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Pricing local emission exposure of road traffic: An agent-based approach

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Abstract

This paper proposes a new approach to iteratively calculate local air pollution exposure tolls in large-scale urban settings by taking the exposure times and locations of individuals into consideration. It explicitly avoids detailed air pollution concentration calculations and is therefore characterized by little data requirements, reasonable computation times for iterative calculations, and open-source compatibility. In a first step, the paper shows how to derive time-dependent vehicle-specific exposure tolls in an agent-based model. It closes the circle from the polluting entity, to the receiving entity, to damage costs, to tolls, and back to the behavioral change of the polluting entity. In a second step, the approach is applied to a large-scale real-world scenario of the Munich metropolitan area in Germany. Changes in emission levels, exposure costs, and user benefits are calculated. These figures are compared to a flat emission toll, and to a regulatory measure (a speed reduction in the inner city), respectively. The results indicate that the flat emission toll reduces overall emissions more significantly than the exposure toll, but its exposure cost reductions are rather small. For the exposure toll, overall emissions *in*crease for freight traffic which implies a potential conflict between pricing schemes to optimize local emission exposure and others to abate climate change. Regarding the mitigation of exposure costs caused by urban travelers, the regulatory measure is found to be an effective strategy, but it implies losses in user benefits.

Keywords: Air Pollution, Exposure, Vehicle Emissions, Road Pricing, Internalization, Agent-based Modeling

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1. Introduction

1.1. Problem statement

Negative externalities in the transport sector are known to lead to market inefficiencies and social welfare losses. The latter exist since individuals base their decisions on marginal private and not on marginal social costs, typically

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yielding demand levels beyond the economic optimum. To correct for these market failures, Pigou [30] proposed to internalize the difference between marginal social costs and generalized prices by a toll. Since then, the concept has been studied widely in the transportation economic literature [see, e.g., 26, 32, 35, 2, 11]. However, all these studies focus on congestion costs. Other important contributions to the total external costs are found to be air pollution, accidents, and noise [27, 29]. Since these environmental externalities have gained more attention over the last decades [28], and some studies find their impact for some regions at the same level as congestion costs [see, e.g., 8], a new approach was proposed by Kickhöfer and Nagel [24] to calculate vehicle-specific time-dependent air pollution tolls that reflect marginal emission costs with respect to congestion and vehicle attributes. However, their tolls did not account for population exposure; this drawback is tackled in the present paper.

Other possibilities to correct for these market failures are discussed in the literature, e.g. so-called backcasting approaches [13, 21]. The idea is to define threshold values based on medical studies, and then to derive avoidance costs in order to reach the desired values. The advantage is that avoidance costs are relatively easy to estimate. However, the definition of threshold values remains rather unclear, and exposure or concentration-response relationships could potentially provide more realistic information since they provide damage cost estimates [37]. For the European Union [15, 19] and the United States [34], this exposure approach typically consists of five steps:

1. Modeling exhaust emissions
2. Modeling emission dispersion
3. Deriving air pollution concentration
4. Estimating exposure of individuals to air pollutants with respect to special population groups like pregnant or ill persons, children and elderly
5. Applying concentration-response functions yielding numbers of cases for mortality, life years lost, hospital admissions, premature mortality, minor restricted activity days, work loss days, etc.
6. Assigning monetary values to each of these cases

1.2. Emission dispersion and air quality models

In the literature, a large number of microscopic and macroscopic dispersion models exists. However, as a review paper by Holmes and Morawska [16] shows, the latter can not provide the spatial resolution that is needed for air pollution concentration modeling within urban-scale scenarios. The former are generally characterized by long computing times and are therefore often not applicable to large-scale urban regions. According to Holmes and Morawska [16], most emission dispersion and air quality modeling tools need geographical and meteorological input data like temperature, altitude, humidity, cloud cover, peak sun, sunrise, terrain elevation data, land cover data, hourly meteorological data, sea and land breezes. These data might not be available for the area of interest.

Despite these data requirements, there exist several attempts to model air quality in urban regions. Hatzopoulou and Miller [14] use the open-source modeling tool CALPUFF-CALMET to evaluate air quality. Calculation of concentration values for 15,000 cells and 62,500 receptors from link-wise aggregated exhaust emissions initially takes them 190 hours of computing time. Hence, such approach would simply not be manageable for the iterative calculation of toll levels as it is attempted in the present paper. The Community Multiscale Air Quality model (CMAQ) and EPA's Modeled Attainment Test Software used by U.S. EPA [34] have their focus on North American scenarios. When applying the models to European scenarios, Appel et al. [1] find Particular Matter ($PM_{2.5}$) concentration values to be underestimated by 24% to 65%. Holland et al. [15] use the Cooperative Programme for Monitoring and Evaluation of the Long-range Transmission of Air Pollutants in Europe (EMEP) combined with Regional Air Pollution Information and Simulation (RAINS) on a 50x50 km grid. However, both tools focus on macroscopic long-range dispersion over whole countries. Hülsmann et al. [18] focus on emission dispersion modeling for street canyons using the Operational Street Pollution Model (OSPM) for a small area of their scenario. Despite the model's complexity and relatively large data requirements, the authors managed to derive air pollution concentrations and time-dependent tolls in order to eliminate emission hotspots in the small research area. Unfortunately, the software is not open-source, and can therefore not be integrated into the transport simulation MATSim[1] for iterative toll calculations.

[1] 'Multi-Agent Transport Simulation', see `www.matsim.org`

1.3. Simplified approach

This paper aims at internalizing air pollution exposure costs, i.e. pricing damages to human health in an agent-based transport model with activity-based demand. This requires the development of a new approach to iteratively calculate local air pollution exposure tolls in large-scale urban settings by taking the exposure times and locations of individuals into consideration. As discussed in Sec. 1.2, none of the emission dispersion models presented there is suitable for such attempt. Thus, the new approach – for now – needs to avoid detailed air pollution concentration calculations and should be characterized by little data requirements, reasonable computation times, and open-source compatibility. As will be discussed later in this paper (Sec. 4), this also implies some limitations. However, the strengths of the approach lie in the computational performance and in translating the activity and travel patterns of the activity-based demand into individual toll levels. The approach is composed of the following three steps:

1. The MATSim-HBEFA[2] emission modeling tool is used which has been developed by Hülsmann et al. [17] and further improved by Kickhöfer et al. [25]. The tool links MATSim's dynamic traffic flows to detailed air pollution emission factors of HBEFA.
2. The resulting vehicle-specific time-dependent exhaust emissions are converted into monetary terms using average cost factors provided by Maibach et al. [27]. Subsequently, these costs are spatially distributed into cells around the causing agent using a stepped Gaussian distribution function.
3. For each agent in the simulation who performs an activity inside the affected cells, exposure times are calculated, and summed up over all affected agents. This results in aggregated exposure times for each cell. Scaling these with the average exposure time over all cells, and multiplying the results with the distributed costs gives each traveler's contribution to the overall emission costs. This contribution is finally mapped back to the causing agent in the form of an individual toll.

In consequence, the individual toll captures the effect of activity location density: driving through a highly populated area results in a higher toll level than driving through a less populated area. Furthermore, the individual toll level at the same location is changing over time of day, since the simulation keeps track of all agents' activity patterns: driving through a highly populated residential area during day time will result in a lower toll than driving through the same area during evening hours. In an iterative process, travelers learn how to adapt their route and mode choice behavior in the presence of this simulated air pollution exposure toll.

The remainder of the paper is organized as follows: After a detailed description of the model in Sec. 2, the implementation is applied to a large-scale real-world scenario of the Munich metropolitan area (Sec. 3). The results of the exposure toll are compared to the impacts of a flat emission toll proposed by Kickhöfer and Nagel [24]. Subsequently, the results are used to evaluate the impacts of a potential real-world policy, a speed limitation in the inner city to 30 km/h. In all comparisons, the focus will be on the mitigation of local air pollution (relevant for exposure), the reduction of CO_2 as a source of global warming, and potential conflicts between these two goals. Furthermore, impacts on user benefits are investigated. Sec. 4 discusses limitations of the current implementation, and how they might influence the results. The paper ends with a conclusion in Sec. 5 where also venues for further research are identified.

2. Model

This section provides an overview of the model to calculate time-dependent vehicle-specific local air pollution exposure tolls. It starts with a short introduction to the agent-based transport simulation MATSim (Sec. 2.1), followed by a description of the emission modeling tool which calculates vehicle-specific warm and cold-start emissions and converts those into monetary terms (Sec. 2.2). Subsequently, the exhaust emission cost distribution model is presented (Sec. 2.3). Finally, the idea of using the activity-based demand model for calculating population exposure times is described in Sec. 2.4. Since, in the present approach, emission costs and not emissions are distributed, this last step directly gives the cost factors for each contributor, i.e. the individual toll levels.

[2] 'Handbook Emission Factors for Road Transport', version 3.1, see www.hbefa.net

2.1. MATSim

In the following, only general ideas about transport simulation with MATSim are presented. For in-depth information of the simulation framework, please refer to Raney and Nagel [31]. In MATSim, each traveler of the real system is modeled as an individual agent. The simulation consists of an iterative loop that is characterized by the following steps:

1. **Plans generation:** All agents independently generate daily plans from survey data. These plans encode among other things their desired activities during a typical day as well as the transport mode for every intervening trip.
2. **Traffic flow simulation:** All plans are simultaneously executed in the simulation of the physical environment. In the car traffic flow simulation, agents interact on the roads which are simulated as first-in first-out queues with flow and storage capacity restrictions [12, 7]. Non-car modes are, in this study, assumed to run emission free and without capacity constraints with a calibrated predefined speed.
3. **Evaluating plans:** All executed plans are evaluated by a utility function with the following functional form:

$$S_{plan} = \sum_{q=0}^{N-1} \left(S_{act,q} + S_{trav,mode(q)} \right), \tag{1}$$

   where S_{plan} is the total utility for a given plan; N is the number of activities; $S_{act,q}$ is the (positive) utility earned for performing activity q; and $S_{trav,mode(q)}$ is the mode-dependent (usually negative) utility earned from traveling to activity $q+1$.[3] Activities are assumed to wrap around the 24-hours-period, that is, the first and the last activity are stitched together. In consequence, there is an equal number of trips and activities.
4. **Learning mechanism:** Some agents obtain new plans for the next iteration by modifying copies of existing plans. This modification is done by several strategy modules that correspond to the available choice dimensions, namely route and mode choice in the present paper. The choice between plans is performed following a multinomial logit model.

The repetition of the iteration cycle coupled with the agent database enables the agents to improve their plans over many iterations. The iteration cycle continues until the system has reached a relaxed state. At this point, there is no quantitative measure of when the system is “relaxed”; the cycle is simply continued until the outcome is stable.

2.2. Emission Calculation and Monetization

The emission modeling tool was developed and tested by Hülsmann et al. [17] and was further improved by Kickhöfer et al. [25]. The tool links MATSim’s traffic flows to the HBEFA database, and essentially calculates warm and cold-start emissions for private cars and freight vehicles. The former emissions are emitted when the vehicle’s engine is already warmed whereas the latter occur during the warm-up phase. In the present model, warm emissions differ with respect to vehicle characteristics, traffic state, and road type. Cold-start emissions differ with respect to vehicle characteristics, accumulated distance, and parking duration.

In a first step, vehicle characteristics are obtained from survey data and typically comprise vehicle type, age, cubic capacity and fuel type. They are then used for very differentiated emission calculations. Where no detailed vehicle information is available, fleet averages for Germany are used. For the calculation of warm emissions, MATSim traffic dynamics are mapped to two HBEFA traffic states: free flow and stop&go. In order to identify road types, information from network data is mapped to HBEFA road types, such as motorway, trunk road, distributor road, or tertiary road. For the calculation of cold-start emissions, parking duration and accumulated distance are monitored in the simulation. The handbook then provides emission factors for the most common pollutants differentiated among the characteristics presented above. For the present paper, the following pollutants are relevant: Sulfur Dioxide (SO_2), Particular Matter ($PM_{2.5}$), Nitrogen Oxides (NO_x), Non-Methane Hydrocarbons ($NMHC$), and Carbon Dioxide (CO_2).[4]

[3] The parameters of the utility functions follow the specification in Kickhöfer and Nagel [24], and imply a Value of Travel Time Savings (VTTS) of 12.15 EUR/h for the car mode, and of 14.43 EUR/h for non-car modes.

[4] Please note that CO_2 is only considered when assessing the impacts of the policies, but not for the calculation of the local air pollution tolls or changes in exposure costs.

Table 1. Emission cost factors (base year 2000) by emission type from Maibach et al. [27, p.54, Table 13]

Emission type	Cost factor [EUR per $1,000\,kg$]
$NMHC$	1,700
NO_x	9,600
$PM_{2.5}$	384,500
SO_2	11,000

In a second step, so-called 'emission events' are generated based on these warm and cold emission factors. The events provide information about person, time, link, and absolute emitted values by emission type. The definition of emission events follows the MATSim framework that uses events for storing disaggregated information as objects in JAVA programming language and as XML in output files. Emission event objects can be accessed during the simulation or generated later on in a post-processing of the standard MATSim events.

Emission cost factors for the relevant pollutants (see Tab. 1) are taken from Maibach et al. [27], and used to convert the emissions events into monetary terms, the emission costs. These factors represent average cost estimates for urban regions in Germany with a population greater than 0.5 million inhabitants. We assume these being correct for the average population density of the respective scenario. This becomes important when calculating the emission exposure toll (see later in Sec. 2.4).

2.3. Emission Cost Distribution

After having obtained exhaust emissions, the typical process of air quality modeling (see Sec. 1.1) continues with an air pollution dispersion model. In the simplest case, Stern et al. [33] propose for single point sources and long time intervals a model with a simple Gaussian distribution function (*plume model*). For multiple and area sources and for air pollution concentration calculations in urban areas, the authors suggest the *box model*, a discretization in grid cells similar to Fig. 1 in the present paper [33, Chapter 18]. Presumably, both models only work for larger numbers of sources and sinks and appropriate time intervals. They are not designed to simulate the dispersion of the emissions of a single car realistically.

As already stated in Sec. 1.3, the present paper – for now – needs to avoid detailed air pollution dispersion and concentration calculations in order to reach computational performance for iterative toll calculations. Hence, the emission costs from Sec. 2.2, are distributed using an approach inspired by the box model. In contrast to the models from above, the proposed model does not account for the height of source or sink, thereby reducing volumes to surfaces. Further climatological influences are excluded resulting in a normal distribution function. The accuracy of such model is highly dependent on the resolution, yielding more precise results with an increasing number of boxes (or cells). In order to find a compromise between accuracy and computability, the research area in this paper is, in an iterative testing process, divided into discrete cells with cell length of $l = 250\,m$. As a result of this process, the discrete emission distribution factors of cell i are calculated according to the following simplified function:

$$d_i = F \cdot exp\left(-\frac{x_i^2}{2l^2}\right) \tag{2}$$

where x_i is the distance between the center of the cell, where a vehicle is causing emissions, and the center of cell i, where individuals might perform activities. That is, the distribution factors depend on the distance between source and receptor cell. To keep computational time within reasonable limits, only cells with a distance of $x = l..3l$ are considered since the factors for cells further away fall below 0.0001; the corresponding distribution factors are therefore set to zero. Fig. 1 shows the resulting emission distribution factors which are then multiplied by the monetary value of every emission event from Sec. 2.2. $F \approx 0.216$ is a normalization factor which guarantees that all emission distribution factors add up to one.

This approach assumes (i) that all pollutants are distributed in the same manner, (ii) that the average cost factors from Tab. 1 are correct for the average exposure time in the scenario (see Sec. 2.4), and (iii) that exposure costs are linear at the operating point. The latter assumption can be argued since changes of air pollution concentrations resulting from transport policy measures are unlikely to move the system far away from the operating point, i.e. a significant change in overall air pollution concentration. However, the operating point might be different for different areas in the same city. This effect is partially covered by including exposure times in the toll calculation (see the next Sec. 2.4). The first assumption clearly is debatable as a study by Karner et al. [23] shows. The authors find that NO_x and *NMHC* follow similar decays, and reach a reduction of 50% from the edge-of-road concentration after roughly 115 *m*, but only declining slowly further away. $PM_{2.5}$, in contrast, does not show similar decay, still being at roughly 80% at a distance of 400 *m*. The decay assumed in the proposed approach rather follows the one of NO_x and *NMHC* from Karner et al. [23], and exposure costs from $PM_{2.5}$ are therefore likely to be underestimated. For further discussion on the above assumptions, impacts on the results, and potential solutions, please see Sec. 4.

0.000 €	0.000 €	0.000 €	0.002 €	0.000 €	0.000 €	0.000 €
0.000 €	0.000 €	0.002 €	0.029 €	0.002 €	0.000 €	0.000 €
0.000 €	0.002 €	0.029 €	0.132 €	0.029 €	0.002 €	0.000 €
0.002 €	0.029 €	0.132 €	0.216 €	0.132 €	0.029 €	0.002 €
0.000 €	0.002 €	0.029 €	0.132 €	0.029 €	0.002 €	0.000 €
0.000 €	0.000 €	0.002 €	0.029 €	0.002 €	0.000 €	0.000 €
0.000 €	0.000 €	0.000 €	0.002 €	0.000 €	0.000 €	0.000 €

Figure 1. Distribution of 1 *EUR* of emission costs emitted in the center cell (in gray). Cells beyond the shown area are assumed to have an emission distribution factor of zero.

2.4. Exposure Cost Calculation

Following Hatzopoulou and Miller [14], daily exposure of an individual is a function of the time spent at every location and the respective pollution concentrations. The simplified approach presented in this paper explicitly avoids emission dispersion and air pollution concentration calculations, and instead directly distributes emission costs C_{em}. Therefore, total exposure costs caused by one emission event C_{ex} are referred to as

$$C_{ex} = \sum_{i=1}^{N} \frac{T_{act,i}}{T_{avg}} \cdot d_i \cdot C_{em} \; , \tag{3}$$

where $N = 25$ is the number of cells around the corresponding link (Fig. 1); $T_{act,i}$ is the actual aggregated exposure time of cell i; T_{avg} is total activity time in all cells per time bin $\sum_{i=1}^{I} T_{act_i}$ divided by the number of all cells in the research area I; d_i is the emission distribution factor of cell i (Fig. 1); and C_{em} are the total emission costs of the vehicle (see Sec. 2.2). To calculate the required actual exposure times $T_{act,i}$, simulation time is split into isochronous one hour time bins. For each of these bins, activity time spent by the agents is recoded for each cell. The result is a three dimensional data structure consisting of time bin, horizontal and vertical position, and the aggregated exposure time of agents in the cell (in person seconds [*Ps*]). To give an example: Consider a discretization of air pollution impact time into time bins of one hour. If an agent arrives at a location in cell (25,32) at 8:30 and leaves at 10:15, then 1800 *Ps* are added to the array at (x = 25, y = 32, *time* = 8:00–9:00), another 3600 *Ps* are added to (x = 25, y = 32, *time* = 9:00–10:00), and 900 *Ps* are added to (x = 25, y = 32, *time* = 10:00–11:00).

The average exposure time over all cells per time bin T_{avg} is calculated in every iteration of the simulation. The ratio between actual and average exposure times is non-negative and the sum of ratios divided by the number of cells I adds up to one. This highlights the design of the exposure cost calculation: it is computed in such way that a uniform distribution of the actual exposure times over all cells would result in equality between the sum of exposure costs and the sum of emission costs.

Having obtained $T_{act,i}$ and T_{avg}, Eq. 3 gives the total exposure costs, i.e. the individual toll level for the causing vehicle. For illustration purposes, consider that the vehicle has emitted 2 *g* of SO_2 in a cell at 9:15. Also consider that 15 people are present in a neighboring cell from 9:00 to 10:00, resulting in $15P \cdot 3600s = 54,000Ps$ actual exposure time. Following the emission cost distribution approach from Sec. 2.3, $2g \cdot 0.011 \frac{EUR}{g} \cdot 0.132 = 0.002904 EUR$ are distributed to the cell with the 15 agents. For an assumed average exposure time over all cells of 5000 Ps between 9:00 and 10:00 (calculated from people's activity times in the simulation), the cell with the 15 agents yields exposure costs of $C_{ex} = \frac{54{,}000 Ps}{5000 Ps} \cdot 0.002904 EUR = 0.0313632 EUR$. Conversely, if no individual is performing an activity in the surrounding cells within the respective time bin, no exposure costs arise. The resulting monetary cost is then mapped back to the causing vehicle, and charged as the individual exposure toll.

3. Case Study: Munich, Germany

This section applies the methodology from Sec. 2 to a large-scale real world scenario of the Munich metropolitan area in Germany. In Sec. 3.2, impacts on absolute emission levels, exposure cost reductions, and system welfare are compared to the effects of the emission toll proposed by Kickhöfer and Nagel [24] who did not account for population exposure (flat toll per gram of pollutant). In Sec. 3.3, the exposure toll is used to evaluate the impacts of a speed limitation in the inner city of Munich to 30 km/h. As a reaction to the different policy interventions, travelers are allowed to change their route when traveling by car, and their mode of transport between car and non-car. Freight vehicles are only allowed to change their route.

The reference scenario (base case) without any policy intervention is the same as the one used by Kickhöfer and Nagel [24]. For a better understanding of the results, it is shortly described next: Network information from VISUM[5] was converted into MATSim format, resulting in a network of 17,888 nodes and 41,942 links. This transport supply was then linked to travel demand from different sources: an activity-based demand for inner-urban traffic was created from survey data based on "Mobility in Germany" [MiD 2002, 10]. This part of the synthetic population consists of roughly 1.4 million individuals with detailed vehicle information for every household. Commuter and reverse commuter were modeled based on data provided by the German Federal Employment Office [5]. This part of the population consists of roughly 0.5 million individuals from which 0.3 million commute to Munich for work; the remaining individuals live in Munich and commute to their workplace in the surroundings of Munich. Freight traffic was also introduced into the model by using data from the German Ministry for Transport [20]. This part of the population consists of roughly 0.15 million freight vehicles who perform one single commercial trip per day.

Starting from a simulation of the 'status quo', the base case and the different policy cases are continued for 500 iterations. For computational performance reasons, a 1% sample is used for this simulation; the results in the following sections are then re-scaled to the full population size, and refer to one typical working day.

3.1. Base Case

In the following, the results of the simulation of the no-measure base case, which is equivalent to the setup from Kickhöfer and Nagel [24], are shortly recapitulated. These results serve as reference case estimations ("business as usual"), against which the different policies are then compared in the subsequent sections. Results are always presented for the four subpopulations from above: urban travelers, commuters, reverse commuters, and freight traffic.

As Fig. 2 shows[6], urban travelers contribute to a relatively small part of total emissions despite representing 68% of the total population. Only their *NMHC* emissions are over-proportionally high. This is due to the fact that urban travelers drive shorter distances and perform more trips, which in consequence yields higher cold-start emissions. Commuters and reverse commuters (14.6% and 9.8% of the total population) cause substantially more emissions than urban travelers since they drive longer distances. Intuitively, Munich attracts more individuals who additionally come from further away (commuters) than there are individuals who are attracted by the surroundings of Munich (reverse commuters). For that reason, the former drive longer distances and emit more emissions per person than the latter. Freight traffic only represents 7.6% of the total population but causes a major part of total emissions. This is most important for $PM_{2.5}$ and NO_x. From the initial emission values of the different subpopulations, it already becomes clear who will bear most of the emission toll payments. However, when pricing local emission exposure, this picture is not so clear anymore: toll payments will depend on activity location density along the route, and will therefore strongly vary between different trips.

[5] 'Verkehr In Städten – UMlegung', see `www.ptv.de`

[6] Please note the different scales for the different pollutants. This scaling is necessary in order to show absolute values of all pollutants in one single graph.

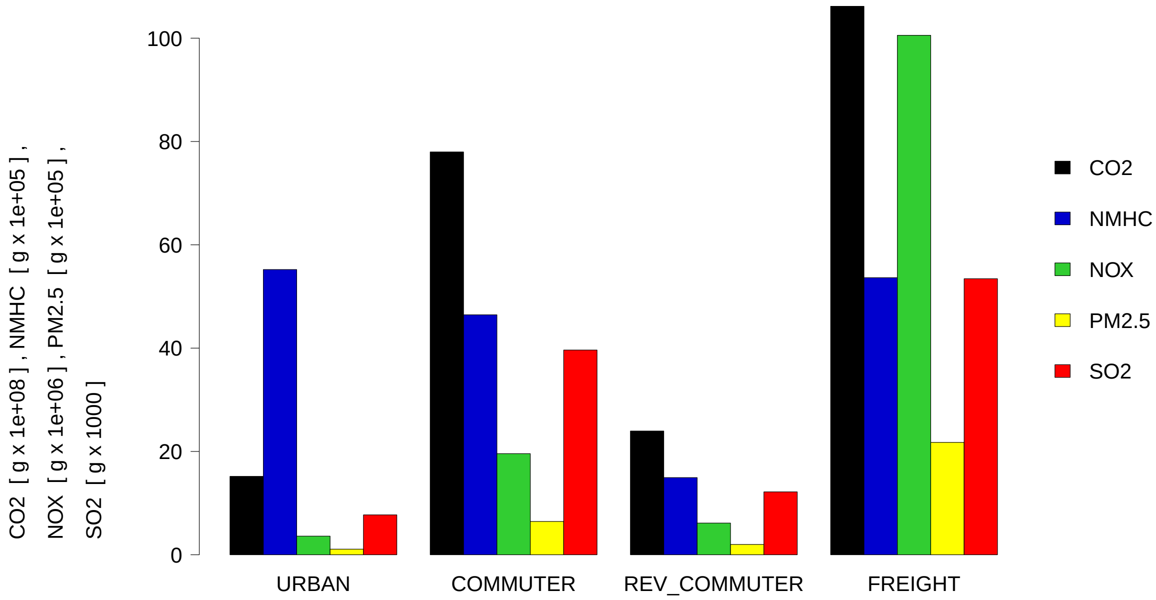


Figure 2. Base case: Absolute daily emission levels by type and *emitting* subpopulation. Values scaled to full population.

3.2. Emission vs Exposure Toll

In order to show the effects of the two toll schemes, changes in emission levels by emitting subpopulation are presented first. As can be seen in Fig. 3, the flat emission toll on the left reduces emission levels of all subpopulations and pollutants. NO_x emissions are overall reduced by −0.25%, most importantly for urban travelers (−1.37%) and least importantly for freight (−0.05%). For $PM_{2.5}$, these figures amount to −0.50% overall, −2.97% for urban travelers, and −0.15% for freight. In comparison, the exposure toll on the right shows a less homogeneous picture: emission levels of most pollutants are reduced for urban travelers, commuters and reverse commuters, but for freight, one can even observe an *in*crease in total emissions. As already explained above, the different subpopulations have different options (choice dimensions) to react on the toll schemes. While urban travelers can adjust their route, *and* can switch to the non-car mode, freight traffic is only allowed to change route. Commuters and reverse commuters have both options available (route and mode choice), but the non-car mode is (in the model) generally less attractive for these demand segments because of their long-distance trips. That is, the more substitutes are available for the respective demand segment, the higher the emission reduction by any of the toll schemes.

Fig. 3 additionally raises the question why the exposure toll increases absolute emissions for some subpopulations. For urban travelers, one observes an increase in *NMHC* despite less car usage of this demand segment. One the one hand, the number of cold-starts decreases, and thus, these emissions are reduced. However, this effect is over-compensated by higher cold-start emission factors which result from cars cooling down for longer periods. For freight traffic, one can observe an interesting particularity of the exposure toll: while routes with less activity locations around them become more attractive, drivers choose longer routes with less potentially exposed individuals, and absolute emission levels therefore increase.

To pick up on this last point, Fig. 4 shows absolute changes in exposure costs by causing subpopulation.[7] For the exposure toll on the right, substantial reductions in exposure costs can be observed, most important for those caused by freight traffic. That is, even though absolute emissions increase for this demand segment, exposure costs decrease. In contrast, for the emission toll on the left, exposure costs for freight slightly increase even though absolute emission

[7]Please note that the focus of the present paper is on exposure costs which are calculated for all scenarios. The values in *emission cost reductions* induced by the two policies from Kickhöfer and Nagel [24] are therefore different in scale compared to the *exposure cost reductions* presented here.

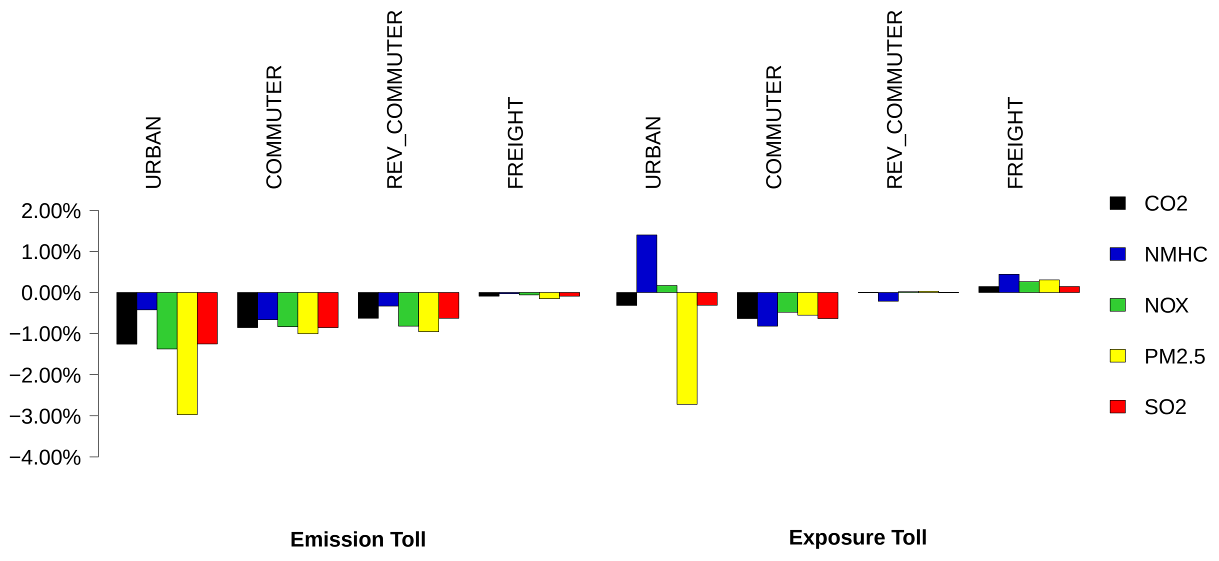


Figure 3. Relative changes in daily emissions by *emitting* subpopulation.

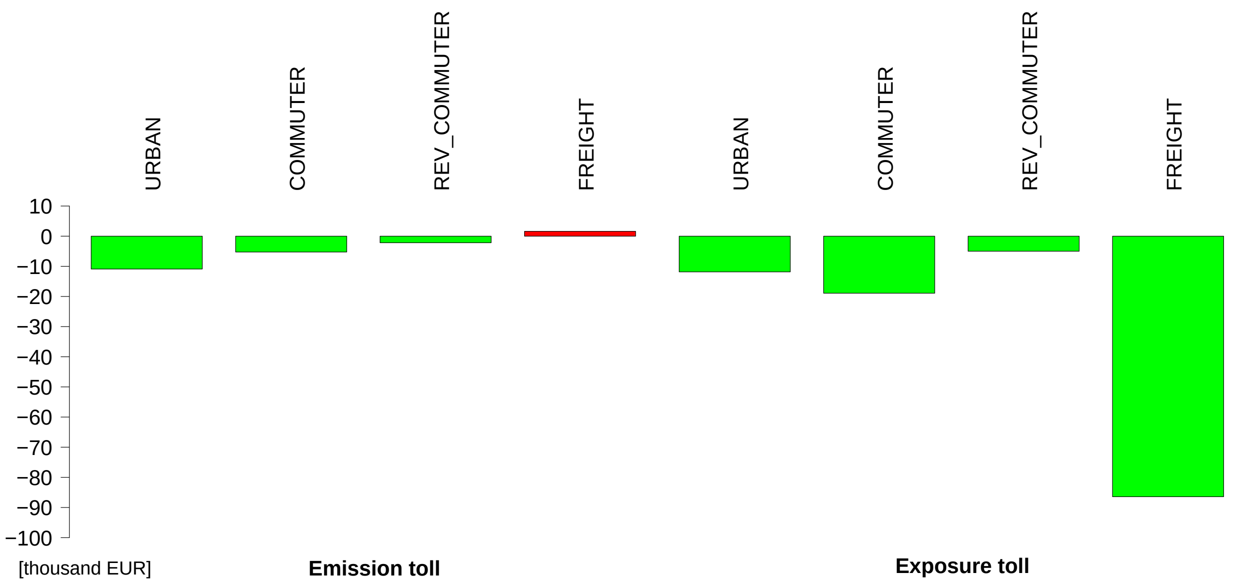


Figure 4. Absolute changes in daily exposure costs by *causing* subpopulation. Values scaled to full population.

Policy case	Subpopulation	Total paid [*EUR* x 100]	Total car distance [*km* x 100]	Average toll [*EURct*/*km*]
Emission Toll	URBAN	736.37	70,504.60	1.04
	COMMUTER	4,370.34	433,581.10	1.01
	REV. COMM.	1,359.56	136,945.07	0.99
	FREIGHT	18,090.77	175,189.89	10.33
Exposure Toll	URBAN	4,072.13	71,622.74	5.69
	COMMUTER	3,287.88	434,214.82	0.76
	REV. COMM.	1,079.57	137,736.48	0.78
	FREIGHT	458.81	175,798.19	0.26

Table 2. Total and average daily toll payments (whole scenario). Values scaled to full population.

Policy case	Subpopulation	Total paid [*EUR* x 100]	Total car distance [*km* x 100]	Average toll [*EURct*/*km*]
Emission Toll	URBAN	720.40	68,497.36	1.05
	COMMUTER	816.69	76,896.23	1.06
	REV. COMM.	264.46	25,957.12	1.01
	FREIGHT	307.03	2,317.24	13.25
Exposure Toll	URBAN	4,057.64	69,508.37	5.83
	COMMUTER	3,060.16	75,817.26	4.04
	REV. COMM.	1,002.58	25,777.11	3.89
	FREIGHT	408.26	1,053.76	38.74

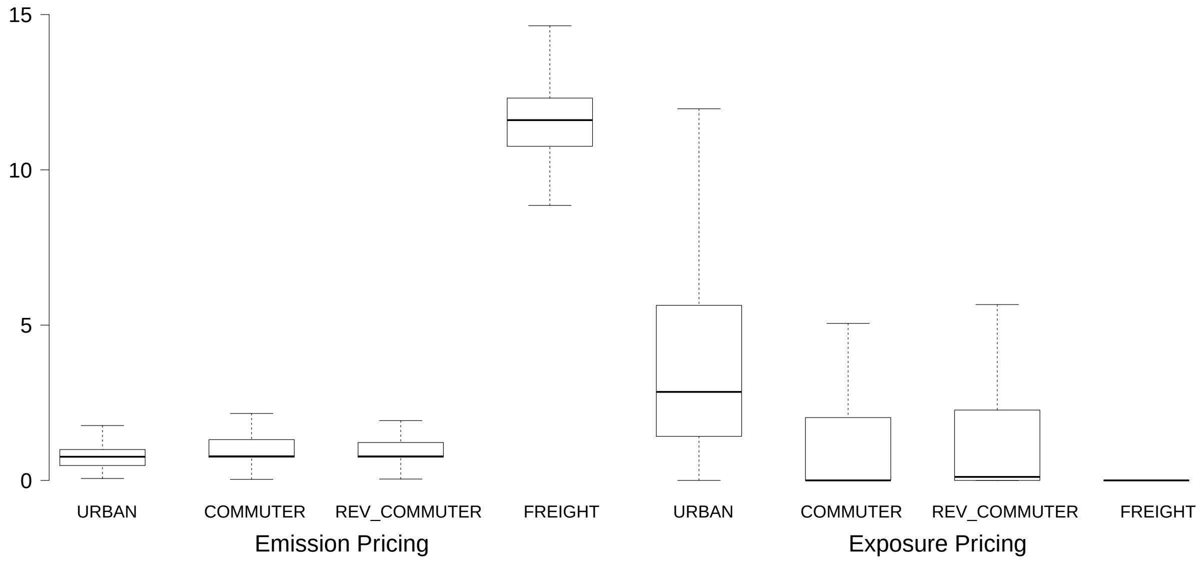
Table 3. Total and average daily toll payments (city area). Values scaled to full population.

levels drop. This is due to the fact that – with the emission toll – freight vehicles tend to choose shorter routes which might lead through areas with higher activity location density. For the other subpopulations, one can also observe that exposure cost reductions are lower than for the exposure toll. This intuitively makes sense since the emission toll aims for a reduction in absolute emission levels, not for finding the optimal air pollution exposure level.

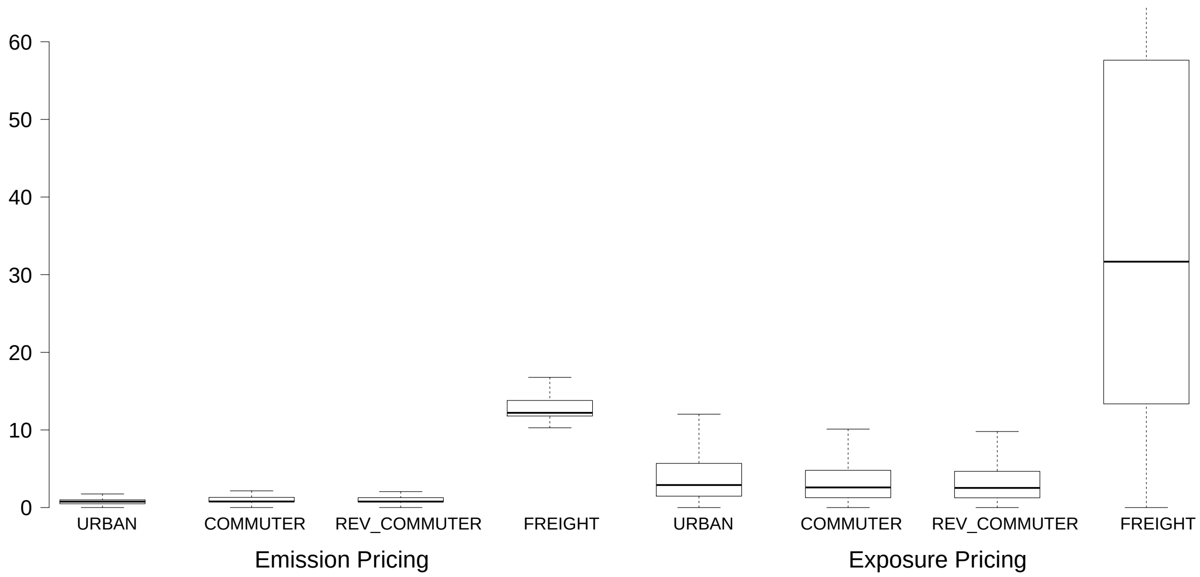
Tab. 2 and Tab. 3 support the findings from above. They present average toll payments for the whole scenario, and for trips within the boundaries of Munich municipality, respectively. Tab. 2 shows that the average *emission* toll per car distance traveled for urban travelers, commuters, and reverse commuters ranges from 0.99 to 1.04 *EURct*/*km*. Since freight traffic causes substantially more emissions per vehicle kilometer, the cost factors are consequently in average by a factor of ten higher than for the other subpopulations (10.33 *EURct*/*km*).

When pricing *exposure* rather than emissions, urban travelers now pay the highest average toll (5.69 *EURct*/*km*), while average tolls of commuters and reverse commuters are roughly lower compared to the emission toll (0.76 and 0.78 *EURct*/*km*, respectively). The average toll for freight now only adds up to 0.26 *EURct*/*km*. Both, the higher average toll for urban travelers and the lower average toll for the other subpopulations in the exposure pricing scheme, can be explained as follows: While urban travelers drive most of their distance traveled within the boundaries of Munich, where information about activity locations and exposure times is available for this scenario, all other subpopulations only drive a relatively small part of their distance traveled in those areas. In consequence, their average exposure toll levels for the whole scenario are low compared to those of urban travelers. However, when looking at the average exposure toll levels paid in the city area (Tab. 3), one notices an increase in the average toll compared to the values for the whole scenario: This increase is relatively small for urban travelers (5.83 *EURct*/*km*), more prominent for commuters and reverse commuters, and most important for freight (38.76 *EURct*/*km*).

Another way to show these effects on a more disaggregated level is provided by Fig. 5. It shows the toll payments for the flat emission toll (left) and for the exposure toll (right) and all subpopulations as box plots. Data points for these plots are obtained whenever a person leaves a road segment, and therefore has to pay a toll. For every such event, the distance toll payment is divided by the length of that road segment.[8]



(a) Whole scenario



(b) City area

Figure 5. Toll payments per kilometer traveled for all individuals and links over one day [$EURct/km$]

For the whole scenario in Fig. 5(a) and the emission pricing scheme, one observes toll payments around 1.0

[8]This means that every road segment has a weight of one in the calculation; the resulting figure therefore implicitly depends on the network topology.

EURct/*km* for urban travelers, and slightly higher values for commuters, and reverse commuters. The width of the distribution can be explained by different vehicle types, as well as by different traffic states. Both influence emission levels. Since no detailed vehicle types were available for commuters and inverse commuters, the variance can only be explained by different traffic states. The same is true for freight traffic which depicts a rather high average toll over all links. In the same figure, but now for the exposure pricing scheme, the width of the average toll payment distribution strongly increases for the first three subpopulations. This is due to the fact that the toll is now additionally influenced by activity location density (and therefore exposure times) along the route. Only for freight, this effect is not present since this most links of their routes are in areas where no activity location information is available in the scenario.

For the tolls paid in the city area of Munich (Fig. 5(b)), almost no change is observed for the emission toll (note the scale differences of the y-axes). This is consistent with Tab. 2 and Tab. 3. For the exposure toll, the distribution of toll payments for urban travelers remains similar. However, for all other subpopulations, the variance strongly increases, showing the impact of activity location density and exposure times on the toll level.

In the literature, several studies give estimates for local air pollution cost factors. Parry and Small [29] base their values on a cost allocation study by the U.S. Department of Transportation. They state that local pollution costs are dominated by health costs, and that for the U.S. automobile fleet of the year 2000, the unit costs range from 0.4 to 10.0 *USDct*/*mile* (≈ 0.26 to 6.58 *EURct*/*km*)[9], with a central value around 2.0 *USDct*/*mile* (≈ 1.31 *EURct*/*km*). Delucchi and McCubbin [9] compare different studies with values for air pollution health costs in year 2006 *USDct*. Values per vehicle mile range from 0.18 to 10.66 *USDct*/*mile*. For trucks, values per vehicle mile range from 6.03 to 112.23 *USDct*/*mile*. This broad range of values is, according to the authors, mainly due to uncertainty in the relationship between air quality and human health, as well as due to different assumptions in the valuation process. Bigazzi and Figliozzi [4] provide an extensive overview of unit cost factors for different pollutants with low, medium, and high cost estimates. In addition, the authors compute, based on the medium cost estimates, optimal pollution and on-road exposure tolls (in 2011 *USDct*/*mile*) for a 3-lane freeway and different saturation states of traffic demand. For congested regimes and on-road exposure (which is not considered in the present study), they find a combined external effect of all pollutants of 43.8 *USDct*/*mile*. For the same regime and air pollution, the optimal toll amounts to 0.5 *USDct*/*mile*. To sum up, comparing the average tolls from Tab. 2, Tab. 3, and Fig. 5, which are obtained by coupling MATSim with HBEFA and unit cost factors from Maibach et al. [27], to the above values from the literature, the following points can be noted: (i) All local air pollution cost estimates obtained by the approach presented in this paper are in a plausible range. (ii) The estimates obtained from the flat emission toll are rather on the lower bound of the cost estimates in the literature. (iii) The estimates obtained from the exposure toll correct for this, and are characterized by more variance resulting from the number of affected individuals.

3.3. Zone 30 vs Exposure Toll

In the following, it is discussed how accounting for population exposure in the toll calculations influences the evaluation results of a real-world policy. For that purpose, the results of the exposure toll from Sec. 3.2 are compared to a speed limitation in the inner city of Munich to 30 *km*/*h*. This comparison is similar to the one performed by Kickhöfer and Nagel [24]. In contrast to that study, the calculation of external cost reductions now accounts in both policy cases for population exposure to local pollution, but not for the reduction in CO_2 emissions. In the following, the exposure toll is used as a market-based benchmark, and the Zone 30 policy as the measure to evaluate. In this context, it should be noted that the benchmark policy is a rather theoretical concept. The main argument here is, that individuals are unlikely to interpret the ever changing price signals in such way that the steering mechanism can unfold its power. However, it might be useful to compare the impacts of real-world measures to such theoretical pricing scheme.

Fig. 6 shows relative changes in emission levels for all subpopulations. The changes for the exposure toll on the right are identical to the values presented in Fig. 3. For the Zone 30 policy one notices a stronger reduction in emission levels for urban travelers than for the exposure toll. That is, mainly because of mode choice effects, the Zone 30 policy leads to emission levels below the benchmark policy. Even though the Zone 30 reduces emission levels of most pollutants for commuters, their and the reverse commuters' emission levels are found to be above those of the benchmark. These demand segments choose new routes around the regulated zone; this, in turn, over-compensates

[9] 1.00 *USD* = 1.06 *EUR*, end of year 2000 exchange rate; 1.00 *mile* = 0.621 *km*.

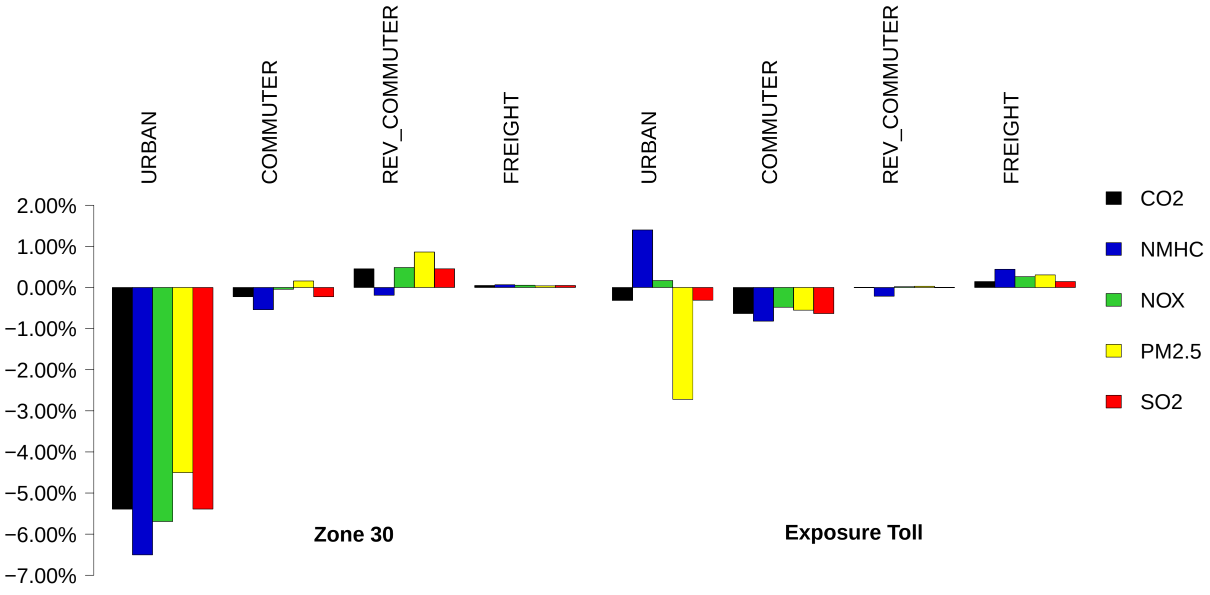


Figure 6. Relative changes in daily emissions by *emitting* subpopulation.

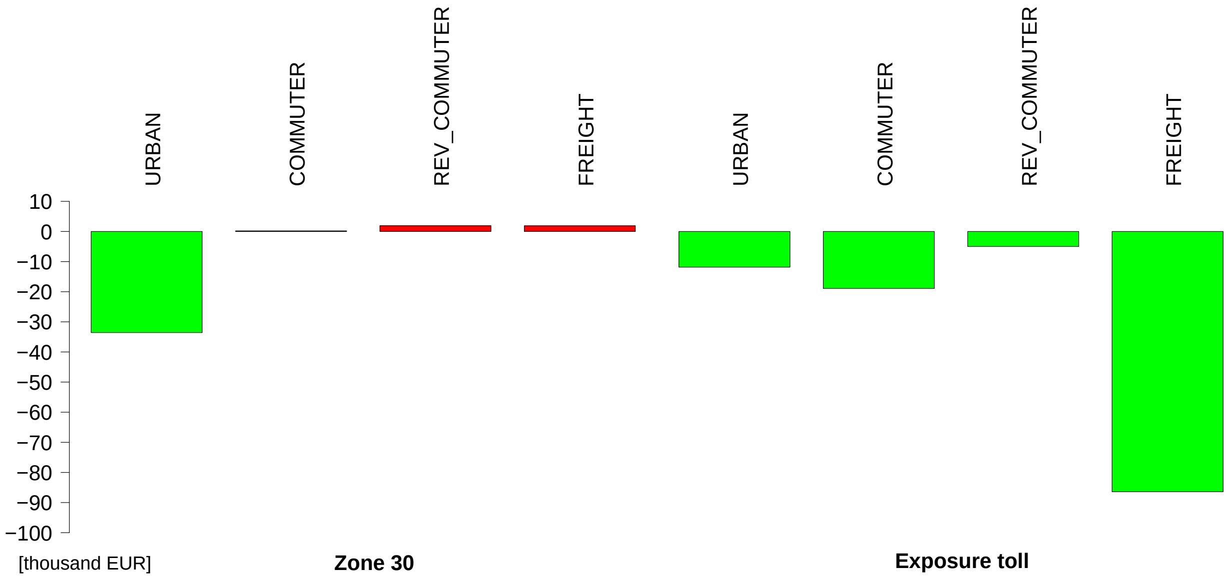
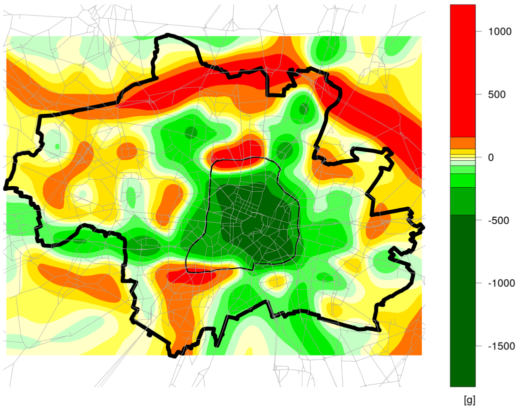
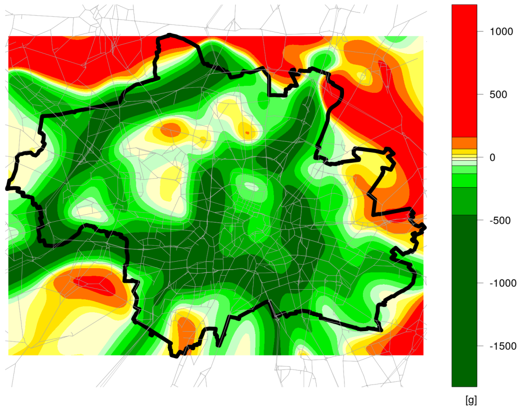


Figure 7. Absolute changes in daily exposure costs by *causing* subpopulation. Values scaled to full population.



(a) Zone 30



(b) Exposure toll

Figure 8. Absolute daily changes in NO_x emissions. Plots based on spatial averaging for all road segments. Values scaled to full population.

the mode choice effect and yields emission levels above the benchmark policy. In terms of absolute emissions, the Zone 30 has only a small effect on freight traffic, yielding an emission level below the benchmark policy.

Fig. 7 picks up the question where in the city these exhaust emissions are produced and how the resulting monetary changes in exposure costs can be characterized. The Zone 30 policy reduces exposure costs caused by urban travelers more significantly than the benchmark (32,000 vs 15,000 *EUR* per day). It therefore seems to be an effective strategy to mitigate air pollution exposure. However, as shown in Fig. 6, this reduction in exposure costs requires a stronger reduction in emission levels than the exposure toll, mainly caused by a modal shift towards non-car. Additionally, the Zone 30 policy leads to an increase in exposure costs for all other subpopulations, mainly because of re-route effects around the zone. In that sense, the regulatory measure can overall not be regarded as an efficient strategy to reduce population exposure to exhaust emissions.

The presence of this re-route effect is also clearly visible in Fig. 8(a). While absolute NO_x emissions are strongly reduced inside the regulated zone (black polygon), emission levels rise on parts of the middle ring road, as well as on tangential motorways and some arterials. The increase in population exposure caused by commuters, reverse commuters, and freight traffic might be due to the fact that activity location density is rather high around the middle ring road. In total, the Zone 30 does not reduce NO_x emissions (±0.0%). The spatial changes of NO_x emissions resulting from the exposure toll scheme are shown in Fig. 8(b). As one can notice, the toll reduces emissions almost everywhere in the city area, most importantly along the major corridors, including the middle ring road. However, outside the city area, substantial increases of NO_x emissions can be observed. That is, the re-route effect is even more important than for the Zone 30 policy as it pushes travelers out of the city area. In consequence, the exposure toll leads to an overall increase in NO_x emissions by +0.1%.

Both, the re-route effects and the modal shift become also visible in the economic analysis of the two policies shown in Fig. 9. It shows user benefits (and for the exposure toll additionally toll payments) for the different subpopulations. As one can see, the Zone 30 reduces user benefits for all subpopulations. This intuitively makes sense because the transport system is slower than in the reference case; this leads to time losses for all car travelers either by switching route or transport mode. The exposure toll, in contrast, yields gains in user benefits for urban travelers, which result from travel time gains (blue bars). Since these bars implicitly include the toll payments (with negative sign), it can be followed that, for urban travelers, gains from reduced travel times over-compensates the negative effect of the toll payments. That is, the exposure pricing is implicitly a congestion charge.[10] When considering the toll

[10]A similar finding was obtained by Kickhöfer and Nagel [24] for the flat emission toll, but it seems that the exposure toll even has a stronger positive effect on congestion relief. This might be due to the fact that the exposure toll is correlated more positively with congestion than the emission toll: densely populated areas are implicitly characterized by higher travel demand and therefore pricing exposure influences congestion relief more positively.

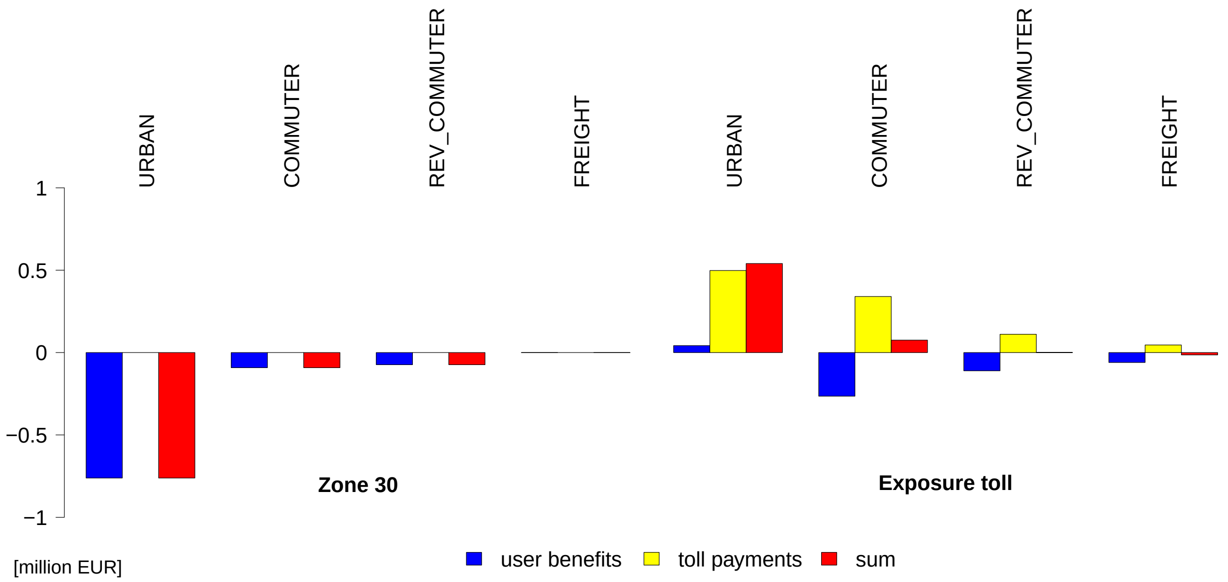


Figure 9. Absolute daily changes in user benefits and toll payments by subpopulation.

payments as transfer payments to some public authority, the exposure toll also has a positive impact on social welfare of the other three subpopulations: Even though, for commuters, reverse commuters, and freight, direct gains from reduced congestion are lower than the negative effect of the toll payments, a redistribution of the toll payments would result in overall benefits for all subpopulations (red bars).

4. Discussion

The goal of this paper is to present a first approach to internalize air pollution exposure costs, i.e. pricing damages to human health in an agent-based transport model with activity-based demand. In this process, it is proposed how to iteratively calculate local air pollution exposure tolls in large-scale urban settings by taking the exposure times and locations of individuals into consideration. The main contributions hereby are the following:

1. **Fully integrated model**:The approach combines activity-based demand, dynamic traffic flows, agent-specific behavior, vehicle-dependent emissions, and time-dependent exposure cost calculations. Only a very limited number of previous studies performed exposure analysis for large-scale urban setting as a post-processing step to the traffic simulation [see, e.g., 14]. To the knowledge of the authors, the approach presented here is the first one to close the circle from the polluting entity, to the receiving entity, to damage costs, to tolls, and back to the behavioral change of the polluting entity.
2. **Static vs dynamic population density**: Most studies investigating air pollution exposure for whole cities assume static population densities, typically from residential data (see, e.g, Jerrett et al. [22] for a review on air pollution exposure models, or Bellander et al. [3] for an typical application using GIS). At the same time, the authors point out that it would be desirable to extend the exposure analysis to other places than the home locations, or to travel itself. Especially a collaboration with transportation experts is encouraged, in order to include activity spaces into the analysis [22]. The present paper can be seen a first step into this direction.
3. **Data requirements, computation time, research use**: The approach is characterized by little data requirements, reasonable computation times, and open-source compatibility. Arbitrary average cost factors from the literature can be used for the model. The computation time for toll calculations, which needs to be performed in each iteration for each individual, only amounts to a few minutes for the scenario considered here. To the

knowledge of the authors (who tested coupling MATSim with OSPM in Hülsmann et al. [18]), there is no current emission dispersion model which is comparable in terms of computational performance. Additionally, since MATSim as a software is meant to be used by other researchers free of charge, the approach outplays any other process that involves proprietary software.

Clearly, given the complexity of such integrated approach, which alludes to the areas of large-scale transport and behavioral modeling as well as to emission and exposure calculations, several assumptions and simplifications had to be made. These, in turn, yield limitations of the model which are discussed next. The focus hereby always lies on the question whether these assumptions and simplifications influence the presented results structurally. If so, this provides research opportunities that should be tackled in the future.

1. **On-road exposure**: According to Bigazzi and Figliozzi [4], on-road exposure can reach a substantial share of marginal social costs, and should therefore not be neglected (also see a study by Wang and Gao [36] on travelers' exposure depending on mode of transport). Similar to Hatzopoulou and Miller [14], the approach in this paper does not account for on-road exposure. This yields a bias in the average and actual exposure times of Eq. 3. In areas with high travel demand and high congestion the ratio between these two factors would increase, in areas with low travel demand and less congestion the ratio would decrease. In principle, integrating this effect is possible. It would require an efficient calculation of expected exposure costs in every cell along the route for every agent, and integrating this into the individual utility function of Eq. 1, similar to time losses.
2. **Decay functions and mitigating factors**: As pointed out in Sec. 2.3, the current approach distributes emission costs, and avoids emission dispersion calculations. This implies that emissions disperse in the same manner which is not found in reality [23]. One could therefore aim at distributing different pollutants with separate decay functions, and monetize them later on. This would require careful testing of the additional computational effort. Similarly, mitigating factors such as vehicle or building shells are not considered in the model. For improvements regarding these simplifications, the trade-off between accuracy and computability and data availability always needs to be kept in mind. It seems that only a proper dispersion model could account for such effects, and joint work by dispersion model and transport model developers could offer a fruitful collaboration in this area.
3. **Background concentrations and time lag**: The results of this paper show that the exposure toll redistributes traffic to areas with less activity location density. However, the model does not account for the impact of the resulting higher emission level on background concentrations and secondary pollutants which typically appear with a certain time lag. Again, only a dispersion model would be able to pick up on such effects. The potential impacts on the results are discussed below.
4. **Composition of unit cost estimates**: The values by Maibach et al. [27] which are used in this paper include health costs, building and material damages, crop losses in agriculture and impacts on the biosphere, and on biodiversity and ecosystems. The authors do not provide disentangled cost factors for every effect separately. Using the values simply as is in an urban environment might therefore lead to an overestimation of the damage costs, and consequently of the toll levels. However, as the results of this paper show, the effects of the exposure toll in terms of emission and exposure cost reduction are rather small despite the use of cost factors that include other costs than damages to human health. One could attempt to disentangle the cost factors, and re-run the simulation. The resulting behavioral changes are, however, expected to be even smaller than now. This issue is discussed below.

As a result of the limitations above, the calculated individual tolls might be wrongly predicted in terms of location or absolute level even though it was shown that they turn out to be in a reasonable range (see Sec. 3.2). Possible improvements comprise the implementation of a proper dispersion model if computing times are kept in mind. Similarly, the use of regression-based approaches for emission exposure could be tested in the future (see, e.g., Briggs et al. [6]).

However, given the rather small effects of the pricing policies on emission and exposure cost reductions, the question arises whether the behavioral model predicts travelers' reactions to the toll levels correctly, i.e. whether the implied elasticities derived from time use surveys are correct. Including more choice dimensions such as vehicle ownership, activity scheduling, or long-term decisions such as residential location choice might have impacts on the results. Still, damage cost factors remain difficult to estimate because of the complex and long-term cause and effect chain [28]. In this context, politicians and decision makers might also try so-called "backcasting approaches" [13, 21] where a emission reduction goal is defined, and transport models can be used to calculate the necessary avoidance costs in order to reach the desired effects.

5. Conclusion

In this paper, a new approach was presented to iteratively calculate local air pollution exposure tolls in large-scale urban settings by taking the exposure times and locations from the agent-based transport simulation MATSim into consideration. For emission modeling, the MATSim-HBEFA tool developed by Hülsmann et al. [17] was used which calculates warm and cold-start exhaust emissions every time a traveler leaves a road segment. Emission values were monetized using average cost factors from Maibach et al. [27]. Subsequently, the resulting costs were distributed using a stepped Gaussian distribution function applied to discrete cells, and exposure times of affected agents were calculated. Finally, the resulting exposure tolls were computed by scaling the actual exposure times in every cell for every time bin with the average exposure time of the scenario. Hence, the approach considers activity location density in external cost calculations.

The main contribution of the presented approach is that it closes the circle from the polluting entity, to the receiving entity, to damage costs, to tolls, and back to the behavioral change of the polluting entity. Additionally, it accounts for dynamically changing population densities throughout the day. Finally, it is characterized by little data requirements, reasonable computation times, and open-source compatibility. However, the idea is based on the assumptions that all pollutants are distributed in the same manner, that the external effects depend on the population density in the same way, and that the average cost factors from the literature are correct for the average exposure time in the scenario. These assumptions yield limitations which mainly influence the accuracy of the levels and locations of the individual tolls. The paper also provided ideas on how to address these shortcomings in the future, e.g. by integrating a dispersion model.

In order to show the applicability for large-scale scenarios, the approach was applied to a real-world case study of the Munich metropolitan area in Germany. The impacts of the exposure toll on absolute emission levels, exposure cost reductions, and system welfare were then compared to the effects of two policies presented by Kickhöfer and Nagel [24], who did not account for activity location density in their toll calculations. The resulting average cost factors obtained from the flat emission toll turned out to be on the lower bound of the cost estimates from the literature. In contrast, the ones obtained from the exposure toll are characterized by a higher overall level and a larger variance picking up on the number of exposed individuals. The flat emission toll was found to lead to a reduction in emissions, but exposure cost reductions are much lower than for the proposed exposure toll. With the latter policy, absolute emissions even increase for some demand segments while exposure costs drop. This points out a potential conflict between attempts to optimize exposure (which includes the possibility to drive longer routes with less exposed individuals), and attempts to reduce vehicle kilometers traveled in order to mitigate global warming.

Both policies – the emission toll and the exposure toll – can be used as a benchmark for evaluating real-world policies, depending on the objectives of the decision makers. Such benchmarking was performed as a final show case for a speed limitation in the inner city of Munich (Zone 30). Regarding the mitigation of exposure costs caused by urban travelers, the regulated zone turns out to be a more effective strategy than the exposure toll. However, for the other demand segments, it yields slight increases in exposure costs resulting from longer distances traveled, and higher emissions in populated areas. Additionally, in order to reach this cost reduction by urban travelers, the Zone 30 requires a stronger modal shift towards non-car than the exposure toll which also implies longer travel times. Consequently, it yields losses in user benefits while the exposure toll scheme shows positive welfare effects.

Overall, it can be stated that the emission exposure toll calculation proposed in this paper improves the evaluation of policies that aim at reducing environmental externalities in urban settings. The eventual goal is to combine the exposure toll with the internalization of other external costs, such as congestion, accidents or noise.

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