Towards high-resolution first-best air pollution tolls: An evaluation of regulatory policies and a discussion on long-term user reactions

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Abstract

In this paper, we present an approach to calculate high-resolution first-best air pollution tolls with respect to emission cost factors provided by [1]. We link dynamic traffic flows of a multi-agent transport simulation to detailed air pollution emission factors. The monetary equivalent of emissions is internalized in a policy which is then used as a benchmark for evaluating the effects of a regulatory measure — a speed limitation to 30 km/h in the inner city of Munich. The calculated toll, which is equal to simulated marginal costs in terms of individual vehicle attributes and time-dependent traffic states, results in average air pollution costs that are very close to values in the literature. Furthermore, we find that the regulatory measure is considerably less successful in terms of total emission reduction. It reduces emissions of urban travelers too strongly while even increasing the emissions of commuters and freight, both leading to a increase in deadweight loss. That is, the regulatory measure leads to higher market inefficiencies than a "do-nothing" strategy: too high generalized prices for urban travelers, too low generalized prices for commuters and freight. Finally, we discuss the implications of long-term changes in the vehicle fleet as a reaction to the internalization policy. The estimations indicate, however, that the price signal of this policy is not strong enough to significantly change long-term behavior.

Keywords: external costs, first-best tolls, internalization, exhaust emissions, policy evaluation, agent-based modeling

1 Introduction

External costs in the transport sector are known to lead to inefficiencies and social welfare losses. This is due to the fact that people base their decisions on marginal private costs (MPC) and not on marginal social costs (MSC), which is a result of market failures. The idea of how to internalize the difference between MSC and prices by a toll has been studied widely in the transportation economic literature. The most important dimensions of external costs are usually found to be congestion, air pollution, accidents, and noise. However, optimal toll levels are difficult to compute since they depend on various factors: in principle, a calculation needs to be done (i) for every street in the network, (ii) for every time step, and, when assuming heterogeneous travelers, additionally (iii) for every traveler that is defined by her characteristics such as individual Values of Travel Time Savings (VTTS) or specific vehicle attributes. For that reason, so-called second-best pricing has been advanced [2].

The computation of second-best tolls has been addressed in several studies [3, 4, 5, 6]. However, most studies focus on congestion pricing (see for exceptions e.g. [7, 8]). This is consistent with current estimates that congestion currently causes the largest part of the external effects (see [1], p.103). There is, however, some perception that non-congestion external effects need to be addressed as well [9]; those become especially important for freight traffic [1]. In this context, it is important to consider regulatory measures that are not based on charging. These might be dis-satisfactory from an economic perspective, since they always forgo some of the benefits that one can obtain with a well-designed pricing scheme. Yet, they have the advantage of better public acceptance in some countries, see, e.g., the "low-emission zones" in German cities. Thus, it is useful to investigate economic benefits of regulatory measures, and how close these benefits come to an optimal first-best toll [10].

The present study presents an approach to (i) internalize emissions costs, and to (ii) consider regulatory measures in comparison. Since congestion was treated in a previous contribution by [11], this study now focuses on air pollution. The eventual goal will be a comprehensive system which treats all external costs simultaneously. First, we present an approach that links dynamic traffic flows of the multi-agent transport simulation MATSim[1] to detailed air pollution emission factors provided by the Handbook Emission Factors for Road Transport [12]. Emissions are computed every time a traveler leaves a road segment and depend on the traffic state on that segment at the specific time, as well as on the traveler's vehicle attributes. Second, we calculate external air pollution emission costs for Sulfur Dioxide (SO_2), Particular Matter (PM), Nitrogen Oxides (NO_x), Non-Methane Hydrocarbons ($NMHC$), and Carbon Dioxide (CO_2), following external emission cost factors provided by [1]. In a third step, travelers are directly charged with the resulting costs when leaving a road segment. In an iterative process, travelers learn "from day to day" how to adapt their route and mode choice behavior in the presence of this simulated first-best[2] air pollution toll. Information about individual generalized costs for possible routes is provided to every traveler based on information from the previous iteration. In the last part of our study, we use the system's state with full air pollution cost pricing as a benchmark for evaluating the effects of a regulatory measure — a speed limitation to 30 km/h in the inner city. All investigations are run for a 1% real-world scenario of the Munich metropolitan area, similar to [13] and [14].

Please note that the present paper is an extension of [15]. In contrast to the latter, we provide more detailed results and compare the calculated toll to values from the literature. Furthermore, we discuss the impact of a first-best emission toll in the context of short-term vs. long-term behavioral reactions, particularly the role of increasing fuel efficiency of vehicles. The remainder of the paper is organized as follows: Sec. 2 describes the agent-based microsimulation framework used to solve the internalization problem, including and overview of the emission modeling tool and the internalization procedure. Sec. 3 introduces the scenario chosen for the simulation, along with the two policy measures and all relevant assumptions. In Sec. 4, the impacts of the two policies on emissions and social welfare are presented. Sec. 5 compares the obtained average cost factors per vehicle kilometer to values in the literature, and discusses implications for the interpretation of results. Finally,

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

[2] Please note that the simulated toll is first-best with respect to average emission cost factors provided by [1]. For a discussion with respect to which dimensions this calculated toll is nonetheless in line with marginal social cost pricing, please refer to Sec. 5.1. In the same section, the reader will also find a discussion on necessary steps towards the calculation of a first-best air pollution toll with respect to all relevant dimensions.

Sec. 6 summarizes the main findings and contributions of this paper and provides venues for further research.

2 Methodology[3]

This section (i) gives a brief overview of the general simulation approach of MATSim, (ii) shortly describes the emission modeling tool that has been developed by [16], and (iii) explains how the emission cost internalization procedure developed by the authors is embedded in the MATSim framework.

2.1 Transport Simulation with MATSim

In the following, we only present general ideas about the transport simulation with MATSim. For in-depth information of the simulation framework, please refer to [17] and the Appendix. In MATSim, each traveler of the real system is modeled as an individual agent. The approach consists of an iterative loop that is characterized by the following steps:

1. **Plans generation:** All agents independently generate daily plans that 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 selected plans are simultaneously executed in the simulation of the physical system.

3. **Evaluating plans:** All executed plans are evaluated by a utility function which encodes in this paper the perception of travel time and monetary costs for the available transport modes.

4. **Learning:** 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. In the present paper, agents adapt their routes only for car trips. Furthermore, they can switch between the modes car and public transit (pt). The choice between plans is performed within a multinomial logit model.

[3] Since the methodology remains unaltered, this section is taken from [15].

The repetition of the iteration cycle coupled with the agent database enables the agents to improve their plans over many iterations. This is why it is also called learning mechanism (see Appendix). 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"; we just allow the cycle to continue until the outcome is stable.

2.2 Emission Modeling Tool

The emission modeling tool was developed by [16] and is further described in [13]. The tool essentially calculates warm and cold-start emissions for private cars.[4] The former are emitted when the vehicle's engine is already warmed whereas the latter occur during the warm-up phase. In the present paper, warm emissions differ with respect to driving speed, vehicle characteristics and road type. Cold-start emissions differ with respect to distance traveled, parking time, and vehicle characteristics. These characteristics are derived from survey data (see Sec. 3.1) and comprise vehicle type, age, cubic capacity and fuel type. They can, therefore, be used for very differentiated emission calculations. Where no detailed information about the vehicle type is available, fleet averages for Germany are used.

In a first step, MATSim traffic dynamics are mapped to two traffic situations of the HBEFA[5] database: free flow and stop&go. The handbook provides emission factors differentiated among the characteristics presented above. In a second step, so-called "emission events" are generated and segmented into warm and cold emission events. These events provide information about the person, the time, the road segment (= link), and the 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 and as XML in output files (see Appendix). Emission event objects can be accessed during the simulation which is necessary in order to assign cost factors to emissions; the monetary value of emissions is then used for the internalization procedure described in the next section.

[4] Public transit is in the present paper assumed to run emission free.

[5] Handbook on Emission Factors for Road Transport, see `www.hbefa.net`

2.3 Emission Cost Calculation: Internalization

After the calculation of person and link specific time-dependent emissions as described in Sec. 2.2, these now need to be converted into monetary units for the calculation of a first-best toll in order to simulate the full emission cost internalization policy. For that purpose, emission cost factors differentiated by emission type are taken from [1], shown in Tab. 1. Clearly, these cost factors are average costs, collected from different studies. They

Table 1: Emission cost factors by emission type taken from [1]

Emission type	Cost factor [EUR/tonne]
CO_2	70
$NMHC$	1'700
NO_x	9'600
PM	384'500
SO_2	11'000

especially differ in terms of a more local or more global impact. To name the two most extreme: CO_2 only has an impact on global warming, no matter where it is emitted. In contrast, PM essentially only has local impacts on human health. Therefore [1] distinguish between three cost factors for PM: in "outside build-up areas" the factor is calculated to 75'000 EUR/tonne, in "urban areas" to 124'000 EUR/tonne, in "urban/metropolitan areas" to 384'500 EUR/tonne. External costs from CO_2 could easily be internalized by a distance based toll (e.g. fuel tax), whereas a distance based toll for PM would either imply too low tolls in urban areas, or too high tolls in non-urban areas. For the present setup, this means that the emission costs outside of Munich are likely to be overestimated.

In consequence, the simulated toll presented in this paper is first-best with respect to the emission cost factors displayed in Tab. 1. Even though it is based on average cost factors, the toll is in line with marginal cost pricing in terms of time-dependent congestion and individual vehicle attributes (see later in Sec. 5.1). It is presumably not first-best in terms of actual exposure.[6] The following two paragraphs will provide an overview of

[6] In order to obtain marginal emission costs also with respect to the effects on human health, in principle the whole impact-path-chain of air pollution needs to be modeled. This would imply an exposure analysis

the first-best emission toll implementation in the MATSim framework, given predefined person- and link-specific, time-dependent costs.

Evaluation of Plans The core of the emission cost internalization is the *emission cost module* which converts any mapping of emission type to a value into monetary terms (see above). This unique cost module is generated once the simulation starts. Every time the simulation produces an emission event, the cost module is asked for the monetary value and triggers an "agent money event" which essentially contains information about person, link, time, and the toll to be paid. One could imagine that, in the simulation, there is a toll gate at the end of each link where travelers directly pay the monetary equivalent of the emissions they produced on that link. When the person's daily plan is evaluated with a (possibly agent-specific) utility function at the end of every iteration, all money events of an agent are considered in the utility calculation. This is a standard MATSim feature which has been used frequently in other contributions [11, 18].

Router Module For the router module, the implementation is not as straightforward. The router is implemented as a time-dependent best path algorithm [19], using generalized costs (= disutility of traveling) as input. At the beginning of every iteration, the router proposes new routes to a certain share of agents based on the attributes travel time and monetary distance costs from the previous iteration. Since travel times and distance costs are equal for all agents, the router only needs to generate new routes based on global information. Now, with the internalization of emission costs, the disutility of traveling on every link is additionally dependent on the agent's vehicle characteristics. Therefore, the router is modified to generate new routes on very disaggregated information by calculating person-specific expected emission costs in every time interval. Even though the implementation is working properly, it makes the simulation relatively slow, for a 10% sample of the scenario in Sec. 3.1, by a factor of 10. In the present paper, we therefore use a 1% sample.

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for the whole population, and a monetization of the resulting effects. A discussion on this will be given in Sec. 5.1.

3 Scenario: Munich, Germany

In this section, we first give a short introduction into the large-scale real-world scenario of the Munich metropolitan area. This is followed by a definition of the available choice dimensions as well as the utility functions. Finally, we define two policy measures: the *zone 30 policy* will be defined as a regulatory measure of limiting the maximum speed in the inner city of Munich to 30 km/h. The *internalization policy* will use the methodology from Sec. 2.3 in order to charge every car user when leaving a link dependent on her individual emissions.

3.1 Scenario Setup[7]

The road network consists of 17'888 nodes and 41'942 road segments. It covers the federal state of Bavaria, being more detailed in and around the city of Munich and less detailed further away. Every link is characterized by a maximum speed, a flow capacity, and a number of lanes. This information is stored in the road type which is for the emission calculation always mapped to a corresponding HBEFA road type. In order to obtain a realistic time-dependent travel demand, several data sources have been converted into the MATSim population format. The level of detail of the resulting individual daily plans naturally depends on the information available from either disaggregated stated preference data or aggregated population statistics. Therefore, *three subpopulations* are created, each corresponding to one of the three different data sources:

- Urban population (based on [20]):

  The synthetic population of Munich is created on the base of very detailed survey data provided by the municipality of Munich [21], named "Mobility in Germany" (MiD 2002). Whole activity chains are taken from the survey data for this population. MiD 2002 also provides detailed vehicle information for every household. Linking this data with individuals makes it possible to assign a vehicle to a person's car trip and thus, calculating emissions based on this detailed information. As of now, there is however no vehicle assignment module which models intra-household decision making. It is, therefore, possible that a vehicle is assigned to more than

[7] Since the scenario setup has been described by [13] and [14], only key figures are presented here.

one person at the same time. The synthetic urban population of Munich consists of 1'424'520 individuals.

- Commuter population (based on [22]):
  Unfortunately, the detailed data for the municipality of Munich does neither contain information about commuters living outside of Munich and working in Munich nor about people living in Munich and working outside of Munich. The data analyzed by [22] provides information about workers that are subject to the social insurance contribution with the base year 2004. With this information, a total of 510'150 synthetic commuters are created from which 306'160 people have their place of employment in Munich. All commuters perform a daily plan that only encodes two trips: from their home location to work and back.

- Freight population (based on [23]):
  Commercial traffic is based on a study published on behalf of the German Ministry of Transport by [23]. It provides origin-destination commodity flows throughout Germany differentiated by mode and ten groups of commodities. After converting flows that are relevant for the study area into flows of trucks, this population consists of 158'860 agents with one single commercial traffic trip.

Overall, the synthetic population now consists of 2'093'530 agents. To speed up computations, a 1% sample is used in the subsequent simulations. For commuters and freight, no detailed vehicle information is available. Emissions are therefore calculated based on fleet averages for cars and trucks from HBEFA.

3.2 Simulation Approach

Choice Dimensions For the mental layer within MATSim which describes the behavioral learning of agents, a simple utility based approach is used in this paper. When choosing between different options with respect to a multinomial logit model, agents are allowed to adjust their behavior among two choice dimensions: route choice and mode choice. The former allows individuals to adapt their routes on the road network when going by car. The latter makes it possible to change the transport mode for a sub-tour (see Appendix) within the agent's daily plan. Only a switch from car to public transit or the other way around is possible. Trips that are initially done by any other mode remain fixed within the learning cycle. From a research point of view, this approach can be seen as defining a system where public transit is a placeholder for all substitutes of the car mode.

Utility Functions In the present paper, travel time and monetary distance costs are considered as attributes of every car and public transit trip. In consequence, the travel related part of utility (see Eq. 3 in the Appendix) is defined by the following functional form:

$$\begin{aligned} V_{car,i,j} &= && \beta_{tr,car} \cdot t_{i,car} + \beta_c \cdot c_{i,car} \\ V_{pt,i,j} &= \beta_0 &+& \beta_{tr,pt} \cdot t_{i,pt} + \beta_c \cdot c_{i,pt} \ , \end{aligned} \tag{1}$$

where t_i is the travel time of a trip to activity i and c_i is the corresponding monetary cost. Travel times and monetary costs are mode dependent, indicated by the indices. The utilities $V_{car,i,j}$ and $V_{pt,i,j}$ for person j are computed in "utils". Due to a lack of behavioral parameters for the municipality of Munich, estimated parameters[8] are taken from an Australian study by [24]; these parameters are shown in Tab. 2, together with the corresponding Values of Travel Time Savings (VTTS). Necessary adjustments of the

Table 2: Estimated parameters, VTTS taken from [24]

$\hat{\beta}_{tr,car}$	-0.96	[utils/h]
$\hat{\beta}_{tr,pt}$	-1.14	[utils/h]
$\hat{\beta}_c$	-0.062	[utils/AUD[a]]
$\hat{\beta}_{perf}$	n.a.	[utils/h]
$VTTS_{tr,car}$	$+15.48$	[AUD/h]
$VTTS_{tr,pt}$	$+18.39$	[AUD/h]

[a] AUD 1.00 = EUR 0.78 (May 2012).

Table 3: Adjusted parameters, VTTS meeting the MATSim framework

$\beta_{tr,car}$	-0.00	[utils/h]
$\beta_{tr,pt}$	-0.18	[utils/h]
β_c	-0.07949	[utils/EUR]
β_{perf}	$+0.96$	[utils/h]
$VTTS_{tr,car}$	$+12.08$	[EUR/h]
$VTTS_{tr,pt}$	$+14.34$	[EUR/h]

parameters are performed in order to meet the MATSim framework. The resulting parameters and VTTS are depicted in Tab. 3. These adjustments are described in more detail in [25, 13]. The argument essentially is that the estimated time related parameters $\hat{\beta}_{tr,car}$ and $\hat{\beta}_{tr,pt}$ consist of the unique opportunity costs of time $-\beta_{perf}$ and an additional mode specific disutility for traveling $\beta_{tr,car}$ and $\beta_{tr,pt}$, respectively. Since MATSim needs

[8] Estimated parameters are in this paper flagged by a hat.

an explicit value for the opportunity costs of time (see Eq. 4 in the Appendix), we assume that traveling with car is not perceived more negative than "doing nothing". This interpretation is done that way since it does not change the VTTS, as a comparison of Tab. 2 and Tab. 3 nicely shows: the VTTS are only rescaled from AUD to EUR. In contrast to [24], the present model does not include access, egress, and waiting times for public transit. Therefore, the alternative specific constant β_0 is re-calibrated by a parametric calibration process that aims at holding the modal split distribution over distance as close as possible to the initial distribution. The best fit is found for $\beta_0 = -0.75$

Simulation Procedure For 800 iterations, 15% of the agents perform route adaption (discovering new routes), 15% change the transport mode for a car or pt sub-tour in their daily plan and 70% switch between their existing plans. Between iteration 801 and 1000 route and mode adaption is switched off; in consequence, agents only switch between existing options. The output of iteration 1000 is then used as input for the continuation of the base case and the two different policy cases:

- **Base case**: unchanged cost structure (see below)
- **Policy case 1 (zone 30)**: maximum speed on all roads within the middle ring road is limited to 30 km/h
- **Policy case 2 (internalization)**: for car users, additional costs apply for every link; they are dependent on the emissions emitted by an agent (see Sec. 2.3)

User costs[9] for car are always fixed to 30 EURct/km. For the internalization policy, additional costs apply (see above). User costs for public transit are assumed to be constant at 18 EURct/km for the base case and both policy cases. All simulations are continued for another 500 iterations. Again, during the first 400 iterations 15% of the agents perform route adaption while another 15% of agents choose between car and public transit for one of their sub-tours. The remaining agents switch between existing plans. For the final 100 iterations only a fixed choice set is available for all agents. When evaluating the impact of the two policy measures, the final iteration 1500 of every policy case is compared to iteration 1500 of the base case.

[9] Please note, that the term "user costs" is referred to as out-of-pocket costs for the users.

4 Results

In this section, we present different changes to the system that result from the two policy measures explained in Sec. 3.2. The main goal is to answer the question how close the regulatory measure (zone 30) comes to an optimal first-best toll (internalization) in terms of emission reduction and economic benefits. A further discussion of the results can be found in Sec. 5. All results in this section are given for the 1% sample simulated for a regular week day as described in Sec. 3.

4.1 Emissions

Starting with analyzing the final iteration of the base case, Fig. 1a shows absolute emission levels by emission type and subpopulation. Note that the commuter population is differentiated into people commuting *to* Munich for work (commuters), and people commuting *from* Munich to work outside of Munich (reverse commuters). Also note that the scale is different for different pollutants in order to make absolute values visible in one graph. One can clearly see that the urban population only contributes to a relatively small part for most emission types, even though these people represent 68% of the total population and perform more trips per day than the other subpopulations. Only $NMHC$ is relatively more important for the urban population. This is presumably due to the fact that $NMHC$ emissions are highest for cold-starts and during the warm-up phase of the vehicle [26]. When analyzing the travel patterns, two possible explanations come to mind: first, urban car travelers drive relatively short distances (median distance traveled: 12 km). This means that — in some cases — the engine is not even completely warmed up when reaching the destination. Second, due to a higher number of trips per day, the urban population produces more cold starts per car user during a day than the other subpopulations who — in our model — only perform two trips (commuters and reverse commuters) or one trip (freight), respectively. Commuters (14.6% of the total population) and reverse commuters (9.8%) seem to have a similar split of the different pollutants. However, commuters emit in total about three times as much as reverse commuters as they drive longer distances (median distance traveled commuters: 100 km; median distance traveled reverse commuters: 65 km). Finally, it is important to note that freight traffic (7.6% of the total population) contributes to a major part of total emissions: its share for CO_2 is roughly

50%, for $NMHC$ 30%, for NO_x 78%, for PM 70%, and for SO_2 47%.

To answer the question on how close the zone 30 policy comes to the internalization policy in terms of emission reduction, Fig. 1b provides important information. It shows the relative change in emissions for the two policies. The zone 30 reduces $NMHC$ by around 2.5%, all other pollutants are only slightly reduced by 0.25% or less, and PM is even increasing. The impacts of an internalization policy result in a much more homogeneous picture: all pollutants are reduced by 0.6% to 1.1%. Fig. 1c decomposes the information from Fig. 1b to the different subpopulations. The picture becomes even more interesting: the zone 30 leads to a strong emission reduction of 5% to 7% for the urban population. All other subpopulations produce *more* emissions, $NMHC$ being an exception. In contrast, the internalization policy leads to a rather strong decrease of emissions, by 1% to 2% for urban travelers and commuters and between 1.5% and 3% for reverse commuters. Only freight traffic does not significantly reduce emissions. Given the available choice

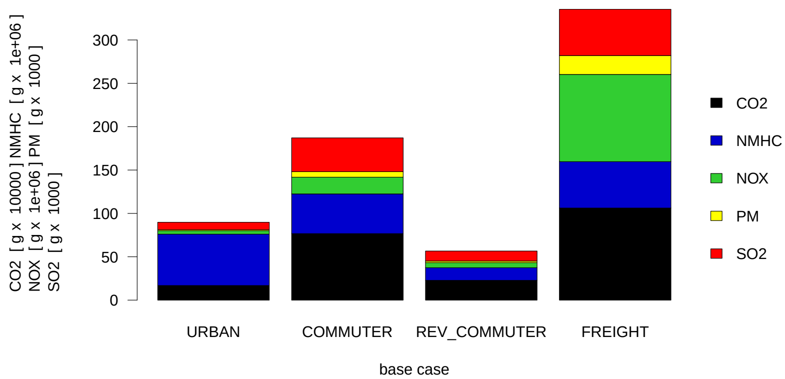
Table 4: Zone 30: changes in modal split and average car distance traveled

Subpopulation	change in car trips [%]	change in avg. car dist. traveled [km]
URBAN	−8.00	−0.39
COMMUTER	−0.78	+1.00
REV_COMMUTER	−0.87	+0.96
FREIGHT	±0.00	+0.04

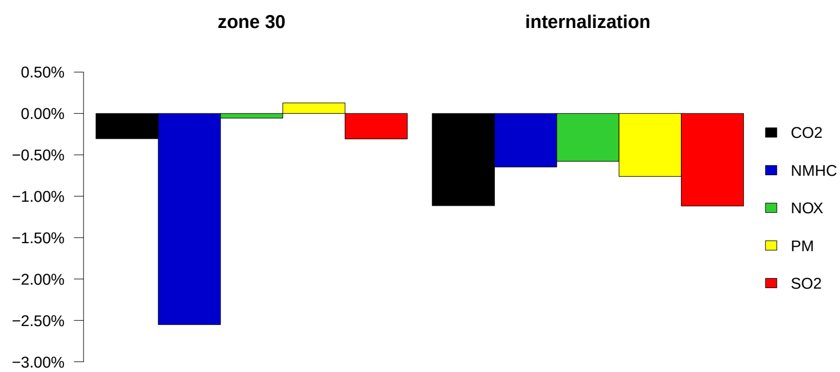
Table 5: Internalization: changes in modal split and average car distance traveled

Subpopulation	change in car trips [%]	change in avg. car dist. traveled [km]
URBAN	−0.59	−0.10
COMMUTER	−0.62	−0.89
REV_COMMUTER	−1.22	−1.52
FREIGHT	±0.00	−0.15

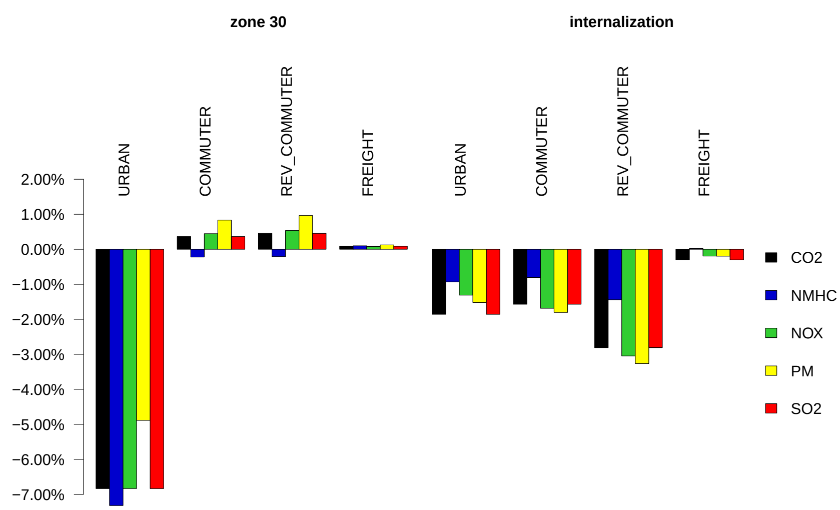
dimensions presented in Sec. 3.2, the above emission effects result directly from re-routing and changes in the modal split. Additionally, they may result indirectly from changes in the traffic situations. Therefore, Tab. 4 and Tab. 5 show the relative change in car trips



(a) Base case: absolute emissions by type and subpopulation



(b) Policy cases: relative changes in emissions by type



(c) Policy cases: relative changes in emissions by type and subpopulation

Figure 1: Emissions by emission type: absolute values by subpopulation for the base case, relative changes (overall and by subpopulation) for the two policy cases

and the absolute change in the average car distance traveled. Expectedly, the car mode becomes less attractive for both policies as the second column in either table shows. The zone 30 reduces car trips of urban travelers by 8%. The remaining car users drive on average shorter distances (-0.39 km). This may be due to the fact that travelers with longer distances have a tendency to switch to pt; or the remaining car users re-route to shorter paths. A combination of the two effects is most likely. When comparing this to the internalization policy, it becomes obvious that the zone 30 pushes too many urban travelers to public transit. For commuters and reverse commuters, the change in number of car trips is not very different for the two policies. However, for the zone 30, the re-route effect for the remaining car users becomes very strong since they drive *longer* distances in order to avoid the unattractive zone with the speed limitation (commuters: $+1.00$ km, reverse commuters: $+0.96$ km). Freight traffic also re-routes around the regulated zone.

Overall, one can conclude that in terms of total emission reduction, the zone 30 is considerably less successful than the internalization policy. Additionally, the zone 30 reduces the emission levels of the urban population too strongly while even increasing the emission levels of the other subpopulations. The latter is — in comparison to the first-best internalization policy — exactly the wrong direction.

4.2 Economic Evaluation

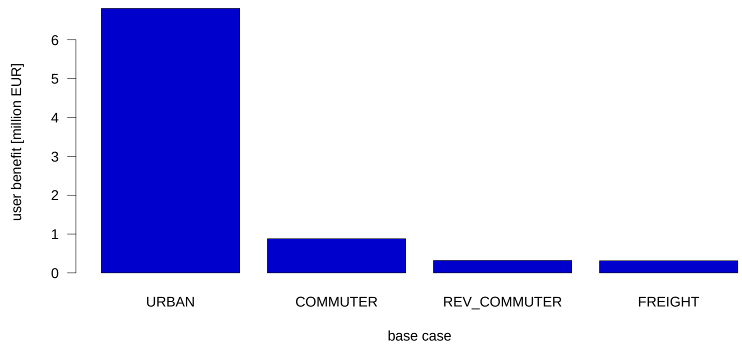
Starting again with analyzing the base case, Fig. 2a shows the absolute user benefits W in million Euro per day. It is calculated as the user logsum or Expected Maximum Utility (EMU) for all choice sets of the users of the respective subpopulation *pop*:

$$W_{pop} = logsum_{pop} = EMU_{pop} = \sum_{j=1}^{J} \left(\frac{1}{|\beta_c|} \ln \sum_{p=1}^{P} e^{V_p} \right) \quad , \tag{2}$$

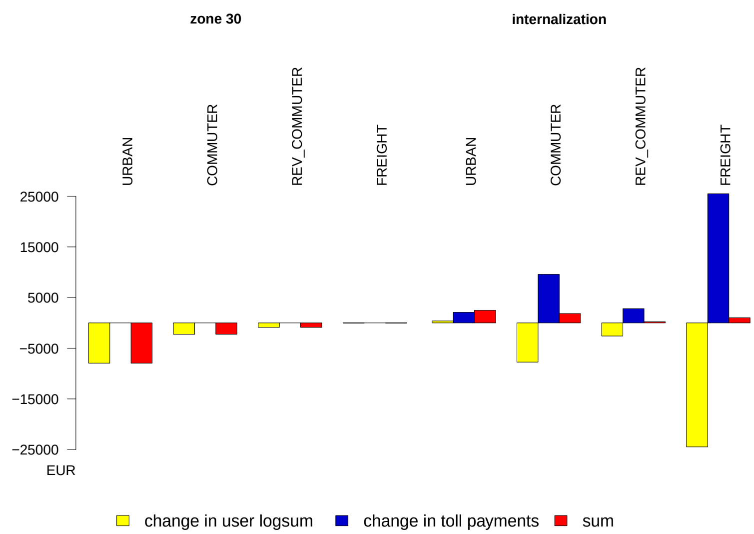
where β_c is the cost related parameter of the multinomial logit model or the negative marginal utility of money, J is the number of agents in the subpopulation, P is the number of plans or alternatives of individual j, and V_p is the systematic part of utility of alternative (= plan) p. The urban population contributes most to overall user benefits. This results, on the one hand, from the fact that they represent a major part of the total population. On the other hand, they spend less time on transport and travel shorter distances and can, thus, spend more time on performing activities, while paying less distance costs. When introducing the two policies, one obtains absolute changes in user benefits by subpopulation, represented by yellow bars in Fig. 2b. The zone 30 policy leads to a loss in user benefit for all subpopulations, with the effect on urban travelers being the strongest, while almost having no effect on freight traffic. That is, urban travelers react most sensible by changing from car to public transit, especially for longer trips. The remaining car users can barely profit from reduced car demand in the city since travel times by car are no longer determined by congestion but by the maximum free speed of 30 km/h. Commuters and reverse commuters change to pt only for shorter trips. The remaining car users drive longer distances (e.g. on the middle ring road) since driving though the inner city has become less attractive due to the speed limit. Freight traffic can only change routes which seems to have a minor effect on user benefit.

The internalization policy on the right side yields quite different results: commuters, reverse commuters and freight all lose in terms of user benefit; this loss is most pronounced for freight traffic. This intuitively makes sense since freight traffic contributes to a major part of total emissions (see Sec. 4.1) and therefore it has to pay a major part of the total emission costs. In contrast, the urban population even gains slightly in terms of user benefit despite the toll they have to pay. That is, time gains for the urban population slightly overcompensate the negative effect of the toll payments. When assuming a redistribution of the toll payments of every subpopulation (blue bars in Fig. 2b) to the respective subpopulation, one obtains the net welfare effect for that population (red bars in Fig. 2b). Interestingly, the redistribution of the toll payments overcompensates the loss in user benefits for commuters and freight. For reverse commuters, the two effects roughly even out. For urban travelers, the welfare gain becomes even more important, being the highest of all subpopulations.

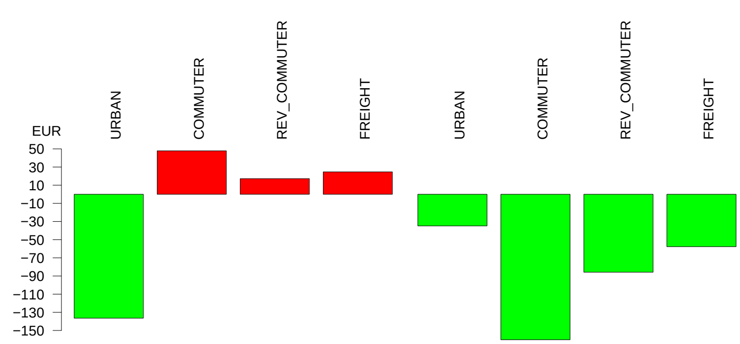
In addition to the sum of user benefit change and toll payments, a comprehensive calculation of the total welfare effect needs to include the absolute monetary change in emission costs resulting from the policies. The emission reduction effect is — in contrast to time gains when applying a congestion pricing scheme — not included in the user logsum; this is due to the fact that emission costs are true external costs for the transport market. Fig. 2c depicts the absolute change in external emission costs resulting from the two policies. When looking at the scaling of the y-axis, it becomes obvious that these changes in emission costs do not have the potential of compensating any losses in user benefit in Fig. 2b. However, the figure allows interesting insights into the welfare effect of



(a) Base case: user benefits (logsum) by subpopulation



(b) Policy cases: absolute changes in user benefits (logsum), redistributed toll payments, and sum by subpopulation



(c) Policy cases: absolute change in external emission cost by subpopulation

Figure 2: Welfare analysis by subpopulation: absolute values for the base case, absolute changes for the two policy cases

the two policies: for the zone 30, the loss in user benefit for commuters, reverse commuters, and freight is even becoming bigger due to higher emissions and therefore higher emission costs for society. The deadweight loss for urban travelers is reduced by a small amount. For the internalization policy, all user groups contribute to a reduction in deadweight loss of society. This figure is naturally quite similar to Fig. 1c. A further discussion of the results will be given in the next section.

5 Discussion

5.1 Simulated first-best air pollution toll

Emission cost factors Tab. 6 shows average external emission costs per vehicle kilometer for the different subpopulations that are calculated from the simulation of the base case.[10] The second column depicts average emission costs per vehicle kilometer including CO_2, the third column excluding CO_2. When comparing the latter to values from the literature, one can state that our approach of coupling MATSim with HBEFA and then using cost factors from [1] leads to plausible average emission costs per vehicle kilometer: e.g. [27] use local pollution cost factors for automobiles of 2.0 US$ct/mile or roughly 1.23 EURct/km. This estimate is very close to the resulting value for urban travelers in our scenario. Obviously, freight traffic causes much higher pollution costs since it produces more emissions. The values for commuter and reverse commuter are identical and distinctly lower than those from the literature or those for urban travelers. This indicates that the emission tool, since it is accounting for different traffic states, feeds the cost calculation module with spatially and temporally differentiated values: commuters and reverse commuters who drive a major part of their routes on a non-congested network outside of Munich produce less emissions per vehicle kilometer. That is, the high-resolution emission costs in our model are *based* on average cost factors; as they are, however, influenced by congestion effects and vehicle attributes, they are not pure average costs any more; they are marginal costs with respect to congestion and vehicle attributes. Nonetheless, in order to calculate marginal air pollution costs also with respect to damage of human health, cost factors

[10] Please note that the numbers in Tab. 6 are an output — not an input — of the simulation in order to compare the values to other sources. Remember that the individual toll is highly differentiated since it depends on vehicle attributes and time-dependent dynamic traffic flows of the simulation.

Table 6: Base case: resulting average emission costs by subpopulation [EURct/km]

Subpopulation	incl. CO_2	excl. CO_2
URBAN	2.71	1.20
COMMUTER	2.27	1.02
REV_COMMUTER	2.25	1.02
FREIGHT	14.51	10.29

would need to differentiate among the number of individuals that are exposed to a certain pollution concentration. The implications of this drawback for the interpretation of results is discussed in the following paragraph.

Implications for the interpretation of results The results in Sec. 4 indicate that in terms of total emission reduction, the zone 30 is considerably less successful than the internalization policy. Additionally, the zone 30 reduces emission levels of urban travelers too strongly, while even increasing the emission levels of the other subpopulations. The latter is — in comparison to the first-best internalization policy — exactly the wrong direction. Looking again at Fig. 2b and Fig. 1c clarifies that the speed limitation to 30 km/h in the inner city of Munich leads to more market inefficiencies than a "do-nothing" strategy. When taking the internalization policy as a benchmark, these two figures show that the emission (cost) reduction is too high for urban travelers; for all other subpopulations, this speed limitation even leads to an increase in emission costs for society. That is, too high generalized prices for the urban population, too low generalized prices for all other subpopulations.

Yet, one could argue that the zone 30 is much better when one looks at *exposure* rather than emissions. Emission cost factors from [1] are average costs and, thus, probably too low in the inner city and too high outside of Munich. For this reason, we plan to model the whole impact-path-chain of air pollution in the near future which implies an exposure analysis of the whole population, and monetizing the effects on human health. Once exposure is considered, one may argue that the optimal toll should be corrected exactly for that effect. I.e. by putting weights on every link that are differentiated by emission type and resulting exposure. Weights for CO_2 would be low since it mostly has a global effect, whereas weights for PM would be high due to its strong local effect on human health. A different approach could also be worth modeling: the calculation of an optimal toll *given* the desired emission reduction in the area under consideration. This may, similar to the zone 30, be dis-satisfactory from an economic perspective but may arguably be more likely to happen in reality than the implementation of a first-best pricing scheme.

5.2 Long-term changes to the vehicle fleet

The results presented in Sec. 4 provide short-term emission and welfare effects with respect to the choice dimensions route choice and mode choice that are available for the users. Long-term reactions might include changes in the vehicle fleet[11]: the environmental toll could induce people to buy more fuel / emission efficient cars. Two possible long-term reactions come to mind: First, some users that — in the short run — changed to public transit would in the long run possibly buy a more emission efficient car and change back to car. Second, users who travel by car before and after the policy could also buy more emission efficient cars. Compared to the short-term impacts of an internalization policy, the first long-term reaction would increase car vehicle kilometers traveled as well as emissions, and therefore also increase toll payments. The second long-term reaction is likely to increase vehicle kilometers traveled but would lower emissions per vehicle kilometer; the impact on total toll payments is dependent on the magnitude of these sub-effects. [27] state that "[...] less than half of the long-run price responsiveness of gasoline consumption is due to changes in VMT" (vehicle miles traveled). According to the authors, the rest of the decrease in gasoline consumption results from changes in the vehicle fleet. This would imply, assuming a linear relationship between gasoline consumption and emissions, that vehicle kilometers in the long run and for the same price signal will drop by less than 0.5 of the reduction in emissions. [29] calculate propensities to change car types from a discrete-continuous choice model for an average fuel price increase of 100%. In principle, it would be possible to transfer the resulting probabilities to the MATSim framework. Since there is, however, not a similar study for the city of Munich, randomly drawing agents in the population would result in biased statistics. The reason for this is that the

[11] Additionally there might be changes in activity location choice, changes in the frequency of performing activities, and changes in bundling activities. A possible approach on how to deal with these possible user reactions within the MATSim framework can be found in [28].

probabilities are not linked to the users' preferences or socio-demographics. Consider the following example with two persons owning a car of the same vehicle class. Assume that the probability of buying a more emission efficient car as reaction to the internalization policy is 50% for their vehicle class. When randomly drawing, one would expect one of the persons to buy a new car. However, if the first person lives next to a public transit line and the second is not, it is more likely that the second person buys a more fuel efficient vehicle; the first could more easily change to public transport and might not buy a new car.

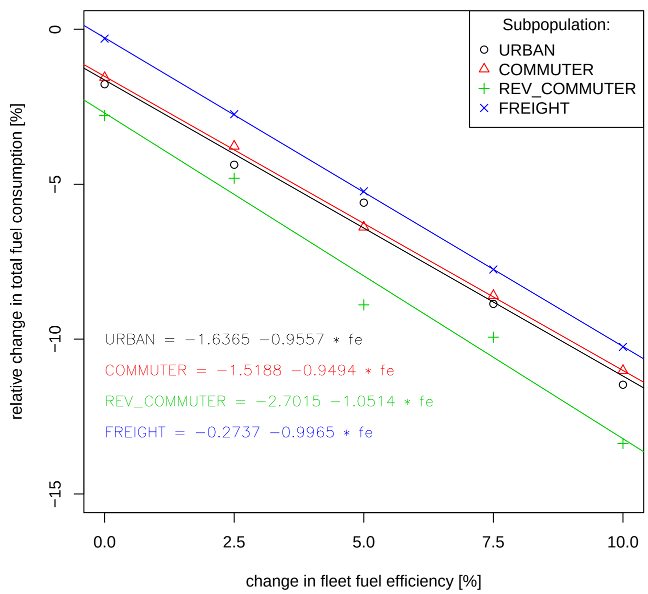


Figure 3: Impacts of fuel efficient cars on fuel reduction: parametric estimates by subpopulation

In order to determine the long-term effect of changes in the vehicle fleet for the current setup, we use an estimate from [29] who predict an average change in fleet fuel efficiency of 5% as a reaction to an average fuel price increase of 100%. Fig. 3 shows parametric estimates of relative changes in total fuel consumption over five different levels of fleet fuel efficiency.[12] Level 0.0% is equivalent to the short term reactions (internalization policy)

[12] Please note that the parametric estimates also take into account second order effects in the sense that higher fuel efficiency lowers the optimal toll; compared to the short term reactions at level 0.0%, this leads in our model to a modal shift towards car and longer distances traveled.

where users are not able to buy more fuel efficient cars. Level 2.5% to 10.0% imply that the whole vehicle fleet is 2.5% to 10.0% more fuel efficient, meaning that users *on average* buy x% more fuel efficient cars as a reaction to the internalization policy. Fig. 3 also provides regression functions for the data points of every subpopulation. As one can nicely see for freight traffic which is only allowed to adjust routes, the short term re-routing reaction to the internalization policy at level 0.0% leads to a relative reduction in fuel consumption of -0.2737%. On top of this effect, the increase in fuel efficiency leads to an almost proportional reduction in total fuel consumption as the slope of the regression function indicates (1% higher fuel efficiency leads to -0.9965% less consumption). Urban travelers and commuters react more sensible to the internalization policy since they are additionally allowed to change to public transit. This is depicted by the stronger change in total fuel consumption at level 0.0% (urban: -1.6365%, commuter: -1.5188%, reverse commuter: -2.7015%). For urban travelers and commuters, a change in fleet fuel efficiency leads to a slightly under-proportional reduction in fuel consumption, reflecting the second order effects of a modal shift to car and longer distances traveled. For reverse commuters, this effect is not found.

Now, the long-term effect of changes in the vehicle fleet can be determined approximately as follows: As Tab. 6 indicates, the average price increase per vehicle kilometer including CO_2 between the base case and the internalization policy is roughly 10% for urban travelers and commuters (2.25 to 2.71 EURct/km on top of the monetary distance costs of 30 EURct/km). Following [29], we therefore assume an increase in the vehicle fleet emission efficiency of 0.5%. We also assume that more fuel efficient cars are not more expensive than normal cars and, thus, changing the vehicle does not imply any additional investment. Using the regression function from Fig. 3, a 0.5% increase in the vehicle fleet emission / fuel efficiency would lead to additional changes in total fuel consumption. As Tab. 7 shows, we expect some additional changes in total fuel consumption due to long-term adjustments in the vehicle fleet. These occur on top of the short-term effect; the differences to the assumed 0.5% increase in the vehicle fuel / emission efficiency are, however, relatively small. One can therefore state that accounting for such car ownership decisions would only have a minor impact on the results obtained in this paper. The reason could be that the price signal of the internalization policy is not strong enough to significantly change long-term behavior.

Table 7: Estimated changes in total fuel consumption due to changes in the vehicle fleet by subpopulation

Subpopulation	change in fuel consumption [%]
URBAN	$-0.9557 \cdot 0.5\% = -0.47785\%$
COMMUTER	$-0.9494 \cdot 0.5\% = -0.47470\%$
REV_COMMUTER	$-1.0514 \cdot 0.5\% = -0.52570\%$
FREIGHT	$-0.9965 \cdot 0.5\% = -0.49825\%$

6 Conclusion

In this paper, we presented a new simulation approach to internalize external air pollution costs for a real-world large-scale scenario using an agent-based model. We used the resulting exhaust emission and welfare effects as a benchmark for the evaluation of a regulatory measure — a speed limitation to 30 km/h in the inner city of Munich. The main methodological contribution was the calculation of a high-resolution first-best air pollution toll in a real-world scenario. This comprised, on the one hand, the implementation of a module that evaluates different alternatives of every agent for the choice model. On the other hand, a router module was implemented which is needed for the calculation of time-dependent least cost paths through the network. Both modules account for individual vehicle attributes and time-dependent traffic states. Since agents additionally interact in the physical environment of the network, the resulting toll is equal to the simulated agent-specific marginal social costs in terms of vehicle attributes and congestion-based emissions. In principle, our approach consists of three different steps: First, we linked dynamic traffic flows of the multi-agent transport simulation MATSim to detailed air pollution emission factors provided by the Handbook Emission Factors for Road Transport [12], similar to [13]. Then, we calculated external air pollution emission costs for Sulfur Dioxide (SO_2), Particular Matter (PM), Nitrogen Oxides (NO_x), Non-Methane Hydrocarbons ($NMHC$), and Carbon Dioxide (CO_2), following external emission cost factors provided by [1]. In a third step, travelers were directly charged with the resulting individual costs whenever leaving a road segment. In an iterative process, travelers learned how to adapt their route and mode choice behavior in the presence of this simulated first-best air pollution toll.

When comparing the regulatory measure to the full emission cost internalization policy, we found that it is considerably less successful in terms of total emission reduction. It reduces emissions of urban travelers too much while even increasing the emissions of commuters and freight, both leading to a increase in deadweight loss. That is, the regulatory measure leads to higher market inefficiencies than a "do-nothing" strategy: too high generalized prices for urban travelers, too low generalized prices for commuters and freight. Additionally, the analysis of our simulated first-best air pollution toll showed that the resulting average emission costs per vehicle kilometer are very close to estimates in the literature. However, they do not reflect marginal costs with respect to damage of human health since they do not differentiate among the number of individuals that are exposed to a certain pollution concentration. Introducing a correction term might improve the emission and welfare effects of the zone 30 policy. For this reason we plan to model the whole impact-path-chain of air pollution which implies an exposure analysis of the whole population and a monetization of these effects.

Our final discussion on long-term changes to the vehicle fleet shows that there are additional changes in total fuel consumption and emissions since travelers might react to the internalization policy by buying more fuel efficient cars. However, due to the rather weak price signal, these long-term effects are not found to significantly change route and mode choice decisions.

Another important, even though more practical contribution of this paper is the following: we could demonstrate that the simulation of first-best emission tolls is possible in a real-world setup and that it could be used as a benchmark for second-best policies. This seems to be highly relevant for politicians and decision makers.

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References

[1] Maibach, M. et al., Handbook on estimation of external costs in the transport sector, Technical report, 2008.

[2] Verhoef, E. T., Marginal cost based pricing in transport. Key implementation issues from the economic perspective, 2001, Paper presented at Seminar One of IMPRINT-EUROPE.

[3] Verhoef, E. T., Transportation Research Part B: Methodological **36** (2002) 707.

[4] de Palma, A. and Lindsey, R., Transport Policy **13** (2006) 115.

[5] van den Berg, V. A. and Verhoef, E. T., Congesting Pricing in a Road and Rail Network with Heterogeneous Values of Time and Schedule Delay, Tinbergen Institute Discussion Papers 11-059/3, Tinbergen Institute, 2011.

[6] Markose, S. et al., Journal of Economic Dynamics and Control **31** (2007) 2001.

[7] Mitchell, G., Namdeo, A., Lockyer, J., and May, A., The impact of road pricing and other strategic road transport initiatives on urban air quality, in *Proceedings of the 8th International Conference on Urban Transport and the Environment in the 21st Century*, pages 481–490, 2002.

[8] Namdeo, A. and Mitchell, G., An empirical study of vehicle emissions under cordon and distance based road user charging, See eprints.whiterose.ac.uk/2481, 2007.

[9] Creutzig, F. and He, D., Transportation Research Part D: Transport and Environment **14** (2009) 120.

[10] Proost, S. and Van Dender, K., Regional Science and Urban Economics **31** (2001) 383.

[11] Nagel, K. et al., Journal of Economics and Statistics (Jahrbücher für Nationalökonomie und Statistik) **228** (2008) 173, Special issue on agent based models for economic policy advice, edited by B. LeBaron and P. Winker.

[12] INFRAS, Handbook Emission Factors for Road Transport 3.1, Technical report, 2010, See www.hbefa.net.

[13] Kickhöfer, B., Hülsmann, F., Gerike, R., and Nagel, K., Rising car user costs: comparing aggregated and geo-spatial impacts on travel demand and air pollutant emissions, in *Smart Transport Networks: Decision Making, Sustainability and Market structure*, edited by Vanoutrive, T. and Verhetsel, A., NECTAR Series, Edward Elgar, 2012, in press, Also VSP WP 11-16; see www.vsp.tu-berlin.de/publications.

[14] Kickhöfer, B. and Nagel, K., Mapping emissions to individuals – New insights with multi-agent transport simulations, in *Proceedings of the Conference on Computers in Urban Planning and Urban Management (CUPUM)*, 2011, Also VSP WP 11-02, see www.vsp.tu-berlin.de/publications.

[15] Kickhöfer, B. and Nagel, K., Using high-resolution first-best tolls as a benchmark for policy evaluation: The case of air pollution costs, in *Proceedings of the Kuhmo Nectar Conference on Transportation Economics*, 2012, Also VSP WP 12-06, see www.vsp.tu-berlin.de/publications.

[16] Hülsmann, F., Gerike, R., Kickhöfer, B., Nagel, K., and Luz, R., Towards a multi-agent based modeling approach for air pollutants in urban regions, in *Proceedings of the Conference on "Luftqualität an Straßen"*, pages 144–166, Bundesanstalt für Straßenwesen, FGSV Verlag GmbH, 2011, Also VSP WP 10-15, see www.vsp.tu-berlin.de/publications.

[17] Raney, B. and Nagel, K., An improved framework for large-scale multi-agent simulations of travel behaviour, pages 305–347, 2006.

[18] Kickhöfer, B., Zilske, M., and Nagel, K., Income dependent economic evaluation and public acceptance of road user pricing, in *Proceedings of the Kuhmo Nectar Conference on Transportation Economics*, 2010, Also VSP WP 10-03, see www.vsp.tu-berlin.de/publications.

[19] Lefebvre, N. and Balmer, M., Fast shortest path computation in time-dependent traffic networks, in *Proceedings of the Swiss Transport Research Conference (STRC)*, Monte Verita, CH, 2007, See www.strc.ch.

[20] Follmer, R., Kunert, U., Kloas, J., and Kuhfeld, H., Mobilität in Deutschland – Ergebnisbericht, Technical report, infas/DIW, 2004, See www.kontiv2002.de.

[21] RSB, Municipality of Munich: Referat für Stadtplanung und Bauordnung, 2005.

[22] Böhme, S. and Eigenmüller, L., Pendlerbericht Bayern, Technical report, IAB, 2006.

[23] ITP/BVU, Prognose der deutschlandweiten Verkehrsverflechtungen 2025, Technical report, 2005.

[24] Tirachini, A., Hensher, D. A., and Rose, J. M., Multimodal pricing and optimal design of public transport services: the interplay between traffic congestion and bus crowding, in *Proceedings of the Kuhmo Nectar Conference on Transportation Economics*, 2012.

[25] Kickhöfer, B., Grether, D., and Nagel, K., Transportation **38** (2011) 849.

[26] Schmitz, T., Hassel, D., and Weber, F.-J., Atmospheric Environment **34** (2000) 4639.

[27] Parry, I. W. and Small, K. A., The American Economic Review **95** (2005) 1276.

[28] Horni, A., Nagel, K., and Axhausen, K., High-resolution destination choice in agent-based demand models, Technical Report 12-1989, 2012.

[29] Erath, A. and Axhausen, K., Long term fuel price elasticity: effects on mobility tool ownership and residential location choice, IVT Working paper 615, Institute for Transport Planning and Systems, ETH Zurich, Zurich, Switzerland, 2010.

[30] Gawron, C., International Journal of Modern Physics C **9** (1998) 393.

[31] Cetin, N., Burri, A., and Nagel, K., A large-scale agent-based traffic microsimulation based on queue model, in *Proceedings of the Swiss Transport Research Conference (STRC)*, Monte Verita, CH, 2003, See www.strc.ch. Earlier version, with inferior performance values: Transportation Research Board Annual Meeting 2003 paper number 03-4272.

[32] Grether, D., Chen, Y., Rieser, M., and Nagel, K., Effects of a simple mode choice model in a large-scale agent-based transport simulation, in *Complexity and Spatial Networks. In Search of Simplicity*, edited by Reggiani, A. and Nijkamp, P., Advances in Spatial Science, chapter 13, pages 167–186, Springer, 2009.

[33] Rieser, M., Grether, D., and Nagel, K., Transportation Research Record: Travel Demand Forecasting 2009 **2132** (2009) 50.

[34] Charypar, D. and Nagel, K., Transportation **32** (2005) 369.

Appendix: Simulation Details

The following paragraphs are meant to present more information about the MATSim simulation approach that is used in this paper. Every step of the iterative loop in Sec. 2.1 is in the following illustrated in more detail.

Plans Generation An agents daily plan contains information about his planned activity types and locations, about duration and other time constraints of every activity, as well as the mode, route, the desired departure time and the expected travel time of every intervening trip (= leg). Initial plans are usually generated based on microcensus information and/or other surveys. The plan that was reported by an individual is in the first step marked as "selected".

Traffic Flow Simulation The traffic flow simulation executes all selected plans simultaneously in the physical environment and provides output describing what happened to each individual agent during the execution of its plan. The *car traffic flow simulation* is implemented as a queue simulation, where each road (= link) is represented as a first-in first-out queue with two restrictions [30, 31]: First, each agent has to remain for a certain time on the link, corresponding to the free speed travel time. Second, a link storage capacity is defined which limits the number of agents on the link; if it is filled up, no more agents can enter this link. The *public transport simulation* simply teleports agents between two activity locations. The distance is defined by a factor of 1.3 times the beeline distance between the locations. Travel speed can be configured and is set in this paper to 25 km/h. Public transport is assumed to run continuously and without capacity restrictions [32, 33]. All other modes are modeled similar to public transport: travel times are calculated based on mode specific travel speed and the distance estimated for public transport. However, the attributes of these modes are not relevant for the present paper since agents are only allowed to switch from car to public transport and the other way around. Trips from the survey that are not car or public transport trips, are fixed during the learning cycle. Output of the traffic flow simulation is a list that describes for every agent different *events*, e.g. entering or leaving a link, arriving or leaving an activity. These events are written in XML-format and include agent ID, time and location (link or node ID). It is, therefore, quite straightforward to use this disaggregated information for the calculation of link travel times or costs (which is used by the router module), trip travel times, trip lengths, and many more.

Evaluating Plans In order to compare plans, it is necessary to assign a quantitative measure to the performance of each plan. In this work, a simple utility-based approach is used. The elements of our approach are as follows:

- The total utility of a plan is computed as the sum of individual contributions:

$$V_p = \sum_{i=1}^{n} \left(V_{perf,i} + V_{tr,i} \right) , \tag{3}$$

  where V_{total} is the total utility for a given plan; n is the number of activities; $V_{perf,i}$ is the (positive) utility earned for performing activity i; and $V_{tr,i}$ is the (usually negative) utility earned for traveling during trip i. Activities are assumed to wrap around the 24-hours-period, that is, the first and the last activity are stitched together. In consequence, there are as many trips between activities as there are activities.

- A logarithmic form is used for the positive utility earned by performing an activity [see e.g. 34, 25]:

$$V_{perf,i}(t_{perf,i}) = \beta_{perf} \cdot t_{*,i} \cdot \ln \left(\frac{t_{perf,i}}{t_{0,i}} \right) \tag{4}$$

  where t_{perf} is the actual performed duration of the activity, t_* is the "typical" duration of an activity, and β_{perf} is the marginal utility of an activity at its typical duration. β_{perf} is the same for all activities, since in equilibrium all activities at their typical duration need to have the same marginal utility. $t_{0,i}$ is a scaling parameter that is related both to the minimum duration and to the importance of an activity. As long as dropping activities from the plan is not allowed, $t_{0,i}$ has essentially no effect.

- The disutility of traveling used for simulations is taken from [24]. More details are given in Sec. 3.2.

In principle, arriving early or late could also be punished. For the present paper, there is, however, no need to do so, since agents are not allowed to reschedule their day by changing departure times. Arriving early is already implicitly punished by foregoing the reward that could be accumulated by doing an activity instead (opportunity cost). In consequence, the effective (dis)utility of waiting is already $-\beta_{perf}\, t_{*,i}/t_{perf,i} \approx -\beta_{perf}$. Similarly, that opportunity cost has to be added to the time spent traveling.

Learning After evaluating daily plans in every iteration, a certain number of randomly chosen agents is forced to re-plan their day for the next iteration. This learning process is, in the present paper, done by two modules corresponding to the two choice dimensions available: a module called *router* for choosing new routes on the road network and a module called *sub-tour mode choice* for choosing a new transport mode for a car or public transport trip. The router module bases its decision for new routes on the output of the car traffic flow simulation and the knowledge of congestion in the network. In the case of the internalization policy, it also uses the knowledge about expected emission costs (see Sec. 2.3). The router is implemented as a time-dependent best path algorithm [19], using generalized costs (= disutility of traveling) as input. The sub-tour mode choice module changes the transport mode of a car sub-tour to public transport or from a public transport sub-tour to car. A sub-tour is basically a sequence of trips between activity locations. However, the simulation needs to make sure that a car can only be used if it is parked at the current activity location. Thus, a sub-tour is defined as a sequence of trips where the transport mode can be changed while still being consistent with the rest of the trips. It is e.g. assured that a car which is used to go from home to work in the morning needs to be back at the home location in the evening. If the car remains e.g. at the work location in order to use it to go for lunch, then the whole sub-tour of going to work and back needs to be changed to public transport.