

Kickhöfer, Benjamin; Grether, Dominik; Nagel, Kai

Conference Paper

Public acceptance and economic evaluation of transport policies

50th Congress of the European Regional Science Association: "Sustainable Regional Growth and Development in the Creative Knowledge Economy", 19-23 August 2010, Jönköping, Sweden

Provided in Cooperation with:

European Regional Science Association (ERSA)

Suggested Citation: Kickhöfer, Benjamin; Grether, Dominik; Nagel, Kai (2010) : Public acceptance and economic evaluation of transport policies, 50th Congress of the European Regional Science Association: "Sustainable Regional Growth and Development in the Creative Knowledge Economy", 19-23 August 2010, Jönköping, Sweden, European Regional Science Association (ERSA), Louvain-la-Neuve

This Version is available at:

<https://hdl.handle.net/10419/119108>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Public acceptance and economic evaluation of transport policies

Benjamin Kickhöfer, Dominik Grether
and Kai Nagel

Transport Systems Planning and Transport Telematics
Berlin Institute of Technology
D-10587 Berlin
+49-30-314 23308
+49-30-314 26269

14.04.2010

Abstract

Public acceptance has often been stated being a key factor for the successful realization of transport projects and policies. One reason why even economically efficient projects might not be accepted by the major part of the population could be the unequal distribution of benefits. For instance, individuals with higher Values of Time are expected to benefit more from user-financed improvements in the quality of service (e.g. speed) of any transportation mode. Beyond that, the implementation of road pricing schemes is currently being discussed to have regressive effects on the welfare distribution under certain conditions.

In order to address these issues, microscopic multi-agent simulation presented in this paper can be used. Policy makers are directly able to compare the impacts of different policy schemes on the welfare distribution and can thus identify alternatives with higher public acceptance. Generally, by using the multi-agent approach, any segregation of individuals among any socio-demographic attribute is possible what allows a more detailed view on the effects of a policy measure. Furthermore, in contrast to applied economic policy analysis, this framework allows choice modeling and economic evaluation to be realised in a consistent way.

This paper shows that (i) the inclusion of individual income in the users' preferences leads to a better understanding of problems that are linked to acceptability, (ii) benefits of transport projects are likely to rise disproportionately with increasing income - both, in terms of utility change and in terms of money -, and (iii) the simulation is already feasible for a real-world large-scale scenario with almost two million individuals.

1 Introduction

Policy measures in transportation planning aim at improving the system as a whole. Changes to the system that result in an unequal distribution of the overall welfare gain are, however, hard to implement in democratically organized societies. Studies indicate that, e.g., tolls tend to be regressive if no redistribution scheme is considered at the same time, and may so increase the inequality in welfare distribution (e.g. Franklin, 2006). An option to reach broader public acceptance for such policies may be to include the redistribution of total gains into the scheme. Hence, methods and tools are needed that simulate welfare changes due to policies on a highly granulated level, e.g. considering each individual of the society. With such tools, policy makers are able to consider impacts of different proposed measures on the welfare distribution. In addition, it is possible to estimate the level of acceptance within the society and, if necessary, to evaluate alternatives for further discussion.

Traditional transport planning tools using the four-step process combined with standard economic appraisal methods (e.g. Pearce and Nash, 1981) are not able to provide such analysis. In order to bridge this gap, multi-agent microsimulations can be used. Large-scale multi-agent traffic simulations are capable of simulating the complete day-plans of several millions of individuals (agents) (Meister et al., 2008). In contrast to traditional models, all attributes that are attached to the synthetic travelers are kept during the simulation process, thus enabling highly granulated analysis (Nagel et al., 2008). Being aware of all attributes enables the possibility to attach to every traveller an individual utility function that is used to maximize the individual return of travel choices during the simulation process. Another advantage of the multi-agent simulation technique is the connection of travelers' choices along the time axis when simulating time dependent policies (Grether et al., 2008).

In the context of policy evaluation, simulation results can immediately be used to identify winners and losers, since the utility scores of the individual agents are kept and can be compared between scenarios agent-by-agent. They can also be aggregated in arbitrary ways, based on any available demographic attributes including spatial information of high resolution. Welfare computations, if desired, can be done on top of that, without having to resort to indirect measures such as link travel times or inter-zonal impedances. The usual problems when monetarizing the individual utility still apply (Bates, 2006), but at least one of the main issues in applied economic analysis is addressed: with multi-agent approaches, *choice modeling* and *economic evaluation* are implemented in a consistent framework, similar to efforts to base such analysis directly on discrete choice models (de Jong et al., 2006).

This paper shows how multi-agent approaches can be used in policy evaluation. It studies why income should be included in utility calculations when considering issues linked with public acceptance. Then, we describe implications on the simulation model and focus on the measurement of welfare effects resulting from policy measures.

The paper is organized as follows: in Sec. 2, the simulation approach and the income-dependent utility function are introduced. Sec. 3 presents the setup for a realistic simulation of regular workday traffic in the Zurich metropolitan area including the policy design of a public transit price and speed increase. Sec. 4 points out the main results of the simulation. In Sec. 5 welfare changes across the income range and resulting issues linked to public acceptance are 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 MATSim¹ 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. 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 with respect 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.

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

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 different income groups differently. This is usually addressed by including income dependent user preferences in the 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 (3), given by:

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

The first summand refers to (4) with $\beta_{perf,i} = +1.86/h$. The second and third summands introduce mode and income dependency to the utility functions: y_j stands for the daily income of person j and c_i is monetary cost for the trip to activity i . The indices *car* and *pt* indicate the mode. Trip costs are calculated using $c_{i,car} = 0.12 \text{ CHF/km}$ and $c_{i,pt} = 0.28 \text{ CHF/km}$. While there is a fourth 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.

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 “hours of leisure time” (Jara-Díaz et al., 2008) needs to be done separately (see Sec. 5).

3 Scenario

The income-dependent utility function is now applied to a large-scale, real-world scenario. The metropolitan area of Zurich, Switzerland, is used which counts about 1 million inhabitants. 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.

The simulated 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.

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 Zurich³ area. A specific median is available for each municipality⁴ of the state⁵ For every person living in Canton Zurich area, the municipality of the person's home location is identified. Then, the median income of

²The 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.

³A Swiss "Canton" is similar to a federal state

⁴"Gemeinde" is the next lower administrative level below "Kanton" in Switzerland, i.e. some kind of municipality

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

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.

3.3 Policy design

In order to evaluate a fictive, but realistic policy measure, the design is based on price and travel time elasticities analysed by Cervero (1990). In his collection of different studies, Cervero (1990) estimates travel time elasticities to be approximately double as high as price elasticities. Therefore, the policy for this paper is designed as a combination of the following measures:

- **public transit price increase:** The price of public transit, $c_{i,pt}$, is raised by 20% from 0.28 to 0.336 CHF/km.
- **public transit speed increase:** The speed of public transit is increased, now taking only 1.8 (instead of 2.0) times as long as the freespeed car. This corresponds to a speed increase of 10%.

Raising public transit prices in order to generate funds for the improvement of the quality of service, is often discussed in the context of public transit pricing. Following Cervero (1990), one would expect almost no shift in the modal split for the combined policy measure.

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. During the second 1000 iterations, time and route adaption are switched off; in consequence, agents only switch between existing options. In the following, the output after 2000 iterations is referred to as the *base case*.

After that, the policy is introduced. It is run for another 1000 iterations, starting from the final iteration of the base case. Again, during the first 500 iterations 10% of the agents perform “time adaptation” while another 10% of agents adapt routes. Agents,

⁶http://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

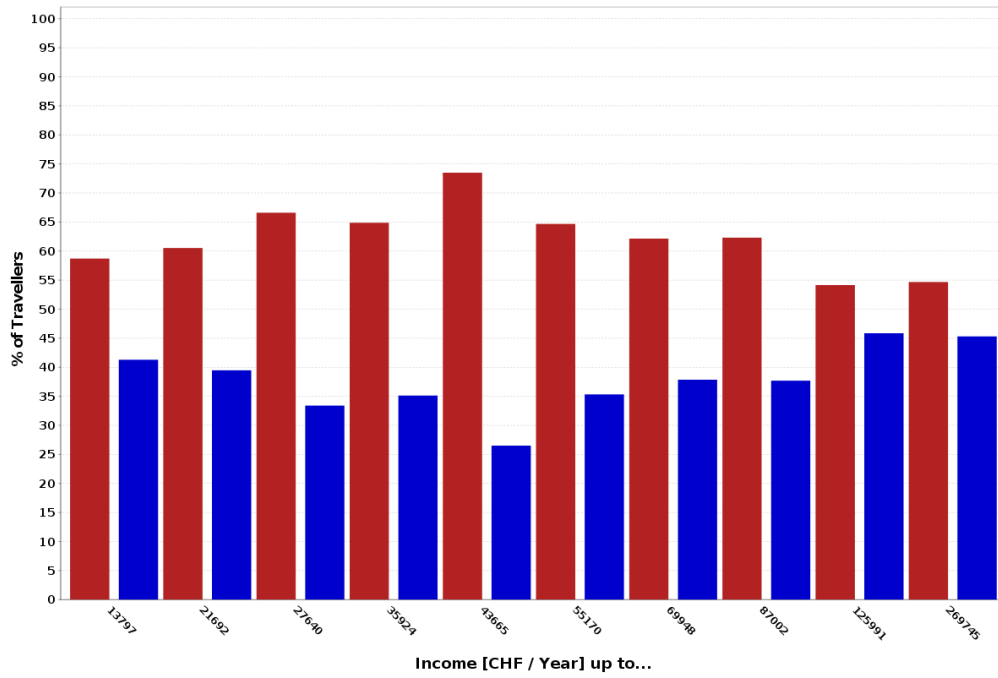
that neither adapt time nor route, switch between existing plans according to (5) and thus only can switch between transport modes. As for the base case, during the final 500 iterations only a fixed choice set is available.

4 Results

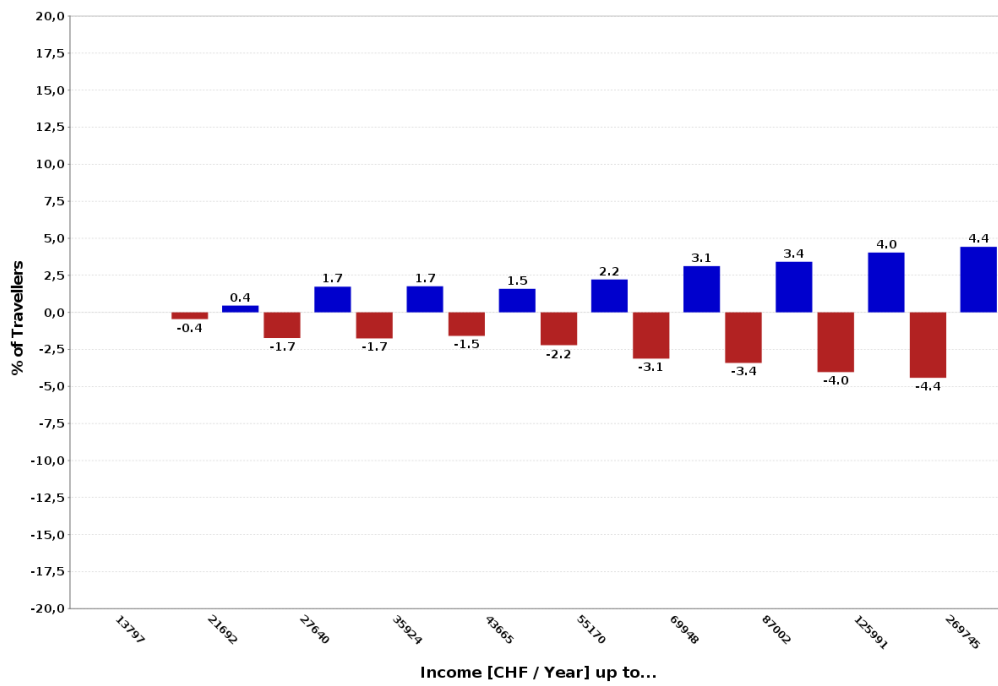
The base case of the Zurich scenario exhibits a modal split of 60.9%:39.1% (car:pt). Fig. 1a depicts the modal split in the income deciles of the population. Both modes are used across all deciles. The highest percentage of car users can be observed from the 3rd to the 6th decile. The policy results in a mode share of 58.5%:41.5% (car:pt). Due to the speed and price increase of the pt, in total 2.4% of car travellers change from car to pt. Fig. 1b presents changes to the modal split in the income deciles of the population compared to the base case. At a quick glance one can observe that with increasing income, more persons switch from car to pt. More precisely one can see a break in the increasing pt shares in the 5th decile, where only 1.5 % change mode while in the 3rd and 4th decile 1.7% change mode. Apart from this outlier the mode choice reflects the decreasing importance of travel costs compared to travel time savings when income increases.

Increasing utility gains of agents with higher income can also be seen in Fig. 2a that depicts the average utility change of each population decile sorted by income. Each dot is located in the middle of the decile and represents the average utility change per decile. For representation purposes the dots are connected with lines. Obviously, one recognizes raising utility gains with increasing income. In terms of utils, the slope of the curve is slightly positive. The subsequent section will show, however, that this increase has even stronger effects when converting utils into money.

Fig. 2b breaks the average utility gains of Fig. 2a down to several groups of persons in each decile. Recall that *four* groups can be identified as a result of the measure: *First*, people using the car mode before and after the measure are represented by red dots. They gain somewhat due to less car traffic on the streets resulting in less congestion and shorter travel times. The *second* group are travelers that use public transit before and after the measure and they are depicted by green dots. In all deciles travel time gains seem to overweight the price increase as in all groups utility is increasing. Again one can observe increasing gains in higher income deciles due to the declining influence of travel cost. A similar effect can be observed for the *third* group, i.e. people switching from car to public transit that are shown by yellow dots. In the lower income deciles one recognizes slight average losses that can only be explained by stochastic effects in the simulation cycle (see Appendix). The last and *fourth* group consists of travelers switching from public transit to car. They are depicted by blue dots and their switch from pt to car results from the increased price of the public transit. Due to the lower mode share of the car mode, some of them gain due to the reduced travel times while other gains in this group are caused by the stochastics of the simulation.

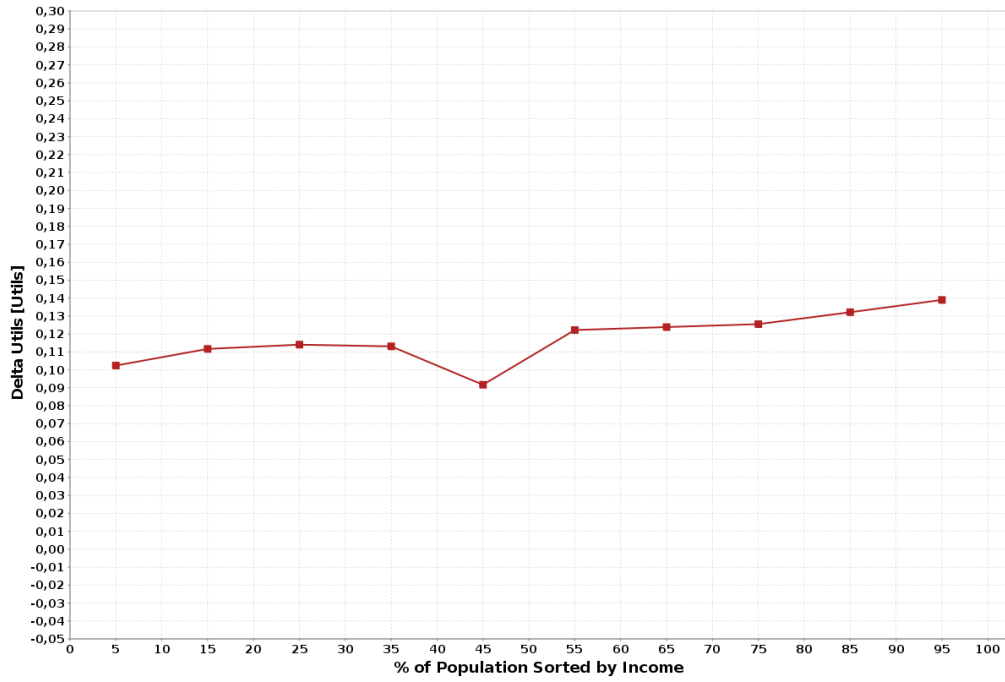


(a) Base Case

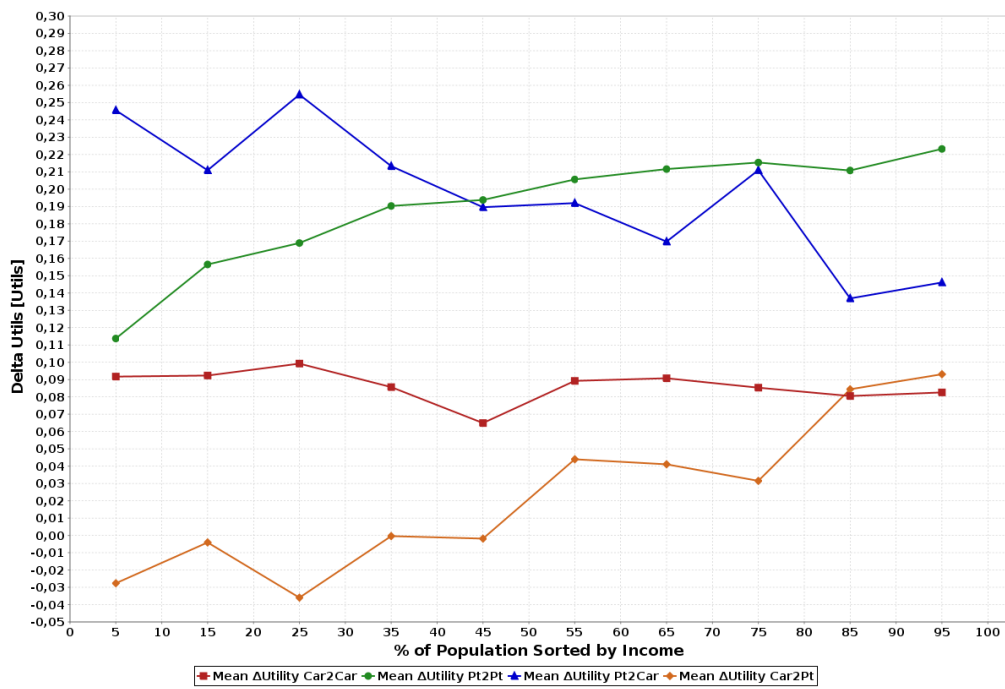


(b) Combined Measure

Figure 1: Modal Split over income deciles. Red bars depict car drivers, blue bars public transit users



(a) Average utility changes



(b) Average utility changes per group

Figure 2: Average utility changes per population decile sorted by income

5 Discussion

In this section, an estimation about the economic benefit of the policy is conducted. After examining the distribution of economic benefit along the income deciles of the population, some consequences regarding the project's public acceptance are discussed.

5.1 Economic evaluation

The overall welfare effect of the policy is calculated by the mean utility gain in the deciles $\overline{\Delta U}_d$ (in terms of money) times the (always equal) number of persons in each group n . According to (1), conversion from utility units into CHF is dependent on individual income y_j and utility changes ΔU_j :

$$\overline{\Delta U}_d = \frac{1}{n} \sum_{j=1}^n \frac{\Delta U_j \cdot y_j}{4.58} \quad (2)$$

Summing this over all ten deciles, the welfare effect of this policy is about 1.23 million CHF per day or almost 300 million CHF per year the computed 10% sample of the Zurich metropolitan population (see Sec. 3.1). Thus, following standard economic evaluation methods, the policy should be introduced if this benefit outweighs its economic costs.

5.2 Public acceptance

Fig. 3 shows in blue the total daily monetarized gains over deciles of the population, sorted by average income. The monetarized gains in every decile can be interpreted as the total willingness to pay for the measure. The red curve tries to explain implementation problems due to low acceptance within the society. If, in a hypothetical case, the same daily welfare gains of 1.23 million CHF were distributed as a monetary lump-sum payment to every member of the population, every person would gain 6.55 CHF per day or every decile 123'000 CHF. This highlights an important implementation problem of policy measures in democratically organized societies: almost 70% of the population would be better off with the lump-sum payment than with the implementation of the measure and are therefore likely to refuse the latter. Thus, if the simulation results are correct, financing this measure with tax revenues would be more appropriate, assuming a progressive income tax. Whereas financed by non differentiated user fees, this policy would have regressive impact on the income distribution.

This example is meant to show 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. Still, there are three main issues that should be addressed in the future: first, for more reliable results,

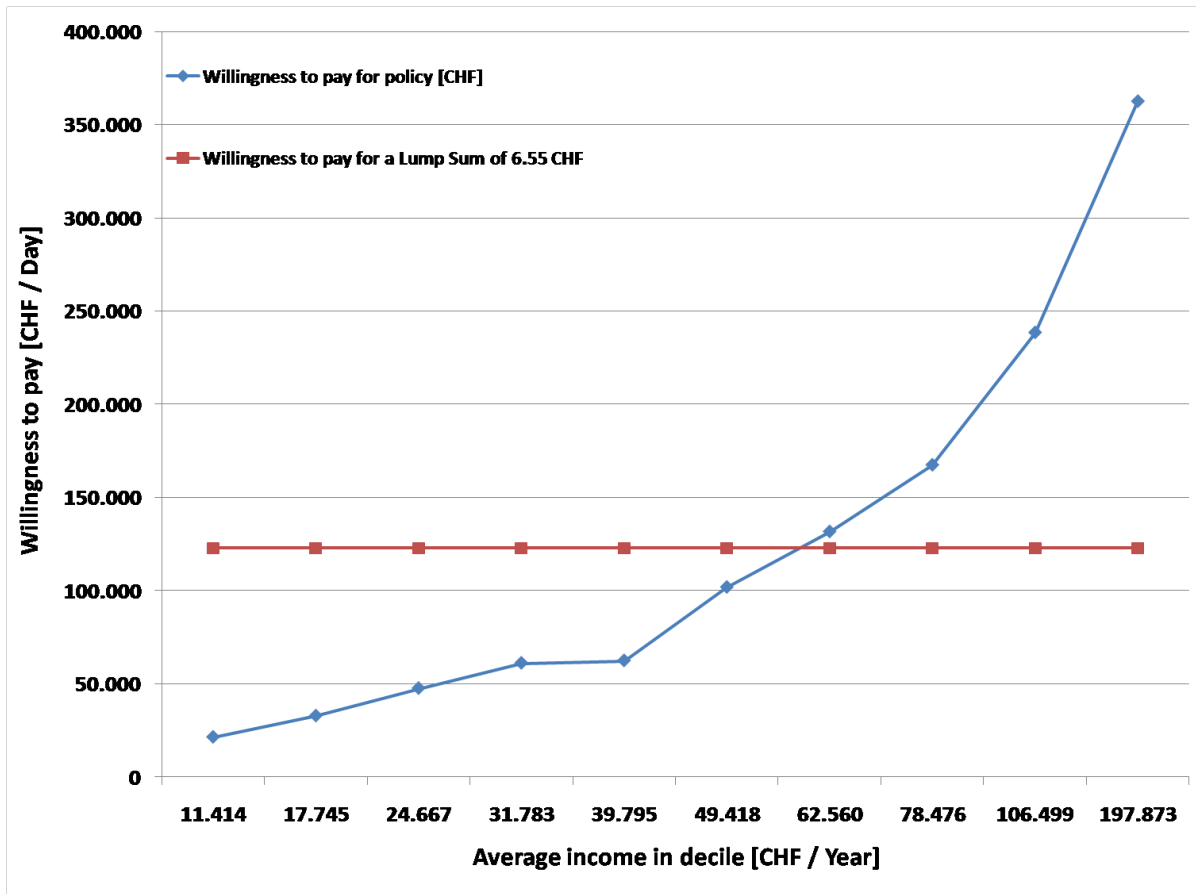


Figure 3: Daily willingness to pay for the policy change over average income per population decile

the survey should be designed in a way that all needed parameters can be estimated independently. Second, public transit is assumed to be 100 % reliable, and no fluctuations due to geographic location or line cycles are considered. In principle, using multi-agent transport simulations, makes it possible to combine multiple demographic attributes of the population of interest, e.g. by viewing the geospatial distribution of winners and losers of a measure (see Grether et al., 2008). Neither the measure of this paper nor the public transit simulation features geospatial diversity. Thus analysis in the geographic dimension is strongly homogeneous and a spatial pattern is not visible. In case of a policy that is targeted on some geospatial impact the multi-agent approach should give interesting insights into geospatial distribution of gains and losses (Rieser and Nagel, 2009). Third, utility changes within the simulation are influenced by stochastic effects in the plan selection process, especially for people that switch mode. Nonetheless, it is shown that with this multi-agent approach, welfare computations and equity analysis can be done on the desired level of (dis)aggregation.

6 Conclusion

Standard economic policy evaluation allows the realisation of projects if the aggregated economic benefit outweighs their costs. In democratically organized societies, the implementation of measures with regressive effects on the welfare distribution tends to be complicated due to low public acceptance.

The microscopic simulation approach presented in this paper is capable to help designing better solutions in such situations. In particular, it is shown that income can and needs to be included in utility calculations for a better understanding of problems linked to acceptability. Furthermore, in contrast to state-of-the-practice project evaluation, choice modeling and economic evaluation are implemented in a consistent framework since the simulation output is directly used for evaluation. Finally, and going beyond Franklin (2006), it is shown that the approach works in a large-scale real world example for which economic benefits are computed.

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 meant to present more information about the MATSim simulation approach that is used in this paper. Every step of the iterative loop in Sec. 2.1 is 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 travel by public transit takes twice as long as traveling by car on the fastest route in an empty network⁸ and that the travel distance is 1.5 times the beeline distance. Public transit is assumed to run continuously and without capacity restrictions (Grether et al., 2009a; Rieser et al., 2009).

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 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.

⁸ 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).

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 score⁹ of a plan is computed as the sum of individual contributions:

$$U_{total} = \sum_{i=1}^n U_{perf,i} + \sum_{i=1}^n U_{tr,i} , \quad (3)$$

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:

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

where t_{perf} is the actual performed duration of the activity, t_* is the “typical” duration of an activity, and β_{perf} is the marginal utility of an activity at its typical duration. β_{perf} is the same for all activities, since in equilibrium all activities at their typical duration need to have the same marginal utility. $t_{0,i}$ is a scaling parameter that is related both to the minimum duration and to the importance of an activity. As long as dropping activities from the plan is not allowed, $t_{0,i}$ has essentially no effect.

- The (dis)utility of traveling used in this paper is estimated from survey data. The disutility is, at this point, not uniform but dependent on the agent’s individual income. It is therefore 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 $-\beta_{perf}$.

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

⁹Note 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.

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 selected 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 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

$$p_{change} = \min(1, \alpha \cdot e^{\beta \cdot (s_{random} - s_{current})/2}) , \quad (5)$$

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.

References

- Proceedings of the meeting of the International Association for Travel Behavior Research (IATBR)*, Kyoto, Japan, 2006. See www.iatbr.org.
- Proceedings of The 12th Conference of the International Association for Travel Behaviour Research*, Jaipur, India, Dezember 2009.
- Proceedings of Swiss Transport Research Conference (STRC)*, Monte Verita, CH. See www.strc.ch.
- M. Balmer, B. Raney, and K. Nagel. Adjustment of activity timing and duration in an agent-based traffic flow simulation. In H.J.P. Timmermans, editor, *Progress in activity-based analysis*, pages 91–114. Elsevier, Oxford, UK, 2005.
- J. Bates. Measuring travel time values with a discrete choice model: A note. *Economic Journal*, 97(386):493–98, June 1987. URL <http://ideas.repec.org/a/ecj/econjl/v97y1987i386p493-98.html>.
- J. Bates. Economic evaluation and transport modelling: Theory and practice. In K.W. Axhausen, editor, *Moving through nets: The physical and social dimensions of travel*, chapter 10, pages 279–351. Elsevier, 2006.
- J. Bottom. *Consistent anticipatory route guidance*. PhD thesis, Massachusetts Institute of Technology, Cambridge, MA, 2000.
- R. Cervero. Transit pricing research. *Transportation*, 17:117–139, 1990. doi: 10.1007/BF02125332.
- N. Cetin, A. Burri, and K. Nagel. A large-scale agent-based traffic microsimulation based on queue model. In *Proceedings of Swiss Transport Research Conference (STRC)* str. See www.strc.ch. Earlier version, with inferior performance values: Transportation Research Board Annual Meeting 2003 paper number 03-4272.
- Y. Chen, M. Rieser, D. Grether, and K. Nagel. Improving a large-scale agent-based simulation scenario. VSP Working Paper 08-15, VSP, TU Berlin, 2008. URL <https://svn.vsp.tu-berlin.de/repos/public-svn/publications/vspwp/2008/08-15/>. See www.vsp.tu-berlin.de/publications.
- G. de Jong, A. Daly, E. Kroes, and T. van der Hoorn. Using the logsum in project appraisal. In *Proceedings of the meeting of the International Association for Travel Behavior Research (IATBR)* iat (2006). See www.iatbr.org.
- J.P. Franklin. *The distributional effects of transportation policies: The case of a bridge toll for Seattle*. PhD thesis, University of Washington, Seattle, 2006.
- C. Gawron. *Simulation-based traffic assignment*. PhD thesis, University of Cologne, Cologne, Germany, 1998. URL www.zaik.uni-koeln.de/AFS/publications/theses.html.
- D. Grether, Y. Chen, M. Rieser, U. Beuck, and K. Nagel. Emergent effects in multi-agent simulations of road pricing. In *Annual meeting of the European Regional Science Association ERSA '08*, 2008.

- D. Grether, Y. Chen, M. Rieser, and K. Nagel. Effects of a simple mode choice model in a large-scale agent-based transport simulation. In A. Reggiani and P. Nijkamp, editors, *Complexity and Spatial Networks. In Search of Simplicity*, Advances in Spatial Science, chapter 13, pages 167–186. Springer, 2009a. doi: 10.1007/978-3-642-01554-0.
- D. Grether, B. Kickhöfer, and K. Nagel. Policy evaluation in multi-agent transport simulations considering income-dependent user preferences. In *Proceedings of the Meeting of the International Association for Travel Behavior Research (IATBR) iat* (2009). URL www.vsp.tu-berlin.de/publications.
- J.A. Herriges and C.L. Kling. Nonlinear income effects in random utility models. *The Review of Economics and Statistics*, 81(1):62–72, 1999. URL <http://www.jstor.org/stable/2646786>.
- S. Jara-Díaz, M. Munizaga, P. Greeven, R. Guerra, and K.W. Axhausen. Estimating the value of leisure from a time allocation model. *Transportation Research B*, 42(10): 946–957, 2008. doi: doi:10.1016/j.trb.2008.03.001.
- T. Kämpke. The use of mean values vs. medians in inequality analysis. 2008. Forschungsinstitut für anwendungsorientierte Wissensverarbeitung.
- D.E. Kaufman, K.E. Wunderlich, and R.L. Smith. An iterative routing/assignment method for anticipatory real-time route guidance. Technical Report IVHS Technical Report 91-02, University of Michigan Department of Industrial and Operations Engineering, Ann Arbor MI, May 1991.
- B. Kickhöfer. Die Methodik der ökonomischen Bewertung von Verkehrsmaßnahmen in Multiagentensimulationen. Master’s thesis, TU Berlin, 2009.
- K. M. Kockelman. A model for time- and budget-constrained activity demand analysis. *Transportation Research Part B: Methodological*, 35(3):255–269, 2001.
- N. Lefebvre and M. Balmer. Fast shortest path computation in time-dependent traffic networks. In *Proceedings of Swiss Transport Research Conference (STRC)* str. See www.strc.ch.
- K. Meister, M. Rieser, F. Ciari, A. Horni, M. Balmer, and K.W. Axhausen. Anwendung eines agentenbasierten Modells der Verkehrsnachfrage auf die Schweiz. In *Proceedings of Heureka '08*, Stuttgart, Germany, March 2008.
- K. Nagel, D. Grether, U. Beuck, M. Rieser, Y. Chen, and K.W. Axhausen. Multi-agent transport simulations and economic evaluation. *Journal of Economics and Statistics (Jahrbücher für Nationalökonomie und Statistik)*, 228(2+3):173–194, 2008. URL <https://svn.vsp.tu-berlin.de/repos/public-svn/publications/vspwp/2007/07-14/>. Special issue on agent based models for economic policy advice, edited by B. LeBaron and P. Winker.
- D. Pearce and C.A. Nash. *Social appraisal of projects: A text in cost-benefit analysis*. Wiley & Sons, London, 1981.

- B. Raney and K. Nagel. An improved framework for large-scale multi-agent simulations of travel behavior. In P. Rietveld, B. Jourquin, and K. Westin, editors, *Towards better performing European Transportation Systems*, pages 305–347, London, 2006. Routledge.
- T. Reinhold. Konzept zur integrierten Optimierung des Berliner Nahverkehrs. In *Öffentlicher Personennahverkehr*. Springer Berlin Heidelberg, 2006. doi: 10.1007/3-540-34209-5_8.
- M. Rieser and K. Nagel. Combined agent-based simulation of private car traffic and transit. In *Proceedings of the Meeting of the International Association for Travel Behavior Research (IATBR) iat (2009)*. URL www.vsp.tu-berlin.de/publications.
- M. Rieser, D. Grether, and K. Nagel. Adding mode choice to a multi-agent transport simulation. *Transportation Research Record: Travel Demand Forecasting 2009*, 2132: 50–58, 2009. doi: 10.3141/2132-06. URL <http://trb.metapress.com/content/57m4638073144846/?p=1e2f747415fc4986b9456e79dc4b1702&pi=5>.
- SFSO. Eidgenössische Volkszählung. Swiss Federal Statistical Office, Neuchatel, 2000.
- SFSO. Ergebnisse des Mikrozensus 2005 zum Verkehr. Swiss Federal Statistical Office, Neuchatel, 2006.
- M. Vrtic, N. Schüssler, A. Erath, K. Meister, and K. Axhausen. Tageszeitliche Fahrtenmatrizen im Personenverkehr an Werktagen im Jahr 2000. Research report, Swiss Federal Department for Environment, Transport, Energy and Communication, Swiss Federal Office for Spatial Development, Swiss Federal Roads Authority and Swiss Federal Office for Transport, IVT, ETH Zürich, Zürich, 2007.