Income dependent economic evaluation and public acceptance of road user charging

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14.05.2010

Abstract

Road user pricing has often been stated to open up new possibilities to a more efficient allocation of limited road capacities in metropolitan areas, to a reduction of negative environmental effects and to raising additional funds for publicly financed projects. In this context, two major questions are frequently posed, one linked to economic evaluation and one concerning the project's public acceptance:

1. How to measure welfare effects of the policy?
2. Why is road user pricing often very unpopular?

This paper aims at linking economic evaluation to the understanding of implementation problems in a model that allows multiple choice dimensions simultaneously, such as route choice, mode choice and time choice. Therefore, a large-scale multi-agent microsimulation is used which is capable to simulate complete daily plans of several million individuals (agents). Within this model, agents optimise the utility of their daily plan with respect to a random utility model. Therefore, this approach allows choice modeling and economic evaluation to be realised in a consistent framework. The utility functions are income dependent and assume decreasing marginal utility of income.

For a real-world scenario of the Zurich metropolitan area in Switzerland, it is shown how the agents react to a morning rush hour toll for eight different distance toll levels. Furthermore, the aggregated individual and the aggregated average willingness-to-pay are calculated and compared as indicators of the overall welfare change. The results indicate that, first, the choice between the two interpretations of the willingness-to-pay might even influence sign of the estimated welfare gain. Second, the distribution of welfare gains among the income range seems to be a possible indicator in order to identify acceptance problems of road user pricing. Finally, this approach could help policy makers to anticipate implementation problems and enables them to design and identify alternatives with higher public acceptance.

1 Introduction

Road user pricing has often been stated to open up new possibilities to a more efficient allocation of limited road capacities in metropolitan areas, to a reduction of negative environmental effects and to raising additional funds for publicly financed projects (e.g. Beckers et al., 2007). In this context, it has fequently been discussed how to measure the welfare effects resulting from the policy and how to consider non-linearity of income in utility calculations (Herriges and Kling, 1999; Mackie et al., 2001; Bates, 2006; Franklin, 2006). Another open issue is why road user pricing is often not supported by a major part of the population (e.g. Schade and Schlag, 2000).

These two questions are usually addressed by different research directions: welfare computations are done by economists using input data from aggregated state-of-the-practice transport planning tools or aggregated supply-demand functions and price elasticities (e.g. Bureau and Glachant, 2008). The major drawback of these approaches is that they typically consider only one choice dimension (route choice or mode choice) as a reaction to a policy change. Because of this limitation, welfare effects are likely to be underestimated.

Implementation problems that are linked to a lack of public acceptance are often examined by psychologists. According to them, road user charges are unpopular because people do not trust the government to reinvest the collected money in a meaningful way and thus perceive the charge as an additional tax (Schade and Schlag, 2000). Furthermore, equity concerns are often mentioned in this context. However, the role of public acceptance has rarely been studied within the context of economic evaluation.

This paper aims at linking economic evaluation to the understanding of implementation problems in a model that allows multiple choice dimensions simultaneously, such as route choice, mode choice and time choice. Therefore, a large-scale multi-agent microsimulation is used which is capable to simulate complete daily plans of several million individuals (agents). Within this model, agents optimise the utility of their daily plan with respect to a random utility model. Therefore, this approach allows choice modeling and economic evaluation to be realised in a consistent framework. The utility functions are income dependent and assume decreasing marginal utility of income.

After introducing the simulation approach in Sec. 2 and defining a real-world scenario of the Zurich metropolitan area in Switzerland in Sec. 3, it is shown how agents react to a morning rush hour toll for eight different distance toll levels (Sec. 4.1). Then, in Sec. 4.2, the aggregated individual and the aggregated average willingness-to-pay are calculated and compared as indicators of the overall welfare change. In Sec. 4.3, a possible dependency between the distribution of welfare effects among income deciles and implementation problems of road user pricing is presented. In Sec. 5 the impact of this study on the methodology of economic appraisal schemes is discussed. The paper ends with a conclusion.

2 Simulation approach

This section aims at describing the simulation approach that is used in this paper. It then introduces the income dependent utility function.

At this point, only a brief overview of the software tool MATSim[1] can be given. For more detailed information, please refer to the Appendix or see Raney and Nagel (2006) or Balmer et al. (2005).

2.1 MATSim at a glance

In MATSim, each traveler of the real system is modeled as an individual agent. The approach consists of an iterative loop that has the following important steps:

1. **Plans generation**: All agents independently generate daily *plans*, that encode among other things his or her desired activities during a typical day as well as the transportation mode. Agents typically have more than one plan ("agent database"). With the current version of MATSim, there is always one plan for each mode.
2. **Traffic flow simulation**: All selected plans are simultaneously executed in the simulation of the physical system.
3. **Scoring**: All executed plans are scored by an *utility function* which is, in this paper, personalized for every individual by individual income.
4. **Learning**: Some of the agents obtain new plans for the next iteration by modifying copies of existing plans. This is done by several *modules* that correspond to the choice dimensions available: time choice, route choice and mode choice. Agents choose between their plans according to a Random Utility Model (RUM).

The repetition of the iteration cycle coupled with the agent database enables the agents to improve their plans over many iterations. This is why it is also called **learning mechanism** which is described in more detail by Balmer et al. (2005). The iteration cycle continues until the system has reached a relaxed state. At this point, there is no quantitative measure of when the system is "relaxed"; we just allow the cycle to continue until the outcome is stable.

2.2 Utility function

There is some agreement that income effects play an important role in transport policy analysis, see, e.g., Herriges and Kling (1999); Kockelman (2001); Bates (1987, 2006); Franklin (2006). The argument essentially is that monetary price changes affect people with different income differently. This is usually addressed by estimating values of time for

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

the income groups. In this paper, non-linear income dependent preferences are included in every agent's utility function.

The functional form used for simulations is loosely based on Franklin (2006) and is similar to Kickhöfer (2009). A detailed derivation of this form and the estimation of the corresponding parameters are illustrated in Grether et al. (2009b). Hence, the utility functions of the two transport modes car and public transit (pt) are, according to (4) in the appendix, given by:

$$\begin{aligned} U_{car,i,j} &= + \frac{1.86}{h} t_{*,i} \cdot \ln(\frac{t_{perf,i}}{t_{0,i}}) - \frac{4.58}{y_j} (c_{i,car} + c_{i,toll}) - \frac{0.97}{h} t_{i,car} \\ U_{pt,i,j} &= + \frac{1.86}{h} t_{*,i} \cdot \ln(\frac{t_{perf,i}}{t_{0,i}}) - \frac{4.58}{y_j} c_{i,pt} \end{aligned} \qquad (1)$$

The first summand refers to Eq. (5), i.e. to the positive utility obtained from performing an activity, with $\beta_{perf,i} = +1.86/h$. With the second summand, mode and income dependency are introduced into the utility functions: y_j stands for the daily income of person j and c_i is the monetary distance cost for traveling to activity i. The indices *car* and *pt* indicate the transportation mode. Toll costs ($c_{i,toll}$) apply when car is chosen for a trip and only when there are any tolled links on the route. Distance costs are calculated using a distance cost factor of 0.12 CHF/km for car and 0.28 CHF/km for pt respectively (given by Vrtic et al., 2007). While there is a third summand for car ($\beta_{tt,car} = -0.97/h$), picking up the linear disutility of travel time t_i, there is no equivalent expression in the pt utility function. Travel time in pt is nonetheless punished by the opportunity costs of time by missing out on positive utility of an activity ($\beta_{perf,i}$) which also implies additional negative utility for the car travel time. It was already pointed out in Grether et al. (2009b) that this implies that in Zurich, pt is the "higher value" mode.

By adding individual income to the utility function, strongly personalized preferences are modeled. Additionally, in a real-world scenario, trip distances and daily plans do also vary individually. Utilities are computed in "utils"; a possible conversion into units of money or "equivalent hours of leisure time" (Jara-Díaz et al., 2008) needs to be done separately (see Sec. 4.2).

3 Scenario

The income-dependent utility function is now applied to a large-scale, real-world scenario. The metropolitan area of Zurich, Switzerland, with about 1 million inhabitants is used. The following paragraphs give a simplified description of the scenario and focus on differences to similar simulations done by Chen et al. (2008) where a full description for a reference scenario can be found.

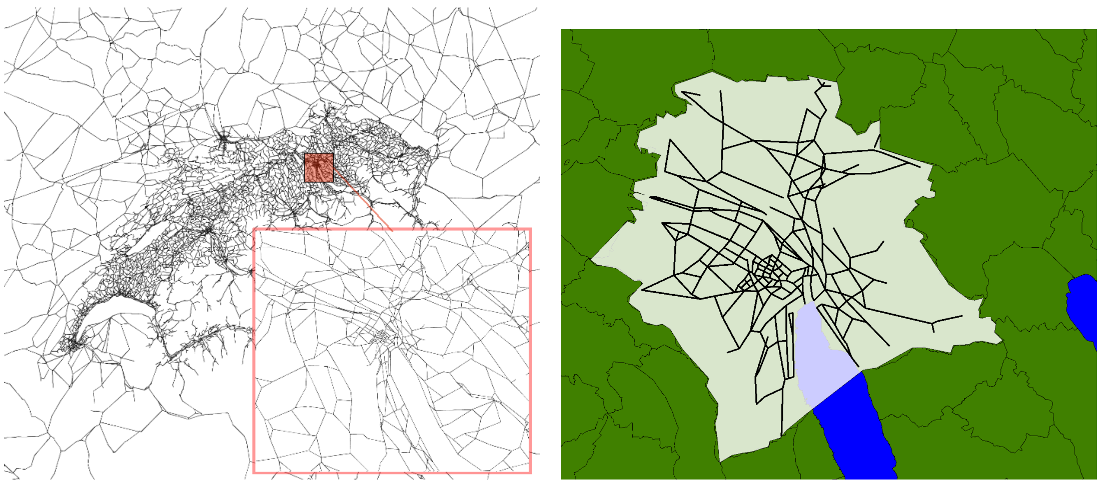
In order to obtain robust results, the correctness and plausibility of the implementation of the income-dependent utility function was verified in a simple test scenario and then calibrated against the reference scenario (Grether et al., 2009b).

3.1 Network and population

The network is a Swiss regional planning network that includes the major European transport corridors. It consists of 24 180 nodes and 60 492 links (see Fig. 1a).

The travel demand consists of all travelers within Switzerland that are inside an imaginary 30 km boundary around Zurich at least once during their day (Chen et al., 2008; Vrtic et al., 2007). All agents have complete day plans with activities like *home*, *work*, *education*, *shopping*, *leisure*, based on microcensus information (SFSO, 2000, 2006). The time window during which activities can be performed is limited to certain hours of the day: *work* and *education* can be performed from 07:00 to 18:00, *shopping* from 08:00 to 20:00, while *home* and *leisure* have no restrictions. Each agent gets two plans based on the same activity pattern. The first plan only uses car as transportation mode, while the second plan uses only public transit.

In order to speed up computations, a random 10% sample is taken from the synthetic population for simulation, consisting of 181 725 agents. In this large-scale scenario, agents can modify their plans with respect to all three choice dimensions available as described in Sec. 2.1.



(a) Swiss road network, area of Zurich enlarged (b) hypothetical toll links in Zurich municipality

Figure 1: Scenario: Switzerland network with toll links for Zurich.

3.2 Income generation

Income is generated based on a Lorenz curve. Due to the lack of exact data the functional form of the Lorenz curve was approximated. Then the income curve, the first derivative of the Lorenz curve, was calculated (Kämpke, 2008).[2] To generate personal incomes for the agents, a random number between 0 and 1 is drawn from a uniform distribution. For this number, the corresponding value on the income curve is calculated and multiplied by the median income. Doing this for all members of the synthetic population, an income distribution was derived, similar to the distribution in reality.

Region specific data is used for the Canton Zurich[3] area. A specific median is available for each municipality[4] of the state[5]. For every person living in Canton Zurich area, the municipality of the person's home location is identified. Then, the median income of this municipality is used for income calculation in conjunction with a Lorenz curve for the Canton Zurich.[6] The scenario focuses on the Zurich metropolitan area. Therefore, the income of persons living outside the borders of Canton Zurich is computed with the median income and the Lorenz curve of the Swiss Confederation.[7] The median income used for the Swiss Confederation is 43665 CHF per household and year. The y_i for Eq. (1) are obtained by (1) allocating the yearly household income individually to every agent, and (2) dividing that number by 240 (working days per year) in order to obtain "daily income".

3.3 Policy design

In order to evaluate an example of road user pricing for the area of Zurich and the consequences with respect to public acceptance, a fictive distance-based city morning toll was designed. The toll area covers, as can be seen in Fig. 1b, all roads within the area of Zurich municipality, but does not include the motorways that lead into and partially around the city. Since these are owned by the Swiss Confederation and not by the city of Zurich, they can not easily be taken into account when the local government decides about the implementation of a city toll. In addition, this setup is also expected to lead to more concentrated car traffic flow on the motorways while pulling flows from residential areas. Therefore, in 2007, this road pricing scheme had been discussed to be implemented (Bundesrat (Government) of Switzerland, 2007).

[2] The Lorenz curve is $L(x) \propto \int_0^x y(\xi)\,d\xi$. Therefore, $L'(x) \propto y(x)$. The correct scaling is given by the fact that $y(0.5)$ is the median income.

[3] A Swiss "Canton" is similar to a federal state.

[4] "Gemeinde" is the next lower administrative level, i.e. some kind of municipality.

[5] `http://www.statistik.zh.ch/themenportal/themen/daten_detail.php?id=759`, last access 30.10.2009

[6] `http://www.statistik.zh.ch/themenportal/themen/aktuell_detail.php?id=2752&tb=4&mt=0`, last access 30.10.2009

[7] `http://www.bfs.admin.ch/bfs/portal/de/index/themen/20/02/blank/dos/01/02.html`, last access 30.10.2009

Based on this toll road network, eight different toll levels are now simulated, starting from 0.35 CHF/km, in each step doubling, up to an almost prohibitive prize of 44.80 CHF/km.[8] The toll is implemented for the morning peak hour from 6:30 am to 9:00 am. This approach helps at finding a toll level near to the optimal toll for this particular system at this time of day only by observing welfare changes over different toll levels. From an economic point of view, the optimal toll is the one where the sum of monetized utility differences and overall paid toll is maximized.

3.4 Simulation Runs

First, a "preparatory run" is performed by running the simulation for 2000 iterations without any policy measure. For 1000 iterations, 10% of the agents perform "time adaptation" and 10% adapt their routes. The other 80% of the agents switch between their existing plans, which implicitly includes mode choice as explained in Sec. 2.1. This means, that during the first 1000 iterations, the *choice set* is being generated; during the second 1000 iterations, where time and route adaption are switched off, agents actually carry out their choice by only switching between existing options. In the following, the output after 2000 iterations is referred to as the *base case*.

After that, the distance toll is introduced for the subnetwork defined in Sec. 3.3. The simulation is run for another 200 iterations, starting from the final iteration of the base case. Again, during the first 100 iterations 10% of the agents perform "time adaptation" while another 10% of agents adapt routes. Agents, that neither adapt time nor route, switch between existing plans according to (6) which includes the switch between transport modes. As for the base case, during the final 100 iterations only a fixed choice set is available.

4 Results

In this section, the simulation results are presented. Overall, nine scenarios have been analyzed, the base case and eight policy cases with increasing toll levels (see Sec. 3.3). In the following, direct observations of traffic conditions as well as the actual behaviour of the agents are discussed. Subsequently, in order to compare the different policies, the willingness-to-pay as an indicator of welfare change is computed based on an innovative economic appraisal scheme. Finally, the results are interpreted in the context of public acceptance of urban road pricing schemes. Please note that for reasons of clarity, not all nine simulation runs are always discussed; but the analysis always contains the lowest and the highest toll level in order to get an idea about the range of possible impacts.

[8] 1 CHF = 1 Swiss Franc ≈ 0.70 Euro, 12.05.2010

4.1 Traffic conditions

In the MATSim framework, agents have several possibilities to react to changes of the system, such as the introduction of a road pricing scheme. In this paper, they can (i) change their transport mode, (ii) change their car routes or (iii) adapt the departure time. So far, there is no location choice model implemented, and neither can agents drop activities from their schedule.

Picking up the first point, Fig. 2 shows a shift in the modal split as a consequence of the toll. The percentage of car trips between activities (= legs) monotonously drops from 61% in the base case to 57% for the highest toll. This effect is likely to be even more important when only looking at people who have an activity within the toll area.

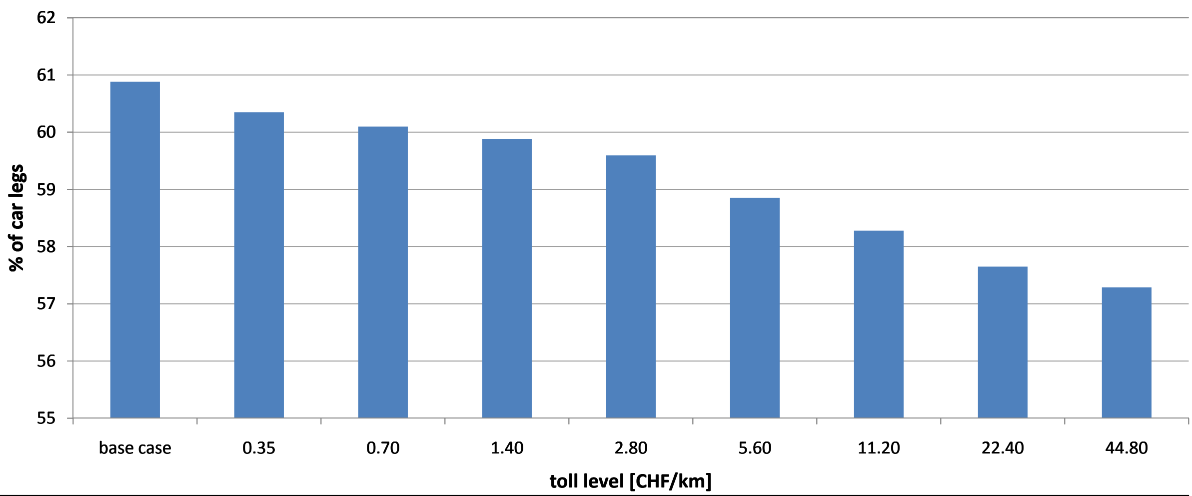


Figure 2: Percentage of car legs for the base case and the different toll levels; the remaining legs are public transit legs

Route and departure time adaption could be analyzed independently, but at this point, a locally more differentiated indicator about the overall impact of the different toll levels on the actual traffic conditions is used: the average speed in central Zurich. Fig. 3 shows the average speed on all links in within a 2 km radius around the center of the city over time of day for several toll levels and for time bins of 5 minutes. For the base case (dark blue line), it can be seen that the average car speed in this area drops from 42 km/h at 6:00 am to about 34 km/h at 6:30 am. It then raises again, up to round about 37 km/h, stays more or less constant until the afternoon peak starts at 4:00 pm.

For the first toll case, where agents have to pay 0.35 CHF/km, one can notice a slight improvement of the average speed in the morning hours from 7:00 am on, represented by the brown line in Fig. 3. With the toll level of 2.80 CHF/km (light blue line), this effect is even more important. Toll levels of 11.20 CHF/km and 44.80 CHF/km, represented

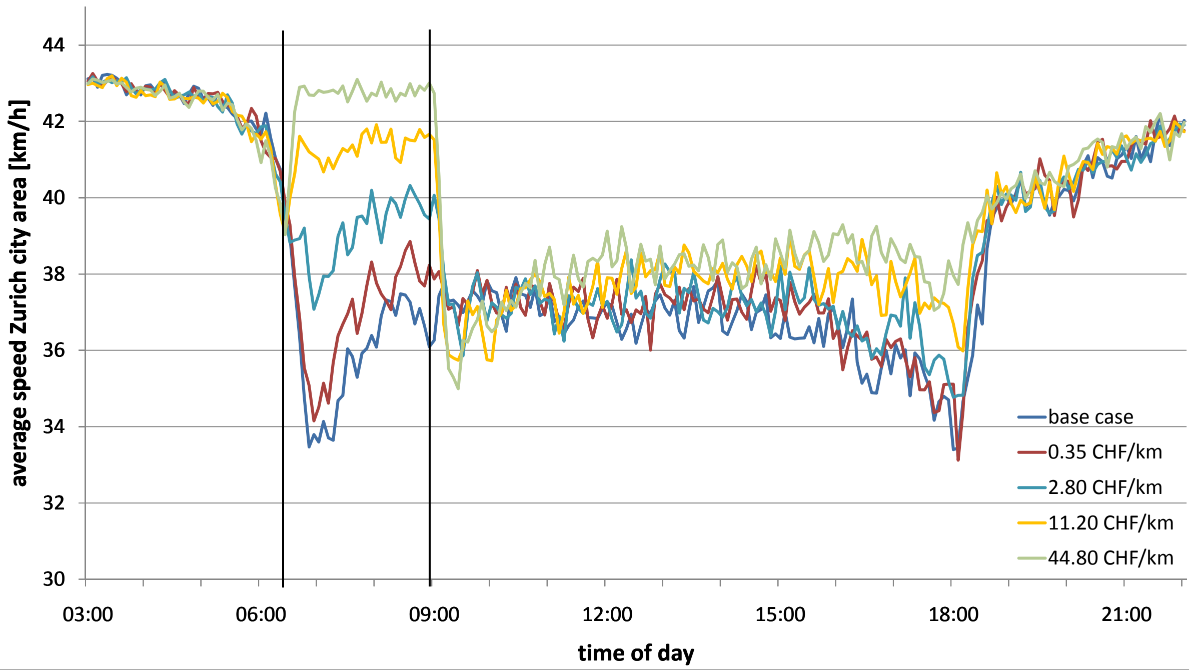


Figure 3: Average speed in Zurich city area over time of day for the base case and selected toll levels

by a yellow and light green line respectively, additionally influence the average speed in the afternoon peak in a positive way. Furthermore these high toll levels indicate that there might be a prohibitive toll level where no agent will take the car for traveling into or out of the city center. This fact is underlined by the decreasing number of people who pay toll during the day when raising the toll level: while for the lowest toll level, there are 11 016 agents paying toll, this number drops to only 1877 agents for the highest toll case, corresponding to only 6% or 1% of the whole population, respectively. Because the simulation uses a 10% sample of the full population, this would correspond to approximately 110 160 for the lowest toll, or 18 770 for the highest toll.

4.2 Economic evaluation

In literature, usually three goals of road user pricing are stated: first, a more efficient allocation of limited road capacities in metropolitan areas, second, a reduction of negative environmental effects and third, raising additional funds for publicly financed (transport) projects (e.g. Beckers et al., 2007). No matter whether politicians aim at realizing only one or even all of them, road user pricing schemes - like all policy measures - should make the system “better” than before. In this context, usually an economic appraisal of the policy is conducted: it is tried to figure out the change of society’s welfare level. In a first step, only a winner-looser analysis can directly be deduced from individual utility changes. Then, in order to compare individual welfare levels, a conversion *either* into units of money *or* into a monetary valuation of "equivalent hours of leisure time" is necessary (Jara-Díaz et al., 2008).

4.2.1 Welfare change as sum of individual willingness-to-pay

Following the monetary interpretation, the aggregated individual willingness-to-pay can be used as an indicator to describe changes in the society's level of welfare. Thanks to the MATSim approach, it is also possible to calculate this indicator on any desired level of (dis)aggregation. Thus, a conversion from units of utility into money terms is performed on an individual level with person specific Values of Time (VoT). Picking up the decreasing marginal utility of money from Eq. 1, the overall welfare change ΔW that results from the different toll levels is given by:

$$\Delta W = \sum_{j=1}^{n} \Delta U_j \cdot \frac{y_j}{4.58} + \sum_{j=1}^{n} c_{i,toll} \tag{2}$$

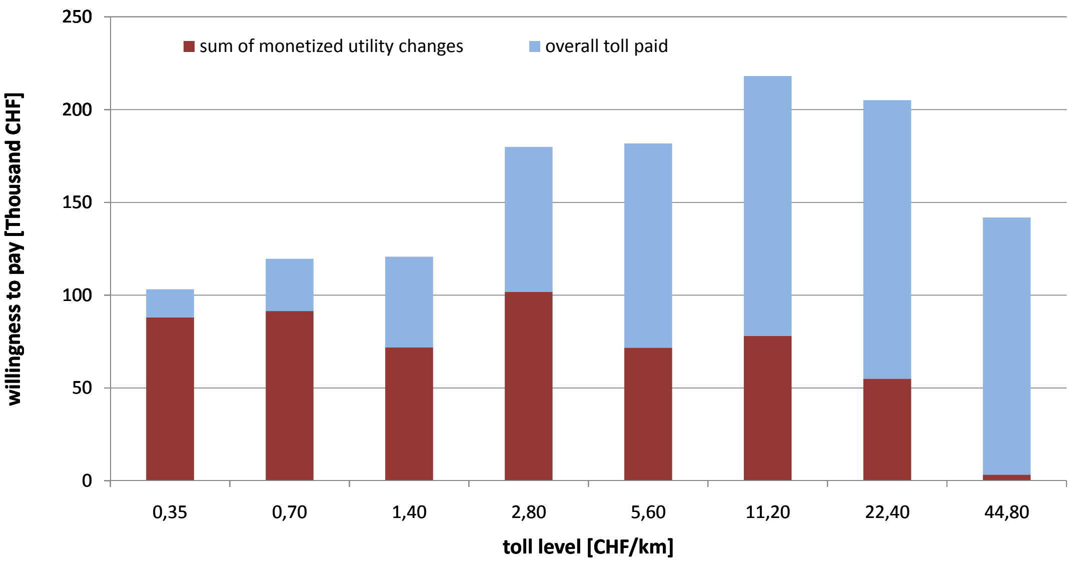
The first summand represents the sum of directly monetized utility changes. It is dependent on the individual utility difference ΔU_j and on the reciprocal value of the income dependent marginal utility of money $y_j/4.58$, where y_j is individual income. The second summand adds the overall paid toll. From a social optimizer's perspective, the toll collected from users only represents a transfer payment to the state and thus are inherent to the system. Another interpretation is that the toll payments did necessarily evoke utility, otherwise it would not have been paid. The two values are visualized in Fig. 4a over the eight different toll levels. Red bars depict the system's direct welfare change from utility changes. Blue bars indicate the toll payments by all users.

Obviously, as can be seen in Fig. 4a, a toll level of 11.20 CHF/km maximizes ΔW. This toll level seems unrealistically high for a real system.[9] However, the figure shows that with the MATSim framework the sum of the income-dependent willingness-to-pay can methodically be calculated and thus be used for project appraisal. Another advantage of this approach is that choice modeling and economic evaluation are implemented in a consistent way since the simulation output is directly used for evaluation.

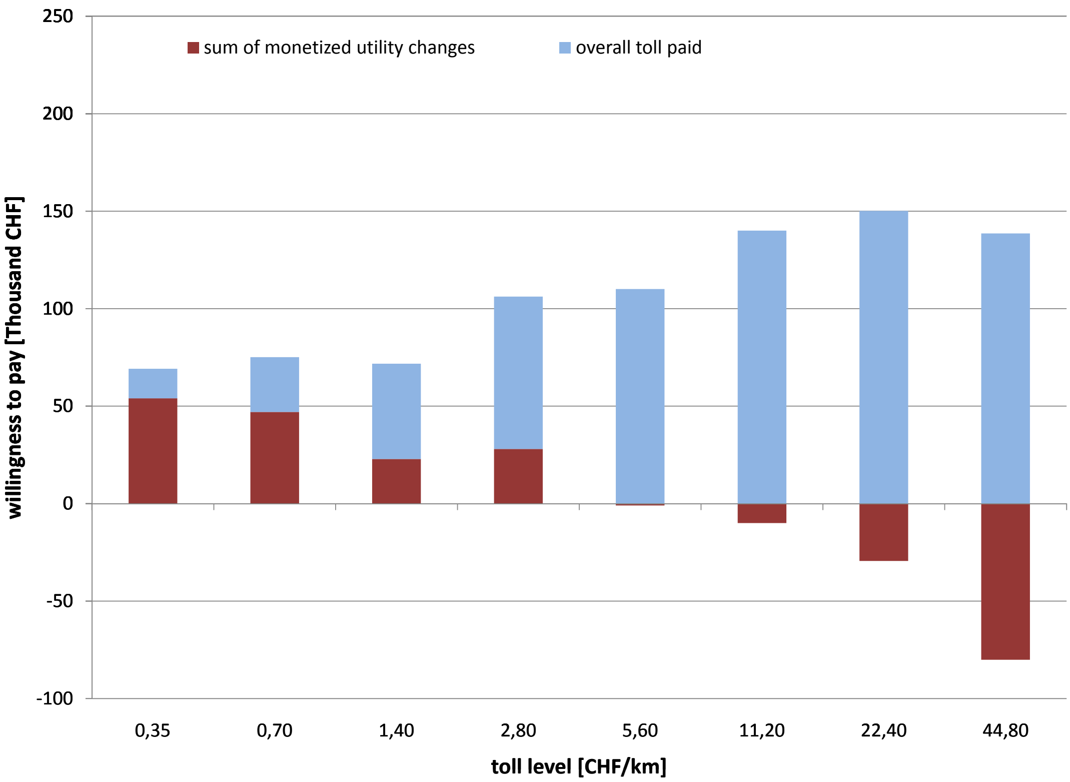
4.2.2 Welfare change as average willingness-to-pay

Following the monetary valuation of leisure time interpretation, an additional assumption needs to be made: society needs to agree that the welfare of all individuals is equally important (Mackie et al., 2001). What follows, is that individual utility changes converted

[9] It is likely that this has to do with the income that was generated from household data, but is, in this model, applied to individuals. Assuming that a division by two would approximately correct for this issue, then a toll level of 5.60 CHF/km would not seem fully implausible for the city of Zurich, especially if one recalls that this could be offset by a tax reduction.



(a) Sum of the individual willingness-to-pay



(b) Sum of the average willingness-to-pay

Figure 4: Different interpretations of the willingness-to-pay as an indicator for welfare changes resulting from various toll levels

into hours of leisure time can be compared between individuals. This is basically similar to:

$$\Delta\tilde{W} = n \cdot \left(\frac{1}{n} \sum_{j=1}^{n} \Delta U_j \right) \cdot \left(\frac{\frac{1}{n} \sum_{j=1}^{n} y_j}{4.58} \right) + \sum_{j=1}^{n} c_{i,toll} \tag{3}$$

Again, the first summand picks up the sum of directly monetized utility changes. Here it is calculated by n times the average utility change that is converted into money terms with the average marginal utility of money. The second summand corresponds to the toll payments, that are naturally the same as in Eq. (2). The perceived improvement of the system as the sum of monetized utility changes in Fig. 4b differs from the interpretation with an individual willingness-to-pay. At this point, it is important to note that already the choice between the two interpretations can change the sign of the sum of monetized utility changes. This is the case for all toll levels of 5.60 CHF/km and higher. Nonetheless, it is quite surprising that apart from the differing overall welfare gain of the two interpretations, the toll level with 11.20 CHF/km turns out to maximize both equations (2) and (3).

4.3 Public acceptance

The main question in the context of public acceptance is whether results from the economic evaluation of toll schemes can be used so as to understand why road user charging is often very unpopular. In order to answer this question, the welfare interpretation of Eq. (2) is used. Note, that in the following the role of the toll revenues is not further examined. The focus is now on the directly monetized utility gains resulting from the different toll levels.

For the two extreme toll levels of 0.35 CHF/km and 44.80 CHF/km, Fig. 5 breaks these overall gains from Fig. 4a down to population deciles that are sorted by income. The dots represent the willingness-to-pay (when positive) or the willingness-to-accept (when negative) for direct utility gains or losses of the people in the corresponding decile. Blue dots for a toll level of 0.35 CHF/km, red dots for a toll level of 44.80 CHF/km. Remember, that they were calculated based on the individual utility function and after that are averaged. All other toll levels have similar curve shapes in between these two. At a closer look, one can see that for the high toll level, only the two highest income deciles have a positive willingness-to-pay for the toll. All other deciles either lose in terms of money or stay almost unchanged. This highlights an important implementation problem of policy measures in democratically organized societies: 50% of the population would be better off without the toll, 30% would have an almost unchanged utility level and only for 20% of the population monetized gains appear. This is why a major part of the population is likely to refuse the introduction of the policy. Moreover, the same might be true for the blue curve even though almost all deciles gain in average: the toll could indeed be seen as an unequal reallocation of utility towards higher income groups.

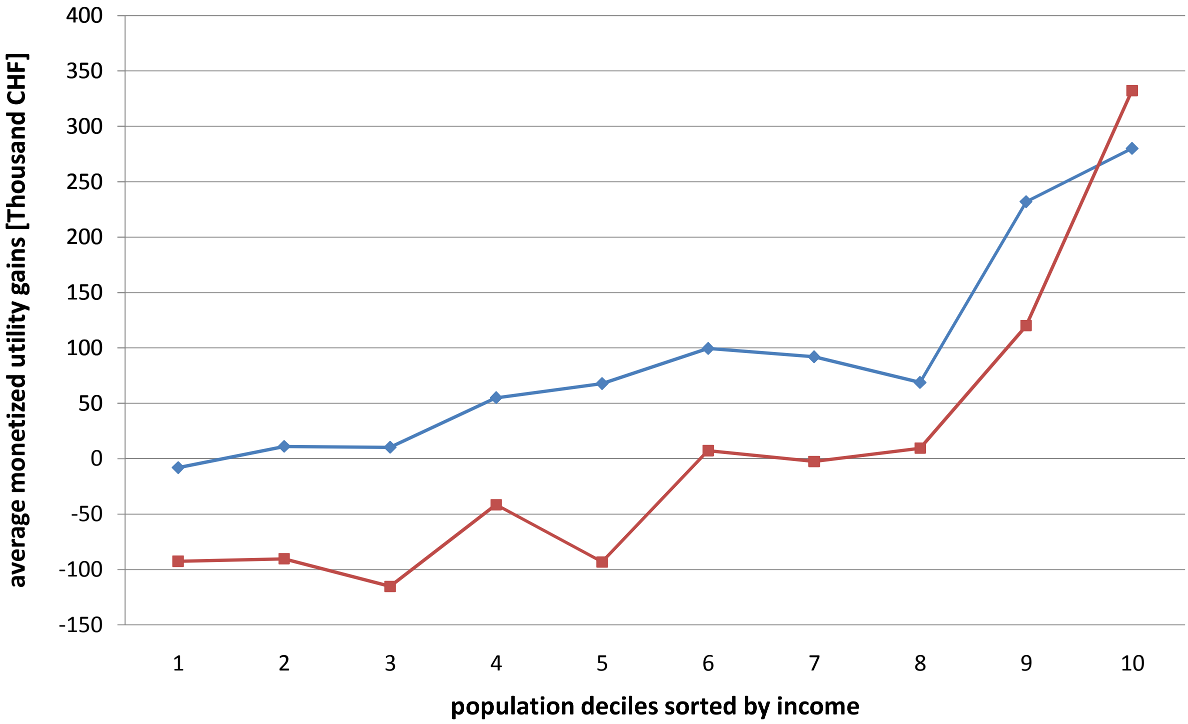


Figure 5: Average monetized utility gains due to the city toll over population deciles sorted by income: blue dots for a toll level of 0.35 CHF/km, red dots for a toll level of 44.80 CHF/km; the connecting lines only lead the eye.

5 Discussion

Until here, we presented several implications of road user pricing in a real world scenario for the inner city of Zurich. Eight different toll levels were examined. We based our simulations on highly personalized utility functions with decreasing marginal utility of income. After finding quite intuitive and obvious consequences for traffic conditions and the actual behaviour of the agents in Sec. 4.1, we showed two different interpretations of the willingness-to-pay as an indicator of welfare changes in Sec. 4.2. Following the first interpretation, a conversion from utility changes of every person to the private willingness-to-pay or willingness-to-accept is performed and the overall welfare change is derived by summing these up. Following the second interpretation, utility changes are converted into equivalent hours of leisure time or directly summed up and then monetized with the average marginal utility of income. We showed that already the choice between the two interpretations might even change the sign of welfare changes.

Finally in Sec. 4.3, we pointed out that road user pricing schemes tend to have a highly regressive impact on the welfare distribution of the society. The same is likely to be true for most of the investments in transport infrastructure that aim at shortening travel times (see Grether et al., 2009b, e.g.). In our opinion, this structural issue needs to be considered when evaluating public transport projects. In the case of road user pricing, such an analysis might help to understand the reasons that lead to low public acceptance and also how to improve the acceptance of unpopular projects. The problem is quite obvious: financing infrastructure projects by non-differentiated user fees, leads to an progressive reallocation of utility towards higher income groups. Financing such projects e.g. by a progressive income tax might be more appropriate. Provided, a progressive income tax system has been set up for making society more equal, then this tax would have to be even more progressive than the utility reallocation by the transport projects. One possibility to address these issues might be the design of "policy packages" where measures like a city toll are directly coupled with a redistribution scheme. By doing so, one could design a policy package that would be supported by a major part of the population.

A property of the first approach is the possibility to identify how welfare gains from a policy measure are distributed among the members of society and how a package deal would have to be designed. This analysis can basically be done on every desired level of disaggregation: it is possible to combine multiple demographic attributes of the population of interest, e.g. by considering the geospatial distribution of winners and losers of a measure (see Grether et al., 2008). Therefore we think that multi-agent simulations should be used in order to improve economic project appraisal and the understanding of problems that are linked to public acceptance.

6 Conclusion

This paper aimed at showing some possibilities of economic policy evaluation that are feasible with multi-agent microsimulations. Agents optimise their daily plans with respect to individual preferences such as individual income or activity location. Based on this framework, a winner-loser analysis can directly be performed using individual utility differences. When it comes to monetizing the individual utility changes in order to evaluate transport policies, a conversion into willingness-to-pay or willingness-to-accept can be done on the desired level of disaggregation. To conclude, the main findings in this paper are:

1. Income can and needs to be included in utility calculations for a better understanding of problems linked to acceptability.
2. Road user charging has an highly regressive impact on the welfare distribution of society. The same is likely to be true for other investments in transportation infrastructure that aim at shortening travel time.
3. Only multi-agent microsimulations allow to monetize utility changes based on individual preferences and attributes.

4. Averaging utility changes before the monetary valuation leads to different results and might even change the sign of welfare changes.
5. With the help of a multi-agent approach, it seems feasible to design "policy packages" where measures like a city toll are directly coupled with a redistribution scheme.
6. By doing so, one could achieve the support of a major part of the population.

Acknowledgments

This work was funded in part by the "Bundesministerium für Bildung und Forschung" (BMBF) within the research project "Adaptive Verkehrssteuerung" (Advest), and in part by the "German Research Foundation" (DFG) within the research project "Detailed evaluation of transport policies using microsimulation". Our computer cluster is maintained by the Department of Mathematics at TU Berlin.

Appendix. Simulation details

The following paragraphs are ment to present more information about the MATSim simulation approach that is used in this paper. Every step of the iterative loop in Sec. 2.1 is now illustrated in more detail.

Plans generation

An agent's daily plan contains information about his planned activity types and locations, about duration and other time constraints of every activity, as well as the mode, route, the desired departure time and the expected travel time of every intervening trip (= leg). Initial plans are usually generated based on microcensus information and/or other surveys. The plan that was reported by an individual, is in the first step marked as "selected". An alternative plan for non-selected transportation mode(s) is constructed.

Traffic flow simulation

The traffic flow simulation executes all selected plans simultaneously in the physical environment and provides output describing what happened to each individual agent during the execution of its plan. It differentiates between car and public transit plans: The *car traffic flow simulation* is implemented as a queue simulation, where each street (= link) is represented as a first-in first-out queue with two restrictions (Gawron, 1998; Cetin et al., 2003): First, each agent has to remain for a certain time on the link, corresponding to the free speed travel time. Second, a link storage capacity is defined which limits the number of agents on the link; if it is filled up, no more agents can enter this link.

The *public transit simulation* simply assumes that traveling takes twice as long as traveling by car on the fastest route in an empty network[10] and that the travel distance is 1.5 times the beeline distance between the activity locations. Public transit is assumed to run continuously and without capacity restrictions (Grether et al., 2009a; Rieser et al., 2009).

This approach is due to the fact that, for the Zurich scenario, there is not enough data available yet for simulating public transit with high resolution, e.g. based on bus or metro lines and the underlying shedules.

The output of the traffic flow simulation is a list that describes for every agent different events, e.g. entering or leaving a link, arriving or leaving an activity. The events data

[10] This is based on the (informally stated) goal of the Berlin public transit company to generally achieve door-to-door travel times that are no longer than twice as long as car travel times. This, in turn, is based on the observation that non-captive travelers can be recruited into public transit when it is faster than this benchmark (Reinhold, 2006).

includes agent ID, time and location (link or node ID). It is therefore quite easy to grab very detailed information and to calculate indicators such as travel time or costs per link (which is used by the router), trip travel time, trip length, percentage of congestion, and many more.

Scoring plans

In order to compare plans, it is necessary to assign a quantitative score to the performance of each plan. In this work, in order to be consistent with economic theory, a simple utility-based approach is used. The elements of our approach are as follows:

- The total score[11] of a plan is computed as the sum of individual contributions:

$$U_{total} = \sum_{i=1}^{n} U_{perf,i} + \sum_{i=1}^{n} U_{tr,i} \ , \tag{4}$$

  where U_{total} is the total utility for a given plan; n is the number of activities, which equals the number of trips (the first and the last activity are counted as the same); $U_{perf,i}$ is the (positive) utility earned for performing activity i and $U_{tr,i}$ is the (usually negative) utility earned for traveling during trip i.
- A logarithmic form is used for the positive utility earned by performing an activity:

$$U_{perf,i}(t_{perf,i}) = \beta_{perf} \cdot t_{*,i} \cdot \ln\left(\frac{t_{perf,i}}{t_{0,i}}\right) \tag{5}$$

  where t_{perf} is the actual performed duration of the activity, t_* is the "typical" duration of an activity, and β_{perf} is the marginal utility of an activity at its typical duration. β_{perf} is the same for all activities, since in equilibrium all activities at their typical duration need to have the same marginal utility. $t_{0,i}$ is a scaling parameter that is related both to the minimum duration and to the importance of an activity. As long as dropping activities from the plan is not allowed, $t_{0,i}$ has essentially no effect.
- The (dis)utility of traveling used in this paper is estimated from survey data. It is, at this point, not any more a homogenous function for all agents but it depends on the agent's individual income as well as on his time, mode and route choice. The functional form is explained in Sec. 2.2.

In principle, arriving early or late could be punished. There is, however, no immediate need for doing so since this is already indirectly punished by foregoing the reward that could be accumulated by performing an activity instead (opportunity cost of time). In consequence, the marginal utility of waiting or being late is $-\beta_{perf}$.

[11]Note that the terms "score" and "utility" refer to the same absolute value. "Utility" is the common expression in economic evaluation and is therefore used in this paper.

The learning mechanism

A plan can be modified by various **modules** that correspond to different choice dimensions. These modules are customizable, they can be independently switched on or off or even be replaced by other modules. In this paper, three different choice dimensions are considered: time choice, route choice and mode choice that are implemented as follows:

1. **Time allocation module**: This module is called to change the timing of an agent's plan. A simple approach is used which just applies a random "mutation" to the duration attributes of the agent's activities (Balmer et al., 2005).
2. **Router module**: The router is a time-dependent best path algorithm (Lefebvre and Balmer, 2007), using for every link generalized costs of the previous iteration.
3. **Mode choice**: This choice dimension is not represented by its own module, but instead by making sure that every agent has at least one *car* and at least one *public transit* plan (Grether et al., 2009a; Rieser et al., 2009).

The modules base their decisions on the output of the traffic flow simulation (e.g. knowledge of congestion) using **feedback** from the multi-agent simulation structure (Kaufman et al., 1991; Bottom, 2000). This sets up an iteration cycle which runs the traffic flow simulation with the seclected plans for the agents, then uses the choice modules to generate new plans; these are again fed into the traffic flow simulation, etc., until consistency between the modules is reached. The feedback cycle is controlled by the **agent database**, which also keeps track of multiple plans generated by each agent.

In every iteration, 20% of the agents generate new plans by copying an existing plan and then modifying the copy in equal parts of 10% either within the time allocation or the router module. All other agents select one of their existing plans. The probability to change from the selected plan to a randomly chosen plan is calculated according to

$$p_{change} = min(1, \alpha \cdot e^{\beta \cdot (s_{random} - s_{current})/2}) \ , \tag{6}$$

where

- α: The probability to change if both plans have the same score, set to 1%
- β: A sensitivity parameter, set to 2
- $s_{\{random,current\}}$: The score of the current/random plan

In the steady state, this model is equivalent to the standard multinomial logit model $p_j = \frac{e^{\beta \cdot s_j}}{\sum_i e^{\beta \cdot s_i}}$, where p_j is the probability for plan j to be selected.

The repetition of the iteration cycle coupled with the agent database enables the agents to improve their plans over many iterations. This is why it is also called **learning mechanism** which is described in more detail by Balmer et al. (2005). As the number of plans is limited for every agent by memory constraints, the plan with the worst performance is deleted when a new plan is added to a person that already has reached the maximum number of plans. The iteration cycle continues until the system has reached a relaxed state. At this point, there is no quantitative measure of when the system is "relaxed"; we just allow the cycle to continue until the outcome is stable.

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