EFFECTS OF FUEL PRICE ON INDIVIDUAL DYNAMIC TRAVEL DECISIONS: BINARY PROBIT SELECTION MODEL USING GPS PANEL DATA

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ABSTRACT

The goal of this study is to explore the impact of fuel price changes as one of exogenous changes on individual's activity-travel behaviour. Previous studies in transportation research have examined the effects of fuel price estimating both short-term and long-term price elasticities on vehicle miles travelled and vehicle stock using aggregated data at the country or sub-national level. This study is one of the few using individual-level panel data. Furthermore, unlike previous research on fuel price elasticity, this study considers context effects such as weather conditions, accessibility and travel company. Non-inclusion of these effects may produce spurious results on the influence of fuel price changes on activity-travel patterns.

Based on a unique panel GPS dataset of around 120 respondents who are living in the Eindhoven area, the Netherlands, corresponding weather conditions data and daily fuel price data obtained from a local website in the Netherlands were collected. A two-step estimation methodology was applied to estimate 1) individuals' decisions of making car-based trips and 2) the influence of fluctuations in real fuel price on car travel distance. The results show that fuel price has significant negative effects on both an individual's decision to use the car and on distance travelled by car. In addition, results indicate that day of the week, weather conditions and three weeks lagged fuel price have significant negative effects on individuals' car use decisions.

Keywords: Fuel prices; weather condition; GPS panel data

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1. INTRODUCTION

Economists have argued the important role of economic instruments, including fuel taxes, in transportation on the grounds of economic efficiency. An increase in fuel taxes is supposed to influence consumers to directly reduce vehicle energy consumption by reducing vehicle miles travelled, buying more efficient vehicles, shifting to a more fuel-efficient driving style, etc. These contentions seem to have found substantial empirical support. Over the past forty years, many researchers have interpreted changes in travel demand to reflect behavioural adaptations to fuel price fluctuation. Most of this literature has been conducted in the context of valuations of travel time (1, 2, 3) or price elasticity of travel demand (4, 5, 6, 7, 8, 9). In addition, a number of meta-analyses of travel demand elasticities have been conducted recently (10, 11, 12, 13). The results of these studies indicate that, on average, traffic volume will go down in the short run if the real price of fuel increases, and builds up to a higher reduction in the longer run. Similar effects have been reported for increased fuel efficiency and lower vehicle ownership. In addition to these general studies, several studies on specific purposes such as commuting, different income groups and different cities have recently been conducted (14, 15).

It is well-known that a model can never be better than the data from which it is estimated. Therefore, it is necessary to consider the kind of data that has been used in these previous studies. In general, the data can be divided into two categories: aggregate and disaggregate data. Most studies at the country or sub-national level have used aggregate level data. This is understandable in the sense that most published data relate to that level of aggregation. However, such aggregate data do not directly reflect individual or household adaptation behaviour. At best, these data only allow the analysis of statistical associations. In contrast, disaggregate data might show such adaptation. However, previous studies have mostly used cross-sectional data, commonly based on one or two day activity-travel diaries, which inherently limits the study of dynamic effects (16), and also represents a challenge in disentangling the effects of fuel price from many other effects. The problem here is that disaggregate time-series data are quite difficult and expensive to collect.

To overcome this limitation, some researchers tried to construct pseudo-panel data by using large cross-sectional data sets from national household travel surveys to model the dynamic effects on disaggregate data (17, 18, 19). Although national travel survey data sets tend to include many respondents, it is however still hard to find sufficiently large monthly or weekly cohort samples to interpret short-term adaptation. Thus, panel data would be most suitable to model dynamic effects of transport mode choice and travel behaviour at the individual level in response to changes in fuel price. It allows tracing the same individuals over time.

Another limitation of this prior research is that few if any context variables such as weather condition, travel company, etc. that may operate on people’s car use decisions have not been taken into account. Ignoring such context effects may imply that the effects of fuel price may have been confounded with non-included context effects. Although the impact of weather conditions on transport mode choice decisions is easy to argue, and indeed several empirical studies have found adverse weather to affect trip generation, trip distribution, mode choice, route choice, departure time choice and speed choice (20, 21, 22, 23), empirical studies on the impact of fuel prices did not control for weather conditions, most likely because such data are not routinely linked to travel survey data.

Clearly, one of the most promising avenues for collecting panel data of individual activity-travel behaviour is the use of GPS surveys. GPS traces provide very precise geographic information about travel and stops. Over the last decade, the use of GPS devices for tracking individual activity-travel behaviour has been explored in a large number of studies (24, 25, 26). Although GPS traces do not directly provide information about transport mode, several algorithms and rules-of-thumb have been applied successfully to induce transport mode from primarily speed and acceleration information embedded in GPS traces (27, 28, 29). Thus, it seems that a GPS-based panel might offer unique opportunities to analyze the dynamic relationship between varying fuel prices and activity-travel behaviour. If, in addition, weather data could be collected and linked to these GPS data, a rich data set for analysis would be obtained.

Thus, to contribute to this scant literature, a GPS panel survey collecting activity-travel patterns of a sample of 126 respondents who are living in Eindhoven areas, the Netherlands is used to analyze the dynamic co-variation of fuel prices and particular aspects of activity-travel patterns. The observations span one year in total. In particular, this study aims at analyzing whether travel time by car co-varies with fluctuations in fuel price, controlling for different weather conditions and socio-demographic characteristics. Using GPS devices and a Web based prompted recall instrument, the space-time behaviour of the respondents was tracked semi-automatically. At the same time, daily fuel price data and weather data were collected from local websites in the Netherlands.

The structure of this paper is as follows. The next section gives a description of the GPS data collection, the key features of the collected data and the results of descriptive analyses. A sample selection model (30) applied in this study is presented in section 3. The results of the analyses are shown in section 4. The paper is completed by a conclusion and discussion.

2. DATA COLLECTION AND DESCRIPTIVE ANALYSIS

As discussed by many researchers, cross-sectional data inherently limit the study of dynamic effects. On the other hand, panel data are quite difficult to obtain for disaggregate analysis of individual or household travel behaviour. To further understand individual’s reactions to energy price fluctuations, activity diary data were collected because they describe behaviour on all relevant facets. To reduce respondent burden and improve data quality, paper-and-pencil questionnaires have been replaced with Internet-based computer-assisted survey instruments (31, 32). However, it has been argued that no sufficiently large panel data set about individual’s activity travel patterns recorded for a substantial number of weeks exists, most likely because it was deemed impossible as respondent burden is too high. It is one of the main reasons hampering further study of dynamics in activity-travel patterns, both endogenously or in response to exogenous change. Recent technological progress such as GPS trackers may reduce that burden substantially.

The data collection used for this study combines GPS logs, dedicated algorithms and data fusion methods to infer or impute information about travel characteristics (33). Because none of these approaches is error-free, the best result can be obtained by combining these technologies. Respondents were invited to check the enhanced GPS traces, respond to queries about possible inconsistencies and provide any missing information through a Web application. The Web-based questionnaire system developed by and for our group was used to program the survey, which included two parts. The first part concerned a set of questions related to personal and household characteristics including age, gender, household composition, net-income, etc. More than 12 socio-demographic variables were included in the questionnaire. The second part of the survey consists of a semi-automatic imputation of GPS traces, complemented with a Web-based prompted recall survey instrument (27, 28). This system was used to collect activity-travel data across a full year. The survey is expected to include around 500 participants from the Eindhoven and Rotterdam areas, the Netherlands. The data used in this paper is based on four waves of the survey in the Eindhoven area. In total, 126 valid respondents who participated in from 1 week to three months unequally of the experiment were selected for this analysis. The 126 respondents participated in different time periods and duration. The shortest duration is 1 week and the longest duration is 3 months. There are 19% respondents participated in this experiment for around 2 weeks, while, 18% participated in from 2 weeks to 1 month. The majority of the respondents (63%) participated in this GPS experiment for over 1 month. Respondents were provided with user accounts and a specific password for system login to upload their data to the website via Internet around twice per week. Respondents were invited to upload multi-day GPS traces. Their data were processed immediately to impute daily activity-travel diaries (transportation modes, activity episodes and other facets of activity-travel patterns) using Bayesian Belief network. Next, respondents were invited to check the data for accuracy and consistency, and provide any missing information such as activity type, travel purposes, parking fee, trip cost etc. Respondents were allowed to change, remove and merge the imputed data, and add new activity/travel data. Both the originally uploaded and validated data were automatically saved in the database. The system differentiates between transport modes (walking, running, bike, motor-bike, bus, car, taxi, train, metro and tram). It imputes activities according to 13 kinds of activities: home, paid work, voluntary work, study, daily shopping, non-daily shopping, service, bring and pick up, leisure, recreation, social, parent-children help and unspecified. In total, 5326 days of travel diary data are available for analysis. The travel diary data span a full year from May, 2012 to May, 2013.

2.1 Socio – demographic data descriptive analysis

Table 1 presents the socio-demographic variables collected in the first part of the survey. The characteristics of the respondents are summarized in Figure 1. The share of male and female respondents is fifty/fifty. Consistent with previous web-based studies, the age distribution of this sample shows the dominance of the young to middle-aged group and the relatively highly educated groups in the sample. The majority of respondents is Dutch. According to the Dutch National Travel Survey, the low-income group represents around 33% of the whole population. The GPS data set thus over-samples the population of middle and high-income group. For other socio-demographic variables, this data set is consistent with the distribution of the Dutch population.

TABLE 1 Socio-demographic Variables

Variables	Name	Description	Type
	Gender	Gender	Binary: 0-woman/1-man
	Age	Age	continuous
	Education level	Education in three levels	Ordinal: low; middle; high
Personal and household	Work status	Situation of working	Nominal (5 levels)
	Net-income	Personal net-income per month in three levels	Ordinal: low; middle; high
	Status	living situation	Nominal (5 levels)
	Household size	Number of people in the household	continuous
	No. of children	Number of children under 18	continuous
	Work status of partner	Work situation of partner	Nominal (6 levels)
	Car ownership	Whether they own a car	Binary: 0-no/1-yes
Transport mode property	Driving license	Whether they have a drive license	Binary: 0-no/1-yes
	Fuel type	Fuel type of the car	Nominal (4 levels)
	Bike ownership	Whether they own a bike	Binary: 0-no/1-yes
	Motorbike ownership	Whether they own a motorbike	Binary: 0-no/1-yes

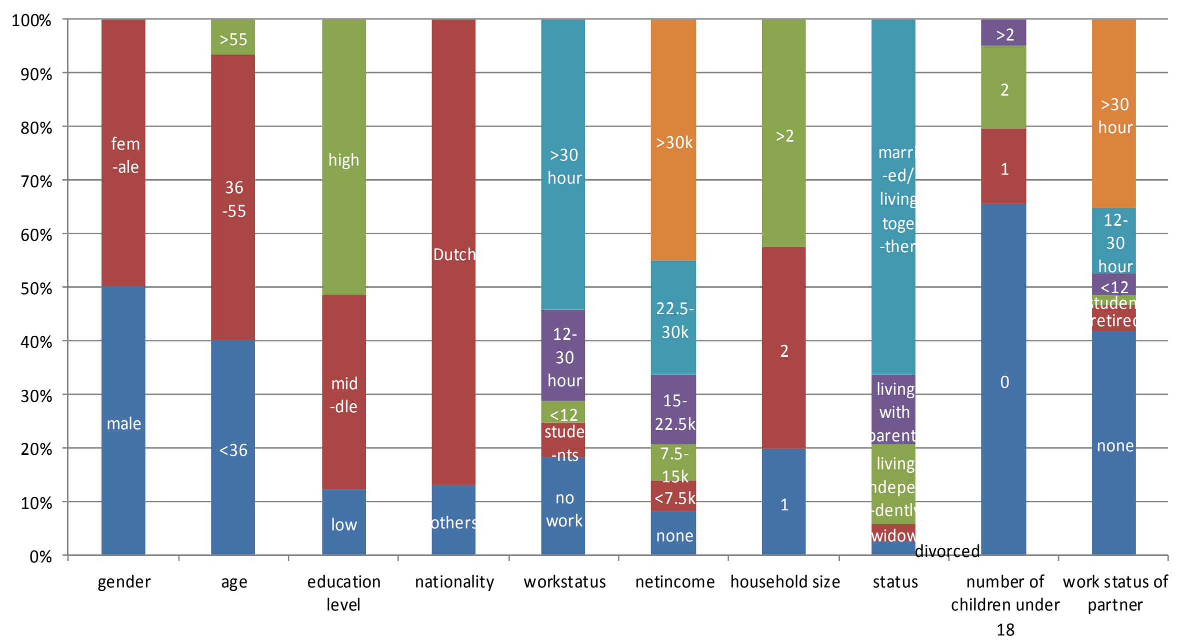

FIGURE 1 Sample Composition.

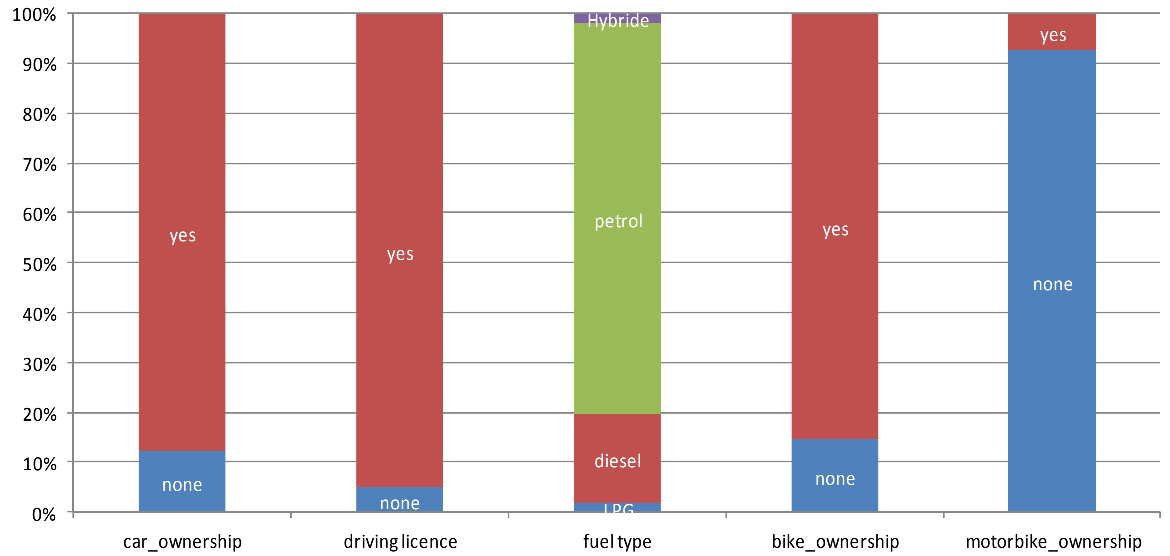

FIGURE 2 The Distribution of Transport Modes in the Sample.

Figure 2 shows the distribution of transport modes in the sample. The majority of respondents have a driver's licence and at least one car in their household. A large percentage of respondents have at least one bike (85%). A relatively small percentage has a motorbike in their household. The motorbikes operate on gasoline. The same applies for the cars.

2.2 GPS data descriptive analysis

Before estimating the model, we first explored the GPS data to better understand the general characteristics of the activity-travel patterns and examined the accuracy of the data for estimation. The explorative analysis helped us to judge the reliability of the data set. Figure 3 shows the average duration of out-of-home activities and how many days in total these activities were conducted across respondents. Overall, the duration seems reasonable for each activity type, except study and bring/pick up and service which are a slightly higher due to the relatively smaller number in the sample. The unspecified activity is due to missing information, checking mistakes or unwillingness to reveal information. It amounts to around 5 hours per day, which is relatively high. It should be noticed that although GPS devices record real geographic information, this is insufficient to reveal activity information.

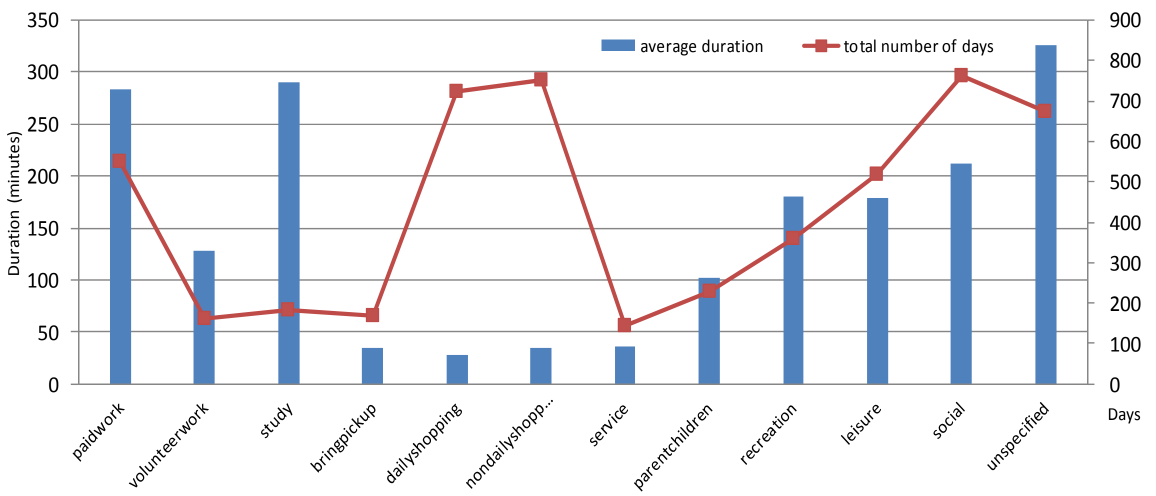

FIGURE 3 Average Duration for Out-of-Home Activities.

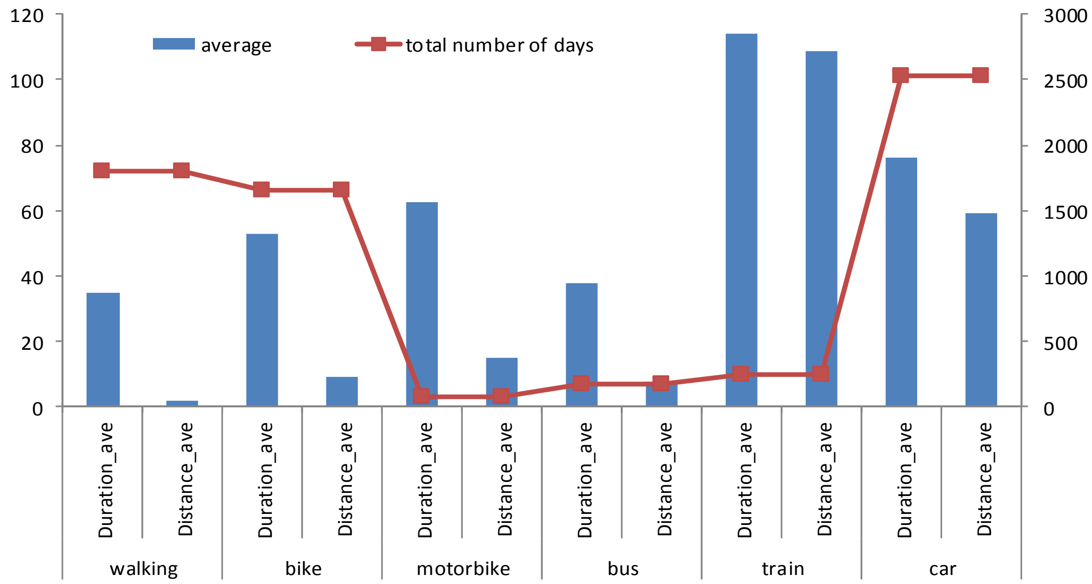

FIGURE 4 Travel Duration and Distance by Different Transport Modes.

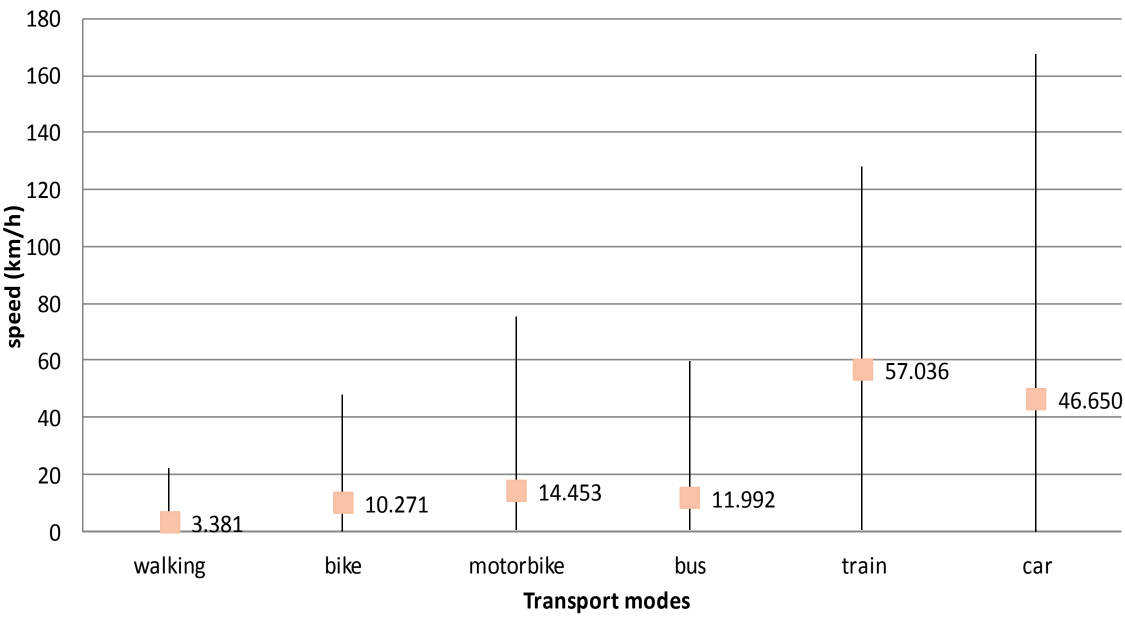

FIGURE 5 Travel Speed for Different Transport Modes.

Figures 4 and 5 show the average travel duration, travel distance and speed for different transport modes. Figure 4 indicates that walking, bike and car are three dominant transport modes in the data set. Figure 5 portrays the lowest and highest travel-speed (line) and average travel speed (square). The average travel speeds are reasonable for all transportation modes compared with the Dutch Travel Survey (MON) 2009 (34). However, the lowest travel-speeds of motorbike, bus, train and car are lower than expected, which may be due to inaccuracies in travel distance calculations.

2.3 Weather conditions and fuel price fluctuation

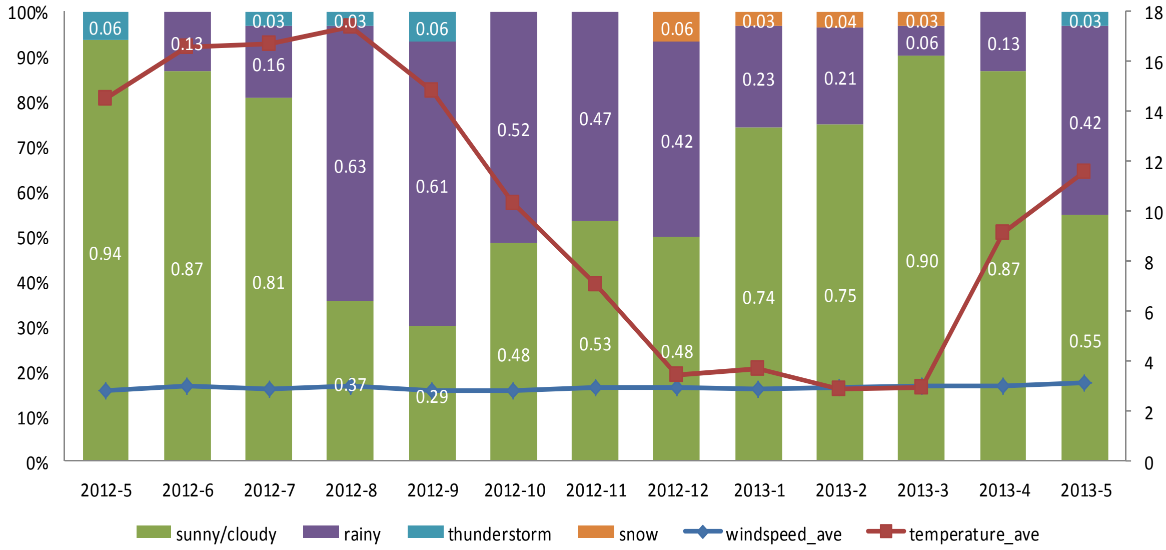

FIGURE 6 Fluctuation of Weather Conditions in the Netherlands.

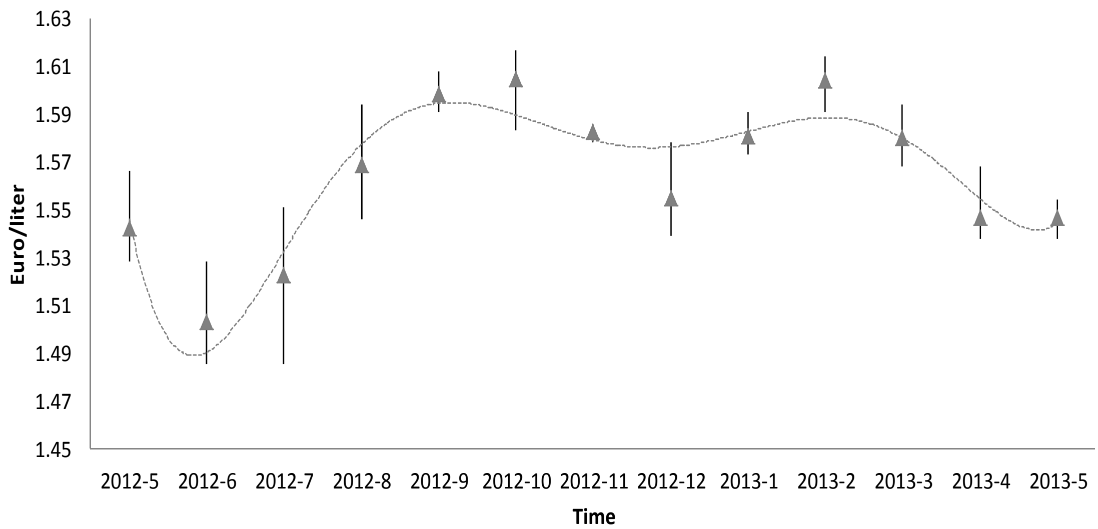

FIGURE 7 Fluctuation of Average Fuel Price in the Netherlands.

We collected daily predicted and real-time weather data for the Eindhoven area. Differences between these two datasets are small. The main difference is that the real-time weather data include details for every 5 minutes. Figure 6 presents predicted weather conditions from May, 2012 to May, 2013 by month. The bar chart shows the percentage of four different predicted weather types in each month. The red line shows the fluctuation in average temperature, while the blue line shows the average wind speed over the year. It shows many rainy days between August and December, 2012. The daily average temperature fluctuated between 3 to 18 degrees Celsius.

Daily fuel price data were retrieved from a Dutch local TINQ website (http://www.tinq.nl/), which provides detailed information for different gasoline types. These data were fused with the GPS data. Figure 7 displays the general fluctuation in fuel price between May, 2012 and May, 2013. The line shows the highest and lowest average fuel price (including LPG, diesel and petrol) for each month and the triangle indicates the average price on that month. The dashed trend line suggests that there is a relatively big price increase from June, 2012 to September, 2012. Later on, the price seems relatively stable until March, 2013.

3. SAMPLE SECLECTION MODEL ON PANEL DATA

Considering the panel dataset at hand and the formulated research question, sample selection models were selected to investigate the effects of weather conditions, socio-demographic variables and fuel price on individual's travel behaviour by car. The sample selection model procedure allow us to examine the two steps of car using decisions in a single model and estimating the effects of exogenous conditions on individual's car use behaviour.

Basically, the choice of sample selection models is motivated by two main reasons. First, the panel data included each individual's activity-travel data unequally for over one week to three months. These data capture individual's regular and non-regular activity-travel behaviour. According to our data, we found that each individual does not use car every day. The data allows exploring the reasons for choosing car as transport mode for certain trips for each individual. Thus it is better to distinguish the two steps involved in individual's car use decisions, whether or not to use the car and the distance of driving the car. Based on the assumption that each individual's car use behaviour is influenced by both endogenous and exogenous factors, there are two steps in the decision to use the car: 1) whether to use the car on a certain day and 2) how far to travel by car. The sample selection model allows examining these two steps in a single model. Assuming each individual may conduct activities regularly for a short period (less than 3 months), we can capture the effects of fuel price on both transport mode choice (using car on a certain day or not) and activity location choice (VMT) with this GPS panel data. Secondly, a bivariate classic regression model is applied to the sample selection equations. If the data are randomly sampled from this bivariate population, the parameters can be estimated by least squares or GLS combining the two equations. In our research question, we assumed that the decision of using the car on a certain day for each individual is not a random selection. Each individual's car using behaviour is influenced by several exogenous factors, such as the days of the week, type of activities conducted on a certain day, predicted weather conditions, and lagged fuel price. Thus, there may be several potential biases if this general selectivity problem of choosing car as a transport mode is ignored. The sample selection model can explicitly resolve the potential sample selection bias.

Sample selection models for cross-sectional data have been intensively explored in social science research. Most studies are based on Heckman's two-step estimation approach which is based on the method of moments. This two-step approach, however, does not provide a sufficient solution for panel data estimation. The literature on panel data models for sample selection models is rather incomplete and ambiguous. Applications are relatively sparse, and few useable general modelling frameworks have been proposed. The earliest contribution appears to be Hausman and Wise's (35) paper on attrition. The Hausman and Wise's (36) model is a two-period fully parametric model. Green (37) suggested a maximum likelihood estimator as a substitution of the two-step method, which can, under appropriate distributional assumptions, provide consistent estimators. For solving the problem at hand, we used random effects sample selection models (38, 39, 40) to capture the time variations of individuals in simple shifts of the regression function. Simulated maximum likelihood rather than two-step least squares is used to fit the model.

The basic structure equations for the sample selection model are a linear regression with a binary probit selection criterion model as shown in equations (1) to (3):

$$y = \beta' x + \varepsilon \tag{1}$$
$$z = \alpha' w + u \tag{2}$$
$$\varepsilon, u \sim N[0,0,\sigma_\epsilon^2, \sigma_u^2, \rho] \tag{3}$$

Values of y and x are only observed when z equals to one. The essential feature of the model is that under the sampling rule, E[y|x,z=1] is not a linear regression in x, or x and z. The development below presents estimators for the class of essentially nonlinear models that emerge from this specification. To extend the basic model for panel data estimation, the random effects, (c_i, d_i) are assumed to be bivariate normally distributed with zero means, standard deviations σ_c and σ_d and correlation θ. The random effects regression model of the panel data is equation (4).

$$y_{it} = \beta' x_{it} + \varepsilon_{it} + c_i, \varepsilon_{it} \sim N[0, \delta^2] \tag{4}$$

The selection mechanism is shown in equations (5) and (6).

$$z_{it}^* = \alpha' w_{it} + u_{it} + d_i \tag{5}$$

$$z_{it} = 1\ (z_{it}^* > 0), u_{it} \sim N[0,1] \tag{6}$$

The correlation between $\varepsilon_{it}\ and\ u_{it}$ is ρ as $Corr[\varepsilon_{it}, u_{it}] = \rho$. Selectivity comes in two forms here, which is the correlation of the unique components ε_{it} and u_{it}, and the correlation of the group specific components, c_i and d_i. The parameters of $\beta'$and α' will be estimated in the model.

4. ANALYSIS AND MODELING RESULTS

In this section, we describe the estimated models and report the results. The first step is to estimate the probit model to define the selection mechanism. Next, the random effects model is estimated using 100 Halton draws. Final results are shown in Table 2. The dependent variable is daily travel distance by car. Results show that McFadden Pseudo R-squared is high with a value of around 0.97. It suggests a significant improvement over the intercept model offered by the full model.

The first stage probit regression analysis evaluates the effects of lagged fuel price, days of the week, weather conditions and substituted transport mode on the car use decision of individuals. It is more reasonable to assume that the lagged fuel price have effects on individual's decision of using the car instead of the current fuel price. There are mainly two reasons why we included lagged fuel price effects instead of current fuel price. In general, consumers' car using behavior is influenced by the price they paid and the price they expect in the future. For the price they paid, they could change their current car use behavior to reduce the consumption if the price was high. For the expected price when they have to refill the car, they may adapt their current behavior to save energy. However, there is no information of when car users refill their cars. We assume that consumers predicted future fuel prices according to the trend of past fuel prices. Therefore, we estimated the effects of 1 to 4 weeks lagged fuel prices on individual's car driving behaviour and present the most significant results.

Table 2 presents the results of this first-step probit regression estimation. The results proved that 3 weeks lagged fuel price has significant negative effects on individuals' decisions to use the car. The estimated coefficients of most explanatory variables have the expected sign and are statistically significant. As expected, car use differs for different days of the week. It is relatively high on Tuesday. However, Monday has significant negative effects on the car use decision. The results suggest that respondents are less likely to drive on Monday. To investigate the reason behind this finding, MON data (2004-2009) was used to compare the percentage of car users among different days of the week. The results indicate that our finding is basically consistent with MON data. There may be many reasons why people are less likely to use their car on Monday. For example, part-time workers usually choose Monday and/or Friday as non-work days. Most social and leisure activities are conducted during weekends, which reduces the probability of conducting these activities again on Monday.

Furthermore, weather conditions especially wind speed and average temperature has a significant influence on the decision to use the car on a specific day. The wind speed is positively related to the probability of using the car. Empirical evidence indicates that individual use the car more often in cold temperatures than in warm temperatures. Moreover, we tested for any substitution between bike and car. The result shows that bike ownership has significant negative effects on people's decision of using the car, which indicates that the bike may be a substitute transport mode for the car in the Netherlands.

TABLE 2 Results of the Sample Selection Model

Variables	Coefficient	Standard Error	z	Prob.|z|>Z*
selection corrected regression parameters				
Fuel price 2 weeks ago	-8.29685*	4.7107	-1.76	0.0782
Travel distance with slow modes	-1.10754***	0.1962	-5.65	0.0000
Conducted leisure activity or not	11.3081***	1.5796	7.16	0.0000
Gender	19.58430***	1.5998	12.24	0.0000
Age	0.03325***	0.0089	3.76	0.0002
Education_low	7.74272***	1.9712	3.93	0.0001
Income_low	-13.7677***	2.3619	-5.83	0.0000
Number of children	26.3138***	0.8820	29.83	0.0000
Average temperature	-0.48906	0.3381	-1.45	0.1480
Season	-4.28163	4.0775	-1.05	0.2937
Selection equation parameters				
Monday	-0.18398***	0.0442	-4.16	0.0000
Tuesday	0.17364***	0.0582	2.98	0.0029
Wednesday	0.04390	0.0488	0.90	0.3678
Thursday	0.03550	0.0459	0.77	0.4388
Friday	0.07613	0.0508	1.50	0.1338
Saturday	0.09987	0.0634	1.57	0.1153
Sunny	0.01976	0.0907	0.22	0.8274
Rainy	0.01065	0.0884	0.12	0.9042
Average temperature	-0.02675***	0.0022	-12.19	0.0000
Wind speed	0.09258***	0.0354	2.62	0.0089
Bike ownership	-0.16509***	0.0418	-3.95	0.0001
Fuel price 3 weeks ago	-0.48970***	0.0894	-5.48	0.0000
Means for random parameters				
One_Regr	11.3172	9.79545	1.16	0.2479
One_Prbt	0.32367	0.21275	1.52	0.1282
Diagonal elements of Cholesky matrix				
sOne_Regr	30.3973***	1.43203	21.23	0.0000
sOne_Prb	0.53575***	0.01193	44.89	0.0000
Below diagonal elements of Cholesky matrix				
RegrPrbt	6.67990***	1.33481	5.00	0.0000
Disturbance standard deviation				
Sigma	0.01481	0.24926	0.06	0.9526
Correlation between regression and probit				
Rho	0.94688***	0.0036	263	00.0000

Note: *** Significance at 1% level, ** Significance at 5% level, * Significance at 10% level.

Table 2 – selection corrected regression parameters - shows the final results of the random effects model. In order to avoid serial correlation, we tested different weeks lagged fuel price variables separately and provide the most reasonable results in Table 2. The most important finding is that 2 weeks lagged fuel price has a significant negative effect on vehicle miles travelled by car. Results suggest that around 1 euro increase in fuel price equals a reduction of around 8 km of car travel distance per day on average. Looking at the effects of slow modes, the significant negative

effects of around 1.1 indicate travel distance by slow modes and the travel distance by car are almost equally substitutable. Moreover, there is a significant positive relationship between leisure activities and travel distance by car. The results indicate that if the person conducts a leisure activity, he/she will travel around 11.3 km more by car per day.

As for the effects of socio-demographic variables, results indicate that males travel longer distances by car. Moreover, with increasing age and number of children, travel distance by car is also increased. People with lower education levels travel longer distance by car, but lower income people travel less distance by car. These results are consistent with the findings of MON data. For season and temperature, the results did not show any significant effects.

The random parameters capture temporal variations across individuals in simple shifts of the regression function, such as changes in the intercepts. The random effects are assumed to be bivariate normally distributed with zero means. The results show that the means values are not significantly different with 0. Standard deviations of random parameters are 30.3973 and 6.70135 with a strong correlation of 0.9968, which is very high. It means that any component of the error that makes selection more likely increases VMT. However, errors are tied up with model specification, alternative specifications change the errors, which in turn changes rho. Moreover, the correlation is intrinsic to the model. Thus, whatever the cause of the correlation between ε_{it} and u_{it} it is inherently un-measurable.

5. CONCLUSION AND DISCUSSION

The study examined the effects of fuel price on individual’s car travel behaviour using GPS panel data. Using a sample selection panel data model, we studied two questions: 1) the effects of fuel price on individual’s transport mode choice based on a day; 2) the effects of fuel price on individual’s travel distance or activity location choice. Moreover, we estimated the effects of weather and days of the week on people’s decision to drive the car. The results show that people are less likely to drive on Monday, but more likely to drive on Tuesday. Moreover, they have a lower probability to use a car on high temperature days and low wind speed days. Furthermore, lagged fuel price influences both people’s decision of using the car and travel distance by car. In this study, we tried to pick up the covariance on the week lagged information and considered the effects of time lags. The results indicate that individuals’ reactions to price changes depend on time. Individual’s decision of using the car or not significantly be influenced by 3 weeks lagged fuel price, while, the more recently fuel price (2 weeks lagged fuel price) has significant negative effects on people’s decision of vehicle miles travelled.

Although this study offers some interesting findings, there are some limitations that need to be addressed in future research. The GPS data is not error free. The input data is subject to uncertainty and the effects on model estimations results should be further explored. Another limitation is the relatively small sample size. Future publications based on a larger sample will allow activity-specific analysis of the effects of fuel price fluctuation on activity-travel patterns.

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