Received: 3 May 2022 | Revised: 15 July 2022 | Accepted: 31 July 2022

DOI: 10.1111/ina.13095

ORIGINAL ARTICLE

WILEY

Field measurements of indoor and community air quality in rural Beijing before, during, and after the COVID-19 lockdown

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Funding information
the United States Environmental Protection Agency, Grant/Award Number: R-82811201; Health Effects Institute (HEI); Canadian Institutes of Health Research, Grant/Award Number: #159477 and #148697

Abstract

The coronavirus (COVID-19) lockdown in China is thought to have reduced air pollution emissions due to reduced human mobility and economic activities. Few studies have assessed the impacts of COVID-19 on community and indoor air quality in environments with diverse socioeconomic and household energy use patterns. The main goal of this study was to evaluate whether indoor and community air pollution differed before, during, and after the COVID-19 lockdown in homes with different energy use patterns. Using calibrated real-time $PM_{2.5}$ sensors, we measured indoor and community air quality in 147 homes from 30 villages in Beijing over 4 months including periods before, during, and after the COVID-19 lockdown. Community pollution was higher during the lockdown ($61 \pm 47\,\mu g/m^3$) compared with before ($45 \pm 35\,\mu g/m^3$, $p < 0.001$) and after ($47 \pm 37\,\mu g/m^3$, $p < 0.001$) the lockdown. However, we did not observe significantly increased indoor $PM_{2.5}$ during the COVID-19 lockdown. Indoor-generated $PM_{2.5}$ in homes using clean energy for heating without smokers was the lowest compared with those using solid fuel with/without smokers, implying air pollutant emissions are reduced in homes using clean energy. Indoor air quality may not have been impacted by the COVID-19 lockdown in rural settings in China and appeared to be more impacted by the household energy choice and indoor smoking than the COVID-19 lockdown. As clean energy transitions occurred in rural households in northern China, our work highlights the importance of understanding multiple possible indoor sources to interpret the impacts of interventions, intended or otherwise.

KEYWORDS
indoor and community $PM_{2.5}$, air pollution sources, cigarette smoking, COVID-19 lockdown, household energy use

1 | INTRODUCTION

The abrupt outbreak of COVID-19 initiated a global prevention response that included closures of businesses, social distancing, and significant reductions in human mobility to curb the spread of the virus. These policies were associated with regional and local reductions in outdoor air pollution throughout China and globally.[1,2] Higher indoor air pollution during the lockdown period was observed in residential settings in China and the U.S., potentially attributable to longer periods spent inside homes and changes in in-home activities including increased cooking, space heating, and personal leisure activities in the home that contribute to indoor emissions of air pollutants.[3-9]

In rural areas, changes in community and indoor air pollution may have been less pronounced than in urban areas during the COVID-19 lockdown due to fewer changes in local business, transport, and daily activities compared with urban areas.[9] More thorough and actionable understanding of the variability in indoor-generated pollutant concentrations associated with human behavior is needed to anticipate potential changes to exposures in the home. The implementation of policies designed to reduce the transmission of COVID-19 created an opportunity to evaluate how indoor and outdoor air quality trajectories differ in the wake of a large external system-level shock. Understanding this is helpful for future studies on policy and measures to control indoor air pollution and personal exposures.

In this study, we enrolled 147 homes from 30 villages in Beijing and monitored indoor and community (i.e., local outdoor) $PM_{2.5}$ during the heating (until March 15) and non-heating (after March 15) seasons in 2020. The purpose of this study was to (1) characterize patterns of indoor and community $PM_{2.5}$ during the different periods of the COVID-19 lockdown; (2) quantify the contributions of indoor sources and community $PM_{2.5}$ to indoor $PM_{2.5}$; and (3) evaluate the impact of the COVID-19 lockdown on indoor air quality in homes with different energy use patterns. This study is among the first to measure the impact of the COVID-19 lockdown on indoor air quality in homes with different energy use patterns and also provides some preliminary insight into the influence of household energy transitions on indoor air quality.

2 | METHODS

2.1 | Study settings

Our study took place in 30 rural and peri-urban villages in Huairou and Miyun districts, which were between 70 and 100 km from the Beijing city center. Households in 10 out of 30 villages relied on electricity and liquefied petroleum gas (LPG) (clean energy) for space heating and cooking, and the others mainly used coal and biomass (solid fuel). Most residents in these villages were farmer or did agriculture-related work.[10]

2.2 | Study design and households

This study was ancillary to the Beijing Household Energy Transition (BHET) study, a longitudinal evaluation of the air pollution and human health impacts of household energy transition. Details on the BHET study design and household recruitment are described elsewhere.[10] Briefly, between December 2018 and January 2019, we recruited 977 households in 50 villages from four districts across Beijing. Villages for the BHET study were those eligible to participate in the coal-to-clean energy program but were not currently participating. In each village, we enrolled 10–23 households (median recruitment rates: 13%) to participate in a household energy questionnaire. In a second winter field campaign (2019–2020), we revisited 865 households from the first campaign (89%) and recruited an additional 197 households into the study. In total, we recruited 1062 households that completed a questionnaire. A random subsample of 300 households (6 in each village) was additionally selected for indoor air quality assessment in the second campaign. Written informed consent was obtained from all enrolled households. The study protocols were approved by research ethics boards at Peking University and McGill University.

2.3 | Data collection

This analysis used questionnaire and indoor air quality data collected in 180 households from 30 villages in the Huairou and Miyun districts. We restricted our analysis to these two districts and the households in those districts that received an indoor air quality assessment, because some villages in those two districts (10 of the 30) had already transitioned from solid fuels to clean energy for space heating, while none of the villages from the other two districts had yet shifted to using clean energy for space heating. Indoor and community air pollution monitors were installed on various dates in November 2019–January 2020 and were programmed to continuously measure $PM_{2.5}$ through April 25, 2020.

We used the study measurements conducted between January 15, 2020, and April 25, 2020, because this period included the COVID-19 lockdown period (January 25–February 25, 2020), the heating season (November 15–March 15, 2020), and the non-heating season (after March 15, 2020) in Beijing. The start of the COVID-19 pandemic, which coincided with the Spring Festival holiday, led to large restrictions on movement and activity within Beijing and across China. Stay-at-home orders were imposed for Beijing and other provinces' residents on January 25, 2020, and a two-week mandatory quarantine was implemented for those traveling into Beijing. After February 25, 2020, Beijing and many other provinces shifted from a first to second of emergency response,[1,11] which included closures of schools and businesses and restrictions on travel between regions.

2.4 | Indoor and community $PM_{2.5}$ measurements

2.4.1 | Sensor-based measurements of indoor and community $PM_{2.5}$

Indoor $PM_{2.5}$ was measured using a commercially available sensor (PMS7003 Plantower, Zefan, Inc.) that measured the $PM_{2.5}$ concentration every 1 min. This laser-based particle sensor has a counting efficiency of 98% for particles of diameter larger than 0.5 μm[12] and was successfully deployed in several large field studies.[5,13–15] The sensor was placed on an elevated surface (~0.8–1.2 m height) in the room where the participants reported spending most of their time when awake. We excluded from analysis at least one season of measurements from 54 households where the sensors sampled for less than 50% of the target sampling period (i.e., 59 and 41 days in the heating and non-heating seasons, respectively) due to failure of the power supply or sensors.

Two sensors were set up to measure community $PM_{2.5}$ at different locations in each village. One sensor was placed near the center of the village, and the other was placed no less than 500 m away from the centrally located sensor. Sensors were placed at least 1.5 m above the ground and in a location without a visible point source of air pollution.

2.4.2 | Filter-based measurements of indoor and community $PM_{2.5}$

We collected filter-based indoor and community $PM_{2.5}$ samples to calibrate the sensor-based $PM_{2.5}$ measurements. Ultrasonic Personal Aerosol Samplers (UPAS, Access Sensor Technologies) and Personal Exposure Monitors (PEMs, Apex Pro) were used to collect filter-based $PM_{2.5}$ samples with the flowrate of 1.0 and 1.8 L/min, respectively.[16] Both samplers housed 37 mm PTFE filters (VWR, 2.0-μm pore size) and were equipped with a cyclone inlet with a 2.5 μm cut point designed to perform under the corresponding sampling flowrate.

A UPAS or PEM was co-located with a $PM_{2.5}$ sensor in 50% of households with indoor $PM_{2.5}$ measurement in each village to collect a concurrent time-integrated, 24-h $PM_{2.5}$ filter sample. The filter-based $PM_{2.5}$ sample collection coincided with the first 24-h of indoor $PM_{2.5}$ sensor measurements. After the first 24-h, the filters were retrieved and the samplers were re-deployed with new filters in other study homes. For community measurements, a UPAS was co-located with each $PM_{2.5}$ sensor in each village in rotation. Every week, the used filters were removed and replaced with a new filter. In total, 137 and 621 paired samples were collected for indoor and community $PM_{2.5}$, respectively. Field blank filters were collected at a rate of ~10%, subject to the same field conditions as samples.

Detailed information on filter analysis can be found in Li et al.[10] In brief, filters were conditioned for at least 24-h and weighed in an environmentally-controlled chamber (21–22°C, 30%–34% relative humidity) on a microbalance (Mettler Toledo Inc., XS3DU) with 1-μg resolution in the Automated Air Analysis Facility (AIRLIFT).[17] Filters were weighed in triplicate or until the differences in at least three weights were less than 3 μg. Filter mass was blank-corrected and $PM_{2.5}$ concentrations were calculated by dividing the mass by the sampled air volume.

2.5 | $PM_{2.5}$ sensor calibration

Given the importance of $PM_{2.5}$ sensor calibration and quality control,[12,15,18] all PM sensors were co-located with a reference-grade $PM_{2.5}$ instrument (Model 5030 Synchronized Hybrid Ambient Realtime Particulate [SHARP] Monitor, Thermo Fisher Scientific) on the rooftop of a building at Peking University campus for 7 to 10 days before and after the field campaign. Sensor-measured $PM_{2.5}$ concentrations were highly correlated with those measured by the SHARP (Spearman correlation coefficients (*rho*) of 0.95 and 0.82 in pre- and post-calibration, respectively (Figure S1)).

We established linear regression models 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 sampling period as the filter-based samples (Figure S2). The slopes of the models were used as the adjustment factors for the sensor-based $PM_{2.5}$ concentrations. Separate regression models were conducted for indoor and outdoor sensors given the sensitivity of the sensors to relative humidity, temperature, particle sources,[15] which likely differ for indoor versus outdoor conditions. The adjustment factors (95% confidence interval: 95% CI) for indoor and outdoor $PM_{2.5}$ sensors are 1.11 (1.02, 1.20) and 0.95 (0.9, 1.00), respectively.

2.6 | Outdoor temperature

Outdoor temperature data were obtained from meteorological stations in Beijing and its neighboring provinces from the National Oceanic and Atmospheric Administration (NOAA) Integrated Surface Data database. We estimated the outdoor temperature for each study home by inverse-distance weighting the hourly temperatures recorded by government meteorological stations within a 100 km radius of their homes (typically 2–4 monitors) and adjusted for altitude using the environmental lapse rate of −6.5°C per 1000 meters for analysis. Detailed information on outdoor temperature estimation can be found elsewhere (https://escholarship.mcgill.ca/concern/theses/1c18dm543).

2.7 | Household questionnaire

A questionnaire was completed for each household to assess household sociodemographic information; house condition, structure, and materials; stove and fuel use; and other in-home behaviors associated with the indoor emissions of $PM_{2.5}$, including smoking status and room occupancy. Further details about questionnaires can be found in Li et al.[10]

2.8 | Estimation of indoor-generated $PM_{2.5}$ and indoor $PM_{2.5}$ of outdoor origin

Indoor $PM_{2.5}$ (C_{in}, μg/m^3) is comprised of indoor-generated $PM_{2.5}$ (C_{ig}, μg/m^3) and of indoor $PM_{2.5}$ of outdoor origin (C_{oo}, μg/m^3). Indoor-generated $PM_{2.5}$ is emitted from indoor sources including solid fuel combustion, cooking, and cigarette smoking. Indoor $PM_{2.5}$ of outdoor origin is $PM_{2.5}$ that is first generated outdoors but passes through the building envelope via infiltration. Indoor $PM_{2.5}$ is best described as the sum of indoor-generated $PM_{2.5}$ and indoor $PM_{2.5}$ of outdoor origin as follows:

$$C_{in} = C_{ig} + C_{oo} \tag{1}$$

and C_{oo} would be determined as the following:

$$C_{oo} = F_{inf} \times C_{out} \tag{2}$$

where F_{inf} is an infiltration factor (dimensionless) that represents the proportion of outdoor $PM_{2.5}$ that is transported across the residential building envelope and remains suspended indoors, and C_{out} is the outdoor $PM_{2.5}$ concentration (μg/m^3). Combining Equations (1) and (2), the indoor $PM_{2.5}$ concentration can be expressed as

$$C_{in} = C_{ig} + \left(F_{inf} \times C_{out}\right) \tag{3}$$

In this way, the infiltration factor for $PM_{2.5}$, F_{inf}, can be obtained by the linear regression equation between C_{in} and C_{out}, which is also known as the random component superposition model (RCS).[6,19,20]

2.9 | Data Analysis

We compared indoor and community $PM_{2.5}$ concentrations in the heating and non-heating seasons. We also compared indoor and community $PM_{2.5}$ concentrations in the different periods of the COVID-19 lockdown, including the periods before (January 15–January 25, 2020), during and after (February 26–March 15, 2020) the lockdown.[5,7] We classified the recruited households into three heating fuel categories: solid fuel, clean energy, and solid fuel and clean energy (i.e., mixed fuel use). Here, we defined exclusive use of clean energy as LPG and electricity.[21,22] We also compared indoor $PM_{2.5}$ in households with/without indoor cigarette smoking.

Hourly average $PM_{2.5}$ concentrations were computed by averaging the 1-minute calibrated sensor-based data described in Section 2.4.1. Indoor and community $PM_{2.5}$ concentrations were described and summarized using arithmetic means and standard deviations (SD), as well as geometric means (GM) and 95%CI, given the tendency for air pollution data to be log-normally distributed. To describe the diurnal variation of indoor $PM_{2.5}$, we clustered the hourly indoor $PM_{2.5}$ into the periods of morning, noon, evening, and midnight, which are corresponding to 6 – 10 am, 11 am – 3 pm, 4 – 8 pm, and 9 pm – 5 am on the next day, respectively. We applied the Student's t-test to test the differences of indoor $PM_{2.5}$ and indoor-generated $PM_{2.5}$ among smoking and non-smoking households that used different heating energy across the different COVID-19 lockdown periods.

The detailed information on wealth index estimation is documented in detail in Li et al.[10] Briefly, to measure relative SES of each household, we created a composite (wealth) index using principal component analysis (PCA) from owned household assets. The following assets were used as proxies of household wealth[23]: car, motorbike, electric scooter, washer, fridge, 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.

We used multivariable mixed-effects regression models with a random effect at the village level to estimate the effect of different COVID-19 lockdown periods (i.e., before, during, and after) on indoor $PM_{2.5}$. The covariates included in the model were ambient temperature, community $PM_{2.5}$ concentration, household wealth index, heating and cooking energy types, household smoking status, and the periods of before/during/after the COVID-19 lockdown.

All statistical analyses were performed in R version 3.5.2. The statistical code can be obtained on OSF (https://osf.io/ewunj/).

3 | RESULTS

3.1 | Characteristics of recruited households

Ten out of 30 villages had completed a household energy transition from coal heating stoves to electricity-powered heat pumps. Although households in these 10 villages replaced their coal stoves with electricity-powered heat pumps, some of them kept their *kangs*, which are traditional biomass-burning cooking and heating stoves commonly used indoors in northern China.[10]

Half of the study homes (57%) exclusively used solid fuels (coal, wood, and straw) for space heating in winter, and 26% used solid fuels in combination with clean energy (electricity) (Table 1). Less than 20% of homes exclusively used clean energy for space heating. In contrast,

TABLE 1 Household energy use patterns and smoking status of the study households ($n = 147$)

	N	Percent
Total[a]	147	/
Heating fuel		
Solid fuel only	83	56%
Solid fuel and clean energy	40	27%
Clean energy only[b]	24	16%
Cooking fuel		
Solid fuel only	1	0%
Solid fuel and clean energy	73	50%
Clean energy only	73	50%
Smoking status		
One or more smokers in the home	84	57%
No smokers in the home	63	43%

[a]This includes 126 households with measurements in both the heating and non-heating season and 21 households with only one season of measurements.

[b]Clean energy defines as liquefied petroleum gas (LPG) and electricity.

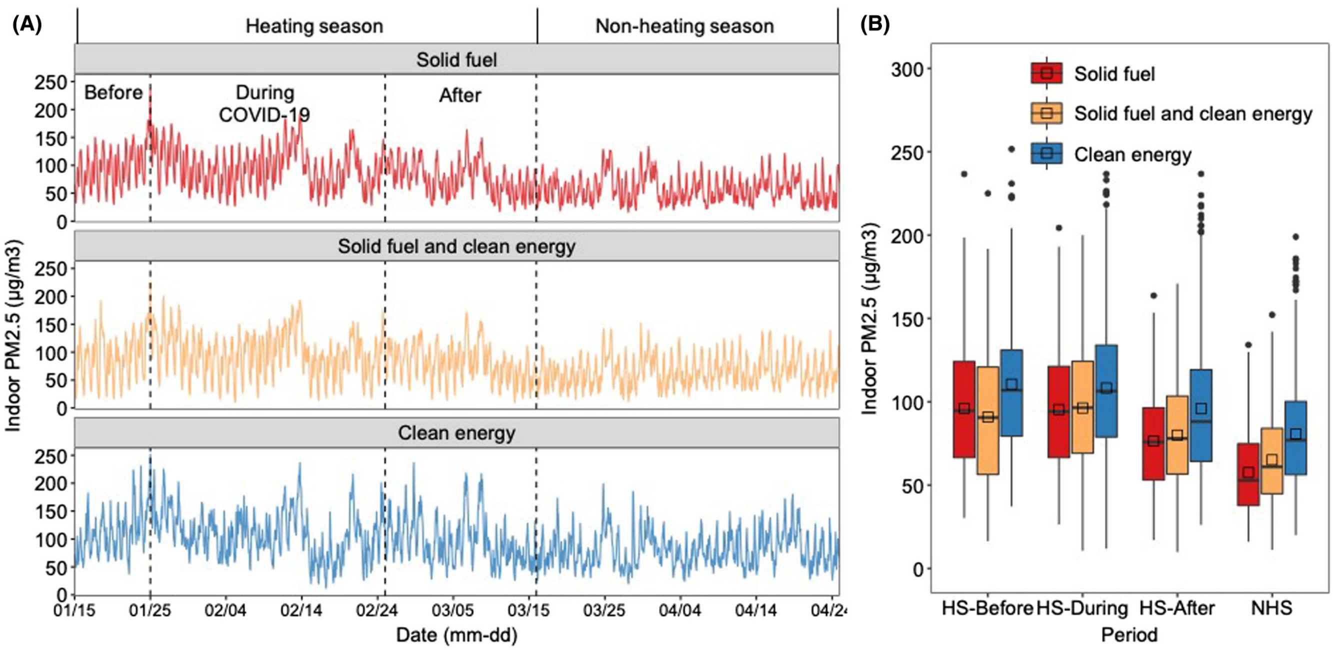


FIGURE 1 Time series (A) and box plot (B) of indoor $PM_{2.5}$ concentrations in households with different energy use patterns. Heating season (HS) defined as from January 15 to March 15, 2020. Non-heating season (NHS) defined as from March 16 to April 25, 2020. COVID-19 lockdown period (HS-during) is from January 25 to February 25, 2020. Before COVID-19 lockdown (HS-before) is from January 15 to February 24, 2020. After COVID-19 lockdown (HS-after) is from February 26 to March 15, 2020. Box midline in the right panel indicates the median; the open square symbol in the box indicates the mean value; the borders of the box represent the upper and lower bounds of the interquartile range (IQR); the whiskers of the box extend from the borders of the box to the maximum/minimum data points within 1.5×IQR; and the points are outliers which are beyond the end of the whiskers.

half of the study households exclusively used clean energy for cooking, while the other half used clean energy in combination with solid fuels. Over half of the homes had one or more current smokers.

The mean (SD) number of people in the households was 2 (1). Residents reported spending an average of 18 (SD: 4) hours per day in their homes during the winter months before the COVID-19 pandemic.

3.2 | Indoor and community $PM_{2.5}$

We obtained complete indoor $PM_{2.5}$ data from 138 households in the heating season and 135 households in the non-heating season. Hourly-averaged indoor and community $PM_{2.5}$ followed similar daily trends (Figures 1A and 2A). The mean (± SD) correlation coefficients (Spearman, *rho*) between indoor and community $PM_{2.5}$

in solid fuel, mixed fuel, and clean energy households during the heating season were 0.54 ± 0.21, 0.58 ± 0.24, and 0.54 ± 0.22, respectively. Indoor and community $PM_{2.5}$ were lower in the non-heating season than the heating across (Figures 1A and 2A). Outdoor temperature went up from the heating to non-heating season (Figure 2A).

Overall, mean (±SD) indoor $PM_{2.5}$ concentrations were 96 ± 83, 98 ± 86, 80 ± 80 μg/m³ before, during, and after the COVID-19 lockdown, respectively. Indoor $PM_{2.5}$ in homes with different heating energy did not increase during the COVID-19 lockdown (Figure 1). Mean community $PM_{2.5}$ (61 ± 47 μg/m³) was higher during the lockdown compared with the period before (45 ± 35 μg/m³, $p < 0.001$) and after (47 ± 37 μg/m³, $p < 0.001$) the lockdown (Figure 2).

The most prominent features of indoor $PM_{2.5}$ time series are the strong daily peaks (Figure 1A), which corresponded with typical indoor cooking times in the morning and late afternoon (Figure S3). An unexpected finding was that indoor $PM_{2.5}$ was the highest (*t*-test, $p < 0.001$) in homes using clean energy for heating compared with those still using solid fuel (Figure 1B), indicating the presence of other indoor emission sources in clean energy homes. Further, more homes using clean energy have double-pane windows (79%) compared to other homes (68%), and thus, were more airtight (to be more energy efficient and reduce loss of indoor heat to the outdoors), which would increase the residence time of indoor-generated air pollutants.

3.3 | Influence of covariates on indoor $PM_{2.5}$

In the multivariable models, we did not find differences in indoor $PM_{2.5}$ across the different COVID-19 lockdown periods. However, higher community $PM_{2.5}$, greater wealth, and the presence of smokers in the homes were positively associated with higher indoor $PM_{2.5}$ (Table 2).

Indoor $PM_{2.5}$ levels in homes with one or more tobacco smokers were two to three times higher than in homes without a smoker (Table S1) and did not show apparent differences by household energy use or the periods of the COVID-19 lockdown.

3.4 | Indoor $PM_{2.5}$ of outdoor origin

Determining infiltration factors can be useful for estimating the fraction of measured indoor $PM_{2.5}$ that is of outdoor origin. Ideally, infiltration factors are determined when the influence of indoor emission sources can be avoided.[24] One approach to estimating infiltration of $PM_{2.5}$ of outdoor origin F_{inf} is to apply a physical model, which is based on several known quantities: air change rate, penetration coefficient of outdoor $PM_{2.5}$, and deposition rate of indoor $PM_{2.5}$. This approach has been widely used in the literature.[24-27] However, these parameters are difficult to obtain for a large number of different households and communities in a large-scale study like ours. The method we used in this study is empirical but could be specific for each household. We estimated infiltration of $PM_{2.5}$ of outdoor origin, F_{inf}, for each household in the heating [mean (95%CI): 0.55 (0.51, 0.59)] and non-heating [0.57 (0.51, 0.63)] seasons separately, when human activities on door- and window-opening behaviors may vary between seasons. Values for the $PM_{2.5}$ F_{inf} estimated in this study were within the range of values for $PM_{2.5}$ F_{inf} (0.32–0.69) in China.[28]

Unlike total indoor $PM_{2.5}$ concentrations, which were not higher during the COVID-19 lockdown, estimated levels of indoor $PM_{2.5}$ of outdoor origin were higher during the COVID-19 lockdown (*t*-test, $p < 0.001$, $p < 0.05$, and $p < 0.01$ for solid fuel, mixed fuels, and clean energy homes, respectively) (Table 3). In homes without smokers, indoor $PM_{2.5}$ of outdoor origin was lower in clean energy homes compared with those using solid fuel stoves in the heating season, likely due to the less infiltration of outdoor air (i.e., more air tightness) in clean energy homes. In the non-heating season, indoor $PM_{2.5}$ of outdoor origin did not differ by household heating energy or smoking status (Table S2).

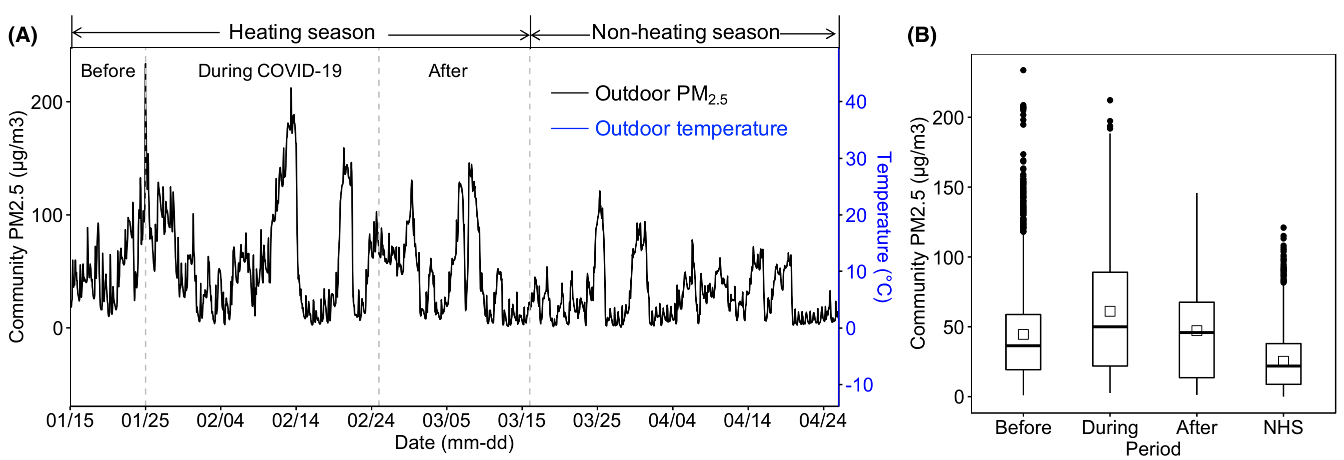


FIGURE 2 Time series (A) of community $PM_{2.5}$ and temperature and box plots (B) of community $PM_{2.5}$ concentrations over the heating season and the non-heating season (NHS), with before-, during-, and after COVID-19 periods also designated. Boxplot features are calculated as described for Figure 1. Outdoor temperature was from the National Oceanic and Atmospheric Administration (NOAA) of the United States (https://www.ncdc.noaa.gov).

TABLE 2 Multivariable mixed-effects model of ln-transformed mean indoor $PM_{2.5}$ in different periods of the COVID-19 lockdown

	Estimate (β)	95%CI	*p*-value
ln-transformed community $PM_{2.5}$	0.48	0.05, 0.91	0.04*
Outdoor temperature	−0.08	−0.28, 0.12	0.46
Heating energy			
Clean energy	ref.		
Solid fuel	−0.01	−0.24, 0.22	0.92
Solid fuel and clean energy	0.004	−0.21, 0.22	0.97
Cooking energy			
Clean energy	ref.		
Solid fuel	−0.14	−0.93, 0.63	0.73
Solid fuel and clean energy	0.08	−0.07, 0.23	0.28
Wealth index	−0.02	−0.04, −0.002	0.037*
Smoking			
No	ref.		
Yes	0.91	0.77, 1.05	<0.001***
COVID-19 period			
During	ref.		
Before	−0.16	−0.69, 0.38	0.57
After	0.24	−0.79, 1.27	0.66
Marginal R^2	0.31		
Conditional R^2	0.44		

Note: **p*-value < 0.10; ***p*-value < 0.05; ****p*-value < 0.001.

TABLE 3 Estimated concentrations of indoor $PM_{2.5}$ of outdoor origin ($\mu g/m^3$) in the heating season

Smoking Status	Period relative to lockdown	Solid fuel		Solid fuel and clean energy		Clean energy	
		Mean (SD)	GM (95%CI)	Mean (SD)	GM (95%CI)	Mean (SD)	GM (95%CI)
Overall	Whole period	30 (23)	21 (20, 22)	33 (22)	24 (23, 26)	30 (23)	21 (20, 22)
	Before[a]	28 (16)	24 (22, 25)	33 (19)	28 (26, 30)	29 (17)	24 (23, 26)
	During[b]	33 (25)	23 (21, 25)	36 (25)	27 (26, 29)	33 (25)	23 (21, 25)
	After[c]	26 (20)	17 (15, 18)	27 (19)	19 (18, 21)	25 (20)	17 (15, 18)
Smoking	Before	29 (16)	25 (23, 26)	41 (25)	35 (32, 37)	31 (18)	27 (25, 29)
	During	34 (26)	23 (22, 25)	46 (29)	35 (33, 37)	36 (28)	25 (24, 27)
	After	27 (21)	17 (16, 19)	35 (23)	26 (24, 28)	28 (22)	18 (17, 20)
Non-smoking	Before	27 (16)	23 (22, 25)	25 (15)	21 (19, 23)	21 (14)	17 (16, 19)
	During	32 (24)	22 (21, 24)	28 (21)	19 (18, 21)	24 (19)	16 (15, 18)
	After	24 (19)	16 (15, 18)	21 (16)	14 (12, 15)	19 (15)	12 (11, 13)

Abbreviations: 95%CI, 95% confidence interval for geometric mean; GM, geometric mean; SD, standard deviation.

[a]Before, Before COVID-19 lockdown is from January 15 to January 24, 2020.

[b]During, COVID-19 lockdown period is from January 25 to February 25, 2020.

[c]After, After COVID-19 lockdown is from February 26 to March 15, 2020.

3.5 | Indoor-generated $PM_{2.5}$

After accounting for the contribution of community $PM_{2.5}$ to indoor $PM_{2.5}$, the daily peaks in indoor-generated $PM_{2.5}$ associated with indoor cooking and heating emissions were more pronounced (Figure 3). In smoking homes, indoor-generated $PM_{2.5}$ did not increase during the COVID-19 lockdown compared with other periods (i.e., before/after) (Figures 3A, 4A and Table S3), and it was the lowest in solid fuel homes than the other homes with clean energy for space heating (Figure 4A and Table S3).

Non-smoking and clean energy homes generated the least $PM_{2.5}$ during the heating season, with estimated indoor-generated $PM_{2.5}$ concentrations of 17 ± 23, 17 ± 16, and $13 \pm 14\,\mu g/m^3$ before, during, and after the lockdown, respectively (Figure 4B). From before the COVID-19 lockdown to after, indoor-generated $PM_{2.5}$ decreased by $11 \pm 22\,\mu g/m^3$ in solid fuel homes without smokers as outdoor temperature increased (Figure 2A), while it remained stable in clean energy homes and increased by $1 \pm 11\,\mu g/m^3$ in mixed fuel homes. These results supported our expectations that solid fuel combustion contributed substantially to indoor $PM_{2.5}$ and the contribution reduced as outdoor temperature increased, and that homes using clean energy should experience lower indoor $PM_{2.5}$ concentrations because solid fuel, as a source of indoor pollutant emissions, is removed from the homes.

Indoor-generated $PM_{2.5}$ tended to increase during the day (Figure 5). In smoking homes, the daily peaks of indoor-generated $PM_{2.5}$ concentrations (Evening: dinner time) did not change before, during, or after the COVID-19 lockdown (Table S4 and Figure 5). However, in non-smoking and solid fuel-using homes, indoor-generated $PM_{2.5}$ decreased during the lockdown period and right after, coinciding with seasonal reductions in solid fuel heating.

4 | DISCUSSION

In this study, we deployed indoor and community $PM_{2.5}$ monitoring sensors in 147 homes from 30 villages in rural Beijing from January to April, 2020. To our knowledge, this is the first large-scale study to investigate the influence of the COVID-19 lockdown on indoor and community air quality in homes with different energy use patterns. We did not find that the COVID-19 lockdown affected indoor $PM_{2.5}$, especially in homes using solid fuel or with smokers. This is likely because daily travel and behaviors in rural Beijing were not as impacted by the different COVID-19 restrictions as in urban areas.

Previous studies based on satellite data have observed large decreases in ambient $PM_{2.5}$ during the COVID-19 lockdown in cities around the world as the lockdown measures on social activities resulting in the cutoff of several air pollution emission sources, including industrial activities, construction activities, and road and air transport.[2,29] In our rural Beijing study, we observed higher community $PM_{2.5}$ during the COVID-19 lockdown, which is consistent with recent studies of air pollution in Beijing.[30-32] This trend was likely attributable to the meteorological conditions that were unfavorable for air quality during the lockdown, including a low planetary boundary layer, low wind speed, and high temperature and relative humidity.[31]

Indoor $PM_{2.5}$ did not change significantly during the COVID-19 lockdown after accounting for community $PM_{2.5}$, temperature, smoking, and other covariates. This is likely because the residents of our study homes were old people and the restrictions on movement and activity during the COVID-19 lockdown did not make huge changes

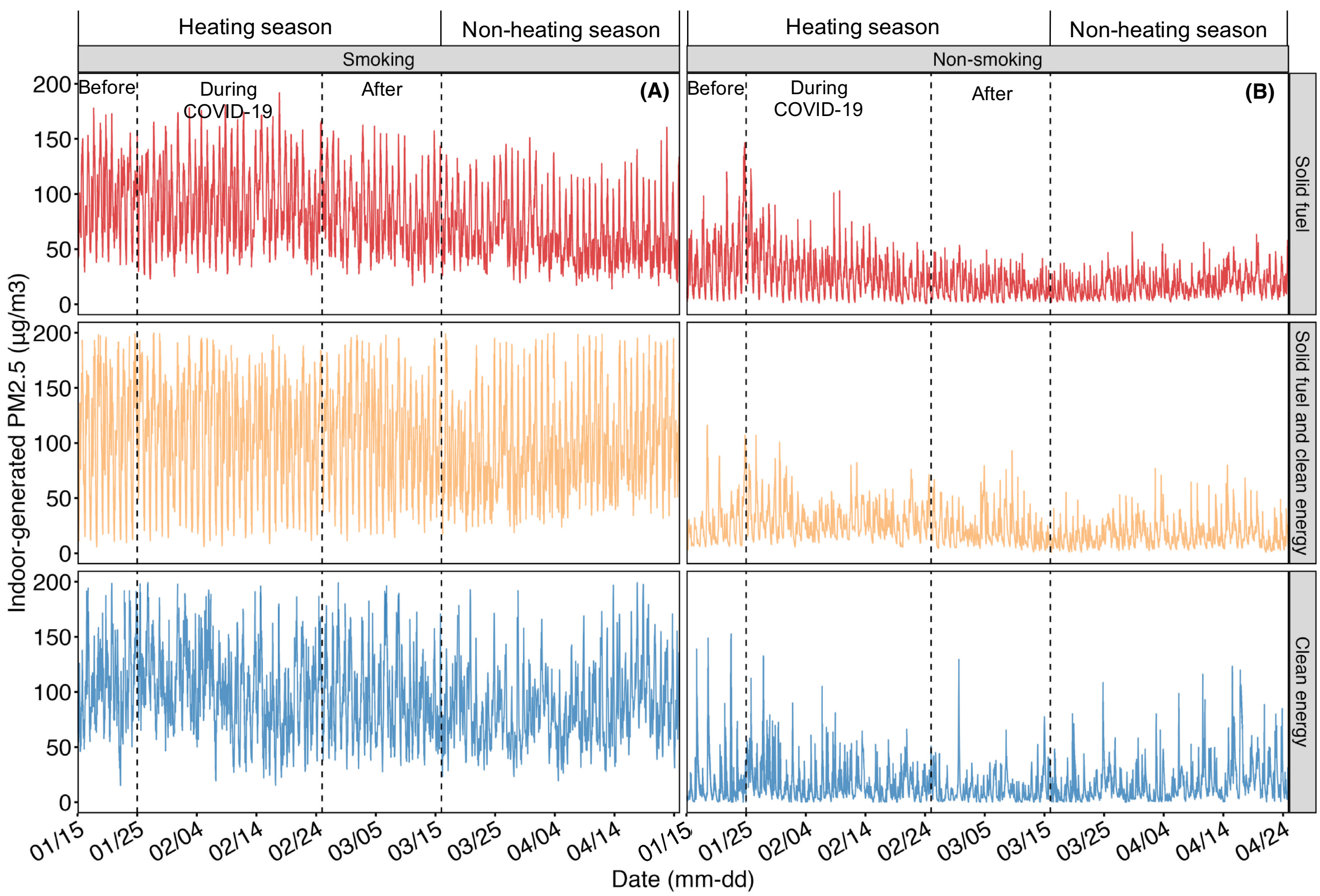


FIGURE 3 Time series of indoor-generated $PM_{2.5}$ in smoking (A) and non-smoking (B) households. “Before” indicates before COVID-19 lockdown, which is from January 15 to January 24, 2020. “During” indicates during COVID-19 lockdown, which is from January 25 to February 25, 2020. “After” indicates after COVID-19 lockdown, which is from February 26 to March 15, 2020.

FIGURE 4 Boxplots of indoor-generated $PM_{2.5}$ by household energy use patterns. Boxplots features are calculated as described for Figure 1. "Before" indicates before COVID-19 lockdown, which is from January 15 to January 24, 2020. "During" indicates during COVID-19 lockdown, which is from January 25 to February 25, 2020. "After" indicates after COVID-19 lockdown, which is from February 26 to March 15, 2020.

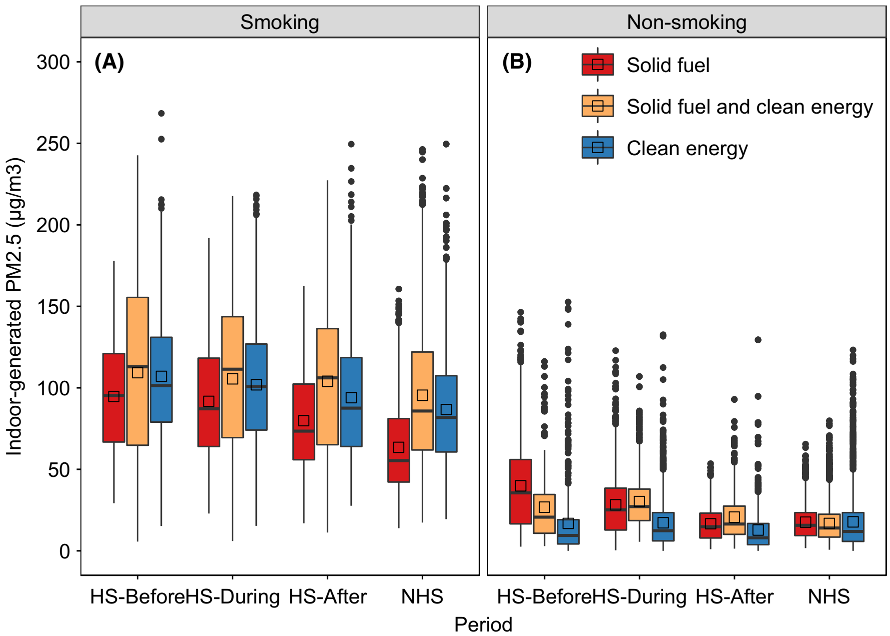
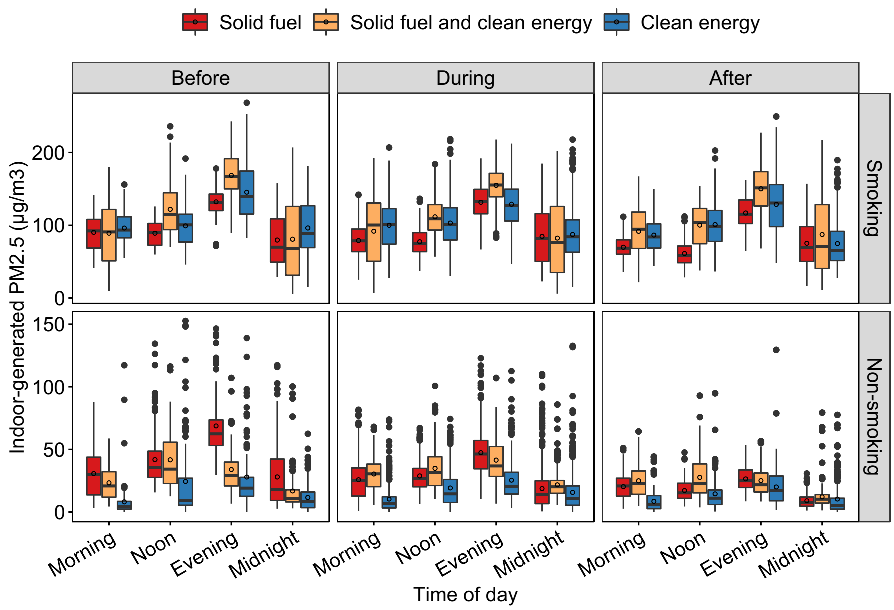


FIGURE 5 Diurnal variation of indoor-generated $PM_{2.5}$. Boxplots features are calculated as described for Figure 1. "Before" indicates before COVID-19 lockdown, which is from January 15 to January 24, 2020. "During" indicates during COVID-19 lockdown, which is from January 25 to February 25, 2020. "After" indicates after COVID-19 lockdown, which is from February 26 to March 15, 2020. "Morning" refers to 6 – 10 am; "Noon" refers to 11 am - 3 pm; "Evening" refers to 4 – 8 pm; and "Midnight" refers to 9 pm – 5 am on the next day.



on their lifestyles. Our finding conflicts with several previous studies in rural China that reported increased indoor $PM_{2.5}$ due to more fuel consumption for cooking and heating caused by larger family sizes during the lockdown than those during the normal days.[4,5]

To isolate the contributions of indoor versus outdoor sources to $PM_{2.5}$, we implemented a simple approach to estimate indoor-generated $PM_{2.5}$ concentrations, which is straightforward and easy to be applied in studies with real-time indoor and community $PM_{2.5}$ measurements. Across all energy use groups, we did not observe indoor-generated $PM_{2.5}$ increased significantly during the lockdown compared with before the lockdown. A likely explanation is that most of our participants are retired and usually stay at home during the winter. Thus, the COVID-19 lockdown did not have as large of an impact on their behaviors.

Indoor $PM_{2.5}$ did not differ by household energy use patterns regardless of smoking status, not consistent with what we known from other studies[33] and what we expected.[34] Indoor $PM_{2.5}$ and indoor-generated $PM_{2.5}$ in homes with smokers were much higher than in homes without smokers. Many other studies in rural China reported large contributions of cigarette smoking to indoor $PM_{2.5}$ and personal exposures.[22,35,36,37] A recent study in urban China also emphasized the significant contributions of indoor cigarette smoking to human exposures in residences, even in those without solid fuel combustion.[38] These authors found that besides cooking, smoking was the second important indoor source of $PM_{2.5}$ to the air people breathe in urban residences, especially when a residence was poorly ventilated, which was similar to what we reported for the contribution of smoking to indoor PM in this study. Our results further demonstrated the importance of accounting for smoking behaviors in studies of indoor air quality and personal exposures, especially those evaluating indoor air quality interventions like improved ventilation or household stoves.

In non-smoking households, total indoor $PM_{2.5}$, indoor $PM_{2.5}$ of outdoor origin, and indoor-generated $PM_{2.5}$ were all the lowest in clean energy homes in the heating season. These results indicate the contribution of indoor solid fuel combustion to indoor $PM_{2.5}$ and the potential to achieve better indoor air quality in clean energy homes in the heating season. Notably, we observed different impacts of the COVID-19 lockdown on indoor-generated $PM_{2.5}$ in households with different energy use patterns. Indoor $PM_{2.5}$ emissions are already decoupled from household energy use patterns in clean energy households, thus the indoor air quality impact of an external shock like the COVID-19 pandemic was minimal.

While many previous studies focused on the regional air quality impacts of the lockdown and other measures to control the COVID-19 pandemic, this study is the first to empirically evaluate indoor air quality before, during, and after the COVID-19 lockdown in homes with a range of energy use patterns. We conducted our study in rural Beijing, China, where our detailed indoor and community measurements and household survey data enabled us to gain more holistic insight on the variation of indoor $PM_{2.5}$. Importantly, our measurements included continuous indoor and community $PM_{2.5}$ concentrations in 30 villages over four months. These measurements constitute a major strength of our study, allowing us to understand the trends of indoor and community $PM_{2.5}$ across the Beijing region. As well, they afforded us the opportunity to estimate the relative contributions of indoor-generated $PM_{2.5}$, and indoor $PM_{2.5}$ of outdoor origin. As a result, we found that indoor air quality in rural Beijing households did not change during the COVID-19 lockdown, and household energy transition from solid fuels to clean energy could improve indoor air quality, especially in homes without smokers.

Our study does have several limitations to bear in mind. Our method for developing infiltration factors to differentiate between indoor versus outdoor sources of $PM_{2.5}$ measured indoors provides useful estimates; however, the method is imperfect as it can only identify the contributions of the bulk indoor and outdoor sources and cannot quantify the contributions of specific sources. As well, the F_{inf} is determined empirically, and therefore, may be larger than 1.0, due to the statistical and empirical nature of the method, even though that value would be physically inaccurate (i.e., it is not possible for the proportion of outdoor originated indoor $PM_{2.5}$ to be greater than 100% of outdoor $PM_{2.5}$). In this study, only two (nine in non-heating season) out of 138 (135) F_{inf} estimates (1.4% and 6.7% in the heating and non-heating seasons, respectively) were > 1.0, and overall, the distribution of F_{inf} estimates was in line with those in other studies in similar settings. In future studies, more intensive methods, such as tracer-based methods, could be applied to calculate the F_{inf} more accurately,[36,39] and applied in conjunction with information on $PM_{2.5}$ chemical composition to apportion source contributions of indoor and outdoor sources to indoor $PM_{2.5}$ more precisely. In this study, we classified household heating energy into three categories, which did not separate the categories of solid fuels and did not consider the impacts of cooking energy use patterns. These considerations could be incorporated into future studies, as both cooking and heating fuel use patterns together have an influence on indoor air quality.

5 | CONCLUSION

In early 2020, the COVID-19 broke out globally and reduced air pollution was observed in many cities in the world. This study monitored indoor and community air quality in rural settings with different household energy use patterns in Beijing and assessed the variation of indoor and community $PM_{2.5}$ under the influence of the COVID-19. Our results revealed that indoor $PM_{2.5}$ did not increase overall during the lockdown. After accounting for cigarette smoking, indoor air quality in homes using clean energy for heating was much better than those using solid fuel. Our study also indicated that indoor air quality may be unchanged if only outdoor air quality improved but indoor emission sources remained uncontrolled. Collectively, our findings support a broader recommendation to account for indoor cigarette smoking in indoor air quality intervention studies.

AUTHOR CONTRIBUTIONS

Xiaoying Li: Conceptualization (lead); investigation (lead); methodology (lead); writing – original draft (lead); formal analysis (lead); writing – review and editing (lead). **Jill Baumgartner**: Conceptualization (lead); methodology (supporting); Writing – review and editing (lead). **Sam Harper**: Conceptualization (lead); methodology (supporting); Writing – review and editing (lead). **Xiang Zhang**: Investigation (lead); software (supporting); writing – review and editing (equal). **Talia Sternbach**: investigation (lead); Software (supporting); writing – review and editing (equal). **Christopher Barrington-Leigh**: Conceptualization (supporting); review and editing (equal). **Collin Brehmer**: Software (supporting); writing – review and editing (equal). **Brian Robinson**: Conceptualization (supporting); review and editing (equal). **Guofeng Shen**: Conceptualization (supporting); review and editing (equal). **Yuanxun Zhang**: Conceptualization (supporting); review and editing (equal). **Shu Tao**: Conceptualization (lead); review and editing (equal). **Ellison Carter**: Conceptualization (lead); methodology (lead); Writing – original draft (supporting); Writing – review and editing (lead).

ACKNOWLEDGMENT

We thank our study participants and field staff, and we are very grateful for support from county-level and village-level leaders to carry out this study. This study was funded by Canadian Institutes of Health Research (CIHR) Project Grant (#148697 & #159477). Research described in this article was conducted under contract to the Health Effects Institute (HEI), an organization jointly funded by the United States Environmental Protection Agency (EPA) (Assistance Award No. R-82811201) and certain motor vehicle and engine manufacturers. The contents of this article do not necessarily

reflect the views of HEI, or its sponsors, nor do they necessarily reflect the views and policies of the EPA or motor vehicle and engine manufacturers.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

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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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Li X, Baumgartner J, Harper S, et al. Field measurements of indoor and community air quality in rural Beijing before, during, and after the COVID-19 lockdown. *Indoor Air*. 2022;32:e13095. doi: 10.1111/ina.13095