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Author names and affiliations:

Robert Tang[1], Linwei Tian[1], Thuan-Quoc Thach[1], Tsz Him Tsui[1], Michael Brauer[2], Martha Lee[2], Ryan Allen[3], Weiran Yuchi[3], Poh-Chin Lai[4], Paulina Wong[4], Benjamin Barratt[5]

1 The University of Hong Kong, School of Public Health, Hong Kong SAR

2 University of British Columbia, School of Population and Public Health, Canada

3 Simon Fraser University, Faculty of Health Sciences, Canada

4 The University of Hong Kong, Department of Geography, Hong Kong SAR

5 King's College London, MRC-PHE Centre for Environment & Health, UK

Corresponding author:

Benjamin Barratt

MRC-PHE Centre for Environment & Health, King's College London, 150 Stamford Street, London SE1 9NH, U.K.

+44 (0)20 7848 4034

benjamin.barratt@kcl.ac.uk

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Robert Tang[1], Linwei Tian[1], Thuan-Quoc Thach[1], Tsz Him Tsui[1], Michael Brauer[2], Martha Lee[2], Ryan Allen[3], Weiran Yuchi[3], Poh-Chin Lai[4], Paulina Wong[4], Benjamin Barratt[5]

1 The University of Hong Kong, School of Public Health, Hong Kong SAR

2 University of British Columbia, School of Population and Public Health, Canada

3 Simon Fraser University, Faculty of Health Sciences, Canada

4 The University of Hong Kong, Department of Geography, Hong Kong SAR

5 King's College London, MRC-PHE Centre for Environment & Health, UK

Abstract

BACKGROUND: Epidemiological studies typically use subjects' residential address to estimate individuals' air pollution exposure. However, in reality this exposure is rarely static as people move from home to work/ study locations and commute during the day. Integrating mobility and time-activity data may reduce errors and biases, thereby improving estimates of health risks.

OBJECTIVES: To incorporate land use regression with movement and building infiltration data to estimate time-weighted air pollution exposures stratified by age, sex, and employment status for population subgroups in Hong Kong

METHODS: A large population-representative survey (N = 89,385) was used to characterize travel behavior, and derive time-activity pattern for each subject. Infiltration factors calculated from indoor/outdoor monitoring campaigns were used to estimate micro-environmental concentrations. We evaluated dynamic and static (residential location-only) exposures in a staged modeling approach to quantify effects of each component.

RESULTS: Higher levels of exposures were found for working adults and students due to increased mobility. Compared to subjects aged 65 or older, exposures to $PM_{2.5}$, BC, and NO_2 were 13%, 39% and 14% higher, respectively for subjects aged below 18, and 3%, 18% and 11% higher, respectively for working adults. Exposures of females were approximately 4% lower than those of males. Dynamic exposures were around 20% lower than ambient exposures at residential addresses.

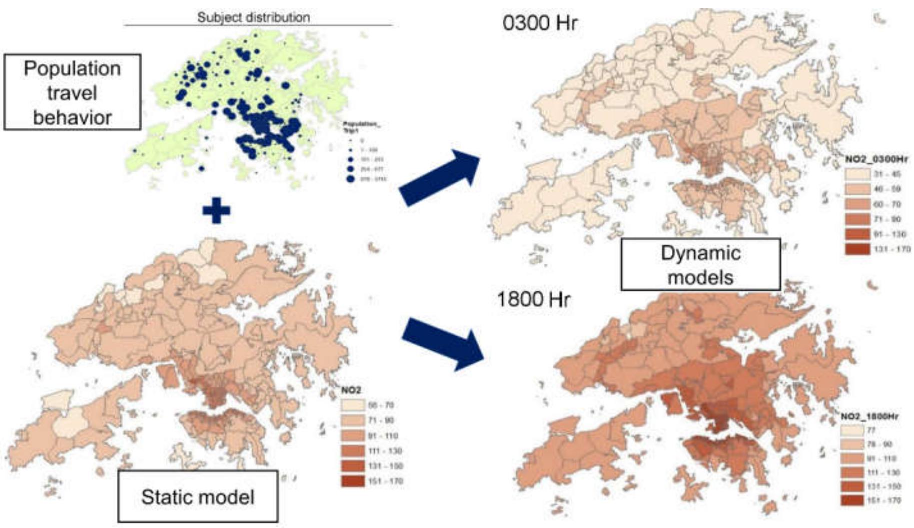
CONCLUSIONS: The incorporation of infiltration and mobility increased heterogeneity in population exposure and allowed identification of highly exposed groups. The use of ambient

concentrations may lead to exposure misclassification which introduces bias, resulting in lower effect estimates than ‘true’ exposures.

Keywords:

Air pollution; dynamic exposure; land use regression; exposure assessment; travel behavior; time-activity

Graphical abstract



Highlights

- The use of ambient concentration may not accurately represent air pollution exposure
- ‘Static’ estimates do not account for time spent in indoor microenvironments
- Time-activity and related exposure differ dramatically across population groups
- Travel survey can be used to derive population mobility and ‘dynamic’ exposure
- Integrating mobility avoid exposure misclassification, reducing biases in analyses

1. Introduction

Epidemiological studies assessing the health impacts of air pollution typically use ambient concentrations of subjects' residential address as individual exposure estimates (Künzli *et al.*, 2000; Hoek *et al.*, 2007, 2008; Brauer *et al.*, 2008). However, the exposure to air pollutants is unlikely to be static in reality, as people may be exposed to air pollution at work, study and other locations and during commute. The pollutant levels in microenvironments are influenced by the spatial and temporal changes in ambient pollution, as well as infiltration rates of different buildings (Allen *et al.*, 2012). In addition, population studies rarely account for subject's movement (Wilson *et al.*, 2005). Since time-activity patterns may differ significantly between population groups, this may lead to variability in exposure within the population that is not considered in estimates based on residential address. The inclusion of mobility data allow dynamic exposure to air pollution to be assessed which may help to avoid exposure misclassifications, and reduce errors and biases in health analyses (Jerrett *et al.*, 2005; Setton, Marshall and Brauer, 2011).

In studies assessing the long-term health effects of air pollution, surrogates of personal exposure including fixed-site monitoring stations (Oglesby, Künzli and Röösli, 2000; Monn, 2001) or modelled concentrations (Jerrett *et al.*, 2004) are often used to assign exposure estimates for large populations. Recently, land use regression (LUR) has been used extensively to model intra-urban pollutant spatial variability (Hoek *et al.*, 2008; Eeftens *et al.*, 2012). However, the use of ambient concentrations, even at the residential address, is unlikely to fully represent the 'true' exposure to air pollution. Evaluation studies have shown that ambient concentrations at home locations were significantly different than personal exposures of subjects (Oglesby *et al.,* 2000; Wilson *et al.,* 2000; Payne-Sturges *et al.*, 2003). The effects of mobility on air pollution exposure

are rarely accounted for in epidemiologic studies, as LUR are static models which do not incorporate travel patterns.

The use of ambient concentrations as exposure estimates assume subjects do not leave home, where in reality people may spend 8-10 hours per day at work or school locations with pollutant levels higher or lower than at their home addresses. This difference becomes significant where there is high pollutant spatial variability in the study area, with a substantial proportion of the population (e.g. working adults) commute from lower pollution outlying areas to highly polluted city centre. In this case, the residence-based exposure estimate will be biased low, directly affecting the strength and significance of relative risk estimates with health outcomes.

Recent studies have used travel surveys (Saraswat *et al.*, 2016), activity-based simulations (Setton *et al.*, 2008; Dhondt *et al.*, 2012), GPS or mobile-based tracking (Dons *et al.*, 2011; de Nazelle *et al.*, 2013), travel smartcard (Smith *et al.*, 2016) or cellular network data (Dewulf *et al.*, 2016) to derive dynamic exposure estimates. These approaches have facilitated detailed spatio-temporal analysis of individual travel behaviors. A number of studies found static estimates underestimated exposure levels (Dhondt *et al.*, 2012; de Nazelle *et al.*, 2013; Dewulf *et al.*, 2016; Nyhan *et al.*, 2016; Saraswat *et al.*, 2016). Simulations based on travel survey and air pollution modeling data found integrating mobility can affect exposure estimates by as much as 30% (Marshall *et al.*, 2006). When these were applied to epidemiologic effect estimates, results indicated bias of effect estimates towards the null when mobility is not considered (Setton *et al.*, 2008). In addition, epidemiological studies also assume subjects of different demographic groups to have the same exposure. This may not be accurate as the time-activity of population groups (e.g. between children/ elderly and adults) can be considerably different. The impact of mobility on exposure is likely to be dependent on spatial heterogeneity of pollutant (Steinle *et al.*, 2013).

The development of dynamic exposure models also allow for scenario analysis to assess the impact of changes in transportation patterns and land use on exposure.

To date, none of these approaches have been integrated with LUR to assess dynamic air pollution exposure which can be applied to investigate of long-term health impacts of air pollution. The aim of this work is to assimilate, characterize and integrate population movement to create a dynamic LUR model layer for the population of Hong Kong (HK). HK is a densely-populated city with significant air quality issues. Using a population-representative travel survey, we incorporated population mobility in LUR models to estimate dynamic time-weighted air pollution exposure for different age, sex and employment groups. This study evaluates the use of static ambient concentrations as exposure estimates, and the effects of stratification of exposure to different population groups of particulate matter ($PM_{2.5}$), black carbon (BC), and nitrogen dioxide (NO_2).

2. Materials and Methods

The method can be divided into three steps: (i) mobility data (i.e. time, location, transport, purpose and duration of trips) were extracted from a territory-wide travel characteristics survey for each subject; then (ii) the microenvironment and time spent were classified and calculated based on the extracted information; finally (iii) the time-activity information were matched with corresponding micro-environmental concentrations to calculate time-weighted dynamic exposure. The modelled outputs (i.e. time-weighted dynamic exposure) account for crossing multiple locations, and can accurately determine the spatial contrast in pollutant concentrations

along the travel route. Detailed maps of the study area are shown in Figures S1 and S2, with the overall process summarized in Figure S3 (Supporting Information).

2.1 Population mobility data

We used a large population-representative survey to characterize travel behavior and derive population movement patterns in HK. The Travel Characteristics Survey (TCS) 2011 Survey (To *et al.*, 2005; Transport Department, 2014), published by the HK Transport Department, polled 50,000 randomly chosen households, with each household member providing detailed trip information, including: start & end locations; form of transport used; number of trips made; time and duration of journeys to place of work or study. In the main survey, trip information and subject characteristics were collected on a weekday (24 hours; not a public holiday). The number of subjects totaled 101,385, with self-reported mode, route and frequency of travel recorded during the sample day. Individual data on age, sex and occupation were available for each subject. In addition, we also used the HK 2011 Census to validate results (Census and Statistics Department, 2012). The use of a travel smartcard is widespread in HK, however these data were not accessible for this study due to privacy and data protection concerns.

From the original number of subjects (N = 101,385), we excluded subjects who may not represent the general population travel patterns or those who were not representative of study population of health effect studies. We excluded subjects who: (1) were professional drivers; (2) were mobile residents and domestic helpers; (3) had cross-boundary trips and trips to airports during the period of the travel survey, as they were assumed to travel outside the study area. After these exclusion criteria were applied, the total number of subjects included in model development was 89,385 (Table S1 in Supporting Information).

Next, we constructed time-activity patterns for each survey subject, based on travel time, location and purpose of the trips made during the day. We assembled population mobility information from the survey data in detail, including movements between tertiary planning units (TPUs) per hour of the day. TPUs are the smallest spatial administrative units in HK (N = 289, Figure S2 in Supporting Information), devised for population census and town planning purposes. The median population size of a TPU was 21,450. Data from the 2011 Census was also available at TPU level.

2.2 Air pollution data

Details of the $PM_{2.5}$, BC, and NO_2 LUR models have been described in Lee *et al.* (2017). The models were developed from a comprehensive monitoring campaign and predictor variables representing traffic, land use and population. We ran a zonal statistics analysis to compute the average pollutant concentrations for each TPU using ArcGIS (ESRI; Version 9.0). There were four components to the air pollution exposure estimates: (1) ambient concentrations for each TPU; (2) indoor microenvironments; (3) transport microenvironments; and (4) diurnal profile factors. We estimated pollutant concentrations in indoor microenvironments with the use of infiltration efficiencies (F_{inf}) derived from seasonal field campaigns monitoring paired indoor/outdoor $PM_{2.5}$ and BC continuously over a seven-day period at 24 naturally ventilated residences during 2016 and 2017. F_{inf} is a unitless quantity defined as the equilibrium concentration of outdoor pollution that penetrates indoors and remains suspended, and was calculated following Allen *et al.* (2012). Indoor/ outdoor (IO) relationships obtained from local studies were used for NO_2 (Lee, Chang and Chan, 1999; Lee and Chang, 2000). Air-conditioning systems are used extensively in non-residential buildings in HK, therefore different infiltration efficiencies were used for indoor microenvironments with natural ventilation or with the use of

mechanical ventilation and air conditioning (MVAC) systems. For transport microenvironments, we re-classified modes of travel in the travel survey, and matched data with monitored concentrations in transport microenvironments from local studies. As only a few studies have investigated in-transit levels of BC and NO_2 in the study area, we estimated pollution levels from personal monitoring studies (Chan *et al.*, 1999; Yang *et al.*, 2015), and used PM ratios to predict concentrations in transport modes which were unavailable (Table 1). Diurnal adjustment factors were derived by calculating the mean ratio of hour of day mean concentration by annual mean concentration across the routine monitoring sites between 1-Jan-2013 and 1-Jan-2015. Factors ranged from 0.86 to 1.13 for $PM_{2.5}$, 0.46 to 1.37 for BC and 0.55 to 1.37 for NO_2 (Supporting Information; Table S3).

2.3 Time-weighted air pollution exposure

Time-activity patterns were derived for each survey subject. We then combined these with predicted air pollution concentrations in outdoor, indoor and transport microenvironments and accounting for diurnal pollution patterns to calculate the time-weighted air pollution. The general form of the equation used to calculate time-weighted exposure was:

$$E_i = \sum_{j}^{J} C_j t_{ij} \tag{1}$$

where E_i is the time-weighted exposure for each subject i; C_j and t_{ij} are the pollutant concentration and the aggregate time that subject i spends in microenvironment j, respectively. J is the total number of microenvironments that subject i moves through during the sample day. This indirect approach of exposure assessment combing time spent in different environments (i.e.

home, work, school) and pollutant concentrations at each location is similar to that used by Watson *et al.*(1988).

We defined the microenvironments where subjects were exposed as: (1) home indoor; (2) commercial indoor; (3) school indoor; (4) other indoor; (5) outdoor; and (6) in-transit. Example building types for each classification are described in the Supporting Information (Table S2).

A staged modeling approach was used to assess the impact of dynamic model components on estimated air pollution exposure, starting with static, then moving to more sophisticated dynamic components representing different outdoor, indoor and transport microenvironments in a series of stages. The modeling stages and associated time weighted exposure equations (TWE) were:

1. Home address outdoor

$$TWE_1 = \frac{[C_{ho}t_{ho}]}{T} \tag{2}$$

2. Home address indoor

$$TWE_2 = \frac{[C_{hi}t_{hi}]}{T} \tag{3}$$

3. Dynamic indoor

$$TWE_3 = \frac{[C_{hi}t_{hi} + C_{wi}t_{wi} + C_{si}t_{si} + C_{oi}t_{oi} + C_{o}t_{o}]}{T} \tag{4}$$

4. Dynamic indoor + in-transit

$$TWE_4 = \frac{[C_{hi}t_{hi} + C_{wi}t_{wi} + C_{si}t_{si} + C_{oi}t_{oi} + C_{o}t_{o} + C_{t}t_{t}]}{T} \tag{5}$$

5. Dynamic indoor + in-transit + diurnal variation

$$TWE_5 = \frac{[C'_{hi}t_{hi} + C'_{wi}t_{wi} + C'_{si}t_{si} \ + C'_{oi}t_{oi} \ + C'_{o}t_{o} + C_{t}t_{t}]}{T} \qquad (6)$$

6. Dynamic outdoor + in-transit + diurnal variation

$$TWE_6 = \frac{[C'_{ho}t_{ho} + C'_{wo}t_{wo} + C'_{so}t_{so} \ + C'_{oo}t_{oo} \ + C'_{o}t_{o} + C_{t}t_{t}]}{T} \qquad (7)$$

where C_{ho}, C_{hi}, C_{wi}, C_{si}, C_{oi}, C_{o} and C_{t} are the pollutant concentrations at home outdoor, home indoor, commercial indoor, school indoor, other indoor, outdoor and in-transit microenvironments respectively; t_{ho}, t_{hi}, t_{wi}, t_{si}, t_{oi}, t_{o} and t_{t} are the time spent each in the respective microenvironment; and T is the total duration of time-activity pattern in hours, based on the subject's movement data. C'denote concentrations which were adjusted by diurnal factors. Stage 6 was included as a sensitivity test to separate the impacts of mobility and infiltration rates (i.e. effects of movement; outdoor concentrations only).

We calculated the time-weighted exposure for each subject for each stage. The total exposure to air pollution in each model component, calculated by multiplying the time each individual spent in each microenvironment by the pollutant concentration at the specific microenvironment considering spatial (i.e. movement between TPUs), and, where relevant, pollutant diurnal profile. Each component estimate was then summed and divided by the total time T.

Table 1: Infiltration efficiency factors of building microenvironments and concentration constants in different transport microenvironments used in the dynamic model components

	Number of trips	$PM_{2.5}$	BC	NO_2
Indoor microenvironments		**Infiltration Efficiency (F_{inf})**		
Home indoor	-	0.82	0.89	0.79
Commercial indoor	-	0.40	0.45	0.72
School indoor	-	0.92	0.88	0.71
Other indoor	-	0.92 natural 0.40 MVAC	0.88 natural 0.45 MVAC	0.70 natural 0.72 MVAC
Transport microenvironments		**Concentration (μg/m^3)**		
Private/Car	10505	71	21	130
Bus	51071	103	31	130
minibus	19104	103	31	109
Truck/Van	212	90	27	130
Train - MTR (underground)	48333	69	21	47
Train - MTR (surface; ex-KCR)	1549	71	21	66
Tram	784	88	26	147
Ferry	24432	64	19	96
Walking	585	44	13	139
Bicycle	318	44	13	139
Motorcycle	10505	44	13	139

2.4 Data Analysis

Following calculation for staged exposure estimates for all 89,358 subjects, we examined how the time-weighted exposures varied across the population. Stratified analysis on age, sex, and population subgroups were undertaken. The survey subjects were categorized into three age

groups: <18, 18 – 65, 65 and above; and into three population subgroups according to their occupations: students, working adults, and those who are neither in work or study. These age categories were derived based on the range and distribution of the youngest and oldest individuals. All statistical analyses were carried out using R (Version 3.4.0).

3. Results

3.1 Exposure and time spent in different microenvironments

On average across the whole population, time spent at home, in work, in school, in transport and travelling outdoors (walking, cycling) was 62%, 22%, 10%, 5% and 1% respectively. Maps showing mean concentrations in each TPU are shown in the Supporting Information (Figure S4). Significantly higher pollutant exposures were found in transport microenvironments and trips made on surface modes of transport contributed notably to the daily exposure of subjects, even though time spent in these microenvironments was considerably less (Table 2). Ambient exposure estimates were typically the second highest, although this varied spatially. For example, residents of the urban area TPUs were exposed to ambient concentrations of $PM_{2.5}$ up to 75% higher than those living in north eastern TPUs. These spatial contrasts were amplified when accounting for diurnal variations, as most subjects travelled during morning and evening rush hour periods. Lowest indoor exposure estimates were found in office buildings due to the low MVAC infiltration efficiency, however, this contrast was lessened slightly with the inclusion of diurnal factors, as these were around somewhat higher than one during typical working hours (between 1.1 and 1.3 dependent on pollutant). As expected, most of the subjects spent most of their time indoors, at their home residential address. The results of the static and dynamic models are presented in Figure 1. Modelled exposure estimates for different population subgroups

throughout a notional 24-hour period are shown in Supporting Information (mean across all TPUs; Table S4).

Table 2: Mean concentrations in microenvironments and average time spent per day

Microenvironment	Mean time spent (hours)	Mean concentration (µg/m^3)		
		$PM_{2.5}$	BC	NO_2
Outdoor	0.1	56.4	8.3	68.1
Home indoor	14.9	50.9	7.5	67.5
Commercial indoor	5.2	31.2	4.6	76.9
School indoor	2.5	50.3	7.4	65.2
Other indoor	0.2	30.6	4.5	65.9
Transport	1.1	61.8	9.1	98.8

Time-weighted exposure by model stage

The constructed time-activity patterns of subjects, and for each modelling stage are shown in Figure 2 and Figure S5 (Supporting Information), respectively. Examining the static models, overall exposures were 19%, 13% and 27% higher outdoors (Stage 1) compared to the indoor concentrations (Stage 2), for $PM_{2.5}$, BC and NO_2, respectively. The mean exposures based on ambient concentrations at residential addresses were 32.0, 9.4, and 92.9 µg/m^3 for $PM_{2.5}$, BC and NO_2, respectively. The calculated time-weighted exposures are presented in Table 3.

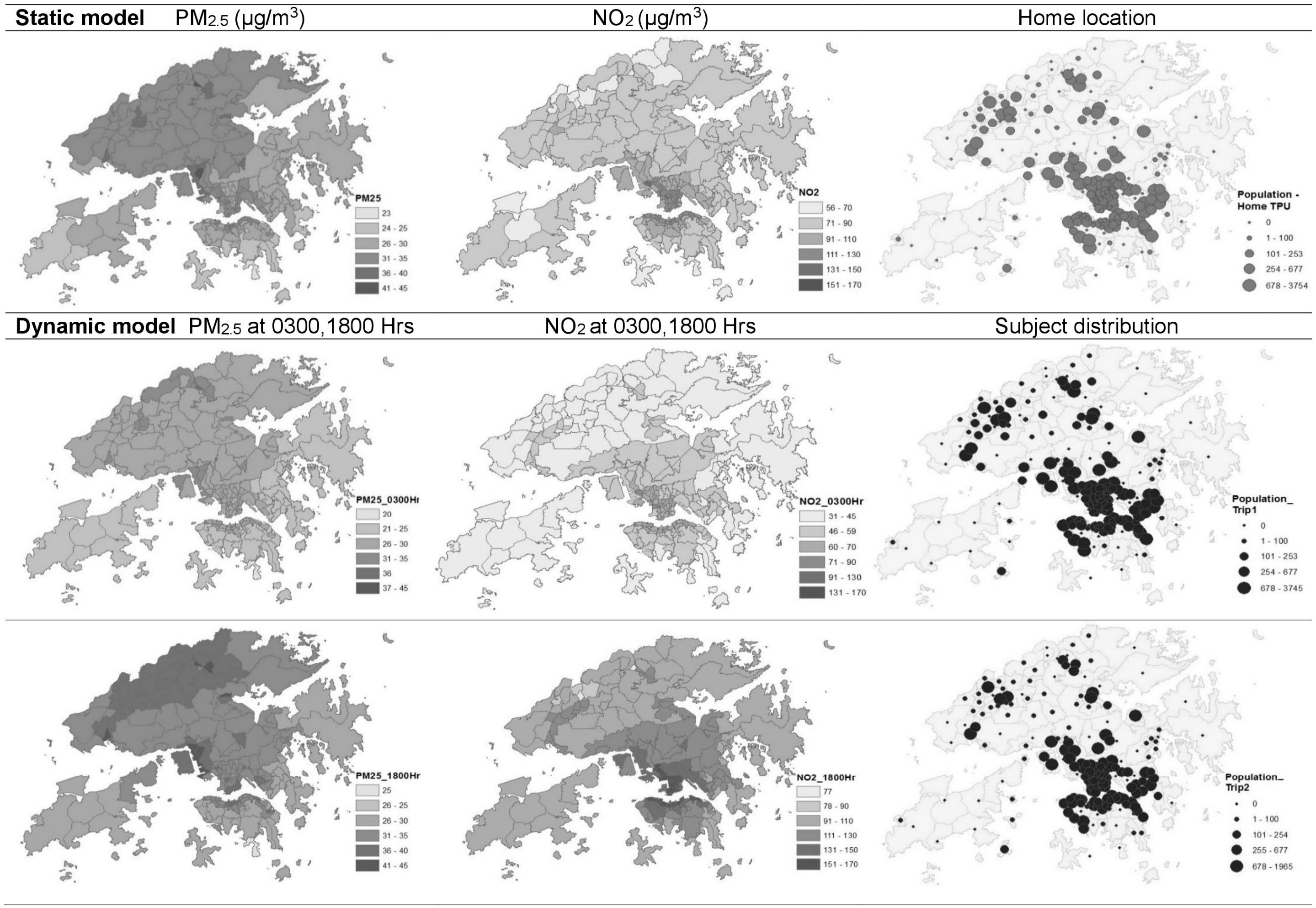


Figure 1: Spatial variation in $PM_{2.5}$ and NO_2 concentrations (µg/m^3) in static (top) and dynamic models (bottom). The dynamic model allows movement of subjects to be accounted, where only residence locations are used in static model.

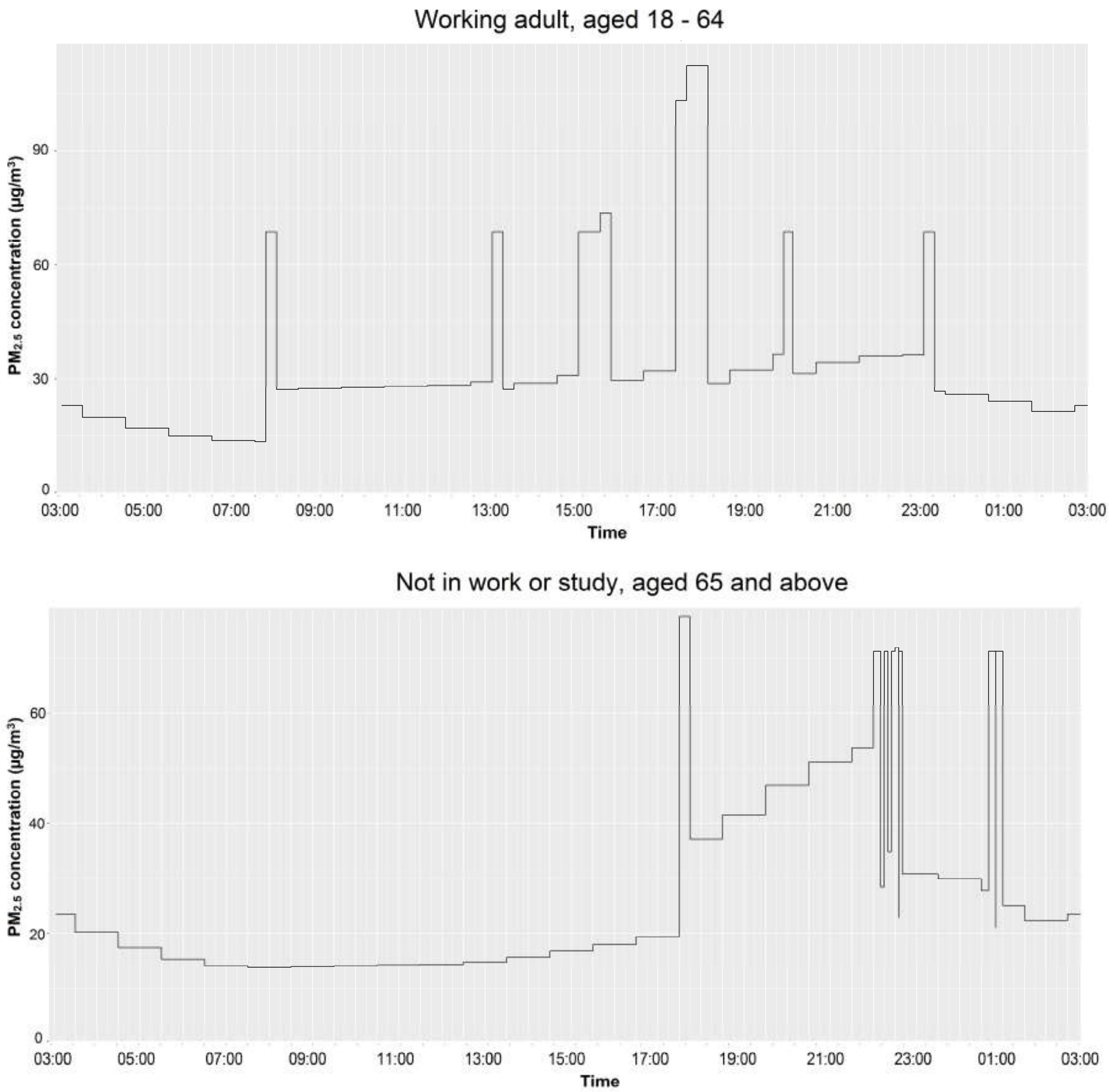


Figure 2: Modelled dynamic $PM_{2.5}$ exposure (Stage 5) of two individuals over a 24-hour period.

Table 3: Time-weighted exposure estimates for all model stages for the survey population.

Stage	Micro-environment	Time-weighted Exposure ($\mu g/m^3$) (N = 89358)											
		$PM_{2.5}$				***BC***				***NO_2***			
		mean	**min**	**max**	**S.D.**	**mean**	**min**	**max**	**S.D.**	**mean**	**min**	**max**	**S.D.**
1	Outdoor	32.0	23.3	40.8	3.4	9.4	2.8	18.5	3.5	92.9	56.2	141.1	15.1
2	Indoor	27.0	19.7	34.5	2.8	8.3	2.5	16.4	3.1	73.4	44.4	111.4	12.0
3	Dynamic indoor	25.0	11.2	38.7	3.9	7.6	1.9	17.0	2.7	73.4	42.9	116.7	10.9
4	Dynamic indoor + transit	27.5	13.1	46.5	4.1	8.4	2.3	18.0	2.6	74.8	44.4	116.7	10.5
5	Dynamic indoor + transit + diurnal	27.1	11.9	46.8	4.2	7.8	1.2	21.5	2.8	71.3	24.9	122.7	14.3
6	Dynamic outdoor + transit + diurnal (movement)	33.8	20.3	50.2	3.9	9.6	1.3	22.0	3.4	90.9	31.5	147.7	18.1

In addition to the home location, time-weighted exposure estimates were calculated from the time they spent at home and work, and other indoor locations (e.g. shopping centers) (Stage 3). Their destination was determined by the trip purpose in the questionnaire and their occupations. Comparing Stage 3 (dynamic indoor) and Stage 1 (home outdoor) results, 28%, 24% and 27% decreases were seen for $PM_{2.5}$, BC and NO_2, respectively, reflecting the impact of infiltration and time spent in indoor microenvironments. When transport microenvironments were added (Stage 4), this difference decreased, to 16%, 12% and 24% respectively, reflecting elevated exposures while in transit. The inclusion of diurnal factors decreased population mean exposure estimates slightly in comparison with the previous stage.

Model Stage 6 was added as a sensitivity test to examine movement effects as distinct from infiltration effects. The mean exposures for Stage 6 were 33.8, 9.6, and 90.9 μg/m^3 for $PM_{2.5}$, BC and NO_2, respectively, which were slightly higher than Stage 1 (static outdoor) exposures for $PM_{2.5}$ and BC.

Overall, the inclusion of dynamic components decreased exposure estimates in comparison with standard residential outdoor exposure estimates, principally driven by the indoor components, despite relatively high infiltration efficiencies. In the case of $PM_{2.5}$, exposure heterogeneity (represented by the standard deviation) increased, but decreased in BC and NO_2 estimates.

3.2 Stratified analysis for different population subgroups

Full numerical results and box plots for each model state and each subgroup are presented in the Supporting Information (Tables S5 – S8; Figures S6 – S11). Time-weighted exposures for each model stage were split by age groups, population subgroup and sex. Static exposure measures did not differ between groups as all behaviors were equal, however, the addition of dynamic components showed lower exposure exposures with the 65+ age group, and the highest for those less than 18 years old. Young people showed an increase of 13%, 39% and 14%, for $PM_{2.5}$, BC and NO_2, respectively, compared to those older than 65 (Figure 3).

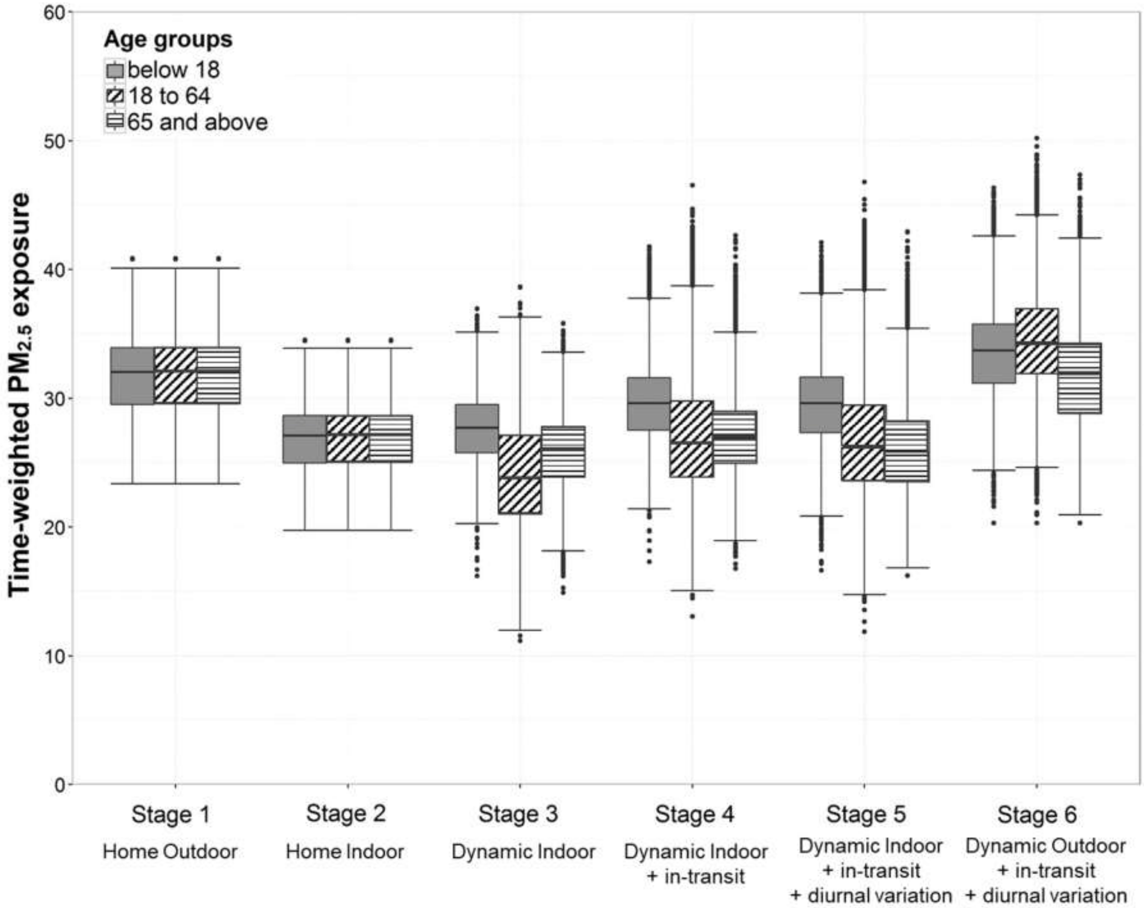


Figure 3: Box-plots of time-weighted $PM_{2.5}$ exposures for each model stage split by age group.

Comparison of exposure estimates split by population subgroups revealed different patterns in static and dynamic models. The static model found that those who were neither in work or study had slightly higher exposure than other subgroups. However, the dynamic models found that students had higher $PM_{2.5}$ and BC exposure than workers, and the lowest exposures were found in the 'others' group, those who are neither in work or study. Students had a 13% and 35% increase compared to the 'others' group for $PM_{2.5}$ and BC, respectively. For students, the mean

time-weighted exposures were 29.7 and 9.2 μg/m^3 for $PM_{2.5}$, and BC respectively. For NO_2, working adults had the highest dynamic exposure, with a mean time-weighted exposure of 75.5 μg/m^3, 2% and 18% higher than students and 'other' subgroups.

Dynamic models found lower exposures for females compared to males for all pollutants, explained by exposure differences in both time-activity (Stage 5), and mobility (Stage 6) in male/female subgroups. Male exposures were 2%, 5% and 4% higher than females in dynamic exposures when compared to static. For male subjects, the mean time-weighted exposures were 27.4, 8.1 and 72.8 μg/m^3 for $PM_{2.5}$, BC and NO_2, respectively.

4. Discussion

In this study, we found that mobility played a key role in estimating air pollution exposure. Using land use regression, building infiltration rates and generalized travel behavior, time-activity patterns were constructed from a population-representative survey to develop dynamic exposure models. It was observed that (1) subjects spend most of the day indoors in environments with considerably lower pollutant levels; (2) there were notable differences in time-weighted exposures between age and occupation subgroups; and (3) this variation was amplified by effects of population movement and changes in day and night time concentrations. The impact of mobility on exposure differed between pollutants dominated by local or regional emission sources.

4.1 'Static' vs. 'dynamic' air pollution exposure

Spatial heterogeneity of pollutants and infiltration were found to be important factors affecting exposure. LUR modelled results showed large spatial contrast in ambient concentrations between

TPUs, indicating high within-community exposure variation in the study area. We found the time-weighted exposures were significantly reduced in some indoor microenvironments due to low building infiltration rates. For instance, F_{inf} for mechanically ventilated office building were 45% and 40% during the cool and warm seasons, respectively. While the office infiltration factors were derived from a limited number of sites, the F_{inf} was similar to those reported in other studies for occupied HVAC buildings (Fisk *et al.*, 2000; Clougherty *et al.*, 2013). Conversely, these buildings have higher power requirements than naturally ventilated buildings and in many cases, will contribute further to regional sources of $PM_{2.5}$ through fossil fuel based electricity generation.

This study adopted a staged modeling approach in order to evaluate the effects of each components of the dynamic models (i.e. indoor, transport, diurnal and movement), and compared these to the baseline static measure of ambient concentration at home location traditionally used in epidemiological studies. Significant differences were found between dynamic and static exposure estimates. As expected, the addition of an indoor component decreased time-weighted exposure estimates, but this was partially offset by inclusion of transport microenvironments. Overall, mean time-weighted exposures for the full dynamic model were around 20% lower than the ambient baseline estimates. The inclusion of diurnal factors were found to amplify spatial contrast of pollutants between day and night time levels. The effects of incorporating mobility in dynamic exposure modeling were also different between pollutants. The impacts were greater for BC and NO_2 exposure estimates than $PM_{2.5}$, due to the smoothing influence of secondary particulate on diurnal $PM_{2.5}$ variation.

4.2 Comparison to other studies

In other studies assessing dynamic air pollution exposure, mobility or time-activity data were derived from transport and activity-based simulation models (Setton *et al.*, 2011; Dhondt *et al.*, 2012), GPS (Dons *et al.*, 2011), mobile-based tracking (de Nazelle *et al.*, 2013), travel smartcard (Smith *et al.*, 2016), travel surveys (Saraswat *et al.*, 2016) or cellular network information (Dewulf *et al.*, 2016; Nyhan *et al.*, 2016). These were combined with air pollution modeling to assess personal and population exposure to pollutants. All these studies reported higher exposures when mobility is integrated, indicating underestimation of exposure when static (residential-only) measure is used. The dynamic exposures to NO_2 were found 12% and 24% higher compared to static estimates in Dhondt *et al.* (2012) and de Nazelle *et al.* (2013), respectively. In another Asian city setting, Saraswat *et al.* (2016) found ignoring effects of mobility led to an underestimation of annual $PM_{2.5}$ population exposure by about 11% in New Delhi. When work locations were considered in addition to residential, exposures to NO_X and NO_2 were found to increase by 5 – 10 ppb (Shafran-Nathan *et al.*, 2017). Nyhan *et al.* (2016) found significant differences between dynamic and static population-weighted exposures in New York City using cellular data with spatiotemporal $PM_{2.5}$ concentrations. It was found travelling to work locations, usually in urban areas with higher pollutant levels, contributed to this variation from home concentrations, particularly time spent in transport microenvironments contributed significantly to overall exposure (Dons *et al.*, 2011; de Nazelle *et al.*, 2013). The effects of daily mobility on exposure were greater for weekday than weekend (Dewulf *et al.*, 2016). The results were somewhat different with those found in this study, when infiltration rates and micro-environmental concentrations were taken into account. Smith *et al.* (2016)s combined a nested dispersion modeling technique with building infiltration factors and travel behavior to create a dynamic exposure model for London. They found that the dynamic model produced estimated

exposures to be 37% lower for $PM_{2.5}$ and 63% lower for NO_2 than the static ambient model. This difference is likely to be driven by the much lower mean F_{inf} values used for London (31% and 56% for NO_2 and $PM_{2.5}$ respectively).

4.3 Implications in epidemiological studies

In environmental epidemiological studies, exposures are often assumed to be the same with different demographic groups. If these differences were equally distributed across the population, then their inclusion would have little impact on health outcome analyses. A stratified analysis of population subgroups was carried out to test the hypothesis that the dynamic model increased heterogeneity in exposure estimates. The stratified analysis confirmed this hypothesis. Higher levels of exposures were found with working adults and students than those neither in work or study due to increased mobility, despite relatively low concentrations in office locations, particularly in BC estimates. The results consistently found higher exposure with persons below age 18, compared to other age groups. The exposures to $PM_{2.5}$, BC, and NO_2 were respectively 13%, 39% and 14% higher for populations who are under age 18, compared to persons who are 65 and above. One explanation for this is that most students' schools were located within the same TPU and many commuted to school by walking. This pattern of increased exposure with longer travel time has been described by others in exposure monitoring studies (Chau *et al.*, 2002; de Nazelle *et al.*, 2013), and has been suggested to partially offset the physical activity benefits of walking (Hankey *et al.*, s2011). We also assumed natural ventilation in schools, with higher infiltration rates than office buildings. Spatial contrasts were amplified when accounting for diurnal variation in pollutants, as most subjects travelled during morning and evening rush hour periods, indicating that population mobility is an important consideration beyond that of

transport microenvironment effects. We found the addition of model components increased the gap between male and female exposures, with the female population having lower exposures to air pollution by approximately 4%. A study in Vancouver (Setton *et al.* 2011), which only studied the working population, found no significant difference in exposure by sex. However, a higher than 50% proportion of women in our survey data were in the non-working category, which is likely to account for the different finding. Overall, the effects of the dynamic component differed by pollutant where some have limited change from ambient concentrations.

4.4 Limitations

Travel characteristic surveys, such as the one used in this study, are available in many cities in the world. The large sample size of these readily available surveys allow population-representative generalized travel behavior patterns to be derived accurately, which can then be directly applied to epidemiological studies to allow adjustments of exposures for cohort participants based on their age, sex, occupation or residential locations. This is possible even when travel patterns of the specific participants of the cohort are not known. Recent studies which used GPS or location tracking devices, cellular network or travel smart card data have limitations in small number of subject, time-intensive for collection of tracking data (Dons *et al.*, 2011), biases in population groups who do not carry mobile phones (de Nazelle *et al.*, 2013), or difficulties in obtaining data due to privacy concerns. The use of city-wide surveys as mobility data have advantages over these methods, and can be integrated in air pollution modeling effectively.

However, one limitation of this study is the lack of validation data. A drawback of using travel surveys as mobility data is that individual subject level data are not often available (e.g. precise residential location). This limited the possibility of validation studies to be carried out, for example, to determine if a static or dynamic model estimate is closer to the ‘true’ exposure value. Conversely, simulation studies and other sources of mobility data with more detailed exposure measurements and demographic information are likely to have a small sample size, therefore difficult to generalize to population scale travel patterns. The future work of this project is to carry out a validation study investigating the agreement between modelled and personal monitoring results, similar to Sahsuvaroglu *et al.* (2009) and Montagne *et al.* (2013).

Whilst the LUR models performed relatively well in capturing pollutant spatial variability, it was noted that these may be biased towards selecting traffic variables as modelling was focused on developed land and roadside sites (Lee *et al.* 2017). The LUR models were suitable for predicting concentrations in the populated areas, which was reasonable as these were developed for application to human exposure estimates. The relatively large number of monitoring sites used for model development also reduced potential bias (Basagaña et al., 2013). All measurements utilized in this study underwent strict protocols on sampling, quality assurance/control and calibration.

Incorporating mobility also had limited effects on $PM_{2.5}$, which is dominated by background emission sources in the study area. In addition, using TPUs as the spatial unit is a limitation in this study, as subject and trip information were only available at TPU level (N =289) in the TCS. Nevertheless, TPUs are relatively small in area (averaged around 5.2 km^2) with similar built environment and pollution characteristics. The pollutant variation within each TPU were further assessed (Table S9 in Supporting Information).

5. Conclusions

The use of ambient concentration at residential address to estimate individual's exposure to air pollution may not provide an accurate representation in population studies. The results from the study provided the first evidence that considering air pollution exposure in a dynamic landscape would benefit exposure assessment. Dynamic models can also identify differential exposures between population subgroups. Infiltration factors found in homes were close to one and residences provided little protection from ambient air pollution. We identified differential exposures between population subgroups that would not be present in static exposure models, including higher exposures in the younger population and marginally higher exposures for male subjects. As more studies incorporate population mobility, such contrasts will become better defined, leading to increased heterogeneity in estimates across a population and between pollutants.

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