Towards high-resolution first-best air pollution tolls

An evaluation of regulatory policies and a discussion on long-term user reactions

B. Kickhöfer · **K. Nagel**

Abstract In this paper, an approach is presented to calculate high-resolution first-best air pollution tolls with respect to emission cost factors provided by Maibach et al. (2008). Dynamic traffic flows of a multi-agent transport simulation are linked 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. It is found 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, long-term changes in the vehicle fleet fuel efficiency are assumed as a reaction to the Internalization policy. The results indicate, however, that the long-term effect of emission reduction is dominated by the short-term reactions and by the assumed improvement in fleet fuel efficiency; the influence of the resulting route and mode choice decisions turns out to be relatively small.

B. Kickhöfer · K. Nagel
Transport Systems Planning and Transport Telematics, Technische Universität Berlin, 10587 Berlin, Germany, Tel.: +49-30-31422542, Fax: +49-30-31426269, E-mail: kickhoefer@vsp.tu-berlin.de

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 (see, e.g., Vickrey, 1969; Arnott et al., 1993; Friesz et al., 2004). 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. Additionally, linkages to other sectors of the economy need to be accounted for (de Palma and Lindsey, 2004). For these reasons, so-called second-best pricing has been advanced (Verhoef, 2001).

   The computation of second-best tolls has been addressed in several studies (Verhoef, 2002; van den Berg and Verhoef, 2011; Markose et al., 2007). However, most studies focus on congestion pricing (see for exceptions, e.g., Mitchell et al. (2002); Namdeo and Mitchell (2007)). This is consistent with current estimates that congestion causes the largest part of the external effects (see Maibach et al. (2008), p.103). There is, however, some perception that non-congestion external effects need to be addressed as well (Creutzig and He, 2009); those become especially important for freight traffic (Maibach et al., 2008). 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 (Proost and van Dender, 2001).

   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 Nagel et al. (2008), this study now focuses on air pollution. The eventual goal will be a comprehensive system which treats all external costs simultaneously. First, an approach is presented 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 (INFRAS, 2010). Emissions are computed every time a traveler leaves a road segment. They depend on the traffic state on that segment at the specific time, as well as on the traveler's vehicle attributes. Second, external air pollution emission costs are calculated 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 Maibach et al. (2008). In a third step, travelers are directly charged with the resulting costs when leaving a road segment. In an iterative process, travelers learn 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

---

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

[2]   Please note that the simulated toll is first-best with respect to emission cost factors provided by Maibach et al. (2008). 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.

provided to every traveler based on information from the previous iteration. The system's state with full air pollution cost pricing 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, Germany.

Please note that the present paper is an extension of Kickhöfer and Nagel (2012). In contrast to the latter, more detailed results are provided and the calculated toll is compared to values from the literature. Furthermore, the impact of a first-best emission toll is discussed in the context of short-term vs. long-term behavioral reactions, particularly the role of more fuel efficient vehicles. The remainder of the paper is organized as follows: Sec. 2 describes the agent-based microsimulation framework to solve the internalization problem, including an overview of the emission modeling tool and the internalization procedure. Sec. 3 introduces the scenario, 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, Sec. 6 summarizes the main findings and contributions of this paper, and provides venues for further research.

2 Methodology

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 Hülsmann et al. (2011), 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, only general ideas about the transport simulation with MATSim are presented. For in-depth information of the simulation framework, please refer to Raney and Nagel (2006). 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 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 (Gawron, 1998; Cetin et al., 2003). In the present paper, the traffic flow simulation for public transit (PT) and all other modes simply teleports agents between two activity locations with a mode-specific travel speed.
3. **Evaluating plans:** All executed plans are evaluated by a utility function with the following functional form:

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

(1)

where V_p 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 (see Sec. 3.2). 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.

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 (see Sec. 3.2). The choice between plans is performed within 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 Modeling Tool

The emission modeling tool was developed by Hülsmann et al. (2011) and is further described in Kickhöfer et al. (2013, in press). The tool essentially calculates warm and cold-start emissions for private cars.[3] 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.[4] 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 states 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 person, time, road segment (= 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 and as XML in output files. 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.

2.3 Emission Cost Calculation: Internalization

The obtained person and link specific time-dependent emissions 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 this purpose, emission cost factors differentiated by emission type from Maibach et al. (2008) are used (see Tab. 1). Clearly, these cost factors are average costs, collected from different studies. They differ in terms of more local or more global

---

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

[4]   In reality, cold start emissions additionally depend on ambient temperature. The model used in the present paper, however, calculates cold start emissions for average ambient temperatures. In principle, HBEFA provides emission factors for different ambient temperatures. For a first attempt on how to use meteorologic data in this context, see Hülsmann et al. (2013, forthcoming).

[5]   Handbook on Emission Factors for Road Transport, version 3.1, see `www.hbefa.net`

Table 1: Emission cost factors by emission type (Maibach et al., 2008)

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

impacts. 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 Maibach et al. (2008) 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. For a more detailed discussion, please see Sec. 5.1. The following two paragraphs will provide an overview of the first-best emission toll implementation developed by the authors, which is based on the available person- and link-specific, time-dependent emission 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. 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 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 already been used in other contributions (Nagel et al., 2008; Kickhöfer et al., 2010).

Router Module For the router module, the implementation is not as straightforward. Currently, the router is implemented as a best path algorithm, which uses time-of-day-dependent link generalized costs (or disutility of traveling) of the previous iteration (Lefebvre and Balmer, 2007). 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 7. Therefore, a 1% sample is used in the present paper.[6]

3 Scenario: Munich, Germany

In this section, a short introduction is given 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, two policy measures are defined: First, the *Zone 30 policy* is a regulatory measure of limiting the maximum speed in the inner city of Munich to 30 km/h. Second, the *Internalization policy* uses 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 Follmer et al. (2004)):
  The synthetic population of Munich is created on the base of very detailed survey data provided by the municipality of Munich RSB (2005), 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 one person at the same time. The synthetic urban population of Munich consists of 1'424'520 individuals.
- Commuter population (based on Böhme and Eigenmüller (2006)):
  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 Böhme

---

[6] In order to run the simulation with a sample of 1%, all flow capacities are scaled down to 1%. This means, for example, that a link with a capacity of 3600/h will now allow one vehicle every 100 seconds. Clearly, this leads to larger fluctuations; for example, one vehicle changing routes has a much larger impact. In order to dampen some of these fluctuations, the link storage capacities, which produce spill-back, were reduced to 3% instead of 1%. Other studies for car traffic indicate that this approach is sufficient to obtain realistic congestion patterns (see, e.g., Nagel, 2008, 2011). Since congestion patterns are plausible, it is assumed that the emissions are realistic as well.

[7] Since the scenario setup has been described by Kickhöfer et al. (2013, in press), only key figures are presented here.

and Eigenmüller (2006) 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 ITP/BVU (2005)):
Commercial traffic is based on a study published on behalf of the German Ministry of Transport by ITP/BVU (2005). 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.[8]

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 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 A logarithmic form is used for the positive utility earned by performing an activity (see e.g. Charypar and Nagel, 2005; Kickhöfer et al., 2011):

$$V_{perf,i}(t_{perf,i}) = \beta_{perf} \cdot t_{*,i} \cdot \ln\left(\frac{t_{perf,i}}{t_{0,i}}\right) \qquad (2)$$

where $t_{perf,i}$ is the actual performed duration of activity i, $t_{*,i}$ is the "typical" duration of activity i, 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.

---

[8] This is a rather simple approach of generating freight traffic which is due to the fact that, in the literature, modeling freight transport has not gained as much attention as passenger transport. However, there is growing interest in this field since the movement of commodities is increasing, and with it the importance of better behavioral modeling of firms and their decision making. For example, Giuliano et al. (2010) base their estimations of freight flows on online sources in order to assure a maximum of transferability and automatic updating. For a new approach of how to model freight transport in the MATSim framework, please refer to Schröder et al. (2012).

Table 2: Estimated and adjusted utility parameters; resulting VTTS

(a) Tirachini et al. (2012)		
$\hat{\beta}_{tr,car}$	-0.96	[utils/h]
$\hat{\beta}_{tr,pt}$	-1.14	[utils/h]
$\hat{\beta}_c$	-0.062	[utils/AUD]
$\hat{\beta}_{perf}$	n.a.	[utils/h]
$VTTS_{tr,car}$	$+15.48$	[AUD/h]
$VTTS_{tr,pt}$	$+18.39$	[AUD/h]

(b) MATSim		
$\beta_{tr,car}$	-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]

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. 1) is defined by the following functional form:

$$
\begin{aligned}
V_{car,i,j} &= \quad\quad \beta_{tr,car} \cdot t_{i,car} + \beta_c \cdot c_{i,car} \\
V_{pt,i,j} &= \beta_0 + \beta_{tr,pt} \cdot t_{i,pt} + \beta_c \cdot c_{i,pt} ,
\end{aligned}
\tag{3}
$$

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[9] are taken from an Australian study by Tirachini et al. (2012); these parameters are shown in Tab. 2a, together with the corresponding Values of Travel Time Savings (VTTS). Necessary adjustments of the parameters are performed in order to meet the MATSim framework. The resulting parameters and VTTS are depicted in Tab. 2b. These adjustments are described in more detail in (Kickhöfer et al., 2011, 2013, in press). 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 an explicit value for the opportunity costs of time (see Eq. 2), it is assumed that traveling with car is not perceived more negatively than "doing nothing". This interpretation is done that way since it does not change the VTTS, as a comparison of Tab. 2a and Tab. 2b nicely shows: the VTTS are only rescaled from AUD to EUR.[10] In contrast to Tirachini et al. (2012), the present model does not include access, egress, and waiting times for public transit. Therefore, the alternative specific constant (ASC) 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 $\beta_0 = -0.75$.[11]

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

---

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

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

[11] Instead of this rather simple parametric calibration, one could use more advanced techniques, e.g. a novel approach developed by Flötteröd et al. (2011); the authors use their own calibration system "Cadyts" in order to manipulate the ASC of every traveler's plan in such way that the simulation better reproduces real-world traffic counts.
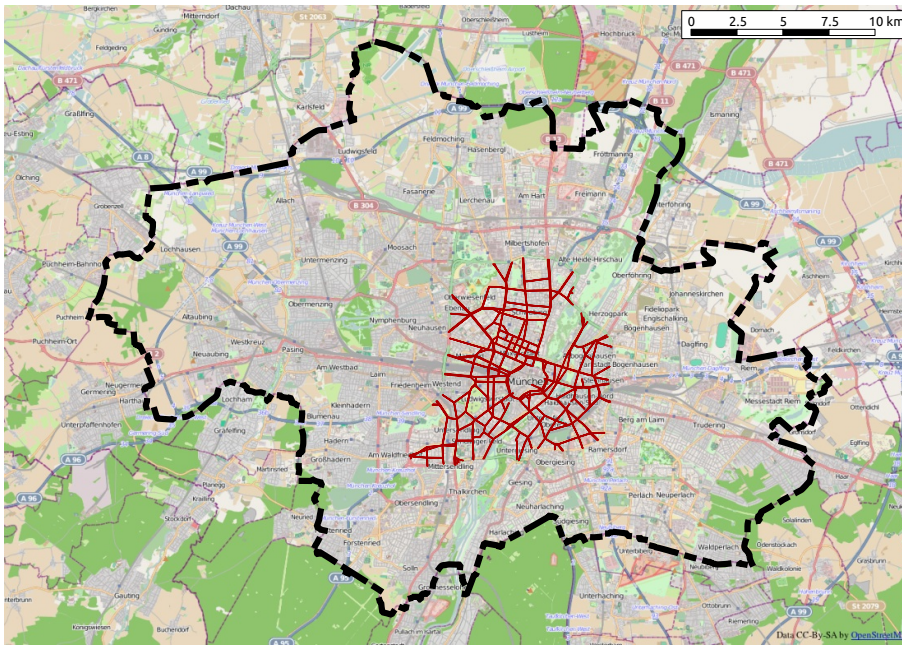
Fig. 1: Zone 30 policy: road segments (in red) where the speed limitation applies.

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 (see Fig. 1)
– **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)

The reason for choosing a speed limitation policy for evaluation is that, in Germany, it is currently discussed to regulate the maximum speed in the inner cities to 30 km/h. The current speed limits are (with some exceptions) 60 km/h on primary roads, 50 km/h on secondary roads, and 30 km/h on tertiary roads.

User costs[12] 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.

---

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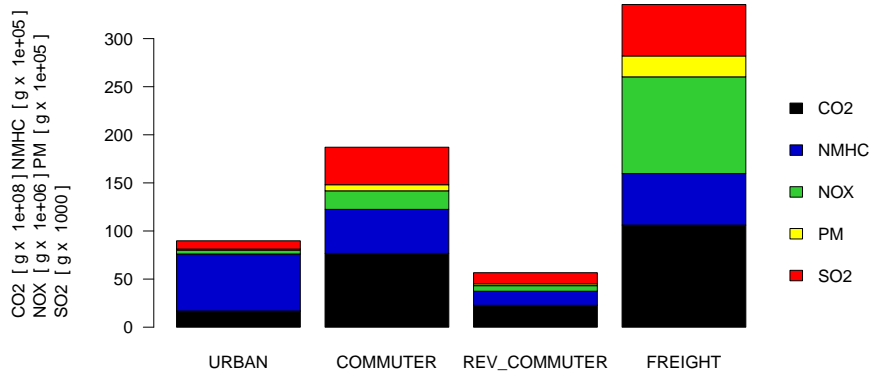
4 Results

In this section, different changes to the system are presented that result from the two policy measures. 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 is provided in Sec. 5. All results in this section are rescaled from the 1% sample to the full scenario for a regular week day in the scenario described in Sec. 3.1.
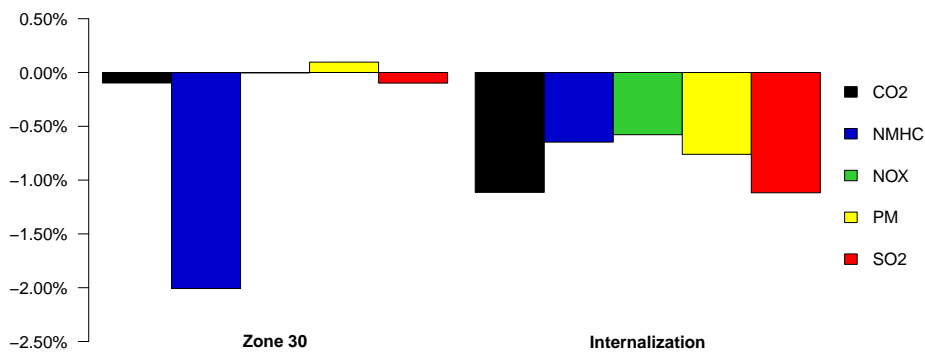
4.1 Emissions

Starting with analyzing the final iteration of the base case, Fig. 2a 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 (Schmitz et al., 2000). Thus, 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 the present 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 commuters: 100 km; median reverse commuters: 65 km). Finally, freight traffic also drives rather long distances (median freight: 110 km). Even though freight traffic represents only 7.6% of the total population, it 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%. Here, the distance effect might play a role, but the major reason presumably is that trucks produce much higher emissions per vehicle kilometer than normal cars.
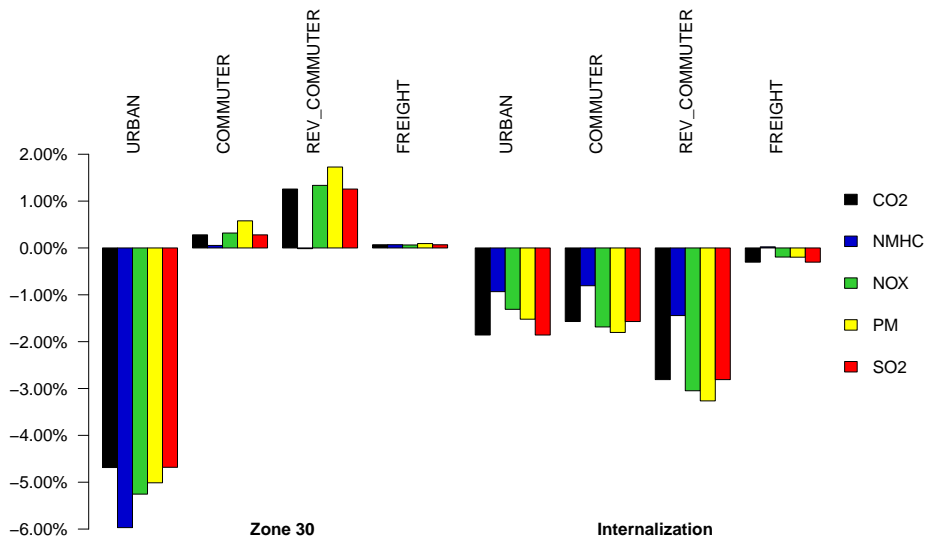
    To answer the question on how close the Zone 30 policy comes to the Internalization policy in terms of emission reduction, Fig. 2b shows the relative changes in emissions for the two policies. The Zone 30 reduces *NMHC* by around 2%, CO_2 and SO_2 are only slightly reduced by 0.1%, NO_x remains unchanged, 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. 2c decomposes the information from Fig. 2b to the different subpopulations. The picture becomes even more interesting: the Zone 30 leads to a strong emission reduction of 5% to 6% for the urban population. All other subpopulations produce *more* emissions. 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 dimensions presented in Sec. 3.2, the above emission effects result directly

(a) Base case: absolute emissions by type and subpopulation; values scaled to a 100% scenario

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

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

Fig. 2: Emissions by emission type: absolute values by subpopulation for the base case, relative changes (overall and by subpopulation) for the two policy cases.

Table 3: Changes in modal split and average car distance traveled

(a) Zone 30 policy

Subpopulation	change in car trips [%]	change in avg. car dist. traveled [km]
URBAN	−7.00	−0.08
COMMUTER	−0.43	+0.29
REV_COMMUTER	−0.87	+1.01
FREIGHT	±0.00	+0.02

(b) Internalization policy

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

from re-routing and changes in the modal split. Additionally, they may result indirectly from changes in congestion. Tab. 3a and Tab. 3b show the relative change in car trips 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 7%. The remaining car users on average drive slightly shorter distances (−0.08 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 visible by *longer* average distances in order to avoid the unattractive zone with the speed limitation (commuters: +0.29 km, reverse commuters: +1.01 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. 3a 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:

$$W_{pop} = logsum_{pop} = EMU_{pop} = \sum_{j=1}^{J} \left(\frac{1}{|\beta_c|} \ln \sum_{p=1}^{P} e^{V_p} \right) , \qquad (4)$$

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
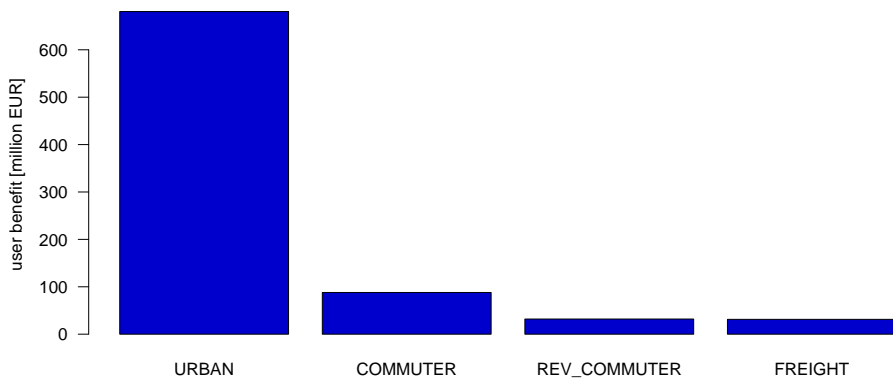
alternatives of individual j, and V_p is the systematic part of utility of alternative (= plan) p. The urban population contributes most to overall user benefits. On the one hand, this stems from the fact that they represent a major part of the total population. On the other hand, they spend less time on transport, 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. 3b. The Zone 30 policy leads to a loss in user logsum 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.
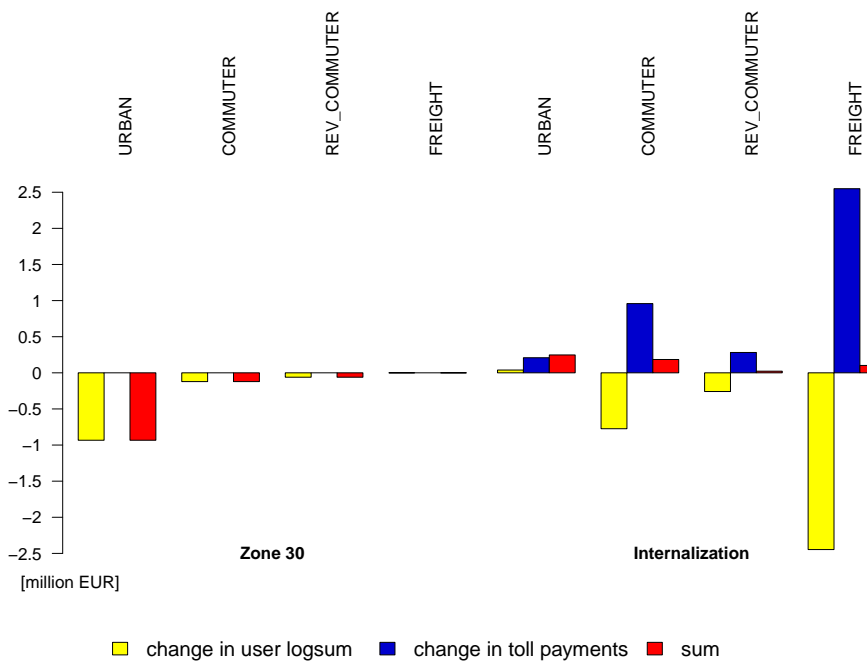
The Internalization policy on the right side yields quite different results: commuters, reverse commuters and freight all lose in terms of user logsum (in yellow); the loss is most pronounced for freight traffic. This intuitively makes sense since freight traffic contributes to a major part of total 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 logsum despite the toll they have to pay. Time gains for the urban population slightly over-compensate the negative effect of the toll payments. When assuming a redistribution of the toll payments of every subpopulation (blue bars in Fig. 3b) to the respective subpopulation, one obtains the net welfare effect for that population (red bars in Fig. 3b). Interestingly, the redistribution of the toll payments overcompensates the loss in user logsum for commuters, reverse commuters, and freight. For urban travelers, the welfare gain becomes even more important, being the highest of all subpopulations. That is, for all subpopulations, the emission toll *implicitly* reduces congestion and in that way also works as a congestion pricing scheme that increases welfare.

In addition to the changes in user benefit 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. Cost reductions for society due to lower emission levels are — in contrast to time gains — not included in the user logsum; this is due to the fact that emission costs are true external costs for the transport market.[13] Fig. 3c 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. 3b. However, the figure allows interesting insights into the welfare effect of 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. 2c. A further discussion of the results will be given in the next section.
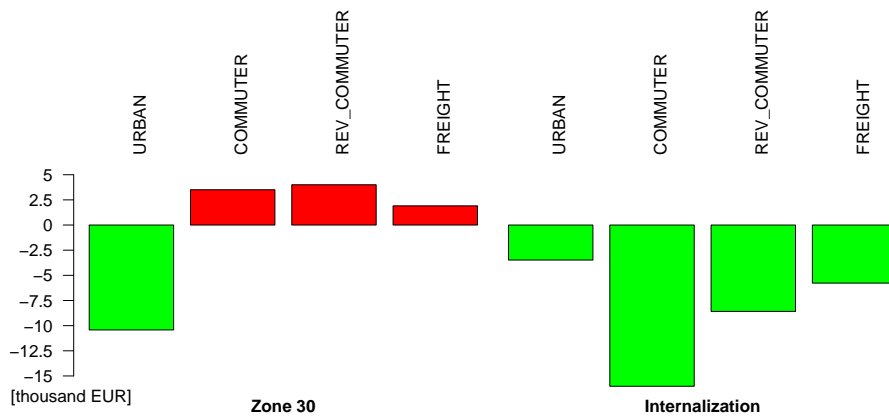
---

[13] The same is true for other external costs that are currently not quantified in the present model, e.g. noise emissions, accidents, etc. It is expected that the emission toll, again, implicitly reduces these external costs and therefore has further positive effects on the wellbeing of residents or property values.

(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

Fig. 3: Welfare analysis by subpopulation: absolute values for the base case, absolute changes for the two policy cases; all values scaled to a 100% scenario.

Table 4: 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

5 Discussion

5.1 Discussion of the Internalization Approach

Emission cost factors: Tab. 4 shows average external emission costs per vehicle kilometer for the different subpopulations that are calculated from the simulation of the base case.[14] 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 the approach of coupling MATSim with HBEFA and then using cost factors from Maibach et al. (2008) leads to plausible average emission costs per vehicle kilometer: e.g. Parry and Small (2005) use local pollution cost factors for automobiles of 2.0 US-Dct/mile or roughly 1.23 EURct/km. This estimate is very close to the resulting value for urban travelers in the present 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 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 the present model are *based* on average cost factors; these are, however, average costs per amount of pollutant, and since these amounts are influenced by congestion effects and vehicle attributes, the resulting costs 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 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 are discussed in the following paragraph.

Implications for the interpretation of results: Looking again at Fig. 3b and Fig. 3c 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 yields much better results when looking at *exposure* to emission concentration rather than emissions. Emission cost factors from Maibach et al. (2008) are average costs and, thus, probably too low in the inner city and too high outside of Munich. For this reason, it is planned to model the whole

---

[14] Please note that the numbers in Tab. 4 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.

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. A first step into the modeling of emission concentration has been done by Hülsmann et al. (2013, forthcoming), who introduce pricing measures for emission concentration hotspots. The next step will be to model the number of people that are exposed to that concentration. And finally, a monetization of this effect. 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 Discussion of Freight Traffic

Lorry types: As mentioned earlier, freight traffic contributes to a major part of total emissions while only representing under 10% of the total population. This is the result of two effects: (i) freight drives longer distances than all other subpopulations. (ii) freight produces more emissions per vehicle kilometer. Additionally to these two effects, it is likely that bigger lorries drive longer distances than small trucks. Since in the present paper, all trucks are assumed to be of the same vehicle type, the contribution to total emissions is, in reality, expected to be even higher than presented in Sec. 4.1.

Behavioral parameters: Originally, the behavioral modeling of freight was not the focus of the present paper. As mentioned in Sec. 3.1, freight demand was included into the scenario in a simplified way for completeness. Since no behavioral parameters for freight were available, they are the same as for all other agents. In consequence, the assumed VTTS is lower than usually found in empirical studies. This implies that the reaction of freight to the different policy cases is too sensitive. In consequence, the results for freight are biased. However, since freight is only allowed to adapt routes and not mode as all other subpopulations, this bias is unlikely to be very important. In order to get an estimate of the resulting effect, the impact of this bias on travel patterns and economic evaluation of the policy cases is discussed next:

– In general: A higher VTTS for freight implies (ceteris paribus) a lower marginal utility of money. Given the computed behavioral reactions, this results in larger absolute welfare changes than presented in this paper when monetizing utility gains.
– Zone 30: A too low VTTS has no effect on routing since there is no trade-off between a toll and travel time. Only the above effect applies in the economic evaluation. The welfare effects for freight are very small (see Fig. 3b), and even multiplying them by a factor would not change the results significantly.
– Internalization: A too low VTTS has an effect on routing: it results in routes with too short distances and too long travel times. A higher VTTS would therefore result in (i) longer distances and (ii) shorter travel times. With longer distances, if the distance effect of emissions dominates the congestion effect, freight would produce even higher emissions and also pay more toll than presented in this paper. With shorter travel times, freight would have higher utility gains due to congestion relief. Additionally, the above

monetization effect applies in the economic evaluation. That is, for the internalization policy, the results presented in this paper underestimate the toll payments of freight, as well as the welfare change after redistribution.

The above clearly shows that there is a strong need for improving demand and behavioral modeling of freight transport. Especially because of its major impact on total emissions, a more profound understanding of the relevant processes in freight transport is necessary in order to be able build policy-sensitive demand on a micro-level.

5.3 Discussion of 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. On a very different level of detail, this section now aims at presenting rough estimates on how big the short-term impact is in comparison to possible long-term user reactions. These long-term reactions might, for instance, include changes in the vehicle fleet[15]: 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 the Internalization policy, the former would increase car vehicle kilometers traveled as well as emissions, and therefore also increase toll payments. The latter 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. Parry and Small (2005) 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 them, the rest of the decrease in gasoline consumption results from changes in the vehicle fleet. Assuming a linear relationship between gasoline consumption and emissions, this would imply that vehicle kilometers in the long run and for the same price signal would drop by less than 0.5 of the reduction in emissions. Erath and Axhausen (2010) 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 propensities to the MATSim framework. Since there is, however, not a similar study for the city of Munich, randomly drawing agents in the population for vehicle replacement would result in biased statistics. The reason for this is that the probabilities would not be linked to the users' preferences, socio-demographics, or locations.[16]

In order to determine the long-term effect of changes in the vehicle fleet for the current setup, parametric studies were performed with the assumption that all vehicles are affected uniformly by the improvement in fuel efficiency. Fig. 4 shows parametric estimates of rel-

---

[15] 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 Horni et al. (2012).

[16] 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.
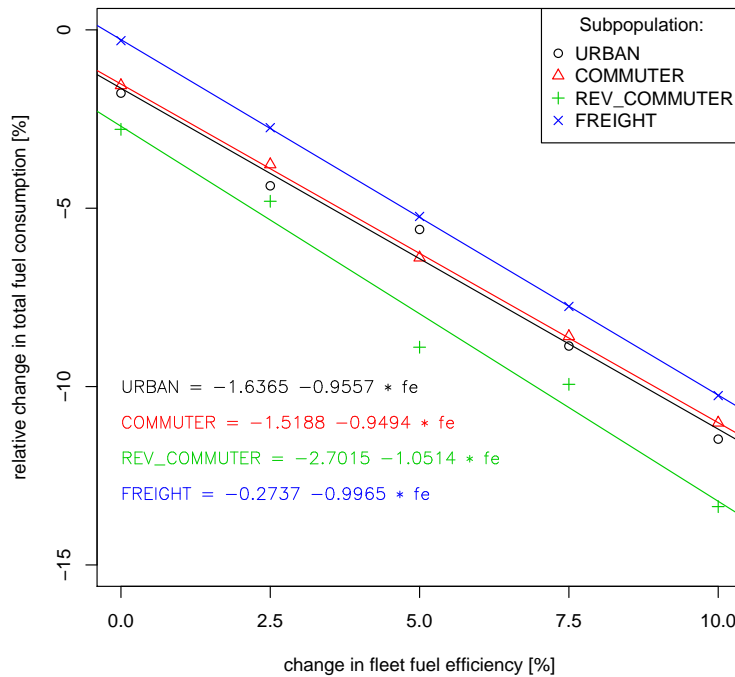
Fig. 4: Impacts of fuel efficient cars on fuel reduction: parametric estimates by subpopulation

ative changes in total fuel consumption over five different levels of fleet fuel efficiency.[17]
Level 0.0% is equivalent to the short term reactions (Internalization policy) presented in
Sec. 4: 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. 4 also pro-
vides 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 consump-
tion 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 in-
dicates (1% higher fuel efficiency leads to −0.9965% less consumption). Urban travelers
and commuters react more sensitively to the Internalization policy since they are addition-
ally 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 ef-

---

[17]   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
the present model to a modal shift towards car and longer distances traveled.

fects of shifting back to car and to longer distances. 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: Erath and Axhausen (2010) predict an average change in fleet fuel efficiency of 5% as a reaction to an average fuel price increase of 100%. As Tab. 4 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 Erath and Axhausen (2010), an increase in the vehicle fleet emission efficiency of 0.5% is assumed. In addition, it is assumed 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. 4, a 0.5% increase in the vehicle fleet fuel efficiency would lead to additional changes in total fuel consumption. Thus, some additional changes in total fuel consumption are expected 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 efficiency are, however, relatively small. One can therefore state that accounting for 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 route choice and mode choice behavior.

6 Conclusion

In this paper, a new simulation approach was presented to internalize external air pollution costs for a real-world large-scale scenario using an agent-based model. The resulting exhaust emission and welfare effects were used 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 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 agent-specific marginal social costs in terms of vehicle attributes and congestion-based emissions.

In terms of absolute emissions, the highest share is contributed by freight, followed by commuters. Urban travelers have a minor impact even though they represent almost 70% of the total population. When comparing the regulatory measure to the full emission cost Internalization policy, it is found that the regulatory measure 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 "donothing" strategy: too high generalized prices for urban travelers, too low generalized prices for commuters and freight. The Internalization policy increases welfare for all subpopulations, even without the benefits from reduced emission costs. That is, the toll implicitly reduces congestion and therefore also works as a congestion pricing scheme. Additionally, it is likely to have further positive effects on welfare, e.g. by reducing noise emissions or increasing property values.

Furthermore, the analysis of the 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, neither the emission tolls nor the estimates from the literature do 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 it is planned 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.

Due to the simplified way of generating freight demand and modeling its behavioral reactions, the total emissions of freight are presumably even higher than in this paper. Additionally, for the Internalization policy, this paper is likely to underestimate the toll payments of freight, as well as the positive welfare change after redistribution. This clearly shows that there is a strong need for research that aims at improving demand and behavioral modeling of freight transport.

The final discussion on long-term changes to the vehicle fleet shows that there are additional changes in total fuel consumption and emissions when assuming that travelers react to the Internalization policy by buying more fuel efficient cars. However, due to the rather weak price signal, this is not found to significantly change long-term route and mode choice decisions.

In principle, the approach presented in this paper allows the evaluation of any regulatory policy. Here, the goal was to present the methodology by means of a fictive speed limitation in the inner city. Other (maybe more realistic) policies come to mind, for example speed limitations or pricing schemes on certain road categories. After solving some of the issues related to freight traffic, the appraisal of these policies provides interesting venues for more practical research in the future. A first step into this direction is a recent paper by Hülsmann et al. (2013, forthcoming), who, in a similar scenario, price roads with high emission concentrations.

Another important, even though more practical contribution of this paper is the following: it could be demonstrated 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.

References

R. Arnott, A. de Palma, and R. Lindsey. A structural model of peak-period congestion: A traffic bottleneck with elastic demand. *The American Economic Review*, 83(1):161–179, 1993.

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

N. Cetin, A. Burri, and K. Nagel. 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.

D. Charypar and K. Nagel. Generating complete all-day activity plans with genetic algorithms. *Transportation*, 32(4):369–397, 2005.

F. Creutzig and D. He. Climate change mitigation and co-benefits of feasible transport demand policies in Beijing. *Transportation Research Part D: Transport and Environment*, 14(2):120–131, 03 2009. ISSN 13619209. doi: 10.1016/j.trd.2008.11.007.

A. de Palma and R. Lindsey. Congestion pricing with heterogeneous travelers: A general-equilibrium welfare analysis. *Networks and Spatial Economics*, 4(2):135–160, 2004. doi: 10.1023/B:NETS.0000027770.27906.82.

A. Erath and K. Axhausen. 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. URL `http://www.ivt.ethz.ch/vpl/publications/reports`.

G. Flötteröd, Y. Chen, and K. Nagel. Behavioral calibration and analysis of a large-scale travel microsimulation. *Networks and Spatial Economics*, 12(4):481–502, 2011. ISSN 1566-113X. doi: 10.1007/s11067-011-9164-9. doi: 10.1007/s11067-011-9164-9.

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

T. L. Friesz, D. Bernstein, and N. Kydes. Dynamic congestion pricing in disequilibrium. *Networks and Spatial Economics*, 4(2):181–202, 2004. doi: 10.1023/B:NETS.0000027772.43771.94.

C. Gawron. An iterative algorithm to determine the dynamic user equilibrium in a traffic simulation model. *International Journal of Modern Physics C*, 9(3):393–407, 1998.

G. Giuliano, P. Gordon, Q. Pan, J. Park, and L. Wang. Estimating freight flows for metropolitan area highway networks using secondary data sources. *Networks and Spatial Economics*, 10(1):73–91, 2010. doi: 10.1007/s11067-007-9024-9.

A. Horni, K. Nagel, and K. Axhausen. High-resolution destination choice in agent-based demand models. Technical Report 12-1989, 2012. Also VSP WP 11-17, see www.vsp.tu-berlin.de/publications.

F. Hülsmann, R. Gerike, B. Kickhöfer, K. Nagel, and R. Luz. 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, 05 2011. ISBN 978-3-941790-77-3. Also VSP WP 10-15, see www.vsp.tu-berlin.de/publications.

F. Hülsmann, B. Kickhöfer, and R. Gerike. Air pollution hotspots in urban areas – How effective are pricing strategies to comply with the EU limits for NO_2? In R. Gerike, K. Roller, and F. Hülsmann, editors, *Strategies for Sustainable Mobilities: Opportunities and Challenges*. Ashgate Publishing Ltd., 2013, forthcoming.

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

ITP/BVU. Prognose der deutschlandweiten Verkehrsverflechtungen 2025. Technical report, 2005. URL `http://daten.clearingstelle-verkehr.de/220/`.

B. Kickhöfer and K. Nagel. 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.

B. Kickhöfer, M. Zilske, and K. Nagel. Income dependent economic evaluation and public acceptance of road user pricing. In *Proceedings of the Kuhmo Nectar Conference on Transportation Economics*, 07 2010. Also VSP WP 10-03, see www.vsp.tu-berlin.de/publications.

B. Kickhöfer, D. Grether, and K. Nagel. Income-contingent user preferences in policy evaluation: application and discussion based on multi-agent transport simulations. *Transportation*, 38:849–870, 2011. ISSN 0049-4488. doi: 10.1007/s11116-011-9357-6.

B. Kickhöfer, F. Hülsmann, R. Gerike, and K. Nagel. Rising car user costs: comparing aggregated and geo-spatial impacts on travel demand and air pollutant emissions. In T. Vanoutrive and A. Verhetsel, editors, *Smart Transport Networks: Decision Making, Sustainability and Market structure*, NECTAR Series. Edward Elgar, 2013, in press.

N. Lefebvre and M. Balmer. Fast shortest path computation in time-dependent traffic networks. In *Proceedings of the Swiss Transport Research Conference (STRC)*, Monte Verita, CH, 09 2007. See www.strc.ch.

M. Maibach, D. Schreyer, D. Sutter, H. van Essen, B. Boon, R. Smokers, A. Schroten, C. Doll, B. Pawlowska, and M. Bak. Handbook on estimation of external costs in the transport sector. Technical report, CE Delft, 2008.

S. Markose, A. Alentorn, D. Koesrindartoto, P. Allen, P. Blythe, and S. Grosso. A smart market for passenger road transport (SMPRT) congestion: An application of computational mechanism design. *Journal of Economic Dynamics and Control*, 31(6):2001–2032, 2007.

G. Mitchell, A. Namdeo, J. Lockyer, and A. May. 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.

K. Nagel. Towards simulation-based sketch planning: Some results concerning the Alaskan Way viaduct in Seattle WA. VSP Working Paper 08-22, TU Berlin, Transport Systems Planning and Transport Telematics, 2008. URL `https://svn.vsp.tu-berlin.de/repos/public-svn/publications/vspwp/2008/08-22`. see www.vsp.tu-berlin.de/publications.

K. Nagel. Towards simulation-based sketch planning, part II: Some results concerning a freeway extension in Berlin. VSP Working Paper 11-18, TU Berlin, Transport Systems Planning and Transport Telematics, 2011. see www.vsp.tu-berlin.de/publications.

K. Nagel, D. Grether, U. Beuck, Y. Chen, M. Rieser, and K. Axhausen. Multi-agent transport simulations and economic evaluation. *Journal of Economics and Statistics (Jahrbücher für Nationalökonomie und Statistik)*, 228(2+3):173–194, 2008. Special issue on agent based models for economic policy advice, edited by B. LeBaron and P. Winker.

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

I. W. Parry and K. A. Small. Does Britain or the United States Have the Right Gasoline Tax? *The American Economic Review*, 95(4):1276–1289, 2005. doi: 10.1257/0002828054825510.

S. Proost and K. van Dender. The welfare impacts of alternative policies to address atmospheric pollution in urban road transport. *Regional Science and Urban Economics*, 31(4):383–411, 2001. ISSN 0166-0462. doi: 10.1016/S0166-0462(00)00079-X.

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

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

T. Schmitz, D. Hassel, and F.-J. Weber. Determination of VOC-components in the exhaust of gasoline and diesel passenger cars. *Atmospheric Environment*, 34(27):4639–4647, 2000. ISSN 1352-2310. doi: 10.1016/S1352-2310(00)00303-4.

S. Schröder, M. Zilske, G. Liedtke, and K. Nagel. A computational framework for a multi-agent simulation of freight transport activities. Number 12-4152, 2012. Also VSP WP 11-19, see www.vsp.tu-berlin.de/publications.

A. Tirachini, D. A. Hensher, and J. M. Rose. 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.

V. A. van den Berg and E. T. Verhoef. 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.

E. T. Verhoef. Marginal cost based pricing in transport. Key implementation issues from the economic perspective, 2001. URL `http://www.imprint-eu.org/public/EV_V2.PDF`. Paper presented at Seminar One of IMPRINT-EUROPE.

E. T. Verhoef. Second-best congestion pricing in general networks. Heuristic algorithms for finding second-best optimal toll levels and toll points. *Transportation Research Part B: Methodological*, 36:707–729, 2002.

W. Vickrey. Congestion theory and transport investment. *The American Economic Review*, 59(2):251–260, 1969.