Using high-resolution first-best tolls as a benchmark for policy evaluation: The case of air pollution costs

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01.06.2012

In this paper, we present an approach to calculate a high-resolution first-best air pollution toll with respect to emission cost factors provided by Maibach et al. [2008]. 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. We find that the regulatory measure is considerably less successful in terms of total emission reduction. It also 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.

Keywords: external costs, first-best toll, 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 [e.g. Verhoef, 2001].

The computation of second-best tolls has been addressed in several studies [e.g. Verhoef, 2002, de Palma and Lindsey, 2006, van den Berg and Verhoef, 2011, Markose et al., 2007]. However, most studies focus on congestion pricing [see, e.g. Mitchell et al., 2002, Namdeo and Mitchell, 2007, for exceptions]. This is consistent with current estimates that congestion currently causes the largest part of the external effects [e.g. Maibach et al., 2008, p.103]. There is, however, some perception that non-congestion external effects need to be addressed as well [e.g. Creutzig and He, 2009]; those become especially important for freight traffic [see, once more, Maibach et al., 2008, p.103].

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 system. 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 [also see 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, 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 [INFRAS, 2010]. 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), Nitrogene 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 "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 Kickhöfer et al. [2012, in press] and Kickhöfer and Nagel [2011].

The reminder 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. Main results are presented and discussed in Sec. 4. Finally, Sec. 5 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)

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

[2] Please note that the simulated toll is only first-best with respect to average emission cost factors provided by Maibach et al. [2008]. For a discussion on how to model the whole impact-path-chain of air pollution and how to derive real marginal cost factors, please refer to Sec. 5.

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 Raney and Nagel [2006] 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 transport (pt). 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. 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 Hülsmann et al. [2011] and is further described in Kickhöfer et al. [2012, in press]. The tool essentially calculates warm and cold-start emissions. 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[3] 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, 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

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

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

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 Maibach et al. [2008], shown in Tab. 1. Clearly,

Table 1: Emission cost factors
by emission type from Maibach et al. [2008]

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

these cost factors are average costs, collected from different studies. They especially differ in terms of a more local or more global impact. To name the two most extreme: CO_2 only has a global 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. In consequence, external costs for 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 overestimated. In order to obtain true marginal emission costs, in principle the whole impact-path-chain of air pollution needs be modeled. This would imply an exposure analysis for the whole population, and monetizing the effects on human health. A discussion on this will be given in Sec. 5.

Please note, that the simulated toll presented in this paper is still first-best with respect to the pre-calculated emission costs. The following two paragraphs will give an overview of a 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 a *emission cost module* which converts any mapping of emission type to a value into monetary terms (see above). This unique cost module is generated when 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 the person, the link, and the time. 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 to the emissions they produced on that link. When the 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 of her plan. This is a standard MATSim feature which has been used frequently in other contributions [see e.g. Nagel et al., 2008, Kickhöfer et al., 2010].

Router Module For the router module, the implementation is not as straightforward. The router is implemented as a time-dependent best path algorithm [Lefebvre and Balmer, 2007], 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 needs to generate new routes on very disaggregated information by calculating expected emission costs based on expected emissions 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.

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 which changes the user costs on every link for every car user dependent on her emissions.

3.1 Scenario Setup

Since the scenario setup has already been described by Kickhöfer et al. [2012, in press] and Kickhöfer and Nagel [2011], only the key figures will be presented here.

The road network consists of 17'888 nodes and 41'942 road segments (= links). 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 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.

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 transport 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 transport 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 transport trip. In consequence, the travel related part of utility (see Eq. 3 in the Appendix) is defined by the following functional form:

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

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 are taken from an Australian study by Tirachini et al. [2012, forthcoming]; these parameters are shown in Tab. 2, 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. 3. These adjustments are described in more detail in several contributions [see e.g. Kickhöfer et al., 2011, 2012, 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. 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

Table 2: Estimated parameters[a] and VTTS from Tirachini et al. [2012, forthcoming]

$\hat{\beta}_{tr,car}$	-0.96	[utils/h]
$\hat{\beta}_{tr,pt}$	-1.14	[utils/h]
$\hat{\beta}_{c}$	-0.062	[utils/AUD[b]]
$VTTS_{tr,car}$	$+15.48$	[AUD/h]
$VTTS_{tr,pt}$	$+18.39$	[AUD/h]

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

[b] AUD is Australian dollar, AUD 1 = EUR 0.78 in May 2012.

Table 3: Adjusted parameters and VTTS accounting for opportunity costs of time

$\beta_{tr,car}$	-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]

and Tab. 3 nicely shows: the VTTS are only rescaled from AUD to EUR. In contrast to Tirachini et al. [2012, forthcoming], the present model does not include access, egress, and waiting times for public transport. Therefore, the alternative specific constant β_0 needs to be re-calibrated. This is performed by a parametric calibration process which aims at holding the modal split distribution over distance as close to the initial distribution as possible. 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 for car are always fixed to 30 ct/km. For the internalization policy, additional costs apply (see above). User costs for public transport are assumed to be constant at 18 ct/km for the base case and both policy cases. Please note, that the term "user costs" is referred to as out-of-pocket costs for the users. All simulation runs 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 transport 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.

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.

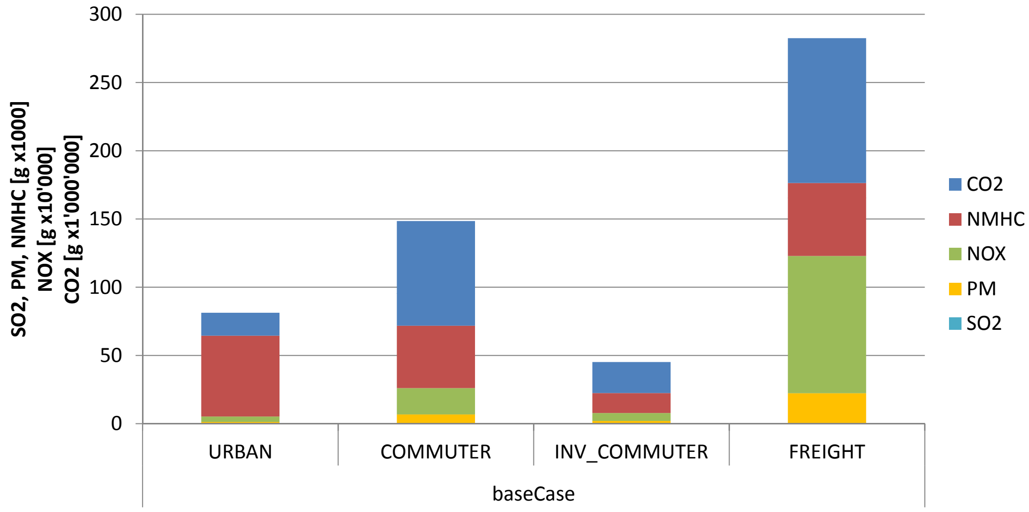
4.1 Emissions

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 (inverse commuters). Also note that the scale of the pollutants is different 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 of total emissions, knowing that they represent 68% of the total population and perform more trips per day than the other subpopulations. PM and SO_2 emission levels are also relatively low for the urban population, whereas $NMHC$ is relatively much more important. This is probably due to the fact that $NMHC$ emissions are significantly higher for cold-starts and during the warm-up phase of the vehicle [see e.g. Schmitz et al., 2000]. The overall contribution of $NMHC$ to the absolute emission level is therefore higher for the urban population due to two reasons: first, they drive shorter distances which means that — in some cases — the engine is not even completely warmed up when they reach their destination. Second, due to a higher number of trips per day, the urban population produces more cold starts per car user over time of day than the other subpopulation who in our model only perform two trips (commuters and inverse commuters) or one trip (freight), respectively. Commuters (14.6% of the total population) and inverse commuters (9.8%) seem to have similar split of the different pollutants. However, commuters emit in total about three times as much as inverse commuters, probably due to longer average distances. Finally, it is important to note that the freight population (only 7.6% of the total population) emits around 50% of total emissions.

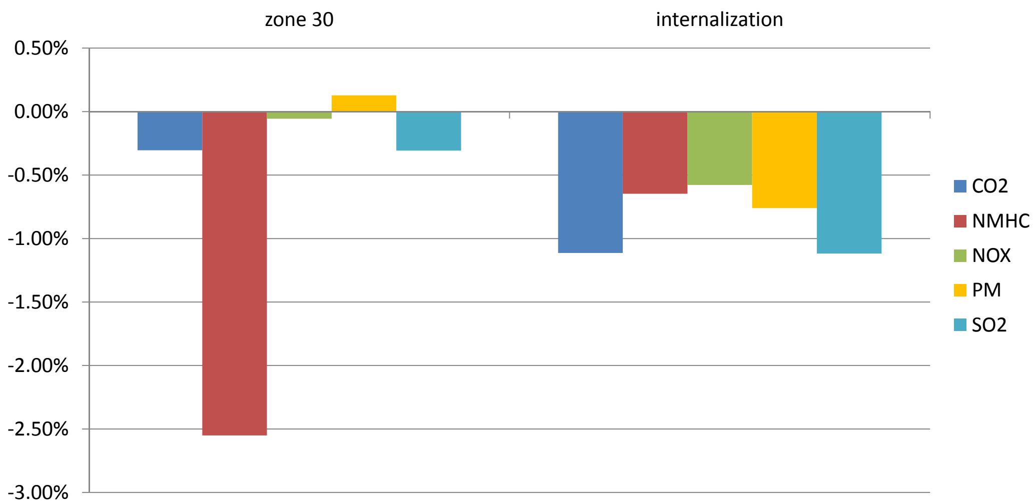
To answer the question on how close the zone 30 policy comes to the internalization policy in terms of emission reduction, Fig. 1b provides important information. It shows the relative change in emissions for the two policies. The zone 30 strongly reduces $NMHC$ by around 2.5%, all other pollutants are 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 probably resulting from a modal shift to public transit. The remaining car users however drive longer distances and therefore emit more emissions. In contrast, the internalization policy leads to a rather strong decrease of emissions, by 1% to 2% for urban travelers and commuters, between 1.5% and 3% for inverse commuters. Only the freight population does not significantly reduce emissions. Overall, one can state that in terms of total emission reduction, the zone 30 is considerably less successful than the internalization policy. Additionally, the zone 30 affects the emission level of the urban population way to negatively and the emission levels of the other subpopulations even positively. The latter is — in comparison to the first-best internalization policy — exactly the wrong direction.

4.2 Economic Evaluation

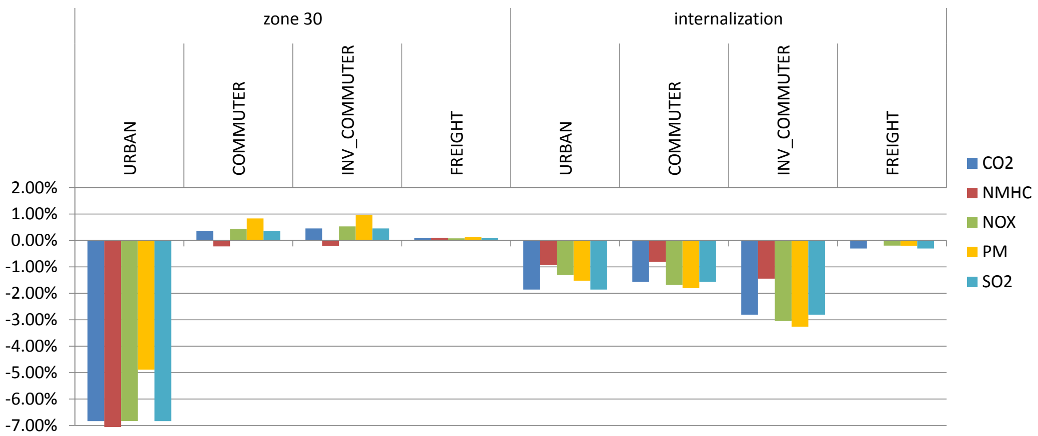
Starting again with analyzing the base case, Fig. 2a shows the absolute user benefits W in million Euro per day. It is calculated as the user logsum or Expected Maximum Utility (EMU)



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



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



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

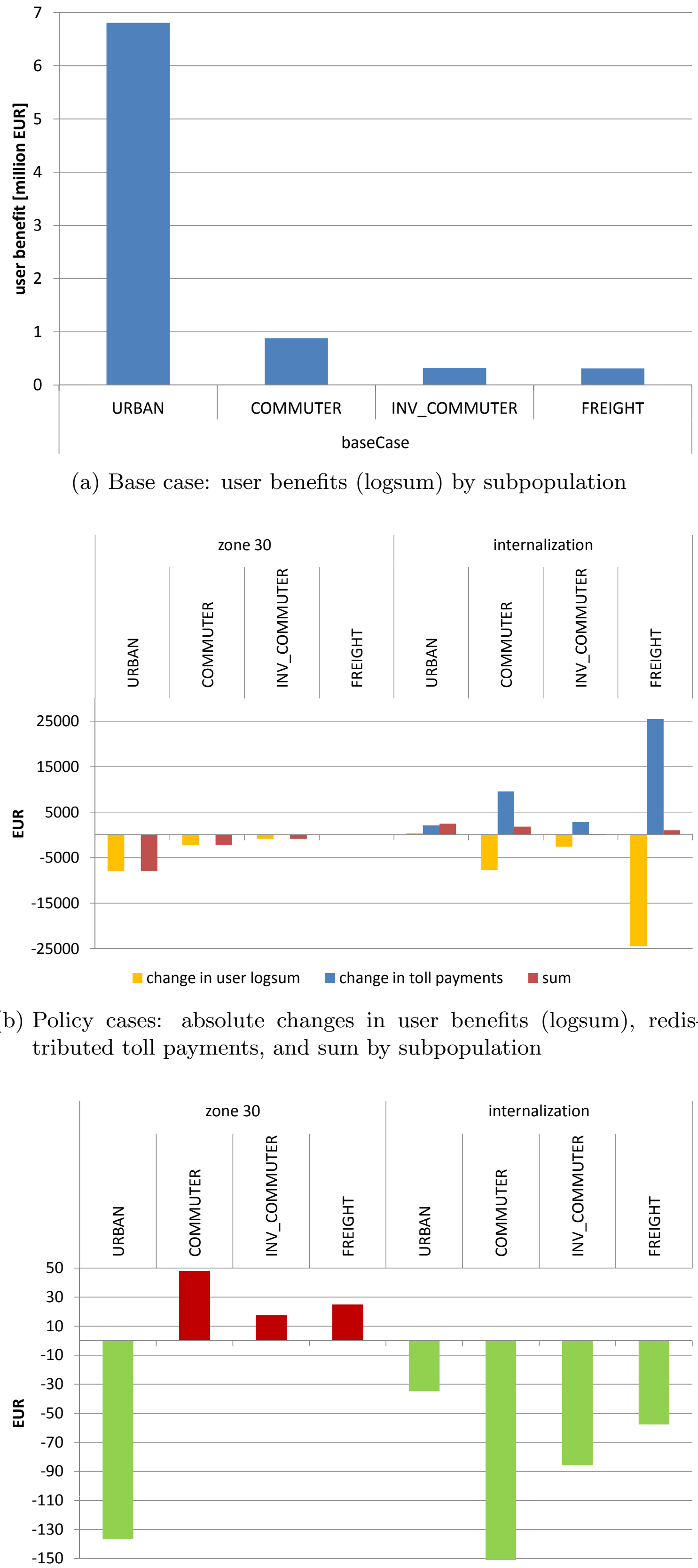
Figure 1: Emissions by emission type: absolute values by subpopulation for the base case, relative changes (overall and by subpopulation) for the two policy cases

for all choice sets of the users of the respective subpopulation *pop*:

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

where β_c is the cost related parameter from the multinomial logit model or the 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 p. The urban population contribute 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 from them spending less time and distance for transport and therefore spending more time performing activities and paying less distance costs. When introducing the two policy cases, 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, most important for the urban population, and almost without effect on the freight population. That is, urban travelers react most sensible by changing especially for longer trips from car to public transit. The remaining car users can barely profit from less car demand in the city since travel times by car are now not any more determined by congestion but by the maximum free speed of 30 km/h. Commuters and inverse 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. The freight population can only change the route which seems to have a minor effect on user benefit. The internalization policy on the right bears quite different results: commuters, inverse commuters and freight all loose in terms of user benefit; this loss is most pronounced for the freight population. That intuitively makes sense since they contribute to half of the total emissions (see Sec. 4.1 and therefore also have to pay half 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.

Now, 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 inverse 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 the two policies: for the zone 30, the loss in user benefit for commuters, inverse commuters, and freight is even becoming worse 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.



(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

5 Discussion and Outlook

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 affects the emission level of urban travelers way too negatively and the emission levels of the other subpopulations even positively. 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 $30m/h$ in the inner city of Munich leads to more market inefficiencies than a "do-nothing" strategy. When taking the internalization policy as benchmark, these two figures show that the emission (cost) reduction is too high for urban travelers; for all other subpopulations, it is even increasing 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 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, 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 would argue that the internalizing prices should be corrected exactly for that effect. I.e. by putting weights on every link that are differentiated by emission type. Weights for CO_2 would be low since it mostly has a global effect, whereas weights for PM would be high due to the 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 might, similar to the zone 30, be dis-satisfactory from an economic perspective but it is also more likely to happen in reality than the implementation of a first-best pricing scheme.

Acknowledgements

This work was funded in part by the German Research Foundation (DFG) within the research project "Detailed evaluation of transport policies using microsimulation". Important data was provided by the Municipality of Munich, more precisely by 'Kreisverwaltungsreferat München' and 'Referat für Stadtplanung und Bauordnung München'. Our computer cluster is maintained by the Department of Mathematics at Berlin Institute of Technology (TU Berlin).

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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 [Gawron, 1998, Cetin et al., 2003]: 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 [Grether et al., 2009, Rieser et al., 2009]. 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:

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

  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. Charypar and Nagel, 2005, Kickhöfer et al., 2011]:

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

  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 Tirachini et al. [2012, forthcoming]. 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 [Lefebvre and Balmer, 2007], 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.