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Peer-reviewed author version

KEULEERS, Bertold; Chow, V.; Thorpe, N.; TIMMERMANS, Harry & WETS, Geert (2006) Behavioural change in activity-travel patterns in response to road user charging. In: Journal of Transport Economics and Policy, 40(1). p. 119-134.

Handle: http://hdl.handle.net/1942/1513

Behavioural Change in Activity-Travel Patterns in Response to Road User Charging

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The authors gratefully acknowledge the support of the UK Department for Transport and the University of Newcastle upon Tyne, which funded the research performed by Vincent Chow, on which this paper is based.

Abstract

The problem of traffic congestion and associated externalities has become a major focus of transport policies in recent years. Legislation has been passed recently in the United Kingdom to empower local authorities to implement road-user charging. This study investigates the effect of a hypothetical road-user charging scheme in the city of Newcastle upon Tyne, UK. Previous studies tend to focus on measuring users' willingness to pay, often neglecting the subsequent impact on activity schedules. This paper focuses on how participants adapt not only their travel behaviour but also their activity participation and rescheduling patterns. Results suggest that the scheme is effective in reducing car use during peak times in the city but that overall activity participation remains largely unchanged.

Date of receipt of final manuscript: June 2005

1.0 Introduction

Road-user charging has traditionally been a topic of major debate, both in the political arena and in academic environments. Political parties across the world hold different opinions about this highly sensitive issue. In general, governments have shown a tendency to move cautiously in the decision making process towards the implementation of road-user charging in an attempt either to reduce car use, or at least to optimise car use across times of the day and/or routes. The sensitivity of the topic is well illustrated by the recent collapse of the Dutch government over this issue, and a general lack of continuation of policy following changes in government and political parties in power.

In addition to contributing to the political debate, the academic community has accumulated a wealth of studies to assist policy makers in reaching well-informed decisions. While there have been many previous studies of road-user charging, the majority tend to focus on issues relating to measuring drivers' willingness to pay, forecasting impacts on travel patterns, public acceptance, and attitudes. Very often these studies neglect the wider implications of these outcomes. Results suggest that drivers might respond to a road-user charging scheme in many ways including changing departure time to (usually) earlier or later to avoid charges (Polak and Jones, 1991; Collis and Inwood, 1996; Hug *et al*., 1997). Other responses include changing mode of travel, and choosing new destinations for certain activities when alternatives of equal or comparable status are available. Golob and Golob (2000) report that individuals respond to price differences by shifting time of departure but that the effect is short-lived. They suggest that changes in travel behaviour need to be further investigated in terms of socio-demographic differences as insignificant aggregate changes may mask significant changes by identifiable segments that cancel each other out. In the longer term, households may adopt adaptation strategies requiring greater personal commitment such as employment or residential relocation.

Observed activity-travel patterns are the outcome of households' adaptation processes. It is argued here that a better understanding of the household adaptation and rescheduling process is vital to the successful implementation not only of road-user charging but also of any future travel demand management policies. Issues of acceptance and equity of any scheme are largely dependent on the adaptability of the household, in particular the ease with which the household can adapt to a new set of circumstances (Doherty *et al*., 2002).

This brief review of the literature suggests that most studies on the impact of road-user charging on travel behaviour are either based on assumptions or on stated response analyses. Moreover, the majority of these studies focus on one particular aspect of travel behaviour, rather than on more comprehensive patterns of movement and activity.

To complement previous research, the present study reports the results of a field experiment in which participants were given an amount of money and asked to behave and use this money as if a real road-user charging scheme was in place. The participants' behaviour was recorded and changes in travel patterns analysed using decision trees. Thus, the contribution of this paper to the literature is twofold. First, it provides a valuable contribution to the growing body of evidence from field experiments of responses to road-user charging (see, for example, Hug *et al*., 1997; Bonsall *et al*., 1998; Wright and Burton, 1999; O'Mahony *et al*., 2000). Second, it is one of the few studies to use rule-induction systems to analyse pseudo real-world 'before' and 'after' data.

The paper is organised as follows. First, we describe the design of the hypothetical charging scheme and the data attributes used in the present analysis (Section 2). This is followed in Section 3 by the analysis of the data using rule-induction systems. Section 4 reports the findings of our analyses on an aggregate day level (focusing on activity suppression and generation) followed by the more disaggregate tour-level analyses (focusing on intra-day activity substitution). The paper concludes in Section 5 with a summary of the main results and a discussion of possible avenues of future research.

2.0 The Field Experiment

To investigate how behavioural responses to road-user charging might affect the spatial and temporal scheduling of activity-travel patterns, a hypothetical charging scheme experiment was undertaken in the city of Newcastle upon Tyne, UK. Real-life experiences allow respondents to appraise the accumulated strength of the constraint. Respondents often have difficulty in imagining and evaluating possible changes in the structure of their lifestyle, which potentially reduces the external validity of more traditional stated response studies.

A total of 50 households were recruited at city-centre car-parks to take part in the experiment. Of these, 33 households (representing 65 people) returned their travel-activity diaries. To make the hypothetical charging scheme as realistic as possible, all participating drivers were allocated a fixed travel budget to pay for any toll charges incurred. The toll was set at £5 per entry per day and drivers were told that they would be allowed to keep any money remaining in their budget at the end of 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 method of allocating real money budgets to respondents was used successfully in a similar study undertaken previously in the city (Thorpe and Hills, 2000).

During the trial, field interviewers undertook random inspections at various car parks to record the registration numbers of all cars using the designated car parks between 0730–1000 hrs throughout the week. Careful attention was given to volunteer drivers who had previously stated that they would consider paying the toll and continue making their usual journey. Subsequent telephone calls were made to the volunteers following the trial to validate the data collected. The results suggest there were no apparent defaulters during the study period — that is, volunteers who claimed not to have travelled to the city by car (hence ‘saving’ the toll) when in fact they had done so.

Participants completed an activity-travel diary for a period of two weeks. The format of the diary was similar to commonly used formats; see, for example, the one used for the Albatross model system (Arentze and Timmermans, 2000). That is, participants reported which activities they conducted where, when, for how long, with whom, and the transport mode involved. During the first seven days, no tolls were charged to provide the ‘before’ data, with the toll being introduced at the start of the second week. This ‘before’ and ‘after’ design allows the identification of any changes in behaviour between the two periods.

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	Household Income	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 years	Continuous
Child16	Number of children present in the household younger than 16 years	Continuous
WkStat	Work Status of the individual	Full-time, Part-time, Homemaker, Student, Others
Hhsize	Total number of persons present in the household	Continuous
Edu	Education level of the 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 individual	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	Class name of specific activity	Work/School, Childcare, Change of mode, Entertainment, Grocery Shopping, Personal Shopping, Household Task, Meal, Medical, Personal Business, Picking up/dropping off passengers, 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: Outside the city
Starttime	Start time of activity	Continuous
Endtime	End time of activity	Continuous
Mode	The associated mode attribute of the trip activity	Car, Car passenger, Bus, Metro, Bike, Walk, Other

Tables 1a and 1b list the household and individual attributes and activity attributes respectively.

Figure 1 shows a map of the charging area within the case-study city. The final cordon design is an extension of earlier work by Newcastle City

Figure 1

Layout of the Hypothetical Charging Cordon (Source; Gordon, 1995)

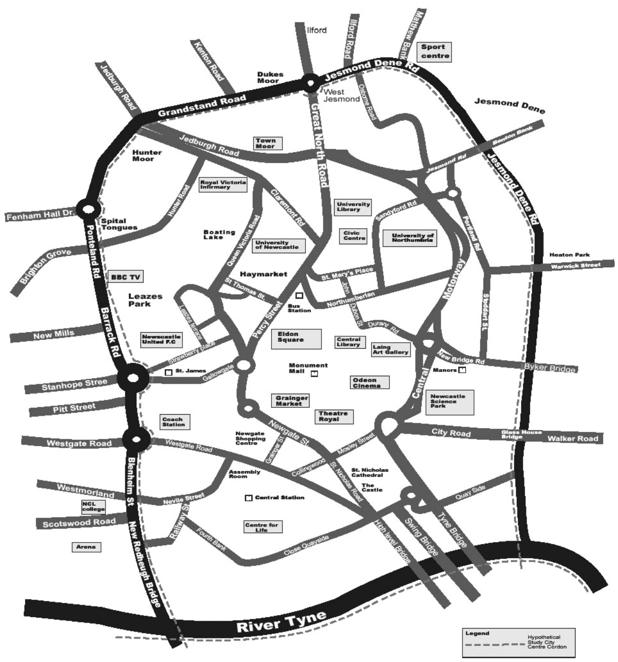
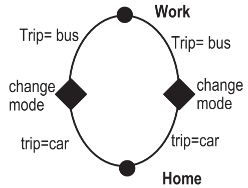


Figure 2
Hypothetical activity pattern



Description

A person leaves home at 0800 hrs and travels by car to a bus station arriving at 0830 hrs. The person waits for 10 minutes which is the duration of the 'change mode' activity before travelling by bus into the city centre for work.

Council as part of its Energy Impact Study in 1995 (Gordon, 1995). Of special interest is the 'change mode' activity. This investigates whether respondents decided to travel into the charged area during peak hours but avoid the toll by changing transport mode (for example, to walk or bus) before crossing the charging cordon. This behaviour was captured by defining a dummy activity and recording it separately.

Figure 2 illustrates a hypothetical sequence of activities to show how the survey captured mode changing behaviour between activities and, in particular, the presence of the 'change mode' activity.

3.0 Method

3.1 Overview

The activity-travel diary provides key information on the various activities undertaken throughout each day, for example where they were conducted and associated transport modes. Thus, in principle, these data can be 'sliced' into different formats and time horizons. Two levels of analysis are reported in this paper. First, the analysis concentrates on daily activity patterns to identify changes in activity frequencies over entire days. Next, the focus narrows onto the individual tours that make up each daily activity-travel pattern to investigate aspects of intra-day activity rescheduling.

Changes in activity patterns as a result of a new policy scenario have been studied previously by applying simulation models (see, for example, Pendyala *et al.*, 1998; Arentze and Timmermans, 2002). The aim of these studies is to predict changes in activity-travel patterns following the implementation of the policy. The study reported here adopts a more descriptive-analytical approach in an attempt to link changes in activity-travel patterns to specific household characteristics using decision trees.

Table 2
Description of Aggregate Day and 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 charged area.
Daycar	Whether a specific day involved car usage.
Daycitypeak	Whether a specific day involved an activity within the charged area during the a.m. peak period.
Daycarpeak	Whether a specific day involved a peak time activity where 'car' is the mode of travel.
Daycarpeakcity	Whether a specific day involved a peak time activity within the charged area where 'car' is the mode of travel. Drivers would incur the toll on these days.
Tourincity	Whether a specific tour involved an activity within the charged area.
Tourpeak	Whether a specific tour involved an activity during the charging period (defined as 0730–1000).
Tourcar	Whether a specific tour involved using a car.
Tourcarpeak	Whether a specific tour involved a peak time activity and the use of a car.
Tourcarpeakcity	Whether a specific tour involved a peak time activity within the charged area and the use of a car. These tours would incur the toll.
Tourtype	Type 1: Home-based tour on a day with work activity that involves a work activity. Type 2: Home-based tour undertaken before a person makes a Type 1 tour. Type 3: Home-based tour undertaken after the last Type 1 tour for that day. Type 4: Work-based tour. Type 5: Home-based tour undertaken on a day without any work activity.

3.2 Data recoding

The following attributes were derived from the dataset. Activities were grouped into tours that form part of the specific daily schedule. Table 2 lists the attributes used in the analysis. These attributes allow us to model explicitly the impact of road-user charging on mode choice, travel during peak times, and travel into the city centre, at both the aggregate day level as well as at the more disaggregate tour level. The day level provides an indication of whether or not activities are still performed during the days following the introduction of the toll, whereas the tour level describes if and how activities have been rescheduled within the day as the tour type description makes explicit use of the temporal component of the data. Thus, the day level describes whether particular activities are still performed during the day during the period after the introduction of the charge and, if they are, the tour level analysis indicates how (if at all) these activities have been rescheduled during each day.

3.3 Decision trees

Decision trees were used to analyse changes in travel and activity patterns following the introduction of the hypothetical road-user charging scheme. Decision trees analysis is a standard data mining tool and many procedures are available in software packages (Quinlan, 1993). Decision trees are generally preferred to other non-parametric techniques because of the readability of their learned hypotheses and the efficiency of training and evaluation. Decision trees are used here to link household characteristics back to the derived activity attributes and thus investigate the relationship between household (or individual) characteristics and the activity attributes and, in turn, how these affect the aggregate day or tour attributes. For each of these aggregate attributes, the decision tree identifies those household (or individual) and activity attributes that have the highest impact. A more traditional approach (such as an ANOVA table or logit model) would be unable 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 attributes (Table 1a and 1b).

4.0 Results

4.1 Day level

The figures in Table 3 suggest that the scheme was very effective at reducing car usage in the charged area during peak times. In the 'before' scenario there were 117 person-days that involved a peak-time activity within the city-centre with the car as the associated mode of travel. This number fell by 60 per cent to 47 person-days in the 'after' phase. Partly as a consequence, the number of person-days that involved a car-based activity during the peak-time also fell from 128 to 77 (−40 per cent), although the number of person-days that involved a peak-time activity in the charged area was less affected with a fall of only 20 per cent from 123 to 98 person-days.

Table 3

Impacts of the Charging Scheme on the Frequency of Peak Time Activity on Work days only (person-days)

Car-based Activities in the Charging Area Only		*Car-based Activities in Total*		*Activities in the Charging Area Only*	
Before	*After*	*Before*	*After*	*Before*	*After*
117	47	128	77	123	98

Table 4
Impact of the Charging Scheme on the Frequency of Car-based Activities (person-days)

	No toll incurred		*Toll incurred*		*Totals*	
Activity	*Before*	*After*	*Before*	*After*	*Before*	*After*
Work	28	89	117	47	145	136
Childcare	6	9	25	19	31	28
Change mode	0	31	1	3	1	34
Entertainment	5	2	2	5	7	7
Grocery shopping	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
Collecting or dropping off passengers	9	9	45	25	54	34
Social	5	16	19	7	24	23
Sport/exercise	7	14	28	10	35	24

Another aim of this study is to assess the impact of the scheme on inter- and intra-day changes in activity participation. For this, changes in activity-travel patterns at the day level are investigated. Table 4 reports the number of person-days that a particular activity was performed in the city during the peak period that involved car use and whether or not they incurred a toll. There is a total of 231 person-days for each of the before and after scenarios (that is, 33 primary drivers generating data for each seven day period) giving a total of 462 person-days of data. The cells in the table describe the number of person-days that involved a particular activity. For example, during the 'before' period there were 145 person-days in total on which work activities occurred that were car-based. This fell slightly (by 6 per cent) to 136 person-days in the 'after' period. Thus, not unexpectedly, there was little suppression of the work activity. Of the 145 work activity person-days in the 'before' period, 28 (19 per cent) would not have attracted the toll (for example, by entering the charged area outside the charging period) and 117 (81 per cent) would have attracted the toll. Following the start of the scheme, the position is changed dramatically as our volunteers modify their behaviour to avoid the toll. Of the 136 work activity person-days in the 'after' period, 89 (65 per cent) person-days did not incur the toll and 47 (35 per cent) person-days did. Thus, the number of work activity person-days incurring the toll fell sharply by 60 per cent (from 117 to 47 person-days) following the introduction of the toll, whereas the number that did not incur the toll increased nearly threefold from 28 person-days in the 'before' period to 89 person-days in the 'after' period.

Table 4 also suggests that the only major changes in activity participation at the day level are for the 'changing mode' activity and the 'collecting or dropping off of passengers' activity. This reveals that the overall change in activity participation at the day level is relatively minor. However, it also suggests that the scheme encouraged a number of our volunteers to change transport mode prior to entering the charged area. This suggests that trip chaining behaviour involving a change of mode was a frequent response from our volunteers to avoid paying the toll. Likewise, the frequency of the 'collecting or dropping off of passengers' activity that incurred the toll is reduced by 44 per cent from 45 to 25 person-days.

The changes for the other activities are also important given the fact that they also occur on working days. However, at the day level, it is not possible to distinguish to what extent our volunteers changed mode, or the location and/or timing of activities.

Table 3 reports the relevant frequencies of how often our volunteers drove a car during the peak period (regardless of being to or from the city) and how often they were inside the charged area during this period (this time regardless of whether they drove a car or not) on normal working days. Table 3 reveals that in response to the charging scheme, volunteers adapted their travel patterns on work days in two different ways. First, the number of working days involving driving by car during the peak period decreased by 40 per cent from 128 person-days to 77. This suggests that our drivers made fewer car trips during the peak period. Second, the number of working days involving trips into and out of the charged area during the peak period decreased by 20 per cent from 123 person-days to 98, suggesting that participants avoided the charged area during the charging period. Both of these changes are significant at the 5 per cent significance level.

From Tables 3 and 4, we conclude that both of these responses are having a complementary effect. The number of person-days when car-based activities were undertaken in the charged area during the charging period (and thus incurred the toll) decreased from 117 to 47. This is due to the reductions in the number of person-days car-based activities were undertaken during the charging period regardless of location (the '*daycar-peak*' variable) and the number of person-days involving activities in the charged area during the charging period (the '*daycitypeak*' variable). We conclude that, as expected, drivers who remain driving during the charging period are more likely to avoid the charged area. Thus, the results reported so far suggest that volunteers changed mode, time and location of activities in response to the charging scheme.

Appendix 1 reports the results of the decision trees that were extracted from the data that link household and individual attributes to these different types of responses. These decision trees suggest that the prediction of car use during the charging period is relatively more straightforward than the prediction of change of location. Not only is the prediction rate of the car use tree better than the one predicting activity location, its set of attributes used for predicting car use is also markedly smaller. This supports the idea that household and individual characteristics may be more influential on car use than for the choice of activity location, which is more likely to be bound to the characteristics of work itself.

Car use during the charging period is primarily affected by the *phase* attribute (that is, 'before' and 'after') which is consistent with our expectations. Only for the Phase 2 weekdays do other attributes become important. The presence of children younger than 12 years of age appears to have an impact followed by a respondent's age and employment status, and the household size and income level attributes.

Household characteristics also play an important role in the second decision tree, although it is surprising that the *phase* attribute seems unimportant. It is, however, the presence of children younger than 12 years of age that appears to be the attribute with the most predictive power. The employment status attribute is the next important attribute, followed by a wide range of other household and individual attributes. As mentioned before, the flexibility of activities in the city-centre is probably more responsible for within city location choice than the household characteristics used in this study. It seems logical that activities involving young children tend to be less flexible. Since this experiment was of limited duration, behavioural changes requiring greater commitment over a longer period of time (such as changing location of work, school and home) were very unlikely to occur.

4.2 Tour-Level

More dramatic changes may be expected to occur in terms of how our volunteers organised their activities over time and space; that is, into tours. In addition to the analysis of changes at the day level, changes were also analysed at the tour level. To that effect, frequencies for the different tour types were calculated (Figure 3), while Figure 4 shows the number of tours for each tour type that incurred the toll.

Figure 3 suggests no significant changes concerning the number of tours for each tour type. The total number of tours has dropped slightly; although a significance test on the average number of tours per day was not significant at the 5 per cent significance level. Figure 4 shows that the number of Type 1 tours subject to the toll decreased from 118 to 48, which is highly significant.

Figure 3

Frequencies of different tour types during the 'before' and 'after' phase

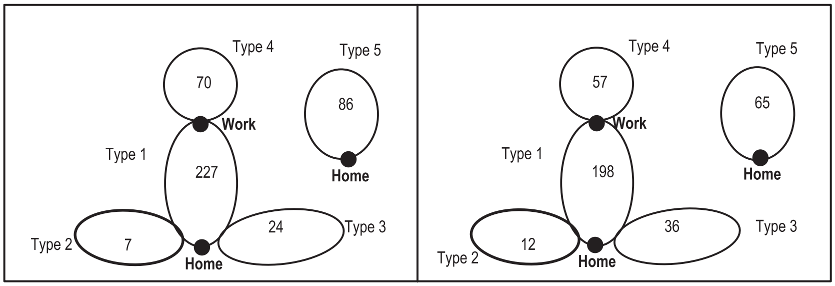
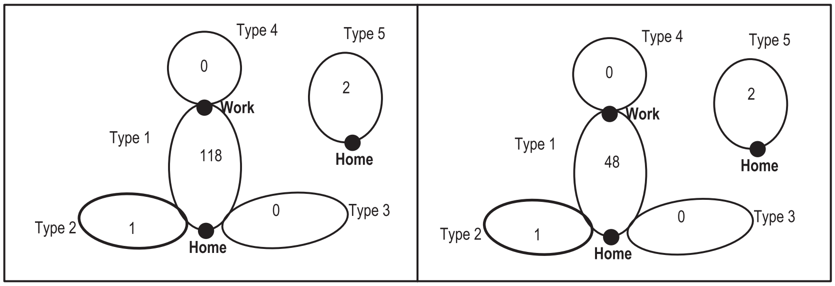


Figure 4

Frequencies of different tour types that incurred the toll



The number of Type 3 and Type 4 tours is zero, which is logical given the late start times for these types of tours. In other words, there are no work based sub-tours commencing during the charging period.

Both Figure 4 and Table 5 confirm that Type 1 tours are affected by the road-user charging scheme. Table 5 reports how the volunteers reacted to the charge by adapting their inbound travel patterns for Type 1 tours during the charging period. All changes are significant at the 5 per cent significance level. One can conclude that participants changed their Type 1 tours not only by changing mode, location or time of tour but that the combination of all three changes is responsible for an overall drop of

Table 5

Impacts of the Charging Scheme on Type 1 Tours (numbers of Type 1 tours)

Number of tours involving an activity in the charged area during the charging period		*Number of tours involving an activity during the charging period*		*Number of car-based tours involving an activity during the charging period*	
Before	*After*	*Before*	*After*	*Before*	*After*
178	136	179	143	125	73

59 per cent in the number of car-based Type 1 tours in the charged area during the charging period from 118 tours to 48. The reduction in the total number of tours performed in the charged area during the charging period suggests that our volunteers were able to change the location of their work tours during peak times by working from home or rescheduling activities to switch out-of-city work activities to a more optimal timeframe. This is only possible for those who have sufficient flexibility in their working arrangements. Again, we reiterate that the relatively short duration of the survey underestimates possible longer-term changes.

The values for the Type 1 tours have already been discussed. For the other tour types, there are no significant changes, suggesting that the charging scheme was not the reason for changing tour frequency. The number of Type 2 tours increased from 7 to 12 in contrast to a decrease for the Type 4 and Type 5 tours, but these changes are not significant. Nevertheless this supports the idea that the volunteers made more out-of-city tours before travelling to work.

Table 6 gives an indication of the activity distribution over the different types of tours before and after the charging scheme was introduced. Although the tour type frequencies do not change significantly, there is an obvious trend for the Type 3 tours concerning grocery shopping. This suggests that volunteers rescheduled grocery shopping activities from Type 1 tours to Type 3 tours, not affecting the work-based sub-tour (Type 4). These results can be attributed to the fact that the use of the car for Type 1 tours dropped significantly, increasing the impedance for grocery shopping activities as part of such a tour. Similar analyses carried out on the other activities did not yield significant results.

Combining both Table 5 and Figure 3, this study suggests that the volunteers rescheduled certain types of activities into a relatively fixed

Table 6

Activity Distribution Over Different Tour Types (number of tours)

	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
Collecting and dropping off pass.	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

pattern of tours. Decision trees were also generated to link household and individual characteristics to the aggregate tour attributes, but the findings were similar to those for the day level.

5.0 Conclusions and Discussion

In this study, the potential effects of a road-user charging scheme in the city of Newcastle upon Tyne, UK, have been evaluated. In particular, this study investigated changes in activity-travel patterns as a function of the charging 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 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 with which activities may be conducted will play an important role in this rescheduling process; for example, shop and office opening hours, public transport facilities and location.

The results lead us to conclude that the hypothetical cordon-charging scheme introduced in Newcastle upon Tyne could have a significant impact on travel patterns but less of an impact on activity participation and activity rescheduling, depending on how reliably the results from our relatively small sample can be extrapolated to the wider population. Our volunteers responded in different ways, by changing times, mode and location. Decision trees were used to link these findings back to specific groups of households. This study shows that change of mode is easier for specific groups of households than change of location and time. We suspect 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 the 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.

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Appendix 1

Decision Tree for Daypeakcar and Daypeakcity for Weekdays

Daypeakcar

```
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), or a leaf (which holds the cases for which all conditions are true).
The first line states that there were 157 Phase 1 weekdays. 21 are wrongly classified, 136 correctly. The third line states that for Phase 2 weekdays (condition 1) the number of children younger than 12 is the most important attribute for predicting the car usage at peak time. See Quinlan (1993) for a fuller explanation of how to interpret decision trees.

Daypeakcity

```
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