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Distribution of Benefits and Losses From Roadpricing Illustrated in a Microsimulation Scenario

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Abstract

This report describes the MATSim simulations performed to illustrate distribution of benefits in a road pricing context with trip-dependent varying preferences. The main hypothesis of the project Surprice is illustrated, that the inequality between income groups, induced by road pricing, in some cases might be smaller if intra-personal variation is also considered in the model rather than if only inter-personal variation is included in the calculation.
1 Introduction and Goal

Value of travel time (VTT) (often Value of travel time savings (VTTS)) specifies the monetary amount one is willing to pay for travel time savings. In other words, travel time reductions $\Delta t$ are chosen if the utility generated by the reductions $U_{\Delta t}$ is larger than the utility generated by the respective amount of money $U_m$. In that case the utility gain is:

$$\Delta U = U_{\Delta t} - U_m$$

with

$$U_{\Delta t} = VTT \cdot \Delta t \cdot \frac{dU_m}{dm}$$

and

$$U_m = m \cdot \frac{dU_m}{dm}$$

where $\frac{dU_m}{dm}$ is the marginal utility of money, $m$ being the toll amount.

It can now easily be seen, that people with a higher VTT overall gain more utility $\Delta U$ due to a travel time reduction $\Delta t$.

VTT is usually defined as:

$$VTT = \frac{\frac{dU_{resource[utils]}}{dt_{resource[h]}} - \frac{dU_{travel[utils]}}{dt_{travel[h]}}}{\frac{dU_m[utils]}{dm[\epsilon]}} \cdot \frac{\epsilon}{h}.$$  \hspace{1cm} (1)

The marginal utility of money is in the denominator of above equation meaning that people with a small marginal utility of money have a large VTT and thus profit more in terms of utility. Marginal utility of money is usually inversely related to income, thus—assuming that the nominator of above equation is stable for the population—one can see, that higher income persons gain more utility due to a travel time reduction.

Still, as identified in the project Surprice the assumption of a stable and identical nominator is not correct. As shown by Börjesson et al. (2013), the direct (dis-)utility of travel time $\frac{dU_{travel[utils]}}{dt_{travel[h]}}$ is dependent on the individual trip including previous trips of the respective person (see also Cirillo and Axhausen (2006)). This means that VTT is not only dependent on the individual but also on the trip. Thus, also low income groups can occasionally have a high VTT and thus an increased utility gain. Road pricing thus generates “self-selection of trips not individuals”
Börjesson et al. (2013) meaning that in some cases the equity effects seem to be smaller than assumed earlier.

The goal of this paper is to identify and illustrate these effects in a real world scenario. This can be seen as an extension of the example presented in Börjesson et al. (2013, p.12).

2 Method

MATSim simulation runs (Section 2.1) are performed to illustrate the basic hypothesis of Börjesson et al. (2013), namely that road pricing does trip self-selection and not person self-selection. A mini-scenario (Section 2.3) and a real-world scenario (Section 2.4) are used.

2.1 MATSim—In Brief

MATSim is an activity-based, extendable, open source, multi-agent simulation toolkit implemented in JAVA and designed for large-scale scenarios. It is a co-evolutionary model. A good overview of MATSim is given in Balmer et al. (2006). In competition for space-time slots on the transportation infrastructure with all other agents, every agent iteratively optimizes its daily activity chain by trial and error. Every agent possesses a fixed amount of day plans memory, where each plan is composed of a daily activity schedule and an associated utility value (in MATSim, called plan score).

Before plans are executed on the infrastructure in the network loading simulation (e.g., Cetin, 2005), a certain share of agents (usually around 10%) is allowed to select and clone a plan and to subsequently modify this cloned plan.

If an agent ends up with too many plans (usually set to 4-5 plans per agent), the plan with the lowest score (configurable) is removed from the agent’s memory. One iteration is completed by evaluating the agent’s day described by the selected and executed plan.

If an agent has obtained a new plan, as described above, then that plan is selected for execution in the subsequent network loading. If the agent has not obtained a new plan, then the agent selects from existing plans. The selection model is configurable. In many MATSim investigations, a weighted random choice based on a logit choice model is used.

In the current standard implementation, agents’ attributes taken into account are age, mobility
tools, occupancy, home and work location. Destinations are characterized by location, activity types, which can be performed there and service hours; here, day-of-week-specific service hours are applied as technically provided by Meister (2008). Income, value-of-time and public transport fares are not yet included by default in MATSim. MATSim validation is mainly based on road count data.

The plan score, computed by the MATSim utility function, is compatible with micro-economic foundations. The basic utility function was formulated in Charypar and Nagel (2005) from the Vickrey model for road congestion as described in Vickrey (1969) and Arnott et al. (1993). The applied parameter setting for this paper is described in Section 2.3 and 2.4.

2.2 Main Modifications of This Project

This project’s two main modifications of the MATSim standard scenario technically concern demand generation and utility function specification. Demand generation is described in Section 2.4 and by Horni and Axhausen (2012).

As will be detailed later, the utility function adaptation includes consideration of a person-specific marginal utility of money and a trip-dependent specification of direct (dis-)utility of travel time. This utility is composed of (dis-)utilities for travel time, travel distance and monetary travel costs. The coefficients $\beta$ are now dependent on mode and trip purpose. Furthermore, lagged variables are included in the calculation.

For the moment the activity scoring itself is not touched but it should be investigated in a future version. Traveling generates opportunity costs, i.e., that time that is lost for performing an activity.

2.3 Mini Scenario

The small-scale two-link scenario uses the network shown in Figure 1. 500 persons starting at home around 8:00 AM (facility on the left) travel either to work or to leisure (facility on the right). Two routes are possible, a long toll-free high-capacity route over node 3 and a short direct toll route (0.25 €). A high and a low income group leading to low and high marginal utilities of money are differentiated (0.1 €/h and 1.0 €/h). Furthermore, the travel time coefficients are varied dependent on trips. Here a single day of car traffic is simulated.
2.4 Real-World Zurich Scenario

The Zurich scenario is frequently used in MATSim development but also for projects in Swiss planning practice (e.g., Balmer et al., 2009). Simulation scenario population is derived from the Swiss Census of Population 2000 (Swiss Federal Statistical Office (BFS), 2000). Here, a 1% sample of car traffic (including cross-border traffic) crossing the area delineated by a 30 km circle around the center of Zurich (Bellevue) is drawn, which results in 17’912 agents simulated. The activity location data set, comprising more than 10⁶ locations is computed from the Swiss Census of Population 2000 and the Federal Enterprise Census 2001 (Swiss Federal Statistical Office (BFS), 2001). The network from the Swiss National Transport Model (Vrtic et al., 2003)—a planning network—is used, consisting of 60’492 directed links and 24’180 nodes. Navigation networks, such as Tele Atlas MultiNet (2010); NAVTEQ (2011), are readily applicable in MATSim.

To date, commonly, a single day was simulated, for which demand is derived from the National Travel Survey for the years 2000 and 2005 (Swiss Federal Statistical Office (BFS), 2006), reporting 33’000 independent person days for Switzerland overall.

For creation of a weekly scenario either longitudinal travel survey studies are required or algorithms creating longer diary periods such as Munizaga et al. (e.g., 2011); Doherty et al. (e.g., 2002); Kuhnminhof and Gringmuth (e.g., 2009), where still the later is calibrated by longitudinal surveys, here with the German Mobility Panel (MOP). Prominent longitudinal surveys are Mobidrive (Axhausen et al., 2002), Thurgau (Löchl et al., 2005) and Uppsala (Hanson and Huff, 1982). As this projects’ models are estimated based on the Thurgau study, MATSim demand is also derived from this study. Clearly, results’ transferability from the rural Thurgau region with the small city Frauenfeld to the urban/sub-urban Zurich agglomeration awaits analysis.

The agents’ individual marginal utilities of money are derived by income groups. Assignment of income group membership to agents is done randomly following the income distribution of microcensus (see Figure 2) showing a rather natural/plausible form than Thurgau data set (see Figure 3). In the future, incomes could be derived from EVE (Swiss Federal Statistical Office (BFS), 2007) possibly integrated with synthetic population generation (Müller, 2011).

In more detail, demand is prepared as follows. After filtering non-home-based plans, days containing trips with undefined modes, days containing inconsistent types and finally persons with incomplete weeks, 116 out of 230 persons are used. In the present version, starting from the MobiDrive classification (Zimmermann et al., 2001, p.6), activity purposes are converted to the MATSim standard values as presented in Table 1. As shown later, for scoring the activity purposes are further merged.
Choice dimensions are included as shown in Table 2. Available modes in MATSim are car (often interpreted as motorized individual traffic), public transport, bike, and walk. Initially all trips are performed by car, where the mode choice module is calibrated to create the mode shares as observed in the Swiss microcensus. Car mode is microsimulated, other modes are handled as pseudo-modes as described e.g., in Rieser and Nagel (2009, p.5). For model testing, traffic count data for 2004-2005 from automatic national, cantonal and municipal count data stations (e.g., ASTRA; 2006) are available.

Utility Function Parameter Setting

Plan utility, described in detail in Charypar and Nagel (2005), is computed as the sum of all activity utilities $U_{act,q}$ plus the sum of all travel (dis)utilities $U_{travel,q}$.

$$U_{plan} = \sum_{q=1}^{n} U_{act,q} + \sum_{q=2}^{n} U_{travel,q}$$

The utility of an activity is defined by:

$$U_{act,q} = U_{dur,q} + U_{late,ar,q}$$

where:

- $U_{dur,q} = \beta_{dur} \cdot t_{typ,q} \cdot \ln(t_{dur,q}/t_{0,q})$ is the utility of performing activity $q$, where opening times of activity locations are taken into account. $t_{dur,q}$ is performed activity duration, $\beta_{dur}$ is marginal utility of activity duration for its typical duration $t_{typ,q}$ and $t_{0,q}$ is minimal duration, or in other words, the duration for which utility starts to be positive.

- $U_{late,ar,q} = \beta_{late,ar} \cdot t_{late,ar,q}$ gives the disutility of late arrival, where $\beta_{late,ar}$ is marginal utility of lateness and $t_{late,ar,q}$ is lateness compared to planned times given in the agent’s day plan.

There may also be additional penalties for staying not long enough, departing too early, or (beyond the implicit opportunity cost of time) for waiting. These are not used in the present paper.

Travel disutility is given as

$$U_{travel,q} = \beta_{t,m,q} \cdot t_{m,q} + \beta_{d,m,q} \cdot d_{m,q} + \beta_{c,m,q} \cdot c_{m,q} \quad (2)$$

where $\beta_{t,m,p,q}$ is marginal utility of travel time with the used mode $m$ and purpose $p$ and $t_{m,q}$ gives the mode-dependent travel time between location of activity $q - 1$ and $q$. $\beta_{d,m,p,q}$ and $\beta_{c,m,p,q}$ are the coefficients for travel distance $d_{m,q}$ and monetary travel costs $c_{m,q}$. 
In this paper, the following utility function parameter setting is applied, which is loosely derived from Balmer et al. (2009, 2010); Horni et al. (2011):

\[
\beta_{dur} = +6.0 \ \text{€}/h
\]

\[
\beta_{late,av} = -18.0 \ \text{€}/h.
\]

The travel disutility is given either stable or varying as mentioned earlier and formulated in detail Section 3.

Following constants are used to calculate travel disutility:

\[
C_{car} = -2.5 \ \text{utils}, \ C_{pt} = -5.0 \ \text{utils}, \ C_{bike} = -7.0 \ \text{utils}, \ C_{walk} = 0.0 \ \text{utils}.
\]

Public transport, bike and walk legs are “teleportet” and not microsimulated as described e.g., in Meister et al. (2010). Teleportation speeds of the modes are chosen as follows.

\[
v_{pt} = 7.0 \ \text{m/s}, \ v_{bike} = 3.33 \ \text{m/s}, \ v_{walk} = 1.11 \ \text{m/s}
\]

where the network distance is approximated as the beeline between the activities with a scale factor of 1.5.

Lagged variables are considered by an additional gain of 1.0 util if the respective mode was also used in the previous day either for the same purpose or in the same time period as specified by Börjesson et al. (2013).

Rough mode choice calibration is given in Table 3; where only distances and times, but not number of legs, are taken into account as in MATSim still access and egress walks are substantially underestimated. The walk to and from the car are not included. Walks to and from the public transport stops are only added if transit is simulated (not teleported). Average weekly values could be used in the future and finer calibration.

Calibration has set mobility simulation flow capacity factor to 0.03, which is high compared to e.g., Balmer et al. (2009), but necessary for a stable score development without system-wide breakdowns (see also Rieser and Nagel (2008)).
3 Results and Discussion

3.1 Mini Scenario

Two configurations are simulated with this scenario. In configuration (0), the travel time coefficient $\beta_t$ is for both activity types, work and leisure, set to $-6 \text{utils/h}$. For configuration (1) the work coefficient is set to $-11 \text{utils/h}$ and the leisure coefficient is set to $-1 \text{util/h}$. Besides the toll score (converted to utilities by the marginal utility of money) and activity duration scoring, no further scoring components are applied.

The number of people that choose the toll road are analyzed per income group. The travelers are utility maximizer, thus, they only chose the toll road if this is the option generating more utility. Figure 4 illustrates the effect on equity due to varying preferences, namely that the low income classes are able to use road pricing to a larger extent than assumed up to now. In configuration (1) the share of “poor” people choosing the toll road is substantially higher than in configuration (0), where the overall toll distance is more or less the same (approx. 300 km).

3.2 Zurich Scenario

For the Zurich scenario also 2 configurations are simulated with varying preferences. In configuration (0), the travel time coefficient $\beta_t$ is for all modes and all purposes set to $-6 \text{utils/h}$. In configuration (1), the commuting coefficient (including work, education and returning home) is set to $-11.0 \text{utils/h}$, the shopping coefficient is set to $-6.0 \text{utils/h}$, and the leisure coefficient is set to $-1.0 \text{util/h}$. For both configurations, the distance coefficients (generic for all purposes) is set to $-0.2 \text{utils/km}$ for car, $0.0 \text{utils/km}$ for pt, $-4.0 \text{utils/km}$ for bike and $-1.0 \text{util/km}$ for walk. Monetary car costs are given as $-0.5 \text{€/km} - 5.0$ (e.g., due to parking costs). Monetary pt costs are defined as $-0.1 \text{€/km} - 5.0$ (e.g., for zone tickets). Constants and lag variables are applied as described earlier.

A link-based road pricing regime is implemented, where in the morning peak (between 5:45 AM and 9:00 AM links are tolled with 0.5 € in a 2 km radius area around Bellevue, a central place in Zurich.

The project Surprice is embedded in a longitudinal context and incorporates 3 kinds of preference variation: (1) interpersonal variation due to person heterogeneity, (2) intrapersonal variation due to changing needs (e.g., trip purpose) and (3) intrapersonal variation due to lagged
variables. A common assumption in transport planning is that, essentially, the longitudinal intrapersonal variation can be approximately observed as cross-sectional interpersonal variation in a cross-sectional analysis. Hence, apart from the lagged effects, the remaining effects can be approximately investigated by a cross-sectional scenario. Thus, first, a one-day simulation is performed. Figure 5 and 6 reveal a similar (but weak) positive effect on equity as observed in the mini scenario. In configuration (1), including varying preferences, the share of low income groups on toll roads is larger than in configuration (0) (stable preferences). But, different than for the mini scenario we have an overall increase of toll travel distance in configuration (1). Hence, parts of the effect could also be due to saturation effects for the high income groups; this should be investigated in the future.

To explore the range of settings for which the effect exists further settings are simulated. In the first setting, the toll is increased to 1.0 €. Figures 7 and 8 show that the changes in the shares are more or less random, meaning that there is no effect or that the effect is hidden by the large random variation probably also coming from the small sample size. The results of most settings tried out here, corresponded to this case. With a further increase of the toll, as shown in Figures 9 and 10, the changes, both increases and decreases of the shares are more or less restricted to the high incomes. For the setting, where the toll is set to 1 € and the travel coefficients for commuting, shop and leisure are defined as \(-7.0\) utils/h, \(-1.0\) utils/h and \(-1.0\) utils/h a completely negative equity effect can be observed in Figures 11 and 12.

Finally a week-long scenario is simulated with the parameter setting of \(-11.0\) utils/h, \(-6.0\) utils/h and \(-1.0\) utils/h and a toll of 0.5 € per link. Two lag variables of \(-1\) util each are applied if the same mode is used either in the same time period or for the same purpose in the previous day. This can be seen as an anti-hysteresis-component. Figures 13 and 14 nicely illustrate the basic hypothesis of the project.

### 3.3 Discussion

It has to be emphasized that the effect is only observed for a small spot of parameter settings, in other words, thorough calibration is necessary to observe it. As illustrated in Figure 15 it is sharply restrained by the interplay of the income distribution (respectively on the distribution of marginal utilities of money), the preference values and the toll amount. Basically it only appears if the preferences related utility dominates over the range of monetary disutilities in other words, if the variation in VTT is larger between trips (i.e., within people) rather than between income groups. The experiences during calibration of the simulation indicate that the spot producing the effect is small; many observed settings lead to an effect being random or even going into the opposite direction. In conclusion, the effect is instable and not observable as a default. Thus, on
the search for positive equity effects, analyzing income-dependent tolling or a flowback to low income groups (as suggested by road pricing proponents) seems to be more efficient. Although, the positive equity effect due to varying preferences only exists for a small spot, it is nevertheless a fascinating theoretical effect, as for some settings an implicit cooperation mechanism between income groups is present as illustrated in Figure 16.

This investigation focuses on relative equity effects. To investigate the *absolute* benefits (for example as consumer surplus (Section 4)) the configurations (0) and (1) probably need to have the same average figures, i.e., the analysis is difficult if the changes in the preferences lead to an overall increased car usage etc.

4 Outlook

Börjesson et al. (2013) provide a very detailed utility function based on Axhausen et al. (2008, p.178). There is not yet enough MATSim demand and supply data to cope with this utility function. Furthermore, especially the $\lambda$-exponents are difficult to interpret in a simulation context, typically characterized by numerous emerging and interacting effects. Thus, in the current simulation setting, a parsimonious utility function setting is chosen still allowing to investigate the hypothesized effects. In a future version, more parts of the estimated function should be used. It also needs to be researched if with an extended utility function the positive equity effects are active for a broader range of settings.

As mentioned, the simulation study is performed for the sake of illustration. It can be seen as a first extension of the example presented by Börjesson et al. (2013) including now some first emergent effects not observable analytically anymore. The study is furthermore focused on relative equity effects. The hypothesis, however, also concerns absolute benefit distribution. The question is if an overall gain or loss results for the income groups. A gain can be achieved if a person gains more due to road pricing (usually shorter travel time than without road pricing on a specific road) when her VTT is high, than she losses when her VTT is low. Clearly, this can only work if non-linearities are included in the system; otherwise gains and losses statistically cancel out. The calculation of absolute benefits is left for future work; it requires extensive calibration and calculation of consumer surplus (de Jong et al., 2005, p.6), for which explicit choice set need to be defined, which has not yet been systematically done for MATSim for other choice dimensions than destination choice.
5 Figures and Tables
Figure 1: Mini Scenario
Figure 2: **Household Income Microcensus** (German)

![Household Income Microcensus](image)

Figure 3: **Household Income Thurgau**

![Household Income Thurgau](image)
Table 1: **Trip Purpose**

<table>
<thead>
<tr>
<th>MobiDrive</th>
<th>MATSim</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home</td>
<td>Home</td>
</tr>
<tr>
<td>Work</td>
<td>Work</td>
</tr>
<tr>
<td>School</td>
<td>Education</td>
</tr>
<tr>
<td>Work related</td>
<td>Business</td>
</tr>
<tr>
<td>Shopping daily</td>
<td>Shop</td>
</tr>
<tr>
<td>Shopping long-term</td>
<td>Shop</td>
</tr>
<tr>
<td>Pick up/Drop off</td>
<td>Leisure</td>
</tr>
<tr>
<td>Private business</td>
<td>Leisure</td>
</tr>
<tr>
<td>Leisure</td>
<td>Leisure</td>
</tr>
<tr>
<td>Other</td>
<td>Leisure</td>
</tr>
</tbody>
</table>

Table 2: **Choice Dimensions**

<table>
<thead>
<tr>
<th>activity chains</th>
<th>derived from Thurgau data</th>
</tr>
</thead>
<tbody>
<tr>
<td>home and work locations</td>
<td>derived from Swiss Census of Population</td>
</tr>
<tr>
<td>shopping, leisure, other and education locations</td>
<td>assigned according to neighborhood search (Balmer et al., 2009, p.36)</td>
</tr>
<tr>
<td>times</td>
<td>derived from Thurgau study for initial demand and later subjected to MATSim equilibration</td>
</tr>
<tr>
<td>routes</td>
<td>MATSim equilibration only</td>
</tr>
<tr>
<td>modes</td>
<td>Starting MATSim equilibration with cars only and then performing sub-tour mode choice, defined in the footnote in Meister et al.: (2010, p.10)</td>
</tr>
</tbody>
</table>
Table 3: **Mode Shares:** Given in [%] per day, according to microcensus (Swiss Federal Statistical Office (BFS); 2006; p.38), (Marti and Waldvogel (2003; p.12)), and (MATSim Monday). Many short (distance and time) egress and access legs (Etappen) are missing as in Mobidrive we have trips with a main mode!

<table>
<thead>
<tr>
<th>mode</th>
<th>distance</th>
<th>time</th>
</tr>
</thead>
<tbody>
<tr>
<td>car</td>
<td>68.8 {69.5} (72.6)</td>
<td>40.7 {43.6} (45.4)</td>
</tr>
<tr>
<td>pt</td>
<td>20.4 {17.7} (22.4)</td>
<td>11.1 {11.4} (26.9)</td>
</tr>
<tr>
<td>bike</td>
<td>2.1 {2.5} (1.6)</td>
<td>4.7 {5.6} (4.0)</td>
</tr>
<tr>
<td>walk</td>
<td>5.5 {4.6} (3.4)</td>
<td>39.7 {34.3} (23.7)</td>
</tr>
<tr>
<td>other</td>
<td>3.2 {5.6} (-)</td>
<td>3.8 {5.2} (-)</td>
</tr>
</tbody>
</table>

Figure 4: **Total Tolled Travel Distance by Income Class**
Figure 5: Setting (0)

(a) Average Toll Distances Per Person

(b) Difference Average Toll Distances Per Person Between the Two Configurations
Figure 6: Setting (0) continued

(a) Shares of Individual Toll Distances

(b) Differences in Shares of Individual Toll Distances
Figure 7: Setting (I)

(a) Average Toll Distances Per Person

(b) Difference Average Toll Distances Per Person Between the Two Configurations
Figure 8: Setting (I) continued

(a) Shares of Individual Toll Distances

(b) Differences in Shares of Individual Toll Distances
Figure 9: Setting (II)

(a) Average Toll Distances Per Person

(b) Difference Average Toll Distances Per Person Between the Two Configurations
Figure 10: **Setting (II) continued**

(a) Shares of Individual Toll Distances

(b) Differences in Shares of Individual Toll Distances
Figure 11: **Setting (III)**

(a) Average Toll Distances Per Person

![Graph showing average toll distances per person for different income groups.](image)

(b) Difference Average Toll Distances Per Person Between the Two Configurations

![Graph showing the difference in average toll distances per person between two configurations.](image)
Figure 12: Setting (III) continued

(a) Shares of Individual Toll Distances

(b) Differences in Shares of Individual Toll Distances
Figure 13: **Week Setting**

(a) Average Toll Distances Per Person

(b) Difference Average Toll Distances Per Person Between the Two Configurations
Figure 14: Week Setting continued

(a) Shares of Individual Toll Distances

(b) Differences in Shares of Individual Toll Distances
Figure 15: **Example for Stable and Varying Preferences:** A trip chain of 3 commuting trips and 1 shopping trip are shown. The red road is tolled, whereas the black road is free. In the example, we assume a large capacity for both roads, such that travel time is only dependent on the road length. Furthermore, in this example, it is assumed that the travel time on the toll road is negligible and thus dominated by the monetary costs. On the bottom the disutility of the toll amount (red line) and of the travel disutility for the free road is plotted for stable preferences (black) and varying preferences (blue). When varying the preferences, here, the travel time coefficient is increased, whereas it is decreased for shopping trips. Positive equity effects are achieved if the toll is set such that either some black circles cross $U_{toll, poor}$ (monetary toll disutility for the poors) downward or if some black circles cross $U_{toll, rich}$ (monetary toll disutility for the rich traveler) upward. In the first case, more poor traveler chose the toll road (as it generates a higher disutility than the toll) and in the latter case, less rich traveler chose the toll road as the free road is associated with less disutility. It is obvious, that the toll amount needs to be set concisely and that there are many configurations, where the effect is inexisten.
Figure 16: **Zipper:** Due to varying preferences there are trips with a high VTT \((tr_1)\) and trips with low VTT \((tr_0)\). Concise calibration of the toll amount can lead to the case, where both income groups only chose the toll road for the high VTT trips. In that case a zipper-like implicit cooperation between the income groups is established.
6 References


