ROAD PRICING AS AN IMPETUS FOR ENVIRONMENTAL-FRIENDLY TRAVEL BEHAVIOR : RESULTS FROM A STATED ADAPTATION EXPERIMENT

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Number of words = 5964
Number of Tables = 6
Words counted: 5964 + 6*250 = 7464 words

Paper submitted: November 13, 2008

ABSTRACT

An important policy instrument for governments to modify travel behavior and manage the increasing travel demand is the introduction of a congestion pricing system. In this study, the influence of a detailed classification of activities is examined to assess likely traveler response to congestion pricing scenarios. Despite the fact that most studies do not differentiate between activity categories, the value of time and in general the space-time properties and constraints of different types of activities vary widely. For this reason, it is of importance to provide sufficient detail and sensitivity in assessing the impact of congestion pricing scenarios. In addition, a first assessment of possible multi-faceted adaptation patterns of travelers is presented. For these purposes, a stated adaptation study was conducted in Flanders (Dutch speaking region of Belgium). The experiment was conducted through an interactive stated adaptation survey. In the stated adaptation experiment respondents could indicate their stated responses to the congestion pricing scenario. The most prevalent conclusion is that the activity type significantly predetermines the willingness to express a more environmental-friendly behavior (i.e. reducing the number of trips, reducing the total distance traveled, switching to more environmental-friendly modes). Also, the willingness to show ecological activity-travel behavior (e.g. carpooling and using public transport) in a non-pricing situation is a major differentiator of future behavior in a congestion pricing scenario.

1 BACKGROUND

Rising concerns over increasingly intolerable economic and environmental externalities have generated particular interest in how transport planning policies might at least moderate the pressures resulting from growth in personal mobility and support the principles of sustainable development. These policies are commonly referred to as travel demand management (TDM) measures, which objective is to influence travel behavior without necessarily embarking on large-scale infrastructure expansion projects.

An important policy instrument for governments to modify travel behavior is the introduction of a congestion pricing system. The term congestion pricing or road pricing, refers to any form of charging for the use of roads during periods of peak demand. There is a significant amount of literature available that discusses the efficiency of road pricing systems, issues of public acceptability or the socio-economic value of a particular road pricing system, e.g. (*1-5*).

Research that has been conducted in the beginning of the 1990s (e.g. *6*) already stated that congestion pricing may be considered as one of the most promising TDM schemes that may cause travelers to modify their routes, means of travel, departure times or activity engagement. And indeed, previous studies (*7-10*) have mainly focused on the effect of congestion pricing on a single or limited number of facets of activity-travel patterns, such as departure time, route destination or mode choice decisions. Such studies do not take into consideration the complex interdependencies facing individuals when scheduling their daily activities. The relationship with activities are certainly necessary because they are able to give us a more coherent and more correct idea about people’s wider reflections and thoughts when considering adaptation (travel) behavior as a result of congestion pricing. The few existing studies that have taken the wider activity context into account in analyzing adaptation behavior indicate that such effects may be significant (*11-14*).

Yet even these more elaborated studies have some limitations. First, these studies do not differentiate between activity categories in their analyses, but often only distinguish between work and non-work activities. However, because the value of time and in general the space-time properties and constraints of different types of activities vary widely, such simple dichotomies may not provide sufficient detail and sensitivity in assessing the impact of congestion pricing scenarios. In an era where activity-based models become operational (*15-20*) and have proven their value in improving the sensitivity of the forecasts to different policy scenarios, a more detailed classification of activities may also prove its value in addressing specific travel demand management measures such as congestion pricing. Second, most previous (stated-preference) studies have assumed that traveler response to congestion pricing scenarios concerns a single facet of their activity-travel patterns (e.g. changing start time or changing routes). However, an individual may consider a change of several facets simultaneously. Especially destination choice, mode choice and choice of departure time may be strongly interrelated.

Thus, the goal of this study and its contribution to the literature is two-fold. First, we will examine whether a more detailed classification of activities provides added value in assessing likely traveler response to congestion pricing scenarios, and second we will perform a first evaluation of possible multi-faceted adaptation patterns of travelers. More specifically, we will investigate whether (i) people take activities into consideration in response to a particular congestion pricing scenario; whether (ii) the dependence of the multi-faceted nature of possible adaptations is dependent on the activity type and also (iii) whether reasons that were stated by respondents in the case they are not willing to make a modal shift is activity-dependent or not. To that end, a stated adaptation study was conducted in Flanders (Dutch speaking region of Belgium). This study elaborates on a previous stated-preference study which was carried out in the Netherlands (*13*).

The remainder of this paper is organized as follows. Section 2 provides the methodology that has been used throughout the research. Section 3 provides a descriptive analysis, followed by a more detailed statistical analysis in section 4. This latter section discusses the different behavioral models that were built in order to assess users’ stated behavioral changes for the different activities in response to the implementation of a congestion pricing scheme.

2 METHODOLOGY

2.1 A Multi-Faceted Stated Adaptation Approach

The research presented in this paper was conducted through an interactive stated adaptation survey, administered on the Internet, containing 311 respondents. It could be argued that sample bias is introduced when only an internet-based data collection is conducted. Previous studies have indeed demonstrated that some socio-economic classes of society, like older-age and lower-education groups, may be more reluctant towards using computer-assisted instruments for the data collection. Despite this, internet surveys allow for the automatic randomization of choice sets that each respondent sees when stated choice experiments are carried out. Also electronic surveys can be completed at the respondent's discretion; they can be visually pleasing and easy to complete. Especially stated-adaptation experiments can be executed more easily through the internet: it is more simple to prompt additional questions based on the situational context that has been entered in the questionnaire. Based on these arguments, we believe that the advantages may outweigh the disadvantages and that web-based surveys are a useful way to complement and collect additional data. In a stated adaptation experiment respondents can indicate their stated responses to the congestion pricing scenario. Several definitions about stated adaptation experiments can be found in the literature (*21*). We view stated adaptation experiments as an alternative to the more widely used stated preference and choice experiments. All have in common the use of experimental designs, allowing the researcher to control the variance-covariance of the data and hence create the optimal conditions for estimating and isolating particular effects, that are often confounded in real world data and cannot be estimated in an unbiased manner in non-experimental stated adaptation data. The key difference between stated adaptation and stated preference and choice experiment is the task posed to respondents. In stated preference experiments, respondents are invited to express the degree of preference to sequentially presented attribute profiles. In stated choice experiments, respondents are shown choice sets of two or more attribute profiles and are asked to choose the profile the like best (or alternatively allocate some fixed budget among the profile). In stated adaptation experiments, respondents are asked to indicate if and how they would change their behavior considering experimentally varied attribute profiles, typically representing scenarios. In the simplest case, only a single attribute is systematically varied.

In the present study, for each activity a congestion pricing scenario was formulated of the following general form:

"Assume that the fixed vehicle taxation is abolished but a variable road price is to be paid for each km travelled by car. The charge will be 7 eurocent on roads at times at which there is no congestion, and 27 eurocent on roads and times at which there is congestion."

In order to facilitate user responsiveness and understanding, we followed the approach, suggested by Arentze *et al*. (*13*). This means that for the activity category under concern, the respondent is asked to indicate the frequency of making trips for each transport mode and the average distance of these trips in his current activity-travel pattern. Based on this data, the system calculates and presents to the respondent the total variable travel costs for the activity under both the current conditions and the scenario condition. This means that for each activity a comparison between the current monthly transport costs (only the fuel costs) and the new monthly transport costs that would arise under a congestion scenario, meaning both the fuel costs and the congestion rate are presented to the respondents. Next, the respondent has to indicate through a list of questions whether, and if so which adaptations he/she would make if the scenario would be effective. An activity-oriented approach is used: work-school, shopping, social, and leisure activities were distinguished in this respect.

After the introduction of the congestion price measure, there are different strategies that individuals can apply in adapting their behavior to completely or partly reduce the increase in costs. In this respect, a differentiation between a long-term and a short-term adaptation seems relevant. For each trip for an activity, we consider the following long-term response alternatives: (i) a change of residential location of the household (move to a location closer to the workplace, closer to relatives, closer to the shopping location,...), (ii) a change of work location of the individual (closer to the residential location) or (iii) no change. Short-term response alternatives mainly aim at reducing trip frequency or travel distance, or circumvent the extra congestion price by making the trip at less congested times or at less congested locations. The following alternatives were defined: (i) eliminate the trip by conducting the activity at home; (ii) eliminate the trip by skipping the activity; (iii) reduce the distance of the trip by conducting the activity close to home; (iv) change the transport mode of the trip; (v) change the departure time of the trip, (vi) change the route of the trip, and (vii) no change

These behavioral alterations have been recoded in the following 5 behavioral changes that were considered for the analysis: structural changes, changes in activity situation, the modal shift towards more environment-friendly transport modes, time-of-day changes, and route changes. For the work activity both job changes and changes in residence are considered as a structural change, while for the other activity types (shopping, leisure, visits) only changes in residences are categorized as structural change. Changing jobs (and thus the job location) is considered as a structural change, while changing the location of other locations is not, because of the significantly higher impact on the mobility behavior that is caused by changing job location. Concerning the changes in activity situation, more teleworking and adopting a compressed work week are the corresponding behavioral alteration of the work activities (both decrease the activity frequency), while for the other activities both changes in activity location and in activity frequency are taken into account.

As said before, most stated preference studies consider these choice alternatives to be mutually exclusive. However, it may also be the case that an individual considers changing several of these facets (for example change both the transport mode and the departure time of a trip) at the same time. In order to investigate the multi-faceted character of possible adaptations, we added a simplified implementation of this functionality to our survey experiment. Indeed, a full implementation would mean that 32 choice alternatives (2 combinations to the power of 5 behavioral changes) can be chosen by the respondent. To this end, after respondents indicated a possible change in transport mode, we asked for each transport mode whether respondents would apply other changes *as a result of this change in transport mode*, for instance change the departure time of the trip or change the route of the trip. In addition, we asked if they would combine several activities, which activities they would combine, and how often they would combine these activities.

2.2 Operationalisation of the Stated Adaptation Approach

In the operationalisation of these concepts, we made a differentiation between the activity and the travel pattern in order to better guide the response process of users. The general structure of the questions is:

"For conducting (the concerned activity), which changes would you apply to your <u>activity pattern</u> as a consequence of the scenario?

> *Performing (the concerned activity) more often at home (choice option 1), less frequently (choice option 2), more often at a location closer to home (choice option 3). Moving closer to the location of (the concerned activity) and change nothing are choice options 4 and 5.*

"For conducting (the concerned activity), which changes would you apply to your <u>travel pattern</u> as a consequence of the scenario?.

> *More often use the car (choice option 1), carpooling (choice option 2), use the train (choice option 3), use the bus/tram/underground (choice option 4), use the bike (choice option 5), walk (choice option 6) for (the concerned activity). It was also possible to indicate that no change would be implemented (choice option 7).*

For each indicated adaptation option, the respondent is asked how often he/she chooses this adaptation option per month. Moreover, for each indicated change in travel mode, the respondent is asked if he/she would apply other changes as a result of this change in transport mode. The general form of these questions is:

"If you would use (the concerned transport mode) for (the concerned activity), would you apply other changes in comparison with the car?

- *A change of the departure time from home to (the concerned activity)*
- *A change of the departure time from (the concerned activity) to home*
- *A change of the route*
- *I would change nothing"*

While the above formulation is shown here to illustrate the multi-faceted nature of questions (several answers could be indicated), it is important to notice that separate departure time and route changes are also inquired independently of transport mode.

2.3 Statistical Analyses

Following the methodology described above (stated-adaptation approach and the operationalisation of this approach), two main simple types of statistical analyses can be conducted. The theoretical context of these analyses is briefly described below.

2.3.1 Pearson Chi-Square Test of Independence

To test independence (this is the null hypothesis) between two multinomial (categorical) variables one could use the Pearson statistic Q_p as an explorative statistical analysis, which is defined by the following equation:

$$Q_P = \sum_i \sum_j \frac{\left(n_{ij} - \hat{\mu}_{ij}\right)}{\hat{\mu}_{ij}},$$

where n_{ij} is the observed frequency in cell (*i*,*j*) , calculated by the multiplying the observed chance by the sample size, and $\hat{\mu}_{ij}$ is the expected frequency for table cell (*i*,*j*). When the row and column variables are independent, Q_P has an asymptotic chi-square distribution with (number of rows minus one)(number of columns minus one) degrees of freedom (*22*).

2.3.2 Logistic regression

For modeling discrete choices, generally the multinomial logit (MNL) model is one of the most applied modeling approaches. In case only two choices are modeled, the MNL model reduces to the logistic regression model. In this study the bivariate case (the logistic regression model) is adopted because of two reasons.

First, MNL models require the choices to be unique *(22)* (among a set of possible choices, exactly one choice alternative must be elected), and thus correspondingly simultaneous behavioral changes are not a feasible modeling option. One could recode the answers to a unique choice variable by selecting the behavioral change that has the largest impact. However, important interdependencies are then neglected. Besides, one could also consider combinations of behavioral changes as an additional choice. However, this would significantly increase the number of choice alternatives (5 unique behavioral alternations, 10 combinations of two behavioral adaptations, 10 combinations of three behavioral changes, 5 combinations of four changes in activity-travel behavior and 1 combination of all five considered changes, augmented by the no change alternative, yielding a total of 32 choice alternatives), and correspondingly the number of parameters to be estimated. Secondly, this paper focuses on the different behavioral changes for different activity types. Additional knowledge is obtained when these separate models are investigated. Especially in the light of policy goals such as the Kyoto norms, an enhanced behavioral insight in the effect of variable road pricing and congestion charging can help policy makers to fine-tune the available policy measures. On the other hand, unlike in a MNL setting, the information of the bivariate model is fragmented over different models, which makes a full behavioral interpretation more difficult. However, as will be shown in section 3, respondents effectively often combine behavioral adaptations in their stated responses and from this fact, the application of the bivariate model seems warranted if one does not want to rely upon the assumptions that were mentioned above.

Formally, the behavioral changes due to congestion charging can be modeled in the following way. Let $\pi_i(x)$ represent the probability of individual *i* considering the behavioral change investigated, then $\pi_i(x)$ can be estimated using the following equation:

$$\pi_i(x) = \frac{\exp\left(\beta_0 + \sum_k \beta_k X_{ik}\right)}{1+\exp\left(\beta_0 + \sum_k \beta_k X_{ik}\right)}$$

where X_{ik} are individual and household level attributes for individual *i* and β the corresponding parameters for these attributes. To ensure that the parameter estimates and corresponding standard errors are reliable, the models are also tested for the presence of multicollinearity. In the case of presence of multicollinearity, signs and magnitudes of regression coefficient estimates can be biased, and consequently incorrect conclusions about relationships between the behavioral changes and the explanatory variables can be drawn. Multicollinearity can be diagnosed by looking at the variance inflation factors for each explanatory variable. More specifically, variance inflation factors (VIFs) that show a value above 2.5 may be a cause of concern (*23*). Is is therefore of importance to investigate whether the problem of multicollinearity is existent or not on the real data by having a close look at the VIFs.

3 DESCRIPTIVE ANALYSES OF THE DATA

The survey described in this paper was conducted in the beginning of May 2008. A total of 311 questionnaires were correctly and completely filled out. The respondents were all approached by email and according to the ‘snowball method’, acquaintances of acquaintances were addressed. The stratification was checked with national statistics which are available for different attributes. The sample stratification proved to be accurate with respect to gender, education level, family income and level of urbanization. A slight overestimation was present in the sample for the attributes age (age class 18-24), employment (students) and family situation (living with parents) due to the fact that the majority of the respondents were recruited in a student environment. The snowball method corrected somewhat for this, but some slight bias remained present in the data, for which additional weighting procedures should be adopted. In total, about 3500 respondents were approached for this survey (exact number unknown due to snowball-method), which resulted in a response rate of almost 10%. In total, the questionnaire consisted of 135 context-dependent questions, meaning that not all of these questions needed to be answered by respondents. In the situation without the congestion pricing, an average worker travels 19 times each month to his workplace. The average work distance is 21 km. The number of shopping trips per month is 3 and the average shopping distance is 13 km. For leisure and social visits, the respective values are 8 trips and 16 km versus 6 trips and 7 km.

In the analyses of the data all household/individual/activity attributes were effect coded. In effect coding, as in dummy coding, an *n*-level attribute is represented by *n-1* binary variables. In contrast to dummy coding, however, the base alternative is coded by a value of *-1* rather than 0 on each binary variable. As a consequence, estimated parameter values for the binary variables can be interpreted as a correction on a mean (*13*). The different independent variables used in the analyses are shown in Table 1. In order to improve the readability of the table, a segmentation is made between socio-demographic, work/school, modal and activity/travel related variables. This table also needs to be used as a reference for an explanation of the abbreviations that were used in subsequent tables of the paper.

In this section statistical analyses have been carried out by means of an independence test (chi-square analysis) as a first examination of the three research questions. For all these research questions, independence is taken as null hypothesis (meaning that activity type has no impact on the research question at hand), and no independence as alternative hypothesis in the analyses. The entries in Table 2 are observed chances for the outcomes of the three different research questions. From these values, the chi-square and corresponding *p*-values can be calculated.

The first research question investigates whether people take activities into consideration in response to a particular congestion pricing scenario. With respect to this research question (Table 2A), the Pearson chi-square value (Q_p) is equal to 173.04, corresponding to a chi-square distribution of (4-1)(5-1) = 12 degrees of freedom, which yields a *p*-value <0.0001. In this case the null hypothesis of independence between behavioral change and activity type can not be accepted. From this, one can conclude that active type indeed predetermines the behavioral change. From the upper part of the table it is also clear that more radical changes (such as for instance change in residence location) are taken for the work activity when compared to other activities: 15.18% of the respondents considers a structural change for work activities, while only 0.35%, 0.71% and 1.41% of the respondents indicate a willingness for structural changes for respectively the shopping, leisure and visit activities. Amongst others, this can be explained by the fact that the total distance traveled for work activities is significantly larger than for other activities (on average, work: 779 km, shopping: 136 km, leisure: 272 km and social visits: 291 km). Correspondingly the financial impact of road and congestion pricing on the household budget is much larger for work activities. One could notice that the sum of the chances to engage different behavioral changes does not equal one. This is due that the fact that the behavioral responses are not mutually exclusive. As noted earlier in this report, respondents were allowed to indicate more than one behavioral adaptation (therefore, the different behavioral adaptations will be estimated separately for each activity using logistic regression models). Nonetheless, the results of the independence test remain valid, as the test is not only valid for a single multinomial sample, but also for more independent multinomial samples (*22*).

The second research questions investigates whether the dependence of the multi-faceted nature (i.e. whether a modal shift yields secondary behavioral shifts) of possible adaptations is dependent on the activity type. With respect to this second research question (Table 2B), the Pearson chi-square value (Q_p) is equal to 28.79, corresponding to chi-square distribution of (4-1)(4-1) = 9 degrees of freedom, which yields a *p*-value of 0.0007. Also now, the null hypothesis of independence between the time-of-day and/or route change and the activity type is rejected and thus one can conclude that the activity type predetermines the time of day or route change and is conditional upon a modal shift. A thorough look at the middle part of Table 2 provides the insight that especially for work activities time-of day changes conditional upon a modal shift are a real option. This can be illustrated by looking at the sum of the propensities for changing the time-of-day alone and changing time-of-day and route simultaneously: 68.52% of the respondents indicates to change the time-of-day of work trips, while only 34.85% will change the time-of-day of their leisure trips. The large values for the work activity again can be explained by the higher financial impact of road and congestion pricing. The significantly lower percentages for leisure trips can be explained by the constraints imposed by the opening hours shop. Therefore, the introduction of for more flexible opening hours of shops could work as a leverage to increase the number of time-of-day chances, and thus to pursue a larger spread over the day and thereby minimizing the externalities caused by congestion.

Finally, Table 2C investigated the activity dependency of reasons that were stated by respondents in the case they are not willing to make a modal shift due to the introduction of congestion pricing. The Pearson chi-square value (Q_p) is equal to 68.19, with a chi-square distribution of (8-1)(4-1) = 21 degrees of freedom, which yields a *p*-value of <0.0001. And indeed, also in this case, the null hypothesis of activity independence cannot be accepted. With respect to work activities, people more often state that the travel time of other alternative transport modes is particularly long. The car is perceived as a necessity for shopping trips, because of the transport of goods from the shop to the home location. This appears to be a significant barrier for a modal shift. Several conclusions can be drawn when we examine this behavior more into detail.

If public transport would be improved (shorter travel times, more comfort, better level of service), 29.80% of the people still using the car as a transport mode after introduction of road pricing systems, would consider switching from car to public transport for working trips compared to 30.00 % for shopping trips, 34.91 % for leisure trips and 35.77% for visit trips. This clearly indicates the wide potential for public transport.

In addition to this, stimulating relocations closer to the work would yield an additional environmental improvement: of all people considering removal closer to work after introduction of road pricing system, 74.20% would switch to more environmental transport modes. Of all people who use the car as the main mode of travel before the congestion pricing, 9.52% would remain using the car, while 90.48% would use more environmental-friendly modes such as public transport and bike. It should be noted that these percentages are particularly high because these numbers are percentages for people who are already relocating, and therefore travel distance is significantly reduced, and correspondingly green modes become a more viable option.

Variable road and congestion pricing also reduces the number of trips. On average every person would make 0.405 commuting trips less a month, 0.238 shopping trips less, 0.334 leisure trips less, and 0.125 visit trips less. The fact that visit trips are not frequently reduced underlines the importance of social networks in people's activity patterns.

4 STATISTICAL ANALYSES: LOGIT MODEL

From the descriptive analyses that were carried out above, it became very clear that the different research questions pointed out that the behavioral adaptations are activity dependent. In this section, the stated behavioral changes in response to a congestion pricing policy (research question 1) have been investigated into more detail. Given the activity dependency, logistic regression model were built for the different behavioral alterations. This allowed to explain the different environmental improvements by means of a set of explanatory variables (socio-demographic information, work/school related attributed, data about activity-travel behavior, including trip chaining behavior and modal preferences). Only significant explanatory variables were included in the final models. To ensure the stability of the results the largest VIFs of each model were also presented. As all VIFs are smaller than 2 (below the benchmark value of 2.5), the stability of the results is guaranteed.

4.1 Behavioral Changes for the Work/School Activity

For the work/school activity category, the significant variables for each stated response have been indicated in Table 3 at three different levels of significance. Several conclusions can be drawn from these results.

First of all, and most obvious, the ***Occup*** variable, indicating whether the respondent is occupationally active or non-active (e.g. students), is of major importance for the work/school activity for every stated response. It is clear that occupationally active people are less inclined to change their residence or work location, modal shift, time-of-day and route choice than occupationally non-active people. In general this means, that occupationally non-active people are more willing to adapt behavior in response to a congestion pricing scenario, because they are both more flexible and more price-sensitive.

The opposite is true for the work/school activity situation change, in which respondents stated that they are willing to compress their work(school)week or do more telecommuting (study at home) as a result of congestion pricing. In this case, the occupationally active people are more willing to change, probably because occupationally active people have more opportunities to change behavior, for instance because telecommuting is accepted or encouraged in their work situation.

With respect to the change in residential location *(Model 1)*, in addition to the occupational status, the total distance for the work/school activity per month (***DisTotWS***) seems to be highly significant. Indeed, the larger the distance, the more financial impact road pricing has and the more inclined one seems to be to change residence or job location. Similar conclusions were found in (*13*).

Examination of the changes in activity situation *(Model 2)*, reveals that the ***Telecom*** variable, representing telecommuting behavior, is highly significant. This means that people that are already telecommuting are more inclined to telecommute even more. This can be explained by the fact that these people already have all the preconditions in place for teleworking. Policy makers can try to stimulate both individuals as well as companies to telecommute even more by bundling financial incentives, and marketing campaigns to promote teleworking. That way the total number of (commuting)trips can be reduced, and thus economic and environmental externalities caused by congestion in particular, and car traffic in general, diminished.

Concerning the modal shift reaction *(Model 3)*, which implies a higher willingness to use more environmental-friendly transport modes, the ***License*** variable seems to be highly significant. A possible explanation is the fact that as a car driver, one feels more victimized than non-car drivers, and accordingly one is more inclined to change transport mode. In addition, also the chaining of trips is highly significant. Due to the fact that people, who combine activities on one trip to reduce the total number of trips, are already expressing an environmental awareness, they are more likely to repeat this behavior and thus make shifts towards more environmental-friendly transport modes.

In terms of a time-of-day reaction towards congestion pricing *(Model 4)*, the ***Decis*** variable is found significant. This is logical because in case one has self decision right with respect to his/her own working hours, one is more willing and more able to make a time of day change. Stimulating companies to let their personnel choose work hours that are more tailored to limit congestion by creating a larger spread over the day, seems to be a viable policy measure that can be taken.

Finally, a last conclusion with respect to the work activity, is that one is more inclined to route changes (Model 5) under a congestion pricing scenario in case the average distance per trip (***DistWS***) is larger. The same reasoning counts as for the ***DisTotWS*** variable: the more financial impact road pricing has and the more eager one seems to be to change the route.

4.2 Behavioral Changes for the Shopping Activity

Interestingly, in contrast with the work activity, completely other variables are found to be highly significant for the shopping activity (see Table 4). This further approves the importance of segmenting the analysis by activity type, and of the activity-based approach in general. Inspection of the significant explanatory variables discloses, first of all, that the ***Carpoolshop*** variable, which indicates whether someone travels together with others for a shopping activity, is of major importance for shopping for three out of four stated responses. This can be accounted for by the fact that people who carpool for the purpose of shopping, already express an environmental-friendly behavior, and are more inclined to a change shop location/frequency (shopping activity situation change), modal shift, and route changes. Clearly an environmental awareness invokes repetitive environmental-friendly behavior (*24*).

With respect to the change in activity situation *(Model 6)*, the number of shopping trips (***NTripShop)*** is found to be significant. A similar explanation can be given as in Model 5: the higher the number of shopping trips undertaken, the more emergent the issue of congestion charging becomes.

In terms of a modal shift reaction to congestion pricing for shopping activities *(Model 7)*, several variables are found to be highly significant. First, the presence of children (***Child***) seems to be an important attribute. This seems logical due to the fact that one is less inclined to shift transport modes because there are fewer alternatives available due to the presence of children. Second, the fact whether a train stop is within biking distance or not (***BTrain***), significantly influences a possible modal shift (for instance to train). Finally, if people are chaining shopping and visit activities (***ChSV***), they are more willing to make modal shifts in the future under a pricing scenario.

With respect to shopping time-of-day changes *(Model 8)*, no variables are significant at the 0.01 confidence level. At the 0.05 level, both working status (***Work***) and the distance to shopping activities (***DistShop***) are significant. One can assume that when people are working, there is less room for changing shopping times due to the fixed regime of their work activity. With respect to distance, a similar conclusion can be drawn as the effect of distance in other models: when the shopping distance is large, people are more inclined to shopping time changes because congestion charging becomes a more pregnant issue.

Finally, with respect to shopping route changes *(Model 9)*, only the ***Work*** variable is highly significant. The model outcome suggests that when people are working, they are not very willing to adopt shopping route changes, due to the fact that they have little time available.

4.3 Behavioral Changes for the Leisure Activity

For the behavioral changes concerning leisure activities there is one variable which emerges as highly significant for three out of four stated responses to the pricing scenario (see Table 5), namely the variable ***PTLeis***, which measures whether public transport is used for performing the trip to leisure location. In case people use public transport for leisure trips, it seems they are more willing to perform a change in their leisure activity situation (leisure location or leisure frequency change), modal shift or time-of-day decisions.

With respect to the change in leisure activity situation *(Model 10)*, two additional variables are highly significant. The first variable, ***CongestLeis***, indicates whether the road which is used for performing the shopping trip is congested or not. Under a congested road, people are more willing to perform leisure activity changes. Second, if chaining of leisure and visit activities occurs (***ChLV***), one is more willing to change leisure frequency and leisure location change) in the future under a pricing scenario.

Similar to the shopping activity situation, several variables (***Occup, License, ChSL, Comp* and *Carav***) are found to be highly significant in the case a modal shift reaction due to congestion pricing is considered *(Model 11)*. The first three variables are already explained in one of the previous models and the interpretation is similar for a modal shift reaction. The *Comp* variable, representing a possible financial compensation for commuting, is positively correlated with a modal shift. In addition, also the *Carav* variable, representing the availability of a car for that particular person, is positively correlated. This indicates that when a car is available, one is obviously considering to make more car trips than in the case no car is available, and consequently one becomes more inclined towards a behavioral change due to congestion pricing.

With respect to time-of-day and route changes for the leisure activity (respectively *models 12 and 13*), no variables are significant at the 0.01 level.

4.4 Behavioral Changes for the Visit Activity

Unlike other behavioral changes, for the visit activity, there is no variable which emerges as highly significant for a majority of the stated responses (see Table 6). With respect to the change in visit activity situation *(Model 14)*, only the total distance for the visit activity per month (***DisttotVisit***) is highly significant. Similar to the work activity, the larger the distance, the more financial impact road pricing has and the more inclined one seems to be to change the activity situation. For the change in modal shift *(Model 15)*, the variables ***Single, Wstatus*** and ***CarAv*** are the most relevant. Concerning time-of-day changes *(Model 16)*, the presence of children (***Child***) is the only variable that plays a key role. After all, the presence of children mainly determines the time of day pattern for visit activities: if children are present, one is less inclined to time-of-day changes. Finally, with respect to route changes *(Model 17)*, no variables are found significant at the 0.01 level.

5 CONCLUSION

In this paper, behavioral adaptations evoked by road and congestion charging were investigated. The most prevalent conclusion is that activity type predetermines the willingness to express a more environmental-friendly behavior (i.e. reducing the number of trips, reducing the total distance traveled, switching to more environmental-friendly modes). The effect of policy measures in general, and road and congestion pricing in specific, thus have to be tailored to the activities that people perform. In addition, analyses of the different behavioral alterations indicated that people who are already inclined to show ecological activity-travel behavior (e.g. carpooling and using public transport) are more likely to express similar behavior. Once a first step towards an increased environmental awareness is achieved, more significant changes can be obtained more easily. In conclusion the challenge for policy makers will be to create a bundle of policy measures that incites that first step. Future research is needed however to examine additional and more detailed multi-faceted adaptation patterns of travelers, which are not solely limited to secondary behavioral shifts.

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TABLE 1 Independent Variables

Label	**Description**
	Socio-demographic data
Gend	Gender: 1: male; -1: female
Age	Age: 1: 40- years; -1: 40+ years
Married	Marital state: 1: couple ; -1: single
Single	Single/multiple person hh: 1: single; -1: multiple
Child	Children: 1: children; -1: no children
Educ	Education: 1: high school or university; -1: all but 1
Urb	Urbanization: 1: urban; -1: non urban
	Work/school related attributes
Occup	Occupational active/non-active: 1: active; -1: non-active
Work	Working status: 1: work; -1: non-work
Study	Student status: 1: student; -1: not a student
WStatus	Work status: 1: part time work; -1: full time work
FixVar	Fixed or Variable working hours: 1: Fixed; -1: variable
Decis	Self-/No self-decision right with respect to own working hours: 1: yes; -1: no
Flex	Flexibility in working hours: 1: flexible; -1: non flexible
CarWork	Car needed for work?: 1: yes; -1: no
Comp	Financial compensation for commuting?: 1: yes; -1; no
Telecom	Telecommuting?: 1: never ; -1: regular or often
	Modal options
License	Driving license: 1: yes; -1: no
CarPos	Car possession: 1: no car; -1: 1 or more cars
CarAv	Car available: 1: always; -1: not always
Bikepos	Bike possession: 1: none; -1: 1 or more
BikeAv	Bike availability on non-home locations: 1: none; -1: 1 or more
PTCard	Season ticket or reduction card for public transport use: 1: no; -1: yes
Wbus	Is the bus stop within walking distance (500m)?: 1: yes; -1: no
Bbus	Is the bus stop within biking distance (2km)?: 1: yes; -1: no
WTrain	Is the train stop within walking distance (500m)?: 1: yes; -1: no
BTrain	Is the train stop within biking distance (2km)?: 1: yes; -1: no
	Activity-Travel behavior (per activity) *{WS: Working or school activity; Shop: shopping activity; Leis: Leisure activity; Visit: Social visit activity}*
Tod{WS;Shop;Leis;Visit}	
Congest{WS;Shop;Leis;Visit}	Is road congested for {activity}: 1: congested; -1: uncongested
Carpool{WS;Shop;Leis;Visit}	Carpool used for {activity}: 1: carpool; -1: no carpool
PT{WS;Shop;Leis;Visit}	Public transport used for {activity}: 1: yes; -1: no
NTrip{WS;Shop;Leis;Visit}	Number of trips per {activity}
Dist{WS;Shop;Leis;Visit}	Average distance of trip per {activity}
DistTot{WS;Shop;Leis;Visit}	Total distance per {activity} per month
DistCar{WS;Shop;Leis;Visit}	Total distance by car per {activity} per month
	Specific Trip chaining characteristics
Tchain	Trip chaining (in general) occurs due to congestion. 1: yes; -1: no
ChWS	Chaining of Work and Shopping activities occurs due to congestion. 1: yes; -1: no
ChWL	Chaining of Work and Leisure activities occurs due to congestion. 1: yes; -1: no
ChWV	Chaining of Work and Visit activities occurs due to congestion. 1: yes; -1: no
ChSL	Chaining of Shopping and Leisure activities occurs due to congestion. 1: yes; -1: no
ChSV	Chaining of Shopping and Visit activities occurs due to congestion. 1: yes; -1: no
ChLV	Chaining of Leisure and Visit activities occurs due to congestion. 1: yes; -1: no
ChO	Other trip chaining occurs due to congestion. 1: yes; -1: no

TABLE 2 Observed Chances used for Hypothesis Testing using Chi-Square Analysis

A. H1: Impact of activity type on behavioral changes due to congestion pricing				
	Work	Shopping	Leisure	Social Visit
Structural change (change in residence or change in work location)	15.18%	0.35%	0.71%	1.41%
Activity situation change (dependent on activity)	22.44%	21.28%	20.14%	7.42%
Modal shift (environment-friendly transport modes or more carpooling)	47.85%	30.14%	40.99%	29.33%
Time-of-day changes	47.52%	47.87%	24.03%	46.29%
Route changes	47.85%	45.74%	42.76%	46.29%
No changes	16.83%	34.04%	33.92%	32.86%
B. H2: Impact of activity type on possible secondary behavioral shift next to modal choice due to congestion pricing				
	Work	Shopping	Leisure	Social Visit
Time-of-day changes	41.67%	18.18%	29.27%	32.84%
Route changes	6.48%	22.73%	12.20%	22.39%
Time-of-day and route changes	26.85%	16.67%	28.05%	11.94%
No changes	25.00%	42.42%	30.49%	32.84%
C. H3: Impact of activity type on reasons for car dependence after introduction of congestion pricing				
	Work	Shopping	Leisure	Social Visit
Car required for activity	12.18%	21.10%	9.87%	11.07%
Distance public transport to far	1.02%	0.46%	0.00%	2.05%
Long travel times other modes	10.66%	4.59%	4.04%	6.56%
Time table does not fit activity hours	3.55%	0.00%	8.52%	3.28%
Comfort	12.18%	14.22%	17.04%	14.34%
Other reasons	6.09%	4.59%	0.00%	4.10%
Combination of two reasons	27.92%	23.85%	25.56%	22.13%
Combination of three reasons	26.40%	31.19%	34.98%	36.48%

TABLE 3 Estimation Results for Behavioral Changes of Work/School Activities

Model nr.	*1*	*2*	*3*	*4*	*5*
Parameter	Structural changes (change in residence or change in work location)	Activity situation change (telecommuting, compressed work week)	Modal shift	Time-of-day changes	Route changes
Intercept	-2.7334 ***	-2.3781 ***	-1.3836 ***	-1.2590 ***	1.0840 **
Gend	-0.3270 *				
Educ					0.3104 *
Occup	-0.8304 ***	0.3697 **	-0.6079 ***	-0.8008 ***	-0.2560 *
Decis				0.7182 ***	
Comp	0.4811 **		0.3171 **		
Telecom		0.7309 ***			
License			0.7083 ***	0.4733 *	
Carav			0.3306 **		
Bikepos		0.6052 **	0.5164 **		
PTCard		-0.3240 *			
Bbus				1.0228 **	
TodWS			0.2772 *	-0.3721 **	
CarpoolWS			0.3744 **		
PTWS	-0.5287 **				
Tchain	-0.6221 *		0.5817 ***		
ChWS	0.7738 **				
ChSL				0.2593 *	
NTripWS					-0.0514 **
DistWS					-0.0326 ***
DisTotWS	0.0010 ***	0.0005 **			
DistCarWS				0.0004 *	0.0007 **
Largest Variance Inflation Factor	1.90	1.25	1.73	1.45	1.96

significance *** < 0.01, ** < 0.05, * < 0.10

TABLE 4 Estimation Results for Behavioral Changes of Shopping Activities

Model Nr.	*6*	*7*	*8*	*9*
Parameter	Activity situation change (changing shopping location, shopping frequency)	Modal shift	Time-of-day changes	Route changes
Intercept	-1.9706 ***	-1.4517 ***	-0.4560 **	0.0651
Single				0.3772 *
Child		-0.7313 ***		
Urb	-0.2862 *			
Work			-0.3171 **	-0.4671 ***
Decis				0.3101 **
Telecom	-0.2818 *			
License		-0.4541 *		
Bikepos		0.6067 **		
BikeAv	0.3301 *			
BTrain		0.4203 ***		-0.3452 **
CarpoolShop	0.5461 ***	0.6148 ***		0.2965 **
Tchain			0.2469 *	
ChSV	0.3617 **	0.4560 ***		
NTripShop	0.1535 ***			
DistShop			0.0278 **	
Largest Variance Inflation Factor	1.04	1.05	1.00	1.32

significance *** < 0.01, ** < 0.05, * < 0.10

TABLE 5 Estimation Results for Behavioral Changes of Leisure Activities

Model Nr.	*10*	*11*	*12*	*13*
Parameter	Activity situation change (changing leisure location, leisure frequency)	Modal shift	Time-of-day changes	Route changes
Intercept	-0.1659	-1.2111 ***	-0.6441 ***	-0.2670
Gend	-0.3246 *			0.2272 *
Child				-0.3444 **
Occup		-0.5132 ***		
WStatus			0.4269 **	
Decis		-0.3470 **		
Flex	-0.4390 **			
CarWork	0.4543 **			
Comp		0.5308 ***		
License		0.9166 ***		
Carav		0.4597 ***		
Bikepos		0.5761 **		
Bikeav				0.2414 *
CongestLeis	0.9821 ***			0.2776 **
CarpoolLeis		0.3453 **		
PTLeis	0.4631 **	0.6727 ***	0.3675 **	
ChWS			0.3304 **	
ChSL		0.3776 ***		
ChLV	0.4425 ***			
NTripLeis	-0.0584 *			
Largest Variance Inflation Factor	1.06	1.,87	1.00	1.02

significance *** < 0.01, ** < 0.05, * < 0.10

TABLE 6 Estimation Results for Behavioral Changes of Social Visit Activities

Model nr.	*14*	*15*	*16*	*17*
Parameter	Activity situation change (changing visit frequency)	Modal shift	Time-of-day changes	Route changes
Intercept	-3.5766 ***	-2.1669 ***	-0.5341 **	0.6758
Married	0.6251 **	-0.3934 **		
Single		-0.8403 ***		
Child		-0.4996 **	-0.4097 ***	
Urb	0.6920 **			
WStatus		-0.9975 ***		
Decis		-0.3029 *		
Telecom	0.4529 *			
License			0.4322 *	
Carpos				-1.0322 *
CarAv		0.5506 ***		
BikeAv	-0.6255 *			
BTrain		0.3042 *		-0.3477 **
TodVisit		0.3323 **	0.2949 **	
CongestVisit				-0.2681 **
PTVisit		0.6871 **		
ChWS		-0.3104 *		
ChSV		0.4334 **	0.3177 **	
ChLV		0.4004 **		0.3034 **
DisttotVisit	0.0012 ***			
Largest Variance Inflation Factor	1.05	1.72	1.03	1.04

significance *** < 0.01, ** < 0.05, * < 0.10