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The correlation of externalities in marginal cost pricing: Lessons learned from a real-world case study

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Abstract The ongoing urbanization process all around the globe is likely to increase negative externalities which already today can amount to a significant share of a country's GDP (Gross Domestic Product). In order to mitigate the resulting efficiency losses, different strategies need to be developed which aim at behavioral changes of individuals. This paper presents an approach to correct for the inefficiencies emerging from two externalities, namely vehicle emissions and congestion. It investigates and compares separate pricing schemes for emissions and congestion, and subsequently proposes a joint internalization of both externalities while considering heterogeneity in individual attributes and choice behavior. The proposed approach is applied to a real-world scenario of the Munich metropolitan area in Germany. On the system level, the results indicate that pricing one externality has positive impacts on the other externality. Furthermore, efficiency gains are found to be most important for the joint internalization policy. However, because of the correlation between the externalities, exogenous emission cost estimates need to reduced for combined pricing schemes to avoid overpricing. Since emissions are found to contribute more to the overall toll in off-peak hours, this reduction needs to be stronger in peak hours. For congestion, which contribute more to the overall toll in peak hours, the corresponding reduction needs to be stronger in off-peak hours. Finally, on the disaggregated level, the results show that pricing emissions moves individuals to shorter distance routes, whereas pricing congestion pushes towards longer distance routes. That is, despite the correlation between the two externalities, isolated pricing strategies influence route

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choice behavior by tendency into opposite directions.

Keywords Air Pollution · Congestion · Vehicle Emissions · Road Pricing · Combined Pricing · Internalization

1 Introduction

Improvements in the transport sector yields positive externalities such as increased accessibilities, increased land values, agglomeration benefits, etc. On the contrary, they also impose negative externalities[1] on society. These include accidents, congestion, damages to the environment and human health (see, e.g., Weinreich et al 1998; Maibach et al 2008). The expected increase in mobility needs in densely populated areas, mainly resulting from urbanization processes, is likely to increase the negative externalities. The presence of negative externalities is known to result in inefficiencies unless the underlying external costs are reflected in the market prices for mobility, i.e. considered in people's mobility decisions. Potential efficiency gains amount to a considerable share of a country's GDP (Gross Domestic Product): For example, the total external costs by motorized traffic in Beijing is estimated to range between 7.5% and 15% of the city's GDP (Creutzig and He 2009). The total external costs in the EU-27 plus Norway and Switzerland is estimated to amount to approximately 5 to 6 % of the union's GDP (van Essen et al 2011).

One option in order to reduce the efficiency loss is to aim for behavioral changes of people. From the economic literature, it is known that internalizing external effects by a tax can change behavior and, thus, increase welfare for society (Pigou 1920). However, only some real-world policies have been implemented in the last decades. Congestion pricing schemes have been introduced in Singapore, London, Stockholm (Eliasson et al 2009), and Gothenburg (Börjesson and Kristoffersson 2015). An air pollution pricing scheme has been implemented in Milan (Rotaris et al 2010). Even though focus and naming are rather driven by political discussions, all pricing schemes have effects on both, congestion and the environment. Percoco (2014) argues that road pricing in Milan has only limited effects on environmental quality and congestion because of an increase in polluting vehicles (motorbikes) and non-polluting vehicles (LPG, bi-fuel and hybrid cars) which are exempted from the toll. Additionally, no significant changes in the flows of prohibited vehicles entering into the city center are observed (Percoco 2015). Similarly, Whitehead et al (2014) investigate the impact of congestion pricing on the demand of new exempted energy efficient vehicles in Stockholm. They show that demand for the exempted energy efficient vehicles increases with a stronger effect on commuters. With a simple example, Nagurney (2000) shows that improvements in travel times may lead to an increase in emissions. Thus, abating congestion and emission can, under certain conditions, turn out to be conflicting goals.

[1] 'Externality' refers in this paper to 'negative externality' unless otherwise stated.

Despite the limited real-world implementations, pricing strategies offer – especially in a simulation context – a great opportunity to estimate the magnitude of potential efficiency gains and to identify and avoid possible flaws before implementation. Especially, a proper investigation about the interrelationship of congestion and air pollution externalities seems promising. In the literature, this potential is, however, only reflected by a relatively small number of contributions: Proost and van Dender (2001) and Chen and Yang (2012) use analytical approaches with static traffic flows; the former considers external effects of congestion, emission, accident and noise for a large-scale scenario of Brussels in Belgium, and the latter obtains Pareto system optimum link flow patterns by simultaneous minimization of travel times and emissions. Wang et al (2014) uses a small test network while considering carbon emission costs with generalized cost of travel. Ghafghazi and Hatzopoulou (2014) quantifies the effect of different traffic calming measures (speed humps, speed bumps, speed limit) on vehicle emission in Montreal.

To the knowledge of the authors, there exists no contribution attempting a joint internalization of emission and congestion externalities in an agent-based framework with dynamic traffic flows and activity-based demand for a whole metropolitan area. This paper attempts to close this gap, and to derive general insights from the analysis possibilities of such detailed model. In a first step, the paper investigates the effect of congestion pricing on emission levels, and the effect of emission pricing on congestion levels. For that purpose, the marginal congestion pricing approach by Kaddoura and Kickhöfer (2014) and the marginal emission pricing approach by Kickhöfer and Nagel (2013) are applied to the a real word scenario of the Munich metropolitan area in Germany. In a second step, the present study combines the two pricing approaches from above in a combined pricing scheme to investigate the aggregated and disaggregated effects of the correlation between congestion and emission externalities on toll levels and agent behavior. Hence, the contribution of the presented combined approach is to determine individual vehicle-specific, time-dependent toll levels that include both externalities under consideration. The outcome are optimal emission-congestion levels for a particular case study. The methodology that is developed can, however, be applied to any scenario worldwide.

Please note that this paper is an extension of a recent study by Agarwal and Kickhöfer (2015) and an edited version of Agarwal et al (2015). In contrast the former, the present paper uses an improved scenario setup with more realistic price elasticities of demand. Furthermore, it provides more detailed and disaggregated analyses of the driving forces behind the increase in system performance for different agent groups, as well as a proper economic evaluation of the different pricing schemes. In contrast to the latter, it focuses more on the correlation between the two externalities under consideration and their isolated impact on the overall toll levels. It also puts more emphasis on deriving relevant policy recommendations.

The remainder of the paper is organized as follows: Sec. 2 describes the transport simulation framework which is used for the study, and presents the

methodology of internalizing external congestion and emission effects within that framework. Sec. 3 introduces the real-world scenario of the metropolitan area of Munich, Germany, and the different pricing schemes that are considered in the present study. Sec. 4 analyses the impacts of the different pricing schemes on agents' behavior and economic indicators and also performs some spatial analysis. Finally, Sec. 5 concludes the study by summarizing the main findings and by identifying venues for further research.

2 Methodology

2.1 MATSim

The multi-agent transport simulation MATSim[2] is used for all simulation runs (see, e.g., Balmer et al 2005, 2009; Raney and Nagel 2004, 2006, for detailed information). MATSim is a framework to simulate transport systems in large-scale scenarios. Required inputs are network data, daily plans of individual travelers, and various configuration parameters. Every individual in the simulation framework is considered as an agent who learns and adapts within an iterative process that is composed of three steps as shown in Fig. 1.

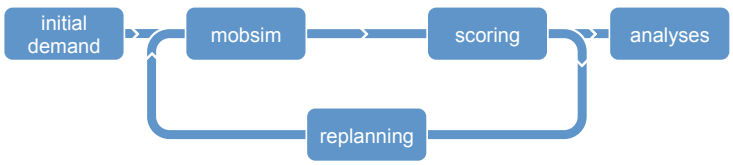


Fig. 1: MATSim cycle (Horni et al in preparation).

1. **Plans Execution (mobsim)**: All selected plans of agents are executed simultaneously in the physical environment. In this study, a state-of-the-art queuing model (Gawron 1998; Cetin et al 2003) is used.
2. **Plans Evaluation (scoring)**: To compare various plans, executed plans are evaluated using a utility function. A plan's utility (S_{plan}) is represented by:

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

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

where N is the number of activities, $S_{act,q}$ is the utility from performing activity q and $S_{trav,mode(q)}$ is the (typically negative) utility for traveling to activity q. In short, the utility earned for performing an activity is given by[3]

$$S_{act,q} = \beta_{dur} \cdot \ t_{typ,q} \cdot \ln(t_{dur,q}/t_{0,q}) \tag{2}$$

where $t_{dur,q}$ and $t_{typ,q}$ are actual and typical durations of activity q, respectively. β_{dur} is the marginal utility of activity duration. $t_{0,q}$ is the minimal duration, which essentially has no effect as long as dropping activities is not allowed. The simplified mode-specific utility from traveling by car or public transport (PT) following Nagel et al (in preparation) is described by:

$$S_{car(q)} = \beta_{trav,car(q)} \cdot t_{trav,q} + \beta_m \cdot \gamma_{d,car(q)} \cdot d_{trav,q} \tag{3}$$

$$S_{PT(q)} = C_{PT(q)} + \beta_{trav,PT(q)} \cdot t_{trav,q} + \beta_m \cdot \gamma_{d,PT(q)} \cdot d_{trav,q} \tag{4}$$

where $t_{trav,q}$ and $d_{trav,q}$ is the travel time and distance between activity q and $q+1$. $C_{pt(q)}$ is the Alternative Specific Constant (ASC) of public transport (PT). As will be illustrated in Sec. 3.2, the present study defines two different PT modes, and in consequence two PT constants: one for urban travelers and another one for commuters and reverse commuters. All behavioral parameters and the resulting Values of Travel Time Savings (VTTS) are listed in Tab. 1.

3. **Re-planning**: For each iteration, a new plan is generated for a predefined share of agents by modifying an existing plan. These modifications are performed by software modules that can be defined arbitrarily. In the present study, route choice and mode choice modules are used.

By repeatedly performing the steps from above, an iterative learning cycle is initiated which finally results in stabilized simulation outputs.

2.2 Pricing of externalities

2.2.1 Emission cost calculation

The emission modeling tool was developed by Hülsmann et al (2011) and further improved and extended by Kickhöfer et al (2013). The tool is coupled with the MATSim framework. Currently, emissions are calculated for free flow and stop and go traffic states. Emissions consist of cold emissions (during warm up phase of vehicle) and warm emissions (while driving); cold emissions essentially depend on parking duration, distance traveled, and vehicle characteristics; warm emissions depend on engine type, road category, and speed of the vehicle. Thus, cold and warm emissions for each agent on each link are calculated using the HBEFA[4] database.

[3] See Charypar and Nagel (2005) and Nagel et al (in preparation), Sec. 3.2, for a more detailed description.

[4] 'Handbook Emission Factors for Road Transport', Version 3.1, see `www.hbefa.net`

Table 1: Behavioral parameters.

Parameter	Value	Unit
Source: Kickhöfer (2014)		
Marginal utility of activity duration (β_{dur})	+ 0.96	$utils/h$
Marginal utility of traveling by car ($\beta_{trav,car}$)	– 0.00	$utils/h$
Marginal utility of traveling by PT ($\beta_{trav,PT}$)	– 0.18	$utils/h$
Monetary distance rate by car ($\gamma_{d,car(q)}$)	–0.30	EUR/km
Monetary distance rate by PT ($\gamma_{d,PT(q)}$)	–0.18	EUR/km
Marginal utility of money (β_m)	– 0.79	$utils/EUR$
Approximate average $VTTS_{car}$	+ 12.15	EUR/h
Approximate average $VTTS_{PT}$	+ 14.43	EUR/h
Calibrated for the present study		
ASC for urban PT	– 0.75	$utils$
ASC for (rev.) commuters PT	– 0.3	$utils$

Furthermore, Kickhöfer and Nagel (2013) developed a method to calculate time-dependent, vehicle-specific emission tolls. In this method, vehicle- and link-specific time-dependent emissions are converted into monetary units (emissions costs) using emission cost factors given in Tab. 2.

Table 2: 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

2.2.2 Congestion cost calculation

The software to compute individual delays[5] and then to internalize those by a marginal social cost pricing scheme in the MATSim framework is provided by Kaddoura and Kickhöfer (2014). It has the ability to track routes and travel times of all agents and to calculate the resulting disaggregated delays on a per-link basis. Hence, causing and affected agents can be identified. The former can therefore be charged with the equivalent monetary amount of the delays caused to the affected agents. Since congestion is – in contrast to emissions –

[5] Delay is in this study defined by the difference between the actual travel time on a link and the link's free flow travel time. That is, delays are calculated on a per-link basis and not for entire routes.

inherent to road traffic, the behavioral parameters from Tab. 1 can be used to convert delays into monetary units. This is done using the approximate average Value of Travel Time Savings (VTTS) of the car mode.[6]

2.3 Internalization

Internalization is the process by which external effects are included into the behavioral decision making of individuals by setting prices according to their marginal external costs. By default, the MATSim utility functions only incorporate marginal private costs (MPC) which correspond to spending time and money for traveling to planned activities (see Eq. 1 and Eq. 3). Marginal social costs (MSC) are the sum of MPC and marginal external costs (MEC) (see, e.g., Walters 1961; Turvey 1963). The external component can result from any of the externalities mentioned in Sec. 1. In the present paper, the MEC computed according to Sec. 2.2.1 for emissions and according to Sec. 2.2.2 for congestion are considered in the utility-based learning cycle of MATSim. This is reached by modifying the utility functions – for the internalization scenarios in Tab. 4 – by vehicle-specific, time-dependent tolls (Δm_q) as follows:

$$S_{car(q)} = \beta_{trav,car(q)} \cdot t_{trav,q} + \beta_m \cdot (\gamma_{d,car(q)} \cdot d_{trav,q} + \Delta m_q) \ . \qquad (5)$$

3 Case study : Munich

This section illustrates the set up of the scenario and the pricing schemes for the real-world case study of the Munich metropolitan area in Germany.

3.1 Input

The initial scenario is taken from Kickhöfer and Nagel (2013) and modified for the present study, as will be described in this section.

Network Network data was provided by municipality of Munich (RSB 2005) in the form of VISUM[7] data. This is converted into a MATSim network, which contains 17'888 nodes and 41'942 links.

[6] The VTTS is defined as the individual willingness-to-pay for reducing the travel time by one hour. For linear utility functions, it is the ratio of the marginal utility of travel time and the marginal utility of money. The former is the sum of the disutility for traveling ($\beta_{trav,mode(q)}$) and the negative utility of time as a resource ($-\beta_{dur}$). Please note that the person-specific VTTS in MATSim can vary significantly with the time pressure which an individual experiences. This is because of the non-linear utility function for performing activities, influencing the actual value of (β_{dur}).

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

Plans A realistic activity-based demand is created using three different data sources: First, inner urban travel demand was synthesized using detailed survey data based on *Mobility in Germany* (MiD 2002, Follmer et al 2004). The synthetic demand contains 1,424,520 individuals with detailed vehicle information. Second, commuters and reverse commuter trips are modeled using data provided by Böhme and Eigenmüller (2006), which contains about 0.5 million individuals, out of these about 0.3 million are commuters and the remaining are reverse commuters. Third, about 0.15 million freight trips are created (0.15 million agents with one commercial trip) from data provided by the German Ministry of Transport (ITP and BVU 2007). In the simulation, urban travelers use car, public transport (PT), bike, walk, and ride as transport modes, whereas commuters and reverse commuters use only car or PT. Freight trips are assumed to use only trucks. PT, bike, walk, and ride trips are in the study assumed to run emission free and without capacity constraints. Therefore, there is no emission and congestion externality for such trips, and thus, in the present study, such travel modes are coupled together as *non-car* travel modes.

Overall, for computational performance reasons, 1% of total population is used for the present study. Agents are categorized among three subpopulations (user groups) namely urban, (reverse) commuters, and freight and therefore, results are discussed based on this classification.

Choice dimensions As a reaction to the policy cases (see Sec. 3.3), new choice sets are generated in the iterative loop of MATSim according to the following rule: In each iteration, (1) 15% of total agents are allowed to change their route and (2) 15% of total agents are allowed to change their travel mode from car to PT or from PT to car.[8] The rest of the agents chose a plan from their existing choice set according to a multinomial logit model. After 80% of the iterations, the choice set is fixed and agents can only chose from existing alternatives. In case of freight, mode choice is not available, i.e. all freight trips use car mode only.

3.2 Base case

A base case is set up by running simulation for 1000 iterations. The base case in the present study is similar to the base case from Kickhöfer and Nagel (2013). However, that study calibrated the ASC for PT assuming a uniform PT speed of 25 km/h for all user groups while matching the modal split for urban travelers. As a consequence, the modal split for commuters and reverse commuter did not match the reference study (see Tab. 3, "*Common* PT speed (it.1000)").

[8] An urban traveler can switch mode between car and slower PT (speed 25 km/h) and similarly, commuters and reverse commuters can switch mode between car and faster PT (speed 50 km/h). See Sec. 3.2 for details on slower and faster PT.

Therefore, in the present study, PT speed (25 km/h) for urban travelers is kept, and for commuters and reverse commuters, it is assumed to be 50 km/h, emulating faster trains between the city center and suburbs. In consequence, the base case is re-calibrated, eventually resulting in an ASC of -0.3 for (rev.) commuters. Tab. 3, "*Different* PT speed (it.1000)", shows the results of this calibration effort. The combined modal split of commuters and reverse commuters is now very close to the initial plans and the reference study. Because of the decrease in car share for commuters and reverse commuters, there is some relief of capacities on the network. In consequence, the share of car trips for urban travelers increases from 20.11% to 21.20% which is also closer to the reference study.

Table 3: Modal split from reference studies, initial demand and calibrated base cases.

	Urban		**(Rev.) commuters**	
	car	non-car	car	non-car
Reference study[9]	26.00	74.00	67.00	33.00
Initial demand (it.0)	22.48	77.52	67.97	32.03
Common PT speed (it.1000)	20.11	79.89	96.59	3.41
Different PT speed (it.1000)	21.20	78.80	66.62	33.38

3.3 Policy cases

After the calibration of the base case, the simulation is further continued for 500 iterations along with the 'Business As Usual' (BAU) case and three pricing schemes (see Tab. 4). The output of the base case after iteration 1000 is used as inputs for all four policy cases. As described in Sec. 2.3, different user-specific external costs are internalized for the scenarios listed in Tab. 4. The final iterations (1500) of the pricing schemes are compared with the final iteration of BAU. Emission costs, congestion costs and toll payments for all four scenarios are computed as follows:

1. **Emissions costs**: Time-dependent and person-specific cold and warm emissions are calculated as described in Sec. 2.2.1. These emissions are then transformed into monetary units using emission costs factors (see Tab. 2). These monetary emissions costs are summed up to get total emission costs in each scenario.
2. **Congestion costs**: As illustrated in Sec. 2.2.2, disaggregated delays are calculated on a per-link basis for each causing agent and then converted into

[9] Follmer et al (2004) for urban travelers and MVV (2007) for commuters and reverse commuters.

monetary units using the approximate average VTTS. Afterwards, these values are summed up to get the total congestion costs for each scenario.

3. **System welfare**: In order to perform economic evaluation for all three pricing scenarios, travel related user benefits are calculated by converting the utility of each agent into monetary terms[10]. Congestion costs and the negative perception of toll payments are both implicitly part of user benefits. Toll payments are, however, simply transfer payments from users to public authorities. Consequently, the change in system welfare is defined as the sum of changes in emission costs, toll payments, and user benefits.

Table 4: Policy cases.

Policy case	Externality	Internalization
Business As Usual (BAU)	none	none
Emissions Internalization (EI)	emissions	see Sec. 2.2.1
Congestion Internalization (CI)	congestion	see Sec. 2.2.2
Emissions and Congestion Internalization (ECI)	both	both

4 Results

In this section, the levels of the external costs are illustrated (Sec. 4.1) and subsequently, the effects of the pricing schemes on system performance is presented (Sec. 4.2). Furthermore, Sec. 4.3 and Sec. 4.4 provide more detailed and disaggregated analyses for different agent groups. The emphasis will thereby be put on the driving forces behind the increase in system performance, and on the isolated impacts of each externality on the overall toll level. All figures in the presentation of the results are for a typical working day and scaled to the full population. The idea behind the comparison of the pricing schemes is (i) to investigate the influence of internalizing one externality on the other externality, and (ii) to test whether the correlation between the two externalities in the combined internalization (ECI) has policy implications.

4.1 BAU: amplitude of externalities

For the Munich metropolitan area, congestion costs amount to approximately 7.3m *EUR* which is about twice as much as the emission costs (3.7m *EUR*)

[10] The user benefits calculated from the utility of the last executed plan are not same as the user benefits calculated from the logsum over all plans of an agent. The latter (also sometimes called expected maximum utility) considers utility from heterogeneity in the choice set and is in theory the preferable figure for calculating user benefits in MATSim (see Kickhöfer and Nagel in preparation). However, as the authors point out, the current MATSim implementation might, under certain conditions, yield biased choice sets. In consequence, the last executed plan is used in the present paper.

. This is in line with estimates from the literature, where congestion cost estimates are higher than emission cost estimates (see, e.g., Maibach et al 2008; Parry and Small 2005).

Fig. 2 shows for the BAU scenario and each user group the share of persons and external costs. The caused emission costs of a user group are total costs of emissions produced by all vehicles of that group. Freight car trips consists of only about 8% (0.15m) of all car trips, but is responsible for more than 65% (2.5m *EUR*) of emission costs. This is due to the fact that freight vehicles (i) emit more emissions than other vehicles and, (ii) have longer travel distances (mean and median trip distances are 111 *km* and 69 *km*, respectively).

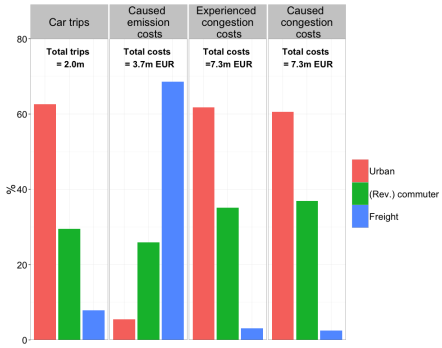


Fig. 2: Share of car trips, emission and congestion costs for different user groups for BAU scenario.

Congestion costs are classified into two categories, namely 'experienced congestion costs' and 'caused congestion costs'.[11] The former are costs experienced, the latter are costs caused by the respective group. Thus, experienced congestion costs are also influenced by agents from other user groups. The share of car trips for urban travelers is more than 60% (1.3m car trips) of the total car trips. They experience and cause about 4.5 and 4.4m *EUR* of the congestion costs respectively. This is expected since they perform most of the trips and congestion is predominant in urban areas. Together with freight, they are causing less congestion (i.e. delays) than they experience. On the contrary, (rev.) commuters cause (2.7m *EUR*) more than what they experience (2.6m *EUR*). In marginal congestion pricing, agents are charged for the delays they cause to others and therefore *caused congestion costs* will be referred to as congestion costs in the remainder of the paper.

[11] A recent study by Kickhöfer and Kern (2015) shows that the framework in principle allows for a similar classification in the case of emission costs. However, in the present study, only *caused emission costs* are considered and referred to as 'emission costs' from here on.

Table 5: Key indicators for all pricing schemes in million *EUR* per typical working day.

	Pricing scheme		
Benefits from ...	**EI**	**CI**	**ECI**
... changes in emission costs (1)	0.10	0.17	0.27
... changes in congestion costs (2)	0.91	3.61	3.96
Changes in travel related user benefits (3)	– 2.75	0.44	– 2.34
Toll revenues (4)	3.61	3.68	6.78
Changes in system welfare (=1+3+4)	0.96	4.27	4.71

4.2 Pricing: system performance

Absolute changes in external costs, toll payments, user benefits and system welfare as a result of the three different pricing schemes are shown in Tab. 5.

The reduction in emission costs for EI, CI and ECI pricing schemes are 2.72%, 4.49%, and 7.22% (0.10m, 0.17m, and 0.27m *EUR*), respectively. The reduction in congestion costs for EI, CI and ECI pricing schemes are 12.70%, 49.66%, and 54.44% (0.91m, 3.61m, and 3.96m *EUR*), respectively.

Internalizing emissions (EI) results in approx. 0.91m *EUR* less congestion costs. Internalizing congestion (CI) results in approx. 0.17m *EUR* less emission costs. Thus, pricing one externality has a positive impact on the other externality. That is, the externalities prove to be positively correlated. The combined pricing scheme (ECI) exhibits the highest reductions in emission costs (0.27m *EUR*) and congestion costs (3.96m *EUR*), and the highest gain in system welfare (4.71m *EUR*). That is, the combined pricing scheme improves system performance the most.

An interesting observation can be made for the changes in 'travel related user benefits': they are negative for EI and ECI and positive for CI. This stems from the fact that, for CI, the reduction in travel times overcompensates the loss from toll payments yielding a positive change in user benefits. For EI and ECI, the reduction in travel times is smaller than the loss from toll payments yielding a negative change in user benefits.

To summarize, the following observations are obtained: (1) pricing congestion (CI) results in a decrease of emissions; (2) pricing emissions (EI) yields a reduction in congestion; (3) the lowest levels of external costs are observed in the combined pricing scheme (ECI); (4) system welfare is highest for ECI. These findings are confirmed for all user groups under investigation. However, when looking at the effects on user groups, some interesting additional observations can be made. In particular:

1. Pricing emissions (EI) diverts freight trips on shorter (Δ average distance $= -0.2\ km$) but more congested links and consequently a slight increase in congestion costs is observed. That is, pricing emissions might yield higher congestion levels (also see later in Sec. 4.4).

2. All three pricing schemes yield a decrease in user benefits for all user groups except for urban travelers. For them, the gain in utility from the reduction in travel times is higher than the loss because of toll payments which eventually produces higher user welfare. When pricing congestion (CI), this gain overcompensates the losses of the other user groups and finally results in increased user benefits for the whole population (see Tab. 5).

For now, the point with the most important policy implication, however, is the following: The sum of toll revenues from the isolated pricing schemes is roughly 7.29m *EUR* whereas the total toll revenues for combined pricing is roughly 6.78m *EUR*.[12] **The lessons learned here are that simply combining the average toll levels from the isolated pricing schemes (EI and CI) for policy making will result in over-pricing. This is due to the correlation between congestion and air pollution externalities. The same is likely to be true for a policy which combines marginal cost factors from the literature, since there are typically no cost estimates for emissions *given* an existing congestion pricing scheme or cost estimates for congestion *given* an existing emission pricing scheme.**

4.3 Pricing: driving forces

The increase in system performance indicators is a combined effect of users' reactions with respect to two choice dimensions, mode choice and route choice (see Sec. 3.1). This section aims at presenting the driving forces behind the increases in system performance by performing a more in-depth analysis.

Modal split Tab. 6 shows the impact of the pricing schemes on modal split. For the EI case, the share of car trips decreases for (rev.) commuters whereas it increases slightly for urban travelers. Because of the higher average toll per trip for (rev.) commuters (see Tab. 7), a significant number of car users in this user group switch to PT. This reliefs some capacity and leads to an increase in the car share of urban travelers. In contrast, for the CI and ECI case, car share decreases for both user groups. This is because the average toll per trip for urban travelers is by a factor of 12 higher than in EI. This effect is less pronounced for (rev.) commuters, however, also their toll increases by a factor of 1.5 and 2.5 from the EI to the CI and ECI case, respectively. On the aggregated level, one observes – as expected – that the higher the toll, the more agents switch from car to PT, depending on the implicit price elasticity of demand. This elasticity is dependent on the availability of substitutes, i.e. if agents are not able to switch mode because of insufficient alternatives, pricing can not be used to increase the system efficiency. On the disaggregated level,

[12] This result has been confirmed by two simulations with different random seeds, which are used to initialize the pseudo random number generator in MATSim . A different random seed will eventually result in different simulation outcomes. For an example of the effect of randomness on optimal supply in MATSim, see, e.g., Kaddoura et al (2015a).

however, the agent-based simulation framework exhibits the complex structure of human interactions in transport decisions. **Because of capacity relief, pricing car emissions might *in*crease the car share for certain agents. Similarly, increasing the toll level (i.e. going from CI to ECI) might *de*crease the reduction in car share for certain agents.**

Table 6: Changes in car share (% points) with respect to BAU for all pricing schemes.

	Urban	(Rev.) commuters	Freight
EI	+ 0.22	– 7.04	0.00
CI	– 0.66	– 16.25	0.00
ECI	– 0.48	– 23.46	0.00

Table 7: Average toll payments (*EUR*) per car trip for all pricing schemes.

	Urban	(Rev.) commuters	Freight
EI	0.16	1.62	16.04
CI	1.96	2.46	0.92
ECI	2.00	4.12	16.96

Travel time Fig. 3 shows the change in average trip travel time for mode switchers and retainers. One observes that the average trip travel time decreases significantly for agents who retain car as transport mode, as well as for agents who change from PT to car: the toll in the car mode improves car travel times, so car gets attractive in particular for short trips. In contrast, travel time is increased for the agents who switch from car to PT. These agents are better off by shifting to the time-consuming PT travel mode than paying toll. Interestingly, with the CI pricing scheme, agents who stay in the car mode are shifting to less congested but longer routes (see Fig. 6c) in order to dampen their toll. In contrast, agents who switch from PT to car prefer to pay toll which is compensated by significant reductions in travel time.

Peak/off-peak tolls Tab. 8 shows the average toll levels in the car mode for peak[13] and off-peak hours, now in $EURct/km$. Peak-hour toll levels are – as expected – higher than off-peak tolls. For CI and ECI, urban travelers exhibit a six to ten times higher toll level per vehicle kilometer than (rev.) commuters whereas for EI, this factor is about 1.2 only. This was not yet visible from the

[13] Peak hours are identified as 07:00–10:00 and 15:00–18:00 considering total travel demand of all user groups in the BAU scenario.

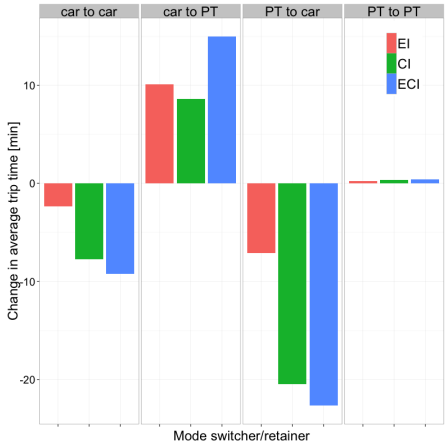


Fig. 3: Changes in average trip travel time for mode switchers and retainers.

Table 8: Average toll levels ($EURct/km$) in the car mode for peak and off-peak hours.

Time	Pricing scheme	Urban	(Rev.) commuters	Freight
Peak	EI	2.61	2.24	14.45
	CI	36.38	3.62	1.28
	ECI	37.83	5.40	15.70
Off-peak	EI	2.56	2.19	14.45
	CI	29.99	2.70	0.63
	ECI	30.46	4.59	15.08

Table 9: Contributions of externalities to the ECI toll levels ($EURct/km$) in the car mode in peak and off-peak hours.

Time	Externality	Urban	(Rev.) commuters	Freight
Peak	Emissions	2.51 (6.6%)	2.22 (41.1%)	14.44 (92.0%)
	Congestion	35.32 (93.4%)	3.18 (58.9%)	1.26 (8.0%)
Off-peak	Emissions	2.49 (8.2%)	2.18 (47.5%)	14.43 (95.7%)
	Congestion	27.97 (91.8%)	2.41 (52.5%)	0.65 (4.3%)

tolls per trip in Tab. 7. Freight tolls are almost not influenced by congestion pricing since the emission toll dominates the overall price level.

Tab. 9 shows the contributions of the two externalities to the overall ECI toll level for peak and off-peak hours. The first important finding is that **the contribution of emissions to the overall toll level is higher in off-peak than in peak hours. This is valid for all user groups.** In comparison with Tab. 8, the figures in Tab. 9 additionally exhibit that, in the EI case, emissions are more strongly overpriced in peak hours than in off-peak hours.

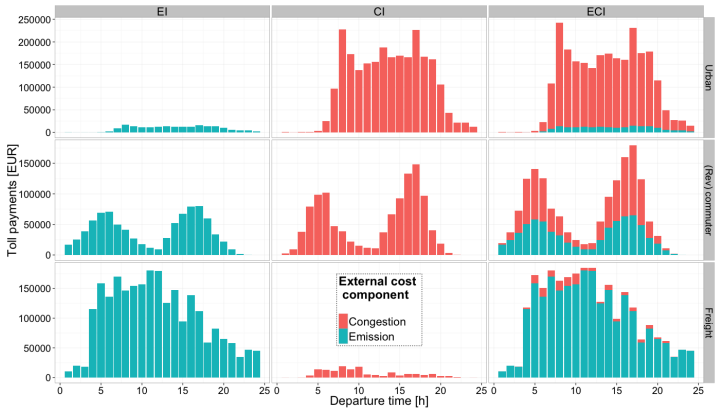


Fig. 4: Toll payments over time of day for all pricing schemes and subpopulations in *EUR*. Values are scaled to full population.

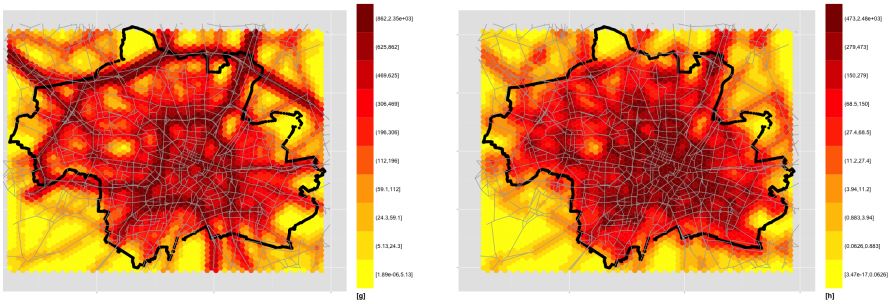
To give an example: in EI, peak hour emission prices for urban travelers are 4.0% ((2.61 − 2.51)/2.51) higher than in the ECI case. In off-peak hours, this price difference only amounts to 2.8%. In contrast, in the CI case, peak hour congestion prices for urban travelers are only 3.0% ((36.38 − 35.32)/35.32) higher than in the ECI case. In off-peak hours, this price difference increases to 7.2%. **That is, for a combined pricing scheme, cost estimates from the literature need to be reduced because of the correlation between air pollution and congestion externalities. For the emission estimates, these reductions should be stronger in peak hours. For the congestion estimates, these reductions should be stronger in off-peak hours.** Alternatively, the joint internalization model as is proposed in the present paper can help to determine the joint amplitude of the externalities and help to design pricing schemes of any desired complexity, ranging from little price differentiations to highly personalized tolls. For illustration purposes, Fig. 4 shows the toll payments for all three pricing schemes and all subpopulations in one hour time bins. It emphasizes the importance of the interrelation of emission and congestion externalities and their variation over time of day and user groups.

4.4 Pricing: spatial distribution

The impact of the three pricing schemes on a spatially disaggregated level is presented in this section.

The spatial dimension of external costs in the BAU scenario is shown in Fig. 5.[14] Time-dependent and person-specific link-based emissions and delays

[14] For the visual presentation, a Gaussian distance weighting function is used to smooth emissions and delays throughout the area of Munich and surroundings. Uniform hexagonal



(a) Absolute NO_2 emission (b) Absolute delay

Fig. 5: Absolute emissions (in [g]) and delays (in [h]). Values are scaled to full population.

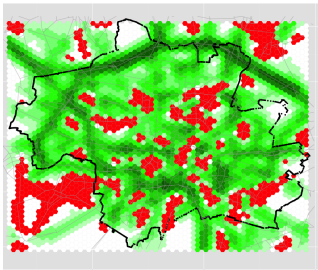
are presented. Fig. 5a shows absolute NO_2 emissions[15] and Fig. 5b shows absolute delays. It can be observed that emissions are most important on primary roads (inner and middle ring road, main arterials, and the tangential motorway in the north-west of Munich). In contrast, congestion is evident on almost all roads inside the city area, but not as important on the tangential motorway.

Fig. 6 shows the changes in NO_2 emissions and in delay for the off-peak hours (i.e. 00:00-07:00, 10:00-15:00 and 18:00-24:00).[16] An increase in emissions or delays is represented by red color, a decrease by green color. The spatial plots on the left show the change in NO_2 whereas the plots on the right show the change in delays with respect to the BAU scenario. For the EI case, Fig. 6a and 6b show that agents are re-routing towards shorter distance routes. This is indicated by an increase of emissions *and* delays in the inner city. As a consequence, NO_2 emissions are decreased in particular on the north-west tangential motorway and other long-distance routes, basically wherever NO_2 emission was high in the BAU. For the CI case, Fig. 6c and 6d show that agents re-route from congested links to non-congested and longer distance routes. Thus, NO_2 emissions and delays are decreased significantly inside the central areas of Munich. On the contrary, NO_2 emissions are increased on parts of the tangential motorway where NO_2 emissions were already high in the BAU scenario. The effect of combined pricing on a spatial level is shown in Fig. 6e and 6f. Since congestion costs dominate emission costs, the patterns in ECI are similar to those from CI. However, the combined pricing yields a decrease in NO_2 emissions *and* delays in most areas of the city.

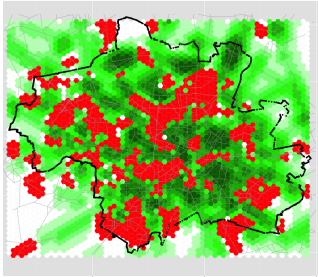
cells of size 500 m are used for this purpose. The smoothing radius is assumed to be 500 m. For more information on the exact visualization procedure, please refer to Kickhöfer (2014).

[15] All important pollutants are considered for pricing. For illustration purposes, the emission plot only shows NO_2.

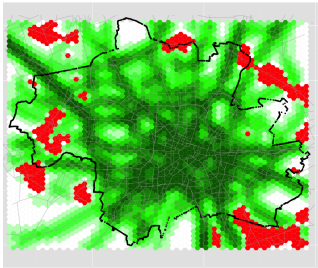
[16] In the peak hours, the congestion pricing scheme and combined pricing scheme exhibit similar patterns.



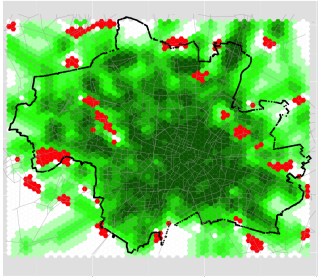
(a) Change in NO_2 levels for EI



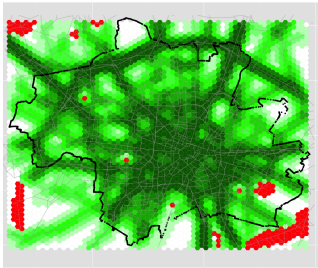
(b) Change in delay for EI



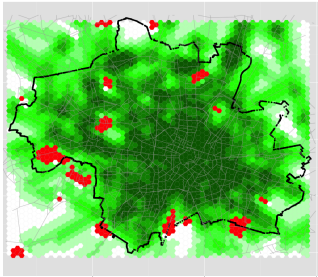
(c) Change in NO_2 levels for CI



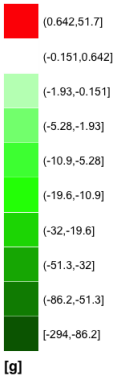
(d) Change in delay for CI



(e) Change in NO_2 levels for ECI



(f) Change in delay for ECI



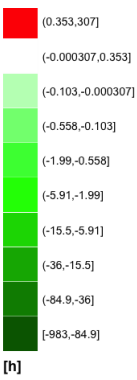


Fig. 6: Changes in NO_2 emissions (in [g]) and delays (in[h]) for all pricing schemes in the off-peak hours. Values are scaled to full population.

The lessons learned here are that – for congested regimes – the two pricing schemes (EI and CI) affect the route choice behavior of agents by tendency into opposite directions: EI towards shorter distance routes, increasing congestion; CI towards longer distance routes, increasing emissions.

5 Conclusion and outlook

This study investigated and compared separate pricing strategies for emissions and congestion, and proposed a joint internalization approach for both externalities. It applied the marginal emission pricing approach by Kickhöfer and Nagel (2013) and the marginal congestion pricing approach by Kaddoura and Kickhöfer (2014) to a real-world scenario of the Munich metropolitan area.

First, the impact of emission pricing on congestion levels was analyzed and vice versa. It was found that pricing one externality reduces the other external externality as well since both externalities are positively correlated. Second, it was demonstrated that the combined pricing yields the lowest level of emission and congestion externalities for whole population as well as for individual user groups. It also yields the highest level of system welfare. However, it was found that simply combining the average toll levels from obtained from isolated pricing schemes or exogenous cost estimates for policy making will result in overpricing. The amplitude of this effect was shown to be more important in peak hours for emissions, in off-peak hours for congestion. Policy makers should, hence, account for the correlations between different externalities and adjust marginal estimates from separate models or the literature. Alternatively, the joint internalization model proposed in this paper was shown to help deriving the correct toll levels and designing simpler pricing schemes based on this information. Clearly, the potential efficiency gains can only be obtained if the implicit price elasticities of car travel demand are captured in an accurate way, e.g. by carefully modeling substitutes to the car mode. Without substitutes, pricing can not unfold its power and contribute to a meaningful reduction in transport-related externalities. This can be seen from the rather simple freight demand which was only allowed for route choice.

Finally, with the help of spatial plots, the spatial distribution of changes in the externalities was analyzed. It was shown that pricing emissions steers agents on shorter distance routes and pricing congestion pushes agents on shorter travel times routes with potentially longer distance routes. Thus, for congested areas, route choice behavior of agents is by tendency affected into opposite direction by the two pricing schemes. This needs to be accounted for when designing real-world policies: An emission (or distance)-based toll might increase congestion whereas a congestion-based toll might increase emissions.

From the findings above, it can be concluded that with the help of the proposed methodology, efficient toll levels for multiple externalities can be derived for policy design purposes. The present study has proven that this is feasible for large-scale scenarios. In future studies, the authors aim to incorpo-

rate emission exposure (Kickhöfer and Kern 2015), noise exposure (Kaddoura et al 2015b), and accidents in the same model. Furthermore, the authors wish to investigate how the simulated price levels relate to so-called backcasting approaches (Geurs and van Wee 2004; IWW et al 1998) which can be used to achieve a politically desired reduction of transport-related externalities.

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