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Real-time Indoor $PM_{2.5}$ Monitoring in an Urban Cohort: *Implications for Exposure Disparities and Source Control*

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Abstract

Fine particulate matter ($PM_{2.5}$) concentrations are highly variable indoors, with evidence for exposure disparities. Real-time monitoring coupled with novel statistical approaches can better characterize drivers of elevated $PM_{2.5}$ indoors. We collected real-time $PM_{2.5}$ data in 71 homes in an urban community of Greater Boston, Massachusetts using Alphasense OPC-N2 monitors. We estimated indoor $PM_{2.5}$ concentrations of non-ambient origin using mass balance principles, and investigated their associations with indoor source activities at the 0.50 to 0.95 exposure quantiles using mixed effects quantile regressions, overall and by homeownership. On average, the majority

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Human subjects
All participants provided informed consent and were compensated for their involvement. All study protocols were approved by the Institutional Review Board (IRB) of the Harvard T.H. Chan School of Public Health. Copies of correspondences documenting IRB protocol approval for *IRB15-1756: Exposure Disparities Related to Resident Behavior and Housing Characteristics* are included with this submission.

Appendix A. Supplementary data
Supplementary data to this article can be found online at: (10.1016/j.envres.2020.110561)

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Footnote: Models adjusted for candle and spray air freshener use; window opening and AC use in the living area; year of sampling; hour of day; indoor relative humidity; occupancy-to-bedroom ratio; and number of levels within unit. The ‘All Households’ strata also adjusted for homeownership and multifamily status. The ‘Homeowners’ strata also adjusted for multifamily status. All households in the ‘Renters’ strata were in multifamily housing.

of indoor $PM_{2.5}$ concentrations were of non-ambient origin (≥77%), with a higher proportion at increasing quantiles of the exposure distribution. Major source predictors of non-ambient $PM_{2.5}$ concentrations at the upper quantile (0.95) were cooking (1.4 – 23 μg/m^3) and smoking (15 μg/m^3, only among renters), with concentrations also increasing with range hood use (3.6 μg/m^3) and during the heating season (5.6 μg/m^3). Across quantiles, renters in multifamily housing experienced a higher proportion of $PM_{2.5}$ concentrations from non-ambient sources than homeowners in single- and multifamily housing. Renters also more frequently reported cooking, smoking, spray air freshener use, and second-hand smoke exposure, and lived in units with higher air exchange rate and building density. Accounting for these factors explained observed $PM_{2.5}$ exposure disparities by homeownership, particularly in the upper exposure quantiles. Our results suggest that renters in multifamily housing may experience higher $PM_{2.5}$ exposures due to a combination of behavioral and building factors that are amenable to intervention.

Keywords

Indoor environment; Air pollution; Real-time monitoring; Housing tenure; Environmental inequality

1. Introduction

Exposure to fine particulate matter ($PM_{2.5}$) indoors is shaped by multiple determinants across nested levels of the neighborhood, building, and household environments (Adamkiewicz et al., 2011). At the neighborhood-level, major ambient sources of indoor $PM_{2.5}$ include dust, vehicle exhaust, and industrial emissions (Abt et al., 2000; Li et al., 2017; Martins and Carrilho da Graça, 2018). Within the home, combustion-related activities are the primary sources of non-ambient indoor $PM_{2.5}$ emissions. They include smoking (Fernández et al., 2015; Ozkaynak et al., 1996; Wallace, 1996; Ferro et al., 2004), cooking (Evans et al., 2008; Militello-Hourigan and Miller, 2018; Olson and Burke, 2006; Wallace et al., 2004), candle burning (Fine et al., 1999; Long et al., 2000; MacNeill et al., 2014), and incense burning (Jetter et al., 2002; Waller et al., 2003). Other non-ambient sources include cleaning products and air fresheners (Nazaroff and Weschler, 2004; Steiber, 1995), walking and frequent contact with furniture and flooring (e.g. vacuuming, sweeping, dusting) that can resuspend particles into the breathing zone (Abt et al., 2000; Qian et al., 2014; Ferro et al, 2004; McCormack et al., 2008), and particle formation from heated metal surfaces (Wallace et al., 2015). Building attributes like age, volume, insulation, and ventilation systems can influence the degree of air exchange between indoor and outdoor environments (Breen et al., 2014; Long and Sarnat, 2004; Meng et al., 2009) and can thus also influence indoor exposure profiles.

Across each of these levels, socioeconomic disparities in indoor $PM_{2.5}$ exposure exist (Adamkiewicz et al., 2011). Several of these observed disparities are associated with tenure status and building type. Low-income households and persons of color are disproportionately more likely to rent (Joint Center for Housing Studies of Harvard University, 2019) and live in multifamily apartments known to be older and leakier, which can lead to greater $PM_{2.5}$ infiltration from the outdoors and neighboring units (Fabian et al., 2016; Rosofsky et al., 2019; Russo et al., 2015). Renters and multifamily households also have higher risks of second-hand smoke exposure and crowding, which can lead to increased particle generation and re-suspension (Dacunto et al., 2013; Adamkiewicz et al., 2011; Baxter et al., 2007; Fabian et al., 2016). In addition, these households are often located in areas with higher outdoor $PM_{2.5}$ concentrations and other environmental justice concerns (O'Neill et al., 2003; Rauh et al., 2008; Rosofsky et al., 2018). Even so, much is still unknown about building-level and behavioral contributors to potential disparities in indoor $PM_{2.5}$ concentrations by homeownership.

In residential settings, indoor $PM_{2.5}$ concentrations are highly variable. Elevated indoor concentrations are predominantly driven by behavioral source activities that generate short-term peaked emissions, at times orders of magnitude above background levels (Abt et al., 2000; Adamkiewicz et al., 2011; Ferro et al., 2004; Liang et al., 2019; Long et al., 2000; Militello-Hourigan and Miller, 2018; Wallace et al., 2006). As such, real-time exposure assessment approaches are important for more precise source characterization and targeting of public health intervention (Delgado-Saborit, 2012; Ferro et al., 2004; Lioy and Smith, 2013; Long et al., 2000). Recent advances in portable lower-cost sensors have made possible the measurement of real-time $PM_{2.5}$ in community-wide settings with sufficient accuracy and precision. These advances allow for more homes to be reliably characterized (Bulot et al., 2019; Gillooly et al., 2019; Lioy and Smith, 2013) with an emphasis on both within-home and between-home variability. In addition, quantile regression, a non-parametric statistical approach to estimate associations at different areas of the $PM_{2.5}$ distribution (Koenker and Hallock, 2001), provides new opportunities to model source contributions that may contribute to adverse health effects. While quantile regression has been applied in studies of ozone (Austin et al., 2015) and ambient and personal particle exposures (Liang et al., 2019), no studies have used it to characterize indoor $PM_{2.5}$ concentrations in residential settings.

Our Home-based Observation and Monitoring Exposure (HOME) Study within the Center for Research on Environmental and Social Stressors in Housing across the Life Course (CRESSH) (www.cressh.org) investigated drivers of $PM_{2.5}$ concentrations of non-ambient origin indoors, with a particular emphasis on behavioral and building-level contributors that are more amenable to intervention. Our study takes place in an environmental justice community (Ou et al., 2018) where the majority of households are low-income and renters (City of Chelsea, 2017). We deployed real-time sensors in a representative sample of households to investigate indoor $PM_{2.5}$ concentrations at fine temporal and spatial scales. We then employed mixed effects quantile regression to identify non-ambient sources associated with indoor $PM_{2.5}$ concentrations at the median and upper exposure quantiles, and evaluated differences in source contributions by homeownership.

2. Materials and Methods

2.1. Study Design and Population

The study was conducted in Chelsea, Massachusetts (MA), a city north of Boston, MA with approximately 35,080 residents within 4.7-square kilometers (km) (City of Chelsea, 2019). CRESSH's Community Engagement Core partnered with GreenRoots, a local community-based environmental justice organization, to recruit participants using purposive sampling stratified by neighborhood and housing types (e.g. multifamily, public housing, elderly/disabled). Eligibility criteria for participation were at least 18 years of age, fluency in English or Spanish, lived in current residence for at least six months, plans to stay for at least another six months, and consent to in-home environmental sampling.

For each household, we conducted two home visits in the non-heating (June to October) and heating (November to May) seasons to account for seasonal variability. Each home visit consisted of a detailed participant interview, a home visual assessment, and placement of a real-time sensor platform in the main living area (usually living room) to collect environmental samples for one week (mean: 7.1 days, range: 4 to 13 days). We also asked participants to complete a daily activity log on each day of the sampling period. A map of the study site is in Supplemental Data, Figure S1. All participants provided informed consent and were compensated for their involvement. All study protocols were approved by the Institutional Review Board of the Harvard T.H. Chan School of Public Health.

From June 2016 to August 2017, we recruited 81 households. Nine households dropped out prior to a home visit. Seventy-two households (89%) completed one home visit, of which 59 completed a second visit. Reasons for non-participation in the second visit included: no longer living in residence (n=5), unable to contact (n=5), and refusal (n=3). Data for one home visit was excluded due to equipment error, resulting in a sample of 71 households and 130 sampling sessions.

2.2. Survey Measurements

Questionnaires asked about sociodemographic and building characteristics and occupant activities in the home. Trained field staff conducted a visual assessment of the home environment, such as general environmental conditions and pollutant sources, including stoves. The daily activity log (DAL) included questions about frequency of home occupancy, air conditioning (AC) use, window opening, and cooking activities per two-hour intervals from 12:00 am to 11:59 pm. The DAL also asked about prevalence of candle use, spray air freshener use, and window opening and range hood use while cooking on each day. A copy of the DAL (Figure S2) and a summary of variables considered for the analysis (Table S1) are in Supplemental Data.

2.3. Environmental Measurements

Real-time indoor environmental measurements were collected using the Environmental Multi-pollutant Monitoring Assembly (EMMA) sensor platform developed by our research team (Figure S3). Details about EMMA have been described previously (Gillooly et al., 2019). In brief, the indoor EMMA platform (0.25m [length], 0.27m [width], 0.11m [height]) was placed on a flat surface about 0.30m to 1.2m above ground and plugged into an electrical outlet in the participant's main living area where there would be minimal occupant interference. The platform consisted of an Alphasense OPC-N2 particle monitor (Alphasense, 2017) paired with a filter-pump system that included a 37mm Teflon filter inside a Harvard mini personal environmental monitor (miniPEM). Particle counts were measured at approximately 1.4-second intervals. To estimate $PM_{2.5}$ mass concentrations, we normalized raw OPC-N2 measurements to the co-located gravimetric miniPEM filter-collected measurement by applying a weekly correction factor for each household-specific sampling session (i.e. average weekly miniPEM filter concentration divided by the average weekly OPC-N2 concentration, multiplied by each real-time OPC-N2 data point). Each miniPEM Teflon filter was weighed pre- and post-data collection in a temperature and relative-humidity controlled room.

Real-time outdoor environmental measurements were collected using a similar real-time sensor platform placed at two locations in Chelsea, MA, approximately 2.0km apart (Figure S1). Each outdoor platform consisted of an Alphasense OPC-N2 particle monitor paired with a filter-pump system that included a 37mm Teflon filter inside a Harvard Impactor for real-time data correction (Marple et al., 1987). The same gravimetric correction process used for indoor $PM_{2.5}$ data was applied to outdoor $PM_{2.5}$ data. We primarily used $PM_{2.5}$ estimates from the Site 1 monitor located southwest of Chelsea as it was deployed two weeks earlier, had fewer missing data, and appeared less influenced by microenvironmental conditions (e.g. landscaping equipment emissions, maintenance shed activity) compared to estimates from Site 2. For periods when data from Site 1 were unavailable (e.g. power outages), we used available data from Site 2.

The indoor and outdoor sensor platforms also contained a Netatmo weather station indoor module (Netatmo, n.d.) that measured carbon dioxide (CO_2) [ppm], temperature [Celsius], and relative humidity (RH) [%] at approximately five-minute intervals. Indoor data were time-averaged to five-minutes and outdoor data were time-averaged to hourly for analysis.

We generated estimates of air exchange rates (AER) using log-linear regression coefficients of CO2 decay curves for each sampling period using methods developed by research team members (Guillermo et al., 2012). In brief, the AER algorithm assumes well-mixed conditions within single-zone spaces, infiltration of external air at constant ambient CO_2 concentration (398 ppm), and indoor CO_2 concentration standardized to 400 ppm. To identify eligible decay curves, smoothing was set as the running average of three points to limit the number of sudden concentration increases within a decay period. CO_2 decay curves with a minimum difference of 50 ppm between the start and the end of the decay period, and a regression fit of $R^2 \geq 0.90$ were considered eligible (See Supplemental Data, Table S2 for eligible AER values per household in each sampling session). From the eligible decay curves, we calculated the daily median AER (h^{-1}) for each household in each sampling period to account for day-to-day variability. We retained the previous or nearest AER for days in which there were no eligible curves. Similar AER estimation approaches using CO_2 data have been validated in laboratory and field settings (Cui et al., 2015; Hou et al., 2015; You et al., 2012).

2.4 Data Quality

Data quality control and validation of environmental measurements have been described elsewhere (Gillooly et al., 2019). In brief, we excluded $PM_{2.5}$ estimates during periods when the sensor lost power or the pump-and-filter stopped, as these periods affected gravimetric filter concentrations for OPC-N2 data corrections. We also trimmed the first two hours and last 15 minutes of each home visit to minimize any team-influenced re-suspension when field team members were at participant's home. Extreme data points were manually reviewed and included if there were no known sensor issues at that time and the data exhibited a peaked pattern. In addition, any concentrations that were below 0.01 μg/m^3 were set to 0.01 μg/m^3, which is the minimum value reported for Alphasense OPC-N2 particle measurements in previous studies (Alphasense, 2017; Badura et al., 2018; Breen et al., 2014; Bulot et al., 2019; Sousan et al., 2016).

Questionnaire, DAL, and visual assessment data were evaluated for internal consistency. In instances where similar information was captured in both the visual assessment and questionnaires (e.g. stove fuel, range hood type, if range hood works), we prioritized data from the visual assessment conducted by trained staff. Non-responses to DAL questions were treated as 'No' responses.

2.5. Calculations and Data analyses

2.5.1. Infiltration factor and fraction of indoor $PM_{2.5}$ concentrations of ambient and non-ambient origins—

Under steady state conditions, assuming no generation or re-suspension of non-ambient sources and using a simple box model, the infiltration of ambient $PM_{2.5}$ concentrations indoors can be characterized as (Equation 1):

$$C_{\text{indoor ambient}} = [Pa/(a+k)] \bullet C_{\text{outdoor}} = F_{\text{inf}} \bullet C_{\text{outdoor}} \qquad \text{(Equation 1)}$$

where $C_{\text{indoor ambient}}$ is the estimated indoor $PM_{2.5}$ concentrations of ambient origin (μg/m^3), C_{outdoor} is the calibrated outdoor $PM_{2.5}$ concentrations (μg/m^3), P is the penetration efficiency (dimensionless), a is the AER (h^{-1}), k is the deposition rate (h^{-1}), and $Pa/(a+k)$ is the infiltration factor (F_{inf}).

P and k theoretically can vary by building type, building envelope tightness, ventilation modes, air exchange rate, window opening, particle size distribution, and meteorological conditions (Chen and Zhao, 2011; El Orch et al., 2014; Chao et al., 2003). Multifamily units generally have different P and k values than single-family units due to fewer walls facing outdoors, differences in airflow patterns, building stack effects, indoor surface types, and surface-to-volume ratios (Chen and Zhao, 2011). P is also higher during periods of window opening. While we expect k to depend on the surface-to-volume ratio, HVAC systems, particle size distribution, and types of indoor surfaces (Breen et al., 2015; Chen and Zhao, 2011), we do not expect k to vary significantly by window opening. Therefore, to account for these factors, we obtained P and k values from studies specific to single-family (Breen et al., 2015) and multifamily (Zhao and Stephens, 2017) housing and differentiated P values by periods of window opening. For single-family households, we used $P_{\text{window open}} = 0.93$, $P_{\text{window closed}} = 0.74$, and $k = 0.21\ h^{-1}$. For multifamily households, we used $P_{\text{window open}} = 0.87$, $P_{\text{window closed}} = 0.73$, and $k = 0.45\ h^{-1}$. Details about our selection of P and k values and sensitivity analyses using various combinations of P and k values are described in Supplemental Data (Tables S3-S5). We did not account for window opening in our estimation of daily median AERs (described in section 2.3) due to the limited number of eligible AERs per day across household-specific sampling sessions (Table S2).

Using the estimated *P*, *k*, and AER values, we calculated F_{inf} specific to single- and multifamily housing by periods of window opening (Table S3). We then estimated indoor $PM_{2.5}$ concentrations of ambient origin [$C_{indoor\ ambient}$] for each sampling period by multiplying the specific F_{inf} by hourly outdoor $PM_{2.5}$ concentrations [$C_{outdoor}$] (Equation 1). Indoor $PM_{2.5}$ concentrations of non-ambient origin [$C_{indoor\ non\text{-}ambient}$] were obtained by subtracting the proportion of Côor ambient from the total indoor $PM_{2.5}$ concentrations [$C_{indoor\ non\text{-}ambient} = C_{indoor\ total} - C_{indoor\ ambient}$]. Any concentrations that were negative were set to 0.01 $\mu g/m^3$. The generation of negative values may be attributed to certain sampling periods with lower than expected indoor $PM_{2.5}$ concentrations and/or that the estimated infiltration factors, although all below 1.0, were higher than what would have fit our data.

2.5.2. Descriptive statistics by homeownership—We compared prevalence of sociodemographic and building characteristics by homeownership using χ^2-test of proportions, or Fisher's exact tests if expected cell counts were below 5. We also compared prevalence of time-varying source activities by homeownership using the Kruskal-Wallis rank sum test. To identify shared behaviors, we generated a phi (φ) coefficient matrix for binary source activities, with coefficients above 0.15 indicating strong associations (Akoglu, 2018). We also generated summary measures of $PM_{2.5}$ and AER estimates and compared them by homeownership using the Kruskal-Wallis rank sum test.

2.5.3. Modeling indoor source activities of non-ambient indoor $PM_{2.5}$ concentrations—We investigated the association of indoor source activities with elevated non-ambient indoor $PM_{2.5}$ concentrations at the 0.50, 0.65, 0.75, 0.85, and 0.95 quantiles of the distribution. Quantile regression allows for the examination of associations at multiple points in the distribution of $PM_{2.5}$ concentrations other than the mean. We ran linear quantile mixed effects models with a random intercept for household cluster (Geraci and Bottai, 2014) using the *lqmm* R package (Geraci, 2014), and estimated 95% confidence intervals with cluster bootstrapping. Predictors of interest were prevalence of DAL-reported source activities and indoor smoking (yes/no). Specifically, we included a DAL indicator for any cooking activity occurring within a two-hour time block concurrent with the environmental sampling period (Figure S2, DAL question 4). We also specified a 30-minute time lag after each two-hour time block to account for potential prolonged durations of cooking emissions and temporal uncertainty in the information collected in our DAL. We adjusted for heating season (vs. non-heating) and prevalence of AC use and window opening (yes/no) to account for behavioral contributors to air exchange. We also controlled for other sources of potential variation in non-ambient indoor $PM_{2.5}$ concentrations such as sampling year (categorical), hour of day (sine and cosine, −1 to 1), indoor relative humidity (centered, continuous), occupant density (i.e. number of occupants per bedroom, continuous), and number of levels within unit (count) (Wallace et al., 2006; MacNeill et al. 2014; Long et al., 2001; U.S. EPA, 2020; Badura et al. 2018; Bulot et al., 2019; Baxter et al. 2007; Price et al., 2006 Akaike Information Criterion (AIC) was used to compare model fit, with lower AIC scores indicating better fit. Effect modification by homeownership was evaluated using stratified models. Eleven sampling sessions were excluded from final models due to missing outdoor

$PM_{2.5}$, DAL, or covariate data, resulting in an analytical sample of 68 households and 119 sampling sessions.

Data management was conducted using SAS 9.4 software (SAS Software, 2020) (SAS Institute Inc., Cary, NC) and data analysis was conducted using RStudio 1.1.4 software (RStudio Team, 2015) (RStudio Team, Boston, MA).

3. Results

3.1. Sociodemographic and Building Characteristics

Our participants were predominantly female (86%), self-identified as Hispanic/Latinx (49%), and had some high school education or an Associate's degree (65%). About one-third completed the interview in Spanish and almost half were foreign-born. The mean age was 52 years old (range 27-87) and mean occupancy was three people (range 1-8). The majority of buildings were constructed prior to year 1971 (90%), did not have central air (76%), and were not weatherized (65%). The majority of households reported that their range hood worked (85%), and 59% reported having a recirculating hood (Table 1).

Over half of households were renters in multifamily units (55%). Compared to homeowners in single- and multifamily units, renters were more likely to be Hispanic/Latinx (67% vs. ≤30%), interviewed in Spanish (54% vs. ≤23%), unemployed (73% vs. ≤15%), and without a Bachelor's degree or higher (85% vs. ≤45%) ($p \leq 0.006$) (Table 2). In addition, renters were more likely to live on the third or higher floors (54% vs. ≤23%), and in homes without central air (90% vs. ≤70%) or weatherization (87% vs. ≤45%) ($p \leq 0.001$).

3.2. Descriptive Statistics of Indoor and Outdoor $PM_{2.5}$ Concentrations

The median indoor $PM_{2.5}$ concentration was 5.8 (5^{th}, 95^{th} percentiles: 1.5, 28.7) μg/m^3, median outdoor $PM_{2.5}$ concentration was 5.1 (2.3, 9.2) μg/m^3, and the median AER was 0.48 (0.26, 1.5) h^{-1} (Table 1). Renters, compared to homeowners in single- and multifamily units, experienced higher indoor $PM_{2.5}$ concentrations at the median (8.2 vs. ≤5.2 μg/m^3) and 95^{th} percentile (39.7 vs. ≤21.6 μg/m^3) of the exposure distribution ($p = 0.002$) (Table 2). Median AER estimates were also higher among renters (AER: 0.59 vs. ≤0.43 h^{-1}) ($p = 0.004$). Outdoor $PM_{2.5}$ concentrations from central site monitors were similar across groups.

On average, non-ambient sources contributed a significant proportion of total indoor $PM_{2.5}$ concentrations for all households (≥77%) (Figure 1), with increasing proportions at higher quantiles of the exposure distribution. Compared to homeowners, renters experienced a higher proportion of non-ambient source contributions across quantiles, from 78% at the median to 95% at the 0.95 quantile. Multifamily homeowners also experienced a higher proportion of non-ambient source contributions than single-family homeowners across most quantiles, with the exception of the 0.95 quantile (Figure 1). The spike in the proportion of non-ambient source contributions for homeowners in single-family units at the 0.95 quantile is attributed to short periods of very high indoor $PM_{2.5}$ concentrations from one household's sampling session during the week of July 4^{th}. Exclusion of this household's sampling session reduced the proportion of non-ambient indoor $PM_{2.5}$ concentrations at the 0.95

quantile to 76% for this group (data not shown). Indoor $PM_{2.5}$ concentrations of ambient origin were similar across groups (Figure 1).

During periods of window opening, indoor $PM_{2.5}$ concentrations of both ambient and non-ambient origins and AERs were generally higher than during periods when the windows were closed for all households and across most quantiles (Table S6).

3.3. Occupant Source Activities Associated with Indoor $PM_{2.5}$ of Non-Ambient Origin

3.3.1. Descriptive statistics—Compared to homeowners in single- and multifamily units, renters more frequently reported indoor source activities like cooking (16% vs. ≤10% per 2-hour sampling period), spray air freshener use (43% vs. ≤22% per day), and incense use (20% vs. ≤10% per session) ($p \leq 0.02$) (Table 2). Notably, smoking was prevalent only among renters (24%) and positively correlated with spray air freshener use (phi coefficient [φ] = 0.24) (Table S7). In addition, renters more frequently reported smoking odors from neighbors (61% vs. ≤40%) and ventilation practices like range hood use (51% vs. ≤22%) and window opening while cooking (34% vs. ≤27%) compared to homeowners ($p \leq 0.03$). For renters, window opening while cooking was also strongly correlated with window opening in the main living area (φ = 0.36) (Table S7).

3.3.2. Associations across quantiles of non-ambient indoor $PM_{2.5}$ concentrations—In multivariable models, cooking, smoking, range hood use, and heating season (versus non-heating) were significant predictors of non-ambient indoor $PM_{2.5}$ concentrations, with strong associations observed in the upper quantiles of the exposure distribution (Figure 2, Table S8a). Cooking activity was associated with increased concentrations at the 0.95 quantile, both for the time period concurrent with the $PM_{2.5}$ measurement ($\hat{\beta}_{0.95}$: 1.4, 95% CI: −0.52, 7.6 μg/m^3) and during the 30-minute exposure period following the cooking activity ($\hat{\beta}_{0.95}$: 22.7 μg/m^3, 95% CI: 11.5, 41.4 μg/m^3) (Figure 2a). By homeownership, the association of non-ambient indoor $PM_{2.5}$ concentrations with concurrent cooking activity was stronger among renters (6.2 vs. −0.16 μg/m^3), while the association with the 30-minute lag following the cooking activity was stronger among homeowners (28.8 vs. 16.3 μg/m^3) at the 0.95 quantile of the exposure distribution (Figure 2a). Range hood use while cooking was also associated with increased non-ambient $PM_{2.5}$ concentrations at the upper quantiles, and particularly for homeowners ($\hat{\beta}_{0.95}$: 9.2, 95% CI: 0.22, 16.8 μg/m^3) (Figure 2b). Among renters, households that reported indoor smoking had higher non-ambient indoor $PM_{2.5}$ concentrations than non-smoking households across quantiles, with differences ranging from 4.5 to 15.1 μg/m^3 (Figure 2e). Also, daily window opening while cooking (Figure 2c) and spray air freshener use (Table S8b) showed negative trends with increasing quantiles of the exposure distribution.

For all households, non-ambient indoor $PM_{2.5}$ concentrations were higher in the heating than the non-heating season, with stronger associations in the upper quantiles of the exposure distribution (Figure 2d). We found no differences in non-ambient indoor $PM_{2.5}$ concentrations by daily candle use after adjusting for all other source activities (Table S8a). Overall, accounting for major source activities, ventilation behaviors, season, and other covariates attenuated observed differences in non-ambient indoor $PM_{2.5}$ concentrations by homeownership, particularly at the 95th percentile (Figure S4).

3.4. Sensitivity analyses

Our multivariable model findings appear generally insensitive to alternative assumptions about P and k, though with some evidence that the effects of smoking, range hood use, and cooking at the 95th percentile of non-ambient indoor $PM_{2.5}$ concentrations may be sensitive to the selection of higher k values (Tables S4 and S5). Also, our model findings for most occupant activities were insensitive to extreme non-ambient indoor $PM_{2.5}$ concentrations and periods of high relative humidity indoors. However, the effect of smoking at the 75th to 95th percentiles may have been underestimated during periods when indoor relative humidity was above 70% (Table S9).

4. Discussion

Using real-time data coupled with non-parametric statistical methods, we quantified the significant role of non-ambient sources in driving elevated $PM_{2.5}$ concentrations indoors in residential settings in a community-wide sample of households. While numerous studies have evaluated indoor source contributions, our combination of study population and statistical methods allowed us to develop valuable insights about exposure disparities. We found that renter households in multifamily units were exposed to significantly higher concentrations of non-ambient $PM_{2.5}$ indoors than homeowner households at the median and upper percentiles of the exposure distribution. Accounting for behavioral and building-level drivers of non-ambient $PM_{2.5}$ concentrations, such as cooking, smoking, range hood use, and building size, explained much of the observed exposure disparities by homeownership.

As documented elsewhere, we found that cooking activity was a significant driver of non-ambient indoor $PM_{2.5}$ concentrations, especially at higher exposure quantiles and consistent with a large but intermittent emissions profile (Abt et al., 2000; Baxter et al., 2009; He et al., 2004; Long et al., 2000; Militello-Hourigan and Miller, 2018; Olson and Burke, 2006; Ozkaynak et al., 1996). In addition, $PM_{2.5}$ concentrations were drastically elevated in the 30 minutes following a cooking event, with a more pronounced effect among homeowners. This delay may be in part explained by temporal imprecision in the cooking indicator, which recorded any activity within a two-hour interval. However, it may also be reflective of particle suspension from cooking emissions (Militello-Hourigan and Miller, 2018), with a greater delay for homeowners given differences in housing volume and mixing times. Homeowners in our study tended to live in larger units (i.e. more bedrooms, multiple floors of living space), which could facilitate longer mixing times (Singer et al., 2017). More generally, this difference points to the importance of characterizing the exposure lags from cooking events in future studies.

In addition to cooking, smoking was a strong driver of non-ambient indoor $PM_{2.5}$ concentrations across all exposure quantiles, consistent with previous findings (He et al., 2004; Ozkaynak et al., 1996; Wallace, 1996; Ferro et al., 2004). The minimal variation in the effect of smoking across quantiles is likely attributed to its data availability as a binary indicator of smoking prevalence in the past 30 days rather than a time-resolved measure like for cooking activity. Smoking households also reported higher use of spray air fresheners, which are widely prevalent in U.S. households and often used to mask smoking and other odors (Nazaroff and Weschler, 2004; Steinemann, 2017). Spray air freshener use is a source of volatile organic compounds and secondary formation of pollutants associated with adverse health effects (Cohen et al., 2007; Nazaroff and Weschler, 2004; Kim et al., 2015). However, these secondary pollutants are likely too small in size and negligible in mass to be detected by our sensors.

The positive association of range hood use with non-ambient indoor $PM_{2.5}$ concentrations is contrary to expectation. However, this could be indicative of reverse causation in which hood use was motivated by periods of intense cooking or accumulation of particles and smells during cooking. There is also the possibility of such actions changing the airflow and particle dynamics in the household in a way that increases $PM_{2.5}$ concentrations in the living area. Notably, the majority of homes had recirculating hoods, which are less efficient at particle removal than vented hoods that move air outdoors and especially if filters are not routinely cleaned or replaced (Jacobs and Cornelissen, 2017; Rojas et al., 2017; Seltenrich, 2014). The positive association could also reflect the range hood's ineffectiveness at particle removal, especially during periods of high emissions (Militello-Hourigan and Miller, 2018). However, we did observe a general negative effect for window opening while cooking among renter households which was consistent with expectation.

Differences in building characteristics by homeownership may also facilitate increased $PM_{2.5}$ infiltration from the outdoors and neighboring units, which we may not have fully accounted for with the use of central site outdoor monitors. In our study, renters lived in older apartment complexes without central air or weatherization and had higher AERs than homeowner and single-family households, consistent with previous studies (Price et al., 2006; Rosofsky et al., 2019). Rental units were also located on the third or higher floors and susceptible to building stack effects (U.S. EPA, 2018; Price et al., 2006). While homeowners in multifamily units could in theory share these building characteristics, in our study they were more likely to live in newer units with central air and weatherization, corresponding to the lower observed AERs. Also, renters more frequently reported second-hand smoke exposure from neighboring units, which is a major source of $PM_{2.5}$ infiltration in multifamily housing consistent with national trends (U.S. CDC, 2019) and previous studies (Meng et al., 2009; Russo et al., 2015; Wallace et al., 2006).

While our quantitative findings are specific to the population under study, the patterns observed are broadly consistent with the literature and previous studies in Boston-area housing. Compared to Boston-area studies by Baxter et al. (2007) and Long et al. (2000), our AERs were similar across season while our median indoor $PM_{2.5}$ concentration of 5.8 $\mu g/m^3$ was lower, though consistent with cohort variability and secular changes in ambient $PM_{2.5}$ concentrations, housing stock, and occupant activities. Also, while our study did not recruit renters in single-family housing, our sample reflects the distribution of housing stock and tenure in our study site of Chelsea, MA, which is predominantly multifamily (>90%) and renter households (~70%) (City of Chelsea, 2017). Given that the majority of households in similar urban communities across the U.S. are renters and live in multifamily housing, our findings have important implications for public health and addressing environmental exposure disparities indoors.

Our study is subject to limitations common to monitoring studies with lower-cost sensors. While lower-cost sensors generally do not meet the performance standards of reference-grade monitors, those used in our study met pre-specified performance criteria and exhibited high sensitivity and reasonable accuracy during testing (Gillooly et al., 2019). That said, measurements on a very short time scale can display substantial and often unexplained heterogeneity. Secondly, estimates of outdoor $PM_{2.5}$ concentrations were from central sites and not spatially resolved. Although we time-averaged outdoor concentrations to hourly estimates, there may be additional time lags in infiltration of outdoor $PM_{2.5}$ concentrations that may introduce error in our estimation of indoor $PM_{2.5}$ concentrations of ambient and non-ambient origins. However, given the small size of our study site (4.7km^2) and close proximity of each household to the central site monitors (within 1.6km), we think any additional error would be minimal. Thirdly, our source activity data were self-reported and could be subjected to information bias, though any bias should be non-differential as participants were likely unaware of their $PM_{2.5}$ levels in real-time. The timescale used for reported occupant activities at the two-hour and daily levels may have been too coarse to detect associations with very short-term $PM_{2.5}$ peaks. Similarly, additional measures of intensity and duration for cooking and smoking activities would have enabled more precise characterization of their influence on $PM_{2.5}$ peaks. Specific information about range hood capture efficiency and having a paired particle sensor in the cooking area would also have enabled better characterization of cooking source strengths and decay rates. Fourth, we did not specifically evaluate re-suspension activity as there was no logical way to formally parameterize this term, though we did control for occupant density. Fifth, the strong effect of heating season in multivariable models suggests other potential contributors to AER and/or seasonal behavioral source activities that should be investigated in future studies. Lastly, our mass balance models to derive non-ambient indoor $PM_{2.5}$, while based on first principles, included some uncertainty given the use of centralized monitors for outdoor $PM_{2.5}$, estimated values for P and k, and assumptions of a single-compartment model for AER estimation, which contribute to overall uncertainty in our regression models. Nevertheless, we were still able to observe strong associations with occupant source activities across quantiles of non-ambient indoor $PM_{2.5}$ concentrations without an excessive burden on participants.

In spite of these limitations, our study provided insights about behavioral and building-level contributors of non-ambient indoor $PM_{2.5}$ concentrations across a diverse set of homes. By using a combination of data collection approaches consisting of validated portable sensors, in-home interviews, visual inspection, and daily activity logs, coupled with non-parametric statistical methods, we were able to better characterize non-ambient predictors of indoor $PM_{2.5}$ at the upper quantiles of the exposure distribution that may be more relevant for health (Pope et al., 2006; Li et al., 2017). We used a novel and efficient method to calculate AER based on CO_2 decay curves that was cost-effective and may be more feasible in large-scale studies than tracer gas methods (Cui et al., 2015). In addition, the use of lower-cost sensors paired with high quality calibrations allowed us to collect intensive data in more homes, which allowed for a larger recruitment size and the inclusion of more diverse housing and household characteristics than many previous studies of indoor $PM_{2.5}$ in residential settings. The small geographic area of our study site also minimized spatial variability in outdoor $PM_{2.5}$ concentrations across households and allowed us to more precisely characterize the role of indoor sources on non-ambient indoor $PM_{2.5}$ concentrations. Furthermore, we identified heterogeneity in source contributions of non-ambient indoor $PM_{2.5}$ concentrations by homeownership, a marker of socioeconomic status, across exposure quantiles that can inform interventions. Renter households in our study had higher levels of indoor air pollution and prevalence of indoor source contributors compared to homeowner households. Renters were also more likely to be non-English speakers, Hispanic/Latinx, unemployed, and without a college degree. As such, our findings have important implications for addressing racial/ethnic and socioeconomic disparities in indoor air pollution, which should be further explored in future studies.

5. Conclusions

To our knowledge, this is the first study to characterize exposure disparities in indoor $PM_{2.5}$ concentrations of non-ambient origin, with an explicit emphasis on homeownership and the behavioral and building-level factors contributing to these differences. Our findings shed light on the need for multi-level interventions at the household and building levels in order to equitably and effectively reduce indoor $PM_{2.5}$ exposure disparities. For renter and multifamily households, building-wide improvements addressing ventilation and source elimination (e.g. smoke-free policies) should be paired with tenant engagement about strategies to reduce source activity-related $PM_{2.5}$ emissions and improve ventilation in the home. Household-level interventions such as replacement of recirculating hoods with vented hoods and smoking cessation programs could be coupled with financial and housing assistance to account for socioeconomic correlates of behavioral source activities. While outdoor sources and regional $PM_{2.5}$ patterns may be challenging to modify at the household-level, especially within a short timeframe, modifying source activities and building conditions that shape $PM_{2.5}$ exposure indoors may be possible and contribute to reducing exposure disparities.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights:

- Quantile regression of real-time data better captures indoor $PM_{2.5}$ variability
- Key sources of indoor $PM_{2.5}$ peaks are non-ambient (cooking, smoking)
- Renters have higher indoor $PM_{2.5}$ exposure and non-ambient sources than homeowners
- Building and behavioral factors explain indoor $PM_{2.5}$ disparities by homeownership

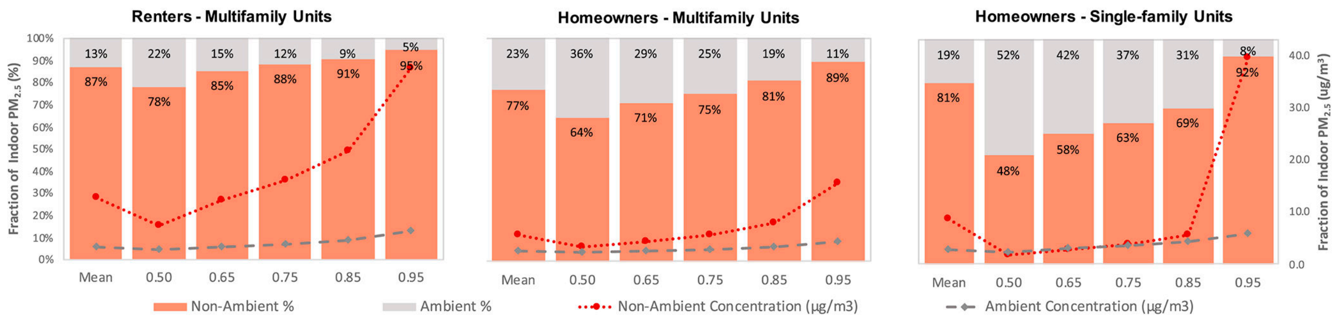
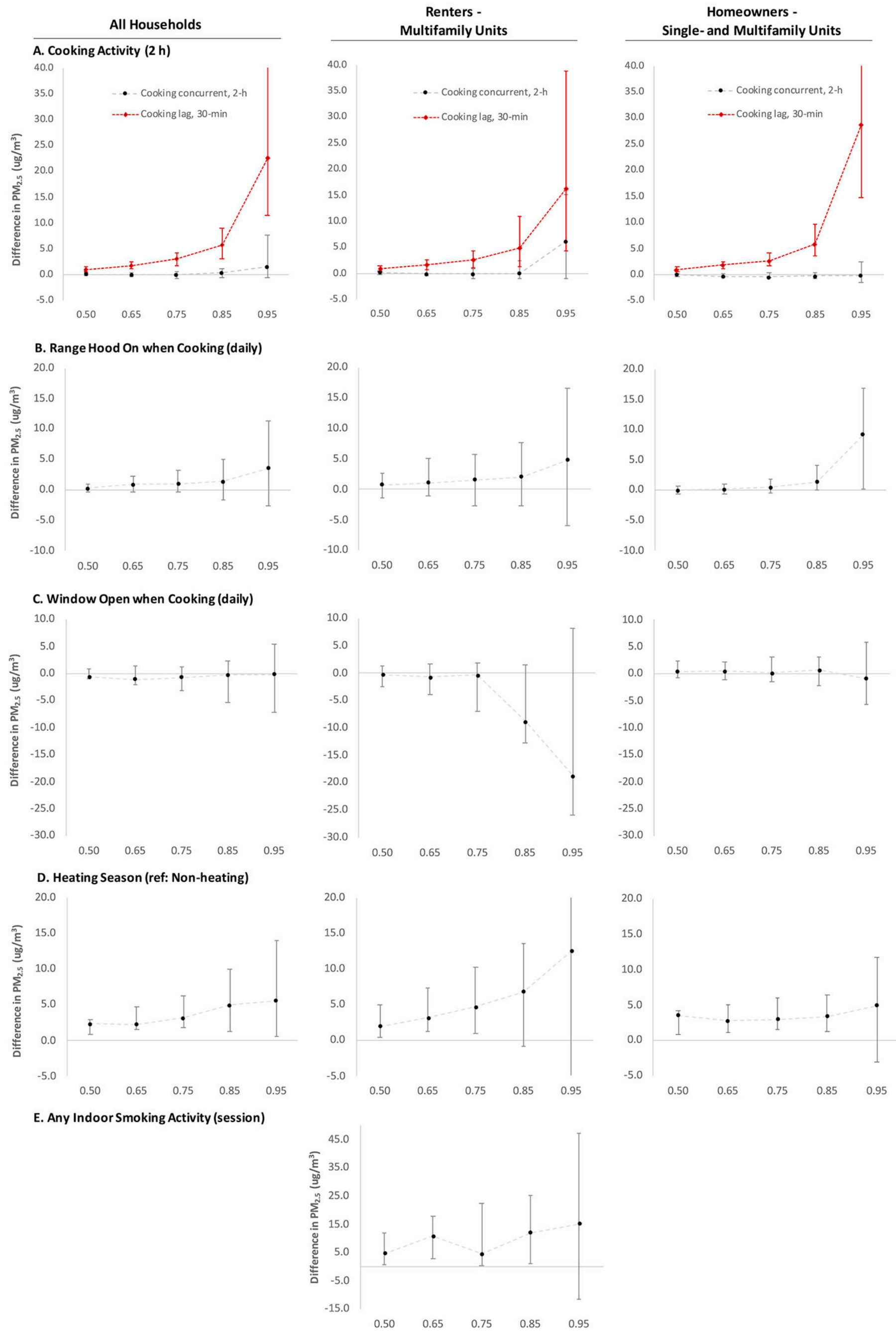


Figure 1.

Percentages (%) and Concentrations (μg/m^3) of Indoor $PM_{2.5}$ from Ambient and Non-Ambient Origins across Quantiles of the Exposure Distribution by Homeownership and Multifamily Status, HOME Study, Chelsea, MA 2016-2017



Figures 2a-e.

Multivariable Regression Coefficients at the 0.50 to 0.95 Quantiles of Non-Ambient Indoor $PM_{2.5}$ Concentrations ($\mu g/m^3$) for Major Occupant Activities, Overall and by Homeownership, HOME Study, Chelsea, MA 2016-2017

Table 1.

Sociodemographic, Building Characteristics, and Environmental Measures, HOME Study, Chelsea, MA 2016-2017

Sociodemographic characteristics (N=71)		
	Mean	Range
Age of householder (years)	52	27 - 87
Number of occupants	3	1 - 8
	N	Percent
Gender of Householder		
Female	61	86%
Male	10	14%
Race/Ethnicity of Householder		
Hispanic or Latinx	35	49%
White Non-Hispanic	28	39%
Other, Non-Hispanic (Black, Asian, Multiracial)	8	12%
Language of Interview		
English	45	63%
Spanish	26	37%
Nativity		
US-born	40	56%
Foreign-born	31	44%
Highest level of education (completed in U.S. or elsewhere)		
Up to Highschool	18	25%
Highschool diploma or GED	11	15%
Some College or Associate's degree	18	25%
Bachelor's degree	13	18%
Graduate degree	11	15%
Homeownership and Tenure		
Renter – Multifamily unit	39	55%
Renter – Single-family unit	0	0%
Homeowner – Multifamily unit	22	31%
Homeowner – Single-family unit	10	14%
Building characteristics (N=71)	N	Percent
Number of bedrooms		
1 bedroom	21	30%
2 bedrooms	22	31%
3 bedrooms	16	23%
4+ bedrooms	12	17%
Year built		
1850-1900	23	32%
1901-1950	18	25%

Sociodemographic characteristics (N=71)		
1951-1970	23	32%
1971-2013	7	10%
Stove fuel type		
Electric	34	48%
Natural gas	37	52%
Range hood type		
Exhaust fan to outside	22	31%
Recirculating hood	42	59%
No range hood (use windows or ceiling fan)	7	10%
Range hood works?^		
Yes	110	85%
No	7	5%
No range hood	13	10%
Central air use		
Yes	14	20%
No	3	4%
No Central air	54	76%
Weatherization		
Yes	23	32%
No	46	65%
Don't know/NA	2	3%
Environmental Measures (N=69) ‡	Mean (SD)	Median (0.05 – 0.95)
Indoor $PM_{2.5}$ ($\mu g/m^3$)	10.4 (12.9)	5.8 (1.5 – 28.7)
Outdoor $PM_{2.5}$ ($\mu g/m^3$)	6.4 (2.6)	5.1 (2.3 – 9.2)
AER (h^{-1})	0.70 (0.41)	0.48 (0.26 – 1.5)

Footnote: Percentages may not add up to 100% due to rounding.

^Denominator is total sessions from heating and non-heating seasons (N=130) instead of total households (N=71)

Abbreviations: GED = General Education Development or High School Equivalence Certificate, AER = air exchange rate, SD = Standard deviation.

‡Data missing for two households

Table 2.

Sociodemographic, Building Characteristics, Source Activities, and Environmental Measures by Homeownership and Multifamily Status, HOME Study, Chelsea, MA 2016-2017

	Renters in Multifamily unit (N=39)		Homeowners in Multifamily unit (N=22)		Homeowners in Single-family unit (N=10)		
Sociodemographic characteristics	N	Percent	N	Percent	N	Percent	p^*
Education							
Up to Highschool, GED, or Some College	33	85%	10	45%	3	30%	<0.001
Bachelor's degree or higher	6	15%	12	55%	7	70%	
Race/ethnicity							
White non-Hispanic	8	21%	14	64%	6	60%	0.006
Hispanic/Latinx	26	67%	6	27%	3	30%	
Other, Non-Hispanic (e.g. Black, Asian, Multiracial)	5	13%	2	9%	1	10%	
Nativity							
U.S.-born	16	41%	16	73%	8	80%	0.062
Foreign-born	23	59%	6	27%	2	20%	
Interview Language							
English	18	46%	17	77%	10	100%	<0.001
Spanish	21	54%	5	23%	0	0%	
Employment status$^{\wedge}$							
Yes	19	27%	34	87%	17	85%	<0.001
No	51	73%	5	13%	3	15%	
Building characteristics	N	Percent	N	Percent	N	Percent	p^*
Entrance to home							
First floor	10	26%	7	32%	10	100%	<0.001
Second floor	8	21%	10	45%	0	0%	
Third floor or higher	21	54%	5	23%	0	0%	
Number of bedrooms							
1-2 bedrooms	27	69%	14	64%	2	20%	0.086
3 bedrooms	9	23%	4	18%	3	30%	
4+ bedrooms	3	7%	4	18%	5	50%	
Number of units in Multifamily							
2 units	5	13%	5	23%	--	--	NA
3-9 units	13	33%	8	36%	--	--	
10+ units	21	54%	9	41%	--	--	
Year home built							
1850-1900	8	21%	9	41%	6	60%	<0.001
1901-1950	11	28%	6	27%	1	10%	
1951-1970	19	49%	1	5%	3	30%	

	Renters in Multifamily unit (N=39)		Homeowners in Multifamily unit (N=22)		Homeowners in Single-family unit (N=10)		
1971-2013	1	3%	6	27%	0	0%	
Central air use							
Yes	1	3%	10	45%	3	30%	<0.001
No	3	8%	0	0%	0	0%	
No Central air	35	90%	12	55%	7	70%	
Weatherization							
Yes	3	8%	12	55%	8	80%	<0.001
No	34	87%	10	45%	2	20%	
Don’t know	2	5%	0	0%	0	0%	
Range hood type							
Exhaust to outdoor	12	31%	7	32%	3	30%	0.998
Recirculating hood	23	59%	13	59%	6	60%	
No range hood (use windows or ceiling fan)	4	10%	2	9%	1	10%	
Range hood works?^							
Yes	58	83%	34	85%	18	90%	0.925
No	5	7%	2	5%	0	0%	
No range hood	7	10%	4	10%	2	10%	
Stove fuel type							
Electric	21	54%	10	45%	3	30%	
Natural gas	18	46%	12	55%	7	70%	0.389
Household Activity per Session^	N	Percent	N	Percent	N	Percent	p^*
Smoking indoors							
Yes	17	24%	0	0%	0	0%	NA
No	53	76%	40	100%	20	100%	
Smoking odors from neighbors							
Yes	43	61%	16	40%	7	35%	0.030
No	27	39%	23	58%	13	65%	
Missing	--	--	1	2%	--	--	
Incense use							
Yes	14	20%	1	2%	2	10%	0.021
No	56	80%	39	98%	18	90%	
Prevalence of Daily Household Activity^	Percent	SD	Percent	SD	Percent	SD	$p^†$
Candle use	15%	31%	7%	19%	11%	27%	0.739
Spray air freshener use	43%	43%	6%	18%	22%	35%	<0.001
Window open while cooking	34%	33%	16%	26%	27%	31%	0.007
Range hood on while cooking	51%	42%	22%	36%	21%	22%	<001
Prevalence of 2-hour Household Activity^	Percent	SD	Percent	SD	Percent	SD	$p^†$

	Renters in Multifamily unit (N=39)		Homeowners in Multifamily unit (N=22)		Homeowners in Single-family unit (N=10)		
Occupancy at home	75%	28%	69%	14%	78%	11%	0.001
Air conditioning in living area	11%	23%	10%	27%	10%	25%	0.744
Window open in living area	21%	32%	22%	34%	31%	33%	0.251
Any Cooking	16%	14%	9%	7%	10%	7%	0.002
Frying/Grilling/Broiling	7%	9%	5%	5%	5%	4%	0.427
Environmental measures‡	Mean (SD)	Median (0.05 – 0.95)	Mean (SD)	Median (0.05 – 0.95)	Mean (SD)	Median (0.05 – 0.95)	*p*†
Indoor $PM_{2.5}$ (μg/m^3)	12.8 (14.3)	8.2 (1.3 - 39.7)	6.01 (4.2)	5.2 (1.9 - 15.0)	8.8 (17.0)	4.4 (1.5 - 21.6)	0.002
Outdoor $PM_{2.5}$ (μg/m^3)	5.6 (2.3)	5.4 (2.8 - 9.7)	5.2 (3.2)	4.6 (2.5 - 9.9)	5.2 (2.1)	5.5 (2.2 - 8.8)	0.354
AER (h^{-1})	0.70 (0.41)	0.59 (0.32 - 1.5)	0.52 (0.39)	0.39 (0.23 - 1.1)	0.58 (0.42)	0.43 (0.34 - 1.7)	0.004

Footnote: Percentages may not add up to 100% due to rounding. The time-scale noted for different household activities (e.g. 2-hour, daily, session) refer to the time period that participants were asked to report on such activity.

^ Denominator is total sessions from heating and non-heating seasons (N=130) instead of total households (N=71)

* From χ^2 or Fisher's exact test (if expected cell counts <5). The p-value pertains to comparisons across the three household groups.

† Kruskal-Wallis rank sum test of household-specific sampling sessions

‡ Data missing for two households

Abbreviations: GED = General Education Development or High School Equivalence Certificate, AER = air exchange rate, Pct. = Percent, SD = Standard deviation, *p* = p-value