Behavioral Change in Activity-Travel Patterns in Response to Congestion Pricing Schemes: Results of a Field Experiment

Bertold Keuleers[1], Vincent Chow[2,] Neil Thorpe[2,] Harry Timmermans[3] and Geert Wets[1*]

[1]University of Limburg, Data Analysis & Modelling Group, Faculty of Applied Economic Sciences, Universitaire Campus, 3590 Diepenbeek, Belgium

Fax: +32(0)11 26 87 00

Tel: +32(0) 11 26 39

E-mail: {Bertold.Keuleers;Geert.Wets}@luc.ac.be

[2]University of Newcastle upon Tyne, Transport Operations Research Group , UK

E-mail: K.M.V.Chow@newcastle.ac.uk

[3]Eindhoven University of Technology, Urban Planning Group, PO Box 513

5600 MB Eindhoven, The Netherlands

Fax: +31 40 247 5882

Tel: +31 40 247 3315

E-mail: H.J.P.timmermans@bwk.tue.nl

[*] Corresponding author

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[1]University of Limburg, Data Analysis & Modelling Group, Faculty of Applied Economic Sciences, Universitaire Campus, 3590 Diepenbeek, Belgium

[2]University of Newcastle upon Tyne, Transport Operations Research Group , UK

[3]Eindhoven University of Technology, Urban Planning Group, PO Box 513
5600 MB Eindhoven, The Netherlands

Abstract. The problem of traffic congestion and associated externalities has become a major focus of transport policies in recent years. In the United Kingdom legislation has been passed to empower local authorities to implement road user charging. This study investigates the effect of a hypothetical congestion charging scheme in the city of Newcastle upon Tyne. Previous studies tend to focus on measuring users' willingness to pay, often neglecting the impact on the activity schedule. This paper focuses on the way participants adapt not only their travel behavior but also their activity participation and rescheduling pattern. These changes are looked at from a two-level approach: the aggregate day level and the the more disaggregate tour level for intra-day activity rescheduling. Results show that the scheme is effective in reducing car usage during peak time in the city. The overall activity participation however remains largely unchanged.

1. INTRODUCTION

Congestion pricing has been a topic of major debate, both in the political arena and in academic environments. Different political parties across the world hold different opinions about this highly sensitive issue. In general, governments have shown a tendency to move very slowly in the decision-making process that should ultimately result in the implementation of congestion pricing policies in an attempt to reduce car use, or at least to optimize car use across times of the day and/or routes. The sensitivity of the topic is for example illustrated by the fact that a Dutch government fell over this issue in addition to taking part in the political debate, the academic community has produced an accumulation of studies that should assist policy-makers in reaching well-informed decisions. In the past, many studies of road charging has been conducted However, the majority of these studies focus on issues such as measuring drivers' willingness to pay, forecasting traffic impacts, acceptability of and attitudes towards such policies. Often these studies tend to neglect the wider implications of the road charging policies. Many previous studies have shown that drivers might respond to a road-user charging scheme in many different ways including changing their departure to an earlier or a later time in an attempt to avoid the toll charges [1], [2], [3]). Other responses include changing transport mode, visiting other destinations for certain activities when alternatives of equal or comparable status are available. Households may also adopt a longer-term adaptation strategy such as finding a new workplace or move house. Golob and Golob [4] found that people responded to price differences by shifting their time of departure, but the effect was short-lived. They suggested that changes in travel behavior need to be further investigated in terms of socio-demographics differences because insignificant aggregate changes might be composed of significant opposite changes according to segment that cancel out at the aggregate level.

This brief review of the literature suggests that most studies on the impact of congestion pricing on travel behavior are either based on assumptions, or on stated preference analysis

. Moreover, most of these studies focus on a particular aspect of travel behavior, rather than on comprehensive activity-travel patterns.

To complement previous research, the present study reports the results of a field experiment, in which participants were given some amount of money and were asked to behave and use this money as if a congestion pricing scheme was put into place. The behavior of the participants was recorded and changes in their travel patterns were analyzed using decision trees. Thus, the contribution of this paper to the literature is two-fold. First, it is the first study we know that is based on a field experiment, and secondly, it is one of the few studies using real-world, before-after data analyzed with rule-induction systems.

The paper is organized as follows. First, we will describe the design of the hypothetical road charging scheme and the data used in the present analysis. This will be followed by a description of the methods of analysis that will be used. Next, we will report the findings of our analyses at the aggregate day level, focusing on activity deletion and insertion, followed by the less aggregate tour-level, focusing on intra-day activity resubstitution. The paper will be completed with a summary of the main results and a discussion of possible avenues of future research.

2. DATA

In order to investigate how behavioral responses to a road user charging scheme can affect the spatial and temporal scheduling of activities-travel patterns, a hypothetical charging scheme field trial was undertaken in Newcastle City. Real-life experience allows respondents to appraise the accumulated strength of the constraint. Respondents may find it difficult to imagine possible changes in their lifestyle, which potentially reduces the validity of stated preference studies that require respondents to imagine change that is quite remote from their every day experience.

To make the hypothetical congestion pricing scheme as realistic as possible, all participating drivers were allocated a fixed travel budget to pay for the toll charges.. The toll level was set at £5 per entry per day and they were told that they would get to keep any money remaining from the budget after the trial. Each driver was subsequently given £25 in cash and asked to provide a post-dated cheque addressed to the University for safekeeping. This feature of allocating real monetary budget to respondents has been successfully tried out in similar study undertaken in Newcastle [5]. A total of 50 households participated in this field experiment. Of these, 33 households, involving 65 people send in their diaries.

Participants were requested to complete an activity-travel diary for a period of 2 weeks. The format of the diary was similar to commonly used formats, for example such as the one used for the Albatross model system [6]. That is, participants were asked to report which activities they conducted where, when, for how long, with whom, and the transport mode involved. During the first seven days, no toll was charged, whereas a toll was charged during the second week. This before-after design allows us to analyze for any differences between the two episodes.

During the trial week, field interviewers made random inspection at various car park locations and the registration numbers of all cars visiting the designated car parks between 0730-1000hrs were recorded using a tape recorder Special attention was given to those drivers who had previously stated that they would pay the toll and continue making their usual journey. Subsequent telephone calls were made to these drivers in the evening following the trial.

Table 1a and 1b list the household/Individual attributes and activity attributes respectively. Figure 1 shows the map of the cordon area within the study area. The final cordon design is an extension of an earlier work by the Newcastle City Council Energy Impact Study in 1995 [7]). Of special interest is the changemode "activity". Because it is relevant to know whether respondents enter the city center during peak hours by changing transport mode before they enter they city center, this behavior was captured by defining a dummy activity and recording it separately. Figure 2 portrays a hypothetical activity sequence that illustrates how the survey is able to capture the change of transport mode in between activities..

3. METHODOLOGY

The activity diary provides information about the various activities conducted throughout the day, where they were conducted, and the transport mode involved. Thus, in principle, this data can be sliced into different formats and time horizons. Two types of analyses are reported in the present paper. First, we will concentrate on daily activity patterns identifying changes in activity frequencies over the whole day. Then, we will zoom in on the tours that make up a daily activity-travel pattern, focusing on intra-day activity rescheduling

Change in activity patterns as a result of some policy scenario has been studied in the past by using/applying a simulation models (see e.g. [89]; [9]). In such studies, the focus is on predicting change in activity-travel patterns should the policy be implemented. In this study, we adopt a more descriptive-analytical approach in an attempt to link changes in activity-travel patterns to specific household characteristics, using decision trees.

3.1. Data recording

The following attributes were derived from the dataset. Activities were grouped into tours which are of course part of the daily schedule. Table 2 lists the attributes that were used in the analysis. These attributes allow us to explicitly model the impact of congestion pricing on mode choice, travel during peak time and travel into the city, at both the day level as well as the more disaggregate tour level. The day level gives us an idea whether activities are still performed during the day or not, whereas the tour level describes how activities are rescheduled within the day as the tourtype makes explicitly use of a temporal component. Thus the day level makes clear whether certain activities are still performed during the day and if so, the tour level gives us a clear indication of intertourtype rescheduling of activities within a day.

3.2. Decision trees

Changes were analyzed using decision trees. Decision trees are a standard tool in data mining, and many are available in packages such as CART and C4.5 ([10]. Decision trees are generally preferred over other nonparametric techniques because of the readability of their learned hypotheses and the efficiency of training and evaluation. Decision trees are used for linking back household characteristics to the derived activity attributes. Thus, we are investigating how household/individual, and activity attributes affect these aggregate day/tour attributes. For each of this aggregate attributes, the decision tree will identify those Household/Individual and Activity attributes that have the highest impact. A more traditional approach (e.g. Anova table, logit model) would not be able to cover the total universe of discourse since there are more than 51 different attribute values for the discrete attributes in addition to the 10 continuous ones.

4. Results

4.1. Day level

From table 4 we can immediately conclude that the pricing scheme was very effective in reducing car use during the peak. In the before scenario there were 117 *daypeakcarcity* days compared to the 47 in the after phase. However, since the aim of this study is to analyze the impact of the scheme on activity participation, the following analysis will focus on activity changes over and within days.

First, we analyzed changes in activity-travel patterns at the day level. Table 3 depicts the frequencies of days that a particular activity by car was performed in the city during the peak period. There are 231 days for each of the before and after scenarios. The cells in this table describe the frequency with which an activity was performed on a particular day. Columns 2 and 3 describe the results for days when drivers had to pay toll, whereas columns 4 and 5 describe the results for the days when they did not have to pay tolls including weekend days

Table 3 shows that the only significant changes in activity participation at the day level are *Changemode* and *Pick/send pax.* This suggests that the overall change in activity participation at the day level can be neglected. However, it also suggests that the scheme induces people to change their transport mode before they enter the city. Likewise, the frequency of the *Pick/send pax* activity is reduced, suggesting that trip chaining behavior involving a change of transport mode is indeed a popular response to avoid toll.

Table 3 also shows that the overall work participation has not changed but that compared to 117 in the before days only 47 were work days subjected to toll in the after days. The changes for the other activities are also significant given the fact that they also fall into these working days. However, at this day level, we are still not able to distinguish to what extent people change mode, location or time.

Table 4 also shows the relevant frequencies whether a person is driving a car during peak time (regardless of being in- or out city) and whether a person is in the city during peak time (regardless of he drives a car or not) for work days. It shows that in response to the congestion pricing scheme, people seem to adapt their travel pattern during work days in two different ways. First, the number of working days when driving by car during the peak period has decreased from 128 to 77, suggesting that drivers are making less car trips during the peak period. Secondly, the number of working days in the city during the peak period has also decreased from 123 to 98, suggesting that participants are avoiding the city center during peak time. Both changes are highly significant.

From Tables 3 and 4, we conclude that two responses have a complementary effect. The daycarpeakcitydays decreased from 136 to 44. Both reductions in *Daypeakcar* and *Daypeakcity* are responsible for this decrease in *Daypeakcarcity*. We conclude that people still driving the car during peak time are more likely to avoid the city during peak time. Thus, the results reported so far demonstrate that participants change mode, time and location in response to the charging scheme. Table 5 reports the results of the decision trees that were extracted from the data and that link household/individual attributes to these different types of responses.

These decision trees suggest that the prediction of car use during peak time is more straightforward than the prediction of change of location during peak time. Not only is the prediction rate of the car use tree better than the one predicting the location at peak time, the set of attributes predicting car use is also remarkably smaller, supporting the idea that household/individual characteristics are more influential in the choice of transport mode than in the choice of location which probably is more bound to characteristics of work itself.

Car use during peak time is primarily affected by the *phase* attribute, which is consistent with our expectations. Only for the phase2 weekdays other attributes are important. The presence of children younger than 12 years of age appears to have an impact followed by the *age, hhsize, incomel* and *workstat* attributes.

For the second tree, the household characteristics also play an important role. Remarkably, the *phase* attribute does not show up to be important at all. It is however the presence of children younger than 12 years of age that appears as the attribute with most predictive power. The *workstat* attribute is the next important attribute followed by a wide range of the other household/individual attributes. As mentioned before, the flexibility of in-city activities is probably more responsible for in-city location choice than the household characteristics used in this study. It seems logical to state that activities involving young children tend to be less flexible. Since this survey is of limited duration, changes involving higher effort over a longer a period of time (e.g. change of work, change of school, change of home location) are not likely to occur.

4.2. Tour-Level

More dramatic changes may be expected in terms of how people organise their activities over time and space into tours. In addition to the analysis of change at the day level, we therefore analyzed changes at the tour level. To that effect, frequencies for the different tour types were calculated. Figure 3 shows the number of tours for each tourtype, while Figure 4 shows the number of tours for each tourtype that were subjected to toll (in city, during peak, driving a car).

Figure 3 illustrates that there are no significant changes in the number of tours for each tour type. The total number of tours has dropped slightly, a significance test on the average number of tours per day was however not significant at the 0.05 significance level. Figure 4 shows that the number of type1 tours subjected to toll decreased from 118 to 48, which is highly significant. The number of type3, type4 tours is equal to 0, which is logical giving the late start times for these types of tours. In other words, there are no work based subtours that start during peak time.

Both figures show that the type1 tour is mainly affected by the congestion charging scheme. Table 6 tells us how respondents reacted towards the congestion pricing scheme in adapting their in-city peak time travel pattern for type1 tours. All changes are significant at the 0.05 significance level. One can conclude that participants changed their type1 tours not only by adapting either mode, location, or tour time but that the combination of all three changes is responsible for the overall Tourpeakincitycar drop from 118 to 48. The tourpeakincity aggregate attributes suggest that participants are able to change the location of their work tours during peak time by working from home or rescheduling their activities switching their out-of-city work activities to a more optimal timeframe. This is only possible for those who have this work flexibility. Again, we re-iterate that the short duration of the survey underestimates possible longer-term changes.

The values for the type1 tours were already discussed in the previous paragraphs. For the other types of tours, there are no significant changes, suggesting that the congestion scheme was not a reason for changing tour frequency. The number of type2 tours has increased from 7 to 12 in contrast to a decrease for the type4 and type5 tours but these changes are not significant. Still this supports the idea that people are making more out-of-city tours before going to work.

Table 7 gives us an idea of the activity distribution over the different types of tours before and after the congestion scheme. Although the tourtype frequencies did not change, there is an obvious trend for the type3 tours concerning *Grocery Shopping*. This suggests that participants are rescheduling their *Grocery Shopping* activities from the Type1 towards the type3 tour, not affecting the work-based subtour (type4). These results can be attributed to the fact that carmode for the type1 tour has significantly dropped, increasing the impedance for G*rocery Shopping* in such a tour. Similar analysis carried out on the other activities did not yield significant results.

Combining both table6 and figure3, this study suggests that people reschedule certain types of activities into a relatively fixed pattern of tours. At this stage, decision trees were also generated for linking the household/individual characteristics to the aggregate tour attributes but the findings were similar to the findings at the day level.

5. CONCLUSIONS AND DISCUSSION

In this study, the effects of a congestion pricing scheme in the city of Newcastle on Tyne were evaluated. In particular, this study investigated change in activity-travel patterns as a function of a congestion pricing scheme at the day level and the tour level. For each level, activity participation was compared for a set of aggregate attributes. Five tour types were defined linking the day level to the tour level, explicitly incorporating temporal and activity sequence information. This temporal component can indeed capture the rescheduling of activities not only between days but also within days into before and after work tours. Following the constraint-based model approach the flexibility of the activities to conduct will play an important role in this rescheduling process, e.g. opening hours, public transport facilities and location, …

The results lead us to conclude that the road charging scheme has a significant impact on the travel patterns but less of an impact on activity participation and activity rescheduling. Participants respond in different ways by changing times, mode and location. Decision trees were used to link these findings to specific groups of households. This study showed that the change of mode could be easier attributed to specific groups of households than the change of location and time, suggesting that the relationship between household characteristics and mode choice is stronger than the relationship between household characteristics and timing and location decisions.

Future work will look at activity substitution between weekdays and weekends and between household members. The granularity of the tour type temporal component will be improved taking different modes and an activity typology into account.

Acknowledgements

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Table 1a: Household/Individual attributes and situational data

Label	Definition	Categories
Hhid	Unique identification of household	Continuous
Pers	Identification of person in a specific household	Continuous
Incomel	Income of household	1:low,…, 6: high
Age	Age of a person in a specific household	Continuous
Child12	Number of children present in the household younger than 12	Continuous
Child16	Number of children present in the household younger than 16	Continuous
WkStat	WkStat of individual	Full_time, Part-time, Homemaker, Student, Others
Hhsize	Total number of persons present in the household	Continuous
Edu	Education level of individual	Degree and Above, A/O/HND, Vocational training, Others
Nbike	Number of bikes available in the household	Continuous
Ncar	Number of cars available in the household	Continuous
Gend	Gender of the person	0:male, 1:female
Ydriver	Person has driving license	0:no, 1:yes

Table 1b: Activity attributes present in the schedule

Label	Definition	Categories
ActivityCode	Classname of specific activity	Work/School, Childcare, Changemode, Entertainment, Grocery Shopping, Personal Shopping, Household Task, Meal, Medical, Personal Business, Pick/send pax, Social, Sport/exercise, Trip, Others
Phase	Stage of the survey	1: before the scheme, 2: after the scheme
Day	Day of the week	1: Monday, ... 7: Sunday
Location	Location of activity undertaken	1: In city, 2: Outcity
Starttime	Starttime of activity	Continuous
Endtime	Endtime of activity	Continuous
Mode	The associated mode attribute of the trip activity	Car, Carpassenger, Bus, Metro, Bike, Walk, Others

Table 2: Aggregate day/tour attributes

Name	Description
Tourid	Every activity is linked to a specific tour identified by this unique tour identification number.
Dayincity	Whether a specific day involved an activity in the city
Daycar	Whether a specific day involved car usage
Daycitypeak	Whether a specific day involved an activity in the city during peak time
Daycarpeak	Whether a specific day involved a peak time activity where mode of that activity is the car
Daycarpeakcity	Whether a specific day involved a peak time activity in the city where the mode is car. These days are subjected to toll.
Tourincity	Whether a specific tour involved an activity in the city
Tourpeak	Whether a specific tour involved an activity performed during the charging period (defined as 7.30 am – 10 am)
Tourcar	Whether a specific tour involved car usage
Tourcarpeak	Whether a specific tour involved a peak time activity involving car usage
Tourcarpeakcity	Whether a specific tour involved a peak time in city activity involving car usage. These tours are subjected to toll
Tourtype	Type1: Home-based tour in a day with work activity, involving a work activity
	Type2: Home-based tour before a person makes a type1 tour
	Type3: Home-based tour after last type1 tour for that day
	Type4: Work-based tour
	Type5: Home-based tour in a day without work activity

Table 3: Frequencies of days subjected to toll disaggregated by activity

	No toll		**Toll**		**TOTALS**	
	Before	**After**	**Before**	**After**	**Before**	**After**
Work	**28**	**89**	**117**	**47**	145	136
Childcare	6	9	25	19	31	28
Changemode	0	31	1	3	**1**	**34**
Entertainment	5	2	2	5	7	7
Grocery shop.	8	21	26	7	36	28
Household task	24	64	66	23	90	87
Meal	28	84	103	40	131	124
Medical	4	1	3	2	7	3
Others	7	17	19	3	26	20
Personal business	2	10	21	4	23	14
Personal shopping	9	21	23	10	32	31
Pick/send pax	9	9	45	25	**54**	**34**
Social	5	16	19	7	24	23
Sport/exercise	7	14	28	10	35	24

Table 4: Daypeakcarcity, Daypeakcar and Daypeakcity frequencies for Work days

Daypeakcarcity		Daypeakcar		Daypeakcity	
Before	**After**	**Before**	**After**	**Before**	**After**
117	47	128	77	123	98

Table 5: Decision tree towards daypeakcar and daypeakcity over weekdays

<table>
<tr><th>Daypeakcar</th><th>Daypeakcity</th></tr>
<tr><td>Phase = 1: 1 (157.0/21.0)
phase = 2
| child12 <= 1
| | ncar <= 2
| | | age <= 29: 0 (10.0)
| | | age > 29
| | | | child12 <= 0: 0 (65.0/27.0)
| | | | child12 > 0
| | | | | hhsize <= 2: 1 (5.0)
| | | | | hhsize > 2
| | | | | | incomel <= 1: 0 (5.0)
| | | | | | incomel > 1
| | | | | | | wkstat = full_time: 1 (30.0/5.0)
| | | | | | | wkstat = part-time: 0 (5.0/1.0)
| | ncar > 2: 1 (16.0/3.0)
| child12 > 1: 1 (10.0)

a b <-- classified as
45 41 | a = 0
22 195 | b = 1

Wrongly classified instances: 63 of 303
Correctly classified instances: 240 of 303

NOTE on reading the tree:
Each line on this tree is either a node (split condition), either a leaf (which holds the cases for which all conditions are true).
The first line states that there were 157 phase1 weekdays. 21 are wrongly classified, 136 correctly.
The third line states that for phase2 weekdays (condition1) the number children younger than 12 is the most important attribute for predicting the car usage at peak time.</td>
<td>child12 <= 1
| wkstat = full_time
| | phase = 1: 1 (126.0/25.0)
| | phase = 2
| | | age <= 38: 1 (51.0/5.0)
| | | age > 38
| | | | ncar <= 1: 0 (10.0)
| | | | ncar > 1
| | | | | day = 1
| | | | | | incomel <= 2: 1 (4.0/1.0)
| | | | | | incomel > 2: 0 (7.0/1.0)
| | | | | day = 2: 1 (11.0/4.0)
| | | | | day = 3: 1 (11.0/2.0)
| | | | | day = 4
| | | | | | child16 <= 0: 0 (8.0/1.0)
| | | | | | child16 > 0: 1 (3.0)
| | | | | day = 5: 1 (11.0/4.0)
| wkstat = part-time
| | edu = AO_level_HND: 0 (10.0/2.0)
| | edu = degree_and_above
| | | day = 1: 1 (6.0/1.0)
| | | day = 2
| | | | child12 <= 0: 1 (4.0)
| | | | child12 > 0: 0 (2.0)
| | | day = 3: 1 (6.0)
| | | day = 4
| | | | hhsize <= 1: 1 (2.0)
| | | | hhsize > 1: 0 (5.0)
| | | day = 5
| | | | gender = male: 0 (2.0)
| | | | gender = female: 1 (4.0/1.0)
| | | day = 6: 1 (0.0)
| | | day = 7: 1 (0.0)
| | edu = Others: 1 (0.0)
| | edu = vocational: 1 (0.0)
child12 > 1: 1 (20.0/2.0)

a b <-- classified as
21 64 | a = 0
17 201 | b = 1

Wrongly classified instances: 81 of 303
Correctly classified instances: 222 of 303</td></tr>
</table>

Table 6: Tourpeakin city, Tourpeak and Tourpeakcar frequencies (type1 tours)

Tourpeakin city		Tourpeak		Tourpeakcar	
Before	**After**	**Before**	**After**	**Before**	**After**
178	136	179	143	125	73

Table 7: Activity distribution over different tour types

	Type 1		Type 2		Type 3		Type 4		Type 5	
Activity	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Work	152	137	0	0	0	0	70	57	0	0
Personal shopping	29	22	0	0	1	3	1	2	18	12
Pick/send pax	46	31	0	1	10	10	1	0	20	10
Grocery shopping	**26**	**19**	2	1	**1**	**9**	**5**	**5**	20	14
Social	17	21	1	1	7	7	7	1	22	17

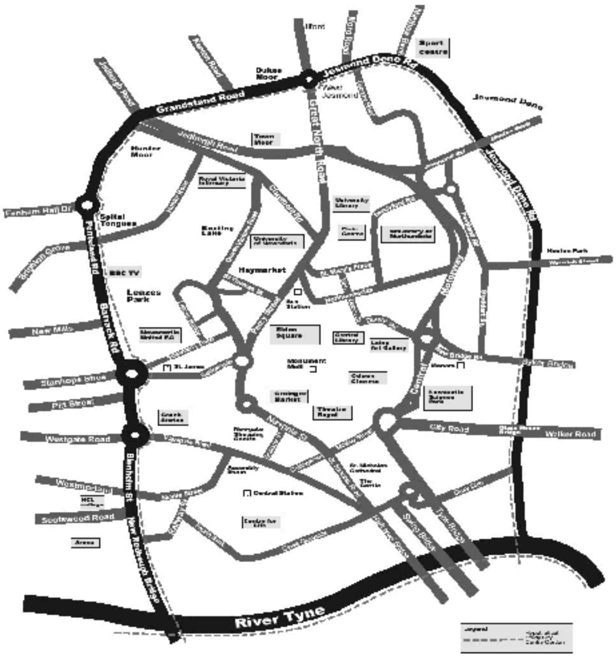

Figure1: Layout of Hypothetical Charging Cordon

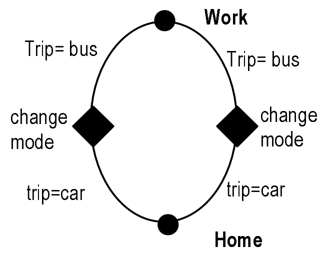

Figure 2: Hypothetical activity pattern

A person leaves the house at 8am travelling by car to a bus station arriving at 8.30am. He waits 10 minutes which is the duration of the changemode activity before travelling by bus into the city center for his work.

Work, Changemode and home activities do not have a mode associated to them.

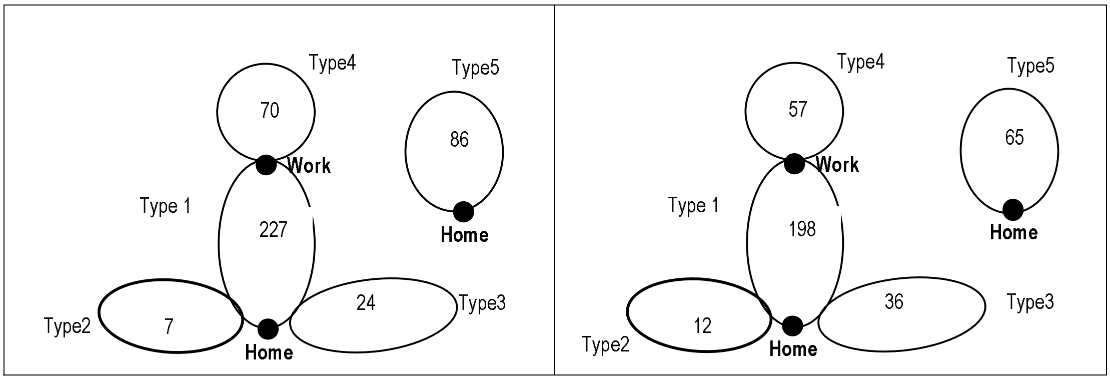

Figure 3: Total tour type frequencies for the before and after phase

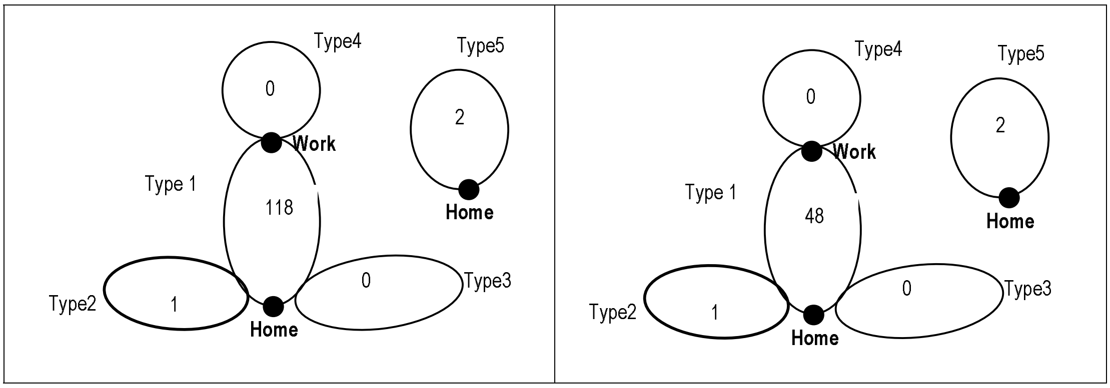

Figure 4: Tour type frequencies subjected to toll for the before and after phase