The Internalization of Congestion and Air Pollution Externalities: Evaluating Behavioral Impacts

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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 study presents an approach to correct 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 aggregated 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 approach. However, the necessary price levels need to be carefully determined as simply combining the average toll levels from the isolated pricing schemes would yield over-pricing. Additionally, the possible efficiency gains highly depend on the implicit price elasticity of demand, which again, depends on the availability of substitutes to car travel. 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 choice behavior by tendency into opposite directions.

Keywords: Air Pollution, Congestion, Vehicle Emissions, Road Pricing, Combined Pricing, Internalization

1 Introduction

Road congestion is a widespread phenomenon across the world and in particular present in metropolitan areas where travel demand is high and capacities are naturally limited by scarce urban road space. The expected increase in traffic mainly resulting from urbanization processes is likely to increase negative externalities[1] such as road congestion, damage to the environment, and human health (see, e.g., Weinreich et al., 1998; Maibach et al., 2008).

The presence of negative externalities is known to result in inefficiencies unless the underlying adverse effects are internalized, i.e. considered in people's mobility decisions. The 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 is estimated to amount approximately 373 billion *EUR* annually – about 3% of the union's GDP (Becker et al., 2012).

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). In the literature, only few studies applied this principle for a simultaneous internalization of emission and congestion externalities (see, e.g. Wang et al., 2014; Proost and van Dender, 2001). These studies follow an analytical approach with static traffic flows. The former study uses a small test network and the latter uses a large-scale scenario of Brussels in Belgium. To the knowledge of the authors, there exist no study attempting a joint internalization of emission and congestion externalities in an agent-based model with dynamic traffic flows and activity-based demand.

This paper attempts to close this gap. In a first step, it 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 scenario to investigate the effects of the correlation between congestion and emission externalities on toll levels and agent behavior. The hypothesis is that *combining the toll levels obtained from the separate pricing schemes would yield*

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

toll levels above those of the economic optimum.

Please note that this paper is an extension of a recent study by Agarwal and Kickhöfer (forthcoming). In contrast to that study, the present paper uses an improved scenario setup with more realistic price elasticities of demand. Furthermore, it provides much more detailed and disaggregated analyses of behavioral changes by different subpopulations, as well as a proper economic evaluation of the different pricing schemes.

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 Munich and the different pricing schemes considered in the present study. Sec. 4 analyses the different pricing schemes and their impact on agents' behavior, economic performance and spatial effects. 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 framework 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 following three steps:

1. **Plans Execution**: 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**: 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] 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:

$$\begin{aligned} S_{car(q)} &= \beta_{trav,car(q)} \cdot t_{trav,q} + \beta_m \cdot \gamma_{d,car(q)} \cdot d_{trav,q} \\ S_{PT(q)} &= C_{PT(q)} + \beta_{trav,PT(q)} \cdot t_{trav,q} + \beta_m \cdot \gamma_{d,PT(q)} \cdot d_{trav,q} \end{aligned} \tag{3}$$

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 Emission pricing

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

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

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)	− 0.0789942	$utils/EUR$
Resulting $VTTS_{car}$	+ 12.15	EUR/h
Resulting $VTTS_{PT}$	+ 14.43	EUR/h
Calibrated for the present study		
ASC for urban PT	− 0.75	$utils$
ASC for commuters/reverse commuters PT	− 0.3	$utils$

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.

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. In the simulation, every time an agent leaves a link, the agent consequently pays the monetary equivalent of the emissions produced by her. Within the iterative learning cycle (see Sec. 2.1), the agents learn how to react on these individual tolls by changing their behavior accordingly. This is referred to internalizing the external emission effect (see later in Sec. 2.4).

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

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

2.3 Congestion pricing

The framework to compute individual delays and then to internalize those by a marginal social cost pricing scheme in an agent-based simulation is provided by Kaddoura and Kickhöfer (2014). This tool is also used along with the MATSim framework which has the ability to track routes and times of all agents and to calculate disaggregated delays.[5] Subsequently, causing and affected agents are identified. The former can therefore be charged with the equivalent monetary amount of the delays they caused for the affected agents. Since congestion is – in contrast to emissions – inherent to road traffic, the behavioral parameters from Tab. 1 can directly be used to convert delays into monetary units. This is done using the Value of Travel Time Savings (VTTS) of the car mode.[6] Again, the monetary payments are considered in the utility-based learning cycle of MATSim, and, hence, the external congestion effect is internalized.

2.4 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,

[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.

[6] The VTTS is defined as the individual willingness-to-pay for reducing the travel time by one hour. For a linear utility functions, it is the ratio of the marginal utility of travel time and the marginal utility of money. As mentioned earlier, the former is the sum of the disutility for traveling ($\beta_{trav,mode(q)}$) and the negative utility of time as a resource ($-\beta_{dur}$).

1961; Turvey, 1963). The external component can result from any of the externalities mentioned in Sec. 1. This study attempts to compute MEC for different pricing schemes listed in Tab. 4, and then correct prices accordingly in order to minimize the external effects and to improve the efficiency of the transport system. In the base case and the "Business As Usual" (BAU) scenario, no externalities are internalized. Thus, utility from traveling to an activity is given by Eq. 3. For all other scenarios, the MEC of emissions and/or congestion is added to the overall utility of every car trip:

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

where Δm_q is the person-specific toll of the different pricing schemes listed in Tab. 4. It is called congestion or emission toll for the emission or congestion internalization strategies, EI and CI respectively, and combined toll for the joint internalization strategy (ECI).

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 Inputs

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

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

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

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 only use trucks. PT, bike, walk, and ride trips are in the study assumed to run emission free and as a 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 four subpopulations (user groups) namely urban, commuter, reverse commuter and freight as illustrated above and therefore, results are also discussed based on this classification.

Choice dimensions As a reaction to the pricing schemes (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 that. In case of freight trips, 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 KPH) and similarly, commuters and reverse commuters can switch mode between car and faster PT (speed 50 KPH). See Sec. 3.2 for details about slower and faster PT.

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

Table 4: Scenarios under consideration.

Scenario	External cost(s)	Internalization method
Business As Usual (BAU)	none	none
Emissions Internalization (EI)	emission costs	see Sec. 2.2
Congestion Internalization (CI)	congestion costs	see Sec. 2.3
Emissions and Congestion Internalization (ECI)	emission and congestion costs	see Sec. 2.2 and Sec. 2.3

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 commuter and reverse 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 to 21.20% which is also closer to the reference study.

3.3 Pricing schemes

After the calibration of the base case, the simulation is further continued for 500 iterations along with three pricing schemes (see Tab. 4). The outputs of base case after 1000 iteration are used as inputs for all four scenarios. As described in Sec. 2.4, different user-specific external costs are internalized for the scenarios listed in Tab. 4. The final iterations (1500) of the pricing schemes are

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

compared with the final iteration of BAU. Emission costs, congestion costs and toll payments for all four scenarios are computed as follows:

Emissions costs Time-dependent and person-specific cold and warm emissions are calculated as described in Sec. 2.2. These emissions are then transformed into monetary units using emissions costs factors (see Tab. 2). These monetary emissions costs are summed up to get total emissions costs in each scenario.

Congestion costs As illustrated in Sec. 2.3, disaggregated delays are calculated on a per-link basis for each causing agent and then converted into monetary units using the VTTS. Afterwards, these values are summed up to get the total congestion costs for each scenario.

System welfare In order to perform economic evaluation for all four scenarios, user benefits are calculated by converting the utility of the last executed plan 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 algebraic sum of changes in emission costs, toll payments, and user benefits.

4 Results

In this section, the levels of the external costs are illustrated (Sec. 4.1), and subsequently, the effect of the pricing schemes on system welfare is presented (Sec. 4.2). Furthermore, Sec. 4.3 and Sec. 4.4 demonstrate the impact of the pricing schemes on agents' behavior. 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) yields toll levels that are lower than the algebraic sum of the toll levels from the individual internalization models.

[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 user benefits in MATSim (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.

4.1 BAU: level of externalities by user group

Fig. 1 shows for the BAU scenario and each user group the share of persons and external costs. The caused emission costs[11] of a user group are total costs of emissions produced by all vehicles of that group. Freight consists of only about 7% of the whole population, but is responsible for more than 65% 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).

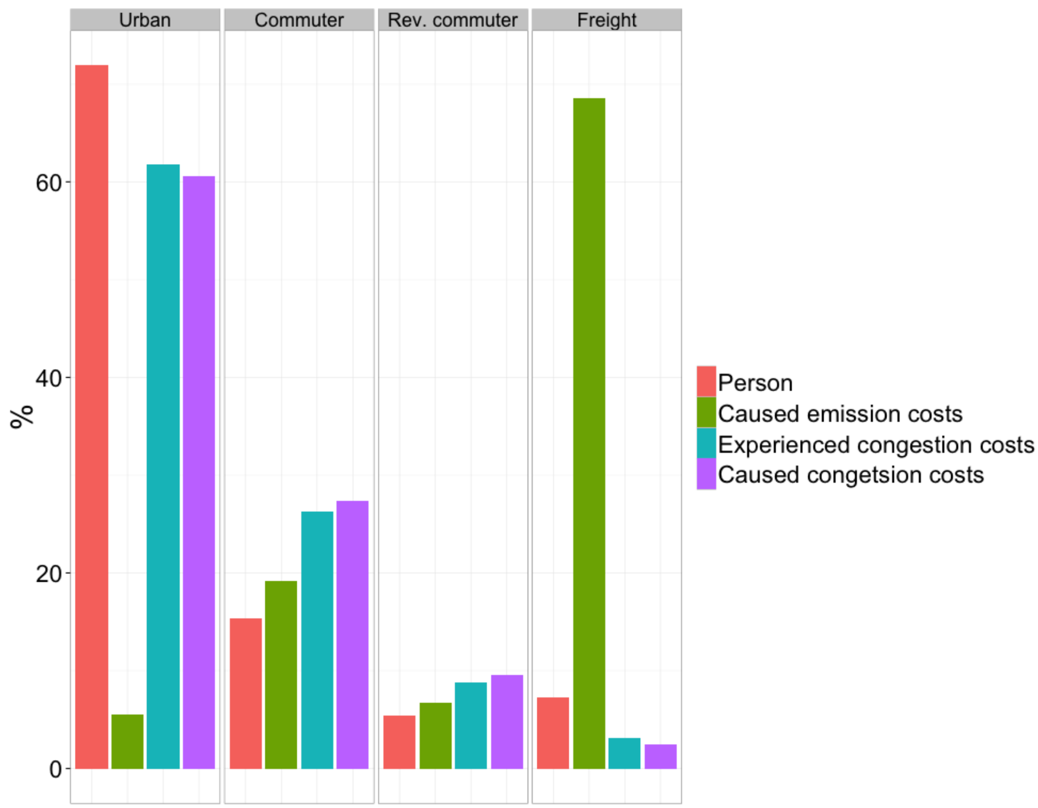


Figure 1: Share of persons, emission and congestion costs for different user groups for BAU scenario.

Congestion costs are classified into two categories, namely ‘experienced congestion costs’ and ‘caused congestion costs’. The former are costs experienced, the latter are costs caused by the respective group. The share of urban travelers is more than 70% of the total population. They

[11] A recent study by Kickhöfer and Kern (2015) shows that experienced exhaust emission costs can also be calculated in the same framework. However, in the present study, only *caused emission costs* are considered and referred to as ‘emission costs’ from here on.

experience and cause the highest congestion costs. This is expected since they perform most of the trips and congestion is predominant in urban areas. For urban and freight user groups, the experienced congestion costs are higher than the caused congestion costs, which means that these users are causing less congestion than they experience. On the contrary, for commuters and reverse commuters, agents cause more than what they experience. 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.

4.2 Pricing: effects on the system level

Absolute change in external costs, toll payments, user benefits and system welfare for whole population and user groups are shown in Tab. 5 and Tab. 6 respectively.

Table 5: Changes in emission costs, congestion costs, user benefits and system welfare with respect to BAU, and absolute toll payments for each pricing scheme. All values are scaled to full population and in *EUR*.

	Pricing scheme		
Change in ...	**EI**	**CI**	**ECI**
... emission costs	– 101,076	– 166,786	– 267,938
... congestion costs	– 908,261	– 3,607,735	– 3,955,052
... user benefits	– 2,749,961	436,382	– 2,339,755
... system welfare	962,232	4,286,376	4,708,329
Toll payments	3,611,118	3,683,208	6,780,146

Whole population For the Munich metropolitan area, congestion costs in BAU amount to 7,333,451 *EUR* which is about twice as much as the emission costs for the same scenario. Other studies in the literature find that congestion costs are typically higher than emission costs (see, e.g., Maibach et al., 2008; Parry and Small, 2005). The above finding is therefore in line with the literature. As shown in Tab. 5, internalizing emission costs (EI) result in 908,261 *EUR* less congestion cost and internalizing congestion costs (CI) result in 166,786 *EUR* less emission costs. Thus, pricing one externality has a positive impact on the other externality. Consequently, the externalities prove to be positively correlated for the case study under consideration. The positive correlation is also found in a study by Beevers and Carslaw (2005), who show that the London congestion charging scheme reduced NO_x and PM_{10} by 12% and 11.9% respectively between 2002 and 2003.

The reduction in emission costs for EI, CI and ECI pricing schemes are 2.72%, 4.49% and 7.22% respectively. These values are in the same order as in a previous study by Agarwal and Kickhöfer (forthcoming) who found reductions in emission costs of 0.57%, 1.94% and 2.48% for the same pricing schemes. However, that study did not account for different PT speeds (see Sec. 3.2), which seems to have an important effect on the price elasticity of car travel demand. The decrease in emission costs is for all pricing schemes more significant in the present paper which indicates that capturing the elasticities accurately has a major impact on the results.

The highest reduction in emission costs is 267,938 *EUR* in the combined pricing scheme (ECI). Similarly the highest reduction in congestion costs is 3,955,052 *EUR*, again for the combined pricing scheme.[12] Clearly, the combined pricing yields the lowest levels of externalities. Since congestion costs are significantly higher than emission cost, the ECI pricing scheme is closely followed by pricing congestion cost (CI). Changes in user benefits are negative for EI and ECI and positive for CI. The user benefits in CI are higher than in BAU, since the reduction in travel times overcompensates the loss from toll payments (congestion relief effect). For EI and ECI, the reduction in travel times is smaller than the loss from toll payments yielding a negative change in user benefits. This is expected since the reduction of environmental effects is – in contrast to congestion – not part of user benefits. Furthermore, the highest gain in system welfare realized by the combined pricing is 4,708,329 *EUR*. The algebraic sum of toll payments from the isolated pricing schemes is 7,294,326 *EUR* whereas the total toll payments for combined pricing is 6,780,146 *EUR*.

In order to check the sensitivity of the approach, BAU, EI, CI and ECI scenarios are simulated again with two different random seeds[13]. The results from the simulation runs with different random seeds approve this finding. The lessons learned here are that simply combining the average toll payments from the isolated pricing schemes (EI and CI) for policy making will result in toll levels beyond those of the combined pricing scheme (ECI). Hence, as an effect of the correlation of

[12] Congestion costs can be avoided if some agents shift to non-car travel modes but emission costs can only be avoided if all agents use non-car travel modes. Therefore, changes in congestion costs seem rather higher compared to the changes in emission costs.

[13] A random seed is used to initialize the pseudo random number generator in the MATSim . A different random seed will generate different random number which eventually produces different simulation outcomes. For an example of the effect of randomness on the optimal supply parameters in MATSim, see, e.g., Kaddoura et al. (2014).

Table 6: Changes in emission costs, congestion costs, user benefits and system welfare with respect to BAU, and absolute toll payments for each pricing scheme and user group. All values are scaled to full population and in *EUR*.

Change in ...	User group	Pricing scheme EI	CI	ECI
... emission costs	Urban	− 155	− 17,582	− 17,643
	Commuter	− 80,642	− 120,774	− 196,379
	Rev. commuter	− 14,426	− 26,587	− 46,787
	Freight	− 5,853	− 1,844	− 7,129
... congestion costs	Urban	− 203,515	− 1,992,550	− 210,1719
	Commuter	− 655,606	− 1,303,920	− 1,507,387
	Rev. commuter	− 50,076	− 275,680	− 311,115
	Freight	935	− 35,585	− 34,831
... user benefits	Urban	276,407	950,195	1,134,478
	Commuter	− 340,929	− 224,138	− 551,841
	Rev. commuter	− 165,558	− 149,311	− 272,556
	Freight	− 2,519,881	− 140,364	− 2,649,836
... system welfare	Urban	479,358	3,394,195	3,654,678
	Commuter	373,055	585,450	647,491
	Rev. commuter	83,779	299,882	363,952
	Freight	26,039	6,849	42,208
Toll payments	Urban	202,797	2,426,418	2,502,558
	Commuter	633,343	688,814	1,002,952
	Rev. commuter	234,912	422,607	589,722
	Freight	2,540,067	145,369	2,684,915

congestion and air pollution externalities, one would charge prices beyond the economic optimum.

User groups Tab. 6 shows the change in external costs, toll payments, user benefits and system welfare for all user groups and pricing schemes. Freight trips are responsible for a major part of emission costs (see Fig. 1) and therefore their toll payments are highest in the EI case. Similarly, toll payments are highest for urban travelers when pricing congestion. In accordance to the results for the whole population, (1) pricing congestion (CI) results in a decrease of emissions for all user groups; (2) pricing emissions (EI) yields a reduction in congestion for all user groups except freight; (3) the lowest levels of external costs are observed in the combined pricing scheme; (4) system welfare is highest for the combined pricing for all user groups. However, some observations can be made that are not in line with the aggregated figures for the whole population. 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 ($+935\ EUR$). This effect is known from a study by Yin and Lawphongpanich (2006), where authors experimented on a 6 node test network and found that emission internalization may sometimes produce less emissions but higher delays.

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. While 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).

4.3 Pricing: behavioral effects

As described in Sec. 3.1, the reduction in external costs is a combined effect of users' reactions with respect to two choice dimensions, mode choice and route choice. This section presents the impact of all three pricing schemes on the behavior of individuals.

Modal split Tab. 7 shows the impact of the pricing schemes on modal split, with a combined value for commuters and reverse commuters. For emission pricing, the share of car trips decreases for commuters and reverse commuters whereas it increases slightly for urban travelers. Because of the higher average toll for commuters and reverse commuters (see Tab. 8), a significant number of car users in these groups switch to PT. This reliefs some capacity and leads to an increase in the car share of urban travelers.

In contrast to EI, for the CI and ECI pricing schemes, car share decreases for all three user groups. The average toll for urban travelers in CI and ECI is about 12 times of the average toll in EI (see Tab. 8). Because of this higher average toll, urban car share decreases slightly (-0.66

Table 7: Changes in modal split with respect to BAU for all pricing schemes.

	Urban		(Rev.) commuters	
	car	non-car	car	non-car
EI	0.22	– 0.22	– 7.04	7.04
CI	– 0.66	0.66	– 16.25	16.25
ECI	– 0.48	0.48	– 23.46	23.46

Table 8: Average toll payments (EUR) per trip

	Urban	(Rev.) commuters	Freight
EI	0.16	1.62	15.94
CI	1.94	2.88	0.92
ECI	2.00	4.12	16.84

and -0.48, respectively). One can observe that the higher the toll, the more agents switch from car to PT, always depending on the implicit price elasticity of demand. This, in turn, is dependent on substitutes, i.e. if agents are not able to switch mode because of little PT supply, pricing can not be used to increase the system efficiency. Daniel and Bekka (2000) have found in their models that potential welfare gains decrease with a decrease in the elasticity of demand. The results in the present paper support this finding.

Route choice In order to investigate changes in agents' behavior, differences in route distance distributions for car and non-car modes are plotted in Fig. 2. For shorter distance routes, non-car (•) travel modes decrease slightly in all three pricing schemes. For longer distance routes, agents switch to non-car in order to avoid the toll. The combined pricing scheme leads to the most important modal shift from car (+) to non-car (•). As mentioned before in Sec. 4.2, congestion costs are about two times of the emission costs, and therefore, the ECI scheme exhibits a similar pattern as the congestion internalization alone.

Average trip time and distance Fig. 3 shows the change in average trip time and trip distance for mode switchers and retainers. From Fig. 3a, one can observe that the average trip time is decreased significantly for agents who retain their car as transport mode, as well as for agents who change from non-car to car: the toll in the car mode improves car travel times. On the other

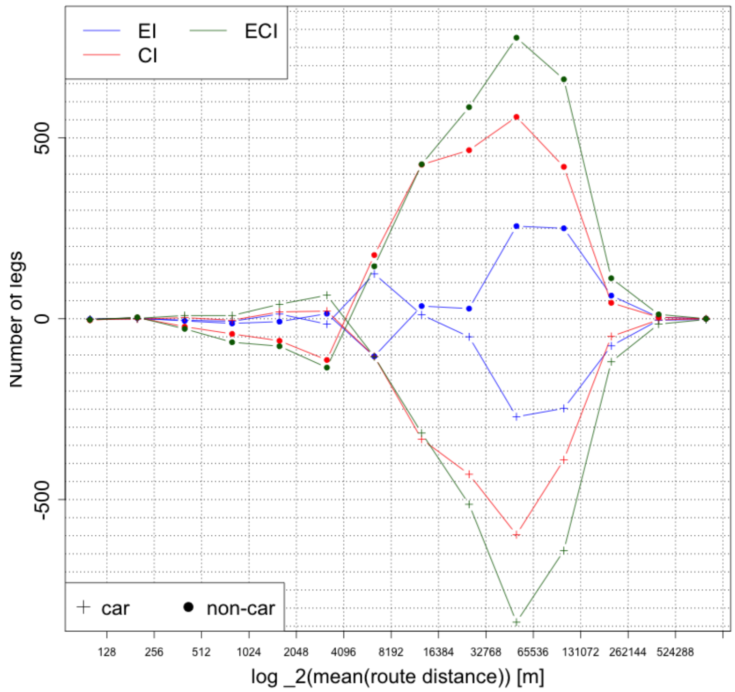
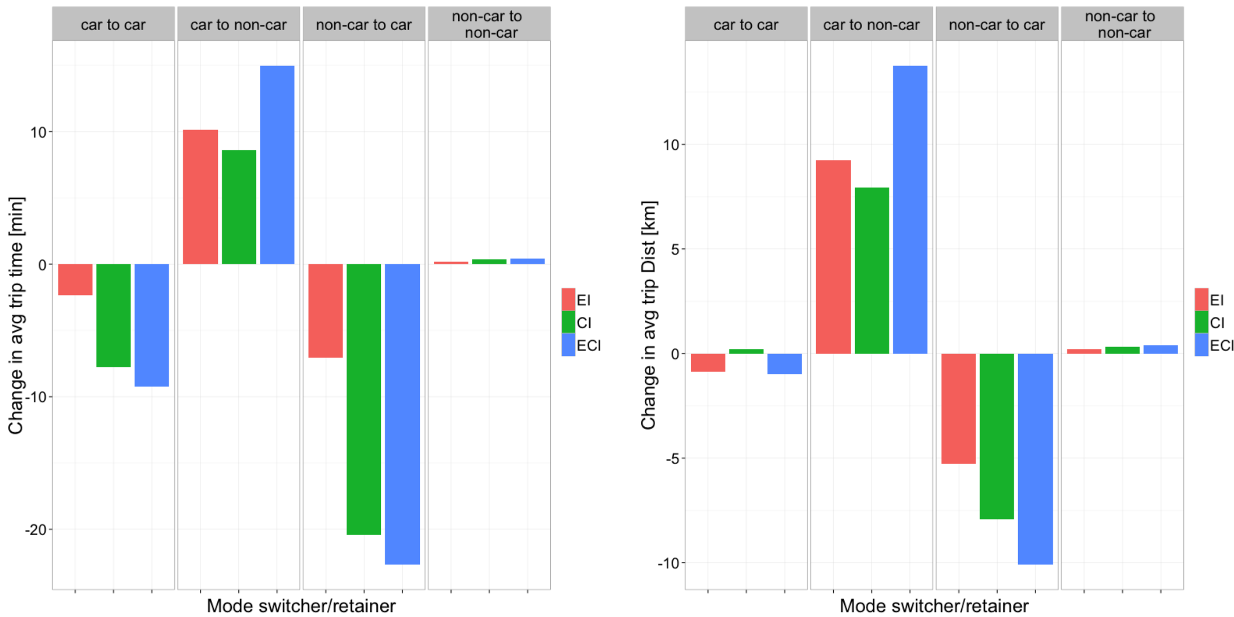


Figure 2: Changes in mode distance distribution over all trips.

hand, travel time is increased for the agents who switch to non-car mode from car. These agents are better off by shifting to longer non-car travel mode than paying toll on shorter routes (also see, Fig. 3b). Interestingly, with CI pricing scheme, agents who retain their car are shifting to less congested but longer routes in order to dampen their toll. In contrast, agents who switch from non-car to car prefer to pay toll and this toll is compensated by significant reduction in travel time and travel distance.

4.4 Pricing: spatial effects

To understand the agents' behavior under different pricing schemes in more detail, this section presents highly disaggregated spatial plots. For the visual presentations, a Gaussian distance weighting function is used to smooth emissions and delays throughout the area of Munich and surroundings. Uniform hexagonal cells of size 500 m are taken for this purpose. The smoothing radius is assumed as 500 m (Kickhöfer, 2014).



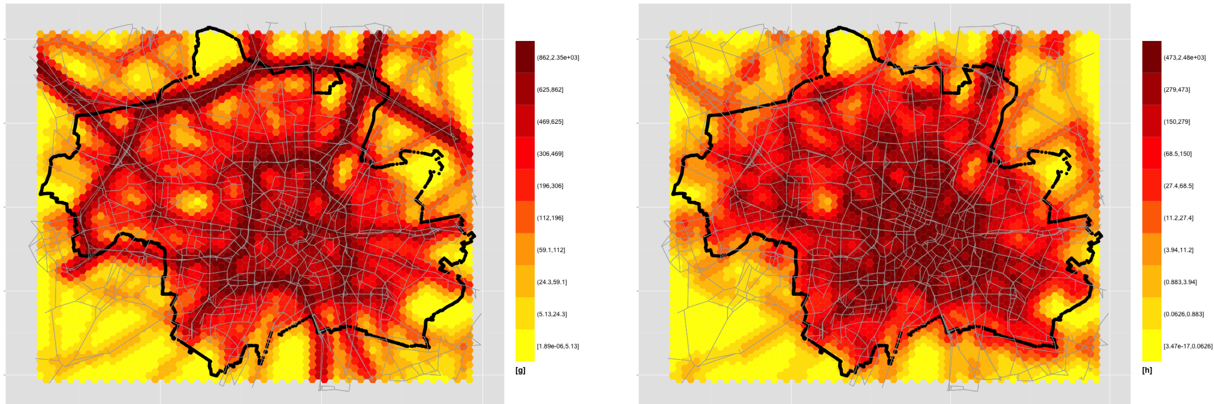
(a) Average trip time **(b)** Average trip distance

Figure 3: Changes for mode switchers and retainers.

Absolute external costs The spatial dimension of external costs in the BAU scenario is shown in Fig. 4 for emissions and delays, respectively. Time-dependent and person-specific link emissions are calculated and thereafter processed by spatial averaging. Similarly, link-based individual delays are calculated and processed by spatial averaging. Fig. 4a shows absolute NO_2 emissions[14] and Fig. 4b shows the absolute delays for the BAU scenario. 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 (see Fig. 4b).

Comparison of the pricing schemes Fig. 5 shows the changes in NO_2 emission and change in delay from 6:00 to 8:00 p.m. The change in emission is shown in colors, and the change in delays is depicted by transparency. For the EI case, Fig. 5 shows that agents are re-routing towards shorter distance routes. This is indicated by an increase of emissions *and* delays in the inner city (dark red, opaque hexagons). In 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 BAU (see, Fig. 4a). In the CI case, Fig. 5 shows that agents re-route from congested links to

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



(a) Absolute NO_2 emission in [g]

(b) Absolute delay in [h]

Figure 4: Absolute emissions and delays. Values are scaled to full population.

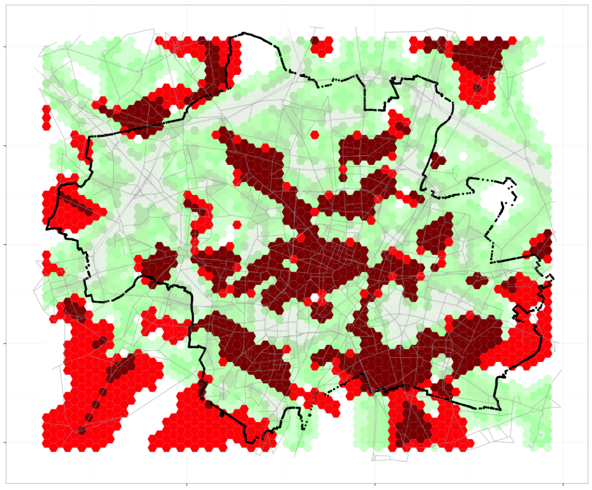
non-congested and longer distance routes (also see Fig. 3a). Thus, NO_2 emissions and delays are decreased significantly inside the central areas of Munich (transparent green hexagons). On the contrary, NO_2 emissions and delays are increased on parts of the tangential motorway (red, opaque hexagons) where NO_2 emission was already high in BAU scenario (Fig. 4a). The lessons learned here is that for congested regimes, the two pricing schemes (EI and CI) affect the route choice behavior of agents by tendency into opposite direction: EI on shorter distance routes, increasing congestion; CI on longer distance routes, increasing emissions.

The effect of combined pricing on a spatial level is shown in Fig. 5. As mentioned before in Sec. 4.2, congestion costs dominate emission costs, and therefore agents' behavior in ECI is similar to that of CI. However, the combined pricing yields a decrease in NO_2 emissions *and* delays in most areas of the city.

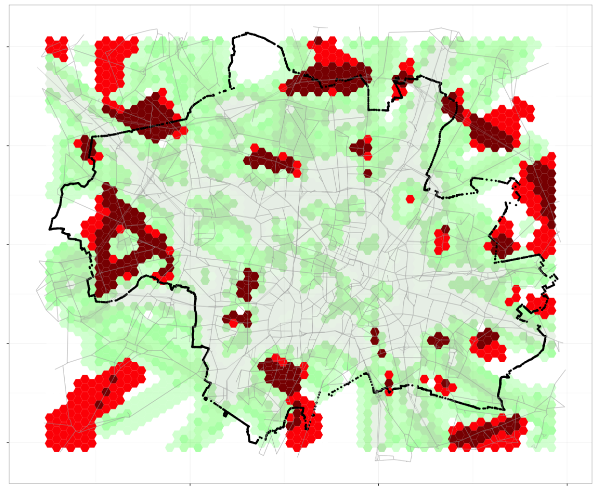
5 Conclusion and outlook

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.

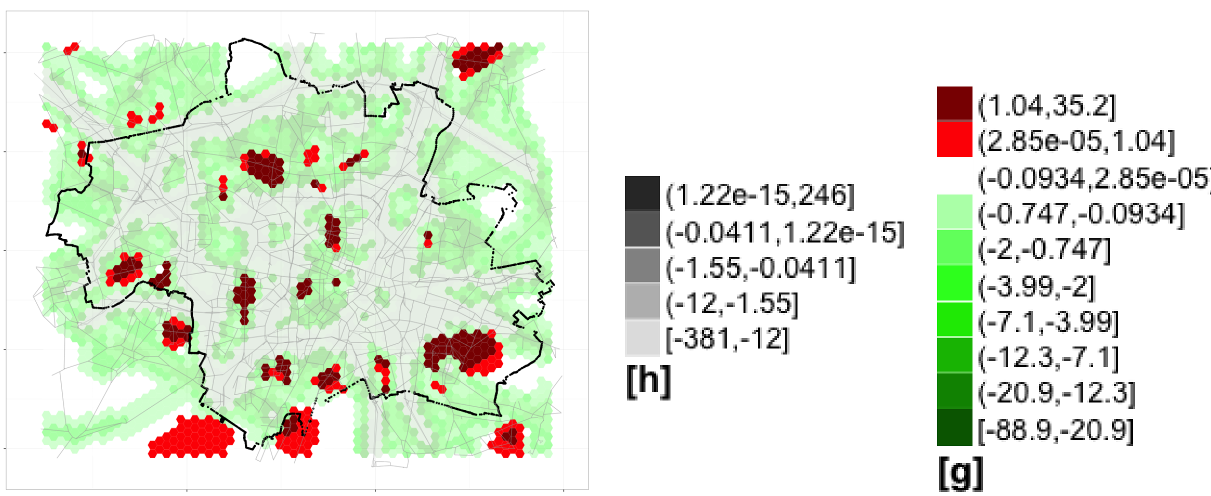
First, the impact of emission pricing on congestion levels was analyzed and vice versa. It was found that pricing one externality reduces the other external externality as well since both



(a) EI



(b) CI



(c) ECI

Figure 5: The effect of pricing schemes on NO_2 emissions from 6:00 to 8:00 p.m. Additionally, transparent colors denote a reduction in congestion whereas opaque colors show an increase in congestion. Values are scaled to full population.

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. Furthermore, it was found that the sum of tolls from the individual pricing schemes is higher than the tolls from the combined pricing scheme. Thus, simply combining toll levels from the two separate pricing schemes would eventually depreciate the system efficiency. The potential efficiency gains can only be obtained when the implicit price elasticities of car travel demand are captured in an accurate way, i.e. by carefully modeling substitutes to the car mode. Without substitutes, pricing can not unfold its full power and contribute to a meaningful reduction in transport-related externalities.

Third, the impact of different pricing schemes on agents' behavior was investigated with the help of spatial plots. It was shown that pricing emissions steers agents on shorter distance routes and pricing congestion pushes agents on shorter travel times routes and potentially longer distance routes. Thus, it can be concluded that for congested areas, route choice behavior of agents is by tendency affected into opposite direction by the two pricing schemes.

Finally, 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. In future studies, the authors aim to incorporate emission exposure (Kickhöfer and Kern, 2015), noise exposure (Kaddoura et al., 2015), 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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