Income-contingent user preferences in policy evaluation: application and discussion based on multi-agent transport simulations

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Application and Discussion based on Multi-Agent Transport Simulations

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Abstract Standard economic policy evaluation allows the realization of projects if the aggregated economic benefit outweighs their costs. The use of one single aggregated welfare measure for evaluating and ranking projects has often been criticized for many reasons. A major issue is that differentiated effects on individuals or subgroups of the population are not taken into consideration. This leads to the need for transport planning tools that provide additional information for politicians and decision makers. The microscopic multi-agent simulation approach presented in this paper is capable of helping to design better solutions in such situations. In particular, it is shown that the inclusion of individual income in utility calculations allows a better understanding of problems linked to public acceptance. First, individual income-contingent utility functions are estimated based on survey data in order to describe human mobility behavior. Subsequently, using the MATSim framework, the implementation is tested in a test scenario. Furthermore, and going beyond Franklin (2006), it is shown that the approach works in a large-scale real world example. Based on a hypothetical speed increase of public transit, effects on the welfare distribution of the population are discussed. It is shown that the identification of winners and losers seems to be quite robust. However, results indicate that a conversion or aggregation of individual utility changes for welfare analysis is highly dependent on the functional form of the utility functions as well as on the choice of the aggregation procedure.

Keywords Policy Evaluation · Public Acceptance · Individual Utility Function · Income-Dependency · Welfare Economics · Agent-Based Modeling

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1 Introduction

Policy measures in transportation planning aim at improving the system as a whole. In democratically organized societies, however, it is quite difficult to realize projects when they have a negative impact on some part of the population even if this is a minority – presumably, this has something to do with the fact that losses are weighted more than gains (Kahneman and Tversky 1979). 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 support level 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 daily 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; Grether et al 2010; Kickhöfer et al 2010). Being aware of all attributes enables the possibility to attach an individual utility function to every traveler which 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 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 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 aggregating or monetizing the individual utility still apply (Bates 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, it describes implications on the simulation model and focuses on the measurement of welfare effects resulting from a policy measure. Note that this paper is an extension of Grether et al (2009b), who considered three policy measures: a public transit (pt) price increase, a pt speed increase, and a combination of the two. The results of the combined measure are also reported in Grether et al (2010). In contrast to the latter, the present paper concentrates on the pt speed increase only. In contrast to both papers, the present paper provides more insights, particularly in the discussion.

2 Simulation Approach

The following describes the structure of the simulation that is used. It is the standard structure of MATSim[1], as described at many places (Raney and Nagel 2006; Balmer et al 2005). Readers familiar with the MATSim approach can skip this section.

2.1 Overview

In MATSim, each traveler of the real system is modeled as an individual agent. The overall approach consists of three important parts:

– Each agent independently generates a so-called *plan*, which encodes its preferences during a certain time period, typically a day.
– All agents' plans are simultaneously executed in the simulation of the physical system. This is also called the *traffic flow simulation* or *mobility simulation*.
– There is a mechanism that allows agents to *learn*. In the implementation, the system iterates between plans generation and traffic flow simulation. The system remembers several plans per agent, and scores the performance of each plan. Agents normally choose the plan with the highest utility[2], sometimes re-evaluate plans with lower utility, and sometimes obtain new plans by modifying copies of existing plans.

A **plan** contains the itinerary of activities that the agent wants to perform during the day and information about the trips between activities. An agent's plan encodes the order, type, location, duration and other time constraints of each activity, and the mode, route and expected departure and travel times of each trip.

A plan can be modified by various **modules**. In the test scenario, the Time Adaptation module is used, while the large-scale application additionally uses a Router module. The *Time Adaptation* module changes the timing of an agent's plan. A very simple approach is used which just applies a random "mutation" to the duration attributes of the agent's activities (Balmer et al 2005). The *Router* is a time-dependent best path algorithm (Lefebvre and Balmer 2007), normally using the travel times of the previous iteration as the link's generalized costs. *Mode choice* will not be simulated by a seperate 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).

One plan of every agent is marked as "selected". The **traffic flow simulation** executes all selected plans simultaneously on the network and provides output describing what happened to each individual agent during the execution of its plan. The

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

[2] 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.

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 travel by car on the fastest route in an empty network (Grether et al 2009a; Rieser et al 2009), and that the travel distance is 1.5 times the beeline distance. Public transit is assumed to run continuously and without capacity restrictions. 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 specific plans for the agents, then uses the planning modules to update the plans; the updated plans 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, some agents generate new plans by taking an existing plan, making a copy of it, and then modifying the copy with the Time Adaptation or the Router module. The other agents reuse one of their existing plans. The probability to change plan is calculated according to

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

where α is the probability to change if both plans have the same utility, set to 1%; μ is a sensitivity parameter, set to 20 for the tests (in order to reinforce the choice effect) and to 2 for the large-scale Zurich simulations;[3] and $V_{\{random,current\}}$ is the utility of the current/random plan (see Sec. 2.2). In the steady state, this model is equivalent to the standard multinomial logit model

$$p_j = \frac{e^{\mu \cdot V_j}}{\sum_i e^{\mu \cdot V_i}} \ , \tag{2}$$

where p_j is the probability for plan j to be selected. In consequence, V corresponds to the systematic component of utility in Random Utility Models (RUM) (e.g. Ben-Akiva and Lerman 1985; Train 2003), where utility is defined as $U = V + \varepsilon$. In RUM, ε is called random component of utility. In the steady state and assuming a Gumbel distribution for ε, the choice model used in this paper is thus equivalent to the standard multinomial logit model.

The repetition of the iteration cycle coupled with the agent database enables the agents to improve their plans over many iterations. 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 which already has the maximum number of plans permitted. If agents have several plan types in their memory, e.g. one plan

[3] For more information concerning the interpretation and influence of μ within the MATSim framework, see Raney and Nagel (2006). For potential conceptual improvements, please refer to Nagel and Flötteröd (2009).

using car and another using public transit mode only, at least one plan of each type is kept. 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 Evaluating Plans

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

– The total utility of a plan is computed as the sum of individual contributions:

$$V_{total} = \sum_{i=1}^{n} \left(V_{perf,i} + V_{late,i} + V_{tr,i} \right) , \tag{3}$$

where V_{total} is the total utility for a given plan; n is the number of activities; $V_{perf,i}$ is the (positive) utility earned for performing activity i; $V_{late,i}$ is the (negative) utility earned for arriving late to activity i; and $V_{tr,i}$ is the (usually negative) utility earned for traveling during trip i. Activities are assumed to wrap around the 24-hours-period, that is, the first and the last activity are stitched together. In consequence, there are as many trips between activities as there are activities.

– A logarithmic form is used for the positive utility earned by performing an activity:

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

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 being late is uniformly assumed as:

$$V_{late,i}(t_{late,i}) = \beta_{late} \cdot t_{late,i} , \tag{5}$$

where β_{late} is the marginal utility (in 1/h) for being late, and $t_{late,i}$ is the number of hours late to activity i. β_{late} is usually negative.

– The (dis)utility of traveling used in this paper is estimated from survey data which will be explained in Sec. 3.

In principle, arriving early could also be punished. There is, however, no immediate need to punish early arrival, since waiting times are already indirectly punished by foregoing the reward that could be accumulated by doing an activity instead (opportunity cost). In consequence, the effective (dis)utility of waiting is already

$-\beta_{perf}\, t_{*,i}/t_{perf,i} \approx -\beta_{perf}$. Similarly, that opportunity cost has to be added to the time spent traveling. No opportunity cost needs to be added to late arrivals, because the late arrival time is spent somewhere else. In consequence, the effective (dis)utility of arriving late remains at β_{late}.

3 Estimation of the Income-Contingent Utility Function

3.1 Related Work

There is some agreement in the literature that income should be considered in transport policy analysis, see e.g. Small (1983); Herriges and Kling (1999); Kockelman (2001); Mackie et al (2001); Bates (2006, 1987); Franklin (2006). The argument essentially is that monetary price changes affect people with different income differently. Conversely, if different income groups need to be compensated for losses or should be taxed for gains from non-monetary policies, the valuation of these offsetting payments is income-contingent.

Franklin (2007) studies the impact of a bridge toll on individual welfare by decomposing it into three different components and calculating the equivalent variation for all of them: first, the effect of paying the toll; second, the effect induced by travel time savings; and third, the benefits resulting from the use of the collected toll revenue. His findings indicate that a toll policy has regressive effects on the welfare distribution of society. The major impact stems from the toll payment itself. He then states that the benefits of travel time savings are also likely to be regressive. However, by using the toll revenue as a equal refund to all users of the bridge (car *and* pt), the regressivity can fully be countered while still creating a net social benefit.

The second point is highly important for the present paper. If travel time savings as a result of a non-monetary policy are also found to be regressive, then there is no toll revenue that can be used to offset regressivity. Furthermore, Franklin (2007) concludes that his analysis is rather limited due to a very simplified scenario: individuals are only allowed to switch mode as a reaction to the toll. Therefore, future work is needed where travel choices are modeled by incorporating time-of-day, destination, route, mode choice, and at the same time including income as a non-linear variable.

This paper can be seen as a step into this direction. It demonstrates how these insights can be used constructively in an agent-based approach which is capable to model more than one choice dimension.

3.2 Estimation Data

Data for estimation of the travel related part of the utility function presented in this paper is taken from surveys run by the Institute for Transport Planning and Systems at ETH Zurich (Vrtic et al 2008). The surveys focused on the description of choices in terms of departure time, mode and route choice. These were conducted as a combination of revealed preference (RP) and stated preference (SP) surveys: The objectives of the RP survey were on the one hand the recruitment of individuals, on the other hand capturing their current mobility behavior. Within the SP surveys, individuals were confronted with hypothetical alternatives (choice set). This choice set was generated based on the individual's reported trips by modifying the characteristics of at least one alternative. Individuals are then asked to make a choice; this provides one data set per decision; by estimating the coefficients of utility functions, the impact of the different variables on the decision making can be investigated and generalized.[4]

In this paper, the estimation of the late arrival penalty is based on the departure time and route choice part of the SP survey. The estimation of all other parameters uses data from the mode and route choice part of the SP survey. The sample size of the former survey is 531, of the latter 669 individuals. In each survey, individuals were confronted with seven choice situations.

3.3 Functional Form

The starting point for the travel related part of the (dis)utility functions used in this paper is loosely based on Franklin (2007) and is similar to Kickhöfer (2009). In these papers, two transport modes are available: car and public transit, resulting in the following initial utility functions:

$$\begin{aligned} V_{car,i,j} &= \beta_{cost} \cdot \ln(y_j - c_{i,car}) + \beta_{tr,car} \cdot t_{i,car} \\ V_{pt,i,j} &= \beta_{cost} \cdot \ln(y_j - c_{i,pt}) + \beta_{tr,pt} \cdot t_{i,pt} \ , \end{aligned} \tag{6}$$

where y_j is the daily income of person j, c_i is monetary cost for the trip to activity i, and t_i the corresponding travel time. Monetary cost and travel time are mode dependent, indicated by the indices. 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. Daily income y_j is obtained by the following calculation:

$$y_j = \frac{y_{year,HH}}{n_{HH} \cdot 240} \ ,$$

where $y_{year,HH}$ depicts the income of the household per year, n_{HH} the number of persons in the household and 240 the number of working days per year.

It is, however, not possible to use this form directly, since the survey data contains relatively long trips, meaning that $y_j - c_i$ can become negative, in which case $\ln(y_j - c_i)$ is not defined.[5] To circumvent this problem, Taylor's theorem is used to approximate the logarithm,

$$\ln(y_j - c_i) \approx \ln(y_j) - c_i \cdot [ln(y_j)]' = ln(y_j) - \frac{c_i}{y_j} \ , \tag{7}$$

which results into the quite normal $1/y_i$ dependency of the cost term and thus seems quite plausible. Applying (7) to (6) and estimating the parameters[6]

$$\hat{\beta}_{cost} = 4.58 \ , \qquad \hat{\beta}_{tr,car} = -2.83/h \ , \qquad \text{and} \qquad \hat{\beta}_{tr,pt} = -1.86/h \ ,$$

[4] The present paper uses the tool BIOGEME for the maximum-likelihood estimation of utility parameters (Bierlaire 2003). For more information see `http://biogeme.epfl.ch/`.

[5] One may argue that in such cases the model should reject the journey completely, at least if it is a regular journey (M. Wegener, personal communication).

[6] Estimated parameters are in this paper flagged by a hat.

leads to the following functional form:[7]

$$
\begin{aligned}
V_{car,i,j} &= +\,4.58\,\ln(y_j/CHF) \,-\, 4.58\,\frac{c_{i,car}}{y_j} \,-\, \frac{2.83}{h}\,t_{i,car} \\
V_{pt,i,j} &= +\,4.58\,\ln(y_j/CHF) \,-\, 4.58\,\frac{c_{i,pt}}{y_j} \,-\, \frac{1.86}{h}\,t_{i,pt}
\end{aligned}
\tag{8}
$$

It might be a bit surprising that the disutility of travel time comes out higher for car than for public transit. It is, however, consistent with the higher costs of $c_{pt} = 0.28$ CHF/km[8] assumed for public transit than for car ($c_{car} = 0.12$ CHF/km), which were used in the survey (Vrtic et al 2008) and will be used in the simulations. Clearly and somewhat unusual, for Switzerland, public transit is the higher value mode compared to car. Due to this specification, Values of Time (VoT) are obviously income *and* mode dependent. The VoT for the median income of the sample ($y_{median} = 155$ CHF per person and day) turn out to be 96 CHF/h for car and 63 CHF/h for public transit , respectively. These values are two to three times higher as those in Vrtic et al (2008). Thus, the inclusion of income in the utility function seems to have unintended impacts on the VoT. This effect should be addressed in future research. However, note that e.g. the VoT for public transit varies from 7 to 330 CHF/h along the income range, which naturally includes the values from the linear model in Vrtic et al (2008).

Another open question at this point is how much of the estimated disutility from traveling are opportunity costs of time, and how much is an additional disutility caused by traveling in the corresponding mode. This approach is consistent with economic approaches where there is an inherent opportunity cost of time and additional utilities or disutilities depending on how the time is spent (e.g. Jara-Díaz et al 2008). Unfortunately, these values cannot be obtained from the survey as it was taken. Because of this, it is assumed that traveling in public transit neither adds nor subtracts from the opportunity cost of time. This implies $\hat{\beta}_{perf} = 1.86/h$ in (4), and modifies the travel related part of the utility functions to:

$$
\begin{aligned}
V_{car,i,j} &= +\,4.58\,\ln(y_j/CHF) \,-\, 4.58\,\frac{c_{i,car}}{y_j} \,-\, \frac{0.97}{h}\,t_{i,car} \\
V_{pt,i,j} &= +\,4.58\,\ln(y_j/CHF) \,-\, 4.58\,\frac{c_{i,pt}}{y_j}
\end{aligned}
\tag{9}
$$

Applying (9), (5) and (4) to (3) results in the two final utility functions used in this paper, which are selected depending on the mode of the *i*th trip:

$$
\begin{aligned}
V_{car,i,j} &= +\frac{1.86}{h}\,t_{*,i}\cdot\ln\!\left(\frac{t_{perf,i}}{t_{0,i}}\right) - \frac{1.52}{h}\,t_{late,i} - 4.58\,\frac{c_{i,car}}{y_j} - \frac{0.97}{h}\,t_{i,car} \\
V_{pt,i,j} &= +\frac{1.86}{h}\,t_{*,i}\cdot\ln\!\left(\frac{t_{perf,i}}{t_{0,i}}\right) - \frac{1.52}{h}\,t_{late,i} - 4.58\,\frac{c_{i,pt}}{y_j}
\end{aligned}
\tag{10}
$$

[7] Two different forms for the alternative specific constants were also estimated. Both, the income-contingent bias term (Franklin 2006) and the general alternative specific constant (Train 2003), were estimated not significantly different from zero and are therefore not considered in the functional form of the utility functions. This essentially means that neither an income-contingent nor a general a-priori preference is found for one of the transport modes.

[8] 1 CHF = 0.92453057 US$, exchange rate at 28.09.2008.

The income-related offset $+4.58\ln(y_j/CHF)$ in (9) can be interpreted as the utility earned from daily income. It is therefore calculated once for each individual, added to the overall utility of daily plans, and is removed from the activity related functions in (10). The marginal utility for being late $\hat{\beta}_{late}$ is estimated similar to Kickhöfer (2009): in a time and route choice survey from ETH Zurich (Vrtic et al 2008) people stated their willingness-to-pay in order to reduce the probability of being late. Based on this data, $\hat{\beta}_{late}$ is estimated and then re-scaled with respect to the cost related behavioral parameter $\hat{\beta}_{cost}$ and the average income of the sample $\bar{y} = 172$ CHF per day in (8). This results in $\hat{\beta}_{late} = 1.52/h$. The parameter for late arrival will only be used in the following test scenario (Sec. 4), but not for the real-world scenario of Zurich metropolitan area (Sec. 5).

Because of the argument regarding the opportunity cost of foregone activity time when arriving early (see Sec. 2.2), the *effective* marginal disutility of early arrival is $\hat{\beta}_{early_{eff}} = -\hat{\beta}_{perf}\, t_{*,i}/t_{perf,i} \approx -\hat{\beta}_{perf} = -1.86/h$ which is equal to the effective marginal disutility of traveling with public transit $\hat{\beta}_{tr,pt_{eff}}$. The effective marginal disutility of traveling by car is, by the same argument, $\hat{\beta}_{tr,car_{eff}} = -\hat{\beta}_{perf}\, t_{*,i}/t_{perf,i} - |\hat{\beta}_{tr,car}| \approx -\hat{\beta}_{perf} - |\hat{\beta}_{tr,car}| \approx -2.83/h$.

For the test scenario, the *effective* values of car travel time would correspond to the values $(\hat{\beta}_{early_{eff}}, \hat{\beta}_{tr,car_{eff}}, \hat{\beta}_{late_{eff}}) = (-1.86,\ -2.83,\ -1.52)$ of the Vickrey bottleneck scenario (Vickrey 1969; Arnott et al 1990).

3.4 Income Generation

Income is generated based on a Lorenz curve. Due to the lack of exact data the functional form of the Lorenz curve is approximated. Then the income curve, the first derivative of the Lorenz curve, is calculated (Kämpke 2010).[9] 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 is derived, similar to the distribution in reality. Adding income at an individual level results in a personalized utility function for each agent. In the test scenario described in the following section, income is the only varying attribute between agents. The real-world scenario in the subsequent section, however, includes varying trip distances and daily plans so that demographic attributes of each agent are strongly personalized.

4 Test Scenario

The goal of this section is to verify the correctness and plausibility of the estimated choice model and the underlying implementation. A simple setup is used in order to test the plausibility of traveler choice reactions resulting from a policy change.

[9] 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.

4.1 Setup

Network The test network consists of a cycle of one-way links with (unrealistically) high capacities so as to minimize their influence on traffic patterns, essentially making it possible for most agents to drive with free speed. One link between home and work location has reduced capacity of 1000 vehicles per hour, building a bottleneck.

The distance from the home to the work location of the agents is 17.5 km, the way back is 32.5 km long. Speed limit is at 50 km/h so the free speed travel time from home to work by car is 21 minutes while 39 minutes are needed for the way back home. Thus, the total free speed travel time by car is 60 minutes. As the agents are forced to remain on that route, the scenario is similar to the Vickrey bottleneck scenario (Arnott et al 1990; Vickrey 1969).

Population The synthetic population consists of 2000 agents. All agents start at their home activity, which they initially leave at 6:00 a.m. They initially drive to work by car, where they initially stay for 8 hours, and then drive home again.

In addition, each agent initially possesses an non-active plan that uses the public transit mode for both trips. These trips take twice as long as by car at free speed, i.e. 42 minutes from home to work, and 78 minutes for the way back. Thus, the total public transit travel time is 120 minutes. In contrast to the car travel times, these pt travel times are not affected by congestion. Since public transit is assumed to run continuously and without capacity restrictions, a home departure at time t will always result in a work arrival at $t + 42min$. Estimation of income for the synthetic population, as described in Sec. 3.4, is based on values for the Kanton[10] Zurich in 2006. The median income for that year is 46 300 CHF per household.

Activities Work opens at 7:00 a.m. and closes at 6:00 p.m. This means that (i) no utility can be accumulated from an arrival earlier than 7:00 a.m., and (ii) any arrival later than 7:00 a.m. is immediately punished with $\beta_{late} = -1.52/h$. The activity of the home activity is "wrapped around", i.e. a departure at 6:00 a.m. and a return at 5:00 p.m. results in a home activity duration of 13 hours. "Typical" durations of $t_{*,work} = 8$ hours and $t_{*,home} = 12$ hours mean that work and home times have a tendency to arrange themselves with a ratio of 8:12 (i.e. 2:3).

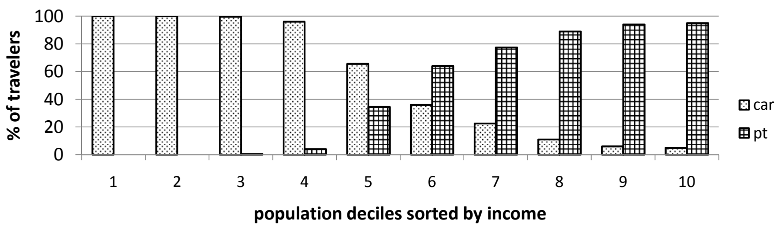
Simulation First, a "preparatory run" is performed by running the base case for 4000 iterations. During the first 2000 iterations, 10% of the agents perform "time adaptation", i.e. they make a copy of an existing plan and shift each element of their time structure by a random number between zero and 7.5 minutes. The other 90% of the agents switch between their existing plans according to (1), which means that they potentially also switch the transport mode. During the second 2000 iterations, time adaptation is switched off; in consequence, agents only switch between existing options according to (1). That is, their choice set now remains fixed to what they have found in the first 2000 iterations, and they choose within this set according to a logit model.

[10] A Swiss "Kanton" is similar to a federal state.

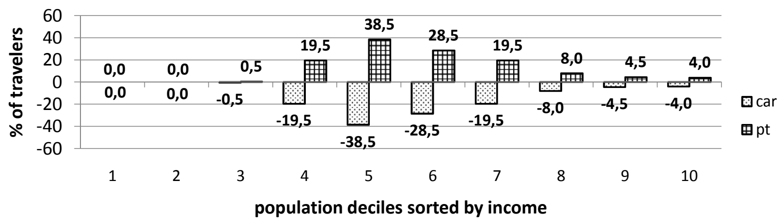
After this, the speed increase for public transit is introduced. It now takes only 1.8 (instead of 2.0) times as long as traveling by car on an empty network. This corresponds to a pt speed increase of 10%. The policy case is run for another 2000 iterations, starting from the final iteration of the base case. For the first 1000 iterations, the time adaption module is again switched on, with the same 10% re-planning fraction. The final 1000 iterations are once more with a fixed choice set. For further analysis, iteration 4000 of the base case is then compared to the final iteration of the policy case.

4.2 Results

Since car is the low value and public transit the high value mode, low income people predominantly use the car while high income people predominantly use public transit (Fig. 1a). When the pt speed is increased, the overall modal split predictably shifts from car to pt, from 54% : 46% to 42% : 58% (car:pt). Also predictably but importantly, this happens through a shift of the income level that divides the two regimes – this level, naturally, moves to lower incomes (Fig. 1b).



(a) Base case



(b) Changes due to the public transit speed increase

Fig. 1: Modal Split over deciles of the population sorted by income. Absolute values for the base case, changes in percentage points for the pt speed increase. Dotted bars depict car drivers, checked bars public transit users.

Fig. 2 shows, agent-by-agent, the utility differences between the base case and the policy case as a scatter plot over deciles of the population. Every decile, summed up over all three plots, contains the same number of agents, sorted by their income. For example, the first decile from 0% to 10% includes the 10% of agents with the lowest incomes. Fig. 2a shows synthetic travelers that choose the same transport mode before and after the policy change, crosses for the car mode, circles for the pt mode. One notices a homogeneous utility increase of about 0.35 for all pt users, and a smaller increase of, in the average, about 0.25 for the car users. This is a plausible consequence of the fact that pt users benefit directly from the policy, while car users benefit from congestion relief due to the reduced car mode share.

The car users face, because of stochastic congestion effects, rather strong fluctuations of their utilities from iteration to iteration. Thus, this effect can also be observed when comparing the base case to the policy case. For pt users, these fluctuations are much less pronounced due to their – by assumption – completely reliable transport mode. Figs. 2b and 2c show synthetic travelers that change their transport mode, Fig. 2b from pt to car and Fig. 2c from car to pt, respectively. With a pt improvement measure, a switch from pt to car (Fig. 2b) is not what should be expected. These synthetic travelers are "logit switchers", in the following sense:

- Those that gain more than the average by the switch, towards the lower income scales, are travelers that could already have achieved a higher utility level in the base case by using car.
- Those that gain less than the average by the switch, towards the higher income scales, are travelers that would have gained even more by staying with pt.

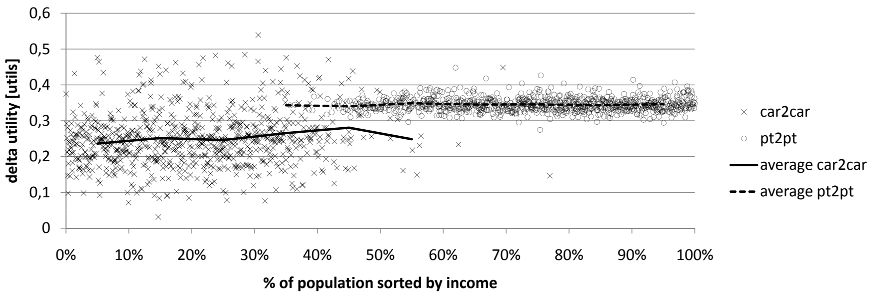
However, in both cases the utility computation is done according to the systematic component of utility as described in Sec. 2.1. The switches are therefore caused by changes in the random component of utility ε.

Fig. 2c also contains those "logit switchers", this time from car to pt. But in addition, it also contains "systematic" switchers who change the mode due to a utility gain in the systematic component. The density of switchers is largest towards middle income groups, since there, the systematic switchers are located. One could, in principle, also attach the random components as random but fixed to every alternative of every traveler.[11] Karlstrom and Morey (2004) and therefore Franklin (2006) also assume such an interpretation in their welfare computations.

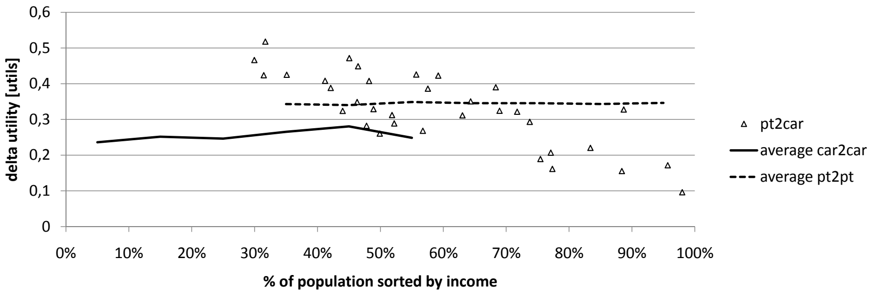
An interpretation of the results according to the well-known "rule-of-a-half" (Jara-Díaz 2007), where the pre-existing users of an improved facility obtain the full utility gains, whereas the users switching towards the improved facility in average obtain half of those gains. In the present case, the situation gets more complicated because of substitution effects: Also users not using the improved facility gain because of congestion relief. Differentiated by user groups, we obtain:

- Average utility gain for users staying with public transit: 0.345 $utils$
- Average utility gain for users switching from car to public transit: 0.297 $utils$
- Average utility gain for users staying with car: 0.250 $utils$

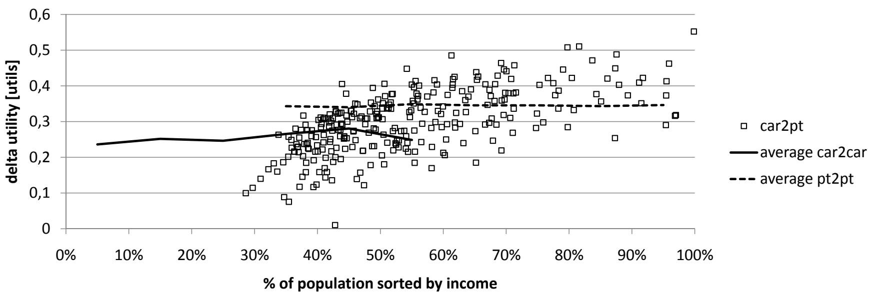
[11] For an example see Horni A, Nagel K, Axhausen (2011, in preparation) Very High-Resolution Destination Choice in Agent-Based Demand Models. IVT, ETH Zürich, see http://www.ivt.ethz.ch/vpl/publications/reports



(a) Utility changes for synthetic travelers who keep their mode



(b) Utility changes for synthetic travelers who switch from pt to car



(c) Utility changes for synthetic travelers who switch from car to pt

Fig. 2: Utility changes, sorted by income. Every synthetic traveler is plotted according to her relative position on the income scale. The lines in Figs. 2b and 2c denote the average utility changes for users keeping their mode (Fig. 2a).

That is, the switchers from car to pt indeed gain, in the population average, the mean value between the (direct) pt gains and the (indirect) car gains. Nevertheless, the situation is confounded by the fact that there are also significant gains for the car users, which could not be computed by considering the pt facility alone.

Overall, the results demonstrate that the approach picks up the distributional effects of transport policy measures. As is plausible, a quality-of-service change affects the higher income groups more when assuming higher VoT with increasing income. Thus, the plausibility test can be regarded as successful.

5 Scenario – Zurich Switzerland

The income-contingent utility function is now applied to a large-scale, real-world scenario. The 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).

5.1 Setup

Network The network is a Swiss regional planning network that includes the major European transit corridors. It consists of 24 180 nodes and 60 492 links.

Population 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 initially have two daily plans that encode their reported activities during a typical working day. This information is taken from microcensus information (SFSO 2000, 2006). The first plan only uses car as transport mode, while the second plan only uses public transit. Again, traveling by public transit takes twice as long as by car at free speed and pt travel times are not affected by congestion.

Income for the large-scale scenario is generated as described in Sec. 3.4. Region specific data is used for the Kanton Zurich since here, income medians are available for each municipality.[12] For every person living in the Kanton Zurich, the municipality of the person's home location is determined. Then the median income specific for this municipality is used for income calculation in conjunction with a Lorenz curve for the Kanton Zurich.[13] Incomes for persons living outside the borders of Kanton Zurich are computed with the help of the median income and the Lorenz curve of the Swiss Confederation.[14] The median income used for the Swiss Confederation in 2006 is 43 665 CHF per household and year.

Activities Activities are classified as *home*, *work*, *education*, *shopping*, and *leisure*. The time window during which activities can be performed is limited to certain hours of the day: *work* and *education* can be performed from 7:00 a.m. to 6:00 p.m., *shopping* from 8:00 a.m. to 8:00 p.m. This means that for these activities no utility can

[12] `http://www.web.statistik.zh.ch/themenportal/themen/daten_detail.php?id=759`, last access 20.05.2011

[13] `http://www.web.statistik.zh.ch/themenportal/themen/aktuell_detail.php?id=2752&tb=4&mt=0`, last access 20.05.2011

[14] `http://www.bfs.admin.ch/bfs/portal/de/index/themen/20/02/blank/dos/01/02.html`, last access 20.05.2011

be accumulated outside of the opening times. In contrast, *home* and *leisure* have no time restrictions. Unlike the test scenario, there is no punishment for being late. This is not possible because agents can have more than one work activity, e.g. one in the morning and one in the afternoon. In such a case it is complicated to specify when an agent starts an activity late or not.

Simulation To speed up computations, a random 10% sample is taken from the synthetic population for simulation, consisting of 181 725 agents. In order to maintain consistency with the test scenarios, the total amount of iterations is reduced but the proportion of the different simulation steps is held constant. This means for the base case:

- For 1000 iterations, 10% of the agents perform "time adaptation" and 10% adapt 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.

After this, the pt speed improvement is introduced. The policy case 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 neither adapting time nor route switch between existing plans and such eventually switch between transport modes. For the final 500 iterations only a fixed choice set is available. For evaluating the impact of the pt speed increase, iteration 2000 of the base case is compared to the final iteration of the policy case.

5.2 Validation

Simulated traffic volumes are compared with the hourly traffic volumes from 159 real-world counting stations. In Fig. 3, circles indicate the mean relative error of the reference Zurich scenario (Chen et al 2008) between hourly flows in reality and hourly flows from the simulation. That model was based on $\beta_{perf} = 6/h$, $\beta_{tr,car} = -6/h$, $\beta_{tr,pt} = -3/h$, and no dependence on travel distance or income was assumed.

The triangles depict the same for the estimated income-contingent utility function. One notices a slight improvement of the mean relative error, especially during day time in comparison with Chen et al (2008). This underlines the advantage of using estimated behavioral parameters for more realistic results. Nevertheless, it is a bit surprising that, at least at the aggregated level, there is so little difference between the simulations. Presumably, this is due to the fact that the activity patterns, preferred activity durations, opening times, and transportation network structure are dominating the results. In particular, given the fact that the traffic counts are reproduced much better between 8:00 a.m. and 7:00 p.m. than the remainder of the day, one may speculate that the need to squeeze all activities into the available opening times is, in fact, the dominating force.

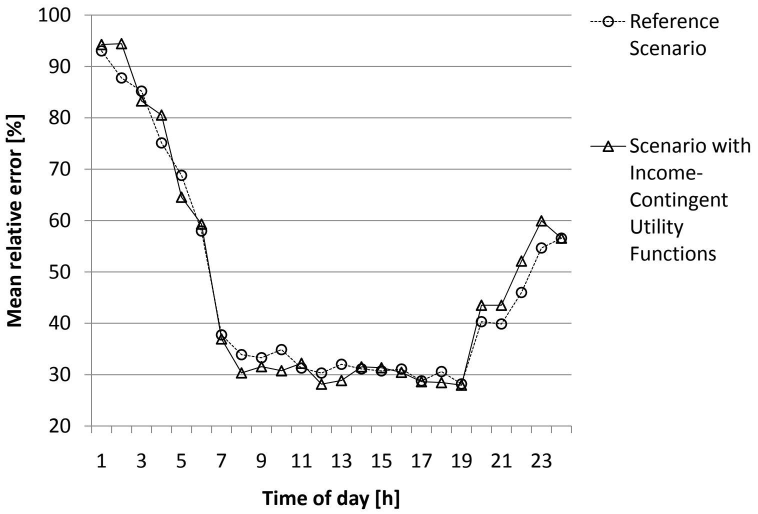


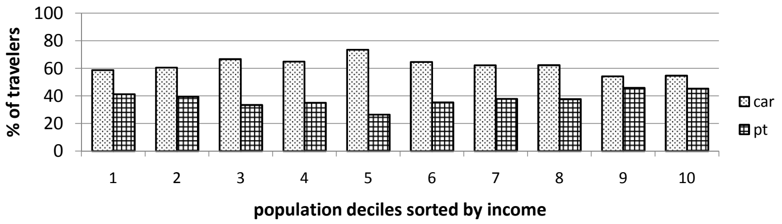
Fig. 3: Realism of the two simulations. Hourly comparison of simulation traffic flows with data from 159 traffic counting stations in the Zurich area. Circles show the mean relative error for the reference scenario, triangles for the scenario using income-contingent utility functions.

Together with the analysis of other traffic condition indicators, such as peak hours, modal split or the average trip duration or length, it can be stated that the base case seems to be a good starting point for investigating the pt speed increase.

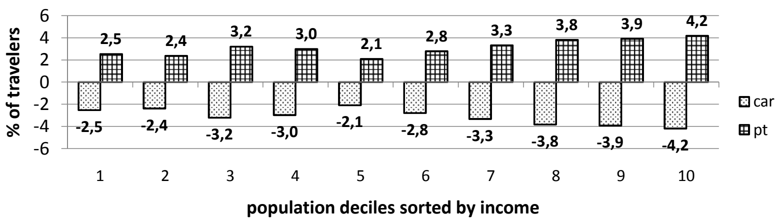
5.3 Results

The base case of the Zurich scenario exhibits a modal split of 60.9%:39.1% (car:pt). Fig. 4a depicts the modal split over income deciles of the population. In contrast to the base case of the test scenario shown in Fig. 1a, the distribution here is more homogeneous: Both modes are used across all deciles. Fig. 4b presents changes to the modal split over income deciles of the population compared to the base case. One can observe that with increasing income, more individuals switch from car to pt.

Increasing utility gains with increasing income are not as pronounced in the large-scale scenario as in the test scenario, as Fig. 5 indicates. Here, each data point is located in the middle of an income decile and represents the corresponding overall utility change with a triangle. For representation purposes the data points are connected with lines. This overall gain in utility is mainly composed of the average utility changes of two different user groups: As expected, synthetic persons using pt both before and after the pt improvement obtain most of the benefits (represented by circles). Synthetic persons using car both before and after the policy (represented by crosses) also gain, but considerably less than the pt users. Results for the mode switchers are



(a) Base Case



(b) Pt Speed Improvement

Fig. 4: Modal Split over deciles of the population sorted by income. Absolute values for the base case, changes in percentage points for the pt speed increase. Dotted bars depict car drivers, checked bars public transit users.

not shown because the stochastic fluctuations overwhelm the signal. Even though the slope of the curves is slightly positive, gains in terms of utility are still distributed quite equally. However, the subsequent section will show that this picture will completely change when converting the individual utility differences into money.

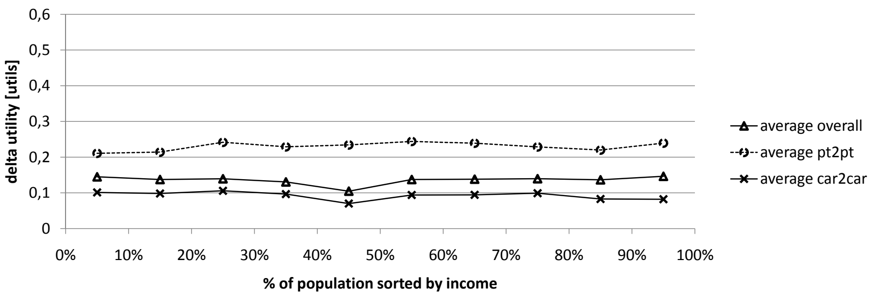


Fig. 5: Average utility changes over deciles of the population sorted by income. Triangles depict the overall change in the income deciles. Crosses indicate the change for car users who keep their mode, circles for pt users who keep their mode.

6 Discussion

This paper starts from estimates of individual utility functions based on the estimation of logit models. A possible interpretation of this approach is that the utility function is simply a device that helps to construct quantitatively descriptive behavioral models of individuals. In this way, one first constructs and estimates the behavioral model, and then runs a simulation model populated with entities (synthetic persons) using this behavioral model.

The interpretation of the utility as an indicator of individual gains or losses is essentially an afterthought, with no meaning to the simulation results except that random utility modeling has something to do with the individual optimization of utility. Still, the identification of winners and losers seems to be inherently quite robust since it results directly from the behavioral model that is based on surveys or observations. It was also shown that it is possible to quantify individual gains and losses with respect to an individual utility level. For a possible aggregation of these quantitative numbers in order to obtain some indicator of welfare change and a discussion of problems, see below. General critical issues of this approach enter from different angles, such as:

- Since the logit model is stochastic, agents are stochastic as well, and some may *de*crease the systematic part of their utility function (what was called "logit switchers" above). This means that the results cannot be interpreted at the single-agent, single-plan level; one either needs to aggregate over subpopulations or over all plans of every agent. The latter is less problematic in terms of the comparability of utility levels between different persons (see below). A different approach to address this issue could be to attach the random components as random but fixed to every alternative of every traveler.[15]
- One may argue that it is invalid to cast human behavior into an optimization problem at all, and one should rather resort to simple procedural rules (e.g. Moss and Sent 1999; Simon 1997).
- Even if individuals' behavior can be cast as an individual optimization problem, it is by no means clear that ex-post happiness is optimized by ex-ante optimization of this descriptive function.

Still, to re-iterate: If one takes into account that one has some random "logit" winners and losers, then the conceptual path leading to the identification of individual winners and losers seems quite straightforward.

Concerning the question whether individual utility changes can somehow be aggregated into some indicator of welfare, three obvious methods come to mind:

- Just add up all individual utility changes, possible by subpopulation (Fig. 5).
- Convert all individual utility changes to individual willingness-to-pay/willingness-to-accept values (Fig. 6). The most common (albeit not the only) way to do this is to convert the utility changes with respect to the inverse marginal utility of

[15] For an example see Horni A, Nagel K, Axhausen (2011, in preparation) Very High-Resolution Destination Choice in Agent-Based Demand Models. IVT, ETH Zürich, see http://www.ivt.ethz.ch/vpl/publications/reports

money (Small and Rosen 1981; Jara-Díaz 2007). Since, in the present model, the marginal utility of money is income-contingent, the conversion factor from utility differences into money is taken from the individual utility function (10). Thus, the individual monetary change of the pt speed increase is given by:

$$\Delta m_j = \frac{y_j}{4.58} \cdot \Delta V_j \ , \tag{11}$$

where y_j is once more the daily income of person j. Given a utility gain by the policy measure, this would be the amount of money one would need to take away to revert the person back to her original level of utility. For a discussion of income effects see below.

– Convert all individual utility changes to individual equivalent "hours of leisure time". Given a utility gain by the policy measure, this would be the amount of leisure time one would need to take away to revert the person back to her original level of utility. One has

$$\Delta V_j \approx \frac{\partial V_j}{\partial t_{perf,leisure,j}} \cdot \Delta t_{perf,leisure,j} \tag{12}$$

and therefore

$$\Delta t_{perf,leisure,j} \approx \left(\frac{\partial V_j}{\partial t_{perf,leisure,j}} \right)^{-1} \cdot \Delta V_j \ . \tag{13}$$

That is, the (linearized) gain/loss of every individual's equivalent hours of leisure time would be computed by multiplying every individual's utility gain/loss by their inverse marginal utility of leisure time. As a more robust alternative to a leisure activity, the "home" activity could be used.

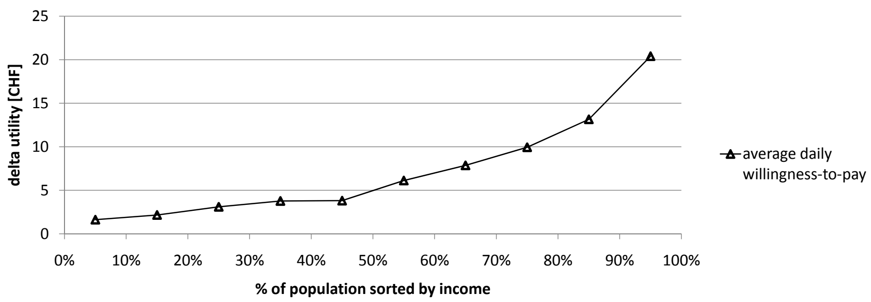


Fig. 6: Average daily willingness-to-pay for the pt speed increase over deciles of the population sorted by income.

The last item brings to light that maybe more effort needs to be made to build quantitative models that include time pressure. Clearly, the vastly different values of time by trip purpose (often up to a factor of four, see Mackie et al 2003) indicate that this needs to be considered. Nevertheless, concentrating on time pressure alone means a different focus than values of time: While (monetary) VoT are also coupled to income, time pressure expressed in equivalent hours of leisure time may be the same for a single mother or for a busy executive.

At any rate, the comparison of Fig. 5 to Fig. 6 makes clear that the selection of the aggregation procedure can lead to quite different equity interpretations: While the simple but conceptually problematic summation of utilities leads to similar gains across all income groups (Fig. 5), the willingness-to-pay, sorted by income group, implies that high income groups would have a disproportionately high willingness-to-pay for the measure considered (here the pt speed increase; Fig. 6). This is, in fact, quite intuitive: Higher income groups have a disproportionately high willingness to pay for good schools, a good health system or a good transport system. In this sense, a progressive tax may not even be re-distributive with respect to such types of government expenses, since it just reflects the willingness-to-pay for improving the corresponding services.[16] Let us stress once more that these different attempts of measuring welfare rely on exactly the same description of human behavior. This highlights that the model predicting the system's reaction to a policy change is independent from the different interpretations of measuring welfare.

Unfortunately, the above observations interact with economic appraisal. The aggregated willingness-to-pay may seem the most consistent approach, but is quite different from approaches to-date where time gains of all individuals are valued equally. Conversely, using aggregated equivalent hours of leisure time may seem more equitable, but it is a bit unclear how to convert them into money for cost-benefit analysis.[17] Given, however, that at this point one has already left the ground of individual monetized consumer surplus, it might be more honest to quantify the benefit no longer in monetary terms, but directly in equivalent hours of leisure time. Projects could be assessed by the equivalent hours of leisure time they would generate per unit of money invested.

Eq. (11) assumes that the conversion from utility into willingness-to-pay or willingness-to-accept, respectively, can be based on the income from before the introduction of the policy. This implies that the marginal utility of money needs to be constant within the range of price and/or quality change. In situations where individuals spend a rather important fraction of their available income on transportation, the issue is not so clear any more, and income effects (Herriges and Kling 1999; Jara-Díaz and Videla 1989) need to be taken into account. For this paper, let it suffice to say that one would need to go back to Eq. (6) or Eq. (7) and trace the effect of the interaction between cost c and income y and how that affects Eq. (11).

7 Conclusion

Standard cost-benefit-analyses require some monetization of positive and negative effects that might result from transport policies under consideration. A policy is usually

[16] Clearly, this is only true if the higher income groups are not operating in a separate system, such as private schools, private health insurance, or private transport systems.

[17] A possible way may be to use some average, i.e. income-*in*dependent, conversion.

recommended if the monetized aggregated economic benefit outweighs the monetary costs. Effects on individuals or subgroups of the population are rarely investigated, even though this would provide valuable insights into problems that are linked to the public acceptance of the policy. This paper proposes how the standard approach could be improved in practice by using a multi-agent simulation that is capable to provide better information for policy makers. Therefore, the evaluation process was decomposed in three different steps:

First, it was shown that the simulation of changes in human mobility behavior as a reaction to transport policies becomes more realistic by using estimations of individual utility functions that are based on survey data.

Second, using the resulting individual utility differences to identify winners and losers seems a quite robust procedure.

Third, the results of this paper indicate, however, that an aggregation and/or monetization of these utility differences in order to derive an indicator of welfare change raises the question about the aggregation procedure: It was shown that a progressive (income) tax might not be re-distributive when using the income-contingent individual willingness-to-pay or willingness-to-accept for policy evaluation. Therefore two other options for project appraisal were discussed, relying on the same description of human behavior given by the estimated utility functions. Even though it is – at this point – unclear how these other options can be used for project assessment, they would lead to different equity interpretations and thus could help designing projects with broader public acceptance. Overall, the results demonstrate that a better understanding of problems linked to public acceptance can be achieved by including individual income into utility calculations. It was often assumed that such models are computationally too complex for large-scale real world scenarios when considering more than one choice dimension; the present paper, however, showed that these calculations now have become feasible.

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