"The Determinants of Urban Households' Transport Decisions: A Microeconometric Study using Irish Data"

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Abstract

This paper uses Irish micro-data to analyse the determinants of urban households' transport decisions by estimating elasticities of demand for car ownership, car use and public transport with respect to income and various household socio-demographic characteristics. This paper uses expenditure data to examine car and public transport use and analyses the latter decision for separate samples of households, namely, those owning one car and those owning no car. A binary probit model is estimated for the car ownership decision, while for the car use and public transport expenditure decisions, Tobit models adjusted for heteroscedastic and non-normal errors are estimated.

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1 Introduction

This paper addresses a number of aspects of urban households' transport decisions by using Irish cross-sectional micro-data to analyse the socio-economic determinants of the demand for car ownership, car use and public transport in the capital city, Dublin. The importance of income and socio-demographic factors in influencing household transport choices has been well documented and studied using cross-sectional data from a variety of sources. While there are numerous studies examining the issue of car ownership at both an aggregated and disaggregated level, few studies have examined the related issues of car and public transport use using expenditure micro-data. In this paper, the analysis of the car ownership decision complements, and adds to, existing literature in the area. A new approach to the analysis of urban car and public transport use is presented through the use of expenditure data. In the case of the public transport decision, the division of the sample into households owning no car and one car helps to highlight the differences between these two groups in their public transport decisions. In addition, the examination of the determinants of taxi fare expenditure as well as bus fare expenditure emphasises the importance of analysing the different components of public transport expenditure separately. Finally, the estimation of these relationships indicates whether the factors influencing the transport decisions of households in the Dublin area are any different to those found for other countries.

The data employed in this study are micro-data from the 1994/1995 Irish Household Budget Survey (HBS), which are the latest data available. A binary probit model is estimated for the car ownership decision. For those households which report ownership of one car, we use a Tobit model to examine car use, which is proxied by petrol expenditure. In analysing public transport expenditure decisions, Tobit models of expenditure on bus and taxi fares are estimated for those households owning no car and those households owning one car. Where relevant, adjustments are made to the models to account for heteroscedastic and non-normal errors.

Section 2 summarises related literature and details the econometric methodologies employed, while Section 3 describes the data used in this analysis. Section 4 presents econometric results for all models and outlines practical aspects of the estimation including the interpretation of the estimated coefficients. Section 5 contains some concluding remarks.

2 Relevant Literature and Econometric Methodologies

2.1 Car Ownership

Earlier studies of the demand for car ownership using cross-sectional data at an aggregated level include those by Button *et al* (1993), Said (1992), Stanovnik (1990), McCarthy (1977), Buxton and Rhys (1972) and Fairhurst (1965). While providing some insight into the general relationships between car ownership and variables such as population density and average incomes at regional or country level, the nature of the data limits the number and type of independent variables that can be considered.[1] In addition, many of the above studies are now outdated and the studies of Button *et al* (1993) and Stanovnik (1990) relate to low-income countries, thus limiting the applicability of the results to Ireland, and in particular to Dublin.

The increasing availability of micro-data in recent years has enabled researchers to overcome many of the problems inherent in aggregated data. It has allowed the formulation of more

[1] A particular problem associated with aggregated data is that if a variable varies more within a region than it does between regions, the true effect of the variable will be difficult to determine (Fairhurst, 1965).

accurate models of car ownership at an individual or household level employing a wider range of socio-economic characteristics as independent variables [see Alperovich *et al* (1999), Dargay and Vythoulkas (1999), Cragg and Uhler (1970) and Bennett (1967)]. The discrete nature of the car ownership decision means that discrete choice econometric methodologies, such as binary and multinomial probit and logit, are often employed in modelling demand [see Alperovich *et al* (1999), Stanovnik (1990) and Cragg and Uhler (1970)]. Recently, the demand for car ownership at the micro-level has also been analysed in the context of other transport decisions such as car use and modal choice using the nested multinomial logit technique [see De Palma and Rochat (2000), Bjorner (1999), Thobani (1984), Train (1980) and Ben-Akiva and Lerman (1975)].

Income is the most consistently important household socio-economic factor found to have a positive relationship with car ownership. However, some studies find that the relationship between income and car ownership is non-linear [Cragg and Uhler (1970)] while others find that income elasticities of car ownership decline in magnitude as income increases [Dargay and Vythoulkas (1999)]. These results suggest that the effect of income on household car ownership is not constant, with the effect being more pronounced at lower income levels. Other variables found to have a significant effect on car ownership include general household characteristics such as the number of adults, children and workers in the household and household location. Head of household (HOH) characteristics such as gender, age, education and occupation are also commonly employed. The results for age of HOH often conflict. Alperovich *et al* (1999) and Bennett (1967) find that the probability of car ownership, while initially increasing, declines once the HOH reaches 40 years and retirement age respectively, while Cragg and Uhler (1970) find that as the age of the HOH increases, the probability of car ownership decreases.

In modelling the demand for car ownership, we use a binary probit model as applied by Alperovich *et al* (1999) and Stanovnik (1990). The binary probit model is employed in situations where the dichotomous dependent variable indicates the choice between two alternatives (e.g. to own a car or not).[2] It is characterised by a continuous latent variable y_i^*, different values of which determine the observed value of the dependent variable y_i, i.e.,

$$
\begin{aligned}
& y_i^* = x_i'\beta + \varepsilon_i , \qquad \varepsilon_i \sim NID(0,1) \\
& \text{and} \\
& y_i = 0 \quad \text{if} \quad y_i^* \leq 0 \\
& y_i = 1 \quad \text{if} \quad y_i^* > 0
\end{aligned}
\qquad (1)
$$

The model is estimated by means of the maximum likelihood method of estimation where the following log-likelihood function is maximised with respect to each of the estimated coefficients:

$$In\, L = \sum_{y_{i=0}} In\,[1 - \Phi(x_i'\beta)] + \sum_{y_{i=1}} In\,\Phi(x_i'\beta) \qquad (2)$$

where Φ is the cumulative standard normal distribution function. A common feature of many binary choice models is that the error terms are heteroscedastic, in which case the estimated coefficients are inconsistent. By allowing the error terms to vary across observations, this problem can be overcome. Heteroscedasticity of the following form is assumed [Greene (1997)]:

$$\sigma_i = \sigma\, exp\left(z_i'h \right) \qquad (3)$$

where z_i is a vector of continuous independent variables assumed to cause the heteroscedasticity. A likelihood ratio test is undertaken to test the null hypothesis of homoscedastic errors ($h=0$).[3]

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[2] The issue of multiple car ownership (for example, using a multinomial logit model) is not considered here due to the small number of observations owning two or more cars (see footnote twelve below).

[3] The test statistic is distributed as χ^2 with the number of degrees of freedom equal to the number of variables included in z_i. The likelihood ratio test of homoscedastic errors is not rejected (see Section 4 and Table 4.1) and so the log-likelihood function adjusted to take account of heteroscedasticity is not presented

2.2 Car Use and Public Transport Expenditure

In contrast to the large number of studies analysing car ownership at both an aggregated and disaggregated level, fewer studies have examined the related issues of car and public transport use. In terms of car use, a common approach is to analyse the decision simultaneously with the car ownership decision. For example, both Bjorner (1999) and Mannering and Winston (1985) use data at the household level to estimate nested multinomial logit models of the joint demand for car ownership and use.[4] Button *et al* (1993) and Mannering (1983) examine car use independently by using mileage data and while the latter uses household level data, the former study uses country level data for a sample of low-income countries. Studies examining petrol expenditures include those by Kayser (2000) and Labeaga and Lopez (1997) who both utilise household micro-data, albeit applying differing econometric methodologies.[5]

The majority of studies analysing public transport demand use specially constructed transport surveys that seek to determine the factors influencing modal choice decisions, in particular for the journey to work. There are two main econometric methodologies employed to model these decisions. Firstly, binary and multinomial probit and logit models analyse the determinants of an individual's decision to travel by a number of alternative modes of transport [see Ben-Akiva and Lerman (1975) and De Donnea (1971) for applications to the journey to work decision]. Secondly, nested multinomial logit models simultaneously examine the two decisions of car ownership and mode of transport. De Palma and Rochat (2000), Thobani (1984) and Train (1980) all use either individual or household level data to determine the factors influencing car

[4] The use of the nested multinomial logit econometric methodology requires the existence of alternative specific characteristics that do not vary across observations, such as fuel costs in the context of car use or journey time in the context of modal choice. Irish Household Budget Survey data provide no such variables.

[5] Kayser (2000) uses the Heckman Sample Selection methodology while Labeaga and Lopez (1997) use an AIDS model.

ownership level and mode of transport to work. To date, little research has been undertaken using expenditure on public transport as a proxy for public transport demand. Exceptions are Bergantino (1997) and Ming-Chu (1994), who use household expenditure micro-data to estimate transport Engel curves and the demand for recreational travel respectively.

Similar independent variables to those used in explaining variations in car ownership levels are employed in determining the socio-economic influences on car and public transport use. A significant finding in many of the car use studies above is the low positive income elasticity of car use; one study [Mannering and Winston (1985)] also shows that the income elasticity is smaller in the later time periods. Kayser (2000) and Labeaga and Lopez (1997) similarly report that petrol may be classified as a necessity due to its income elasticity of demand being less than unity. Both Bjorner (1999) and Mannering (1983) find that the age of the HOH has a consistently negative effect on car use, a finding that is different to the positive, but declining effect of the age of the HOH on car ownership found by Alperovich *et al* (1999) and Bennett (1967). In terms of public transport use, De Palma and Rochat (2000) find that households in which the household size is large and the HOH is older than 50 years are significantly more likely to use public transport rather than the car for the journey to work.

The econometric methodology employed in this paper to examine household car and public transport use follows most closely the approach of Ming-Chu (1994) and other studies which use Tobit models to estimate the demand for various commodities based on micro-data [see Cai (1999), Gould and Kim (1998), Yen *et al* (1996), Hamilton Lankford and Wyckoff (1991) and

Bennett (1967)[6]]. The Tobit model is used in situations where the dependent variable is censored, i.e., values in a certain range are all reported as a single value, usually zero. It is widely employed in modelling cross-sectional expenditure decisions in which a large proportion of respondents report zero expenditure. In common with the binary probit model considered above, it also assumes the existence of a continuous latent variable y_i*, the values of which determine the actual value of the observed limited dependent variable y_i, i.e.,

$$
\begin{aligned}
&y_i^* = x_i'\beta + \varepsilon_i , \qquad \varepsilon_i \sim NID(0, \sigma^2) \\
&and \\
&y_i = 0 \quad if \quad y_i^* \le 0, \\
&y_i > 0 \quad if \quad y_i^* > 0
\end{aligned}
\tag{4}
$$

The continuous latent variable is assumed to represent desired expenditure, thus allowing for negative desired expenditure. All negative and zero values of desired expenditure are transformed to a single value of zero for observed expenditure. The Tobit model therefore assumes that zero observations are due to corner solutions[7], i.e. if relative prices or income changes, expenditure occurs. The model is estimated by maximum likelihood estimation whereby the following log-likelihood function is maximised with respect to each of the estimated coefficients:

[6] Cai (1999), Gould and Kim (1998), Hamilton Lankford and Wyckoff (1991) and Bennett (1967) all use the Tobit methodology to estimate the demand for food, dairy products, charitable donations and cars respectively. While Cai (1999), Hamilton Lankford and Wykcoff (1991) and Bennett (1967) use expenditure data, Gould and Kim (1998) use quantity data. Yen *et al* (1996) analyses the concentration of nitrate in American water supplies using quantity data.

[7] The validity of assuming that this is the correct process determining zero values of expenditure is often questioned. Alternative sources of zero expenditures including infrequency of purchase and non-participation in the market are ignored in the Tobit model. In addition, the Tobit model does not consider that there may be a difference between the effect of a variable on the participation decision and the effect of that variable on the consumption decision, e.g. the effect of children on the probability of going on holiday is negative but once expenditure takes place, the effect of children on expenditure is positive [Verbeek (2000)]. An alternative to the Tobit model is the Double Hurdle model, originally formulated by Cragg (1971), which allows for corner solutions as well as non-participation in the market. The double hurdle model is not considered here.

$$In\, L = \sum_{y_i=0} In\left[1-\Phi\left(\frac{x_i'\beta}{\sigma}\right)\right] + \sum_{y_i>0}\left[-In\,\sigma + In\,\phi\left(\frac{y_i - x_i'\beta}{\sigma}\right)\right] \qquad (5)$$

where Φ and ϕ are the cumulative standard normal distribution and standard normal probability density functions respectively.

The estimated Tobit coefficients are also sensitive to the distributional assumptions that are made about the error term. If the error terms are heteroscedastic and/or non-normal, the coefficient estimates are inconsistent.[8] Heteroscedasticity of the same form as in the binary probit model is assumed. To adjust for non-normality, an inverse hyperbolic sine (IHS) transformation is applied to the dependent variable as follows:

$$y_i\,(\theta) = log[\theta\, y_i + (\theta^2 y_i^{\,2} + 1)^{1/2}]\,/\,\theta \qquad (6)$$

where θ is a parameter estimated by the model [Yen *et al* (1996) and Reynolds and Shonkwiler (1991)]. This transformation overcomes the problem of non-normality caused by the presence of outliers by behaving logarithmically for large values of the dependent variable [Reynolds and Shonkwiler (1991)]. Likelihood ratio tests are undertaken to test the null hypotheses of a homoscedastic error structure, a normal error structure and the joint null hypothesis of a homoscedastic and normal error structure respectively.[9] The log-likelihood function incorporating the adjustments for heteroscedastic and non-normal errors is:

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8 See papers by Reynolds and Shonkwiler (1991), Arabmazar and Schmidt (1982) and Nelson (1981).

9 The test statistics are distributed as χ^2 with the number of degrees of freedom equal to the number of variables included in the heteroscedasticity function and/or the IHS parameter. The likelihood ratio test of a heteroscedastic and non-normal error structure is not rejected for all five Tobit regressions and performs the best of all the likelihood ratio tests. Therefore, the log-likelihood functions adjusted for heteroscedasticity and for non-normality separately are not presented.

$$In\,L = \sum_{y_i=0} In\left[1-\Phi\left(\frac{x_i'\beta}{\sigma_i}\right)\right] + \sum_{y_i>0}\left[In\left(1+\theta^2 y_i^2\right)^{-\frac{1}{2}} - In\,\sigma_i + In\,\phi\left(\frac{y_i(\theta)-x_i'\beta}{\sigma_i}\right)\right] \qquad (7)$$

When $\theta = 0$ and $\sigma_i = \sigma$ the log-likelihood reduces to that of the standard Tobit log-likelihood (5) presented above.

3 Data

The data employed in this analysis are micro-data from the 1994/1995 Irish Household Budget Survey (HBS).[10] The survey consists of 7,877 urban and rural (farm and non-farm) households. This study focuses on the 2,148 households in the Dublin area. Each household was asked to complete a questionnaire containing information on various household income and socio-demographic characteristics and ownership of durable goods as well as an expenditure diary recording every item of expenditure by each member of the household over a two-week survey period. Since the data are cross-sectional at a point in time, we cannot estimate price effects and thus we concentrate on the income and socio-demographic determinants of transport demand. Variable definitions are presented in Table 3.1 while summary statistics for the transport variables extracted from the survey are detailed in Table 3.2 and those for the household income and socio-demographic variables are presented in Tables 3.3 and 3.4 below.

In examining car ownership, the dependent variable is a binary variable indicating whether or not the household owns a car. For the car use decision, the dependent variable is petrol expenditure, which is adjusted for seasonality[11]. Public transport use is proxied by bus and taxi fare

[10] The 1994/1995 Irish HBS was conducted by the Central Statistics Office (CSO) between May 1994 and July 1995 and is the most current data set available.

[11] All expenditure variables are adjusted for seasonality because the HBS was conducted over a fifteen month period between May 1994 and July 1995.

expenditures separately, adjusted for seasonality and household size. Household income is proxied by total weekly household expenditure, also adjusted for household size and seasonality.

Table 3.1 Variable Definitions

Variable Name	*Definition*
Transport Variables	
CAR	=1 if the household owns one or more cars =0 otherwise
CYCLE	Number of Motorcycles
PETROLEXP	Petrol Expenditure
BUSEXP	Bus Fare Expenditure
TAXIEXP	Taxi Fare Expenditure
FREETRAV	Number entitled to free pension/school travel
EXPENSES	=1 if the household receives motor expenses =0 otherwise
Continuous Household Income and Socio-Demographic Variables	
HHEXP	Total Weekly Household Expenditure (divided by 100)
ADULTS	Number of Adults 18+ years
CHILDREN	Number of Children aged 17 years and younger
Discrete Household Socio-Demographic Variables	
Accommodation Type	
APART, SEMI	APART=1 if the household lives in an apartment or bedsit, =0 otherwise SEMI=1 if the household lives in a semi-detached house, =0 othereise *(Base Category = household lives in a detached house)*
Household Working Status	
WORKING	=1 if at least one household member 15+ years at work =0 otherwise
Gender of HOH	
FEMALE	=1 if household is headed by a female who is the only adult in the household =0 otherwise
Age of HOH	
SIXTY, FIFTY, FORTY, THIRTY	SIXTY =1 if the HOH is 60+ years, =0 otherwise FIFTY =1 if the HOH is 50-59 years, 0 otherwise FORTY=1 if the HOH is 40-49 years, 0 otherwise THIRTY=1 if the HOH is 30-39 years, 0 otherwise *(Base Category = HOH is aged 20-29 years)*
Highest Education Level of HOH	
PRIMARY, SECONDARY	PRIMARY=1 if the HOH has a primary school education only, =0 otherwise SECONDARY=1 if the HOH has a secondary school education only, =0 otherwise *(Base Category = HOH has a third level education)*

The HBS does not record information relating to distance travelled to work, distance from city centre, public transport availability etc. and so the type of household accommodation is used, albeit imperfectly, to proxy these factors. This assumes that those living in detached houses are more likely to live in outlying areas of Dublin and thus have longer distances to travel to the city centre and/or poorer public transport links than those living in semi-detached houses or apartments. A complicating issue for the bus fare expenditure models is the fact that all pensioners are entitled to free public transport at off-peak times in Ireland. This means that in the case of pensioners one of the most important assumptions of the analysis is violated, i.e., that public transport use is reflected in public transport expenditure in the survey. To overcome this problem, a dummy independent variable indicating that there is at least one person in the household entitled to free public transport is included. Similarly, for the car and public transport use regressions for car-owning households, a dummy variable indicating whether at least one person in the household receives remuneration for motor expenses such as petrol is included.

An examination of the summary statistics in Tables 3.2, 3.3 and 3.4 below reveals large differences between non-car and car-owning households, in terms of their transport expenditures and their income and socio-demographic characteristics. For those households which do not own a car, expenditures per capita on bus and taxi fares are considerably higher than in car-owning households, while the proportions recording these expenditures are also higher in non car-owning households. In terms of household income and socio-demographic characteristics, significant differences between non car- and car-owning households are evident for many of the variables, especially household income, the gender and education level of the HOH and the type of accommodation and working status of the household. On the basis of these differences, and in an attempt to avoid multicollinearity, the regressions for bus and taxi fare expenditures are estimated separately for (a) households not owning a car (950 households or 44.2 per cent of the total sample), and (b) households owning one car (935 households or 43.5 per cent of the total sample).

Table 3.2 Transport Variables

	Full Sample				*No Car*				*One Car*[12]			
Variable	*Mean*	*St.Dev.*	*Max.*	*% pos*	*Mean*	*St.Dev.*	*Max.*	*% pos*	*Mean*	*St.Dev.*	*Max.*	*% pos*
CAR	0.56	0.50	1.00	55.8								
CYCLE	0.02	0.14	2.00	1.7	0.02	0.13	2.00	1.3	0.02	0.15	1.00	2.2
PETROLEXP	9.40	12.33	88.76	53.3	0.69	3.33	34.41	7.4	14.41	11.10	88.76	89.1
BUSEXP	1.66	2.79	24.32	53.7	2.22	3.45	24.32	56.3	1.26	2.06	14.17	52.21
TAXIEXP	1.09	3.41	63.14	24.4	1.36	4.32	63.14	25.1	0.90	2.60	34.98	22.5
FREETRAV	0.30	0.58	3.00	23.8	0.39	0.61	3.00	32.5	0.25	0.57	3.00	18.3
EXPENSES	0.14	0.35	1.00	14.0	0.01	0.10	1.00	1.1	0.17	0.37	1.00	16.7

Table 3.3 Household Income and Socio-Demographic Variables (Continuous)

	Full Sample				*No Car*				*One Car*			
Variable	*Mean*	*St.Dev.*	*Max.*	*% pos*	*Mean*	*St.Dev.*	*Max.*	*% pos*	*Mean*	*St.Dev.*	*Max.*	*% pos*
HHEXP	1.98	1.29	11.87	100.0	1.32	0.82	7.46	100.0	2.33	1.26	8.98	100.0
ADULTS	1.98	0.96	7.00	100.0	1.72	0.92	7.00	100.0	2.07	0.89	6.00	100.0
CHILDREN	0.96	1.32	7.00	44.1	0.82	1.34	7.00	36.3	1.03	1.32	7.00	48.0

Table 3.4 Household Socio-Demographic Variables (Discrete): Percentage of Sample in each Category

Variable	*Full Sample*	*No Car*	*One Car*
APART	19.3	35.4	7.5
SEMI	70.7	61.4	80.1
(Base=Detached)	10.0	3.2	12.4
WORKING	60.7	35.9	76.8
(Base= No household member working)	39.3	64.1	23.2
FEMALE	20.7	33.2	13.8
(Base=All other households)	79.3	66.8	86.2
SIXTY	34.4	39.5	32.2
FIFTY	15.9	11.3	17.3
FORTY	23.7	15.9	30.3
THIRTY	19.0	19.2	18.6
(Base =20-29 years)	7.0	14.1	1.6
PRIMARY	34.8	55.3	20.9
SECONDARY	42.7	32.1	53.2
(Base=Third Level Education)	22.5	12.6	25.9

[12] Due to the small number of households owning two or more cars (263 households or 12.3 per cent of the total sample) and the consequent poor fit of the regressions, only the regressions for samples owning no car and one car are reported and discussed.

4 Estimation Results

For all six regressions, the same set of independent variables is employed for comparison purposes. For all the continuous household income and socio-demographic independent variables, non-linear terms are included in the specification where they are significant[13] to account for the fact that the effect of these independent variables may differ over the range of the variables [see Alperovich *et al* (1999) and Cragg and Uhler (1970)]. All models are estimated using the LIMDEP econometric package.

Likelihood ratio tests were used to decide on the most appropriate model specification. In allowing for heteroscedasticity, only significant continuous independent variables were included in the heteroscedasticity function [Yen *et al* (1996)]. In the binary probit model, all of the independent variables in the heteroscedasticity term were insignificant, i.e., the likelihood ratio test of a homoscedastic error structure was not rejected at the one per cent level. However in all of the Tobit models, the significance of at least one continuous independent variable in the heteroscedasticity adjustment and of the IHS parameters resulted in a rejection of the null hypothesis of a homoscedastic and normal error structure at the one per cent level of significance.[14]

In both the binary probit and Tobit models, the estimated β coefficients cannot be interpreted in the same way as in a linear regression model. Marginal effects for the continuous independent variables in the model are calculated by differentiating the expected value of the dependent

[13] Non-linear terms significant in the standard Tobit models were also included in the specification of the adjusted Tobit models.

[14] In all cases the models adjusted for heteroscedasticity and non-normality performed the best in terms of the estimated log-likelihood values. See Tables B1-B3 of Appendix B for the results of the three likelihood ratio tests of heteroscedastic errors, non-normal errors and heteroscedastic and non-normal errors.

variable with respect to the independent variable of interest, evaluated at the sample mean of this independent variable. This enables the calculation of elasticities of demand with respect to these continuous independent variables. The marginal effects for discrete independent variables are calculated as the difference in expected values when the variable takes the value one and when it takes the value zero. In order to ascertain the reliability of all marginal effects, standard errors for the marginal effects must be calculated. These are approximated using the delta method as presented in Yen *et al* (1996).

The formulae for calculating marginal effects in both the probit and Tobit models are presented in Appendix A while those for the standard errors are presented in Appendix B. As the calculation of standard errors for the marginal effects in the non-normal and heteroscedastic Tobit models is work in progress, the standard errors and significance levels presented are those of the estimated coefficients. Tables 4.1 to 4.3.2 below present the estimated marginal effects for the correctly specified car ownership, car use, bus fare expenditure and taxi fare expenditure models respectively. For comparison purposes, the marginal effects for the unadjusted Tobit models are presented in Tables C1-C3 of Appendix C. Table D1 of Appendix D reports the estimated elasticities of demand with respect to the three continuous independent variables for all models.

4.1. Car Ownership

The car ownership model performs particularly well with all variables significant at the five per cent level or less. Most of these results are in line with those of other studies with the exception of the effect of the age of the HOH, which exerts a positive effect on the probability of car ownership. The income elasticity of car ownership demand of 1.15 supports the results of many studies that have classified the demand for the private car as a luxury good [see Blundell *et al* (1993), Button *et al* (1993), Stanovnik (1990), Thobani (1984), McCarthy (1977), Buxton and Rhys (1972), Bennett (1967) and Fairhurst (1965)].[15]

Table 4.1 Binary Probit Model of Household Car Ownership

Variable	*Marginal Effects*
Constant	-1.415 (0.196)***
HHEXP	0.323 (0.089)***
ADULTS	0.055 (0.169)**
CHILDREN	0.104 (0.032)***
APART	-0.406 (0.070)***
SEMI	-0.156 (0.059)***
WORKING	0.155 (0.037)***
FEMALE	-0.189 (0.051)***
THIRTY	0.378 (0.077)***
FORTY	0.480 (0.079)***
FIFTY	0.485 (0.080)***
SIXTY	0.626 (0.077)***
PRIMARY	-0.378 (0.049)***
SECONDARY	-0.106 (0.044)**
Number of Observations	*2,148*[16]
Non-Linear Terms	$HHEXP^2$, $HHEXP^3$, $ADULTS^2$, $ADULTS^3$, $CHILDREN^2$
Log-Likelihood	*-823.844*
Heteroscedastic Log-Likelihood	*-819.031 (3)*
Elasticities:	

[15] However many studies show that the income elasticity of car ownership demand is declining over time with the private car now increasingly regarded as a necessity rather than a luxury [see Bjorner (1999), Dargay and Vythoulkas (1999) and McCarthy (1977)]. In addition many of the former studies that found income elasticities in excess of unity employed data on low income countries or are now out of date.

[16] The car ownership regression is estimated using the full sample of 2,148 households (i.e., those households owning two or more cars are also included). An examination of Table E1 in Appendix E reveals little difference between these results and those based on the sample of households one car or less.

HHEXP	*1.145****
ADULTS	*0.197***
CHIDLREN	*0.178****

Notes: (i) * significant at 10% level, ** significant at 5% level, *** significant at 1% level
(ii) Standard errors for elasticities are those of the marginal effects.

For all the continuous independent variables (income and the number of adults and children in the household), non-linear terms are found to be significant. This is consistent with Dargay and Vythoulkas (1999), Cragg and Uhler (1970) and Bennett (1967) who also found that the positive effect of income on the probability of car ownership decreases in magnitude as income increases while Alperovich *et al* (1999) found a similar result for the number of adults in the household. In addition, the significance of the cubed terms suggests that once household income and the number of adults increases above a second threshold, the probability of car ownership increases at an increasing rate once more. For the number of adults and children in the household, the significance of the squared term may indicate a scale economies effect while the significance of the cubed term for the number of adults may suggest initial increasing returns to scale that diminish as the size of the household becomes larger.

The effect of accommodation type supports the inclusion of this variable as a proxy for distance and the quality and quantity of public transport links with those households living in apartments being least likely to own cars in comparison with the base category of those living in detached houses. Numerous studies also find that as distance from the city centre increases, population density declines and public transport provision deteriorates, the demand for car ownership increases [see Alperovich *et al* (1999), Dargay and Vythoulkas (1999), Train (1980), McCarthy (1977), Buxton and Rhys (1972), Cragg and Uhler (1970), Bennett (1967) and Fairhurst (1965)]. The positive effect of having at least one person in employment in the household is in agreement with the results of Cragg and Uhler (1970) and Bennett (1967) and indicates the effect that the presence of individuals in the household with regular mobility needs has on car ownership probability.

While there is no a priori reason why the gender of the HOH *per se* should influence the probability of car ownership, single female-headed households are significantly less likely to own cars than other household types. The results for age of HOH show that the probability of car ownership increases with the age of the HOH. These results are in conflict with those of Alperovich *et al* (1999), Dargay and Vythoulkas (1999) and Bennett (1967) where the effect of the age of HOH, while initially positive, decreases in magnitude as the age of the HOH increases[17]. Explanations for this divergence may lie in different costs, with the costs of car insurance being particularly high for young people in Ireland. Finally, the highest level of education variable suggests that those with a primary education are least likely to own a car relative to the base category of those with a third level qualification. Alperovich *et al* (1999) also find that those with the highest levels of education are most likely to own cars although they admit that there is no obvious reason why this should be the case, given that household income has been taken into account.

[17] Cragg and Uhler (1970) even find that increasing the age of the HOH linearly reduces the probability of car ownership.

4.2 Car Use

Table 4.2 IHS Heteroscedastic Tobit Model of Household Car Use

Variable	*Marginal Effects*	*Heteroscedastic Terms*
Constant	2.430 (3.169)	
HHEXP	3.183 (0.959)***	0.123 (0.022)***
ADULTS	1.564 (0.372)***	
CHILDREN	1.605 (0.308)***	0.074 (0.021)***
APART	-3.500 (1.257)**	
SEMI	-2.493 (0.842)***	
WORKING	2.805 (0.801)***	
FEMALE	-2.632 (1.002)**	
THIRTY	0.056 (2.534)	
FORTY	-0.190 (2.535)	
FIFTY	0.643 (2.593)	
SIXTY	-0.421 (2.556)	
PRIMARY	1.610 (0.923)	
SECONDARY	0.389 (0.760)	
MOTOR	3.366 (1.821)*	
EXPENSES	-5.711 (0.776)***	
σ		5.702 (0.376)***
θ		0.043 (0.006)***
Number of Observations	*935*	
Non-Linear Terms	*$HHEXP^2$*	
Log-Likelihood	*-3301.768*	
IHS Het Log-Likelihood	*-3231.681 (3)*	
Elasticities:		
HHEXP	*0.514****	
ADULTS	*0.225****	
CHILDREN	*0.115****	

Notes: (i) *significant at 10% level, ** significant at 5% level, *** significant at 1% level
(ii) Standard errors (in parentheses) and significance levels are those of the estimated coefficients

In explaining variations in petrol expenditure for those households owning one car, household income, the number of adults and children, household location, the presence of workers in the household and the gender of the HOH are all significant explanatory factors. For those households owning one car, household income enters as a positive and significant variable in explaining household car use, in part reflecting the costs such as petrol, tax and insurance that are incurred in running a car. It may also indicate that households with higher incomes place a greater value on time savings and comfort relative to poorer households, thus choosing the car over more time consuming and less comfortable methods of transport such as cycling or using the bus. The low but positive income elasticity of 0.51 suggests that car use demand may be classified as a necessity, a result consistent with those of Bjorner (1999), Labeaga and Lopez (1997), Blundell *et al* (1993) and Mannering (1983). The significance of the squared term indicates that a non-linear relationship exists, a result also found by Kayser (2000). The effects of the number of adults and children[18] in the household on petrol expenditure are both positive and linear, indicating the effects of the number of eligible drivers and diverse household activity patterns on car use.

The accommodation type variables are of the expected sign, showing how car use increases with distance and/or the non-availability of public transport. The results are very similar to those of Bjorner (1999) who finds that relative to those living in the city of Copenhagen, those living in rural areas of Denmark use their cars the most in terms of annual mileage. In common with the result of Kayser (2000), the presence of one or more persons in employment increases car use, suggesting that the effect of regular commuting patterns on car use is positive. The effect of a single female HOH is negative and significant, consistent with the results of Kayser (2000),

[18] Kayser (2000) finds no effect for the number of children in the household on petrol expenditure.

Bjorner (1999) and Mannering (1983). This may mean that such single women are engaged in activities that require less travelling such as part-time local work and/or are more willing to walk and use public transport than men.[19] Even with access to a car, single female households use their cars less than all other household types. The age of the HOH is not significant although the signs of the effects are, with one exception (50-59 years), consistent with the results of Bjorner (1999) and Mannering (1983) who find that car use declines with the age of the HOH.

[19] This is assuming that the HOH is the principal driver in the household.

4 Public Transport Expenditure

4.3.1 Bus Fare Expenditure

Table 4.3.1 IHS Heteroscedastic Tobit Models of Household Bus Fare Expenditure 1994/1995

Variable	*No Car*		*One Car*	
	Marginal Effects	*Het Terms*	*Marginal Effects*	*Het Terms*
Constant	-2.051 (1.147)***		-3.232 (0.893)***	
HHEXP	1.155 (0.578)***	0.218 (0.056)***	0.046 (0.076)	
ADULTS	0.839 (0.473)***	-0.071 (0.034)**	1.049 (0.397)***	-0.125 (0.041)**
CHILDREN	-0.054 (0.082)	-0.056 (0.022)**	-0.093 (0.055)	-0.099 (0.023)***
APART	0.082 (0.736)		-0.409 (0.384)	
SEMI	0.120 (0.711)		0.025 (0.210)	
WORKING	0.730 (0.212)***		0.382 (0.223)**	
FEMALE	0.601 (0.324)***		0.728 (0.347)***	
THIRTY	-0.248 (0.385)		-0.362 (0.544)	
FORTY	-0.506 (0.424)*		-0.090 (0.534)	
FIFTY	-0.335 (0.465)		-0.129 (0.541)	
SIXTY	-1.174 (0.465)***		-0.249 (0.542)	
PRIMARY	-0.761 (0.405)***		-0.172 (0.226)	
SECOND	-0.611 (0.399)**		-0.091 (0.179)	
FREETRAV	-0.902 (0.210)***		-0.749 (0.192)***	-0.162 (0.084)*
CYCLE	-2.341 (0.308)***	-1.128 (0.251)***	-0.080 (0.405)	
EXPENSES			-0.265 (0.194)**	
σ		2.392 (0.269)***		2.627 (0.277)***
θ		0.211 (0.033)***		0.429 (0.070)***
Number of Observations	*950*		*935*	
Non-Linear Terms	*$HHEXP^2$, $ADULTS^2$*		*$ADULTS^2$*	
Log-Likelihood	*-1711.631*		*-1407.935*	
IHS Het Log-Likelihood	*-1638.249 (5)*		*-1357.785 (4)*	
Elasticities:				
HHEXP	*0.686****		*0.085*	
ADULTS	*0.652****		*1.720****	
CHILDREN	*-0.020*		*-0.076*	

Notes: (i) significant at 10% level, ** significant at 5% level, *** significant at 1% level

(ii) Standard Errors (in parentheses) and significance levels are those of the estimated coefficients

Significant differences exist between car- and non car-owning households in terms of the factors influencing per capita bus fare expenditures. While household income has a positive and significant, but diminishing, effect on the demand for bus travel in non car-owning households, it is insignificant in explaining variations in per capita bus fare expenditures in car-owning households. In non car-owning households therefore, the demand for urban bus travel may be classified as a necessity with an income elasticity of 0.69. This result is similar to that found for public transport by Bergantino (1997) on the basis of UK micro-data. The number of adults in the household impacts positively on per capita bus fare expenditure in both samples with the significance of the squared terms indicating that a non-linear relationship exists. The high positive elasticity of 1.72 in car-owning households suggests that household members may compete for the use of the household car. The effect of the number of adults on expenditure in both non car- and car-owning households is particularly significant given that the dependent expenditure variable is already adjusted for household size. While the effect of the number of children under the age of 17 years is insignificant in explaining expenditure on bus fares in both sets of households, the negative sign of the elasticity in car-owning households is consistent with the results of De Palma and Rochat (2000) and Bergantino (1997) who find that the effect of children on public transport demand is negative, reflecting perhaps the returns to scale involved in driving children to school.

A positive and significant relationship exists between a single female HOH and per capita bus fare expenditure. Even when single female households have access to a car, they spend more on bus fares per capita than other car-owning households thus reinforcing the point of Mannering (1983) that females select frequencies and types of activities that require less vehicular travel than males. The age of HOH variable is insignificant in car-owning households but explains some variation in bus fare expenditures in non car-owning households. The results indicate that only those households with a HOH aged 40-49 and 60 years and over spend significantly less amounts to those households with a HOH in the base category. The latter result is all the more significant given that the presence of free public transport for pensioners is also controlled for and exerts a negative and significant effect on per capita bus expenditures. These results, while only significant for non car-owning households, are in direct contrast to those of De Palma and Rochat (2000) and Bergantino (1997) who find that older people are more likely to use public transport than younger people. The level of education of the HOH is only significant in the non car-owning sample and indicates that those with a third level education spend the most per capita on bus fares. This result may be explained by households consisting solely of third level students who use the bus to travel to college. De Palma and Rochat (2000) similarly find that those with a third level education are more likely to use public transport to travel to work, although this effect was found for individuals owning cars. Finally, for bus fare expenditure in car-owning households, the presence of at least one person entitled to remuneration for motor expenses reduces per capita expenditure on bus fares, indicating that if the option of cheaper private transport is available it will be chosen.

4.3.2 Taxi Fare Expenditure

Table 4.3.2 IHS Heteroscedastic Tobit Models of Household Taxi Fare Expenditure

Variable	*No Car*		*One Car*	
	Marginal Effects	*Het Terms*	*Marginal Effects*	*Het Terms*
Constant	-2.293 (2.252)***		-2.358 (2.914)***	
HHEXP	0.968 (0.512)***	0.179 (0.063)***	0.457 (1.082)***	0.191 (0.066)***
ADULTS	0.055 (0.270)***	-0.163 (0.040)***	0.280 (0.324)***	-0.148 (0.044)***
CHILDREN	-0.041 (0.212)**	-0.087 (0.042)**	0.017 (0.269)	
APART	0.066 (1.410)		0.389 (1.292)	
SEMI	0.320 (1.314)		0.414 (0.829)***	
WORKING	0.331 (0.526)***		0.232 (0.819)	
FEMALE	0.120 (0.708)		0.157 (1.057)	
THIRTY	-0.259 (0.832)		-0.834 (1.707)***	
FORTY	-0.474 (0.898)**		-0.977 (1.725)***	
FIFTY	-0.502 (0.964)**		-0.808 (1.693)**	
SIXTY	-1.059 (1.040)***		-1.122 (1.721)***	
PRIMARY	0.067 (0.993)		0.140 (0.789)	
SECOND	0.047 (0.913)		0.002 (0.659)	
CYCLE	0.059 (1.629)		-0.040 (1.011)	
EXPENSES			-0.037 (0.618)	
σ		5.777 (0.829)***		4.376 (1.034)***
θ		0.105 (0.029)***		0.115 (0.040)***
Number of Observations	*950*		*935*	
Non-Linear Terms			*$HHEXP^2$*	
Log-Likelihood	*-1053.625*		*-913.305*	
IHS Het Log-Likelihood	*-998.567 (3)*		*-882.933 (2)*	
Elasticities:				
HHEXP	*0.934****		*1.178****	
ADULTS	*0.069****		*0.641****	
CHILDREN	*-0.025***		*0.020*	

Notes: (i) significant at 10% level, ** significant at 5% level, *** significant at 1% level
(ii) Standard Errors (in parentheses) and significance levels are those of the estimated coefficients

The differences between non car- and car-owning households' taxi fare expenditures are less obvious than for the bus fare expenditure case. Household income has a positive and significant effect in both non car- and car-owning households with the effect also found to be non-linear in car-owning households. The former result is in contrast to that found for the bus fare expenditure case where household income was only significant in explaining bus fare expenditures in non car-owning households. However, the elasticity of demand is slightly higher in non car-owning households than in car-owning households meaning that households without cars are more responsive to changes in income than those with cars. The marginal effect of increasing number of adults in the household is positive and linear in both samples, with the large positive elasticity of 0.64 in car-owning households suggesting that there is competition for the household car. The effect of children is insignificant, a result consistent with expectations[20].

The effect of accommodation type shows that there are no significant differences between households living in apartments and households living in detached houses in terms of their taxi fare expenditure but those in semi-detached houses spend significantly more. This result may mean that distance and cost influences taxi fare expenditure with those living furthest away from the city centre (detached homes) spending least because of cost while those living near the city centre (apartments) can use alternative, cheaper forms of transport such as walking and taking the bus. The presence of at least one working member in the household has a positive and significant effect on taxi fare expenditure only in non car-owning households, which may indicate the use of taxis for occasional commuting. The insignificant effect in car-owning households suggests that taxis are used mainly for leisure travel rather than commuting.

[20] It is difficult to explain why the presence of children should be significant in explaining variations in taxi fare expenditure except where it may proxy household type.

The positive effect of a single female HOH is a result consistent with the increased safety concerns that women face in travelling alone at night, while the effect in car-owning households reinforces the points made above about females using their cars less in general than males. The effect of increasing HOH age on taxi expenditure is generally negative in both samples with those households with a head aged 20-29 years spending the most per person on taxi fares. This perhaps reflects the difference in activities undertaken by households in different stages of the life-cycle and the general reticence of older people to use taxis, for example, younger households may socialise more than older households and therefore require late night transport, of which taxis are a popular and often necessary form due to the poor night bus service in the city.

6 Conclusion

In this paper Irish Household Budget Survey micro-data are used to estimate the income and socio-demographic determinants of urban households' transport decisions. The most significant results relate to the effects of income (as proxied by total household expenditure), the number of adults in the household and the gender and age of the HOH. Household income is, with one exception[21], positive and significant in explaining differences in households' transport decisions. An examination of income elasticities of demand reveals that while private car ownership may be classified as a luxury, car and public transport use are necessities. Along with the higher elasticities of demand for taxi fare expenditure, the insignificance of income in explaining variations in per capita bus fares in car-owning households may suggest that factors other than income and price are more important in determining bus fare expenditure, particularly in car-owning households. While the effects of the number of adults on household car ownership and use are very similar, in terms of public transport expenditure there are significant differences

[21] Household income is insignificant in explaining variations in bus fare expenditure in car-owning households.

between non car- and car-owning households. The effect of the number of adults is highly elastic in car-owning households for both bus and taxi fare expenditure suggesting that competition for the household car induces some members to choose alternative forms of transport. The positive effect of the number of adults on per capita taxi fares in non car-owning households, given that household size has already been accounted for, may be explained by the tendency for larger households to consist of unrelated individuals who do not travel together.

The gender of the HOH is consistently significant in explaining variations in car ownership, car use and public transport expenditures. While car ownership and use are more likely for households headed by a male, even in households that own a car, bus and taxi fare expenditures are higher for households that are headed by a single female. The effects of the age of the HOH on car use, bus fare expenditure and taxi fare expenditure are consistent with the expectation that younger households are more mobile and are engaged in more activities than older households. The positive effect of age of the HOH on car ownership is however in conflict with many other studies and may reflect different costs of car ownership in Ireland in comparison with other countries, with the costs of insurance being particularly high for young people.

In conclusion, the results highlight the significance of household income and socio-demographic characteristics in determining differences in household transport behaviour. The use of expenditure data to proxy car and public transport use is justified by results that are broadly in line with those of previous research in the area. The division of the samples for the bus and taxi fare regressions emphasises the differences in travel behaviour for households owning cars and those not owning cars while the analysis of bus and taxi expenditures separately shows the usefulness of examining transport expenditures at more disaggregated levels. Finally, the importance of correct model specification is highlighted through the improvements in estimated log-likelihoods as a result of the inclusion of non-linear terms for the continuous independent variables and the adjustments to the Tobit models for non-normality.

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Appendix A

Probit Marginal Effects

$$\frac{\partial\, y_i}{\partial\, x_{ij}} = \phi\,(\,x_i'\,\beta\,).\beta_j$$

Tobit Marginal Effects

$$\frac{\partial\, y_i}{\partial\, x_{ij}} = \Phi\left(\frac{x_i'\,\beta}{\sigma}\right)\beta_j$$

IHS Heteroscedastic Tobit Marginal Effects

$$ME_{ij} = \frac{\partial\, y_i}{\partial\, x_{ij}} = \int_0^\infty \left(\begin{array}{l} \dfrac{y_i}{\sigma_i\sqrt{1+\theta^2 y_i^{\,2}}}\,\phi\left(\dfrac{y(\theta)-x_i'\,\beta}{\sigma_i}\right)\times \\ \left(\left(\dfrac{y(\theta)-x_i'\,\beta}{\sigma_i}\right)\left(\dfrac{\beta_j}{\sigma_i}\right)+\left(\dfrac{y(\theta)-x_i'\,\beta}{\sigma_i}\right)^2 h_j - h_j\right) \end{array} \right) dy_i$$

where Φ is the cumulative standard normal distribution function, ϕ is the standard normal density function, σ_i is the estimated standard error, θ is the estimated IHS parameter, β_j is the estimated coefficient on the independent variable of interest and h_j is the estimated heteroscedastic term. All such marginal effects are calculated at the sample means of the independent variables.

Appendix B

Calculation of Standard Errors for IHS Heteroscedastic Tobit Models

$$\frac{\partial\, ME_{ij}}{\partial\, \beta_q} = \int_0^\infty \left(\begin{array}{l} \frac{y_i}{\sigma_i \sqrt{1+\theta^2 y_i^2}} \phi\left(\frac{y(\theta) - x_i'\beta}{\sigma_i}\right) \times \\ \left(\frac{y(\theta) - x_i'\beta}{\sigma_i}\right)\left(\frac{x_{iq}}{\sigma_i}\right) \times (.) \\ -\left(\frac{x_{iq}\beta_j}{\sigma_i^2}\right) - 2\left(\frac{y(\theta) - x_i'\beta}{\sigma_i}\right)\left(\frac{x_{iq}h_j}{\sigma_i}\right) \end{array} \right) dy_i$$

$$\frac{\partial\, ME_{ij}}{\partial\, \beta_j} = \int_0^\infty \left(\begin{array}{l} \frac{y_i}{\sigma_i \sqrt{1+\theta^2 y_i^2}} \phi\left(\frac{y(\theta) - x_i'\beta}{\sigma_i}\right) \times \\ \left(\frac{y(\theta) - x_i'\beta}{\sigma_i}\right)\left(\frac{x_{ij}}{\sigma_i}\right) \times (.) \\ -\left(\frac{x_{ij}\beta_j}{\sigma_i^2}\right) - 2\left(\frac{y(\theta) - x_i'\beta}{\sigma_i}\right)\left(\frac{x_{ij}h_j}{\sigma_i}\right) \\ +\left(\frac{y(\theta) - x_i'\beta}{\sigma_i}\right)\left(\frac{1}{\sigma_i}\right) \end{array} \right) dy_i$$

$$\frac{\partial\, ME_{ij}}{\partial\, h_q} = \int_0^\infty \begin{pmatrix} \dfrac{y_i}{\sigma_i \sqrt{1+\theta^2 y_i^{\,2}}}\,\phi\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)\times \\ -z_{iq}\times(.)+\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)^2 z_{iq}\times(.) \\ -\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)\left(\dfrac{z_{iq}\beta_j}{\sigma_i}\right) \\ -2\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)^2 \left(z_{iq}h_k\right) \end{pmatrix} dy_i$$

$$\frac{\partial\, ME_{ij}}{\partial\, h_j} = \int_0^\infty \begin{pmatrix} \dfrac{y_i}{\sigma_i \sqrt{1+\theta^2 y_i^{\,2}}}\,\phi\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)\times \\ -z_{ij}\times(.)+\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)^2 z_{ij}\times(.) \\ -\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)\left(\dfrac{z_{ij}\beta_j}{\sigma_i}\right) \\ -2\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)^2 \left(z_{ij}h_j\right) \\ +\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)^2 -1 \end{pmatrix} dy_i$$

$$\frac{\partial\, ME_{ij}}{\partial\,\theta} = \int_0^\infty \left(\begin{array}{l} \dfrac{y_i}{\sigma_i \sqrt{1+\theta^2 y_i^{\,2}}}\,\phi\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)\times \\ -\left(\dfrac{\theta y^2}{1+\theta^2 y^2}\right)\times(.) \\ -\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)\left(\dfrac{y}{\theta y\sqrt{1+\theta^2 y^2}}\right)\times(.) \\ +\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)\left(\dfrac{y(\theta)}{\theta\sigma_i}\right)\times(.) \\ +\left(\dfrac{y}{\theta y\sqrt{1+\theta^2 y^2}}\right)\left(\dfrac{\beta_j}{\sigma_i}\right)-\left(\dfrac{y(\theta)}{\theta\sigma_i}\right)\left(\dfrac{\beta_j}{\sigma_i}\right) \\ +2\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)\left(\dfrac{y}{\theta y\sqrt{1+\theta^2 y^2}}\right)(h_j) \\ -2\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)\left(\dfrac{y(\theta)}{\theta\sigma_i}\right)(h_j) \end{array} \right) dy_i$$

where $(.)=\left(\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)\left(\dfrac{\beta_j}{\sigma_i}\right)+\left(\dfrac{y(\theta)-x_i'\beta}{\sigma_i}\right)^2 h_j - h_j\right)$

Appendix C

Table C1 Tobit Models of Household Petrol, Bus and Taxi Fare Expenditure (Estimated Coefficients)

Variable	*Car Use*	*Bus - No Car*	*Bus - One Car*	*Taxi – No Car*	*Taxi – One Car*
Constant	0.245 (3.942)	-5.712 (1.561)***	-6.269 (1.290)***	-21.227 (3.700)***	-15.131 (3.186)***
HHEXP	5.349 (1.038)***	3.939 (0.675)***	0.100 (0.107)	5.549 (0.497)***	3.884 (0.947)***
$HHEXP^2$	-0.395 (0.138)***	-0.671 (0.141)***			-0.354 (0.126)***
ADULTS	1.551 (0.538)***	2.912 (0.764)***	4.186 (0.604)***	2.302 (0.525)***	3.663 (0.433)***
$ADULTS^2$		-0.259 (0.131)**	-0.401 (0.097)***		
CHILDREN	1.760 (0.386)***	-0.022 (0.150)	-0.048 (0.101)	0.544 (0.380)	0.078 (0.323)
APART	-4.082 (1.818)**	0.456 (0.947)	-0.879 (0.540)*	3.912 (2.946)	1.836 (1.541)
SEMI	-2.617 (1.173)**	0.262 (0.907)	-0.014 (0.327)	4.202 (2.833)	2.356 (1.049)**
WORKING	2.807 (1.186)**	1.660 (0.384)***	0.926 (0.352)***	2.985 (0.918)***	1.287 (1.083)
FEMALE	-2.923 (1.276)**	1.417 (0.479)***	1.698 (0.468)***	2.304 (1.083)**	3.130 (1.108)***
THIRTY	-0.240 (3.066)	-0.616 (0.538)	-1.184 (0.818)	-2.372 (1.280)*	-6.788 (1.952)***
FORTY	-0.688 (3.061)	-0.989 (0.603)*	-0.701 (0.816)	-4.143 (1.502)***	-8.570 (1.976)***
FIFTY	0.751 (3.113)	-0.375 (0.644)	-0.701 (0.828)	-4.097 (1.584)***	-8.380 (2.010)***
SIXTY	-0.878 (3.121)	-2.178 (0.642)***	-0.792 (0.839)	-7.809 (1.550)***	-10.287 (2.043)***
PRIMARY	2.180 (1.273)*	-1.193 (0.575)**	-0.405 (0.354)	0.695 (1.437)	1.084 (1.022)
SECONDARY	0.448 (0.972)	-0.779 (0.539)	-0.179 (0.265)	0.352 (1.286)	-0.409 (0.776)
FREETRAV		-2.381 (0.379)***	-1.718 (0.282)***		
CYCLE	3.586 (2.503)	-2.249 (1.105)**	-0.635 (0.672)	0.065 (2.696)	0.635 (1.754)
EXPENSES	-5.521 (1.068)***		-0.642 (0.287)**		0.479 (0.791)
σ	*11.158*	*4.078*	*2.710*	*8.365*	*6.387*
Number of Observations	*935*	*950*	*935*	*950*	*935*
Log-Likelihood	*-3301.768*	*-1711.631*	*-1407.935*	*-1053.625*	*-913.305*
Het Log-Likelihood	*-3257.769 (3)*[22]	*-1659.714 (5)*	*-1389.238 (2)*	*-1005.869 (3)*	*-888.850 (2)*
IHS Log-Likelihood	*-3246.277 (1)*	*-1664.273 (1)*	*-1374.683 (1)*	*-1017.068 (1)*	*-902.036 (1)*
IHS Het Log-Likelihood	*-3231.681 (3)*	*-1638.249 (5)*	*-1357.785 (4)*	*-998.567 (4)*	*-882.933 (3)*

Notes: (i) Standard errors are reported in parentheses
(ii)* significant at 10% level, ** significant at 5% level, *** significant at 1% level

[22] The figures in parentheses represent the number of degrees of freedom, i.e., the IHS parameter and/or the number of continuous variables included in the heteroscedasticity function.

Appendix D

Table D1 Elasticities of Demand (Unadjusted Results)

	Car Own	*Car Use Petrol*	*Bus No Car*	*Bus One Car*	*Taxi No Car*	*Taxi One Car*
HHEXP	1.145***	0.506**	0.672***	0.089	0.929***	1.005***
ADULTS	0.197**	0.199***	0.817***	1.990***	0.504***	1.463***
CHILDREN	0.178***	0.113**	-0.004	-0.019	0.057	0.016

Table D2 Elasticities of Demand (Adjusted Results)

	Car Own	*Car Use Petrol*	*Bus No Car*	*Bus One Car*	*Taxi No Car*	*Taxi One Car*
HHEXP	1.145***	0.514***	0.686***	0.085	0.934***	1.178***
ADULTS	0.197**	0.225***	0.652***	1.720***	0.069***	0.641***
CHILDREN	0.178***	0.115***	0.020	-0.076	0.025**	0.020

Appendix E

Table E1 Binary Probit Models of Household Car Ownership (Estimated Coefficients)

Variable	*Car Own A*	*Car Own B*[23]
Constant	-3.607 (0.495)***	-3.434 (0.507)***
HHEXP	1.630 (0.226)***	1.612 (0.242)***
$HHEXP^2$	-0.258 (0.071)***	-0.269 (0.078)***
$HHEXP^3$	0.013 (0.006)**	0.014 (0.007)**
ADULTS	0.935 (0.431)**	0.861 (0.447)*
$ADULTS^2$	-0.305 (0.147)**	-0.300 (0.155)*
$ADULTS^3$	0.029 (0.015)*	0.029 (0.016)*
CHILDREN	0.343 (0.082)***	0.322 (0.085)***
$CHILDREN^2$	-0.042 (0.017)**	-0.038 (0.017)**
FEMALE	-0.478 (0.131)***	-0.463 (0.130)***
APART	-1.078 (0.178)***	-1.054 (0.184)***
SEMI	-0.408 (0.151)***	-0.395 (0.157)**
WORKING	0.395 (0.094)***	0.380 (0.096)***
THIRTY	1.135 (0.196)***	1.069 (0.198)***
FORTY	1.517 (0.200)***	1.459 (0.202)***
FIFTY	1.727 (0.202)***	1.629 (0.205)***
SIXTY	2.001 (0.195)***	1.901 (0.197)***
PRIMARY	-0.986 (0.127)***	-0.934 (0.131)***
SECONDARY	-0.269 (0.113)**	-0.232 (0.118)**
Number of Observations	*2,148*	*1,885*
Log-Likelihood	*-823.844*	*-795.365*
Heteroscedastic Log-Likelihood (df)	*-819.031 (3)*	*-793.097 (3)*

Notes: (i) Standard errors are reported in parentheses
(ii)* significant at 10% level, ** significant at 5% level, *** significant at 1% level

[23] Excluding households owning two or more cars.