Simulation-based optimization of congestion, noise and air pollution costs: The impact of transport users' choice dimensions

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Abstract In this study, the Pigouvian taxation principle is applied to an agent-based simulation framework. In a number of different external cost pricing simulation experiments, the interrelation of isolated congestion pricing (C), isolated noise pricing (N), isolated air pollution pricing (A) and simultaneous congestion, noise and air pollution pricing (CNA) is investigated for the real-world case study of the Greater Munich area. In contrast to previous studies, in this study, simulation experiments are carried out for different assumptions regarding transport users choice dimensions: only route choice (r) as well as mode and route choice (m+r). Overall, this study contributes to a better understanding of the interrelation of transport related external effects. For both assumptions regarding the transport users choice dimensions with and without mode choice, the simultaneous congestion, noise and air pollution pricing scheme reduces all external effects and increases the overall system efficiency. Also, with and even without mode choice, the isolated external cost pricing yields a reduction of all three external effects and an increase in overall system efficiency (positive correlation). However, this positive correlation which is observed at the aggregated level is not confirmed by a spatially disaggregated analysis: Even though isolated external cost pricing yields an overall reduction in total traffic congestion, noise and air pollution costs in the entire study area, the spatial effects are significantly different yielding some parts of

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the population better off and other parts worse off. Furthermore, this study highlights the importance to correctly account for all relevant choice dimensions. Only accounting for route choice and neglecting the fact that transport users also adjust their mode of transportation in order to react to a transport policy may underestimate the great potential of pricing.

Keywords Optimal pricing · External effects · Congestion · Noise damages · Air pollution · Simulation · Route choice · Mode choice

1 Introduction and problem statement

Following the concept of Pigouvian taxation, the system welfare is maximized by charging a toll which is equivalent to the marginal external effect. During peak times, most studies find traffic congestion to be the most significant transport related external effect (see e.g. Maibach et al., 2008; de Borger et al., 1996). During off-peak times, environmental effects such as noise and air pollution exposures are more signficant external cost components, in particular for heavy good vehicles (Maibach et al., 2008).

Several studies focus on a single external effect, i.e. traffic congestion, and address strategies, e.g. dynamic pricing, to increase the overall system efficiency (see e.g. Vickrey, 1969; Arnott et al., 1994; Friesz et al., 2004; de Palma and Lindsey, 2004).

Some studies go beyond the consideration of a single external effect and address the correlation of transport related external effects (see e.g. Calthrop and Proost, 1998; Ghafghazi and Hatzopoulou, 2014). Makarewicz and Galuszka (2011) use a speed-flow diagram to predict road traffic noise levels and find traffic congestion and noise to be inversely related, i.e. a reduction in traffic congestion increases the average noise level. In several studies, the correlation of speed level and air pollution is described as "U"-shaped, with high emission costs for low and high speed levels and low emission costs for intermediate speed levels (Barth and Boriboonsomsin, 2009; Wismans et al., 2011). The HBEFA[1] provides emission factors and differentiates, inter alia, between different area types, speed limits and the traffic states "free flow", "heavy", "saturated" and "stop-and-go". For urban roads and the traffic state "stop-and-go", emission factors are approximately twice as high compared the other traffic states.

Only few studies address the simultaneous optimization of several externalities. Shefer and Rietveld (1997) address the simultaneous optimization of congestion level and accident costs. Shefer and Rietveld (1997) highlight the importance to account for the interdependence of different external effects in cost-benefit analyses. Verhoef and Rouwendal (2003) develop a model in which car drivers optimize their speeds taking into consideration congestion and accident costs. Shepherd (2008) investigates the simultaneous pricing of CO_2 emissions and accident costs. Shepherd (2008) finds model assumptions

[1] Handbook Emission Factors for Road Transport, Version 3.1 (INFRAS, 2010)

for external effects to have a crucial effect on the policy recommendations. Li et al. (2014) develop an analytical model to address the optimal design of a cordon pricing scheme which simultaneously accounts for traffic congestion and air pollution. Li et al. (2014) find that ignoring the congestion externality, dramatically decreases the cordon toll level.

Most of the existing studies on the simultaneous optimization of several externalities make use of analytical models that are applied to illustrative and rather simplistic case studies. In few recent studies, a simulation-based optimization methodology is developed and applied to real-world case studies: Agarwal and Kickhöfer (2015) propose simultaneous internalization of traffic congestion and air pollution costs. The approach is applied to the Munich metropolitan area. The authors find that the two externalities are positively correlated and the combined pricing scheme yields the highest gain in system welfare. In a following study, Agarwal and Kickhöfer (2016) identify the amplitude of the correlation of externalities between the two externalities and provide the corrected average toll levels for peak and off-peak hours. The reduction in emission costs found in Agarwal and Kickhöfer (2015) is lower compared to a later study by Agarwal and Kickhöfer (2016). This is triggered by providing a more realistic (fast) public transit alternative to commuters and reverse commuters. This emphasize the need of a detailed investigation of transport users' choice dimensions. The computation of air pollution costs by Agarwal and Kickhöfer (2016) follows a simplified approach in which actual population exposures are neglected and an average cost factor is used to convert emissions into costs. This emission cost calculation approach is extended by Kickhöfer and Kern (2015) who explicitly account for population exposures to local air pollutants. Kaddoura et al. (2017b) internalize noise damages caused by road users and find traffic volumes on main arterial routes to increase which indicates an increase in traffic congestion. Kaddoura and Nagel (2017a) simultaneously internalize traffic congestion and noise damages for the Greater Berlin area. Despite the observation that traffic congestion and noise are negatively correlated, i.e. internalizing one effect increases the other one, the simultaneous pricing policy reveals a reduction in both external effects; with traffic congestion being the more significant external cost component during peak times; and noise exposure costs being the more significant external cost component during off-peak times. In the study by Kaddoura and Nagel (2017a), possible user reactions are limited to route choice, neglecting e.g. demand elasticity resulting from mode choice. Solé-Ribalta et al. (2017) simulate the effects of a congestion pricing scheme in the city center region of Madrid and find a local reduction of air pollutants, in particular during peak times. However, Solé-Ribalta et al. (2017) only account for route choice and do not compute the system wide effects, e.g. the change in global pollution.

This study provides several extensions compared to previous simulation-based external cost studies:

- Previous simulation-based pricing studies only address the internalization of a single external effect, (e.g. Kickhöfer and Kern, 2015; Kaddoura et al.,

2017b), or only two external effects, e.g. traffic congestion and air pollution (Agarwal and Kickhöfer, 2016), or traffic congestion and noise (Kaddoura and Nagel, 2017a). In contrast to previous studies, this study addresses the investigation and internalization of all three external effects, i.e. traffic congestion, noise damages and air pollution costs.
- In previous simultaneous internalization studies, the population density which is used to compute emission exposure costs, is assumed to be equally distributed in the study area, i.e. average factors are used to convert emissions to monetary costs (Agarwal and Kickhöfer, 2016). In contrast, this study accounts for the person-specific exposures to exhaust, integrating the approach by Kickhöfer and Kern (2015) into the simultaneous congestion and noise internalization framework.
- In previous simultaneous external cost pricing studies, the computation of congestion charges follows an approach by Kaddoura and Kickhöfer (2014) and Kaddoura (2015) in which person-specific road charges depend on the position in the queue, in particular the number of following road users. In this study, an improved congestion pricing approach is used, which computes road-specific and time interval-based congestion charges that are updated from one iteration to the next one based on the level of traffic congestion (Kaddoura and Nagel, 2017b).
- Going beyond the scope of previous studies, this study explicitly investigates the impact of transport users' choice dimensions in the context of external cost pricing. All simulation experiments are carried out for two different assumptions regarding transport users' choice dimensions: In a first simulation setup, transport users are only allowed to adjust their transport routes. In a second simulation setup, transport users are allowed to adjust their transport route *and* mode of transportation.
- In contrast to previous studies, this study provides a more detailed look into the spatial network effects resulting from the simultaneous pricing scheme.

This paper is structured as follows: Sec. 2 describes the applied transport simulation framework as well as the simulation-based external cost pricing approaches. Sec. 3 describes the case study of the Munich municipality region and the simulation experiments. Sec. 4 provides the simulation results and discussion. The simulation outcome is analyzed with regard to the enabled choice dimensions both at the aggregated and spatially and temporally disaggregated level. Finally, Sec. 5 briefly summarizes the main findings.

2 Methodology

2.1 Transport simulation: MATSim

The applied optimization approach makes use of the open-source transport simulation framework MATSim (Multi-Agent Transport Simulation, see `www.matsim.org`). In MATSim, transport users are considered as individual agents.

Each agent's behavior is described by a daily travel plan, e.g. when to end an activity and how to travel to the next activity location. The agents are enabled to iteratively adjust their travel behavior. Every iteration, (1) the daily travel plans are executed (Traffic flow simulation), (2) evaluated (Evaluation) and (3) modified (Learning).

1. **Traffic Flow Simulation** The agents simultaneously execute their daily travel plans and interact in the simulated physical environment. The traffic flow simulation is based on a queue model. Each road segment (link) is modeled as *First In First Out* queue (Gawron, 1998) and has the following attributes: length, number of lanes, free speed and flow capacity c_{flow}. The flow capacity limits the outflow of vehicles, e.g. to one vehicle every 2 seconds if the flow capacity is set to 1800 vehicles per hour. The storage capacity is defined by the link's length and number of lanes. An agent's travel time results from the free speed travel time plus the delay at the current link's queue or spillback from downstream links. The resulting traffic flows are consistent with the fundamental diagram (see e.g. Agarwal et al., 2015). *Link* and *road segment* are used interchangeably; a link typically describes the connection from one junction to the next one; in case there is a significant change of road attributes (e.g. number of lanes, free speed level) between two junctions, additional links are used to account for the network characteristics.
2. **Evaluation** The agents evaluate their travel behavior, i.e. the executed plans, based on predefined utility functions and behavioral parameters. A plan's utility is typically composed of a trip-related disutility (e.g. travel time, toll, distance-based cost) and a utility gained from performing activities. The latter part follows the approach by Charypar and Nagel (2005) where the marginal gain is typically positive but decreases with the time spent performing an activity, see Eq. 1.

$$V_{p,a} = \beta^{perf} \cdot t_a^{typ} \cdot \ln\left(t_{p,a}^{perf} / t_{0,a}\right) \ , \tag{1}$$

   where $t_{p,a}^{perf}$ is the time person p performs activity a, t_a^{typ} is an activity's *typical duration*, β^{perf} is the marginal utility of performing an activity at its typical duration, and $t_{0,a}$ is a scaling parameter, see Horni et al. (2016, Sec. 97.4.2) for a discussion of this setting.
3. **Learning** During the phase of choice set generation, a predefined share of randomly chosen agents generate new plans by making a copy of an existing plan and changing parts of the copied plan such as the transport route (the sequence of links) or the mode of transportation (e.g. car, public transit, bicycle, walk). The other agents, or all agents in the phase of choice set selection, choose among their existing plans based on a multinomial logit model.

A repetition of these steps enables the agents to improve and obtain plausible daily travel plans, and the simulation outcome stabilizes. Assuming each agent's set of daily travel plans to represent a valid choice set, the outcome is an approximation of the stochastic user equilibrium (Raney and Nagel, 2006; Nagel and Flötteröd, 2012; Horni et al., 2016).

2.2 Internalization of congestion, noise and air pollution costs

The Pigouvian taxation principle is applied to MATSim as follows: MATSim is used to iteratively compute and adjust an approximation of the optimal toll levels: In a first step, toll levels are computed based on the external congestion, noise and air pollution costs. In a second step, transport users are enabled to react to these road charges by adjusting their transport route and/or travel mode. Then, the toll levels are adjusted based on the updated external costs, and so on.

For each road segment, user, and time of day, the toll is computed as the sum of a congestion charge, marginal noise cost and marginal air pollution cost. A detailed description of the applied external cost pricing approaches is provided below.

Congestion pricing The computation of congestion charges follows the interval-based list pricing approach presented in Kaddoura and Nagel (2017b). For each road segment and time bin, the congestion charge is computed based on the congestion level and adjusted from iteration to iteration. In this study, the congestion charge is set to a value proportional to the average delay. All agents traveling on the same road segment and within the same time interval are charged the same amount. The price per road segment is adjusted as follows:

$$m_{r,t,k} = K_p \cdot d_{r,t,k} \ , \qquad (2)$$

where $m_{r,t,k}$ denotes the toll per link r and time interval t, k is the iteration in which the toll is adjusted, K_p is a tuning parameter and $d_{r,t,k}$ is the average delay per transport user. K_p is set to twice the value of travel time savings (VTTS) which in previous simulation experiments produces good results in terms welfare maximization and may economically interpreted as an approximation of the marginal congestion costs (Kaddoura and Nagel, 2017b).

Noise pricing The computation of noise levels follows the methodology described in Kaddoura et al. (2017a). In a first step, hourly noise levels are calculated based on the German RLS-90 approach ('Richtlinien für den Lärmschutz an Straßen', FGSV, 1992) taking into account the traffic volume, the share of heavy goods vehicles and the speed level. In a second step, the potentially affected individuals are dynamically computed, making use of the dynamic and activity-based simulation framework. The resulting population densities account for all agents performing any type of activity (e.g. home, work, leisure); on-road exposures are not considered. In a third step, the population densities and noise levels are used to compute noise damages following the methodology described in the German EWS approach ('Empfehlungen für Wirtschaftlichkeitsuntersuchungen an Straßen') which suggests a time-dependent, threshold-based monetization (FGSV, 1997). In a final step, for each road segment, time interval and vehicle type, marginal noise damage costs are computed following the methodology described in (Kaddoura and Nagel, 2016): Marginal noise exposure costs are

$$\begin{aligned} mc_t^{car,r} &:= \sum_j \left(C_{j,t}(I_{j,t}^{car,r}) - C_{j,t}(I_{j,t})\right) \\ mc_t^{hgv,r} &:= \sum_j \left(C_{j,t}(I_{j,t}^{hgv,r}) - C_{j,t}(I_{j,t})\right) \end{aligned} \tag{3}$$

where $mc_t^{car,r}$ are the marginal costs of an additional car on link r in time interval t; $mc_t^{hgv,r}$ are the marginal costs of an additional HGV on link r; and $C_{j,t}$ are the noise costs at receiver point j; $I_{j,t}^{car,r}$ is the noise level resulting from an additional car on link r; $I_{j,t}^{car,r}$ is the noise level resulting from an additional HGV on link r; and $I_{j,t}$ is the current noise level.

Air pollution pricing The applied air pollution emission modelling tool is developed by Hülsmann et al. (2011) and, further improved and extended by Kickhöfer et al. (2013). In a first step, vehicle characteristics (vehicle type, age, cubic capacity, fuel type etc.), dynamic attributes (parking duration, distance travelled, speed) and road types are used to get the cold (during warm up phase of vehicle) and warm emissions from HBEFA[2] database. In a second step, the exhaust emissions are converted to monetary units using the average emission cost factors (see Tab. 1) given by Maibach et al. (2008). In this study, for local air pollutants[3], population exposures are computed based on the methodology proposed by Kickhöfer and Kern (2015). For this, the network is divided into discrete cells of size $l = 250\ m$. The effect of air pollution is distributed to the neighboring cells using Eq. 4.

$$d_j = F \cdot \exp(-\frac{x_j^2}{2l^2}) \tag{4}$$

where x_j is the distance between the center of the cell in which a vehicle is causing emissions (source-cell) and the center of the cell j where agents perform activities (receptor-cell). F is a normalization factor such that distribution factors for all neighboring cells sum up to unity. The resulting costs are then charged from the causing agent. Since CO_2 is a global air pollutant, the CO_2 emission costs are charged from the causing agent using the average cost factor by Maibach et al. (2008) without any computation of population exposures.

[2] Handbook Emission Factors for Road Transport, Version 3.1, see www.hbefa.net (INFRAS, 2010)

[3] In this study, Sulfur Dioxide (SO_2), Particular Matter (PM2.5), Nitrogen Oxides (NO_x), Non-Methane Hydrocarbons (NMHC), and Carbon Dioxide (CO_2) are considered as local air pollutants.

Table 1: Emission cost factors. Source: 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

3 Case study

3.1 Greater Munich area, Germany

The case study of the Greater Munich area was initially generated by Kickhöfer and Nagel (2016) and further improved by Agarwal and Kickhöfer (2016). The MATSim network is generated based on a VISUM[4] data (RSB, 2005) model. Demand for greater Munich area is categorized into three parts. (a) inner urban demand is created using detailed survey data (Follmer et al., 2004, MiD 2002) which contains more than 1.4 million individuals, (b) commuters and reverse commuters are synthesized using data provided by Böhme and Eigenmüller (2006) in which about 0.3 million are commuters and about 0.2 million are reverse commuters and, (c) about 0.15 million freight trips are generated using data provided by German Ministry of Transport (ITP and BVU, 2007).

3.2 Simulation experiments

In this study, different pricing schemes, i.e. no pricing, isolated congestion pricing (C), isolated noise pricing (N), isolated air pollution pricing (A), and simultaneous congestion, noise and air pollution pricing (CNA), are applied to the case study of Munich. Each combination of pricing scheme and case study is investigated for two different assumptions regarding the transport users' choice dimensions, i.e. route choice only (r) vs. mode and route choice (m+r). A summary of all simulation experiments is provided in Tab. 2.

To improve the computational performance, in this study, the sample size is reduced to 1% of the total population. Each link's flow and storage capacity (see Sec. 2.1) is accordingly reduced; the flow capacity is reduced to 1% and the storage capacity is reduced to 3% which in previous studies is found to provide more realistic traffic congestion patterns. That is, the underlying queue model accounts for the reduced sample size (see e.g. Agarwal et al., 2017) and produces realistic congestion patterns.

[4] 'Verkehr In Städten UMlegung', see www.ptv.de

Table 2: Simulation experiments

	route choice only (r)	mode and route choice (m+r)
Base case continued (No Pricing)	✓	✓
Isolated congestion pricing (C)	✓	✓
Isolated noise pricing (N)	✓	✓
Isolated air pollution pricing (A)	✓	✓
Simultaneous congestion, noise and air pollution pricing (CNA)	✓	✓

4 Results and discussion

4.1 Aggregated effects

Tab. 3 provides the simulation outcome for the pricing experiments with and without mode choice. The system welfare is computed as

$$W = V^{users} + R - C^{noise} - C^{air} \tag{5}$$

where W is the system welfare per day, R are the total daily toll revenues, C^{noise} are the total daily noise costs, C^{air} are the total daily air pollution costs and V_{users} are the daily user benefits which include the congestion costs and are computed as

$$V^{users} = \frac{1}{\beta_m} \cdot \sum_p \sum_a V_{p,a} - \sum_p C_p^{trip} \tag{6}$$

where $V_{p,a}$ is a person's p positive utility for performing an activity a (see Eq. 1), β_m is the marginal utility of money and C_p^{trip} are the person's trip-related costs including the monetary toll payments. All pricing experiments are found to yield a positive change in system welfare compared to the base case (no pricing). The simultaneous pricing experiment (CNA) results in the largest increase in system welfare.

The additional choice dimension of transport users adjusting their mode of transportation is observed to increase the absolute change in external costs. That is, allowing for mode choice reinforces the impact of pricing. The increase in system welfare resulting from the pricing policy is much larger for the simulation experiments with mode choice compared to the simulation experiments without mode choice. In the simulation experiments with mode choice, the toll revenues are much lower compared to the simulation experiments without mode choice. This is explained by the additional choice dimension, i.e. transport users with high toll payments and no meaningful alternative route are now enabled to avoid the toll payments by switching to the toll-free public transit mode. Also, the increase in system welfare in relation to the toll revenues becomes much larger.

Table 3: Changes in aggregated simulation results compared to the base case; scaled to full population; typical work day.

Only route choice

Change in ...	C	N	A	CNA
number of car trips	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
average travel distance per car trip [km]	≈ 0 (1.14%)	≈ 0 (0.02%)	≈ 0 (-0.03%)	≈ 0 (1.11%)
average travel time per car trip [sec]	-287 (-11.40%)	-11 (-0.45%)	-15 (-0.61%)	-273 (-10.84%)
delay [hours]	-139,631 (-29.68%)	-5,474 (-1.16%)	-3,564 (-0.76%)	-135,446 (-28.79%)
noise costs [EUR]	-9,488 (-1.66%)	-19,168 (-3.35%)	-26,127 (-4.57%)	-31,721 (-5.55%)
air pollution costs [EUR]	-90,133 (-2.64%)	-50,506 (-1.48%)	-262,964 (-7.72%)	-290,147 (-8.51%)
toll revenues [EUR]	5,242,709	187,370	3,145,114	8,632,478
system welfare [EUR]	3,123,797	75,051	653,041	3,187,310

Mode and route choice

Change in ...	C	N	A	CNA
number of car trips	51,500 (2.56%)	-500 (-0.02%)	-103,300 (-5.13%)	-92,500 (-4.60%)
average travel distance per car trip [km]	-2 (-6.31%)	≈ 0 (-0.69%)	-2 (-5.01%)	-4 (-10.54%)
average travel time per car trip [sec]	-404 (-16.12%)	-42 (-1.66%)	-275 (-10.99%)	-555 (-22.18%)
delay [hours]	-141,292 (-30.34%)	-16,003 (-3.44%)	-111,480 (-23.94%)	-203,817 (-43.77%)
noise costs [EUR]	-3,550 (-0.63%)	-18,991 (-3.38%)	-42,026 (-7.49%)	-58,185 (-10.37%)
air pollution costs [EUR]	-74,070 (-2.23%)	-71,563 (-2.15%)	-521,652 (-15.71%)	-606,226 (-18.25%)
toll revenues [EUR]	4,769,564	187,522	2,799,642	6,926,436
system welfare [EUR]	3,523,119	421,959	2,610,615	5,087,305

Allowing transport users to switch to an alternative mode of transportation, in the simultaneous pricing experiment, the number of car trips decreases by 4.6% (shift towards the public transit mode). An interesting observation is that in the isolated congestion pricing scheme (C) the number of car trips increase by 2.56%, yet, the total car travel distance and delays within the car mode are reduced. This is explained by a capacity relief effect in the city area, i.e. long distance commuters switch from car to alternative modes which reduces traffic congestion and makes the car mode more attractive for short distance inner urban travelers. A similar finding is reported by Agarwal and Kickhöfer (2016) in which emission pricing results in an increase in urban car trips.

In the only route choice simulation setup, toll payments can only be avoided by switching to alternative roads. Changes in average travel distance per car trip slightly increases in experiment C, N and CNA and slightly decreases in experiment A.

For both assumptions regarding the users' choice dimensions, isolated external cost pricing results in a reduction of the internalized effect, i.e. a decrease in total delay for experiment C, a decrease in noise costs for experiment N, and a decrease in air pollution costs for experiment A. Furthermore, simultaneous pricing experiments (CNA) results in an overall reduction of all three internalized external effects.

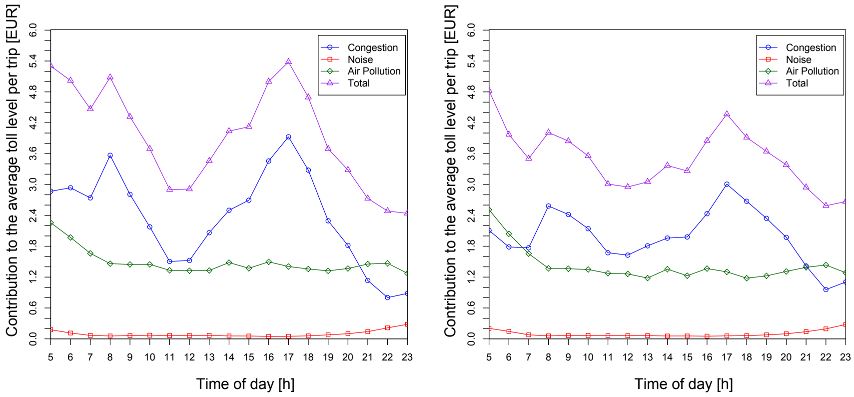
For all pricing experiments with and without mode choice, there is a positive correlation between the different external costs, i.e. pricing one effect results in a reduction of all external effects. Similar positive effects at the aggregated level are also observed in Agarwal and Kickhöfer (2016) and Agarwal and Kickhöfer (2015). For the simulation experiment with mode choice this intuitively makes sense since transport users switch from car to alternative modes. For the simulation experiment without mode choice, this observation may be explained by the spatial structure in the Munich region, in particular a positive correlation of congested roads and densely populated areas with potentially large air pollution and noise exposure costs.

The positive correlation observed in Tab. 3 in only valid at the aggregated level. At the spatially disaggregated level, the correlation effects are observed to be different, see below in Sec. 4.5.

4.2 Resulting toll payments

In the simultaneous pricing experiments, the average toll per trip varies between 3.00 EUR and 5.40 EUR (without mode choice), and 2.50 EUR and 4.80 EUR (with mode choice), depending on the time of the day. Fig. 1 provides a temporal analysis of each external effects' contribution to the average toll per trip. Noise-related toll payments are observed to be at a very low level, in particular during peak times. This may be related to the logarithmic scale of noise, i.e. marginal noise cost tolls decrease for higher traffic volumes. The congestion externality seems to be the most significant externality; during the day, congestion charges are higher compared to air pollution charges. Congestion-related toll payments increase during the morning and afternoon/evening peak which can be explained by the overall larger congestion level. The contribution of noise charges to the average toll is slightly larger in the early morning, late evening and the night. This is explained by lower cost thresholds, larger population exposures and higher marginal noise cost due to lower absolute traffic volumes. The contribution of air pollution charges to the average toll level decreases during peak times which can be explained by the higher relevance of congestion charges during these times as well as a reduced number of exposed people (on-road exposures are not considered[5]).

[5] For a study which explicitly accounts for on-road exposures, see Agarwal and Kaddoura (2018).



(a) only route choice (r) (b) Route and mode choice (m+r)

Fig. 1: Munich: Tolls per time of day (CNA)

4.3 Mode switch analysis

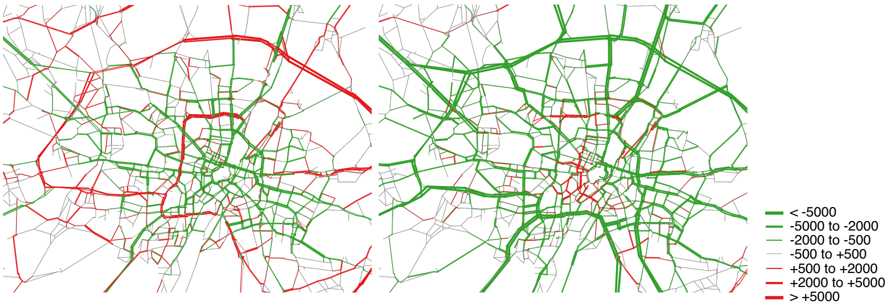
In Tab. 4, the simultaneous pricing experiment without mode choice is analyzed for two different user types: “car retainers” and “car to non-car switchers”. The user type is identified by looking into the simulation outcome of the pricing experiment with mode choice (m+r). Average toll payments by “car retainers” are observed to be much lower compared to the average toll payments by “car to non-car switchers”. That is, “car retainers” prefer to pay the relatively low tolls rather than switching to an alternative mode. In contrast, “car to non-car switchers” prefer to avoid the relatively high tolls by switching the mode of transportation—in case they are allowed to do so (simulation experiments with mode choice; m+r).

Table 4: Average toll per trip (CNA; r)

	Contribution of each external effect			
Considered users	Congestion	Noise	Air pollution	$\sum$
Car retainers	2.11	0.06	1.33	3.50
Car to non-car switchers	2.89	0.12	1.55	4.55

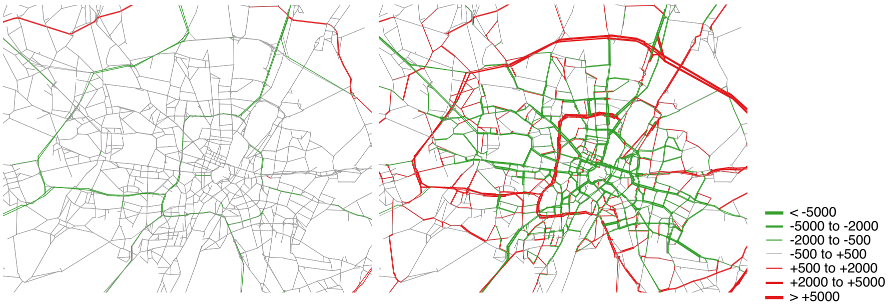
4.4 Changes in traffic volume

Fig. 2 depicts the changes in daily traffic volumes resulting from the simultaneous pricing experiment. In the only route choice (r) simulation setup, transport users shift from the densely populated inner-city area to the western inner-city ring road as well as to the outer-city motorway ring road. In contrast, with mode and route choice (m+r), overall traffic volumes are reduced on most roads including the outer-city motorway ring road. Only for some roads in the city center area an increase in traffic volume is observed.



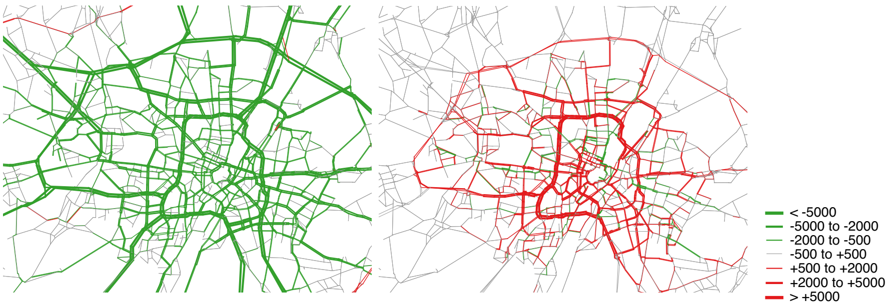
(a) Only route choice (r) (b) Mode and route choice (m+r)

Fig. 2: Total changes in daily traffic volumes resulting from the simultaneous pricing experiment (CNA).



(a) Freight traffic (b) Inner urban traffic + commuters

Fig. 3: A more detailed look into Fig. 2a: Changes in daily traffic volumes per user type resulting from the simultaneous pricing experiment (CNA - only route choice).



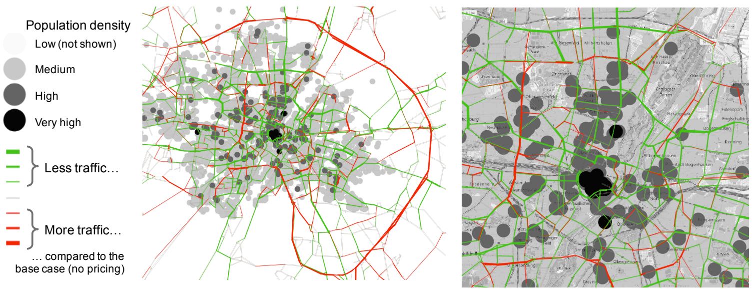
(a) Freight traffic + commuters (b) Inner urban traffic

Fig. 4: A more detailed look into Fig. 2b: Changes in daily traffic volumes per user type resulting from the simultaneous pricing experiment (CNA - mode and route choice).

Fig. 3 shows the change in traffic volume per user type resulting from the simultaneous pricing experiment in the route choice only setup (Fig. 3a: change in freight vehicles, Fig. 3b: change in inner urban traffic and commuters). Fig. 3a points out that the number of freight vehicles decreases on the western inner city ring road. In contrast, the number of inner urban travelers and commuters increases (see Fig. 3a) which yields the increase in overall traffic volume on the western inner city ring road observed in Fig. 2a.

The increase in traffic on inner-city roads in the route and mode choice simulation setup (m+r) observed in Fig. 2b is explained by the overall lower level of traffic congestion caused by long-distance commuters, which makes the car mode more attractive for short distance trips in the inner-city center area. This effect is visualized in Fig. 4 which provides the changes in daily traffic volumes resulting from the simultaneous pricing scheme (CNA) filtered by user type. The number of freight vehicles and commuters decrease for most road segments (see Fig. 4a). In contrast, inner urban traffic increases on most road segments (see Fig. 4b). This spatial observation is supported by the reduction in average trip distance which decreases by 4 km compared to the base case (see Tab. 3).

Fig. 5 depicts two layers: the changes in traffic volumes per road segment between 3.00 and 4.00 p.m. resulting from the simultaneous pricing scheme (CNA) without mode choice (r) and the population density in the base case for the same time bin. Overall, transport users avoid the city center area by

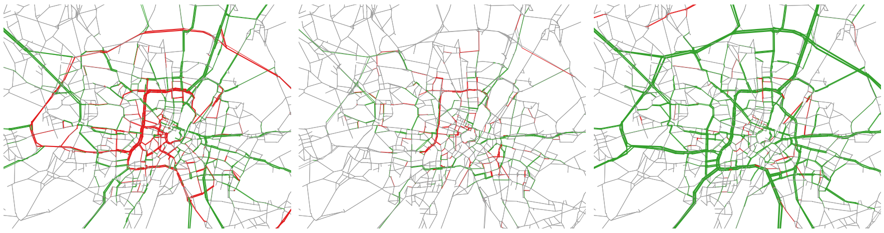


(a) Greater Munich area (b) Munich city center area

Fig. 5: Changes in traffic volumes resulting from the simultaneous pricing experiment (CNA) without mode choice (r); 3-4 p.m.; Map layer: © OpenStreetMap contributors.

taking the outer-city motorway ring road, where (i) population densities are very low and (ii) congestion effects are at an overall lower level. A closer look into the city center area reveals the same effects: transport users avoid (i) areas with high and very high population densities and (ii) typically congested roads, e.g. in Munich, by using the inner-city ring road around the city center area instead of direct routes through the city center area.

Fig. 6 depicts the changes in daily traffic volume resulting from the isolated pricing experiments with mode choice (m+r). The effects observed in the isolated pricing experiments may help to understand the changes in traffic volume resulting from the simultaneous pricing experiment shown in Fig. 2b. An interesting observation is that isolated congestion pricing (C) and air



(a) Exp. C (b) Exp. N (c) Exp. A

Fig. 6: Change in daily traffic volume resulting from the isolated pricing schemes; Simulation setup with mode choice (m+r).

pollution pricing (A) show a contrary effect regarding the changes in traffic volume. Congestion pricing increases the usage of the inner- and outer city ring roads. In contrast, air pollution pricing yields reduced traffic volumes on the inner- and outer city ring roads.

4.5 Changes in air pollution and noise

Fig. 7 depicts the changes in daily NO_x (Nitrogen Oxides) and noise L_{den} levels (day-evening-night index) resulting from the simultaneous pricing scheme (CNA). With and without mode choice the NO_x and noise level is significantly reduced in the inner-city area. For NO_x levels, similar results are also observed in Agarwal and Kickhöfer (2016). In the simulation setup with mode choice, this effect is stronger compared to the simulation setup without mode choice. This is explained by the reduction in number of car trips and average car travel distance.

A comparison of Fig. 7 with Fig. 2 reveals that for some roads the change in NO_x and noise levels do not correlate with the change in traffic volume (see e.g. the western inner-city ring road in the route choice only case). This is explained by Fig. 3 which shows the change in traffic volume per user type resulting from the simultaneous pricing experiment in the route choice only setup (left: change in freight vehicles, right: change in inner urban traffic and commuters). Fig. 3a points out that the number of freight vehicles decreases which causes the observed reduction in NO_x emissions.

Changes in noise levels are observed to be very large even though changes in daily traffic volumes are minor (see e.g. in the southwestern Greater Munich area). This may be explained by the logarithmic scale of noise. Also, the temporal distribution of travel demand plays an important role, i.e. the L_{den}

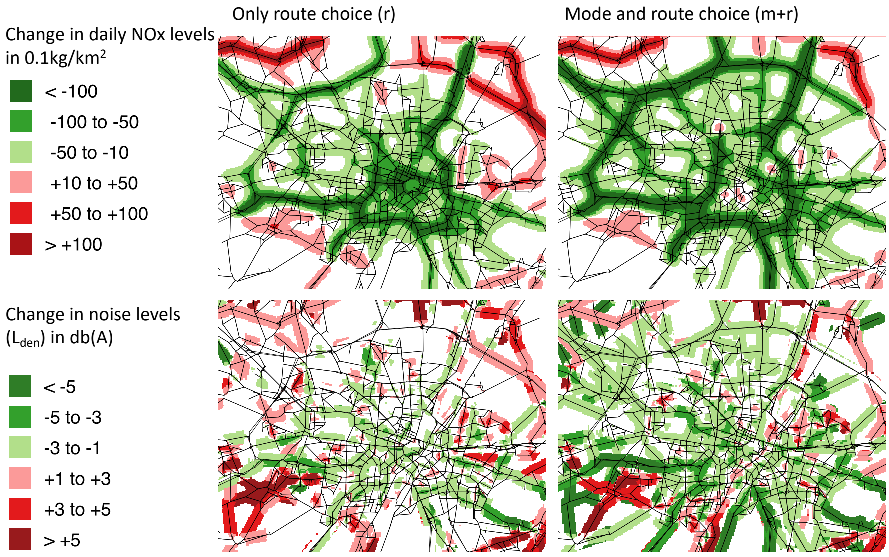


Fig. 7: Changes in air pollution exposures and noise levels resulting from the simultaneous pricing scheme (CNA) with (m+r) and without mode choice (r).

noise index adds a penalty of several dB(A) to noise levels in the evening and night time periods.

Fig. 8 and Fig. 9 depict the changes in NO_x and noise L_{den} level for each isolated pricing experiments. Local changes in NO_x are observed to be very different in experiment C, N and A. Isolated congestion pricing yields an increase in NO_x in the outer city ring road as well as in the city center area which is explained by the increase in inner urban traffic. Isolated noise pricing yields slight reduction in NO_x in the city center area and increase in NO_x along the outer city ring road. Isolated air pollution pricing yields an overall reduction in NO_x in the city center area as well as along the outer city ring road. Changes in noise levels are observed to be very low in the isolated congestion (C) and noise pricing (N) scheme. In the isolated air pollution pricing scheme (A), the changes in noise levels are similar to the changes in experiment CNA.

4.6 Discussion

At the aggregated level, congestion, noise and air pollution are found to be positively correlated. For the simulation setup with mode choice, this is in line with previous studies (see e.g., Agarwal and Kickhöfer, 2015, 2016) and intuitively makes sense since the internalization of a single externality is expected to make the car mode less attractive and to yield a shift from the car mode to alternative modes. The simulation outcome reveals that this speculation is only partly correct. In the isolated congestion pricing scheme a rebound effect

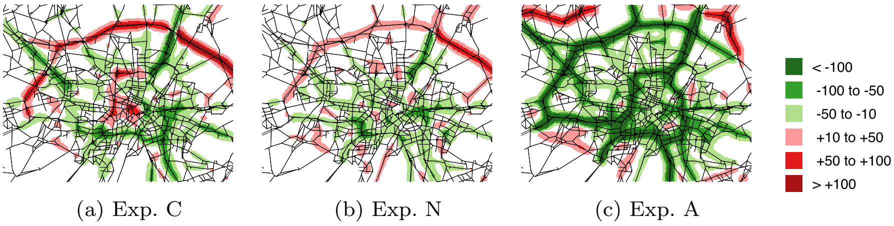


Fig. 8: Change in daily NO_x levels in $0.1 kg/km^2$ resulting from the isolated pricing schemes; Simulation setup with mode choice (m+r).

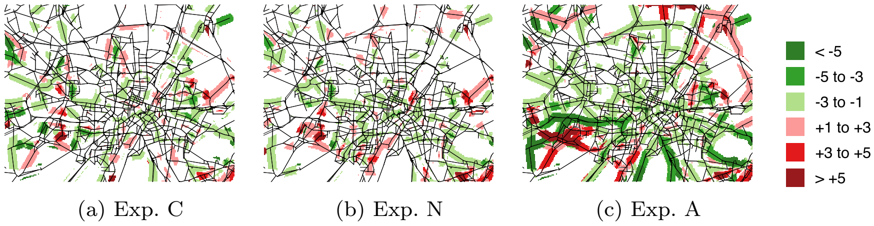


Fig. 9: Change in noise L_{den} levels in dB(A) resulting from the isolated pricing schemes; Simulation setup with mode choice (m+r).

is observed, i.e. the number of long-distance car trips (commuters) are replaced by a larger number of short distance car trips (inner urban traffic). Yet, the overall level of traffic congestion is significantly reduced.

One of the finding is, that in the Munich case study, the positive correlation of congestion, noise and air pollution is also observed in the simulation setup without mode choice. This stands in contrast to a previous study by Kaddoura and Nagel (2017a) for the case study of the Greater Berlin area, where the correlation of congestion and noise was found to be negative. An explanation for this may be a different spatial correlation of traffic congestion effects and population densities in the Berlin and Munich case study. The positive correlation indicates that traffic congestion occurs in areas with high population densities where the number of people potentially exposed to air pollution and noise is high.

A further finding is that the positive correlation which is observed at the aggregated level is not confirmed by the spatially disaggregated effects, i.e. the changes in traffic volume per road segment and the resulting changes in traffic congestion, air pollution and noise. That is, isolated external cost pricing yields an overall reduction in total traffic congestion, noise and air pollution costs in the entire study area, however, spatially the effects are significantly different yielding some parts of the population better off and other parts worse off. With mode choice one might have speculated that mode shift effects from car to alternative modes result in reduced noise and air pollution levels in the entire area. This is, however, not the case and may be explained by the rebound effect described above, i.e. some parts of the population (in particular long distance commuters) shift from car to the public transit which makes the car mode more attractive for other parts of the population (in particular inner urban travelers) with spatially different travel patterns (origins, destinations and routes).

The effect of noise tolling is found to be rather low in the Munich case study. In contrast, in previous studies for the Greater Berlin area, the impact on transport users' route choice decisions was much larger (Kaddoura and Nagel, 2017a, 2016). This may be explained by the network resolution: In previous studies for the Greater Berlin area, the road network contains all road types, including minor roads where traffic volumes are rather low and consequently marginal cost noise tolls are at a higher level. In contrast, the present case study of the Greater Munich area only accounts for the main road network where traffic volumes are higher and consequently marginal noise toll levels are rather low, in particular during peak times.

In this study, the alternative modes of transportation, i.e. bicycle and public transit, are simulated in a simplified way, i.e. transport users are teleported with a predefined speed from one activity location to the next one. That is, spatial or temporal differences in the public transit mode are not accounted for. Furthermore, capacity constraints and external effects, such as delays imposed on other travelers within the public transit mode (see e.g., Kaddoura et al., 2015), are neglected. Accounting for capacity constraints and extending the external cost pricing scheme to all alternative modes is expected to make the alternative modes less attractive and weaken the observed mode shift effects.

This study neglects the fact that transport users may have some flexibility in their activity scheduling decisions and may travel earlier or later. Departure time choice allows travelers to remain within the car mode but still to avoid congested peak times or high toll payments, e.g. congestion charges during peak times or noise charges in the early morning or late evening. That is, departure time choice increases the attractiveness of the car mode. This, in consequence, may weaken the observed mode shift effects and reduction in external costs: Car travelers will rather travel earlier or later in order to reduce their external cost toll payments than switching to an alternative mode where their external cost payments would have been zero.

This study also neglects mode-specific operating and maintenance costs which vary depending on the level of usage. Adding these cost components to the system welfare may have a substantial effect on the overall results.

This study only focuses on congestion, noise and air pollution. Accounting for further external effects, such as accident costs, may have an impact on the optimal route and mode choice decisions. Assuming marginal external accident costs to correlate with the population density, accident cost pricing may push towards the same direction as the air pollution and noise pricing schemes, where costs are also computed accounting for the population density. Since accident costs may be assumed to be larger for higher speed levels (Shefer and Rietveld, 1997; High Level Group on Transport Infrastructure Charging, 1999), without mode choice, there might be a negative correlation with congestion pricing, which reduces congestion and increases the speed level. In contrast, with mode choice, accident cost pricing is expected to be positively correlated with the other external cost pricing schemes since the overall car toll level increases and pushes further towards alternative modes of transportation.

5 Conclusion

In this study, the Pigouvian taxation principle is applied to an agent-based simulation framework. In a number of different external cost pricing simulation experiments, the interrelation of isolated congestion pricing (C), isolated noise pricing (N), isolated air pollution pricing (A) and simultaneous congestion, noise and air pollution pricing (CNA) is investigated for the real-world case study of the Greater Munich area for two different assumptions regarding the transport users choice dimensions, only route choice (r) as well as mode and route choice (m+r).

Overall, this study contributes to a better understanding of the interrelation of transport related external effects both at the aggregated and disaggregated level. For both assumptions regarding the transport users choice dimensions (with and without mode choice) the simultaneous congestion, noise and air pollution pricing scheme reduces all external effects and increases the overall system efficiency. At the aggregated level, the isolated external cost pricing experiments are found to reduce all other external effects (positive correlation of external effects). This is even found for the simulation setup without mode choice which indicates that traffic congestion occurs in areas with high population densities where the number of people potentially exposed to air pollution and noise is at a higher level. In contrast to previous studies, this study also looks into the spatially disaggregated effects. Even in the simulation experiments with mode choice, for certain areas the correlation in traffic congestion, noise and NO_x is found to be negative, yielding different parts of the population better off and worse off. Nevertheless, at the aggregated level, the correlation of external effects is positive and pricing a single external effect reduces all other external effects.

Furthermore, this study highlights the importance to correctly account for all relevant choice dimensions. Only accounting for route choice and neglecting the fact that transport users also adjust their mode of transportation in order to react to a transport policy may underestimate the great potential of pricing. On the other hand, as discussed in Sec. 4.6, neglecting further choice dimensions such as departure time choice, may overestimate the mode shift effects and the resulting increase in system welfare.

Based on these findings, the overall policy recommendation is that transport policies should be designed very carefully. Transport policies that only address a single externality may have a positive effect at the aggregated level, however, may lead to a negative effect at the disaggregated level, e.g. an increase in air pollution in some areas, which leaves some parts of the population worse off. Designing a policy which accounts for all external effects seems to be a good strategy to keep the local negative side effects low, however, does not provide a guarantee to reduce all external effects in the entire study area or prevent undesired rebound effects. To prevent such undesired rebound effects (here: increase in inner-urban traffic), it seems reasonable to combine the concept of external cost pricing with further transport policies.

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