual-level BC exposure (55 $\mu g/m^3$) was observed in Mentougou (Figure S7).

The within-village variances (σ_ε^2) were larger than the between-village variances (σ_b^2) for personal $PM_{2.5}$ (0.95 vs 0.18) and BC (0.89 vs 0.13) (Table S6). Even after including variables of outdoor $PM_{2.5}$ and temperature, smoking status, heating fuels, and wealth index in the models, the within-village variances remained much larger than the between-village variances. Further, the proportion of the total variability in personal exposures attributed to between-village differences was low (ICC: 0.10−0.16 and 0.08-0.13 for personal $PM_{2.5}$ and BC, respectively). In most villages, personal $PM_{2.5}$ and BC exposures were strongly correlated (Spearman $\rho > 0.7$, Figures S8 and S9). Personal BC exposures were weakly or negatively correlated with personal $PM_{2.5}$ (Spearman $\rho < 0.4$) in two villages (MTG6 and FS36), suggesting that different sources contributed to BC exposures compared with $PM_{2.5}$ exposures in those villages. For example, MTG6 is a remote village with few air pollution sources other than rural residential solid fuel combustion, while at the time of our study, several new housing developments were being constructed. Otherwise, FS36 is close to a major road, which connects several surrounding villages, and traffic emissions may contribute more to personal exposures in these villages.

$PM_{2.5}$ and BC Exposure Distributions by Energy Use and Socioeconomic Patterning. *Patterns of Air Pollution Exposures by Heating Energy Use.* Exposures to $PM_{2.5}$ were the lowest among participants who reported on using a centralized coal stove with a radiator system [GM (95% CI): 68 (61, 76) $\mu g/m^3$], compared with those using both clean energy heating devices and coal stoves [GM (95% CI): 73 (32, 167) $\mu g/m^3$] or a traditional coal stove (without a radiator system) [GM (95% CI): 97 (73, 129) $\mu g/m^3$] or a *kang* [GM (95% CI): 85 (54, 135) $\mu g/m$] (Figure S10). BC exposures followed a similar trend where exposures were the lowest among those using centralized coal stoves with radiator systems [GM (95% CI): 2.4 (2.2, 2.6) $\mu g/m^3$] and highest among participants using traditional coal stoves [GM (95% CI): 3.3 (2.4, 4.4) $\mu g/m^3$]. The results were statistically significant (Wilcoxon test) for both $PM_{2.5}$ and BC exposures.

There was some evidence that use of coal for space heating was concentrated among wealthier participants and that biomass use was concentrated among poorer participants (Figure 3a, f and Tables S7 and S8). For example, the wealthiest one-third of participants used, on average, 1.7 times more coal than the poorest one-third of participants; yet, they only burned approximately half (55%) of the biomass that the poorest one-third of participants burned in winter. In Fangshan, poorer participants burned 10 times more biomass than the wealthier (Table S8). Our findings suggest that wealthier participants burned more coal for heating, while poorer participants were more likely to heat with biomass fuel, likely due to its lower cost compared with coal. However, the use of coal per heated house area did not show an apparent trend with the wealth index (Figure S11).

Air Pollution Exposures by Wealth Index. Overall, $PM_{2.5}$ and BC exposures were distributed evenly by SES, although

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exposures to both pollutants were slightly more concentrated among the poorer participants. The concentration index (95% CI) was −0.05 (−0.10, 0.01) for $PM_{2.5}$ (Figure 3a and Table S9), indicating that $PM_{2.5}$ exposures were similar across the range of SES. The concentration index (95% CI) for BC was −0.09 (−0.16, −0.02) (Figure 3f and Table S9), indicating a slightly uneven distribution, with higher BC exposures marginally more concentrated among poorer participants. The poorest 20% of participants accounted for 23 and 25% of cumulative personal $PM_{2.5}$ and BC exposures, while the wealthiest 20% of participants accounted for only 17 and 14%, respectively (Figure 3a,f).

At the district level, distributions of air pollution exposures by SES were different, while they were generally evenly distributed with concentration index varying between −0.15 and 0.11 (Figure 3 and Table S9). In Mentougou and Huairou, $PM_{2.5}$ exposures were distributed evenly, while BC exposures were concentrated among poorer participants with a concentration index of −0.15 and −0.08. In Fangshan, both $PM_{2.5}$ and BC exposures were concentrated among poorer participants; however, they were concentrated among wealthier participants in Miyun. More detailed discussions are provided in the Supporting Information (Text S8).

Patterns of Air Pollution Exposures by Smoking Status. Participants' occupation and education levels were not associated with air pollution exposure levels; however, smoking status was an important determinant (Figure S12). Current smokers had higher $PM_{2.5}$ [GM (95% CI): 115 (96, 139) $\mu g/m^3$] ($p < 0.001$) and BC [GM (95% CI): 3.4 (2.9, 4.0) $\mu g/m^3$] ($p < 0.001$) exposures than non-smokers. Exposures among non-smokers were higher for those living with current smokers [for $PM_{2.5}$, GM (95% CI): 82 (69, 97) $\mu g/m^3$ ($p < 0.001$) and for BC, GM (95% CI): 2.9 (2.4, 3.4) $\mu g/m^3$ ($p < 0.001$)] compared to those who did not [for $PM_{2.5}$, GM (95% CI): 48 (41, 55) $\mu g/m^3$ and for BC, GM (95% CI): 1.8 (1.6, 2.1) $\mu g/m^3$]. Smoking status was not strongly correlated with wealth index (Table S10), and air pollution exposures for participants in different smoking statuses were also almost evenly distributed by wealth index (Figure S13). The personal $PM_{2.5}$ and BC exposures were 80 (69, 93) $\mu g/m^3$ and 2.7 (2.3, 3.1) $\mu g/m^3$ for male participants, respectively, which were higher than those for females [$PM_{2.5}$, GM (95% CI): 67 (59, 77) $\mu g/m^3$; BC, GM (95% CI): 2.4 (2.1, 2.7) $\mu g/m^3$]. However, gender differences were no longer evident after accounting for tobacco smoking, which is more common among males (Table S11).

DISCUSSION

The GM (95% CI) of $PM_{2.5}$ and BC exposures were 72 (65, 80) and 2.5 (2.3, 2.8) $\mu g/m^3$ in this study and varied more within villages than between villages. Further, village-level personal $PM_{2.5}$ showed a weak correlation (Spearman ρ = 0.28) with outdoor $PM_{2.5}$, and the P/O ratios of $PM_{2.5}$ were greater than 1 in most villages (46 out of 50 villages). Inequalities in personal $PM_{2.5}$ and BC exposures were not apparent across the wealth distribution. Air pollution exposures varied with heating energy use patterns and smoking status. Participants who used traditional stoves (traditional coal heating stoves and/or *kang*) and were current smokers had higher air pollution exposures than others. These findings indicate that, more so than village-level outdoor air pollution, indoor and household source emissions associated with personal activities influenced exposures. For example, the use of *kangs* for cooking and heating and the prevalence of indoor smoking were likely two main reasons for the variability in exposures observed across all villages.

Personal $PM_{2.5}$ exposures in this study ranged nearly 3 orders of magnitude across individuals, and the within-village variance was much larger than the between-village variance. Other studies also observed similarly wide ranges in personal exposures among households using solid fuels in China. For example, Lee et al. (2021) reported that daily (24 h) personal exposures to $PM_{2.5}$ ranged from 0.01 to 1528 $\mu g/m^3$ in rural settings in China.[48] In a coal village in Shanxi Province in northern China, personal $PM_{2.5}$ exposures were as low as 15 $\mu g/m^3$ and as high as 741 $\mu g/m^3$.[28] In the present study, our results suggest that the large variability in exposures was more likely related to variability in indoor personal activities, such as how solid fuels are burned (e.g., fire-tending and stove-fueling behaviors) or tobacco smoking habits, than to patterns of outdoor air pollution because our participants reported on spending much, or most, of their time indoors in winter.

Personal air pollution exposures varied by household energy use patterns. Participants with centralized coal stoves with radiator systems had lower exposures than those with traditional coal stoves or *kangs*. Coal use intensity for space heating increased monotonically with wealth index. Poorer households were likely more fuel-limited and, thus, tended to use biomass as a household fuel, which is both less expensive (than coal) and highly polluting (Tables S7 and S8).[52] The higher emission rates of biomass burning in poorer households and burned more coal in wealthier households resulted in the non-monotonic relationships between air pollution exposures and SES (Figure 3). Due to the limited biomass burning in Fangshan (0.4 tons per household in winter vs 1.2, 2.2, and 2.0 tons in Mentougou, Huairou, and Miyun), personal exposures were concentrated among poorer participants. Given the lack of variation in exposures with SES, but the persistent differences in fuel use, we conclude that personal exposure is often a large enough mix of the indoor and outdoor environments and that we see little individual effect from differences in household energy sources in this context when most use coal and biomass. Therefore, we might expect personal exposure levels for wealthier households to decrease significantly after the household energy transition as their coal use is replaced by electricity. However, since poorer households still have access to biomass, and the energy cost of electricity can still be a large burden, exposure among poorer households may not see similar declines.

Kangs (described in Table S2 and Text S7) represent a common heating system in northern China; these systems are usually fueled by biomass, which is not regulated by the household energy transition program. Participants using *kangs* exclusively (n = 37; 8%) had higher air pollution exposures in our study. This result is not surprising, given that the combustion efficiency of *kangs* is typically the lowest among solid fuel-burning stoves.[53−56] While the fraction of households in our study reporting exclusive use of *kangs* was low (8%), any use of *kangs* in combination with other household energy options was high, with 76% participants reporting the use of *kangs* for cooking and/or heating in winter. We expect that *kang* usage is a likely contributor to variability in personal air pollution exposures, although difficult to accurately track and quantify. As the heating energy transition progresses throughout Beijing and across northern China, households may supplement electricity-based heating with use of their

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kangs to maintain thermal comfort and save money, which could limit the impact of household energy transition on air pollution exposures.

Cigarette smoking is an important source of indoor $PM_{2.5}$ and some toxic air pollutants, for example, formaldehyde, benzene, and toluene.[57] Consistent with previous exposure papers,[19,48,58] smokers had higher exposures than non-smokers, and smoking also contributed to exposures among non-smokers who lived with a smoker. Initially, personal air pollution exposures among men appeared higher than among women; however, this difference was no longer observed after accounting for smoking status, which is consistent with the findings of Lee et al. (2021) in an exposure study in northern and southern China.[48] In that study, men had higher exposures than women in peri-urban areas of China where residents also relied on solid fuel energy; however, gender difference was largely eliminated after accounting for cigarette smoking. Although smoking contributed to personal exposures in our study as well, smoking status did not alter the trends observed with the concentration curves (Figure S13), which indicated that air pollution exposures were almost evenly distributed across wealth index.

This paper presents a baseline evaluation of the distributions of personal exposures to $PM_{2.5}$ and BC, two pollutants emitted from household combustion of solid fuels. Notable strengths of our study include (i) assessment of personal exposure for over 400 participants across 50 villages that represent a large geographic area of Beijing, and the age structure of our study participants is similar to the age structure of the population in rural Beijing; (ii) a well-designed questionnaire to assess participants' demographic information, SES, and household energy use patterns and evaluate their associations with personal exposures; (iii) one of the headmost studies to investigate the distribution of personal exposures by SES and evaluate how these two patterns intersect in rural Beijing. There are also several limitations that could be considered in future studies. First, we have not yet assessed the contributions made to exposure from different air pollution sources (e.g., coal, biomass, traffic, agricultural burning, and industry). Planned chemical species analysis of the samples will enable us to quantify source contributions and their patterns across sociodemographic characteristics. Second, our sampling duration was limited to a single 24 h measurement in only the winter season. This measurement may not be as representative of wintertime personal exposures as repeated measures in the same season. However, given the challenges of conducting such a large-scale, field-based study, this measure may still provide insights into personal exposures that other measures (e.g., questionnaire-based assessment and outdoor or indoor air quality measurements alone) would not. Third, it is not appropriate to combine the single 24 h measurement of personal exposure with seasonal fuel consumption to estimate the association between them, which can be solved by estimating the day-specific consumption of fuels on the day when personal exposure is measured. Finally, the wealth index estimation was limited to the socioeconomic variables we collected in this study; the inclusion of these variables was informed by past studies in a similar setting,[11] but may still not have fully captured all factors that contribute to household SES in this region.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.1c07402.

> Characterization of recruited villages and districts; study design and participant recruitment; personal exposure sample collection and filter analyses; outdoor $PM_{2.5}$ measurements; questionnaires; PCA of wealth index estimation; classification of heating systems; distributions of air pollution exposures by wealth index at the district level; characteristics of study villages; characterization of different stove types; summary of personal exposure to $PM_{2.5}$ and BC at the district level; personal exposure to $PM_{2.5}$ and BC by village; seasonal mean of outdoor $PM_{2.5}$ by village and district; mixed-effects regression model; fuel use intensity by wealth index; fuel use intensity by wealth index in four districts; concentration index; distributions of participants in different smoking statuses by wealth index quintile; personal $PM_{2.5}$ and BC exposures by gender; principal component coefficients; locations of recruited villages and districts; linear regression between $PM_{2.5}$ measured by a reference instrument and real-time $PM_{2.5}$ sensor; linear regression between outdoor gravimetric $PM_{2.5}$ and time-averaged sensor-based $PM_{2.5}$; design of questionnaire on household energy use patterns; histogram of log-transformed annual income; scatter plot and linear regression between outdoor $PM_{2.5}$ and mean personal exposure to outdoor $PM_{2.5}$ (P/O) ratios at the village level; participant personal BC exposures; scatter plot of personal $PM_{2.5}$ and BC; Spearman correlation coefficients between personal $PM_{2.5}$ and BC; cumulative distribution of personal $PM_{2.5}$ and BC by heating energy source; concentration curves for personal exposure; cumulative distribution of personal $PM_{2.5}$ and BC by occupation, education, and smoking status; concentration curves of $PM_{2.5}$ and BC exposures by smoking status; monotonicity of wealth index components; and monotonicity of income, house area heated, electricity cost, and quantity of coal briquettes used by wealth index quintile (PDF)

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Notes

The authors declare no competing financial interest.

This research has been reviewed and approved by research ethics boards at Peking University (IRB00001052-18090) and McGill University (A08-E53-18B).

The data generated and/or analyzed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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