

Emerging urban form – Emerging pollution: Modelling endogenous health and environmental effects of traffic on residential choice

Environment and Planning B: Urban
Analytics and City Science
0(0) 1–20

© The Author(s) 2018

Reprints and permissions:
sagepub.co.uk/journalsPermissions.nav

DOI: 10.1177/2399808318783206

journals.sagepub.com/home/epb



Mirjam Schindler 

Geospatial Research Institute, University of Canterbury, New Zealand

Geoffrey Caruso

University of Luxembourg, Luxembourg; Luxembourg Institute of Socio-Economic Research (LISER),
Luxembourg

Abstract

Air pollution bears severe health and environmental impacts and is of increasing concern to urban planners but densification strategies have ambiguous impacts. We analyse how households' aversion to generating and being exposed to traffic pollution at the residential place and during their commute influences emerging urban structures and how these structures in turn affect pollution exposure and the residential choice of households. Resulting spatial patterns are difficult to predict because of this feedback and the spatial form of urbanisation and road networks. We address this complexity with a micro-economic agent-based residential choice model dynamically coupled with a cellular automata model for pollution dispersion and its perception in neighbourhoods. Our simulation experiments on a theoretical grid suggest that the spatial scale of this perception is important. We also find that if both health and environmental concerns are to be addressed, a combination of reducing commuting distances and preserving local green spaces is necessary. In particular, locally dispersed urban development and intra-urban green spaces next to busy roads can mitigate pollution exposure.

Keywords

Residential choice, traffic-induced air pollution, urban structure, agent-based model

Introduction

Urban air pollution has severe impacts on the environment and human health, with traffic being its major source. Traffic-induced air pollution varies locally within cities depending on traffic patterns that arise from the spatial arrangement of land uses and activities and the

Corresponding author:

Mirjam Schindler, Geospatial Research Institute, University of Canterbury, Christchurch, New Zealand.
Email: mirjam.schindler@canterbury.ac.nz

derived travel demand across time. Studies analysed the link between urban form and traffic flows (e.g. Vos and Witlox, 2013) and between urban form and traffic-induced air pollution with respect to environmental (e.g. Stone, 2008; Verhoef and Nijkamp, 2003) and health impacts (e.g. Martins, 2012; Schindler and Caruso, 2014). Yet, the endogenous feedback of resulting air pollution patterns on residential decisions is almost unknown. Spatial responses by residents to health risk factors and their individual environmental consciousness may have important consequences on urban structures and, in turn, traffic patterns and the subsequent emission, distribution and exposure to air pollution. Moreover, both health and environmental aspects are to be jointly addressed. In fact, environmental consciousness about emissions may conflict with health consciousness related to local pollution. For example, households which choose to reduce their commuting for environmental reasons and live closer to the city are actually more exposed to the traffic generated by suburban residents. Such a tension may command spatial responses in terms of relocation and again a new distribution of air pollution and exposure. The feedback loop between air pollution levels, distribution and residential choice constitutes a complex spatial interaction that needs to be further understood in light of preferences and environmental sustainability goals. Understanding this complex and dynamic feedback is the focus of this study.

Consciousness of air pollution exposure problems is raising both at the residential place (e.g. Bayer et al., 2009; Chay and Greenstone, 2005; Smith and Huang, 1995) and as an encounter during daily activities (e.g. Nyhan et al., 2016; Yoo et al., 2015). This is most notably the case during the commute – where pollution levels are high – and it is demonstrated that concentrations within vehicle micro-environments can exceed ambient concentrations (e.g. Ragetti et al., 2013; Zuurbier et al., 2011). Some (e.g. Day, 2007; Gatersleben and Uzzell, 2000) also argue that peoples' perception of pollution might be even more influential on behaviour than knowledge of actual pollution levels. While one can easily recognise the need for better information about pollution levels (and environmental exposure in general) to be gathered in a spatio-temporal fashion (e.g. Kwan, 2013), feeding in perception of pollution exposure in standard models where commuting is a key behaviour and exposure taken up at residential places is arguably a timely modelling effort, in which we engage here.

1D urban economics models demonstrated ability to represent the role of commuting in residential choice, showing that residential choice is not a matter of minimising the costs of one or the other, but a fundamental trade-off between both. These models explicitly included a series of spatial interactions in the form of externalities (Fujita, 1989). However, they cannot cope well with complex interactions between residents and the built environment, such as those described above for pollution. Equilibria become quickly intractable when externalities vary strongly in space and time, and when the spatial form of the city and networks influence those externalities or their perception by households. Schindler et al. (2017) developed a tractable model that endogenises traffic-induced pollution. They demonstrated that pollution exposure consciousness leads to more expanded and flattened cities, and that a social optimum can be reached by a distance-based tax that re-concentrates households. However, strong simplifications of space and the externality, and the disregard of pollution dispersion processes were required to ensure mathematical tractability.

Agent-based models (ABM) have been identified as more flexible and effective strategies to integrate dynamic complexities arising through spatial interactions (Ausloos et al., 2014; Batty, 2005; Bretagnolle et al., 2003; Parker and Meretsky, 2004). ABMs allow emerging macro-scale land use patterns and aggregate urban attributes to be understood by simulating micro-scale behaviour of households and their spatial interactions (Batty and Torrens, 2001).

ABMs are now increasingly and successfully used in integrated models of land use and transport interactions (LUTIs). They allow for variety in residential and travel decision-making processes by different individuals while accounting for more complex sets of activities and interactions in both space and time. Some integrated environmental externalities (e.g. green space in Gerber et al., 2018) but overall the integration of environmental sub-models is still scarce in LUTI models (Acheampong and Silva, 2015) and even more so for exposure feedbacks onto individuals. Considering further difficulties of transferring from one case to another, because of varying geographies (e.g. Thomas et al., 2018) and the inherent applied goals of LUTI models, it seems wiser at this stage to build theory from more parsimonious modelling experiments.

Some ABMs are actually more parsimonious and rely strongly on urban economics formalism while letting dynamic and geographical complexity arise in theoretical spatial settings (for instance to explore the emergence of sprawl or polycentricity (Caruso et al., 2007, 2015; Lemoy et al., 2017; Magliocca et al., 2015; Peeters et al., 2014)). These models come at the expense of granularity in transport and residential behaviour but can discriminate impacts of some parameters on urban forms and related policy levers.

The present paper falls within this tradition of theoretical micro-economic ABMs. Schindler and Caruso (2014) simulated the effects of different local characteristics of urban form (such as intra-urban green space or local street design) on the distribution of and exposure to pollution, but did not consider the feedback of air pollution concerns onto urban form and residential decisions. Here, we develop a model with local pollution externalities arising from car commuting to analyse the effect of households' aversion to generating and being exposed to this pollution on urban structure and pollution patterns. We extend previous literature on urban form, residential choice and pollution in four ways. First (i), we endogenise local pollution externalities *and* residential choice, therefore introducing this necessary feedback loop between pollution and urban form. Second (ii), we consider both environmental (emissions) and health concerns (exposure) within the residential choice of households, therefore introducing potentially conflicting aspirations. Those two innovations derive directly from the discussion above and the need of urbanisation models that account for such complexities. Additionally, we account for the increasing attention paid in the pollution literature to the spatio-temporal variations of pollution exposure. To that end we (iii) add exposure during the commute to the exposure at the residential place, and (iv) introduce traffic congestion since it causes locally varying excess emissions and aggravates proximity effects of exposure near highly travelled roads. These additions may lead to shorter commutes, but since our road network is also endogenous (following Caruso et al., 2011), it can potentially extend the road network and the city, thus increasing emissions but mitigating exposure. This effect is unclear a-priori. We discuss the performance of theoretically emerging cities after switching on and off each of the above effects. Performance criteria include city aggregates (e.g. total emissions, total exposure, spatial extent of the city) as well as location-dependent disaggregates (spatial pattern of land rents, exposure, and road network).

The remainder of this paper is structured as follows. Section "A 2D city with traffic-induced air pollution" presents the micro-economic ABM. Section "Households' aversion to air pollution exposure at the residential location" simulates effects of aversion to traffic-induced air pollution at the residential place on urban structures and the distribution of exposure and emissions within the city. It discusses also the influence of spatial scale at which households express their aversion. Section "Households' aversion to air pollution exposure during the commute" adds households' exposure aversion during the commute and Section "Household's aversion to own emission contribution" extends the residential

trade-off with environmental concerns. Section “Discussion and conclusion” discusses and concludes.

A 2D city with traffic-induced air pollution

The model simulates residential growth with a spatial and economic setting inspired by Caruso et al. (2007, 2011), to which we refer for further justification of the short and long-run dynamic mechanisms.

The model runs on a square grid and starts from an entirely agricultural area with a CBD – hosting all jobs – located at the centre at the crossing of two perpendicular roads. Land parcels have a unitary size (grid cells) and each parcel can only be occupied by one land use, that is either agriculture, residential or road infrastructure. Sequentially, homogeneous households migrate into the area as long as they can gain a utility superior to the utility obtainable in the rest of the world. They either develop agricultural cells or move to places already developed. Road segments are created on demand each time a new urbanised cell cannot access the CBD using prior network links. As more households sequentially enter the city, traffic volumes T and, thus, traffic-induced pollution increases and disperses in the city and affects located households.

We reconcile the different time scales of residential choices, commuting trips and pollution dispersion by assuming households’ residential choice to be based on rush-hour commuting patterns. All households (one person per household) commute at the same time, while for instance children and another person stay at home (e.g. tele-working). Although we recognise that the life-time of pollutants depends on many factors (e.g. meteorological conditions, pollutant type), we assume constant conditions and a generic pollutant that spans a period of few hours within the surface boundary (as for instance NO_x , one of the main primary pollutants stemming from traffic). Short-range pollution dispersion occurs, from the road network out, and pollution distributions derive from the commuting of all located households.

In the long-run, the model outputs a spatial pattern of residential and agricultural land and the road network. Depending on households’ aversion to generating and being exposed to air pollution, more compact or more dispersed spatial patterns emerge as well as different local land use arrangements.

Residential behaviour

A Cobb-Douglas¹ utility function U represents households preferences and writes as

$$U_i = Z_i^{1-\alpha} H_i^\alpha P_i^{-\beta} \tilde{P}_i^{-\gamma} E_i^{-\phi} \quad (1)$$

where i denotes the location of a parcel. α , β , γ and ϕ are positive parameters so that utility U increases with the consumption of housing space H and the non-spatial composite good Z , and decreases with pollution externalities. Pollution externalities are exposure P at the residential place to local pollution caused by passing commuting traffic T , exposure \tilde{P} during the commute to the CBD, and the emissions E generated by a household due to its own commute. P and \tilde{P} reflect the health perspective of urban air pollution (exposure), while E reflects the environmental perspective (emissions).

Utility maximisation is subject to the following budget constraint:

$$Y = Z_i + H_i R_i + t r_i + \theta \rho_i + c \quad (2)$$

where Y is the income of each household, t the transport cost per unit network distance, r the road network distance to the CBD, θ the monetary valuation of travel time as share of hourly income of the travel delay ρ due to traffic congestion, c the road construction cost per household and R the rent paid per housing space H .

At each time step, a household migrates in the cell where the indirect utility function V (3) is maximum. V is obtained from the maximisation of (1) subject to (2).² Newcomers perceive the city, i.e. the distribution of transport costs and externalities, as in the previous time step, thus evaluate V without the consequence of their own location choice.

The indirect utility function is

$$V = (1 - \alpha)^{1-\alpha} H_i^\alpha (Y - t r_i - \theta \rho_i - c) P_i^{-\beta} \tilde{P}_i^{-\gamma} E_i^{-\phi} \quad (3)$$

where $c = C/N$. C are the total road construction costs that arise at a time step after connecting all developments to the existing road network. Infrastructure costs are equally shouldered by all N residents.

Parcel sizes are unitary but housing space within each parcel can vary across locations. Based on optimal V , households can either convert a parcel of agricultural use in the previous time step into residential development or densify already developed parcels. In the latter case, the fixed parcel space is shared among multiple households by adding additional housing units vertically such that commuting costs are equal for all households in the same parcel.³ Commuting costs are based on the shortest path on the road network to the CBD. At each time step, the shortest path to the existing network and subsequently to the CBD is calculated for each location using the A^* Algorithm.⁴

At each time step, the last migrant determines the utility level of all residents. We therefore model a series of short-run equilibria that prevent the relocation of households within the city (see Caruso et al., 2007). Rents are adapted at each time step to reflect changes in the city (pollution, congestion and infrastructure costs). Rents are given by

$$R_i = \lambda (Y - t r_i - \theta \rho_i - c)^{1/\alpha} P_i^{-\beta/\alpha} \tilde{P}_i^{-\gamma/\alpha} E_i^{-\phi/\alpha} \quad (4)$$

where $\lambda = \bar{u}^{-1/\alpha} \alpha (1 - \alpha)^{(1-\alpha)/\alpha}$. Note that land is only converted to residential use if rents are higher than the exogenous agricultural rent R_A , which is a constant opportunity cost across the area. In case, an update of rents yields $R < R_A$ (e.g. because of increased local pollution exposure levels), households at that location outmigrate, but land conversion is irrevocable.

The total number of households migrating into the urban area is endogenous and depends on the external utility \bar{u} . Migration stops, i.e. a long-run equilibrium is reached, as soon as there is no location left where households can gain a higher utility level than \bar{u} .

Figure 1 illustrates the key dynamics of the ABM.

Pollution emission and dispersion

The air pollution source is commuting traffic. Thus, depending on the intra-urban household distribution, commuting traffic volumes T are calculated on each road cell and multiplied by an emission factor b . Additionally, the model accounts for excess emissions due to cold-start emissions and traffic congestion as described in the following.

Cold-start emissions. The emission factor b can be linear with distance driven or decrease with the operating temperature of the car (and thus distance driven). A car emits pollutants in excess (cold-start emissions) as long as it has not reached its normal operating temperature.

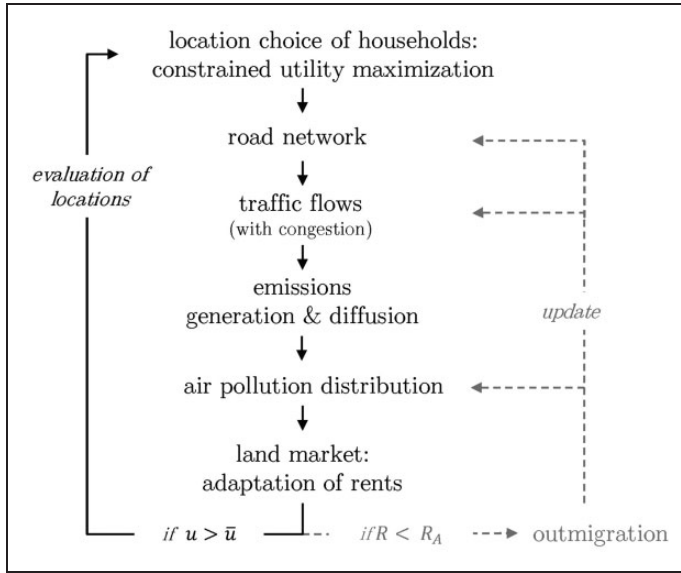


Figure 1. Processes of the ABM with the feedback of traffic-induced pollution on residential location choice.

ABM: agent-based models.

Thus, it emits more at the first kilometres of the commute up to a cold-distance d_c . For some pollutants, the majority of total emissions are due to cold-start emissions (Weilenmann et al., 2009). The cold-distance depends on the pollutant type, engine type, speed and meteorology conditions. The emission factor is then a function of distance driven \tilde{r} , summing normal emissions b and excess emissions $b(\tilde{r})$ (EC, 1999)

$$b(\tilde{r}) = k_3 \left(1 - k_2^{(\tilde{r} k_1)/d_c} \right) / \left(1 - k_2^{-k_1} \right) \tag{5}$$

where k_1 , k_2 and k_3 are technical constants.

Traffic congestion. Traffic congestion reduces the speed of travel. The generation of emissions is for most pollutants a parabolic function of average driving speed (Niemeier et al., 2011) and thus on-road emissions are higher with low average speed. Higher emissions ($b + b(\rho)$) are therefore generated locally where the capacity of a road segment is exceeded. These extra emissions $b(\rho)$ are a function of the travel delay ρ . The travel delay ρ of a commute to the CBD r of a household along the commuting route D including locations j is (adapted from Lomax et al., 1997)

$$\rho_i = s/v \sum_{j \in D_i} T_j/F_j \tag{6}$$

where F is the capacity of a road segment, s the cell resolution and v the free flow travel speed.

Pollution dispersion. Pollution is diffused in space by wind. Higher wind speeds yield higher diffusivity rates. The diffusivity rate is the share of pollutant concentration that is dispersed

to neighbouring cells w_1 equally. We assume equal diffusion in all directions but the diffusivity rate depends on the distance-weighted d population density within the neighbourhood to account for the effect of buildings $(1 - ((d - 1)/w_1))$. The diffusivity rate in more densely populated neighbourhoods is, thus, lower than in low density neighbourhoods. The range of dispersion w_1 may be chosen from very small scale (the Moore neighbourhood) to very large (the entire city). Dissipation rates, which state how much of the pollution concentration in one cell is removed through decomposition or other chemical processes, are not considered in this model.

Externalities

Exposure at the residential place. A household's perception of air pollution depends on the pollution level in the perception neighbourhood \tilde{n} . Within distance x from a location, spatially differentiated pollution concentrations on the roads enter the utility function according to a distance-decay function. A perception neighbourhood (\tilde{n}) of 1, for instance, reflects households' concern about air pollution stemming only from the cells adjacent to the residential location. The perceived pollution exposure externality at a residential location is given by

$$P_i = a + \sum_{i \in \tilde{n}_i} w_i (b + b_i(\tilde{r}) + b_i(\rho)) T_i + 1 \quad (7)$$

where a is a constant non-traffic-induced prevailing background pollution level experienced in the city and w is a weight factor depending on the distance of a parcel i in the perception neighbourhood x to the residential location. The definition of weight factors w depending on the distance of a parcel at location i in the perception neighbourhood x to a residential location is given by $1 - ((d - 1)/x)$ with d being the distance of a parcel in the neighbourhood x to the residential location i . This definition reflects a simple distance-decay function.

Exposure during the commute. Traffic-induced pollution varies spatially across the city and is not only present at residential locations but predominantly along all roads. Residents commute by car to the CBD along these roads. Thus, they are affected within micro-environments of cars by the pollution concentration outside. Several studies have shown that commuters are at particular risk because of their daily exposure to traffic-related air pollution (Miao et al., 2015; Ragetti et al., 2013; Zuurbier et al., 2011) and since air pollutants in vehicles are considerably higher than ambient urban concentrations (HEI, 2010). On these grounds, households may not only be concerned about the exposure level at their residential location, but also about the exposure during their commute.

Exposure \tilde{P}_i during the commute on the shortest path to the CBD D including locations j is defined as

$$\tilde{P}_i = a + \sum_{j \in D_i} (b + b_j(\tilde{r}) + b_j(\rho)) T_j + 1 \quad (8)$$

Although we acknowledge that the calculation of exposure levels differs in the literature (e.g. Briggs et al., 2008; Gulliver and Briggs, 2004; Kaur et al., 2007) between micro-environments since different factors play pivotal roles (e.g. transport mode, ventilation), we apply the same model since we only consider potential external exposure. Emission

concentrations in all road cells D along the commuting trip are summed up. Depending on the relative aversion households express to exposure during the commute γ and at home β , their residential choice is affected by the interplay between the two exposure externalities. This relative importance indirectly accounts for the time spent and associated risk at a location.

Households' own emission. Besides health concerns, households may also be concerned about impacts of traffic-induced air pollution on the environment. Then, they consider how much emissions they generate by their commute. Environmental concerns of air pollution have been the dominant focus of the literature (e.g. Gagné et al., 2012; Kyriakopoulou and Xepapadeas, 2011; Le Boennec, 2014; Legras and Cavailles, 2016; Regnier and Legras, 2018; Verhoef and Nijkamp, 2003). We endogenise both health and environmental preferences and explore potential interactions between both concerns. The emissions E generated by a household commuting from location i the network distance r to the CBD along the route D including locations j are defined as

$$E_i = br_i + \sum_{j \in D} (b_j(\tilde{r}) + b_j(\rho)) + 1 \quad (9)$$

Simulations

We run three sets of simulations with increasing complexity: First (Section “Households’ aversion to air pollution exposure at the residential location”), we introduce air pollution exposure at the residential place and discuss the influence of spatial scale at which households perceive air pollution externalities. Second (Section “Households’ aversion to air pollution exposure during the commute”), we add households’ aversion to exposure during the commute (as of (8) with $\gamma > 0$). Third (Section “Household’s aversion to own emission contribution”), we introduce the interaction between health and environmental concerns (as of (9) with $\phi > 0$).

Technical parameters common to all simulations are reported in online supplementary appendix. In the benchmark households’ aversion to exposure at the residence is $\beta = 0.2$ and other preferences are switched-off. For comparing simulation outputs, population is fixed according to this benchmark (i.e. not all models run until their long-run equilibrium). Since our goal is to identify local sensitivity and trends, we do not analyse transition phases based on a full understanding of the parametric space but show reasonable variations from the benchmark. To save space, the reader is referred to Schindler (2016) for a discussion of the growth process and equilibrium stability.

Households’ aversion to air pollution exposure at the residential location

In this section, we analyse the effects of households’ aversion to pollution exposure at the residential place. Households do not express any aversion to exposure during the commute ($\gamma = 0$) or to environmental impacts ($\phi = 0$).

Urban equilibrium and pollution pattern. Without households’ aversion to traffic-induced pollution exposure ($\beta = 0$) or zero pollution from cars ($b = 0$), households locate along the two exogenous perpendicular roads (Figure 2(a)). This is the basic trade-off between housing space and transport costs which yields monotonically decreasing rent and density gradients (e.g. Fujita, 1989; Fujita and Thisse, 2002).

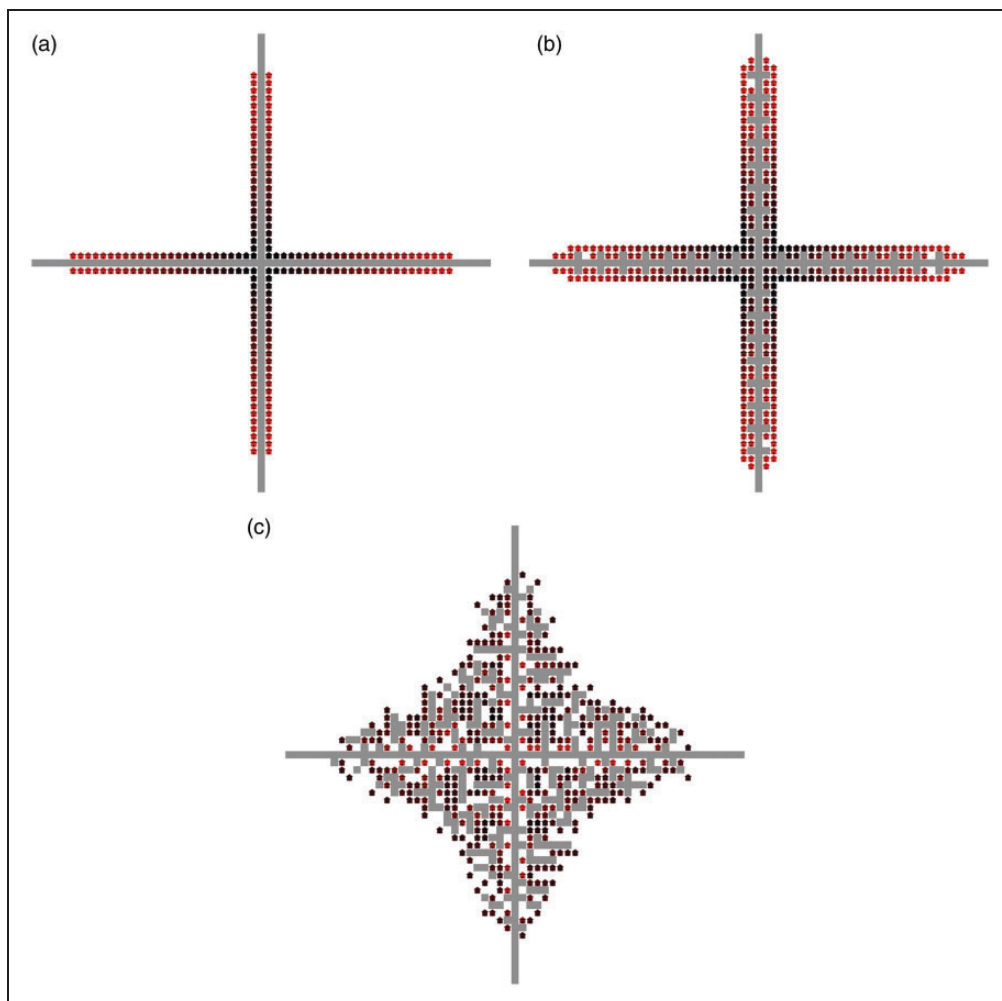


Figure 2. Urban structures as result of an increasing aversion β to pollution exposure ($\gamma = \phi = 0$): land rent of residential (black: high, red: low), road network (grey) and agricultural cells (white). (a) $\beta = 0$. (b) $\beta = 0.01$. (c) $\beta = 0.2$.

Households' aversion ($\beta > 0$) to exposure at the residence pushes residents away from the CBD and roads with high traffic and pollution concentrations (Figure 2(b)). Additional short roads with lower traffic emerge to set back residences from busy roads. The city spreads further and densities are reduced.

A stronger aversion to traffic-induced air pollution breaks the cul-de-sac pattern and results in more roads branching off from main transport axes and less dense cities with more undeveloped parcels (Figure 2(c)). Short roads are built to divert traffic across the area and locations at the end of roads gain in attractiveness, while parcels adjacent to or enclosed by roads with high traffic volumes are left undeveloped.

There are two effects observable: Firstly, households escape from roads with high traffic volumes which links to studies that found significant local effects for the influence of road networks on pollution concentrations (e.g. Su et al., 2009) and residential exposure

(e.g. Brugge et al., 2007). Secondly, households move further away from the centre where traffic and pollution agglomerate, which links to previous analytical work in 1D (Schindler et al., 2017). Hence, our 2D model highlights that households can escape from pollution not only by moving to the city fringe, and thereby increasing the city area, but also by particular local land use arrangements. Households' aversion to exposure results in a large city perimeter such that many fringe locations are created.

In aggregate terms, households' aversion to exposure results in more roads (Table 1, rows 1–3).⁵ This allows households to escape from pollution and, thus, reduce population exposure at the expense of higher total emissions due to longer commuting distances. Households benefit from undeveloped (green) spaces around busy roads (Figure 2(c)) such that a stronger aversion to residential pollution exposure yields cities with more green parcels left inside the city boundary.

Figure 3(a) and (b) contrasts the disaggregate health and environmental perspective of air pollution respectively. Figure 3(a) depicts exposure of all households at network distance r from the CBD. Without an aversion to residential exposure ($\beta=0$), household exposure decreases monotonically with commuting distance. A clear distance effect is observable.

Table 1. Aggregate performance measures. Benchmark with $\beta = 0.2$ and variations from it in bold: aversion to exposure at the residential location (β , rows 1–3); spatial horizon of households' perception (x , rows 3–5); aversion to exposure during the commute (γ , rows 3, 6–7); environmental concerns (ϕ , rows 3, 8–9).

β	γ	ϕ	x	Exposure	Emissions	Travel/N	Roads/N	Green-ratio
0.00	0.00	0.00	1.5	468	373	14.00	0.05	0.03
0.01	0.00	0.00	1.5	197	377	14.24	0.16	0.06
0.20	0.00	0.00	1.5	103	422	15.61	0.69	0.27
			2.0	130	568	16.90	0.76	0.30
			2.5	138	940	21.20	1.15	0.42
0.20	0.01	0.00	1.5	90	426	15.72	0.70	0.29
0.20	0.03	0.00	1.5	89	425	15.66	0.73	0.30
0.20	0.03	0.00	1.5	89	425	15.66	0.73	0.30
0.20	0.03	0.10	1.5	96	422	15.42	0.73	0.30
0.20	0.03	0.30	1.5	94	420	15.10	0.75	0.29

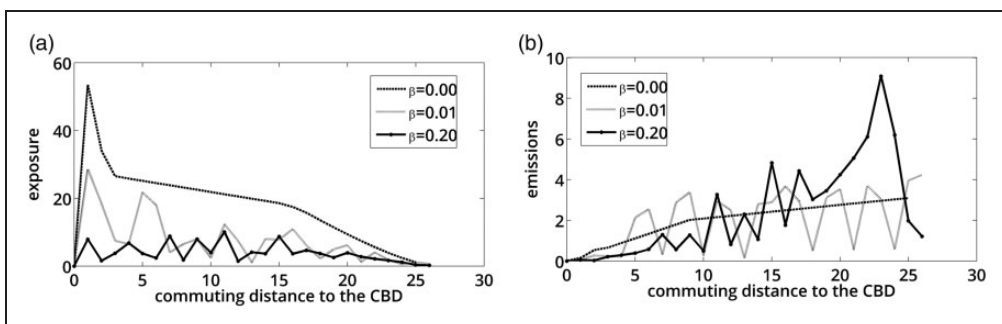


Figure 3. Households' exposure (a) and emission contribution (b) averaged across network distances with an increasing aversion β (with $\gamma = \phi = 0$).

As the aversion to exposure increases, however, local land use arrangements become important besides the commuting distance: household exposure in general falls with distance to the CBD, but depicts local peaks. Peaks occur where more households locate close to a busy road. In contrast, Figure 3(b) reflects the environmental perspective by depicting the average amount of emissions generated by households at commuting distance r . Without an exposure aversion, emissions generated by households at distance r increase linearly. With households' exposure aversion, the fringe distance is increased and average contributions per network distance are generally higher and no longer simply related to distance: the local arrangement of land uses also matters.

Spatial horizon of households' perception. Households' perception of air pollution is influenced by psychological processes (Gatersleben and Uzzell, 2000), vision and lived experience (Bickerstaff and Walker, 2001), local knowledge (Howel et al., 2003) and understanding of the sources and impacts of pollution (Crowe, 1968). Depending on the level of risk perception associated with air pollution and the size of the perception neighbourhood, perceived air pollution can differ from actual levels measured at a location. In the following, we analyse how the spatial scale at which households perceive pollution (perception neighbourhood \tilde{n}), affects their location choice.

An increase in \tilde{n} yields more dispersed structures and leapfrog development (Figure 4(c)). The size of the leapfrog is influenced by the size of \tilde{n} as in Peeters et al. (2014). A pronounced branch-like road network with many short roads (often cul-de-sac) emerges along which households prefer to locate to avoid main traffic axes. Not only many parcels close to the CBD but also around these network branches are left undeveloped (green).

Average travel distances per agent and aggregate emissions and exposure are increased (Table 1, rows 3–5), due to more undeveloped and road parcels, which increase the city size.

In case households' perception neighbourhood covers the entire city as in previous literature (e.g. Verhoef and Nijkamp, 2003), pollution effects are global and households locate close to the CBD as they do not perceive benefits from local dispersion. This links to analytical results in Schindler et al. (2017) and Robson (1976) which have shown that the source of pollution (local/regional, point-source/non-point source) impacts location choices and that large-scale air pollution counteracts shifts of population to suburban locations triggered by pollution from localised sources.

Households' aversion to air pollution exposure during the commute

Households might not only be concerned about air pollution at their residential place but also during their commute. Since highest concentrations of short-lived pollutants are usually in proximity to their source, thus, on roads, maximum exposure levels can well be higher during the commute than at home. Yet, the commuting time is short relative to the time spent at home. Given our model framework, we therefore assign lower residential aversion parameters to exposure during the commute (γ) than at home (β).

Table 1 (rows 3, 6–7) shows that the share of roads increases with aversion towards exposure during the commute; average travel distances rise, as do emissions, but population exposure decreases. Households avoid taking busy roads and, therefore, demand additional less frequented roads. This directly affects their own exposure during the commute but at the same time limits exposure at residential locations close to already busy roads. Further, this leaves undeveloped parcels next to the main roads (Figure 5), which reduces residential exposure (Table 1, rows 3, 6–7), especially in central locations (Figure 6). Rent gradients show a more pronounced distance effect (Figure 5(c)) since households aim to

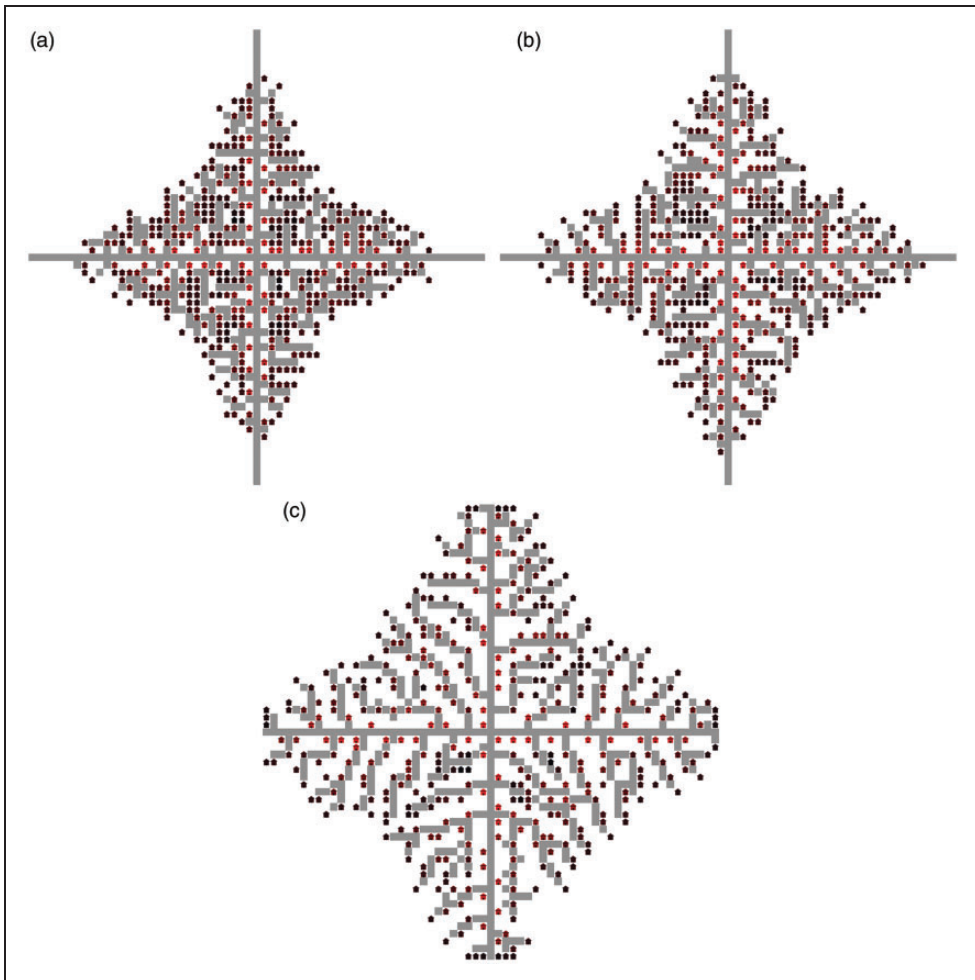


Figure 4. Urban structures as result of increases in households' perception neighbourhood \tilde{n} ($\beta = 0.2, \gamma = \phi = 0$). (a) $x = 1.5$. (b) $x = 2$. (c) $x = 2.5$.

reduce their commuting distance not only to save on transport costs but also to limit the time spent on polluted roads.

Thus, a concern about exposure during the commute offers a simultaneous potential to reduce exposure at the residence and on the commute, while keeping undeveloped parcels within the city. This finding links to work by Agarwal and Kickhöfer (2015) who study the effect of an exposure toll (contribution to exposure of others during their localised activities) on transport route choice and show that agents avoid busy roads and populated locations to minimise the amount of toll to be paid. This indirectly reduces population exposure, while it leads to higher emissions and longer travel routes to circumscribe populated areas.

Household's aversion to own emission contribution

So far, we analysed the performance of emerging urban structures based on households' health concerns due to traffic-induced air pollution. Finally, we turn to endogenising both

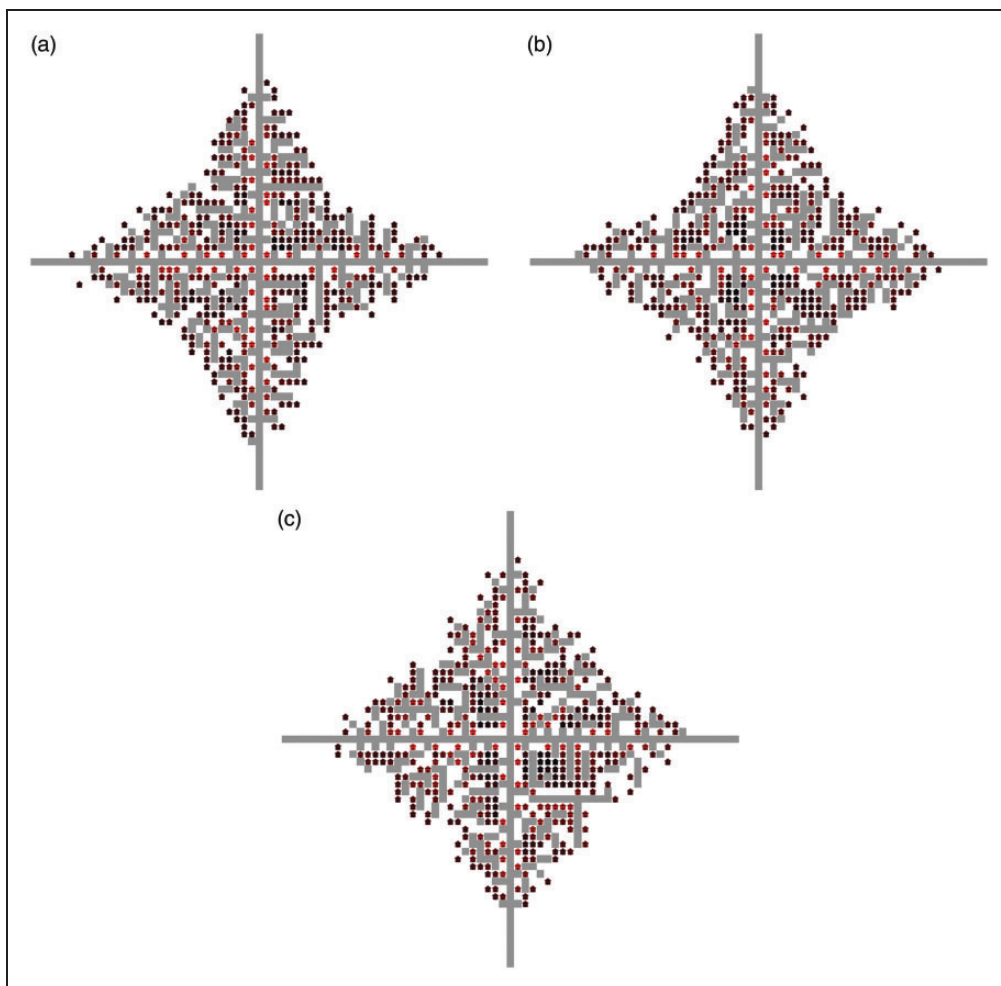


Figure 5. Urban structures as result of the interaction between households' aversion γ to exposure during the commute and at their residential location ($\beta = 0.2, \phi = 0.0$). (a) $\gamma = 0.00$. (b) $\gamma = 0.01$. (c) $\gamma = 0.03$.

health and environmental concerns and analyse their interrelations. Thus, we analyse the complete model described in Section “A 2D city with traffic-induced air pollution” with positive β, γ and ϕ . Environmental concerns in households' location choice are expected to act oppositional to health concerns. Yet, the trade-off between both is reflected in the emergence of local arrangements and neighbourhood effects.

Urban structures resulting from increases in environmental preference ($\phi > 0$) relative to exposure aversion at the residence place and during the commute ($\beta = 0.2, \gamma = 0.03$) are depicted in Figure 7(b) to (c). Endogenised environmental concerns lead to smaller cities, a compact road network and residential development along main transport axes with fewer undeveloped parcels. Some central locations are, however, still undeveloped as result of households' aversion to exposure. Green spaces are mostly reduced in fringe locations, while still many parcels along main transport axes and central locations tend to remain undeveloped. However, population exposure increases despite a reduction of emissions

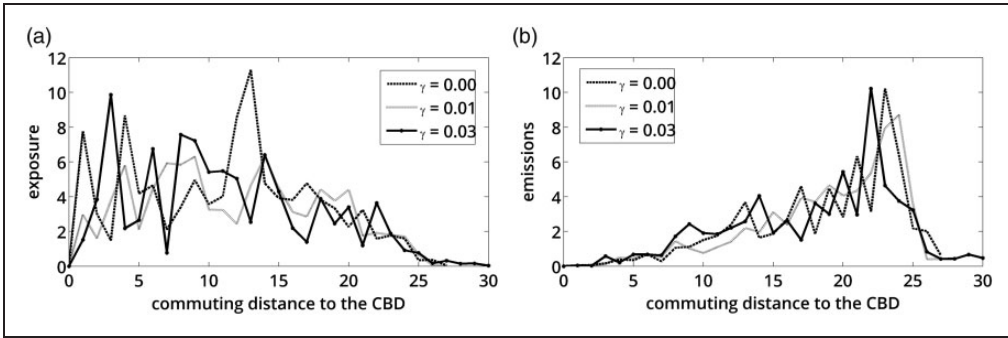


Figure 6. Households' exposure (a) and emission contribution (b) averaged across network distances with increasing aversion γ to exposure during the commute ($\beta = 0.2, \phi = 0.0$).

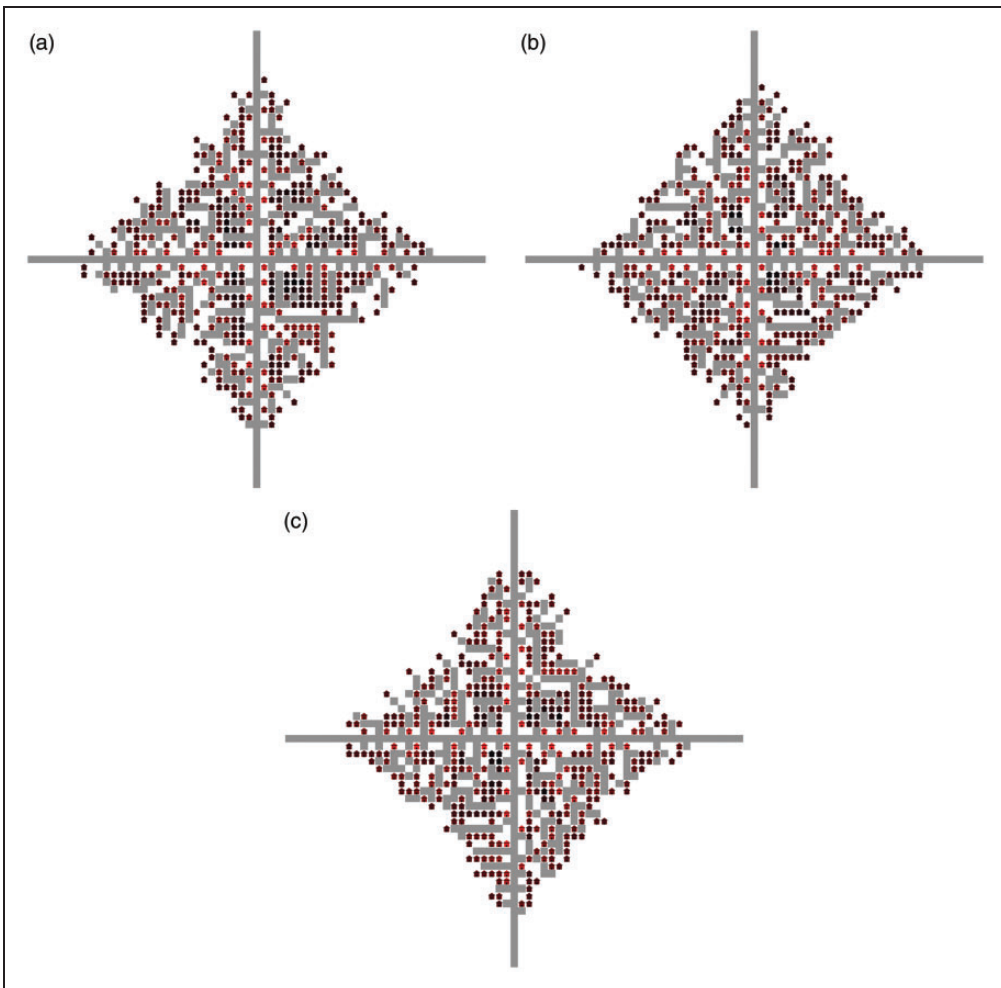


Figure 7. Urban structures as result of the interaction between environmental and health concerns ($\beta = 0.2, \gamma = 0.03$). (a) $\phi = 0.0$. (b) $\phi = 0.1$. (c) $\phi = 0.3$.

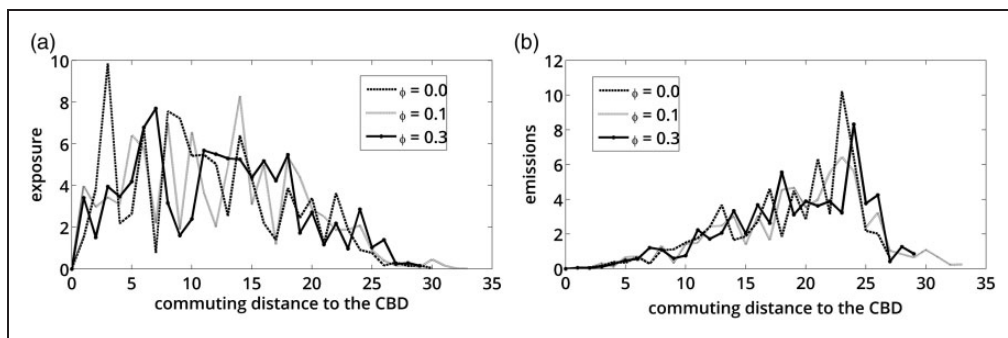


Figure 8. Households' exposure (a) and emission contribution (b) averaged across network distances with endogenised environmental concern ϕ of own emission contributions ($\beta = 0.20$, $\gamma = 0.03$).

(Table 1, rows 3, 8–9) attributed to less scattered development near the fringe and, thus, reduced commuting distances.

This highlights the tension between environmental and health effects of air pollution. A reduction of emissions not necessarily implies a simultaneous reduction of population exposure. Figure 8 clearly illustrates the reduced spatial variability of distance-based exposure and contribution to emissions and the reduced spatial extent. The simulations, however, also clearly highlight the benefit from inner-city green spaces to balance health and environmental concerns due to traffic-induced air pollution.

Thus, interactions between health and environmental concerns related to traffic-induced air pollution result in a combination of reducing commuting distances and preserving local green spaces. The location of local effects (such as green spaces) differs from effects of each single concern: environmental concerns densify central locations and reduce city size (e.g. Verhoef and Nijkamp, 2003); health concerns keep central areas undeveloped and result in larger cities as shown in this paper; in contrast, interrelations of both concerns densify fringe and mid-distance locations but keep some undeveloped parcels near the CBD and busy roads, which may indirectly limit city size.

Discussion and conclusion

We presented an ABM to simulate complex spatial interactions resulting from the feedback between local traffic-induced air pollution and urban structures. Our analysis extends previous studies and demonstrates the potential of an ABM framework applied to a theoretical space to study complex spatial interactions in the context of urban traffic-induced air pollution where effects are difficult to predict.

Dispersed development and interspersed undeveloped parcels are beneficial to mitigate population exposure, while local city characteristics matter particularly. Inner-city green parcels retain households' utility, function as buffers to traffic-induced air pollution and mitigate population exposure despite potential augmentation of total emissions through increased commuting distances. In comparison to Schindler and Caruso (2014), where green space is an explicitly expressed preference in the utility, green spaces here emerge to allow for set-backs of houses from main pollution sources without green space being valued as such. Mitigation occurs especially in central locations and near roads with high traffic volumes.

While the paper focussed on endogenising health concerns to balance previous environmental literature (e.g. Gagné et al., 2012; Kyriakopoulou and Xepapadeas, 2011;

Le Boennec, 2014; Legras and Cavailhes, 2016; Regnier and Legras, 2018; Verhoef and Nijkamp, 2003), the ABM framework poses a framework to additionally integrate environmental concerns related to traffic-induced air pollution. From this, we find that the interrelation between health and environmental concerns prevents scattered development in fringe areas, which reduces commuting distances, but still preserves green spaces in central locations and along major transport axes.

Synergies are also found between the effects of aversion to exposure during the commute and at the residential location. In case of health concerns during the commute, households choose residential locations – and indirectly commuting routes – with low traffic volumes, which limits population exposure. This suggests that low traffic routes circumscribing highly populated residential areas can reduce population exposure despite generating more emissions due to longer driving distances. Thus, diverting traffic flows and refraining high traffic volumes from residential areas can improve households' utility and mitigate health impacts. Future work should include commuting route choices based on on-road pollution exposure.

Our experiments suggest to focus planning strategies on the local nature of traffic-induced air pollution and the local perception of households. This can promote local measures, like local green and neighbourhood arrangements which then avoid extensive spatial expansion of cities but balance the generation of emissions and population exposure. Local structures allow undeveloped central and near-road locations which would otherwise exhibit maximum exposure levels and divert traffic such that distance-based spatial discrepancies are reduced.

Integrative approaches of urban economics and emerging geographic details allow contrasting distance as well as local neighbourhood effects. In our case, it contributes to further integrating the health perspective into the debate about urban form, densification and sustainability.

Our analysis emphasises the importance of understanding residential preferences and their effects on urban structures and their performance regarding air pollution. It emphasises the influence of residential preferences in aggravating or mitigating air pollution effects. Knowledge about the complexity of underlying spatial interactions based on certain framework conditions (commuting and road costs, scale of perception, etc.) and processes of air pollution (diffusion, cold-start emissions, etc.) were shown to be essential before devising policies. As a matter of fact, not everyone avoids to generate or be exposed to pollution because of lack of information or because of stronger budgetary constraints; however, with increasing urban population and advanced knowledge of health and environmental effects of pollution (through live mobile technology), the awareness about these will likely be increased in the future and residential/commuting choice reconsidered to avoid such effects. It is therefore crucial to better understand potential impacts of pollution-related residential preferences for future policy design.

Our framework surely encounters limitations due to its theoretical nature and simplifying assumptions. Future studies should advance the experiments with model calibration and case study applications. Increasing the number of spatial processes and model parameters would likely reduce the ability to fully control and capture underlying complexities, but would get the model closer to real-world representation. Equipped with a first theoretical basis, one can now propose extensions to, for instance, consider non-work related travel or non-monocentric settings, using activity-based analysis and related exposure intake. This would come closer to applied integrated LUTI models, which can bring further understanding about the specific behaviour of some population segments or impacts of particular location patterns. Real case applications may also provide pragmatic solutions to local planners well informed of local heterogeneities. Each model component could be treated in more detail depending on the study perspective. Our approach is the first to include such health and environmental

feedback within a model that can still be attached to more classic urban economics and the formalisation thereof. Future work might think of altering the representation of externalities, the utility function or assumption of homogeneous households to relax the full rationality behaviour and address even more complex residential behaviour.

Finally, we believe future research should focus on the relative weight given to health or environmental issues, especially with equity concerns in mind and in hand with analytical groundwork to comprehensively study the interactions between urban form, pollution externalities and sustainability.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Notes

1. The choice of functional form of the utility is aligned with previous urban economics work on air pollution, such as Fisch (1975), Robson (1976) and Schindler et al. (2017).
2. In case, multiple cells yield the same indirect utility a random tie-breaker is applied. Since the model is not stochastic, no Monte-Carlo simulation is needed.
3. This is conversely to e.g. Caruso et al. (2011) who assume varying housing lot sizes by varying the number of households migrating into one parcel at one time step according to housing demand at this location. In the context of traffic-induced pollution and an ABM, a one-by-one migration process is preferable.
4. The NetLogo implementation is based on the Astartemo1-model (<http://ccl.northwestern.edu/netlogo>).
5. $roads/N$ is the sum of all endogenous roads in the city divided by the total population N . The *green-ratio* is the sum of agricultural cells within the city divided by the city area, which are all cells within radius 1 of endogenous roads, considering also undeveloped cells at the fringe with access to the road network.

ORCID iD

Mirjam Schindler  <http://orcid.org/0000-0001-6279-4510>.

References

- Acheampong R and Silva E (2015) Land use-transport interaction modeling: A review of the literature and future research directions. *The Journal of Transport and Land Use* 8(3): 11–38.
- Agarwal A and Kickhöfer B (2015) Agent-based simultaneous optimization of congestion and air pollution: A real-world case study. *Procedia Computer Science* 52(1): 914–919.
- Ausloos M, Dawid H and Merlone U (2014) *Spatial Interactions in Agent-Based Modeling*, pp.1–29. Available at: [arXiv:1405.0733v1](https://arxiv.org/abs/1405.0733v1)[physics.soc-ph].
- Batty M and Torrens P (2001) Modeling complexity – The limits to prediction. *Cybergeo: European Journal of Geography* 201: 1–29.
- Batty M (2005) *Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals*. Cambridge, Massachusetts: The MIT Press.

- Bayer P, Keohane N and Timmins C (2009) Migration and hedonic valuation: The case of air quality. *Journal of Environmental Economics and Management* 58(1): 1–14.
- Bickerstaff K and Walker G (2001) Public understandings of air pollution: The ‘localisation’ of environmental risk. *Global Environmental Change* 11: 133–145.
- Bretagnolle A, Daudé E and Pumain D (2003) From theory to modelling: Urban systems as complex systems. *Cybergeo: European Journal of Geography* 335: 1–26.
- Briggs D, De Hoogh K, Morris C, et al. (2008) Effects of travel mode on exposures to particulate air pollution. *Environment International* 34(1): 12–22.
- Brugge D, Durant JL and Rioux C (2007) Near-highway pollutants in motor vehicle exhaust: A review of epidemiologic evidence of cardiac and pulmonary health risks. *Environmental Health* 6: 23.
- Caruso G, Peeters D, Cavailles J, et al. (2007) Spatial configurations in a periurban city. A cellular automata-based microeconomic model. *Regional Science and Urban Economics* 37: 542–567.
- Caruso G, Cavailles J, Peeters D, et al. (2015) Greener and larger neighbourhoods make cities more sustainable! A 2D urban economics perspective. *Computers, Environment and Urban Systems* 54: 82–94.
- Caruso G, Vuidel G, Cavailles J, et al. (2011) Morphological similarities between DBM and a microeconomic model of sprawl. *Journal of Geographical Systems* 13(1): 31–48.
- Chay KY and Greenstone M (2005) Does air quality matter? Evidence from the housing market. *Journal of Political Economy* 113(227): 376–424.
- Crowe MJ (1968) Toward a “Definitional Model” of public perceptions of air pollution. *Journal of the Air Pollution Control Association* 18(3): 154–157.
- Day R (2007) Place and the experience of air quality. *Health & Place* 13(1): 249–260.
- EC. (1999) *Methodology for Calculating Transport Emissions and Energy Consumption*. Luxembourg: Transport Research Laboratory, European Commission.
- Fisch O (1975) Externalities and the urban rent and population: The case of air pollution. *Journal of Environmental Economics and Management* 2: 18–33.
- Fujita M (1989) *Urban Economic Theory: Land Use and City Size*. Cambridge: Cambridge University Press.
- Fujita M and Thisse JF (2002) *Economics of Agglomeration. Cities, Industrial Location, and Regional Growth*. Cambridge: Cambridge University Press.
- Gagné C, Riou S and Thisse JF (2012) Are compact cities environmentally friendly? *Journal of Urban Economics* 72(23): 123–136.
- Gatersleben B and Uzzell D (2000) The risk perception of transport-generated air pollution. *IATSS Research* 24(1): 30–38.
- Gerber P, Caruso G, Cornelis E, et al. (2018) A multi-scale fine-grained LUTI model to simulate land use scenarios in Luxembourg. *Journal of Transport and Land Use* 11(1): 255–272.
- Gulliver J and Briggs D (2004) Personal exposure to particulate air pollution in transport microenvironments. *Atmospheric Environment* 38(1): 1–8.
- HEI (2010) *Traffic-related air pollution: A critical review of the literature on emissions, exposure, and health effects*. HEI Special Report 17. Boston, MA: HEI, Health Effects Institute.
- Howel D, Moffatt S, Bush J, et al. (2003) Public views on the links between air pollution and health in Northeast England. *Environmental Research* 91(3): 163–171.
- Kaur S, Nieuwenhuijsen M and Colvile R (2007) Fine particulate matter and carbon monoxide exposure concentrations in urban street transport microenvironments. *Atmospheric Environment* 41: 4781–4810.
- Kwan MP (2013) Beyond space (as we knew it): Toward temporally integrated geographies of segregation, health, and accessibility. *Annals of the Association of American Geographers* 103(5): 1078–1086.
- Kyriakopoulou E and Xepapadeas A (2011) Spatial location decisions under environmental policy and housing externalities. *Environmental Economics and Policy Studies* 13: 195–217.
- Le Boennec R (2014) Externalité de pollution versus économies d’agglomération: Le péage urbain, un instrument environnemental adapté? *Revue d’économie régionale et urbaine* 1: 3–31.
- Legras S and Cavailles J (2016) Environmental performance of the urban form. *Regional Science and Urban Economics* 59: 1–11.

- Lemoy R, Raux C and Jensen P (2017) Exploring the polycentric city with multi-worker households: An agent-based microeconomic model. *Computers, Environment and Urban Systems* 62: 64–73.
- Lomax T, Turner S, Shunk G, et al. (1997) Quantifying congestion. *Transportation Research Board* 1.
- Magliocca N, McConnell V and Walls M (2015) Exploring sprawl: Results from an economic agent-based model of land and housing markets. *Ecological Economics* 113: 114–125.
- Martins H (2012) Urban compaction or dispersion? An air quality modelling study. *Atmospheric Environment* 54: 60–72.
- Miao Q, Bouchard M, Chen D, et al. (2015) Commuting behaviors and exposure to air pollution in Montreal, Canada. *Science of the Total Environment* 508: 193–198.
- Niemeier D, Bai S and Handy SL (2011) The impact of residential growth patterns on vehicle travel and pollutant emissions. *Journal of Transport and Land Use* 4(3): 65–80.
- Nyhan M, Grauwijn S, Britter R, et al. (2016) ‘Exposure Track’ – The impact of mobile device based mobility patterns on quantifying population exposure to air pollution. *Environmental Science & Technology* 50: 9671–9681.
- Parker DC and Meretsky V (2004) Measuring pattern outcomes in an agent-based model of edge-effect externalities using spatial metrics. *Agriculture, Ecosystems & Environment* 101(2–3): 233–250.
- Peeters D, Caruso G, Cavailhès J, et al. (2014) Emergence of leapfrogging from residential choice with endogenous green space: Analytical results. *Journal of Regional Science* 55(3): 491–512.
- Ragetti MS, Corradi E, Braun-Fahrländer C, et al. (2013) Commuter exposure to ultrafine particles in different urban locations, transportation modes and routes. *Atmospheric Environment* 77: 376–384.
- Regnier C and Legras S (2018) Urban structure and environmental externalities. *Environmental and Resource Economics* 70(1): 31–52.
- Robson A (1976) Two models of urban air pollution. *Journal of Urban Economics* 284: 264–284.
- Schindler M (2016) *Spatial modelling of feedback effects between urban structure and traffic-induced air pollution – Insights from quantitative geography and urban economics*. PhD Thesis, University of Luxembourg, Luxembourg.
- Schindler M and Caruso G (2014) Urban compactness and the trade-off between air pollution emission and exposure: Lessons from a spatially explicit theoretical model. *Computers, Environment and Urban Systems* 45: 13–23.
- Schindler M, Caruso G and Picard P (2017) Equilibrium and first-best city with endogenous exposure to local air pollution from traffic. *Regional Science and Urban Economics* 62: 12–23.
- Smith VK and Huang JC (1995) Can markets value air quality? A meta-analysis of hedonic property value models. *Journal of Political Economy* 103(1): 209–227.
- Stone BJ (2008) Urban sprawl and air quality in large us cities. *Journal of Environmental Management* 86: 688–698.
- Su JG, Jerrett M, Beckerman B, et al. (2009) Predicting traffic-related air pollution in Los Angeles using a distance decay regression selection strategy. *Environmental Research* 109(6): 657–670.
- Thomas I, Jones J, Caruso G, et al. (2018) City delineation in European applications of LUTI models: Review and tests. *Transport Reviews* 38(1): 6–32.
- Verhoef E and Nijkamp P (2003) Externalities in the urban economy. Tinbergen Institute Discussion Paper 078(3).
- Vos JD and Witlox F (2013) Transportation policy as spatial planning tool: Reducing urban sprawl by increasing travel costs and clustering infrastructure and public transportation. *Journal of Transport Geography* 33: 117–125.
- Weilenmann M, Favez JY and Alvarez R (2009) Cold-start emissions of modern passenger cars at different low ambient temperatures and their evolution over vehicle legislation categories. *Atmospheric Environment* 43(15): 2419–2429.
- Yoo E, Rudra C, Glasgow M, et al. (2015) Geospatial estimation of individual exposure to air pollutants: Moving from static monitoring to activity-based dynamic exposure assessment. *Annals of the Association of American Geographers* 105(5): 915–926.
- Zuurbier M, Hoek G, Oldenwening M, et al. (2011) Respiratory effects of commuters’ exposure to air pollution in traffic. *Epidemiology (Cambridge, Mass.)* 22(2): 219–227.

Mirjam Schindler holds a PhD in geography from the Institute of Geography and Spatial Planning at the University of Luxembourg and a postdoctoral fellowship at the Geospatial Research Institute at the University of Canterbury in Christchurch, New Zealand. Her research lies at the interface between quantitative geography and urban economics and focuses on modelling spatial interactions between urban structure, traffic and air pollution. Her research is devoted to spatial analysis to inform residential and transport planning on environmental and health concerns with respect to urban form.

Geoffrey Caruso is professor at the University of Luxembourg and holds the Luxembourg Institute of Socio-Economic Research (LISER) chair in Urban Analysis and Modelling. Before, he was Associate Professor in GIS and spatial analysis at the University of Luxembourg, Research Associate at CORE in Louvain-la-Neuve (BE), at the Martin Centre at the University of Cambridge (UK), and Research Assistant in Geography at the Université catholique de Louvain (BE). His research is devoted to understanding spatial patterns and dynamics with specific foci on urban forms and residential choice, their impact on transport and the environment, the role of green space, and the integration of geosimulation and urban economics.