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Citation for final published version:

Santos, Georgina , Maoh, Hanna, Potoglou, Dimitris and von Brunn, Thomas 2013. Factors influencing modal split of commuting journeys in medium-size European cities. Journal of Transport Geography 30 , pp. 127-137. 10.1016/j.jtrangeo.2013.04.005

Publishers page: http://dx.doi.org/10.1016/j.jtrangeo.2013.04.005

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The definitive, peer-reviewed and edited version of this article is published and can be cited as

Santos, G., Maoh, H., Potoglou, D. and and T. von Brunn (2013), 'Factors influencing modal split of commuting journeys in medium-size European cities', *Journal of Transport Geography*, Vol. 30, pp. 127-137. DOI: 10.1016/j.jtrangeo.2013.04.005

Factors influencing modal split of commuting journeys in medium-size European cities

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Abstract

This paper attempts to identify factors that influence modal split for journeys to work in 112 medium size cities in Europe. Using a discrete choice modelling approach we find that: (a) car share increases with car ownership and GDP per capita; (b) motorcycle share decreases with petrol price and increases with motorcycle ownership; (c) bicycle share increases with the length of the bicycle network in the city; (d) public transport share increases with resident population, GDP per capita and the number of buses (or bus equivalents) operating per 1000 population, and decreases with public transport fares, number of days of rain per year, proportion of people aged 65 and over living in the city and the proportion of households with children; (e) the number of students in universities and further education establishments per 1000 resident population is positively associated with the shares of public transport, motorcycle, bicycle and walking. Policies aimed at increasing the bicycle network are likely to increase cycling share. Policies aimed at increasing the number of buses (or bus equivalents) and reducing public transport fares are likely to increase public transport share. Policies aimed at discouraging car ownership are likely to reduce car share.

Keywords

Mode share, Mode choice, Sustainable transport, Commuting journeys, Journeys to work, Logit model

1. Introduction

Sustainable transport has become an important topic on most national, regional and local governments' agendas. Sustainability in transport, typically defined along economic, environmental and social (or equity) dimensions (European Commission, 2008, p.12), can be achieved with sustainable modes of transport (as well as with sustainable travel behaviour). In general, there is consensus that the private car does not enhance sustainability, whereas public transport and non-motorised modes, such as walking and cycling, do (Black, 2010). It is therefore important to understand what drives people *towards* and *away from* the private car, public transport and non-motorised modes, respectively. Once this is done, appropriate policies can be designed in order to enhance transport sustainability.

This paper works towards that objective by analysing the factors that influence the modal split for journeys to work[1] in 112 medium-size cities in Europe. These are defined, for the purposes of our study, as cities with populations of 100,000 to 500,000. We contend that understanding travel behaviour by identifying common factors that have an impact on modal split in medium-size European cities can provide the basis for designing sustainable transport policies.[2] Newman and Kenworthy (1999, p. 86) explain that journeys to work account for most peak demand on road networks. Commuting is a major component of daily travel demand and an important source of congestion and pollution (Antipova et al., 2011, p.1010; Habib et al., 2011, p.588). Santos et al. (2010, p. 84) point out that addressing commuter trips is essential for relieving congestion in urban areas.

This paper attempts to answer the following questions:

- What are the significant factors most likely to cause an increase or decrease in the share of certain travel mode for journeys to work in medium-size European cities?
- What type of sustainable transport policies can be advocated based on these significant factors?

To address the above mentioned questions, we develop a set of discrete choice models using the 2001 and 2004 modal split shares of 112 medium-size European cities. City-level variables mainly depicting demographic and socio-economic factors are used in the specification of the modal-split models. Using a rich data set, Winston and Shirley (1998) develop a discrete choice model, where they combine mode and departure choice, for the largest 116 urbanised areas in the United States. Such type of data are not available for Europe and to our knowledge the type of regional analysis at European level we present in this paper is novel and has not been addressed in previous studies. More specifically, our efforts contribute to the existing transport geography literature by highlighting significant factors influencing the observed modal split in mid-size European cities. By contrast, the

[1] Solely concentrating on journeys to work may, however, overstate public transport, since it is particularly strong in that market (Kenworthy et al., 1999, p. 17).

[2] It should be noted that although mode share is not the best indicator for measuring travel-related sustainability, it is still considered among the most important indicators. When travel sustainability is mainly concerned with the environmental impacts that travel causes, other measures such as vehicle kilometres travelled (VKT) are more favoured. This is because while a lower share of trips by car may go some way towards limiting the amount of carbon emissions, for example, it is VKT that really determine the level of emissions for a given region.

majority of the existing studies on mode choice behaviour have been conducted for a given single city or a small group of cities.

The remainder of this paper is organised as follows: Section 2 reviews the most relevant literature for this study; Section 3 presents the data used and the model specifications; Section 4 presents the results and finally, Section 5 summarises the main findings and offers policy recommendations and suggestions for further research.

2. Previous work

Modal split is related to a number of factors, ranging from individual mode choice, which in turn depends on individual and mode characteristics, to land use and population density. In this section we summarise previous work relevant to this study. Although the papers we cite range in the methods used (literature reviews, qualitative analysis of data, individual and aggregate discrete choice models, OLS regressions, to name the most prominent ones) and their geographic and temporal scope, as well as in their objectives, we highlight the issues of interest to the aims of the present research. The literature reviewed is extensive and in order to save space, we present the main points, in a systematic way, on Table 1. Population density was not included in our models, even though we had reliable data for that variable. The reason for not including it was that it was not found to be significant or gave counter-intuitive signs due to multicollinearity with other variables. Trip distance and land use mix, the last two categories in Table 1, include variables we were unable to include in our models due to lack of data. All the other rows contain variables we included in our models, although we used ‘number of buses (or bus equivalents) operating in the public transport per 1,000 population’ as a proxy for ‘public transport service frequency’.

Schwanen (2002), Scheiner (2010), Susilo and Maat (2007) and White (2009), all find links between city size and either modal split at city level or individual mode choice. In general the share of trips by car decreases and the share of trips by public transport increases with city size. The findings regarding the share of non-motorised modes, on the other hand, are not clear cut.

In general, car ownership is found to increase the share of trips by car and decrease the share of trips by public transport (Balcombe et al., 2004; Chen et al., 2008; Kain and Liu, 2002; Pinjari et al, 2007; to name just a few papers from Table 1). Dargay and Hanly (2007) also conclude that car purchase costs and petrol prices have a negative impact on commuting by car.

There also seems to be a positive link between income and car use, although the link between income and other modes (such as public transport or walking and cycling) differs from one study to another. Table 1 presents the direction of the link for income by mode, according to some authors.

As people get older they may have different preferences regarding mode choice. Their health, physical and functional abilities may deteriorate and their confidence in walking and driving, for example, may change as a result of that (Naumann et al., 2009). We report the links found by Kim and Ulfarsson (2008) and Sabir (2011) on Table 1.

Chen et al. (2008) include 'household with children' as a variable in their model for commuting mode choice and find a positive association with cars and a negative one with public transport. Dargay and Hanly (2007) also analyse commuting trips and find similar results: positive association with car and negative for all other modes. Kim and Ulfarsson (2008) analyse mode choice on short home-based trips and also find a positive link with cars and a negative one with public transport (and with walking).

Table 1: Association of different factors for mode choice and modal split according to the reviewed literature

Factor	Author	Suggested association				
		Private car	Public transport	Motorcycle	Bicycle	Foot
City size (measured by resident population)	Schwanen (2002)	na	+	na	--	--
	Scheiner (2010)	--	+	na	+ (for distances under 1.5 km)	+ (for distances under 1.5 km)
	Susilo and Maat (2007)	--	+	na	na	na
	White (2009)	na	na	na	+	na
Car ownership	Balcombe et al. (2004)	+	--	na	na	na
	Chen et al (2008)	+	--	na	na	na
	Kain and Liu (2002)	+	--	na	na	na
	Kim and Ulfarsson (2008)*	+	--	na	--	--
	Kitamura (2009)	+	=	na	na	na
	Paulley et al. (2006)	+	--	na	na	na
	Pinjari et al (2007)	+	--	na	+	+
	Sabir (2011)*	+	--	--	--	+
	Scheiner (2010)	+	--	na	--	--
	White (2009)	+	--	na	na	Na
Income	Balcombe et al. (2004)	+	--	na	na	na
	Chen et al. (2008)	+	--	na	na	na
	Dargay and Hanly (2007)	+	na	na	na	na

	Kitamura (2009)	+	+	na	na	na
	Paulley et al. (2006)	+	--	na	na	na
	Sabir (2011)*	+	--	--	--	+
Age (elderly)	Kim and Ulfarsson (2008)	+	=	na	--	--
	Sabir (2011)*	+	--	--	--	--
Households with children	Chen et al. (2008)	+	--	na	na	na
	Dargy and Hanly (2007)	+	na	na	na	na
	Kim and Ulfarsson (2008)	+	--	na	na	--
Public transport fares	Asensio (2000)	na	=	na	na	na
	Balcombe et al. (2004)	+	--	na	na	na
	Buchanan (1964)	+	--	na	na	na
	Cervero (1998)	+	=	na	na	na
	Chen et al. (2008)	+	--	na	na	na
	Paulley et al (2006)	+	--	na	na	na
	Zhang (2004)	+	--	na	na	na
Public transport service frequency	Asensio (2000)	na	+	na	na	na
	Balcombe et al. (2004)	--	+	na	na	na
	Cervero (1998)	--	+	na	na	na
	Kitamura (2009)	--	+	na	na	na
	Paulley et al. (2006)	--	+	na	na	na
	White (2009)	--	+	na	na	na
Rain	Sabir (2011)*	+	+	--	--	+
Population density	Balcombe et al. (2004)	--	+	na	na	na
	Cervero (1998)	--	+	na	+	+
	Chen et al. (2008)	--	+	na	na	na

	Dargay and Hanly (2007)	--	na	na	na	na
	Newman and Kenworthy (1989, 2006)	--	+	na	+	+
	Pinjari et al (2007)	na	na	na	+	+
	Schwanen (2002)	na	+	na	--	--
	Souche (2010)	--	+	na	--	--
	Susilo and Maat (2007)	--	+	+	+	+
	Zhang (2004)	--	+	Na	+	+
Trip distance	Kim and Ulfarsson (2008)	na	+	na	na	--
	Sabir (2011)*	+	+	--	--	--
	Scheiner (2010)**	+	+	+	+ and --***	--
Land-use mix	Balcombe et al. (2004)	na	=	na	na	na
	Cervero (1998)	--	+	na	+	+
	Frank et al (2008)	--	+	na	+	+
	Newman and Kenworthy (1999)	--	+	na	+	+
	Pinjari et al (2007)	na	+	na	na	na
	Van Acker and Witlox (2011)	--	+	na	+	na

Key: (+) stands for positive association, (--) stands for negative association, (=) stands for no association and (na) stands for not applicable, meaning the source cited did not analyse the association

Note: *Sabir (2011) does not model 'motorcycles' as a mode of transport but includes motorcycles under 'other' mode of transport, which he defines as moped, motor, scooter, taxi, lorry and delivery van . He includes three variables regarding rain in his model: a dummy variable for rain up to 0.1 mm, a dummy variable for rain higher than 0.1 mm, and the duration of rain (in minutes), all at the hour of departure. The results reported on the table above correspond to the dummy variable rain up to 0.1 mm, which is average (as non-extreme) rain.

**Scheiner (2010) includes cars and motorcycles in one category

*** + up to 1.5 km and – for distances longer than 1.5 km

Buchanan (1964) expects a noticeable modal shift from low public transport fares, whereas Asensio (2000) and Cervero (1998) expect higher influence from frequent services. Balcombe et al. (2004) regard high frequencies and affordable tickets as equally influential in the long term and do not consider vehicle comfort as particularly decisive. A number of other authors have also analysed the link between public transport fares and public transport use (or share or choice as a transport mode) and between public transport frequency and public transport use (or share or choice as a transport mode). Their findings are summarised in Table 1.

Curiously, weather variables are not typically included in these types of study. Sabir (2011) is an exception and we report his findings regarding rain on Table 1.[3]

Newman and Kenworthy (1989, 2006) and Cervero (1998) point out the importance of population density for the viability of public transport and non-motorised modes. Other studies find that population density plays an important role in people's mode choice for trips to work (for example, Chen et al, 2008; Dargay and Hanly, 2007; Kain and Liu, 2002) and for urban trips in general (Souche, 2010). Dargay and Hanly (2007) find a negative association between higher population density and commuting by car and Schwanen (2002) finds a positive association between population density and commuting by public transport.

In addition to the variables described above, distance to be travelled and land use mix have also been included in a number of models whose results are reported on Table 1. Finally, there are studies that concentrate on one or two modes only, such as for example Pucher et al. (2011). Their results are not included in Table 1 but they are compared with ours in Section 4.

As it becomes clear from the above, a number of studies have attempted to identify at least some of the factors affecting either modal split or mode choice. These vary greatly in geographical coverage and methodology used. Typically, however, micro data from travel surveys is used or if the data are aggregate, the studies only cover one or a small group of cities, with the exception of Winston and Shirley (1998). The present study, on the other hand, uses aggregate data to compare 112 medium size European cities, with a view to deriving recommendations specific to such European context, in order to inform the on-going transport policy debate at EU level. As highlighted above, analysis at this regional level

[3] Pucher et al. (2011) and Sumalee et al. (2012) do take rain into account but their studies are not empirical studies on modal split like ours.

analysing modal split for so many cities has not been conducted before for the case of Europe.

3. Data and modelling approach

3.1 Data

Petrol prices were retrieved from 'Energy Prices and Taxes' (International Energy Agency, 2008). GDP per capita was retrieved from the International Monetary Fund (IMF) website.[4] The rest of the data used in this paper come from the Urban Audit from the Directorate-General for Regional Policy and Eurostat (European Commission, 2004).

The Urban Audit provides information on selected urban areas across Member States of the European Union and the Candidate Countries. It is coordinated by Eurostat and involves a number of partners including National Statistical Offices, the towns and cities themselves, existing inter-city cooperation networks, international organisations, the European Commission and national governments. Much data already exists at the National Statistical Offices in their databases or in administrative registers linked with them. The remaining part of the data needs to be collected by the very towns and cities. National Urban Audit Coordinators compile this data and Eurostat amalgamates the data coming from the different countries.[5]

The database is freely accessible at: http://www.urbanaudit.org/index.aspx. It covers 357 cities, 336 variables and three spatial levels. *Core cities* refer to areas of local government responsibility, *larger urban zones* or *functional urban areas* usually exceed the core city boundaries and *sub-city districts* are used for comparing disparities within cities (European Commission, 2004, pp. 5, 9, 12). Although larger urban zones are the most suitable spatial reference, due to limited data availability (the data set has many missing values) we use core city data instead. The main problem is that the larger urban zones concept 'is not defined for all cities involved in the Urban Audit, and even where it is defined the criteria and principles are not the same' (European Commission, 2004, p. 11).

Table 2 lists the 112 cities that are extracted from the Urban Audit to form our sample. These are medium-size European cities with population between 100,000 and 500,000. Overall, there are 394 medium-size cities in Europe, but only 112 of them are accounted for

[4] http://www.imf.org/external/data.htm

[5] The data that we extracted from the Urban Audit and used in our models comes either from different National Censuses or are collected by the town or city in question.

in the Urban Audit. As such, our sample represents 28.4% of all medium-size European cities. Although our sample represents little over one quarter of all medium-size European cities, it provides a fair coverage across 12 European countries, as shown in Table 2.

Table 2: The sample medium-size cities in the Urban Audit

Country	Cities
Denmark	Aalborg, Aarhus, Copenhagen, Odense
Germany	Augsburg, Bielefeld, Bochum, Bonn, Darmstadt, Dresden, Erfurt, Freiburg, Gottingen, Halle an der Saale, Karlsruhe, Kiel, Koblenz, Leipzig, Magdeburg, Mainz, Moers, Mönchengladbach, Mülheim, Nurnberg, Potsdam, Regensburg, Saarbrucken, Trier, Wiesbaden, Wuppertal
Estonia	Tallinn, Tartu
Finland	Tampere, Turku, Oulu
Italy	Firenze, Bari, Bologna, Catania, Venezia, Verona, Trento, Trieste, Perugia, Ancona, Pescara, Taranto, Reggio di Calabria, Sassari, Cagliari
Netherlands	The Hague, Utrecht, Eindhoven, Tilburg, Groningen, Enschede, Arnhem, Apeldoorn, Nijmegen, Breda, Almere
Portugal	Porto, Braga, Funchal, Coimbra, Setubal
Slovakia	Bratislava, Kosice
Spain	Murcia, Las Palmas, Valladolid, Palma de Mallorca, Vitoria / Gasteiz, Oviedo, Pamplona / Iruña, Santander, Badajoz, Logroño, Santa Cruz de Tenerife, L'Hospitalet de Llobregat, Gijón, Vigo, Alicante/Alacant, Córdoba, Bilbao
Sweden	Örebro, Gothenburg, Jönköping, Linköping, Malmö, Umeå, Uppsala
Switzerland	Bern, Geneva, Lausanne, Zurich
UK	Bradford, Bristol, Cambridge, Cardiff, Coventry, Exeter, Kingston-upon-Hull, Leicester, Liverpool, Manchester, Newcastle, Nottingham, Portsmouth, Stoke-on-Trent, Wirral, Wolverhampton, Wrexham

The data used in the subsequent analysis are based on averages for the years 2001 and 2004. The averaging is performed to address the issue of missing values, which occurred in many variables across cities. To maintain consistency, the averaging of the 2001 and 2004 values is applied on both the modal split shares and the independent variables used in the estimation of the statistical models. In cases where there are missing values for both 2001 and 2004, the average value of the country for which the city belonged to is used to populate the variable.

Identifying and testing relevant variables was informed by the literature review and our prior expectations regarding the causal relationship between these variables and the observed modal split. This was further coordinated by the validity and availability of relevant information in the data given the missing or inconsistent values across the sample of cities. Table 3 presents the coding and definition of the variables used in the analysis, together with our a priori expectations. One variable not included in any of the reviewed studies but included in ours is the proportion of students in a city. This proved to be a significant variable in relation to public transport, motorcycle, bicycle and foot, as we explain in Section 4, probably because it acts as a proxy for cities which are pedestrian and cycling friendly and public transport oriented.

Table 4 provides descriptive statistics for each of the explanatory variables.

Following Rodrigue et al. (2009, pp. 241, 336) we define *modal split* or *mode share* as the proportion of trips that is made by each transport mode. This is the dependent variable. The different mode shares include *car*, *motorcycle*, *bicycle*, *walking* and *public transport*. We concentrate on *journeys to work* or *commuting journeys*, which are defined according to the European Commission (2004, p. 46) as the 'shortest trip from place of residence to the work place, including change of transport mode'. These morning commute trips ignore trip chaining, understood as a stop (for shopping or dropping children off at school, for example) during travel between two anchors, such as home and work. As a consequence, the database we used does not take into account trip chaining. This does not necessarily mean that all the trips used to compile the data in our data set were free from trip chaining. Commuters may drop their children at school on their way to work, but this is not recorded in the Urban Audit.

The Urban Audit endeavours to guarantee data quality. According to the European Commission (2004, p.77), this is achieved by setting a range for each variable (where possible), checking the data falls within that range, reviewing the data for anomalies and subsequently validating or correcting it.

Table 3: City level variables used in the analysis and expected parameter signs

Variable	Description	Prior expectation
A SHARE	Car share in city k	
M SHARE	Motorcycle share in city k	
B SHARE	Bicycle share in city k	
F SHARE	Walk share in city k	
T SHARE	Public transport share in city k	
BIKE NETWORK	Length of bicycle network (dedicated cycle paths and lanes) per 1,000 population	Positive correlation with *B SHARE*
BUS RATE	Number of buses (or bus equivalents) operating in the public transport per 1,000 population	Positive correlation with *T SHARE*
CAR RATE	Number of registered cars per 1,000 population	Positive correlation with *A SHARE* and negative correlation with *T SHARE*
ELDERLY	The proportion of total population aged 65 and over	Positive correlation with *A SHARE* and negative correlation with all other modes
GDP PER CAPITA	Gross Domestic Product per capita (in EUROS - 2004 prices)	Positive correlation with *A SHARE* and *F SHARE.* Correlation with *T SHARE* has been found to be positive by one study and negative by other studies.*
HOUSE WITH CHILD	Proportion of households with children aged 0-17	Positive correlation with *A SHARE* and negative correlation with *T SHARE*
MOTORCYC RATE	Number of registered motor cycles per 1000 population	Positive correlation with *M SHARE*
PETROL PRICE	Petrol price per liter (in EUROS - 2004 prices)	Negative correlation with *A SHARE* and *M SHARE*
POPULATION	Total resident population	Negative correlation with *A SHARE* and positive correlation with *T SHARE*
RAIN	Number of days of rain per year	Negative correlation with *B SHARE* and positive correlation with *A SHARE*, *T SHARE* and *F SHARE*
STUDENTS	Number of students in universities and further education establishments per 1,000 resident population	Positive correlation with *B SHARE* and *F SHARE* and negative correlation with *A SHARE*

TRANSIT FARE	Cost of a monthly ticket for public transport (for 5-10 km)	Negative correlation with *T SHARE*

*Most of the reviewed studies used personal income and were conducted at household level, so comparisons between our and their results should be taken with caution.

Table 4: Descriptive Statistics

Variable	Minimum	Maximum	Median	Mean	Standard Deviation
A SHARE	15.94	91.30	61.38	59.02	15.82
M SHARE	0.00	27.46	1.57	2.96	4.66
B SHARE	0.05	38.85	5.02	9.66	11.33
F SHARE	1.21	35.29	9.83	10.53	6.59
T SHARE	3.05	71.15	14.93	17.83	12.04
BIKE NETWORK	0.00	3.60	0.35	0.71	0.77
BUS RATE	0.17	7.91	0.76	1.36	1.43
CAR RATE	31.05	688.62	394.16	385.25	125.98
ELDERLY	7.12	26.68	16.24	16.66	3.34
GDP PER CAPITA	5432.93	41083.78	27131.57	25228.38	6817.12
HOUSE WITH CHILD	14.53	59.17	26.81	28.08	10.63
MOTORCYCLE RATE	4.06	136.53	33.33	37.13	27.74
PETROL PRICE	0.85	1.42	1.12	1.12	0.17
POPULATION	100094	500406	214788	237476	9956
RAIN	67.00	239.00	169.50	162.01	46.07
STUDENTS	0.00	263.83	97.09	104.66	55.54
TRANSIT FARE	0.27	108.00	37.13	36.28	21.77

N = 112 Cities

3.2 Modelling approach

The aim of the modelling approach is to explore which (of the available) variables are most likely to influence modal split for commuting in our 112 cities. The five modes considered included C ={car (A), motorcycle (M), bicycle (B), walk (F) and public transport (T)}. Following Greene (2003, pp. 686-687), Ortúzar and Willumsen (2001, p.204), and Small and Verhoef (2007, pp. 9-10) a discrete choice modelling framework is used to model the factors that affect modal split during the morning commute period. The share of a given mode *i* is modelled by calculating the probability of choosing that mode P(*i*) such that:

$$\text{for all } i \neq j \text{ and } i, j \in \mathrm{C} \qquad [1]$$

where is a vector of parameters, is a vector of independent variables, and is an error term with infinite range.

Different assumptions about the type of distribution of the error terms result in different model formulations. For instance, the probability P(*i*) conforms to the well-known Multinomial Logit model (MNL) when is assumed to follow a Type I extreme-value Gumbel distribution and is identically and independently distributed (iid) across alternatives and observations. That is:

[2]

P(*i*) in Eq[2] represents the share of mode *i*. The MNL model in Eq[2] assumes that the choice of one alternative mode is independent from the choice of any other mode (see Figure 1-a).

If the independence assumption is violated (also known as the independence of irrelevant alternatives (IIA) property), one can resort to the Nested Logit (NL) model. Such model relaxes the iid assumption among the different alternative modes by allowing for correlation to exist among certain alternatives. Within the NL modelling framework, various nesting structures can be assumed and tested, as shown in Figure 1. For instance, if there is reason to believe that the choice of a given motorised mode (e.g. car, motorcycle or public transport) and non-motorised mode (e.g. walk, cycle) is correlated then the choice structure in Figure 1-b can be tested. Alternatively, if the choice of private modes (car or motorcycle) is correlated, one can test the structure shown in Figure 1-c. Within the NL approach, the probability of choosing mode *i* is calculated as the product of two probabilities:

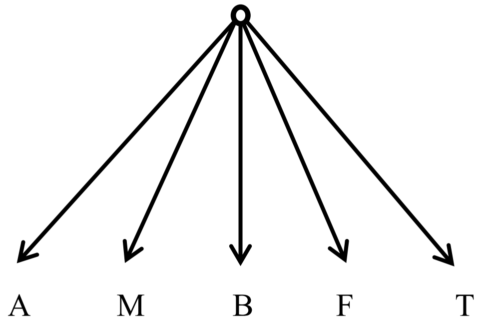
[3]

where is the probability of choosing upper level alternative mode *M* and is the marginal probability of choosing mode *i* conditional on choosing alternative *M*. An example of *i* in Nested Structure 1 would be *car* whereas *M* would be *motorised mode*. The marginal probability is obtained then by a MNL model estimated across the modes listed under alternative *M*. On the other hand, the probability is estimated by an MNL model with the alternatives listed at the upper level. For example, in Nested Structure 1 is an MNL model across two alternatives: motorised and non-motorised, whereas in Nested Structure 2 is an MNL model across three alternatives: private, public and other.

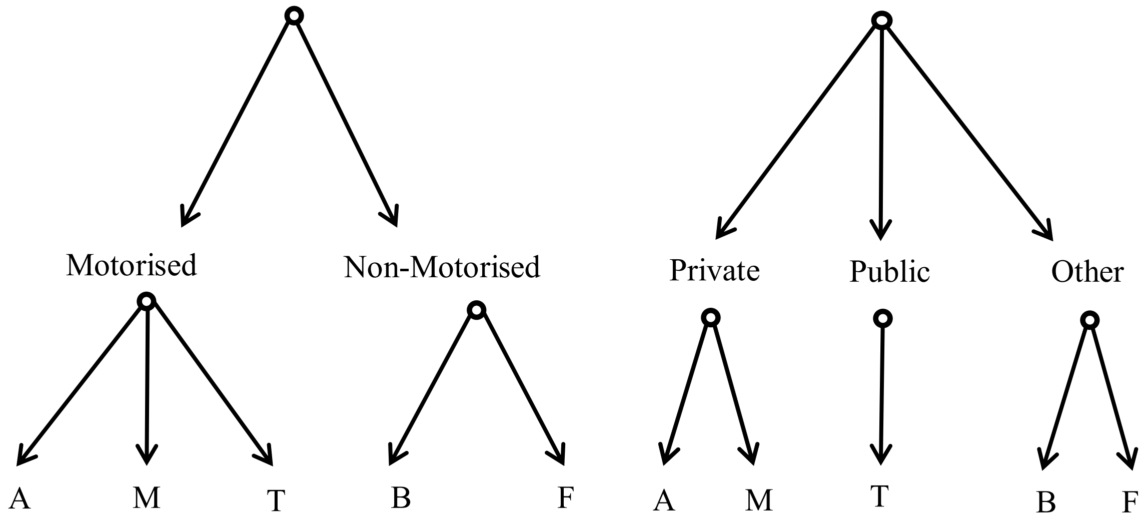
Finally, the Mixed Logit (MXL) model, which is a fairly recent advance, offers flexibility when choosing the distribution of the error term, . According to Train (2009), MXL allows the decomposition of into a randomised component that captures all the correlation among the alternatives and/or decision makers, and another unobserved component that is iid (i.e. correlation free). The correlated component can be assumed to follow any theoretical distribution such as the normal, log-normal or triangular to name a few.

Parameter estimates for MNL, NL and MXL models were obtained using NLogit v.4 (Greene, 2008). The mode shares [6] from each of the 112 cities *e* are used to represent the dependent variable P(*i*) in NLogit. Here, data for each city *e* is represented by five records that correspond to the five modes available to commuters for the journey to work. As such, each of the five records is weighted by the share of the mode *i* that was chosen in that city. A total of 560 data points (5 records *times* 112 cities) are then used to construct the log-likelihood of the logit models. Various variables, as described in Section 3.1, are joined to the 560 modal share data points based on the city for which a particular record belongs. The result is a database that contains the modal shares (i.e. dependent variable) along with a number of socio-economic factors (i.e. independent variables) that are used to estimate the models shown in Figure 1.

6



(a) MNL Structure



(b) Nested Structure 1 **(c) Nested Structure 2**

Figure 1: MNL and NL Model Structures

4. Results and Discussion

Table 5 presents statistically-significant parameters of explanatory variables using the three model structures described above: multinomial logit, nested logit and mixed logit. The results are consistent across the three models in terms of our a priori expectations (described on Table 3) and level of significance. The results further suggest that the estimated parameters can shed light on some of the factors that might influence the modal split of commuting trips in mid-size European cities.

The MNL parameter estimates show that city-level share of car is likely to increase as the number of registered cars per 1,000 residents (CAR RATE) increases, as expected and in line with Balcombe et al. (2004), Chen et al (2008), Kain and Liu (2002), Kim and Ulfarsson (2008), Kitamura (2009), Paulley et al. (2006), Pinjari et al (2007), Sabir (2011), Scheiner (2010) and White (2009). As expected, car share is also likely to increase with GDP per capita. Although our study is at city and not individual level, this seems to be in line with Balcombe et al. (2004), Chen et al. (2008), Dargay and Hanly (2007), Kitamura (2009), Paulley et al. (2006) and Sabir (2011).

Not surprisingly, higher number of students in universities and further education per 1,000 resident population (STUDENTS) is positively associated with all modes of transport except the car, which is an intuitive result. Other things being equal, cities with a higher proportion of students are prone to increased shares of public transport and green and active modes such as bicycle, foot and motorcycles. This is intuitive since university and college cities in Europe tend to be more pedestrian oriented in terms of their land use development and normally benefit the existence of reliable public transport systems. Therefore, it is not surprising to find that cities with higher proportion of students will be associated with commuting trips that are less dependent on the car, *ceteris paribus*.

The share of motorcycle (M SHARE) as a travel mode to work is more likely to be higher in cities with high numbers of registered motorcycles per 1,000 population (MOTORCYC RATE) and lower with increasing petrol prices (PETROL PRICE). As expected, bicycle share (B SHARE) is positively associated with length of the bicycle network (BIKE NETWORK), in line with Pucher et al.(2011). Walk share (F SHARE) is positively associated with GDP per capita, in line with Sabir (2011), although Sabir (2011) estimates a model at household level.

The share of public transport (T SHARE) increases with population size, in line Schwanen (2002) and Susilo and Maat (2007) and decreases with the cost of a monthly ticket (TRANSIT FARE), in line with Balcombe et al. (2004), Cervero (1998), Chen et al. (2008), Paulley et al (2006) and Zhang (2004). Public transport shares are also negatively associated with the proportion of households with children aged between 0 and 17 years (HOUSE WITH CHILD). The intuition behind this is that families may not find public transport a convenient mode of transport, as it typically entails walking to and from a stop or station and waiting, on top of the actual journey, which entails a number of stops and sometimes a detour relative to the final destination. Also, families with young children are more likely to own a car for their household mobility needs. When such an investment in owning a car occurs, the household is more likely to rely on the car for commuting, among other travel activities, and as such will be less likely to use public transport. Although we are only interested in commuting trips and the data does not explicitly include trip chaining, there may be trip chaining. Dropping children at school or day care on the way to work would help explain why modal split for commuting trips seems to be affected by the proportion of households with children. Dargay and Hanly (2007) also find a positive association between commuting by car and the presence of children, even though they do not take trip chaining into account either. Chen et al. (2008) does include trip chaining in his commuting trips and also finds a positive association between the presence of children and the use of car for commuting purposes. Kim and Ulfarsson (2008) model home based short trips and find the presence of children to be positively linked to the car. We did not include HOUSE WITH CHILD in the specification of car utility because it returned a non-significant parameter, unlike the case of public transport utility, where it returned a significant parameter.

The number of buses (or bus equivalents) per 1,000 population (BUS RATE) is positively associated with public transport share. This is in line with Asensio (2000), Balcombe et al. (2004), Cervero (1998), Kitamura (2009), Paulley et al. (2006) and White (2009). GDP per capita is positively associated with increased shares of public transport at the city level. Kitamura (2009) is the only study that finds a positive association between income and public transport, although he does so for a model at household level.

While the elderly may not necessarily be part of the labour force and commute to work on a daily basis[7], share of public transport is found to decrease with the proportion of elderly population (ELDERLY), in line with Sabir (2011), who finds a negative association between

[7] We note that in Europe, Directive 2000/78/EC (European Commission, 2000), establishing a general framework for equal treatment in employment and occupation, does not allow age discrimination. Most EU member states have age discrimination legislation in place as a result, and many had it even before the directive.

people over 60 and public transport as a mode to travel to work in the Netherlands, and Kim and Ulfarsson (2008), who also find a negative association for people over 65 and public transport for short home-based trips in the Puget Sound region of Washington State in the US. Interestingly, public transport share also seems to decrease with the number of days of rain per year (RAIN). This result is not in line with the findings by Sabir (2011). However, Sumalee at al. (2012, p.339) point out that 'anecdotal evidences also suggest that people are less willing to travel by public transport or walk under adverse weathers'. Sumalee et al. (2012) propose a theoretical multi-modal transport network assignment model taking into account uncertainties due to adverse weather conditions and find that the demand for bus travel decreases and the demand for underground travel increases with rain, and also the demand for bus travel increases with rain when there are weather proof pedestrian facilities. The data we use do not differentiate between bus and underground and we do not have data on weather proof pedestrian facilities. Our negative association therefore may be signalling that our case study cities do not have weather proof walking facilities and bus dominates over underground. We did not include RAIN in the specification of bicycle utility because it returned a non-significant parameter. Nonetheless, the evidence regarding the link between rain and cycling is not strong. Sabir (2011) finds a negative association while Pucher et al. (2011) do not report any association.

Further to the MNL model, we explore different NL model specifications, including the two structures shown in Figure 1-b and 1-c. The purpose for developing NL models is to capture potential violations of the IIA property. Our a priori expectation is that some of the alternatives may be more related to each other. For example, car, motorcycle and public transport being motorised modes may share more similarities than walking and cycling as being non-motorised modes (Figure 1-b); similarly car and motorcycle may share more similarities as being private modes vs. public transport and non-motorised modes (Figure 1-c). From all the tree specifications mentioned, the nested structure 1 in Figure 1-b is the only specification, which results in statistically significant inclusive value (*IV*) parameters. The NL-model estimation in Table 5 is based on the RU1 normalisation (Hunt, 2000).

The results from the *IV* parameters suggest that the NL is no different than the MNL. All the estimated parameters are consistent across the MNL and NL models. Although the NL implies some correlation among the motorised modes, the estimated inclusive value is relatively high and very close to 1 (i.e. 0.88). Accordingly, the correlation among motorised modes is fairly weak. Therefore, the MNL structure in Figure 1-a can still be used to explain the observed mode split shares. However, the estimated parameters in the MNL model are most likely inefficient due to serial correlation[8]. The latter is caused by the repeated city-level values used to construct the independent variables across the 5 records within a given city (see Section 3.2). To account for any potential serial correlation in the data, a mixed logit (MXL) model was also estimated. The MXL also accounts for any unobserved heterogeneity (i.e. random effects) in the estimated parameters.

All parameters in the MNL model are tested for potential random effects, and three emerge as significant. Based on the significance of the estimated standard-deviation parameters, the results suggest that GDP PER CAPITA in the car alternative, PETROL PRICE in the motorcycle alternative, and RAIN in the public transport alternative are random parameters that follow the normal distribution. The estimated mean values and corresponding standard deviation of these parameters are listed in Table 5. The estimates are in line with the results obtained from the MNL and NL models as far as the *a priori* expectation and level of significance. However, the MXL model as expected corrects serial-correlation effects. Compared to the MNL results, the t-statistic values for most of the estimated parameters in the MXL model are smaller, thus efficient. Furthermore, the MXL is also a significant improvement over the MNL specification as inferred from the log-likelihood ratio test [= -2 (LL_{MNL}-LL_{MXL}) = 268.52 vs. 7.81 at 5% level of significance].

It should be noted that some Urban Audit variables other than those reported in Tables 2 - 4 were also tested. For instance, average size of households was included in the utility of car (A SHARE) to test if larger households would be more inclined to select car over other modes. Also, median disposable annual household income was tried instead of GDP per capita in all equations. A proxy variable for parking cost (namely, maximum charge of on-street parking in the city centre per hour) was also used to test if increased cost of parking in central areas was negatively associated with the shares of car and motorcycle. The length of public transport network per inhabitant (km/capita) was also tried in T SHARE to examine if a more developed public transport infrastructure had a positive association with the share of commuting trips by public transport. The same was done with the variable number of stops of public transport per square-km, RAIN for B SHARE and HOUSE WITH CHILD for A SHARE. Population density was also tested for all equations and petrol prices for A SHARE. All the above variables were insignificant and in some cases had an opposite sign to the expected one and as such were dropped from the specification of the model. We believe the

[8] An inefficient parameter is usually associated with an inflated t-statistics value since the standard error of the parameter is usually small.

insignificance and/or counter-intuitive signs were due to either correlation with some of the existing variables reported in Table 5 or due to a lot of missing values in some of these tested variables.

Table 5: Estimation results of mode share models

		MNL			NL			MXL		
	Alternative	Beta	t-stats	p-value	Beta	t-stats	p-value	Beta	t-stats	p-value
CONSTANT	A	-8.686	-9.6	0.000	-8.758	-9.4	0.0000	-6.502	-4.5	0.0000
CAR RATE *	A	2.175	6.7	0.000	2.247	6.3	0.0000	4.790	5.1	0.0000
GDP PER CAPITA ** (+)	A	0.608	10.4	0.000	0.671	5.9	0.0000	1.370	5.4	0.0000
STUDENTS	M, B, F, T	0.006	6.6	0.000	0.006	6.1	0.0000	0.016	5.6	0.0000
CONSTANT	M	-9.640	-9.9	0.000	-9.723	-9.7	0.0000	-5.722	-3.5	0.0005
MOTORCYC RATE	M	0.171	7.9	0.000	0.174	7.7	0.0000	0.232	6.6	0.0000
PETROL PRICE (+)	M	-0.965	-2.5	0.013	-0.830	-1.9	0.0605	-3.349	-3.2	0.0016
CONSTANT	B	-9.517	-10.9	0.000	-8.650	-6.0	0.0000	-6.532	-4.2	0.0000
BIKE NETWORK	B	1.003	19.5	0.000	0.992	18.4	0.0000	1.080	15.1	0.0000
CONSTANT	F	-9.325	-10.6	0.000	-8.429	-5.6	0.0000	-6.451	-4.1	0.0000
GDP PER CAPITA **	F	0.271	4.1	0.000	0.256	3.7	0.0002	0.346	5.2	0.0000
POPULATION ***	T	0.427	5.2	0.000	0.422	5.0	0.0000	0.561	4.8	0.0000
GDP PER CAPITA **	T	0.513	5.4	0.000	0.575	4.2	0.0000	0.635	5.5	0.0000
ELDERLY	T	-0.302	-13.9	0.000	-0.302	-13.6	0.0000	-0.248	-6.8	0.0000
TRANSIT FARE	T	-0.033	-9.3	0.000	-0.032	-8.9	0.0000	-0.036	-7.9	0.0000
BUS RATE	T	0.211	6.6	0.000	0.203	5.8	0.0000	0.330	6.8	0.0000
RAIN (+)	T	-0.005	-3.9	0.000	-0.005	-3.9	0.0001	-0.001	-0.4	0.7255
HOUSE WITH CHILD	T	-0.147	-12.5	0.000	-0.147	-12.2	0.0000	-0.118	-6.2	0.0000
Inclusive Values in NL Model										
IV(MOTORISED)					0.882	5.4	0.0000			
IV(NON-MOTORISED)					1.000 (~)	Fixed Parameter				
Derived Standard Deviation of Randomised Parameter Distribution in MXL Model										
GDP PER CAPITA (+)	A							1.879	3.6	0.0003
PETROL PRICE (+)	M							1.835	4.8	0.0000
RAIN (+)	T							0.005	3.0	0.0023
L(0)			-19150.82			-19150.82			-19150.82	

$L(B)$	-12816.43	-12816.20	-12782.17
Rho-square	0.331	0.331	0.333

* Parameter scaled by 1,000

** Parameter scaled by 10,000

*** Parameter scaled by 100,000

(+) Randomised Parameters

(~) IV(Non-Motorised) is set to a fixed value of 1.000 to make sure it remains within the boundaries of discrete choice theory

5. Conclusions and policy recommendations

This paper identifies factors influencing modal split for journeys to work in 112 European cities with populations between 100,000 and 500,000. To our knowledge, this is the first study that covers such a big number of cities for Europe. Previous studies are reviewed, and city-level data from the Urban Audit (European Commission, 2004) together with national petrol prices from the International Energy Agency (2008) and GDP per capita from the IMF website are used.

Three models are estimated: a multinomial logit, a nested logit and a mixed logit. Virtually all the results are in line with expectations and findings reported in the literature. Car ownership is positively correlated with the share of commuting trips by car. Therefore, policies aimed at discouraging car ownership, such as high registration fees or annual excise duties, may help reduce the share of car use for trips to work. Unsurprisingly, GDP per capita is also positively associated with car share. The number of students in universities and further education per 1,000 resident population (STUDENTS) is positively associated with all modes of transport except the car.

Public transport shares are negatively associated with the cost of a monthly ticket, which would point towards the idea of cheaper (perhaps, subsidised) fares in order to increase the share of public transport in commuting trips to work. Unfortunately, we do not have data on public-transport subsidies across the 112 cities examined and this is an area worth of research. Leaving to one side that there is some economic efficiency justification for public transport subsidies (Parry and Small, 2009), White (2009) reports a positive relationship between public transport subsidies and public transport use. Policies aimed at attracting potential public transport users, including current car users, with cheap fares are 'carrot' policies. Perhaps they could and should be complemented with 'stick' policies, discouraging car ownership (as discussed above) and car use. Policies designed to reduce car use include road pricing and high parking charges. None of the cities in our sample has road pricing and we do not have enough data on parking charges to test such hypotheses[9], so more research is needed on this front as data become available.

From our model results, it is clear that policies in favour of public transport, such as reducing fares and increasing the number of buses, are likely to increase the share of public transport in trips to work. Finally, there is a clear positive association between bicycle share

[9] As explained above, we tested parking charges but the variable had a counter-intuitive sign and too many missing values.

and the length of bicycle network. Reallocating road space from motorised transport to bicycles (for example by designating cycle lanes) and even building cycle lanes are relatively inexpensive policies that are likely to achieve an increase in bicycle share of trips to work.

There are some caveats in this study. First, it would have been more accurate to conduct the analysis for 'functional urban areas' rather than for 'cities' as defined by the administrative city boundaries. Traffic does not recognise administrative boundaries. Also, traffic problems can be better addressed by considering functional urban areas (Bratzel, 1999). Second, since our database (except for petrol prices and GDP per capita) is the Urban Audit, we are unable to include some variables which may help explain modal split because there are either too many missing values or the values are missing altogether. These omitted variables include average distance between home and work for each city, average monetary (out-of-pocket) costs of each mode in each city, public transport subsidies, parking charges, some measure of pedestrian zones, and some measure (perhaps an index) of land use mix. In addition to that, the very dependent variable, mode share, does not include any trip chaining, and this would have been useful to consider. Third, as already highlighted in the introduction, modal share is an important issue for analysis and policy, but total vehicle kilometres travelled by the different modes would have complemented and enhanced the study, especially from a sustainability perspective.

Acknowledgements: We are grateful to the School of Planning and Geography at Cardiff University for financial assistance. We are also indebted to two anonymous reviewers for helpful comments on earlier versions of this paper.

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