Modelling childhood exposure to indoor air pollution across socio-economic groups

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SUMMARY
Population exposure to indoor air pollution may be modified by socio-economic factors in a number of ways, but such factors are rarely considered in indoor air quality models. Here, we present a model which estimates exposure to indoor $PM_{2.5}$ across income groups for the Greater London childhood population. The model uses a national time-activity database, which gives the percentage of each population group in different residential and non-residential microenvironments and links this to simulated domestic indoor concentrations from the building physics model, EnergyPlus, and for non-residential microenvironments to a mass-balance model with empirically measured building air change rates selected according to a probabilistic approach. The results display distributions of exposure across income groups for children in London, where median daily exposure is 14.4 ug/m^3 for children in the lowest income quintile versus 11.7 ug/m^3 for those in the highest income quintile.

KEYWORDS
Indoor air pollution; socio-economic status; indoor environment modelling; building physics; population exposure;

1 INTRODUCTION
Associations between indoor air pollution and detrimental health outcomes have been demonstrated in the literature for different population groups (Gaffin et al., 2018). Recognition of the variation in indoor exposure and susceptibility that exists between different subgroups of the populations has led to the development of indoor air pollution models which estimate exposure between age groups (Dimitroulopoulou et al., 2017), but this is not yet reflected for populations of different socio-economic status (SES).

Population exposure to indoor air pollution may be modified by SES in a number of ways: Lower-income homes are on average more airtight with smaller floor areas, which has limitations for the removal of indoor-sourced air pollution. Individuals of low SES are more likely to smoke, live in areas with higher concentrations of outdoor air pollution, and in overcrowded homes where cooking durations will be longer to accommodate the larger household size (Ferguson et al., 2021).

Children are highly susceptible to developing negative health impacts from air pollution exposure due to their immature immune and lung systems. Those between the ages of 7 – 12 years old may spend upwards of 87% of their time indoors, and those younger than 3 years old up to 100% of their time (Coombs et al., 2016), making children from low-income homes particularly vulnerable to indoor exposures.

Quantifying personal exposure across SES requires incorporating variations in time-activity patterns, physical characteristics of indoor microenvironments and socio-economic determinants, but no integrated assessment of these factors has been undertaken to date. Here, we present a model which estimates exposure to indoor $PM_{2.5}$ across income groups for the Greater London childhood population. Determinants of inequalities and policy implications are discussed.

2 MATERIALS/METHODS

2.1 Model overview

The model takes results from EnergyPlus simulations for the home and combines them with estimates for other indoor micro-environments to produce a library of indoor concentrations for domestic and non-domestic micro-environments. Indoor concentrations in non-domestic micro-environments are estimated using a probabilistic framework where indoor levels are modelled as a function of outdoor concentrations using a mass-balance approach. The library of indoor concentrations is then overlayed with childhood time-activity patterns inferred from empirical survey data to produce estimates of indoor exposure for different income groups.

2.2. Time-activity survey

Childhood time-activity patterns for all indoor micro-environments (domestic and non-domestic) were inferred from the NatCen Time-use survey (Gershuny & Sullivan, 2017). The survey collected data for 4,741 UK households between 2014 - 2015 on respondent's daily activities in ten-minute intervals via a self-completed diary. From the data, reported activities/locations were broadly grouped into twelve micro-environments:

- Indoor domestic (bedroom, lounge, kitchen, bathroom);
- Indoor non-domestic (school, workplace, commercial buildings);
- Outside;
- Transport (bus, car, train and tram/underground).

Across the child survey population, micro-environments where ≥ 10% of the population were for any given 10-minute interval were included in the analysis. The selected micro-environments were: Bathroom, bedroom, kitchen, lounge, outdoors, school, car and bus microenvironments. The resulting dataset showed the proportion of the total population in each of the eight final micro-environments in ten-minute intervals for a representative weekday and weekend. Population time-activity data was further disaggregated by each child's household income group, to link with the concentration data.

2.2. Home concentrations

The building physics tool EnergyPlus (US DoE, 2020) was used to model domestic indoor $PM_{2.5}$ concentrations for the 1,996 London buildings surveyed in the 2010 English Housing Survey (EHS) (DCLG, 2011b) for a representative summer and winter week. Eight dwelling archetypes broadly representative of the London housing stock were used and reported building fabric properties were parameterised using the Reduced data Standard Assessment Procedure (Rd SAP) (BRE, 2009). Simulation results for each of the 1,996 buildings were then weighted by a household grossing factor to produce regional estimates for Greater London, approximately 3,049,047 households in 2010. This sample was subset to include only households with at least one child aged under 18 in residence, resulting in 1,032,222 households.

Concentrations of $PM_{2.5}$ from cooking, smoking and outdoors were included in the model. Dwellings in the EHS sample with at least one occupant who identified as a smoker were assumed to allow smoking to occur indoors, in the living room. This was carried out at a frequency of eleven cigarettes per day, which is in line with empirical data for the UK (ONS, 2017). Within the EHS sample, the proportion of households with at least one smoker was 23.1% for homes in the lowest income quintile, versus 9.6% for those in the highest income quintile. Analysis of the NatCen Time-use survey suggested that those of lower SES may spend, on average, a greater amount of time per day in the dwelling and it was assumed that those who spend a greater amount of time indoors will have longer cooking durations. This is supported by the literature, which found individuals of lower SES spent between 10 and 20 minutes longer cooking per day (Adams & White, 2015). Within EnergyPlus, households which identified as being below the low-income threshold (LIT) were assumed to spend an extra 20 minutes cooking per day on weekdays.

2.3. Outdoor concentrations

Data for outdoor concentrations was obtained from the London Datastore, which has annual mean $PM_{2.5}$ concentrations in 2013 for Greater London output areas (GLA, 2017). Concentration data from 2013 was selected as this is the most concurrent year to the EHS dataset (2010) for which mapped $PM_{2.5}$ data is available. Area-$PM_{2.5}$ concentrations were overlaid with Lower Layer Super Output Areas (LSOA) boundaries and paired with the equivalent local-area measure of SES, in this case the 2010 Indices of Multiple Deprivation (IMD) data (DCLG, 2011a). The IMD ranks small areas on a number of domains characterising the local environment to give each LSOA a ranking of relative deprivation in England. Areas are then aggregated by deprivation deciles. Information regarding each dwellings 2010 IMD classification is also included in the EHS dataset, thus the two datasets could be linked. Average outdoor $PM_{2.5}$ concentrations were spatially joined with each LSOAs 2010 IMD classification, aggregated by decile. Summary statistics for outdoor concentrations are outlined in Table 1. For each dwelling in the EHS, a random outdoor concentration was sampled from one of the ten distributions shown in Table 1, depending on the household's 2010 IMD classification.

Table 1. Summary statics for outdoor $PM_{2.5}$ concentrations per IMD decile.

IMD decile	Mean (μg/m^3)	SD (μg/m^3)	Minimum (μg/m^3)	Maximum (μg/m^3)
1- Most deprived	16.3	0.627	14.7	18.9
2	16.2	0.675	14.6	19.5
3	16.2	0.721	14.5	20.2
4	16.1	0.764	14.5	19.6
5	16.1	0.790	14.5	19.8
6	16.0	0.767	14.3	20.3
7	15.9	0.772	14.4	19.4
8	15.9	0.860	14.3	21.1
9	15.7	0.772	14.3	21.0
10 - Least deprived	15.4	0.458	14.4	19.2

2.4. School concentrations

Indoor concentrations in the classroom were estimated using a mass-balance approach, which models indoor $PM_{2.5}$ as a function of outdoor concentrations and building air change rates. Taking the outdoor concentration level selected for each child's home environment, school concentrations were estimated using the general mass-balance equation that describes the indoor concentration profile;

$$\frac{dC_{in}(t)}{dt} = a \cdot P \cdot C_{out}(t) - (a + k) \cdot C_{in}(t) + \frac{Q}{V} \qquad 1)$$

Where $C_{in}(t)$ and $C_{out}(t)$ are the indoor and outdoor concentrations, respectively (µg/m^3); P is the penetration factor (dimensionless); a is the air change rate (h^{-1}); k is the deposition rate (h^{-1}); V is the volume of the indoor space (m^3); Q is the indoor emission rate (µg/hr).

A distribution of building air change rates (ACH) was constructed based on empirical measurements carried out in eight UK primary schools. Average classroom ACH was 4.0 ± 0.3 h^{-1} when windows were open and 0.6 ± 0.1 h^{-1} when windows were closed (Bakó-Biró et al., 2012). Distributions for both scenarios were assumed to follow a lognormal distribution and are displayed in Figure 1. To estimate classroom ACH, each distribution was randomly sampled from, assuming classroom windows were closed in the winter and open during summer. Deposition rate was assumed to be 0.15 h^{-1} and 0.10 h^{-1} in winter and summer, respectively (Long et al., 2001) and the penetration factor was kept constant at 0.8. The volume for school classrooms was assumed to be 137.5 m^3, in line with space requirements for UK classrooms. In the absence of combustion-sources, the literature suggests that resuspension of infiltrated particles by occupant movement is the primary cause of high indoor concentrations (Kalimeri et al., 2019). The indoor emission rate due to occupant movement was assumed to be 2.3E+01 µg/hr per pupil, taken from an empirical study (Nasir & Colbeck, 2013) and the number of pupils per class was assumed to be 28, the London average for Key Stage 1.

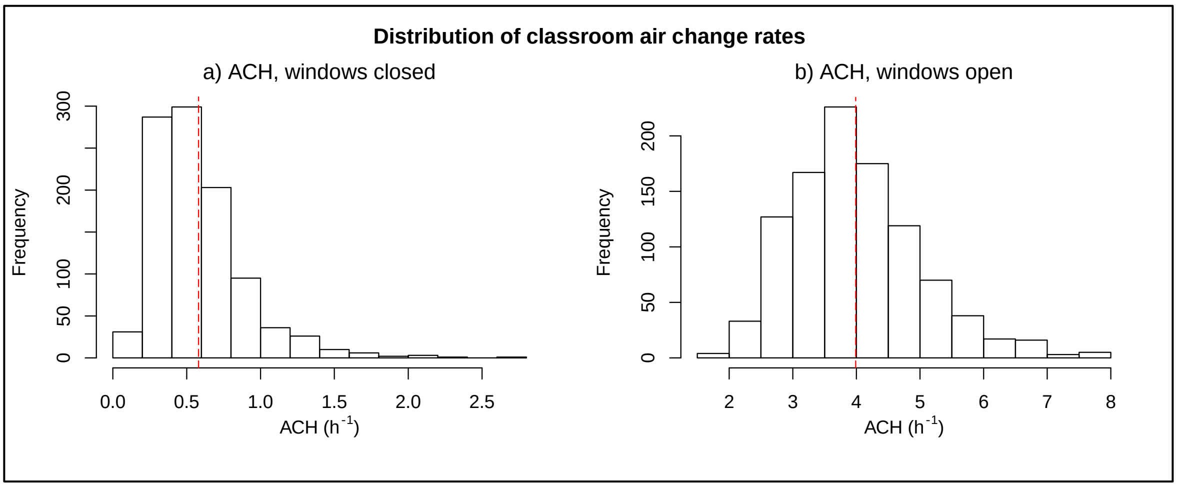

Figure 1. a) Sampling distribution (n = 1000) for school classrooms ACH (h-1) with windows closed (a) open (b). Mean values highlighted in red.

2.5. Travel concentrations

For travel micro-environments, the parameters for deposition and penetration were assumed to be the same as the classroom environment. A distribution of vehicle air change rates for cars and buses was generated using reported ACH (h^{-1}) values in published studies. Values for car and bus volume were 2.5 and 66 m^3, respectively, as used by Smith et al. (2016). No indoor sources were assumed apart from resuspension by occupant movement. Buses were assumed to have 50 passengers (Smith et al., 2016) whilst cars were assumed to have two. Distributions for all scenarios followed a lognormal distribution and are shown in Fig 2. Mean ACH were 39 h^{-1} and 12.6 h^{-1} for cars, and 18.3 h^{-1} and 2.9 h^{-1} for buses when windows were open and closed, respectively.

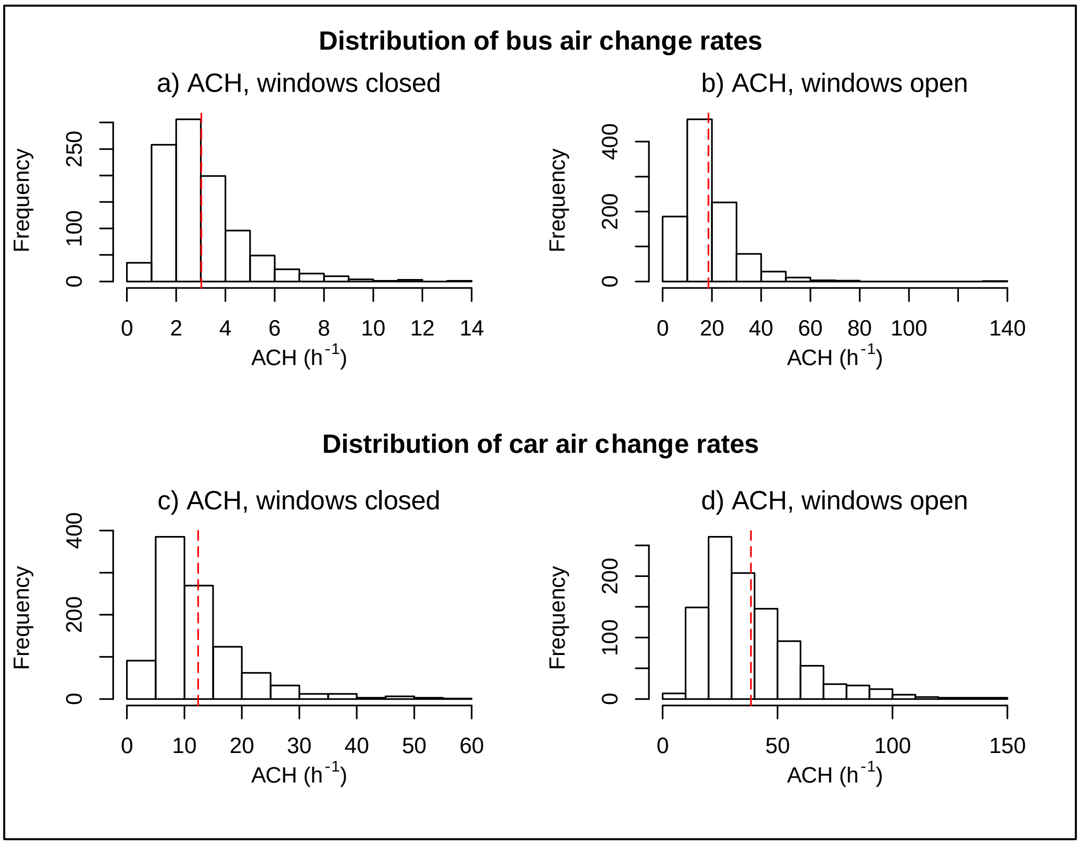

Figure 2. Sampling distribution of vehicle ACH (h-1) (n=1000) for bus (a-b) and car (c-d) microenvironments. The red dashed line represents the mean value for each distribution.

2.6. Data processing

A library of indoor concentrations was constructed by running the model *n*=1000 times to stabilise results for each of the approximately 2 million children, across 1,032,222 different households. The library of indoor concentrations of $PM_{2.5}$ was then overlayed with the time-activity information, using Equation 2, to produce a time-weighted average exposure to $PM_{2.5}$ for each ten-minute interval. Results were aggregated by household income quintile to examine inequalities.

$$E(t_i) = \sum_{j=1} C(t_i)P(t_i) \quad (2)$$

Where $E(t_i)$ is the total exposure for the child population at each ten-minute time interval; $C(t_i)$ is the indoor concentration in microenvironment *j* for the equivalent time-stamp and $P(t_i)$ is the proportion of the population in micro-environment *j*.

3 RESULTS

Mean and median daily exposure for each income group is shown below in Table 2. Median concentrations may better represent the exposure faced by children in each group as data was lognormally distributed. Children in the lowest income quintile have the highest exposure to $PM_{2.5}$, whilst those in the highest quintile have the lowest exposure, but this relationship is non-linear, and those in the fourth income quintile are exposed to higher $PM_{2.5}$ concentrations than those in the third quntile.

Table 2. Distribution of daily exposure to $PM_{2.5}$, by childhood household income quintile.

Household income quintile	Population (*n*)	Mean (μg/m^3)	SD (μg/m^3)	Median (μg/m^3)	IQR (μg/m^3)

1	217,024	22.7	19.6	14.4	18.4
2	405,646	20.5	16.1	13.8	13.2
3	337,798	20.4	15.2	12.9	13.8
4	487,091	19.9	16.0	13.5	12.9
5	552,802	17.5	14.3	11.7	9.97

3.2. Daily variations

To analyse how exposure varies throughout the day, the median for each ten-minute interval was calculated for the five populations shown in Table 2. Daily peaks were largely driven by indoor sources, such as cooking and smoking events. On weekdays, the peak before 8am is driven by cooking, which then drops to background school concentrations (~9 μg/m^3) where there are no indoor sources other than resuspension (Fig 3). Likewise on weekends, peak concentrations are driven by indoor sources in the home micro-environment. As indoor sources are the main drives of exposure, concentrations are highest in winter as lower window-opening frequencies limits the role of ventilation to reduce indoor concentrations. Night-time exposure is the lowest, as bedroom concentrations are not driven by indoor combustion events but by outdoor background levels.

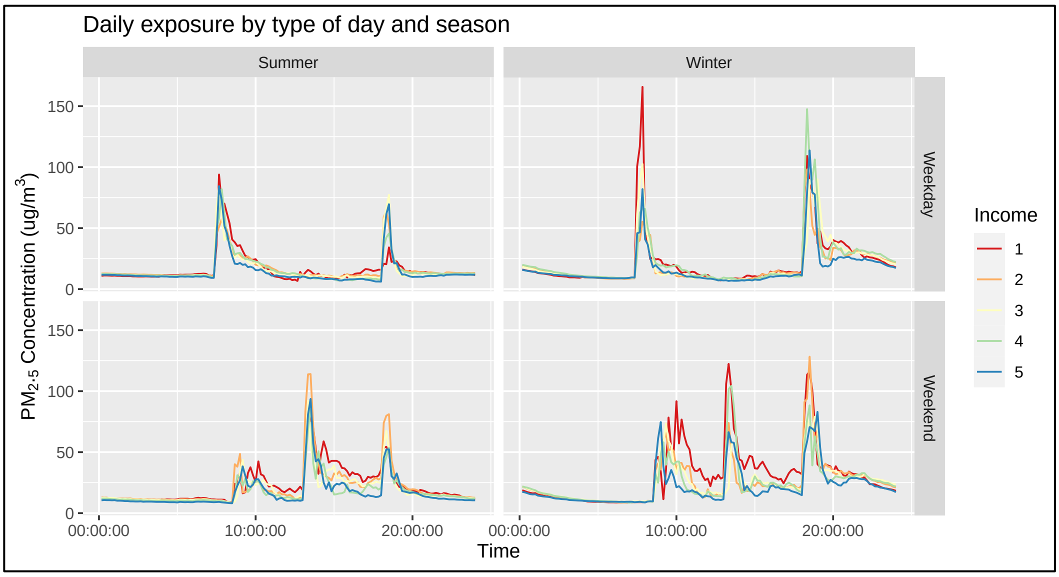

Figure 3. Daily variations in exposure by type of day and season, aggregated by childhood household income status.

3.3. Test for significance

To assess if differences in $PM_{2.5}$ exposures between income groups were statistically significant, the assumption of normality was checked using a Shapiro-Wilk's test which confirmed data was not normally distributed (p=2.50e-57). A Kruskall-Wallis rank sum test was then carried out and confirmed that there were significant differences between income groups (p=2e-12, df=4). Pairwise comparisons were then computed using Wilicoxon rank sum test to analyse within group variance. P-values between income groups are shown below in Table 3. Results suggest that only children from households in the lowest and highest income categories have significantly *higher* and *lower* exposure to $PM_{2.5}$, respectively.

Table 3. P-values between income groups.

Household income quintile	1	2	3	4

2	0.42	-	-	-
3	0.06	0.17	-	-
4	0.03	0.16	0.81	-
5	1e-10	1e-09	3e-07	7e-06

4 DISCUSSION

Children from lower-income homes had the highest exposure, and this was driven by higher smoking rates, longer cooking durations, higher ambient concentrations and dwellings with smaller floor areas for the distribution of internal pollution. Results align with empirical data, where indoor exposure to $PM_{2.5}$ ranged between 19 – 29 µg/m^{-3} across the child sample (Wheeler et al., 2000). The high peaks shown in Fig. 3 from cooking activities align with measurements conducted in the South-East of England, where $PM_{2.5}$ concentrations reached 120 µg/m^3 for electric cooking (Nasir & Colbeck, 2013).

Actions to drive down childhood exposure in London should focus on reducing outdoor concentrations in deprived parts of the city, increasing awareness regarding the harm of indoor smoking and ensuring homes are properly ventilated when cooking. Reducing pupil class sizes may prevent the indoor environment at the school acting as a reservoir for outdoor air pollution.

4.1. Limitations

The approach here assumed two deterministic occupancy cooking schedules, varied by SES, as indicated by the time-use data. Whilst based off of empirical survey data, two occupancy cooking schedules will not capture the full range of cooking techniques across the London population, which can lead to appreciable differences in indoor air pollution (Abdullahi et al., 2013).

A simple mass-balance approach was used to estimate indoor concentrations in the school and travel micro-environments where the only socio-economic effect were the outdoor air pollution concentrations. Pupil class-size has steadily increased in state-funded primary and secondary schools in England, which may result in greater particle concentrations due to resuspension from occupant movement (Kalimeri et al., 2019). As the mass-balance approach considers the impact of resuspension for a given number of occupants, there is scope to introduce variable classroom occupant densities within the work presented here, but sufficient data to parameterise the equation for varied occupancy across levels of school deprivation was not available when the model was developed.

5 CONCLUSIONS

The work here provides an estimation of childhood exposure to indoor $PM_{2.5}$ across multiple microenvironments for the London population. The tool aims to quantify exposure disparities, accounting for the variations in the quality of the building, characteristics of the surrounding environment and population time-activity patterns, so that changes to which can be understood in terms of their contribution to indoor air pollution inequalities. Highlighting how indoor exposures may vary for populations of different SES draws attention to wider issues regarding housing and environment inequalities. With rising inequality in London, environmental exposures play an important role in generating health inequalities from social disadvantage.

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