

Characterising personal, household, and community PM_{2.5} exposure in one urban and two rural communities in China

Ka Hung Chan^{1,2*†}, Xi Xia^{3,4*}, Cong Liu⁵, Haidong Kan⁵, Aiden Doherty^{2,6,7}, Steve Hung Lam Yim^{8,9,10}, Neil Wright¹, Christiana Kartsonaki^{1,11}, Xiaoming Yang¹, Rebecca Stevens¹, Xiaoyu Chang¹², Dianjianyi Sun^{13,14}, Canqing Yu^{13,14}, Jun Lv^{13,14}, Liming Li^{13,14}, Kin-Fai Ho^{4†}, Kin Bong Hubert Lam^{1‡}, Zhengming Chen^{1,11‡} on behalf of the China Kadoorie Biobank collaborative group[§]

- ¹ Clinical Trial Service Unit and Epidemiological Studies Unit, Nuffield Department of Population Health, University of Oxford, UK
- ² Oxford British Heart Foundation Centre of Research Excellence, University of Oxford, UK
- ³ School of Public Health, Shaanxi University of Chinese Medicine, China
- ⁴ The Jockey Club School of Public Health and Primary Care, The Chinese University of Hong Kong, Hong Kong SAR
- ⁵ School of Public Health, Key Lab of Public Health Safety of the ministry of Education and NHC Key Lab of Health Technology Assessment, Fudan University, China
- ⁶ Big Data Institute, Li Ka Shing Centre for Health Information and Discovery, University of Oxford, UK
- ⁷ National Institute of Health Research Oxford Biomedical Research Centre, Oxford University Hospitals NHS Foundation Trust, John Radcliffe Hospital, UK
- ⁸ Asian School of the Environment, Nanyang Technological University, Singapore
- ⁹ Lee Kong Chian School of Medicine, Nanyang Technological University, Singapore
- ¹⁰ Earth Observatory of Singapore, Nanyang Technological University, Singapore
- ¹¹ MRC Population Health Research Unit, Nuffield Department of Population Health, University of Oxford, UK
- ¹² NCDs Prevention and Control Department, Sichuan CDC, China
- ¹³ Department of Epidemiology and Biostatistics, School of Public Health, Peking University Health Science Center, China
- ¹⁴ Peking University Center for Public Health and Epidemic Preparedness and Response, China

*Joint-first authors; †corresponding authors; ‡senior authors; §full member list in text S1

Address for correspondence

Dr Ka Hung Chan, Clinical Trial Service Unit and Epidemiological Studies Unit, Nuffield Department of Population Health, University of Oxford; email: kahung.chan@ndph.ox.ac.uk;

Prof Kin-Fai Ho, JC School of Public Health and Primary Care, The Chinese University of Hong Kong; email: kfho@cuhk.edu.hk

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1 Abstract

2 **Background:** Cooking and heating in households contribute importantly to air pollution
3 exposure worldwide. However, there is insufficient investigation of measured fine
4 particulate matter (PM_{2.5}) exposure levels, variability, seasonality, and inter-spatial
5 dynamics associated with these behaviours.

6 **Methods:** We undertook parallel measurements of personal, household (kitchen and living
7 room), and community PM_{2.5} in summer (May-September 2017) and winter (November
8 2017-Janauary 2018) in ~480 participants from one urban and two rural communities in
9 China. These recorded ~61,000-81,000 person-hours of processed data per
10 microenvironment. Age- and sex-adjusted geometric means of PM_{2.5} were calculated by
11 key participant characteristics, overall and by season. Spearman correlation coefficients
12 between PM_{2.5} levels across different microenvironments were computed.

13 **Findings:** Overall, 25.1% reported use of solid fuel for both cooking and heating. Solid fuel
14 users had ~90% higher personal and kitchen 24-hour average PM_{2.5} exposure than clean
15 fuel users. Similarly, they also had a greater increase (~75% vs ~20%) in personal and
16 household PM_{2.5} from summer to winter, whereas community levels of PM_{2.5} were 2-3
17 times higher in winter regardless of fuel use. Compared with clean fuel users, solid fuel
18 users had markedly higher weighted annual average PM_{2.5} exposure at personal (77.8
19 [95% CI 71.1-85.2] vs ~40 µg/m³), kitchen (103.7 [91.5-117.6] vs ~50 µg/m³) and living
20 room (62.0 [57.1-67.4] vs ~40 µg/m³) microenvironments. There was a remarkable diurnal
21 variability in PM_{2.5} exposure among the participants, with 5-minute moving average 700-
22 1,200µg/m³ in typical meal times. Personal PM_{2.5} was moderately correlated with living
23 room (Spearman r: 0.64-0.66) and kitchen (0.52-0.59) levels, but only weakly correlated
24 with community levels, especially in summer (0.15-0.34) and among solid fuel users (0.11-
25 0.31).

26 **Conclusion:** Solid fuel use for cooking and heating was associated with substantially
27 higher personal and household PM_{2.5} exposure than clean fuel users. Household PM_{2.5}
28 appeared a better proxy of personal exposure than community PM_{2.5} in this setting.

29

30

1 1. Introduction

2 The growing population and energy demand from rapid urbanisation, coupled with
 3 continued reliance of fossil fuels, have aggravated the ambient air pollution in many low-
 4 and middle-income countries (LMICs). On the other hand, about 3 billion individuals are
 5 still relying on solid fuels (e.g. coal, wood) for cooking and heating, which can result in
 6 intensive household air pollution.^{1,2} Fine particulate matter (PM_{2.5}) from domestic use of
 7 solid fuels and ambient sources together constitute the top environmental risk factor of
 8 disease burden globally, estimated to account for more than 6 million premature deaths in
 9 2019.¹ Despite the global health significance,^{3,4} there remains substantial uncertainties in
 10 the exposure-disease relationships and thus disease burden estimation, as most existing
 11 epidemiological studies relied on exposure proxies, namely modelled ambient air pollution
 12 levels around residential addresses and self-reported fuel use for indoor or household air
 13 pollution exposure.^{3,5}

14 Until recently, directly measured air pollution exposure data are rarely available in large
 15 population-based epidemiological studies. Most measurement studies had relatively small
 16 sample sizes, assessed primarily kitchen PM_{2.5} levels, and were limited to one or a few
 17 rural communities, with limited repeated measurements across seasons.⁶⁻¹⁴ The largest
 18 relevant study to date (PURE-Air) collected 48-hour aggregated kitchen and personal
 19 PM_{2.5} data in ~2400 households and ~900 individuals, respectively, in rural areas from
 20 eight LMICs.⁶ They found substantial variability in kitchen and personal PM_{2.5} levels by
 21 cooking fuel types and across countries, with solid fuel users tend to show significantly
 22 higher exposure. However, the short measurement window, limited repeated seasonal
 23 measurements, and inadequate coverage of heating season exposure leave ambiguity to
 24 both within-week and seasonal exposure variability within and between individuals. There
 25 is also a need of time-resolved data and parallel assessment of not only personal and
 26 kitchen PM_{2.5} but also living room and ambient levels to better understand the spatial-

temporal dynamics of PM_{2.5} exposure. Data from urban areas will also offer additional insight into the urban-rural contrast in PM_{2.5} exposure patterns.

We report detailed analyses of questionnaire data on personal characteristics, fuel use, and time-resolved PM_{2.5} exposure data at personal, household, and community levels in ~480 participants from one urban and two rural areas in the China Kadoorie Biobank (CKB), repeatedly in the warm and cool seasons.¹⁵ The present report aims to i) examine both aggregated and time-resolved PM_{2.5} levels by fuel use and other key characteristics; and ii) clarify personal-household-community gradient of PM_{2.5} exposure.

2. Materials and Methods

2.1 Study design and sample

CKB is an ongoing prospective cohort study of ~512,000 adults aged 30-79 years recruited from ten diverse areas of China during 2004-2008.^{16,17} The CKB-Air study was nested within CKB, and details of the design, data collection procedures, data cleaning and processing, and participant characteristics have been published previously.¹⁵ Briefly, 488 participants (mean age 58 years, 72% women) were recruited from two rural (Gansu, Henan) and one urban (Suzhou) CKB study sites (**eFigure 1**), selected to capture a diverse range of fuel use patterns.¹⁸ The study involved repeated assessment of air pollution and time-activity in the warm (May–September 2017; hereafter referred to as ‘summer’) and cool (November 2017–January 2018; ‘winter’) seasons, with a household questionnaire on participant characteristics and usual fuel use patterns administered in winter. Subsequently, 451 individuals participated in the summer assessment, of whom 37 were not available in winter and were replaced by other eligible CKB participants in the same community. The participants included in the two seasons were similar in their socio-demographics and lifestyle characteristics documented in 2004-2008 during the baseline assessment.¹⁵

1 The study was approved by the Oxford University Tropical Research Ethics Committee,
2 Oxford, UK (Ref: 5109-17) and the institutional review board of Fuwai Hospital, Chinese
3 Academy of Medical Sciences, Beijing, China (Ref: 2018-1038). All participants provided
4 written informed consent upon recruitment.

5 *2.2 Questionnaire data*

6 Trained health workers administered a laptop-based household questionnaire in the cool
7 season, to assess personal characteristics (age, sex, household income, occupation,
8 smoking, environmental tobacco smoke exposure) and exposure to household air pollution
9 (cooking and heating patterns and all fuel types used) (**Text S2**). For those who reported
10 different cooking patterns or fuel use in summer, additional questions on exposure during
11 summer were asked. While many previous studies focused on a single primary cooking or
12 heating fuels, we attempted to capture the increasingly recognised ‘fuel stacking’
13 phenomenon by assessing all fuel types used.¹⁸ Cooking fuel combinations were derived
14 based on all fuel types reported to be ‘used in most meals’ or ‘sometimes’. A similar
15 approach was undertaken to derive ‘heating fuel combination’ based on the duration of
16 heating fuel use during winter. Clean fuels include gas, electricity, solar, and city-wide
17 district heating (for heating only); solid fuels include coal (smoky/smokeless), coal
18 briquette, charcoal, wood, and crop residue. The electronic questionnaire have built-in
19 error and logic checks to minimise missing data and human errors.

20 *2.3 Air pollution data*

21 *2.3.1 Air pollution monitors*

22 The study involved ~120 consecutive hours of measurements (at 1-minute resolution) of
23 fine particulate matter (PM_{2.5}; µg/m³) levels, temperature, and relative humidity (%) in three
24 different microenvironments (personal, kitchen, and living room) for each participant, both
25 in summer and winter except for those who only participated in one season (n=74). The

1 measurements were taken using PATS (Particle and Temperature Sensor; Berkeley Air
2 Monitoring Group, CA, USA), an internationally validated low-cost nephelometer-based
3 device (R^2 range: 0.90-0.99 with reference to both with well-established time-resolved
4 instruments [e.g. TSI DustTrak] and gravimetric measurements) developed for high
5 household air pollution settings ($PM_{2.5}$ detection range: 10-30,000 $\mu g/m^3$).¹⁹ At each study
6 site, community air pollution (PM_1 , $PM_{2.5}$, PM_{10} , carbon monoxide, ozone, and nitrogen
7 oxides) was measured on the roof top of a building in a central location away from any
8 proximal sources of pollution, using two tailor-made research instruments (NAS-AF100;
9 Sapiens Environmental Technology, Hong Kong, China).

10 Details of quality control and device calibration have been described previously.¹⁵ In brief,
11 all devices were factory-calibrated against wood smoke by the manufacturers, and further
12 calibrated using filter-based personal and static samplers for PM measurements.

13 Randomly selected PATS (n=15) were also tested for consistency through co-location
14 comparison tests in controlled settings for 24 hours, with good agreement demonstrated
15 (correlation coefficients: 0.85-0.99). Before and after each deployment, the PATS devices
16 were calibrated against HEPA-filtered air for 10 minutes, following the manufacturer's
17 standardised procedures.

18 *2.3.2 Data cleaning and processing*

19 Participants with corrupted data files due to human or device error were excluded from the
20 $PM_{2.5}$ analyses (**eFigure 2**). Twenty-nine and 115 participants in the warm and cool
21 seasons, respectively, had no community air pollution data from NAS-F100 due to delays
22 in deployment or other logistical challenges (**eFigure 2**). The time-resolved $PM_{2.5}$ data
23 from each PATS were then inspected and processed by i) downsizing to 5-minute moving
24 averages time-series to facilitate computation, ii) applying 20-minute moving median
25 smoothing to replace sporadic extreme spikes, and iii) adjusting data points at persistently
26 high or low (i.e. at the lower limit of detection of 10 $\mu g/m^3$) levels by cross-device

1 calibration. Specifically, potentially erroneous data from one device were replaced by
2 imputed data based on levels recorded in the other devices using generalised linear
3 regression. The persistently high levels were likely caused by particles lodged inside the
4 nephelometer or sustained direct light impact; whereas the persistently low levels, most of
5 which were found in the personal PATS data during winter, are likely due to an obstructed
6 air inlet (e.g. covered by clothing) or that the PATS was placed inside an enclosed
7 environment (e.g. in a drawer when participants took it off during bathing or sleep).
8 Overall, only <5% of the PM_{2.5} data recorded were flagged as persistently high or low,
9 indicating generally high data quality (**eTable 1**).

10 We first removed data from the first and last hour of the measurement period when
11 participants' exposure was likely affected by the study procedures. We then removed
12 participants with <24 hours of effective data, which could happen due to battery failure.
13 Subsequently, each of the remaining participants had at least 24 hours' worth of data per
14 PATS per season (median_{summer} [Q1-Q3]: 117 [105-119] hours, median_{winter} [Q1-Q3]: 113
15 [94-117] hours) (**eTable 2**). To further enhance the quality of the analytical dataset, we
16 undertook a conservative approach to remove participants (n=36) with >50% data flagged
17 as persistently high or low in any one PATS (regardless of the quality of the other two
18 device), thereby restricting the analyses to participants with data of satisfactory quality
19 across all three PATSs (n_{summer}=419 [92.7%]; n_{winter}=365 [81.1%]). Thirty-five participants
20 in summer who did not provide household questionnaire data were further excluded.

21 The numbers of participants excluded at each stage of data analysis are shown in **eFigure**
22 **2**. After data cleaning, the primary analyses on PM_{2.5} included 384 participants, with a total
23 of 80,980 person-hours of PM_{2.5} data each at the personal, kitchen, and living room, and
24 67,326 person-hours of data at the community level (**eTable 2**).

25 2.4 Data analysis

1 Using linear regression, we estimated age- and sex-adjusted (where appropriate)
 2 geometric means and 95% confidence intervals (CI) of personal and household (kitchen
 3 and living room) PM_{2.5} concentrations levels, by demographic characteristics (age, sex,
 4 study area, education, occupation, smoking, household size) and household air pollution-
 5 related exposures (cooking frequency, self-reported 'smoky home' while cooking or
 6 heating, and cooking and heating fuel combinations), stratified by season. We also
 7 averaged the time-resolved data to produce season-specific 24-hour PM_{2.5} time-series at
 8 personal, household, and community levels, according to different cooking and heating
 9 fuel combinations.

10 We obtained regional temperature data during 2005-2017 (corresponding to the follow-up
 11 period of the CKB cohort up till the commencement of CKB-Air) from local meteorological
 12 offices and calculated the proportion of months with an average temperature <10°C in
 13 each region (0.25 for Suzhou, 0.42 for Gansu, 0.33 for Henan), which was used as a
 14 weighting coefficient to approximate heating fuel usage. We then estimated
 15 microenvironment-specific annual PM_{2.5} exposure levels as a weighted average of
 16 exposure levels across summer and winter, by cooking and heating fuel combinations:
 17 $annual\ average_{ij} = w_{ij} * (1 - p_k) + c_{ij} * p_k$, where w_{ij} is the summer average and c_{ij} the
 18 winter average for microenvironment i (personal, kitchen, living room, or community)
 19 among participants in category j of cooking and heating fuel combination (no cooking or
 20 heating, clean fuels only, any solid fuels), and p_k is a region-specific weighting coefficient
 21 of heating fuel usage described above.

22 As a preliminary investigation to understand the relationships between PM_{2.5} levels across
 23 microenvironments and by season, we have examined the season-specific Spearman
 24 correlation of log-transformed PM_{2.5} levels across the four microenvironments overall and
 25 by cooking and heating fuel combinations.

1 *Role of the funding source*

2 The study funders had no role in study design, data collection, analysis, interpretation, or
3 writing of the report. KHC, XX, KH, KBHL, and ZC had access to all data and had final
4 responsibility for the decision to submit for publication.

5 **3. Results**

6 *3.1 Basic characteristics and PM_{2.5} levels*

7 Of the 384 participants included in the main analyses, the mean age was 58.2 [SD 6.6]
8 years, 74.7% were women, and 32.0% and 52.2% used solid fuels for cooking and
9 heating, respectively. In particular, those who used solid fuels for cooking were more likely
10 to be women, from rural areas, less educated, agricultural workers or home-makers, and
11 to use solid fuel for heating (**eTable 3**). Moreover, substantially more solid fuel users
12 reported observing a smoky home while cooking or heating compared to clean fuel users.

13 Overall, levels of exposure to PM_{2.5} were generally higher in younger (<65 years)
14 participants, women, and those with lower education, with markedly higher levels in winter
15 than in summer (**Table 1**). Agricultural workers, active smokers, and participants who
16 reported a smoky home while cooking had particularly high PM_{2.5} exposure, most notably
17 at personal and kitchen levels, both in summer and winter. For example, average kitchen
18 PM_{2.5} in summer for those observing smoky home while cooking was 53.7 [95% CI 49.7-
19 58.0] compared to 40.9 [38.5-43.5] for those without such observation, and in winter 119.5
20 [107.7-132.5] µg/m³ compared to 61.8 [56.6-67.6] µg/m³. Participants who reported smoky
21 home while heating had somewhat lower personal and living room PM_{2.5} levels in summer,
22 but significantly higher personal (82.0 [74.9-89.7] vs 55.3 [51.2-59.8] µg/m³), kitchen
23 (127.9 [114.8-142.4] vs 72.6 [66.2-79.6] µg/m³), and living room (72.5 [66.4-79.2] vs 54.2
24 [50.2-58.4] µg/m³) levels in winter. There was no clear pattern by household size.

25 *3.2 PM_{2.5} levels by fuel use patterns*

1 Compared across primary cooking and heating fuel combinations, solid fuel users had
2 ~90% higher personal and kitchen PM_{2.5} levels than those who used clean fuels or did not
3 cook or heat (**Figure 1A**). Personal and household PM_{2.5} levels were significantly (~75%)
4 higher in winter among solid fuel users, but less so for other participants (~20%), whilst
5 community levels were 2-3 times higher across different fuel combinations. Broadly similar
6 patterns were observed when examining cooking and heating fuel combinations separately
7 (**Figures 1B and 1C**), but there was a more obvious gradient of exposure at personal and
8 kitchen levels across cooking fuel combinations (as opposed to heating fuel), from the
9 lowest in non-cooking households (winter: ~50 µg/m³) to the highest in solid fuel users
10 (~115µg/m³). A sensitivity analysis restricted to participants who personally cooked
11 regularly showed similar patterns (**eFigure 3**). Consistently, participants who had used
12 solid fuels for cooking or heating had the highest weighted average annual PM_{2.5} exposure
13 at the personal (77.8 [71.1-85.2] µg/m³; ~90% higher), kitchen (103.7 [91.5-117.6] µg/m³;
14 ~130% higher), and living room (62.0 [57.1-67.4] µg/m³; ~65% higher) levels, compared to
15 those who reported using clean fuels or not cooking or heating (**Table 2**). There was no
16 material difference in annual community PM_{2.5} levels by these groups. Similar patterns
17 were observed when examining by cooking and heating fuel combinations separately.

18 When examining the aggregated diurnal PM_{2.5} patterns by cooking fuel combinations, we
19 observed major peaks at around noon and evening time for both solid fuel and clean fuel
20 users (less so for non-cooking households), and these peaks were substantially higher in
21 solid fuel users, up to ~600 and ~1200µg/m³ in summer and winter, respectively (**Figure**
22 **2A-C**). A small morning peak (~08:00) was also found in the kitchen in winter (**Figure 2B**).
23 Interestingly, personal, kitchen, and living room PM_{2.5} levels were considerably higher
24 most of the time among clean fuel users than non-cooking households. Solid fuel users
25 appeared to have the lowest community PM_{2.5} exposure in summer, but highest in winter,
26 with broadly concordant diurnal variations for all three fuel use categories (**Figure 2D**).

1 The differences in diurnal exposure levels by heating fuel combinations were largely
2 similar to those by cooking fuels in summer, but in winter the exposure levels in individuals
3 who did not have heating were just slightly lower than the solid fuel users but much higher
4 than clean fuel users (**Figure 3**).

5 *3.3 PM_{2.5} exposure models and inter-spatial correlation*

6 We found moderate correlation between measured PM_{2.5} at personal, living room (r: 0.64-
7 0.66), and kitchen (0.52-0.59) levels, whilst the correlation of personal and household
8 levels with community levels was weaker, especially in summer (r_{range_summer}: 0.15-0.34;
9 r_{range_winter}: 0.41-0.55) (**Figure 4**). Stratified by cooking and heating fuel combinations, we
10 found the highest correlation of personal and household with community levels among
11 those reporting no cooking or heating (r_{range_summer}: 0.52-0.65; r_{range_winter}: 0.55-0.62), and
12 weakest among those who used solid fuels (r_{range_summer}: 0.11-0.31; r_{range_winter}: 0.29-0.52)
13 (**eFigures 4A-C**).

14 **4. Discussion**

15 We reported integrated and time-resolved PM_{2.5} levels at personal, household (kitchen and
16 living room), and community environments by cooking and heating fuel combinations and
17 other key characteristics in ~360 adults from one urban and two rural areas of China. Solid
18 fuel use for cooking and heating was associated with significantly higher estimated annual
19 PM_{2.5} exposure at both personal and household levels, with personal PM_{2.5} exposure at ~3
20 times and 5 times the World Health Organization 24-hour Air Quality Guidelines (WHO
21 AQG) level (15µg/m³) in summer and winter, respectively, and an estimated annual
22 personal exposure at over 15 times of the WHO annual AQG level (5µg/m³)²⁰. The PM_{2.5}
23 levels across all microenvironments were higher in winter than summer, with ~2-3 times
24 higher community levels regardless of fuel use. Time-resolved data showed vast inter- and
25 intra-personal variability in PM_{2.5} exposure within and across seasons, with remarkably

1 high exposure (5-min moving-average up to $1200\mu\text{g}/\text{m}^3$) recorded in typical cooking times
2 (~2-4 hours per day), most notably in the kitchen but also personal monitors among solid
3 fuel users.

4 Previous studies assessing exposures to air pollution were highly heterogeneous in
5 settings, sample size, prevalent fuel types, and recorded $\text{PM}_{2.5}$ levels,⁶⁻¹⁴ but there has
6 been broadly consistent evidence that solid fuel use for cooking was associated with
7 higher personal and kitchen $\text{PM}_{2.5}$ levels as reported in our study. For logistical and
8 technical reasons, most previous studies primarily measured kitchen $\text{PM}_{2.5}$,^{6-14,21} while
9 some had parallel measurements of personal^{6,7,14} or ambient^{10,14,21} exposure, with most
10 personal measurements done in a subset of participants. Notably, the largest single
11 sample (n=998; ~48,000 person-hours) of personal $\text{PM}_{2.5}$ measurements (alongside
12 kitchen measurements in 2,541 households) came from the PURE-Air study focussing on
13 cooking fuel in rural areas across eight countries.⁶ With 48-hour integrated $\text{PM}_{2.5}$
14 measurements, they found lower $\text{PM}_{2.5}$ levels by cooking fuel types moving up the
15 traditional 'energy ladder' (i.e. from heavily polluting biomass to coal, then to gas and
16 electricity),²² but they also found substantial heterogeneity within each solid fuel category
17 and between countries (e.g. kitchen $\text{PM}_{2.5}$ for primary wood use was 50 [45-55] $\mu\text{g}/\text{m}^3$ in
18 China and 105 [96-116] $\mu\text{g}/\text{m}^3$ in India), possibly due to varying fuel use behaviour or
19 infrastructure, chemical constituents of fuels, and different climate conditions. With the
20 parallel and repeated time-resolved assessment of personal, kitchen, living room (~81,000
21 person-hours for each measure), and community (~67,000 person-hours) level $\text{PM}_{2.5}$ in
22 summer and winter, we provided further insight into the complex relationships between
23 fuel use behaviour and $\text{PM}_{2.5}$ levels across the personal-household-community exposure
24 spectrum.

25 Consistent with the few existing studies that ascertained multiple fuel use,^{6,10,14} we showed
26 that fuel stacking was common in rural China, and mixed use of solid and clean fuels was

1 associated with substantially elevated PM_{2.5} exposure, especially in winter. As fuel
2 stacking is increasingly common in many developing economies, this highlights the
3 importance of capturing usage information beyond a single, primary fuel type, in order to
4 more accurately assess household air pollution exposure and the associated disease
5 burden. On the other hand, until recently, both researchers and policymakers have largely
6 overlooked heating as a major contributor of air pollution.^{18,23-25} Our findings add to the
7 previous field measurement studies,²⁶⁻²⁸ showing solid fuels for heating to be associated
8 with 76-125% higher PM_{2.5} exposure at personal and household levels in winter. It may
9 seem counterintuitive to observe a higher level in the kitchen than in the living room, but
10 previous studies have noted poorer ventilation in winter and that solid fuel users may stay
11 in the kitchen longer to get warmth from the cookstove to save fuel.²² In line with a slower
12 rate of modernisation of heating (versus cooking) fuel in China (as in many other
13 LMICs),^{18,24} about 50% of CKB-Air participants who had used clean fuels for cooking still
14 relied on solid fuels for heating. Adding to the complexity, the lack of heating in rural China
15 was associated with a lower socioeconomic status and greater likelihood of using solid
16 fuels for cooking compared to clean fuel users.¹⁸ This, together with the likely reduced
17 ventilation (to keep warm) in winter time, may explain the considerably (~30%) higher
18 personal and household PM_{2.5} levels (in both seasons) among our participants who
19 reported 'no heating', compared with the clean heating fuel users.

20 While the community PM_{2.5} level was markedly higher in winter regardless of fuel use
21 categories, there was an interesting contrast that solid fuel users had the lowest
22 community PM_{2.5} in summer, but the highest in winter. The 'winter smog' phenomenon in
23 densely populated (often urban) areas of China is well-documented, as increased energy
24 consumption, reliance on coal-fired power plants, and meteorological factors (e.g.
25 temperature inversion) drive heightened regional ambient air pollution.²⁹ On the other
26 hand, most solid fuel users resided in rural areas with lower population and vehicle

density, which tend to be associated with lower ambient air pollution. In winter, however, the intensive use of solid fuels for heating (most participants reported heating throughout the day) could result in major rise of neighbourhood PM_{2.5} in addition to regional ambient air pollution, as supported by previous studies.^{14,30} It is also worth noting that the increase in personal and household levels was much higher in solid fuel users than in other participants, whose personal and household levels were less than 50% of the community levels.

As in many previous studies^{14,21} we observed relatively weak correlation between personal and community PM_{2.5} levels, which poses challenges to the previous disease burden estimates for ambient air pollution in LMICs based mainly on epidemiological studies using modelled ambient levels without accounting for inter-spatial variability and people's time spent indoors (typically 70-80%).³¹ This may be less problematic in HICs with relatively low exposure from non-ambient sources, although the re-emergence of wood-fire heating may raise concern.³² The relatively strong correlation (0.52-0.66) between personal and household measurements is consistent with previous evidence (e.g. PURE-Air: person-to-kitchen correlation = 0.69). Our evidence adds further support for more granular household measurements along with housing characteristics questionnaires, simple personal GPS trackers, and advanced ambient air pollution modelling approaches^{33,34} to better approximate personal exposure in large-scale epidemiological studies. More in-depth modelling analysis on our data will generate further insight for better exposure approximation in future studies.

Our time-resolved data also illustrated the remarkable short-term intra- and inter-personal variability in PM_{2.5} exposure even within each fuel use category. The diurnal patterns of kitchen PM_{2.5} appeared consistent with the previously reported time-activity patterns in CKB-Air,¹⁵ such as the exposure peaks (averaged twice in summer; 3 times in winter) at typical meal times. Furthermore, we observed stronger and longer-lasting evening peaks

1 of personal and household levels among individuals who used solid fuels in winter, which
2 is consistent with typical space heating practices with reduced ventilation at night. The vast
3 diurnal variations, with personal PM_{2.5} exposure as high as 400µg/m³ and as low as
4 10µg/m³, lead to the question of whether and how long-term average exposure could
5 compare to an accumulation of repeated bursts of extreme exposure in relation to disease
6 development risk.³⁵ The mystery might be solved by the increasing availability of more
7 refined air pollution data, the use of chamber studies, and the emerging multi-omics
8 technologies that facilitate a better understanding of the toxicology and pathophysiology.

9 CKB-Air offers one of the most detailed parallel and repeated seasonal assessments of
10 personal, household, and community level PM_{2.5} with one of the largest time-resolved
11 datasets (up to ~80,000 person-hours per microenvironment). Moreover, we assessed not
12 only the role of parallel fuel use for cooking but also for heating on both average and time-
13 resolved PM_{2.5} exposure, shedding light on the complexity of fuel use behaviour and PM_{2.5}
14 exposure. However, several limitations warrant discussion. First, despite the relatively
15 large amount of data captured, the number of participants representing each fuel use
16 combination beyond the aggregated categories on solid versus clean fuels was small.
17 Also, the large inter-and intra-personal variability means that we could not reliably estimate
18 PM_{2.5} levels by >10 different fuel combinations captured. Second, unlike some previous
19 studies that used gold-standard gravimetric samplers in measuring integrated PM_{2.5}
20 exposure,⁶ we used a nephelometer in order to obtain detailed time-resolved data. Despite
21 the field- and lab-based validation and calibration, our instruments inevitably entailed
22 measurement error, but this should not result in major biases that would affect the
23 applicability in epidemiological studies. Third, we assessed community PM_{2.5} at a single
24 location, and we lacked pairwise data of street and regional levels. Fourth, the study
25 sample was recruited via convenient sampling from three purposively selected areas in

1 China, so the estimated exposure levels would not be generalisable to China or other
2 populations.

3 **5. Conclusions**

4 This study has demonstrated the feasibility and value of collecting detailed air pollution
5 exposure measurement data to capture intra- and inter-personal variations over short
6 (weekly) and medium (seasonal) term, in rural and urban China. Most notably, the
7 individuals who used solid fuels for cooking or heating were found to have annual personal
8 PM_{2.5} exposure over 15 times higher than the latest WHO AQG. The relatively weak
9 correlation of personal with community PM_{2.5}, in contrast to the stronger correlation
10 between personal and household levels, supports the use of reliable, low-cost household
11 static monitors in improving personal air pollution exposure assessment in large-scale
12 epidemiological studies. Our findings underscores the complexity of air pollution exposure
13 and the need for cross-disciplinary investigation involving exposure science, toxicology,
14 epidemiology and statistics.

15

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1 **Figure Legend**

2 **Figure 1. Age- and sex-adjusted geometric mean PM_{2.5} concentrations (µg/m³)** 3 **recorded in the personal, kitchen, living room, and community monitors by season** 4 **and the combination of primary cooking and heating fuels**

5 Each vertical bar represents adjusted geometric means of each microenvironment by
6 exposure groups, with vertical black lines showing the corresponding 95% confidence
7 intervals (CIs). Non-overlapping CIs between bars indicate statistically significant
8 difference. From left to right the four bars in each group are personal, kitchen, living room,
9 and community PM_{2.5} levels. Participants reporting using unspecified “other” fuels for
10 heating were excluded due to small sample size (N_{summer} = 1; N_{winter} = 2).

11 **Figure 2. 24-hour average time-series plots for PM_{2.5} concentrations (µg/m³)** 12 **recorded in the personal, kitchen, living room, and community monitors by season** 13 **and primary cooking fuel combinations**

14 There were 123 (13761 person-hour), 167 (18663 person-hour) and 94 (10607 person-
15 hour) subjects for the “Solid fuels included”, “Clean fuels” and “No cooking” group in
16 summer, respectively; There were 126 (13174 person-hour), 173 (17956 person-hour) and
17 65 (6819 person-hour) subjects for the “Solid fuels included”, “Clean fuels” and “No
18 cooking” group in winter, respectively. Smaller plots nested within panels are “zoom-in”
19 version of the corresponding plot, as the use of a universal y-axis limit up to 1200 with
20 reference to the kitchen exposure levels impaired the readability of those plots.

21 **Figure 3. 24-hour average time-series plots for PM_{2.5} concentrations (µg/m³)** 22 **recorded in the personal, kitchen, living room, and community monitors by season** 23 **and primary heating fuel combinations**

24 There were 200 (22539 person-hours), 47 (5226 person-hours) and 136 (15147 person-
25 hours) subjects for the “Solid fuels included”, “Clean only” and “No heating” group in

1 summer, respectively; There were 207 (21772 person-hours), 43 (4261 person-hours) and
 2 112 (11701 person-hours) subjects for the “Solid fuels included”, “Clean only” and “No
 3 heating” group in winter, respectively. Smaller plots nested within panels are “zoom-in”
 4 version of the corresponding plot, as the use of a universal y-axis limit up to 1200 with
 5 reference to the kitchen exposure levels impaired the readability of those plots.

6 **Figure 4. The correlation matrix between the log-transformed concentrations of**
 7 **PM_{2.5} at personal, kitchen, living room and community levels**

8 Red area under curves and dots are summer data; blue area under curves and dots are
 9 winter data; black numbers in boxes are overall Spearman correlation coefficient; red and
 10 blue numbers are summer- and winter-specific correlation.

Table 1. Age- and sex-adjusted geometric mean (95% CI) PM_{2.5} concentrations (µg/m³) recorded in the personal, kitchen, and living room monitors by season and key characteristics.

Characteristics	Summer				Winter			
	N*	Personal	Kitchen	Living room	N*	Personal	Kitchen	Living room
Personal characteristics								
Age[†]								
< 65 years	323	42.0 (40.2-43.9)	43.9 (41.8-46.2)	33.5 (32.1-34.9)	305	59.5 (56.2-63.1)	82.8 (77.2-88.8)	56.1 (52.9-59.4)
≥ 65 years	61	33.5 (30.7-36.5)	43.0 (39.0-47.5)	31.9 (29.4-34.6)	59	48.9 (43.6-54.9)	62.9 (54.7-72.2)	49.2 (43.9-55.1)
Sex[‡]								
Female	287	40.9 (39.3-42.6)	44.4 (42.4-46.5)	32.7 (31.4-33.9)	267	66.1 (62.6-69.8)	87.6 (82.1-93.5)	61.1 (57.9-64.5)
Male	97	39.8 (37.2-42.7)	43.3 (40.1-46.9)	33.7 (31.6-36.0)	97	50.2 (45.8-55.0)	72.0 (64.5-80.4)	49.4 (45.1-54.1)
Education								
No formal education	97	48.9 (45.1-53.1)	52.3 (47.6-57.5)	38.2 (35.3-41.3)	92	75.8 (67.9-84.7)	112.6 (98.7-128.5)	70.2 (62.9-78.3)
Primary & middle school	133	38.8 (36.5-41.4)	42.8 (39.8-46.0)	30.4 (28.7-32.3)	125	58.5 (53.8-63.5)	84.0 (76.1-92.8)	58.4 (53.8-63.4)
High school or above	154	38.4 (36.3-40.7)	41.6 (39.0-44.4)	33.3 (31.5-35.1)	147	50.9 (47.1-55.0)	66.0 (60.2-72.4)	47.4 (44.0-51.2)
Occupation								
Agricultural worker	140	53.2 (50.3-56.3)	59.9 (56.2-63.9)	38.0 (36.0-40.2)	138	74.6 (69.2-80.4)	120.0 (109.6-131.3)	69.0 (63.9-74.4)
Factory worker	20	34.4 (29.7-39.9)	39.1 (33.0-46.2)	31.7 (27.4-36.6)	18	59.0 (47.9-72.7)	59.2 (46.0-76.1)	36.9 (29.9-45.5)
Home-maker	106	40.1 (37.3-43.2)	43.2 (39.7-47.0)	32.9 (30.6-35.4)	109	68.6 (62.3-75.5)	88.4 (78.8-99.2)	65.3 (59.3-72.0)
Non-manual labour	9	33.4 (27.0-41.4)	29.0 (22.7-37.0)	26.2 (21.2-32.4)	10	62.0 (47.1-81.8)	46.0 (33.0-64.2)	45.2 (34.2-59.7)
Self/ un-employed or other	109	29.1 (27.2-31.1)	30.7 (28.4-33.1)	28.5 (26.7-30.5)	89	31.6 (28.7-34.8)	43.7 (39.0-49.1)	37.4 (33.9-41.2)
Smoking now								
No	328	38.6 (36.5-40.8)	44.7 (42.0-47.6)	29.2 (27.7-30.8)	303	52.1 (48.2-56.3)	75.0 (68.3-82.3)	49.1 (45.5-53.0)
Yes	56	45.1 (40.7-50.1)	41.9 (37.2-47.2)	45.6 (41.3-50.3)	61	71.9 (62.7-82.4)	90.2 (76.5-106.3)	70.5 (61.6-80.7)
Household air pollution-related factors								
Household size								
≤ 4 persons	196	39.6 (37.7-41.7)	42.6 (40.2-45.2)	34.2 (32.6-35.9)	190	55.5 (51.8-59.5)	78.9 (72.6-85.8)	55.9 (52.2-59.9)
> 4 persons	188	41.2 (39.0-43.5)	45.3 (42.6-48.1)	32.0 (30.5-33.7)	174	60.0 (55.8-64.5)	79.9 (73.3-87.2)	53.8 (50.1-57.8)
Cooking frequency								
Daily	301	41.4 (39.1-43.8)	43.7 (41.0-46.6)	34.4 (32.7-36.3)	280	59.1 (54.6-64.0)	82.4 (74.9-90.6)	55.3 (51.1-59.8)
Daily but not personal/ infrequent	83	38.6 (35.7-41.8)	44.2 (40.3-48.3)	31.1 (28.8-33.5)	84	55.2 (49.5-61.5)	74.9 (65.7-85.3)	54.4 (48.8-60.6)
Smoky home while cooking								
No	222	37.2 (35.2-39.2)	40.9 (38.5-43.5)	32.4 (30.8-34.1)	196	45.7 (42.4-49.1)	61.8 (56.6-67.6)	46.8 (43.4-50.3)
Yes	120	46.1 (43.0-49.3)	53.7 (49.7-58.0)	35.1 (32.9-37.4)	127	74.9 (68.7-81.6)	119.5 (107.7-132.5)	67.7 (62.1-73.8)
Smoky home while heating								
No	163	44.3 (41.8-47.0)	44.1 (41.3-47.2)	34.0 (32.1-35.9)	151	55.3 (51.2-59.8)	72.6 (66.2-79.6)	54.2 (50.2-58.4)
Yes	85	39.9 (36.8-43.1)	51.4 (46.9-56.4)	29.5 (27.4-31.8)	101	82.0 (74.9-89.7)	127.9 (114.8-142.4)	72.5 (66.4-79.2)

1 * Number of subjects. † Only adjusted for sex. ‡ Only adjusted for age.

2

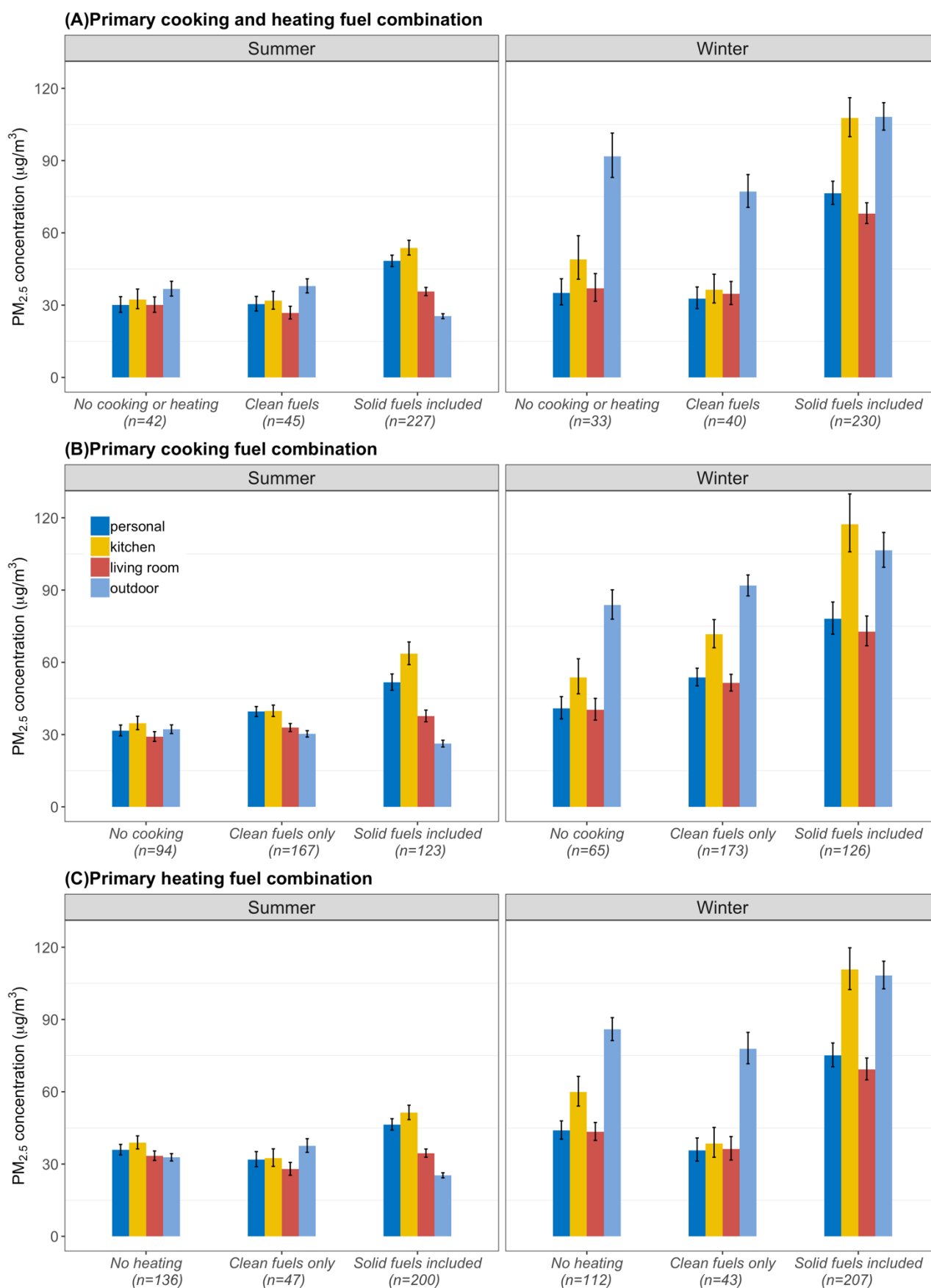
3

Table 2. Age- and sex-adjusted estimated annual mean PM_{2.5} exposure levels (µg/m³) for the personal, kitchen, living room, and community environments by cooking and heating fuel category *

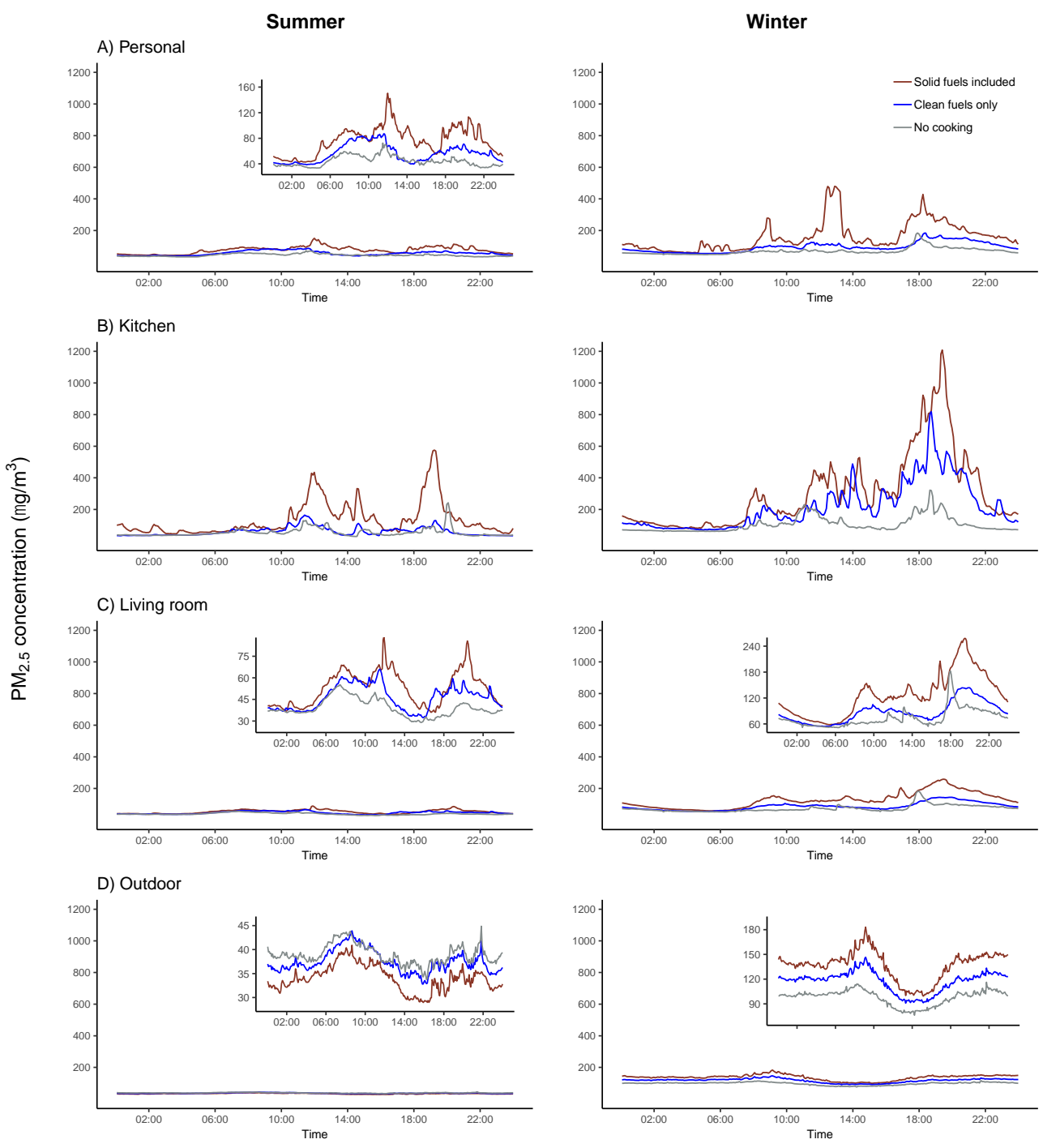
Cooking and heating fuel category	Personal	Kitchen	Living room	Community
Primary cooking fuel combination				
No cooking (n=71)	45.2 (39.3-52.1)	60.6 (49.9-73.6)	42.6 (37.7-48.3)	55.0 (49.7-60.9)
Clean fuels only (n=135)	57.8 (52.3-63.9)	69.5 (60.5-79.9)	49.9 (45.7-54.6)	56.3 (52.1-60.8)
Solid fuels included (n=101)	86.7 (76.5-98.3)	121.6 (102.3-144.6)	68.9 (61.7-76.9)	63.1 (57.1-69.8)
Primary heating fuel combination				
No heating (n=98)	50.2 (44.4-56.8)	65.9 (55.7-77.9)	47.2 (42.4-52.7)	56.3 (51.8-61.2)
Clean fuels only (n=39)	43.4 (36.1-52.2)	44.5 (34.6-57.2)	39.3 (33.4-46.3)	53.7 (47.7-60.6)
Solid fuels included (n=169)	76.3 (69.2-84.2)	103.5 (90.6-118.3)	61.3 (56.3-66.9)	61.4 (56.3-66.9)
Primary cooking and heating fuel combination				
No cooking or heating (n=29)	38.4 (31.0-47.6)	50.1 (37.2-67.6)	41.1 (33.8-50.1)	60.0 (51.2-70.3)
Clean fuels only (n=37)	40.9 (34.2-48.9)	43.5 (33.9-55.8)	37.9 (32.1-44.7)	53.2 (46.7-60.7)
Solid fuels included (n=189)	77.8 (71.1-85.2)	103.7 (91.5-117.6)	62.0 (57.1-67.4)	61.7 (56.4-67.6)

* Annual mean level was estimated using the regional temperature data from 2005-2017, the number of months with average temperature <10 degrees are 3/12 in Suzhou, 5/12 in Gansu, 4/12 in Henan. Using the same data, the proportion of days with ≤10 degrees daily average temperature are 1233/4717 (26.1%) in Suzhou, 1921/4717 (40.7%) in Gansu, 1524/4717 (32.7%) in Henan.

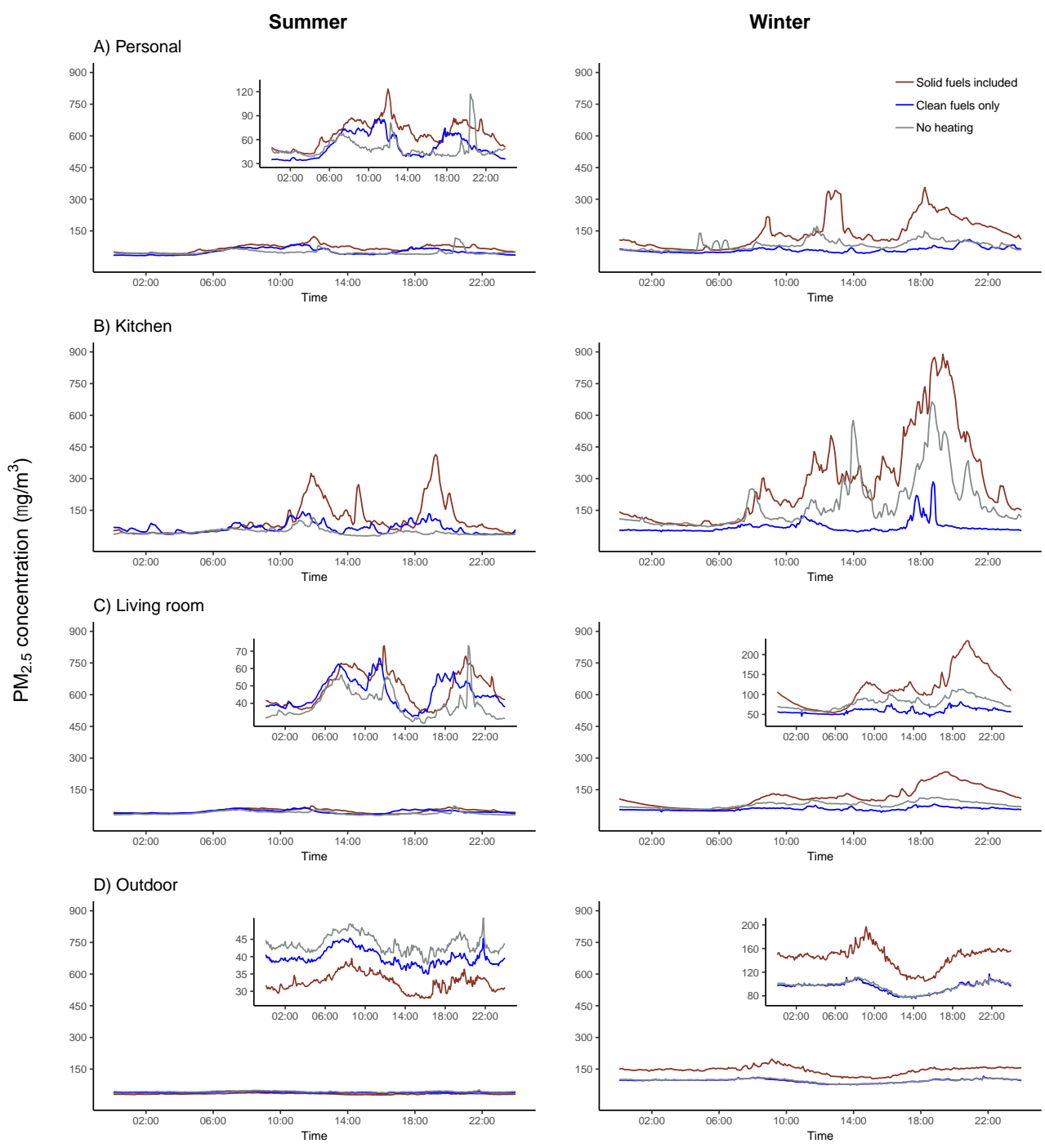
1 **Figure 1. Age- and sex-adjusted geometric mean PM_{2.5} concentrations (µg/m³) recorded in the personal, kitchen,**
2 **living room, and community monitors by season and the combination of primary cooking and heating fuels**



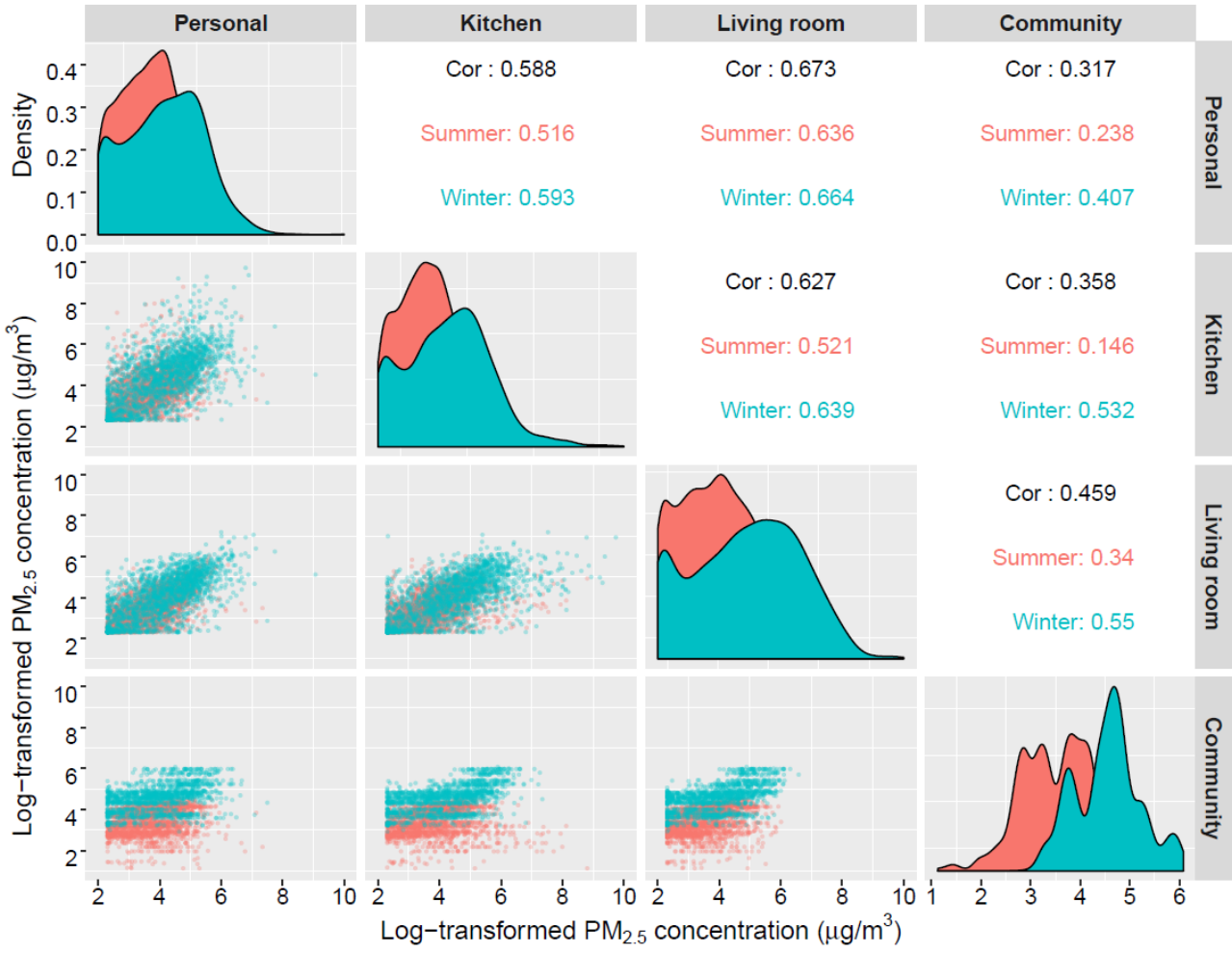
1 **Figure 2. 24-hour average time-series plots for PM_{2.5} concentrations (µg/m³) recorded in the personal, kitchen,**
2 **living room, and community monitors by season and primary cooking fuel combinations**



1 **Figure 3. 24-hour average time-series plots for PM_{2.5} concentrations (µg/m³) recorded in the personal, kitchen,**
2 **living room, and community monitors by season and primary heating fuel combinations**



1 **Figure 4. The correlation matrix between the log-transformed concentrations of PM for personal, kitchen, living**
2 **room and community levels**



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1 of Open Access, the author has applied a CC-BY public copyright licence to any Author
2 Accepted Manuscript version arising from this submission.

3 **Data Access Statement:**

4 The China Kadoorie Biobank (CKB) is a global resource for the investigation of lifestyle,
5 environmental, blood biochemical and genetic factors as determinants of common
6 diseases. The CKB study group is committed to making the cohort data available to the
7 scientific community in China, the UK and worldwide to advance knowledge about the
8 causes, prevention and treatment of disease. For detailed information on what data is
9 currently available to open access users and how to apply for it,
10 visit: <http://www.ckbiobank.org/site/Data+Access>.

11 Researchers who are interested in obtaining the raw data from the China Kadoorie
12 Biobank study that underlines this paper should contact ckbaccess@ndph.ox.ac.uk. A
13 research proposal will be requested to ensure that any analysis is performed by bona fide
14 researchers.

15 **Declaration of interest:**

16 The authors declare no known conflict of interest.

17 **CRediT authorship contribution statement:**

18 Ka Hung Chan: Conceptualization, Methodology, Software, Formal analysis, Investigation,
19 Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization,
20 Project administration, Supervision. Xi Xia: Methodology, Software, Formal analysis,
21 Investigation, Writing – review & editing, Visualization. Cong Liu, Haidong Kan:
22 Methodology, Resources, Data curation, Writing – review & editing. Aiden Doherty:
23 Methodology, Investigation, Writing – review & editing. Hung Lam Steve Yim:
24 Methodology, Resources, Writing – review & editing. Neil Wright, Christiana Kartsonaki:

1 Methodology, Software, Data curation, Writing – review & editing. Xiaoming Yang,
2 Rebecca Stevens: Resources, Data curation, Software. Xiaoyu Chang: Resources, Project
3 administration. Canqing Yu, Jun Lv, Liming Li: Resources, Project administration, Funding
4 acquisition. Kin-Fai Ho: Conceptualization, Methodology, Resources, Writing – review &
5 editing, Supervision. Kin Bong Hubert Lam, Zhengming Chen: Conceptualization,
6 Methodology, Resources, Writing – review & editing, Project administration, Supervision,
7 Funding acquisition.

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