ESTIMATING THE NUMBER OF CARS IN UK AND US HOUSEHOLDS

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ESTIMATING THE NUMBER OF CARS IN UK AND US HOUSEHOLDS

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ABSTRACT

The quest towards resolving concerns about transportation energy consumption and emissions across nations has created more interests to investigate factors responsible for households' car ownership. While literature holds an extensive body of investigation usually compartmentalised in individual different disciplines, limited efforts have been made to promote inter-linkages of this strand of research across different disciplines. To fill this gap, this study developed an integrating Multinomial logit (MNL) model to examine the impact of some rarely-investigated and conventional explanatory variables, including: ethnicity, accommodation tenure, settlement nature, mental belief, environmental concern, geographical regions, household structure, driving licence, number of household income earners and household income, on car ownership.

Analysis based on rich data sets of British Household Survey and US Consumer Expenditure Survey found not only the conventional explanatory variables to be significantly linked to the number of cars in the US and UK households, but also the rarely-investigated psychological variables were found to be significantly linked as well. As Socio-demography, Geography and Psychology impact on how people and households process information and assess market offers (e.g., products and services), this study presents findings which have beneficial implications for policymakers and transportations planners, including those who would like to alter people's behaviour from private car ownership to public transportation use, car sellers in terms of how to identify and reach potential customers, provision of alternative forecasting approaches to car ownership scholars as well as possible consideration for general car ownership decision making. Caution should be taken when interpreting the relationship between psychological factors and car ownership since the psychological factors adopted are measure representatives from databases used with limitations in the factor structure for a representative sample of the countries' population.

Keywords: Car Ownership, Household Characteristics, Consumer behaviour, Consumer Expenditure Survey, Multinomial Logit, Nested Logit, National Travel Survey

DEDICATION

This work is dedicated to the memory of my mom, elder (Mrs) Olufunmilayo Ejide Lawal and my sister, Abiola Oyelami, who I lost during my sojourn here in the UK and to my immediate loving family.

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I am also most fortunate to have undertaken my studies among supportive colleagues and staff within the division.

I am most indebted to Sue Baker of the International office of the University, whose supportive role in my academic sojourn at the University dates back to October, 2009. I remain most grateful to her. My appreciation to Professor Saeed Akbar and Dr Mark Baimbridge for their advice and supports

Finally, I would like to thank my family, who have endured my absence over a very difficult period for us all, considering having to juggle between my young family responsibility and the PhD demands within very scarce resources. I have always known that if a mind can envision a dream and keeps it with God's grace, no obstacles will deny the dream from seeing the reality. This is the story of the environment within which this pursuit is achieved.

LIST OF ABBREVIATIONS

AIDS	*Almost Ideal Demand System*
CAPI	*Computer Assisted Personal Interview*
CE	*Consumer Expenditure survey*
CL	*Conditional Logit*
CO2	*Carbon Dioxide*
CPI	*Consumer Price Index*
DCM	*Discrete Choice Model*
EV	*Electric Vehicle*
IIA	*Independence of Irrelevant Alternatives*
MNL	*Multinomial Logit*
NL	*Nested Logit*
NTS	*National Travel Survey*
ONS	*Office for National Statistics*
PAF	*Postcode Address File*
PBC	*Perceived Behavioural Control*
PUMD	*Public-Use Microdata*
RUM	*Random Utility Maximisation*
SP	*Stated Preference*
SEM	*Structural Equation Model*
SUV	*Sport Utility Vehicle*

Table of Contents

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

CONSUMER PREFERENCES: INVESTIGATION OF CAR OWNERSHIP DETERMINANTS

1. INTRODUCTION

The car industry and associated industries remain significantly important to many economies. For instance, within the Europe, the car industry directly employs over two million people and about 10 million people when related activities in associated industries are included (Rota et al., 2016). Further, it is the largest private industrial activity promoting research and development (R&D) activities (ACEA, 2008; 2012). The importance of the car market in terms of its economic function and other areas, such as fuel use and government fiscal policy, define why the sector commands increasing attention of both research scholars and policy makers. In the light of this, Kitamura (2009) posited that a better insight of car ownership is required. Meanwhile, a very old question in the literature is the car market saturation level or car ownership determinants. In his work, Citroën noted in 1929 that:

> "What is the limit of consumption?' (…) Could it be infinite as in the United States? (…) Will we reach the cipher of one automobile per 5 people one day?"
>
> …(Citroën, 1929).

Thus, research into the determinants of the ownership function of the car industry is not only expansive but dates back to several decades (McFadden,1974; Carlson,1978; Wheaton, 1982; Gruenspecht,1982; Mogridge, 1989; TAE HOON OUM ll et al.,1992; Greenman,1996; Dargay et al.,2007; Train and Winston, 2007; Baltas and Saridakis, (2013); Saridakis and Balta, 2016; Jansson et al., 2017; Belgiawan et al. 2017; Acheampong and Cugurullo,2019; Roos et al.,2020).

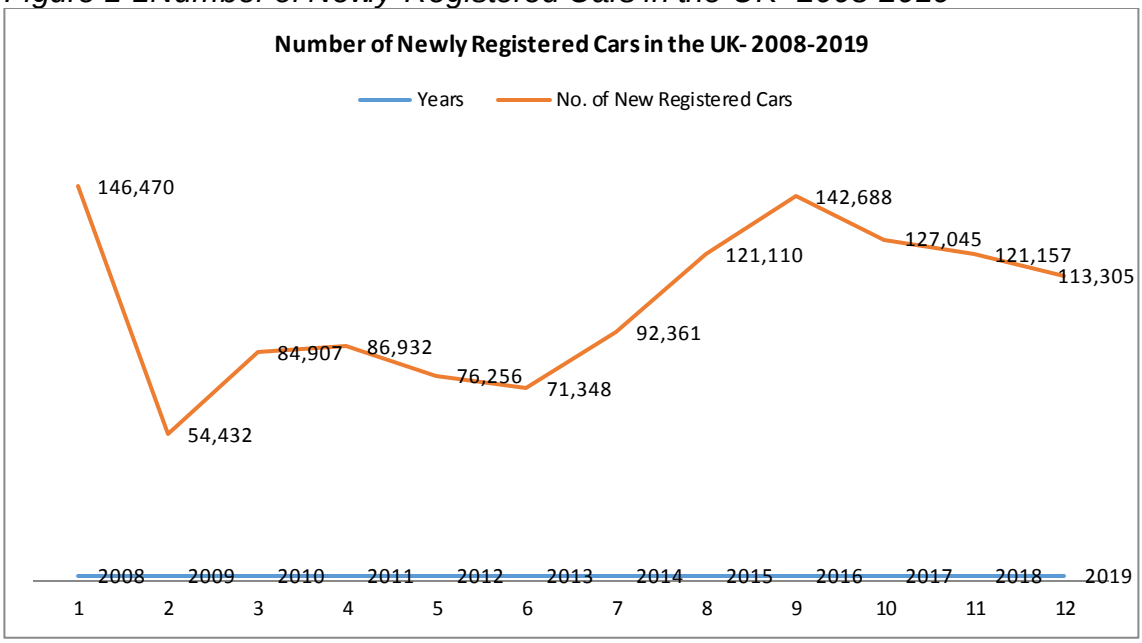
In the meantime, analysing the current trend of data on car ownership in several developed countries, car ownership appears to be reaching its peakalthough in terms of aggregagate number of cars ownership, countries are still recording increase. For instance, between 1951 and 2001, the UK recorded more than a tenfold increase in the number of cars licensed as the number rose from 2.6 million to 27 million and within the following twelve years (between 2001 and 2013), a further 30% increase was recorded as the total

number of licensed car moved to 35 million in 2013 (National Statistics, 2015). Over the same period there has been a steady increase in the average number of cars per household, just as there is a steady increase in the proportion of households with access to more than one vehicle.

Similarly, within the US, passenger vehicles, which include: light trucks, vans, sports utility vehicles (SUV) and motorcycles are used for more than 8 of every 10 trips (FHWA, Highway Statistics, 2017). Furthermore, between 1970 and 2009, total vehicle registrations in the US have risen to more than twice the figures recorded in 1970. Thus, from 1970 to 2009, all vehicle registrations increased at an annual rate of 2.1 % in the US (FHWA, Highway Statistics, 2017). Thus, the aggregate car ownership level in the UK and the US, as inother developed countries is still rising, but at a diminishing rate (See thefigures1-1and1-2 below for graphical trend).

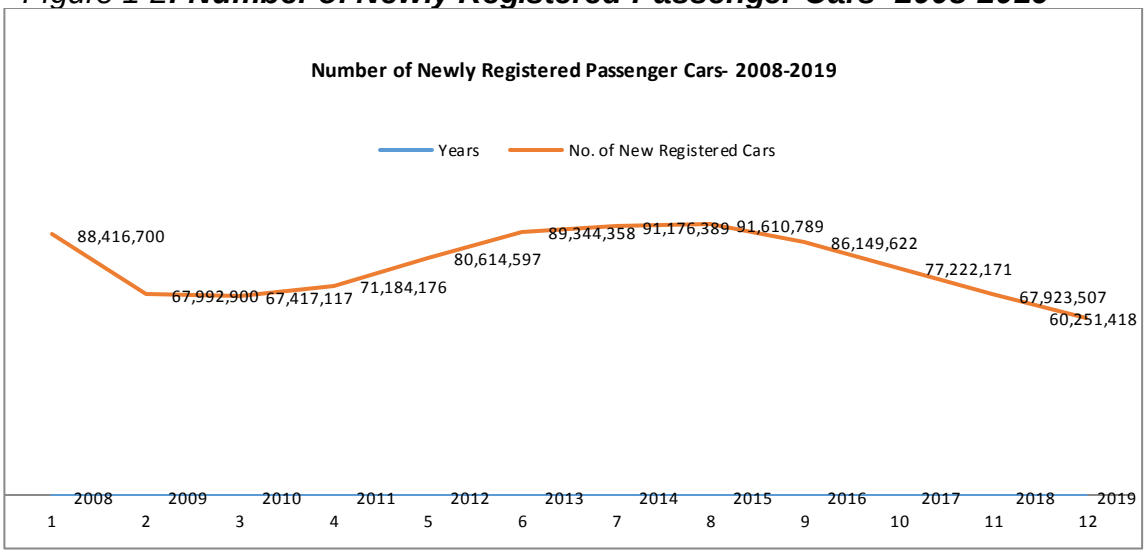
Observing and probing the figures 1-1 and 1-2 below suggest that some factors are responsible for the outlook of the graphs. For instance, why did many households choose less cars in 2008 compared to pre-2008? The 2008 was a period of global recession and prior to this period, the general global economy was on track. Periods between 2008 and 2010, household incomes was adversely affected and as such, the number of cars held by households diminished. Thus, household incomes is one of the factors, among others, identified to have impacted on the outlook of the graphs. Hence, there is a connection between variables that impacts on households and the number of cars a household can hold. In order to gain understanding of the impacts of these factors on car ownership within households, research scholars from diverse disciplines have continued in investigating these factors from their different discipline standpoints. It is in this quest to gain better understanding of how ouseholds' car ownership is by these factors that this research brings its contribution.

Figure 1-1Number of Newly Registered Cars in the UK -2008-2019



Data Source: Central Statistics Office (2020)

*Figure 1-2**: Number of Newly Registered Passenger Cars- 2008-2019***



Countryeconomy.com(2020).

Reviewing the literature on general travel demand within developed countries, there seems to be changing features, indicating emerging trends of passenger lifestyles, which are responsible for diminishing increase of car ownership (Goodwin and Van Dender, 2013; Manting, 2014; Hopkins and Stephenso, 2016). Meanwhile, car use constitutes major percentage of the general travel demand of households and as such, whatever impacts on the general travel demand impacts on the car use demand and vice versa. For instance, as at 2012, passenger cars, vans, buses and trucks constitute almost 87% of the US mode of passenger transport, while in the UK, cars, vans and taxis constitute

about 83% of its mode of transportation as at 2015 (Bureau of Transportation Statistics, 2014). Remarkably, the use of private cars (vehicles in general), usually measured in vehicle miles travelled (VMT) in developed countries has recently gone through a period of stagnation as suggested by different studies (Hopkins and Stephenso, 2016; Circella et al., 2017). Mostly, the average per-capita VMT has continued to reduce, after several decades of steady increase in many developed countries. Meanwhile, a growing strand of empirical studiesargues that developed countries, might have passed the peak of per-capitavehicle ownership/ use (Sivak,2015; Sivak and Schoettle, 2011; Deshmukh, 2018), though in general terms, there is still growth in the number of cars used by the collective body of households in the developed countries.

So far, the conclusions highlighted in various studies as the reasons behind diminishing growth in the private car ownership and its relationships with the use of other travelling modes appear not completely clear (Manting, 2014; Sivak 2015; Hopkins and Stephenso, 2016). Of course, numerous probable explanations have been put forward by scholars for this emerging trend in car ownership behaviour; among which are: influence of the global economic recession, fluctuations in oil and gas prices, changing demographic trends, changing nature of the urban systems across developed cities as well as the emerging variations in households' preferences and lifestyles, just to name a few (e.g. Puentes, 2013; Kenworthy, 2018). It is on this backdrop that this study decided to investigate some determining factors responsible for the number of cars households hold.

Meanwhile, car ownership area has become a major area, which carries huge influence on virtually every area of household life. Perhaps, this is why this strand of research keeps growing among scholars of various disciplines. In view of the importance of the car sector as highlighted above, this study comes within the broad area of deepening understanding of car ownership investigation, particularly, focussing on the determinants of car ownership level in developed countries using UK households and US households as case studies. Of course, the general ownership of cars has promoted major socioeconomic opportunities for households, businesses and government finance, hence, the reason it has continued to command attention of research

scholars across various disciplines. Similarly, this reason makes policy makers to continuously adapting public regulations as car producers are constantly investing in the production of more sustainable technologies (European Automobile Manufacturer's Association (ACEA), 2012).

Conventionally, economist and market researchers have demonstrated efforts in understanding and identifying factors responsible for why individuals or households buy cars. Their quest for this understanding has led to the development of different models of vehicle type choice; many of which are disaggregate in nature. Precisely, these disaggregate choice models like multinomial logit (e.g. Lave and Train, 1979; Manski and Sherman, 1980; Mannering and Winston, 1985; Kitamura, et al., 2000) and nested logit (e.g. Hocherman, et al., 1983; Berkovec and Rust, 1985) have been adopted to offer explanation to why individuals and households make different vehicle type choice. These models are associated with some characteristics. Firstly, there have been huge concentration of interests in the understanding of objective factors (such as, incomes, price etc.,) (McFadden, 2000; Yamamoto and Kitamura, 2000; Hess and Yeung, 2006; Bhat and Sen, 2006; Train and Winston, 2007; Fang, 2008; Bhat et al., 2009; Adjemian et al., 2010; Caulfield, 2012). This was the pattern of many studies till recently. It was an era when scholars dwelled on traditional objective-modal attributes to explain car ownership. Secondly, there are scholars, whose works focussed on intangible-subjective variables (such as, perceptions of yard sizes and off-street parking availability, brand loyalty, product line characteristics, and dealerships) in models to explain determinant of car ownership (Cao et al., 2007; Train and Winston, 2007; Baltas and Saridakis, 2013).

The third characteristic identified in the literature is that most studies that sought to explain households' car ownership dwelled mainly on vehicle types: body types, vintage or model types. For instance, the literature shows that scholars have investigated vehicle type based on different body types (e.g. sedan, coupe, pickup truck, sports, make /model), fuel type, body type and vintage or make/model and vehicle acquisition type (Mannering and Mahmassani, 1985; Brownstone et al., 2000; Mohammadian and Miller, 2003; Cao et al., 2007; Baltas and Saridakis, 2013, Saridakis and Baltas, 2016).

Furthermore, critical reflection of the current literature reveal that studies have always been carried out within the theoretical prescription and restriction of individual disciplines. For example, the microeconomic model suggests that consumers are autonomous, rational, and deliberative decision makers, whose behaviours are based on a choice set to maximize their individual net benefits (or satisfaction or utility) with reference to their static preferences (Potoglou and Kanaroglou, 2007; Hidrue et al, 2011). Similarly, other disciplines have always investigated car ownership using theoretical proposition embedded in each of the various disciplines. Thus, discipline-based methods and approaches have characterised car ownership studies. These studies failed to offer holistic perspectives in their analyses due to lack of synchronisation of all insights within these different disciplines. This is an area this study attempted to explore.

No doubt, the future outlook of the world's transport systems, and essentially, each country's car ownership decisions continue to gain attention of countries all over. This is so as these decisions impact on a number of issues; including ability to reduce climate change and overcome a variety of other sustainable development difficulties. To resolve these issues both technological and socio-behavioral factors are critical in car ownership research. Within car ownership research, a lot of these factors have been studied in details by various research scholars employing different methodology and approaches. Somewhere in the middle of these developments sit modelers, using, interdisciplinary method, on the thinking of individual disciplines. Modelers' approaches come in various forms. Most approaches are individual discipline-based, focussing on a specific discipline when it comes to the factors to be included in the model. Not many modelers integrate many disciplines in their models. For instance, some dwell only on the transport sector in a specific country while, others focus on more than one country the energy-economic system of the entire world. Several models are forward-looking and thus are applied for medium-to-long-term analyses, offering benefits for energy, transport, and sustainable development policy making. Many of these models adopt technological and socio-behavioral factors in building their analyses. Bridging the gap within these elements has historically presented a difficulty (Avineri, 2012; Turnheim et al., 2015). This study attempts to advance an

holistic approach, which integrate elements in various disciplines in car ownership analysis.

Premised on this background, further review of theories and literature were carried out. As against the current modelling approaches, this thesis presents an alternative modelling approach, a baseline disaggregate multinomial choice model, which integrated various discipline factors into an all-embracing estimating model used in estimating the relationship between these factors and the number of car ownership in UK and US households. They were selected because of the relevance of their peculiarities and characteristics in line with the aim of this study. The findings from this study specifically aimed at serving as useful references for transportation stakeholders in the developed countries, including car ownership researchers, car businesses and relevant government agencies alike. Thus, both countries were selected as they constitute key countries, whose global positions in terms of international relations, international politics and diplomacy allow them to carry relevant influence and responsibility towards engaging in global issues and problems.

Furthermore, while the UK reflects characteristics of a number of developed countries within Europe, the US appears to be in a different platform. For instance, going through car ownership literature, there is huge amount of body of research on car ownership while the UK has few studies. Furthermore, the two countries in view of their positionings constitute right examples for illustrating current trends in car ownership among western nations. Lastly, since this study is constrained in time, it is expedient to limit the number of study countries adopted. Thus, the reason for the selection of the two countries.

Based on the baseline disaggregate multinomial choice model of the car ownership, the impacts of different discipline based factors on the number of cars owned by households were estimated. Among others, the adopted estimation methods provided for the opportunity to test if the proposed model offered more insights into the car ownership research in comparison with other existing approaches. In the light of the foregoing, this thesis adopts an inclusive modelling approach as it takes into consideration different disciplines' variables to investigate determinants of the number of car ownership in the UK and the US households. In other words, this study investigated the relationship between car ownership level and different discipline-based factors. Essentially,

demographical factors, psychological factors, economic factors and sociological factors and their relationships with households' different levels of car ownership were investigated using Multinomial logit (MNL) modelling approach and comparing the approach with Nested logit (NL) modelling approach.

Data used for the investigations were drawn from the British Travel Survey and USA Travel Survey. Apart from other benefits, the analytical methodology bridges the afore-mentioned identified gap. The response variables used were mapped out from various disciplines, which literature has identified in car ownership analysis. These factors include: demographical factors (driving licence holding and household structure), sociological factors (ethnicity, regional locations, accommodation tenure, settlement nature), economic factor(household income and earning poweras well as psychological factor, which is individual mental belief regarding car impact on environment or environmental concern. While some of these factors have history of investigation in car research literature, others have not and as such, this study creates not only the opportunity for investigating such factors, but also the opportunity to use updated household micro data for the investigation.

Scholars have found that various different causal variables appear to work in different ways in investigating a great variety of variables in relation to behavior in an environmental context, there is still no agreement regarding which of these variables seems to the robust determinants of Pro-Environmental Behaviour (PEB)(Stern, 2000;Gardner and Stern, 2008; Gifford, 2014). Prior to specifying hypothetical model adopted for the study, concepts of psychological factors, sociological factors, economic factors and demographical factors were closely examined and their interactions in influencing household behaviours regarding the number of car ownership. Thus, the main objective of the study is to estimate the impact of various discipline based factors in influencing car ownership within households by investigating the number of cars owned by UK and US households as dependent variable using various discipline based factors (determinants) as independent variables.

1.1 SIGNIFICANCE OF THE STUDY

Based on the objectives stated in section 1.0, the study successfully matched and combined different discipline-based factors (determinants) identified in car ownership literature and as available in the British Social Attitude Survey (2016) and Consumer Expenditure Survey (CE) (2016) into an estimating model to analyse the number of car ownership level within the UK and the US households. To set a good footing for this work, a review of various car ownership determinants was carried out; mapping out different factors (determinants) adopted for this study. As against using primary surveys, this study made use of secondary data at household level from the stated household surveys. Meanwhile, the overriding purpose of this thesis could be split into three.

Firstly, the investigation aimed at examining whether inclusion of discipline-based determinants in an estimating number of car ownership model is able to provide more insights into analysis of car ownership determinants in the specified countries. That is, whether such analysis and insights derived will surpass conclusions derived prevailing analyses from contemporary works. Secondly, the investigation aimed at estimating some rarely investigated car ownership determinants and to know whether such investigation can enrich the literature. Thirdly, this study, by adopting the most frequently adopted modelling approach(MNL) and comparing its results with NL approach in a car ownership analysis using the same set of data, this thesis further provided the opportunity to confirm or invalidate scholars' assertion regarding which of the two modelling approaches is better for analysis of car ownership investigations.

Thus, the findings of this study, among others seek to help setting priority in governmental policy decision, towards offering useful information based on analyses carried out for transport system planners towards designing sustainable transport policies, aid car manufacturers/sellers towards channelling their marketing focus on possible car buyers and last but not the least, towards sensitising car ownership research scholars on alternative modelling approaches for investigation of car ownership determinants. It is a known fact that the government departments of transportation fund the construction of highways with reference to the number of vehicles in use, just as air quality boards propose policies that help to reduce air pollution based on

the projected vehicle use. In addition, it is important to note that the number of cars owned by households bears a huge impact on profits of car manufacturers, related companies and by extension, employment of household members, who are gainfully employed by the organisations. Based on these benefits, relevant literature on car ownership has remained an interesting research area in recent past decades.

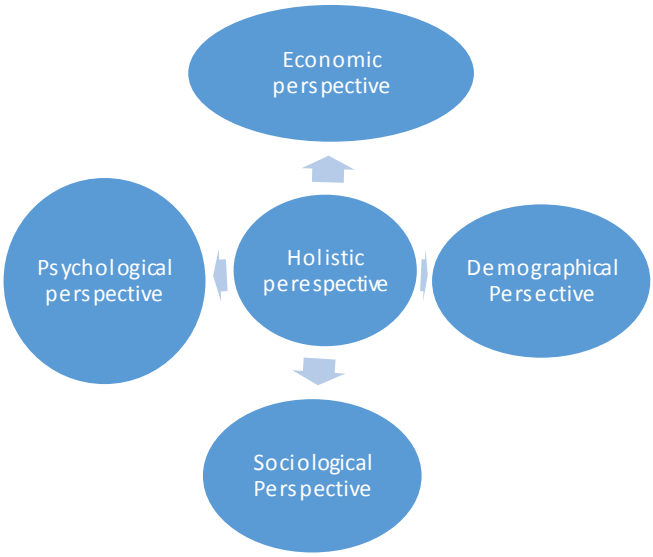
Furthermore, as there are limited up-to-date studies in the literature on car ownership that adopted such investigative approach (i.e. an analytical approach that allows different discipline based determinants to be included in a model) (Baltas and Saridakis, 2013, Saridakis and Baltas, 2016) as used in this study, this study becomes timely. No study has incorporated the range of diverse disciplines' factors as utilised in this thesis to investigate car ownership. At best, each of the current studies in the literature is either based on economic determinants (Axsen and Kurani, 2012; Mannberg et al., 2014) or non-economic determinants (Wall et al., 2007; Yadav and Pathak, 2016; Belgiawan et al, 2017; Roos et al.,2020). This is a gap, which this study attempted to fill. Thus, the motivation is embedded in seeing holistic approach adopted to investigate car ownership in households.

1.2 THE SCOPE OF THE STUDY

It is important to note that the core traditional economists have set the foundation for understanding of car ownership analysis and this has provided footing for further perspectives that cut across different disciplines. Importantly, this study highlights departure from the core traditional approaches in car ownership research. Unlike the Classical School perspectives, which hold restrictive view on determinants of cars, this current study; in line with emerging trend, has suggested other determining factors beyond the boundary of the Classical Economics.

Generally, individual separate disciplines have studied the determinants of car ownership, using concepts and terminologies to describe factors that motivate customers' purchases. Thus, expansive theories and literature from separate disciplines (including, Economics, Psychology, Sociology, etc.) exist on what constitutes consumers' characteristics with majority of them offering discipline-based explanations to suggest factors that determine car ownership (Campbell,1991; Solomon et al, 2010; Mehta and Chugan,2019).

Figure 1.2-1 Relationship between Holistic Perespective and Individual Discipline based Perspective



Lawal (2021).

The above figure captures the focus of this study, seeking to integrate different individual discipline based perspectives into a whole with the motive of gaining better understanding of how different discipline based factors influence the number of car ownership in households. Thus, in this study, a selection of different factors within different disciplines is examined in order to illustrate some concepts used in the identification of consumers' motivation in choosing the number of cars they own.

Thus, this study examines two broad perspectives: economic and non-economic perspectives for estimation of determinants of car ownership. Within the non-economic perspectives, demographical perspectives, sociological perspectives and psychological perspectives were considered. Thus, the thesis proposes a novel pathway in car ownership research as it explored bridging the gap between Economics and other disciplines in the area of car ownership research. In doing this, the study adopted a multinomial logit model to estimate car ownership determinants and these determinants cut across different disciplines. Consequently, the main objective of this study is to estimate the impact of various discipline based determinants of car ownership on the number of cars owned by UK and US households.

Premised on this objective, the following five main research questions were resolved in this study:

1. Does each category of disciplined based factors exhibit significant relationship with car ownership in both countries: UK and US?
2. What are the implications of the proposed car ownership determinants to UK and US transport stakeholders?
3. Does the proposed 'number of cars ownership' estimating model reflect more insights into the UK and the US households' car ownership; especially, in the light of its holistic approach?
4. Does the analysis in this study offer possible number of car ownership preferences for the households in the two countries?
5. In terms of sensitivity analysis, how does a change in independent variables impact on the number of car ownership in households across the two countries?
6. Are there similarities or differences identified in various determinants' estimates between the two countries and what are the likely explanations to this?

The research questions were resolved through two pieces of main chapters, chapter 5 and 6 of this thesis.

1.3 STRUCTURE OF THE STUDY

Given the aim of this thesis has three essential preparatory and motivational chapters: 2, 3 and 4, followed by the two essential main chapters, chapter 5 and 6, while the last chapter presents thesis conclusions, limitations and areas for further study. The chapter 2 outlines the main theoretical underpinning car ownership, highlighting key discussions in relations to determinants of car ownership. This allows readers to understand where this thesis fits in the current literature. Chapter 3 focuses on specific literature on car ownership determinants. It expands on different approaches on car ownership determinants as identified by various disciplines and highlights the main factors, which could be mapped out from secondary databases used for the main empirical chapters. Chapter 4, which serves as a prelude to the two empirical chapters focuses on the review, development and specification of models and estimation approaches of car ownership. The chapter also justifies why the modelling approaches adopted for the study were used.

Chapter 5 of this thesis dwells on investigating whether 'number of car' estimating model, proposed in this study would yield more insights into the UK household car ownership behaviours; highlighting different implications of the study findings to UK transport stakeholders. Chapter 6 adopted the proposed model to investigate whether a 'number of car' estimating model would give more insights into the US households' car ownership; highlighting different implications to the US transport stakeholders. Conclusions, recommendation, overall implications and limitations form the chapter 7 of the thesis as well as possible future areas of study.

CHAPTER 2

THEORETICAL PERSPECTIVES OF BUYING DECISIONS

2.0 INTRODUCTION

The study of consumer behaviour, including its characteristics has never been easy. For instance, it is possible to see consumers expressing desires to purchase certain commodities, and still in reality act in the absolute opposite direction. Many a times, they are not even aware of determining factors behind their buying decisions or might even react to these determining factors last minute, prompting changes in their purchases. Although, consumers' physical decisions (as demonstrated in demand) are relatively easy to notice and quantify, the Psycho-physiological process behind them are very difficult to take into account (Kotler and Armstrong, 2008). Perhaps, it is because of this that research related to consumer behaviours has always been approached and seen from different dimensions with diverse relationships in different disciplines. The aim of this chapter is to examine theoretical factors considered by different disciplines as determinants for car ownership with a view of bringing these various positions into a whole.

Therefore, this chapter reviewed different perspectives by various disciplines regarding ownership of cars in households. Thereafter, conclusions derived from these various disciplines regarding determinants of car ownership are used to derive footing to propose estimating model for car ownership by UK and US households. The next section analysed theoretical determinants underpinning demand, projecting the motivation behind car ownership, which is the specific focus of this thesis.

2.1 THEORETICAL DETERMINANTS UNDERPINNING BUYING

In modern society, 'market' as a concept is central to the business world as it seems to have captured the imagination of people, defining business language. Thus, market connotes a scheme of values and features that need no further meaning to those in the know. In some sense, markets could be viewed in terms of people's understanding of trading and the manner in which trading is carried out. A market refers to a group of buyers

and sellers of a particular good and service. While buyers, through the way they function as a group determine the demand for the product, the sellers through the way they behave determine the supply for the product (Mankiw, 2014). In other words, markets involve people in a fundamental human activity of exchange of goods and services. It thus means that markets are controlled by human characteristics in terms of their views of wants, tastes, how they pursue or achieve these wants and tastes and their respective positions in the market either as buyers or sellers.

One key proposition is that there is no market without people and demographical trends, and the number of buyers constitutes major determinants of how buyers function in markets. The functioning of consumers in the market, in terms of what they want to consume and are able to purchase within their budget, is within the theory of consumer preferences, usually discussed in consumer behaviour area. This has long been of interest to scholars and this field could be traced to about 300 years ago with works from some early economists, including: Nicholas Bernoulli, John von Neumann and Oskar Morgenstern, who examined the basis of consumer decision making (Richarme, 2007; Bray, 2008).

Meanwhile, consumer behaviour theory, which examines how consumers purchase commodities and services consumed and how these purchases impact on their daily living is one of the few economic theories that have attracted extensive research. Generally, choosing to do or not to do something (e.g. acquisition of specific number of cars as in the context of this thesis) remains a common state of activity engaged by people within every society. So, consumer preferences and its determinants have attracted interest from researchers from various fields.

Generally, empirical analysis of consumer behaviour possesses an extensive and rich history within not only Economics, but also Econometrics. The earliest estimation of consumer preferences could be traced back to Moore (1914), when estimation was basically limited to reducing data, and as such possessed little relationship with economic postulations or theories. Leading work by Stone (1954) in Econometrics

using estimation for demand systems struggled with finding and use of flexible functional forms, which do not impose difficulties that the data cannot overcome, while maintaining a connection to economic theory (either by imposing it, or finding ways to test it). Among the various models that have been used by scholars in estimating consumer systems are the Rotterdam model (Theil, 1965; and Barten, 1966), the Translog model (Christensen, et. al, 1975), and the Almost Ideal Demand System (Deaton and Muellbauer, 1980). For a more comprehensive review of this literature, see Deaton (1986).

In the meantime, a similar line of research considers goods as bundles of attributes, as against qualitatively various products (Gorman, 1980; Rosen, 1974). Under this class of attribute-based models, prevalent work is the study of discrete choice (McFadden, 1974), which is similar to the work on demand model and dwells on the direct and close connection between economic theory, Econometrics and empirical work. Consider McFadden (1981, 1984) and Train and Winston (2007) for surveys of this trend of research. This is the consideration given to cars in this thesis. That is, the number of cars, which is associated or owned by each household is seen as a bundle of attributes, which the household has chosen. Furthermore, the factors resident in decision makers in households could not have been only economic factors or psychological factors or any other determining factors embedded in a singular discipline. Thus, to restrict car ownership investigations to only singular discipline is inadequate. Rather, such investigations should benefit from holistic perspectives that encompasse different perspectives embedded in individual disciplines.

Furthermore, since the middle of the 1980s, a lot of scholars (Potoglou and Kanaroglou, 2007; Hidrue et al, 2011; Axsen and Kurani, 2012; Mannberg et al., 2014) in applied Micro-econometrics have begun to focus on estimation of ‘assumed’ causal, or treatment effects and models, using natural and quasi experiments in dealing with consumer behavioural problems. Going through the literature, it is observed that this approach was not uniform within all fields of Microeconomics. While economists are interested in estimating consumer behaviour for maximisation of economic

benefits in demand during market transactions, other disciplines have their interests in consumer behaviour by trying to understand how the various actions and decisions that precede the demand took place.

For instance, an average potential car buyer might have to think about certain demographical issues affecting his/her family or himself before making purchase of the car e.g. ages of household members, issue of driving licence, perhaps, social class or status that owning a car gives to him/her and many more. All of these are not only associated to demand, which happens when the car is actually bought, but rather other indirect issues associated to demand. For example, social class or status feeling that owning a car brings the potential car buyer is associated to the demand for car in an indirect manner since it deals with his/her psychological feeling.

Thus, consumer behaviour, more than ever before, has in recent times attracted scholars of diverse disciplines. An area, which is the focus of this work (i.e. car ownership research) is one area that has attracted scholars from both Economics and Management fields. Accordingly, it is the interest of this study to provide explanations on the impacts of different discipline-based determinants on the number of cars owned by UK and US households. Therefore, human demand as purchase of cars, is based on habit, experience, advertising, peer pressure, environmental constraints, accumulated view, household and family constraints among others (Axsen and Kurani, 2012; Baltas and Saridakis, 2013; Mannberg et al., 2014). Hence, these factors suggest the temporal nature of choice making and outcomes (Louviere et al, 2000; Train, 2009).

This suggests that human demand cannot be restricted to theories within a single discipline. Thus, a selection of different determinants of car ownership drawn from the data sets adopted was used to represent discipline based determinants in the empirical chapters of the thesis. Premised on this, a framework was developed for this study. As noted in Chapter 1, traditional economists provided the foundation for understanding consumer behaviour theory, for which other disciplines build

on. Therefore, the important point of departure from the core traditional School is that literature has identified other factors within other disciplines as determinants of consumer preferences. The next section reviews some of these different submissions and conclusions of different disciplines on determinants of consumer preferences in order to understand inter-relationships within these discipline based factors.

2.2 DEMAND THEORIES: ECONOMIC PERSPECTIVES

Usually, economic literature deals with consumer preference in its rudimentary form based on perfect competition theory. Consumer preference, which is premised on demand is analysed with concepts of self-interest of consumers and their rational pursuit. Desire to spend or 'act of purchase' is usually relevant to demand estimation. Meanwhile, the decision to pay for commodity implies that the consumer has less to expend on other things and this aids explanation of his/her outlays over given commodities. An economic agent, known as an individual consumer is assumed to allocate an income of γ over n market goods $q_{i,}$ which can be purchased at unit prices of P_i in such a way that a 'utility' (satisfaction) function defined over the n *goods*, $\varphi(q_1, \dots \dots . . q_n)$, is at a maximum.

Whatever may be the nature of a consumer expenditures, spending cannot exceed total income (plus cash already saved or accessible through borrowing, or sale of existing asset(s)) during the period. These whole sums represented by *'y'* (income) in the solution below may be further explained in the sense that some may be taken away for taxation; constituting further limitation on consumer' purchasing power. Thus, the amount considered in the demand analysis is a consumer's 'disposable income' usually sourced from wages/salaries, dividends, interest and rent, plus any family allowances, retirement pension or social benefits he/she is receiving, minus any amount he/she has to pay in direct (i.e. income) taxation.

Formally represented, purchase decisions are assumed to follow the solution to the following constrained maximisation problem:

$$q_i \quad i = 1, \ldots., n, that\ maximises\ the\ function\ \varphi(q)$$
$$= \phi(q_1, \ldots\ldots. q_n), \qquad 2.1$$

subject to the condition that

$$\sum p_i q_i$$
$$= y \qquad 2.2$$

To solve the problem, the following expression is formulated

$$\phi(q, \lambda) = \phi(q) - \lambda(y - \sum p_i q_i) \qquad 2.3$$

Where λ is a Lagrangean multiplier representing the marginal utility (additional satisfaction received from an additional unit of consumption) of income, differentiates this expression with respect to q_i and λ:

$$\frac{\delta\phi}{\delta q_i} = \frac{\delta\phi}{\delta q_i - \lambda p_i,}, \quad i = 1, \ldots n \qquad 2.4$$

$$\frac{\delta\phi}{\delta\lambda} = y - \sum p_i q_i \qquad 2.5$$

This is properly presented in the neoclassical demand theory described below.

Neoclassical demand theory

Neoclassical Economics refers to an approach to Economics, which relates supply and demand to individual rationality and his ability to maximize utility. This aspect of Economics adopts mathematical equations and methods to investigate different aspects of the economy. Neoclassical Economics was developed in the 19th century, premised on works by William Stanley Jevons , Carl Menger and Leon Walras among others, but gained popularity in the early 20th century(Jevons, 1970)[1].

Consider 'n' consumption cars that can be chosen by car consuming household. The consumer's problem is:

$$\max_x u(x) \ \ subject\ to\ p^1 x = y, \qquad 2.6$$

[1] William Stanley Jevons, an English economist and logician lived between 1835 and 1882, Carl Menger, an Austrian economist and founder of Austrian School of Economics lived between 1840 and 1921 and lastly, Leon Walras, a French Mathematical economist and Georgist lived between 1834 and1910

Where: n refers to the $n*1$ vector of cars and other goods; p is the corresponding vector of prices; and y connotes the household total expenditure on cars and other goods (often referred to as, nominal income).

Marshallian demand

Marshallian ordinary demand functions are used to resolve the first order conditions of utility maximization

$$x = x(p,y) \qquad 2.7$$

Usually, demand systems are presented in budget share forms, where:

$S_j = P_j X_j / y$ refers to the expenditure share of good j (car and others), and $S = (S_1, \ldots, S_n)$. The Marshallian demand system satisfies these properties: (i) positivity (ii) summability, $P^1 x$(p,y)=y^1 (iii) homogeneity of degree zero in (p,y), implying absence of money illusion; (iv) matrix of substitution effects, $S = \frac{\delta x(p,y)}{\delta p^1} + \left(\frac{\delta x(p,y)}{\delta y}\right) x(p,y)^1$, is symmetric and negative semi definite. It is observed that these demand system properties provide 'integrabiblity conditions' since they permit reconstruction of the preference pre-ordering from the demand system. Consider, for instance, Hurwicz and Uzawa (1971). When and if these properties are tested empirically and cannot be rejected, then it could be concluded that there exists a utility function that generates the demand system.

Indirect utility

Highest level of utility at given prices and incomes, $h(p,y) = \cup\ (x(p,y))$, refers to indirect utility function. The direct utility function and the indirect utility function are equal representations of the underlying preference pre-ordering. Using h, the demand system could be derived by straightforward differentiation, without going through solution via simultaneous equations, as would be the case with direct utility function first-order conditions.

In particular, Roy's identity,

$$x(p,y) = -\frac{\frac{\delta h(p,y)}{\delta p}}{\frac{\delta h(p,y)}{\delta y}}, \qquad 2.8$$

ensures that the demand system is derived if there is an interior solution and that $p > 0$ and $y > 0$. Alternatively, the logarithmic form of Roy's identity,

$$s(p,y) = -\frac{\frac{\delta log h(p,y)}{\delta log p}}{\frac{\delta log h(p,y)}{\delta log y}},$$

or Diewert's (1974, p. 126) modified version of Roy's identity,

$$S_j(v) = \frac{v_j \nabla h(v)}{v_j \nabla h(v)}, \qquad 2.9$$

can be adopted to derive the budget share equations, in which $v = [V_1, \ldots., V_n]'$ is a vector of expenditure normalized prices, with the jth element being $V_j = \frac{P_j}{y}, and\ \Delta h(v) = \delta h(v)/\delta v_j$.

Meanwhile, the indirect utility function is continuous in $(p;y)$ and has these properties: (i) positivity; (ii) homogeneity of degree zero in$(p;y)$; (iii) decreasing in (p) and increasing in y;(iv) strictly quasi convex in (p); and (v) satisfies Roy's identity (E.q. (2.8)).

In total, properties (i)-(iv) are referred to as the `regularity conditions'. Thus, Caves and Christensen (1980) note that an indirect utility function is `regular' at a given $(p;y)$ if it satisfies the above properties at that $(p;y)$. Likewise, the 'regular region' is the set of prices and income at which an indirect utility function satisfies the regularity conditions.

Hicksian demand

Associated to the utility maximization problem is the problem of minimizing the cost or expenditure required to obtain a fixed level of utility, u, given market prices, p,

$$C(p,u) = \min_x p'x\ subject\ to\ u(x) \geq u \ldots. \qquad 2.10$$

If the cost function is differentiable with respect to p, then Shephard's (1953) lemma,

$$\tilde{x}(p,u) = \frac{\delta C(p,u)}{\delta p} \qquad 2.11$$

can be used to derive the expenditure minimizing demands, $\tilde{x}(p,u)$, which are the Hicksian compensated demand functions. Apart from the fact that Hicksian demands are positively valued, it has these properties: (i)

homogeneous of degree zero in p; and (ii) the Slutsky matrix, $\tilde{x}(p,u)/\delta\hat{p}$, is symmetric and negative semi-definite. Lastly, the cost or expenditure function, $C(p,u) = p\tilde{x}(p,u)$, has these properties: (i) continuous in $(p;u)$; (ii) homogeneous of degree one in p; (iii) increasing in p and u; (iv) concave in p; and (v) satisfies Shephard's lemma (2.10).

Elasticity relations

The elasticity measures can be calculated from the Marshallian demand functions, $x = x(p,y)$. Specifically, the income elasticity of demand, $\eta_{iy}(p,y), for\ I = 1,\dots n$ is

$$\eta_{iy}(p,y) = \frac{\delta x_i(p,y)}{\delta y}\ \frac{y}{x_i(p,y)} \qquad 2.12$$

When $\eta_{iy}(p,y) > o$, the ith good is considered as normal at $(p;y)$, and as inferior when $\eta_{iy}(p,y) < 0\eta_{iy}$. In addition, when $\eta_{iy}(p,y) > 1$, the ith good is considered as a luxury, and as a necessity, when $\eta_{iy}(p,y) < 1$.

The uncompensated (Cournot) price elasticities, $\eta_{iy}(p,y)$, for $i,j = 1,\dots\dots n$, i, are

$$\eta_{iy}(p,y) = \frac{\delta x_i(p,y)}{\delta y}\ \frac{y}{x_i(p,y)}$$

When $\eta_{iy}(p,y) > o$, the goods are Cournot gross substitutes. When $\eta_{iy}(p,y) < 0$, they are gross complements; and if $\eta_{iy}(p,y) = 0$, they are independent.

Slutsky equation is

$$\frac{\delta x_i(p,y)}{\delta p_i} = \frac{\delta \widetilde{x_\iota(p,u)}}{\delta p_i} - x_j(p,y)\frac{\delta x_i(p,y)}{\delta y} \qquad 2.13$$

for all $(p;y)$,u=$(p;y)$, and $i,j = 1$,….n, where $\delta x_i(p,y)/\delta p_j$ refers to the total effect of a price change on demand, $\delta\widetilde{x_i}(p,u)/\delta p_j$ means the substitution effect of a compensated price change on demand, and $-x_j\,(p,y)\ \delta x_i(p,y)/\delta y$ is the income effect. Based on Hicks (1936), $\delta\widetilde{x_\iota}(p,u)/\delta p_j > 0$ suggests substitutability, $\delta\widetilde{x_\iota}(p,u)/\delta p_j < 0$ means complementarity, and $\delta\widetilde{x_\iota}(p,u)/\delta p_j = 0$ suggests independence.

Slutsky symmetry can be written in elasticity terms as:

$$\eta_{iy}(p,y) + \frac{\eta_{ij}(p,y)}{s_j(p,y)} = \eta_{iy}(p,y) + \frac{\eta_{ji}(p,y)}{s_i(p,y)} \qquad 2.14$$

or adopting Allen elasticities of substitution, changing the equation to:

$$\sigma_{ij}^{a} = \eta_{iy}(p,y) + \frac{\eta_{ij}(p,y)}{s_j(p,y)} = \eta_{iy}(p,y) + \frac{\eta_{ji}(p,y)}{s_i(p,y)}$$
$$= \sigma_{ji}^{a}(p,y) \qquad 2.15$$

In which $\sigma_{ji}^{a}(p,y)$ refers to the Allen (1938) elasticity of substitution between goods i and j. When $\sigma_{ji}^{a}(p,y) > 0$, goods i and j are Allen substitutes and if $\sigma_{ji}^{a}(p,y) < 0$, then the goods are Allen complements. Allen elasticity of substitution remains the traditional measure, though; other measures are available, such as: the Morishima (1967) elasticity of substitution,

$$\sigma_{ij}^{m}(p,y) = s_i(p,y)(\sigma_{ji}^{a}(p,y) - \sigma_{ii}^{a}(p,y) \qquad 2.16$$

which measures the net change in the compensated demand for good j when the price of good i changes. Goods will be Morishima complements (substitutes) if an increase in the price of i causes x_i/x_j to decrease (increase). Consider Davis and Gauger (1996), Blackorby and Russell (1989) and Davis et al., (2013) for details on other measures of elasticity of substitutions.

While this process of product differentiation is often considered artificial, its impact usually goes a long way to determine what consumers eventually buy and how much they pay for commodities (Mankiw, 2014). This make analysis of demand challenging. In empirical choice analysis as the analysis of this thesis, each choice made by consumer is viewed as different from others (Baltas and Saridakis, 2013; and Fang et al, 2014). For instance, based on the data set used for the analysis in chapters 5 and 6, each choice of number of car owned by each household in the database is viewed differentiated from other choice selections available in the data set (each household could either own no car, one car, two cars or three or more cars).

Therefore, in such analysis, a consumer is viewed to have agreed to pay for a particular commodity with all its peculiarities being different from any other alternative in choice selection. In addition, whatever price is paid for a

commodity relates to cost from manufacturer and all other costs attached up until the point of presenting the commodity to the consumer. Lastly, there is a complication in that commodities are continually changing over time. So, the demand for a commodity might appear to have changed when it is really the commodity that has changed.

However, in order to overcome all these complications during analysis, Lancaster (1966) argued that consumers should be viewed as choosing between groups of 'characteristics' rather than 'commodities'. It is important to note here that same idea is mainly behind the use of 'hedonic' price index-numbers for measuring year-to-year changes; instead of comparing the price of a commodity in this year with those prevailing in past years. In this thesis, demand for a commodity is viewed as 'all-embracing' commodity characteristics (including seen and unseen aspects of the commodity); combining to form a whole entity paid for by the consumer. This section has discussed consumer preference assumptions in order to set the foundation for understanding the standard axioms of the theory, which are the focus of the next section.

2.3 DEMAND THEORIES: NON-ECONOMIC PERSPECTIVES

2.3.1 Demand Theories: Psychological Perspective

As noted earlier demand as an interesting area of social interaction has been approached in several ways and multiple methods, depending on discipline based inclination of consumer researchers. Psychologists have participated in the 'why' and 'how' consumers behave when making their purchases that has been left out in economic perspectives. The psychological approach has been studied using identified processes people undergo in the acquisition, use and disposal of commodities. Psychology as a discipline is mainly focused on biological and cognitive processes through which consumers think and react to stimulus, and how they evolve attitudinal dispositions that influence the commodities they buy and use. It is noted that since the late 1970s the focus of consumer research has been within inquiry performed from the point of view of social psychology, with insights offered by behavioural decision researchers (Bagozzi et al., 2002, Bagozzi, 2017; Roos et al.,2020). These interests are still evolving. To

understand determinants of demand is to understand the motivation or why consumers do what they do.

From a psychological perspective, there is a motivation that precedes 'actions' and 'in-actions', which makes consumers to either purchase or not to purchase a product or service. Motivation occurs when a *need* is aroused within the consumer that he/she wishes to satisfy. Usually, this need could either be utilitarian (a desire to meet a specific functional benefit, e.g. to eat in order to quench hunger) or hedonic (an experiential need, involving emotional responses or fantasies). The desired state the consumer aims to attain is his/her *goal.* Whether the need is utilitarian or hedonic, it creates a form of tension. The magnitude of this tension brings about the urgency with which consumer wants to meet the need, the urgency then creates what is called a *drive.* While a need can be satisfied using different paths, a particular path any consumer chooses is a function of his/her personal, cultural, religious, ethnic or natural factors. It is these cultural and personal elements that combine to create a 'want' (Solomon et al., 2010).

Meanwhile, the degree to which a consumer is willing to expend resources to attain his/her goal as opposed to others having similar goal is dependent on his/her underlying motivation, which captures what psychologists' view as determinants of consumer demand. A number of theories have been adduced to explain determinants of demand and some of these are briefly explained below.

Biological theory of motivation

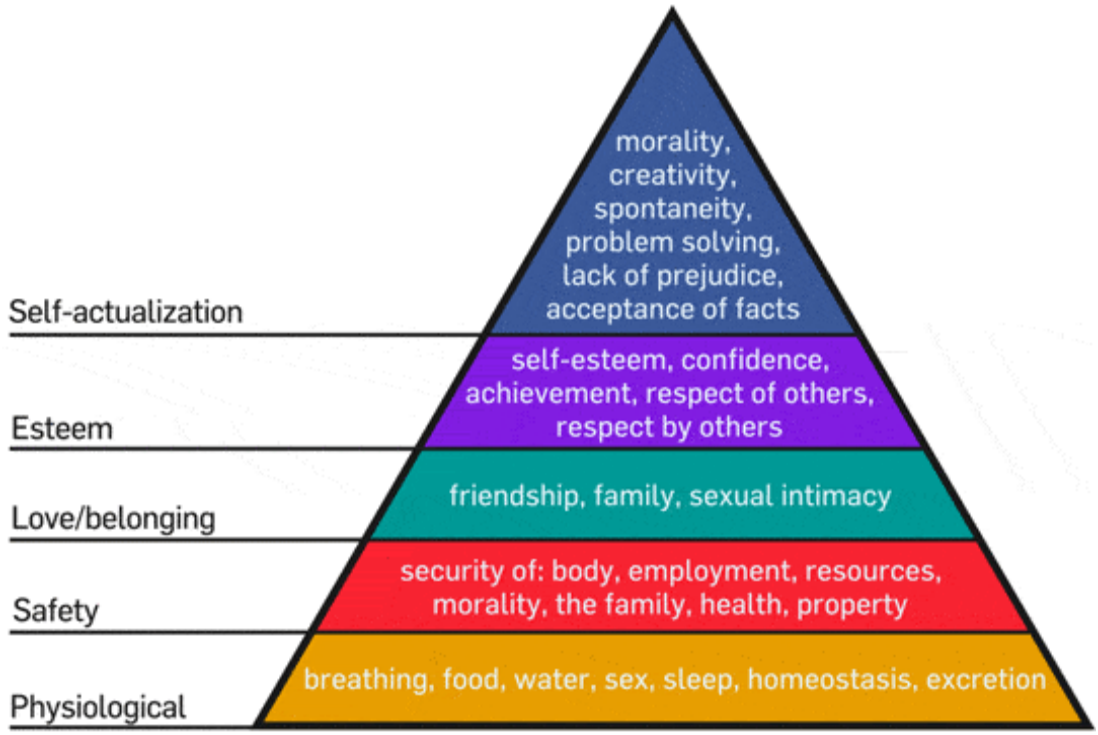
Early work on understanding of consumer behaviour associates motivation to *instinct*- natural patterns of behaviour universal in species. This view has since been discredited. Part of this biological theory is the *drive theory*, which focuses on biological needs that lead to unpleasant state of arousal (e.g. hunger). The proposition of this theory notes that a consumer, after arousal is made to act in order to reduce tension caused by this arousal. Thus, any attempt to reduce tension is seen to function in determining demand. This theory however, runs into difficulty as it fails to explain some facets of consumer behaviour that run counter to its supposition. For

instance, consumers usually do things that increase a driven state rather than decreasing it.

Hierarchy of Human Needs

Another model that explains motivation behind consumer behaviour was proposed by the psychologist, Abraham Maslow. Maslow's approach is a general one, originally developed to understand personal growth and the attainment of 'peak experiences' (Maslow, 1970). According to his proposed hierarchy of biogenic and psychogenic needs, certain levels of motives are specified. This *hierarchical* approach suggests that the order of development is fixed – that is, a certain level must be attained before the next, higher one is activated. Thus, consumers make their demand based on level of the hierarchy they belong. In other words, this model indirectly specifies certain types of commodities (benefits) people might be looking for, depending on the different stages in their development and/or their environmental conditions. Nevertheless, a lot of problems have been identified with this model. For instance, at each level, different priorities exist in terms of the product benefits a consumer is looking for. Based on this model, consumer progresses up the hierarchy until his or her dominant motivation becomes a focus on 'ultimate' goals. Unfortunately, this state is difficult to achieve; majority of consumers have to be satisfied with occasional glimpses, or 'peak experiences'. Figure 2.3.1-1 below depicts Maslow's proposed hierarchy of needs.

Figure 2.3.1-1 : Maslow Hierarchy of Needs



Source: Maslow (1970)

The above figure 2.3.1-1, which captures Abraham Maslow's most important contributions to psychology seeks to explain humans' motivation and their quest ofhappiness. From the list of basic needs that that is contained in each category of different levels of human needs, Maslow opined that for maximum psychological health to be achieved, all the needs must be achieved(Maslow, 1999). According to Abraham Maslow, as individuals meet one category of needs, another higher category of needs arises until the apex category of needs, which is self actualisation of needs are achieved.

According to Maslow (1999), physiological needs includes: breathing, food, drink, sleep, sex and excretion among others. Basically, these needs are biological and physical necessities of human living. As soon as they are met, individuals' quest to meet safety needs is kicked started. The safety need, which Maslow views to mean more than just physical safety includes,economic safety, social safety, vocational safety,among others. These safety needs impacts on the being of individuals. For example, when an individual loses her job, cars, family, home, life savings, etc., the individual is likely to feel insecure and vulnerable.

Love or belonging needs constitute third category of Maslow hierarchy of needs. It is posited that as humans, family, friendships and close connections enable people to go through the ups and downs of life. On the other hand, lack of interactions or poorrelationships or poor ense of belonging could lead to depression. As people meet their love needs, esteem needs arise. According to Maslow, there is a difference between love and respect or esteem need. As humans, aspiration to excel or be exceptional, to be recognised for our unique talents and capabilities are parts of the needs we crave for. It is opined that some measure of self-esteem and confidence is required in order to be creative and to grow as well (Maslow, 1987, pp. 21-22).

The apex of Maslow's hierarchy of needs is self-actualisation, which is the desire for individuals to be self fulfilled. People carry long term dreams, which they hold dear to their hearts and their ability to achieve them brings self fulfilment to them.This inclination might be summed up to be the quest to become more and more what one is. In other words, the desire to become everything that one is capable of achieving is self actualisation. Maslow desire to study happy people in order to determine what it was thatcreatedhappiness or, self-actualization(Maslow, 1987, p. 22).

Relating Maslow's theory to household car ownership, it is easy to find the relevance of the theory. For instance, Nordbakke and Schwanen (2015) used nationally representative data from Norway to analyse the relationship between transport and wellbeing by examining the level to which older adults agree that their needs for 'out-of-home' activity involvement remains unsatisfied. The research shows that such transport-related factors, such as: having a driving license and individual assessments of public transport supply define the degree of unmet needs for 'out-of-home' activity. Their study also identified other factors that help explain differences in the degree of unmet activity needs. These include: actual participation in out-of-home activities, self-perceived health and difficulty with walking, perspective about life, residential location and indices of social support and social networks.

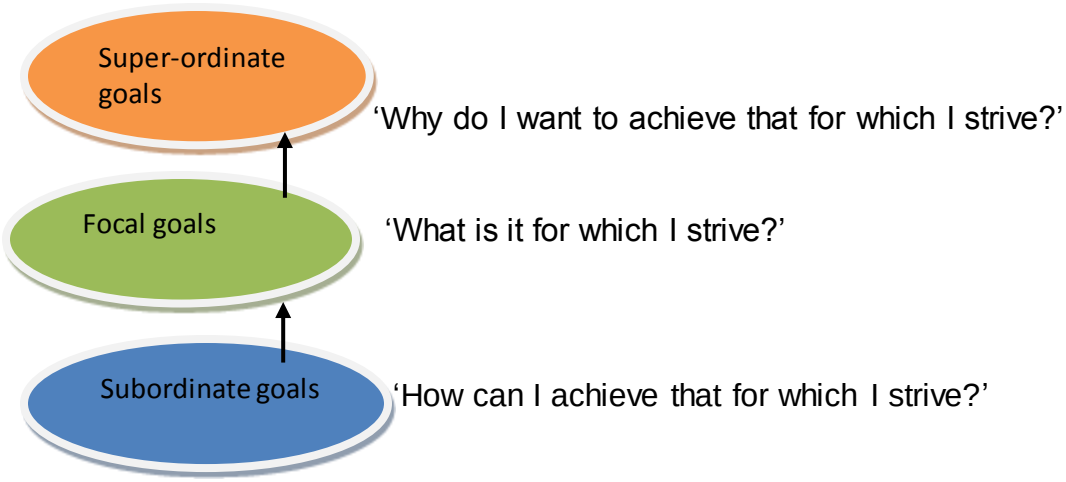
Therefore, it is argued that policymakers aiming to improve the wellbeing beyond a minimum threshold of what is considered as a decent life should improve older adults' capacity to drive in old age and car availability, reduce the distance to public transport stops, and increase the connectivity that public transport provides to destinations. The analysis of Nordbakke and Schwanen (2015) shows that an average adult in the society ranks access to means of transportation very high in his/her hierarchy of needs and as such, individual adults associate access to means of transportation to yardstick of measuring his/her personal wellbeing.

Means-end chain Theory

This theory was actually developed for relating consumer product knowledge to their self-knowledge (Audenaert and Steenkamp, 1997; Zanoli, and Naspetti, 2002; Jiang et al., 2015) as determinants of their choice. Knowledge is assumed to be organised in hierarchical with tangible thoughts linked to more abstract thoughts in a sequence advancing from means to ends. There is a threefold category of knowledge presumed under this theory. Knowledge about product features is connected to more abstract ideas in respect of psychological and social consequences of the features, and the consequences are, in turn, associated with more abstract values (Reynolds and Gutman, 1988).

Below in figure 2.3.1-2 is an expanded goal hierarchy consisting of three fundamental tiers. For example, one could have a focal goal of 'buying a car within a year'. This goal is located at the centre of the hierarchy and answers the question, 'what is it for which I strive'. Subordinate goals, create a means of achieving the focal goal and answer the question: 'how can I achieve that for which I strive?' At the top of the hierarchy are super ordinate goals, which answer the question, 'why do I want to achieve that for which I strive?'

Figure 2.3.1-2: A three-tiered goal hierarchy



Source: (Bagozzi, Gurhan-Canli, and Priester, 2002, pp.24)

Multi-attribute Attitude model

This model places importance on gender of consumers as important factor that dictates how and what products they purchase (Sirkeci et al., 2011). It could be said that this framework features more in modern market research. Psychologists have been concerned with personality attributes that characterise males and females and their roles when they make purchases (Ekebas-Turedi et al,2020). According to Palan (2001), males are characterised by: i. Independence; ii. Assertiveness; iii. Rationality; iv. Competitiveness; and v. Focus on individual objectives. Females on the other hand, are characterised by: i. Caring; ii. Understanding; iii. Responsibility; iv. Consideration; v. Sensitivity and vi. Intuition. It is believed that all these features determine what and how consumers make their purchase decisions for products and services.

2.3.2 Consumer demand Theories: sociological perspective

Generally, individuals belong to various groups based on their gender, religion, political orientation and nationality, among many others. Nevertheless, whether being in a particular group actually results to intergroup behaviour depends on the individual degree of identification with such group (Hogg, 2006; Goldman et al., 2014). Based on social identity theory (Tajfel and Turner, 1986; Thomas et al., 2016), the relationship of an individual with the group is a relevant factor in explaining when and why people identify with and exhibit behaviour as member of a group. In line

with social identity theory, individual self-image involves an individual as well as a group component. Social identity is seen as “that part of an individual self-concept which derives from his knowledge of his membership of a social group (or groups) together with the emotional significance attached to that membership” (Tajfel, 1974, p. 69). Furthermore, social identity theory posits that individuals strive to attain positive social identity, thereby increasing their self-esteem and that this positive identity comes mainly from favourable comparisons between their own group (in-group) and other groups (out-groups) (Tajfel and Turner, 2004; Hogg, 2006; Reimer et. al, 2020).

Since groups entail some boundary between ‘in’ and ‘out’, in-groups typically connote the groups, which the individual identifies or at least affiliates with (Turner, 2010), whereas out-groups are considered as everything else. Better put Brewer (1999, p. 432) posits, “ in group formation involves differentiation of the social landscape into those that are acknowledged to be ‘us’ and those that fall outside that boundary.” In a country setting, the home country is normally viewed as the focal in-group, while foreign countries imply the out-groups (Shankarmahesh, 2006; Verlegh, 2007).

2.4 DEMAND THEORY: INTER-RELATIONSHIP OF DIFFERENT DISCIPLINES

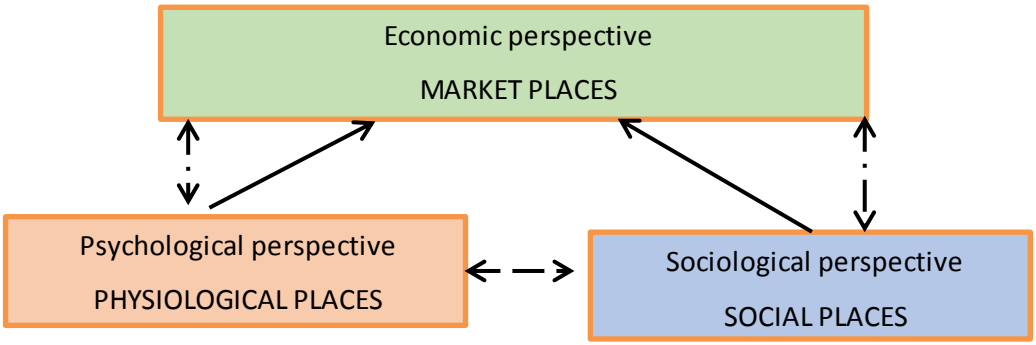
Apart from the psychological and sociological perspectives that were reviewed under the non-economic perspectives above, it is important to note that there are several other disciplines apart from Sociology and Psychology that have contributed to theory of demand. There are perspectives in different literature including: Marketing literature, International business literature and demography just to mention a few. However, for the sake of limitation of this thesis in terms of focus, only two disciples were considered as non-economic perspectives. Meanwhile, it is essential to understand the inter-relationship among the three discipline areas considered.

Psychological perspective suggests that consumers make their demand based internal reactions motivating the demand. For instance, in the case of the hierarchy of human needs, different stages or levels in individual development dictate how and types of demand such individuals decide to go for. In the case of sociological perspective, physical interaction of individuals in terms of what social groups they belong to, what religious affiliations or cultural groupings they are associated with tend to dictate how and what type of products they demand. However, economic perspective suggests the end functioning of these other areas in which the individual concerned concludes that buying the product yields a form of satisfaction and this translates to purchase.

Thus, all the various perspectives tend to influence demand through at least one of the three ways described above. Figure 2.4-1 depicts the interrelationship between different disciplines. From the framework, it is suggested that psychological perspective describes various motivations that take place within the physiological component of individual and how the individual reaches the conclusion of demand. Similarly, sociological perspective describes various interactions within social places, social groups in connection with an individual before reaching conclusion of demand. Lastly, economic perspective describes the interaction of an individual in market place before making his demand.

Note, the dashes lines that link various pair of perspectives together in the framework show that the two-way relationship could also take between different pairs of perspectives. For instance past experience within a physiological place (body of an individual) as a result of what he bought in market place or experience of another buyer within the social places could influence subsequent demand. The foregoing further buttresses the reason why it is important for demand research scholars to always adopt holistic approaches for their investigations.

Figure 2.4-1: Analytical Framework of Theoretical Conceptualisation of Demand



Lawal (2021).

2.5 CONCLUSION

Though economic views of the determinants of demand rooted in rational, hedonistic and maximising principles have been questioned, economists have responded that economic agents may not seek or possess complete information, or the cognitive power to cope with the huge number of decisions to be made to maximise precisely their interest. Rather, their choices are made mainly based on incomplete information and rules based on conscious and subconscious learning (Smith, 2003). This is the basis of the concept of *bounded rationality* developed by Simon (1982). Similarly, reservations have been made on motivation in the acquisition of some goods and services. For example, it has been noted that a consumer may buy some products not because of any physical need, but in order to meet a psychological desire; perhaps, to project a particular position in the society or acquire people's esteem. This is considered as conspicuous consumption (Bannock et al., 1998). It is on this background that Lisciandra (2018) advocated for improvement in the level of knowledge transfer between psychology and economics in the study of social preferences.

Furthermore, while economic perspectives, which deal with aspect of purchases, are important, all other perspectives which dwell on how and why these decisions to purchase are made should be accorded with importance, otherwise, researchers might not capture complete understanding of consumers and their characteristics. This is the basis of inclusion of other perspectives in estimating models if better explanations and conclusions of car ownership decision making will be achieved. Hence,

this chapter has not only considered economic perspectives, but also adopted sociological perspective and psychological perspectives.

CHAPTER 3

LITERATURE REVIEW: CAR OWNERSHIP

3.0 INTRODUCTION

Like theoretical perspectives underpinning consumer preferences, ownership of cars by households have gained interests of both economists as well as research scholars from other fields. As noted in the introductory chapter, the growth of car ownership has been sustained over the past few decades in many countries around the globe, though; the growth seems to be faster in the developing countries compared to the developed countries (Dimitrou and Gakenheimer, 2011; Habitat, 2013). It is important to note that some countries, particularly, European countries including: Germany, Switzerland, and Austria have been at the front line of encouraging other modes of transportation including walking, cycling, and public transport using several innovative programmes to reduce level of cars owned by households. These programmes, which are promoted at both the national and local levels, are aimed at discouraging the number of cars used by households, particularly, within the city centres and residential neighbourhoods (Buehler et al., 2016; Asplund and Pyddoke,2019). However, it is believed that if government transport policy will achieve its desired goal, researchers have an important role to play.

As scholars interests in car ownership research keep growing, there is also a growing inclination towards investigation of new factors responsible for ownership of cars at general household level. Therefore, this chapter reviewed car ownership literature to ascertain what car ownership determinants could be identified from different disciplines. It is worth investigating different factors that have been adopted by both economic and non-economic researchers, particularly, what dominate explanatory variables in different empirical studies. The purpose of this chapter is to elucidate perspectives held by various disciplines when investigating car ownership towards proposing a framework that synchronise these different explanatory variables into a whole for better understanding of car ownership and their characteristics. Thereafter, the chapter maps out various factors identified in specific country based database to set a research framework for this study.

3.1 ECONOMIC APPROACHES TO CAR OWNERSHIP

The consumer research literature in the last four decades has certain characteristics that define how scholars estimate car ownership generally. For instance, between 1980s and 1990s, ownership of cars was mainly explained by aggregated models, cohort models and disaggregated microeconomic models (see de Jong et al., 2004). It was an era when choice modelling research showed that the prices of cars, socio-demographics, income, household elements and location mainly determine consumers' buying decisions. Empirical studies of the period include: Lave and Train, 1979; Manski and Sherman, 1980; Hocherman et al., 1982; Winston and Mannering, 1984; Berkovec and Rust, 1985; Dargay, 2001, 2002). Thus, the era saw scholars focussing more on the objectives and socioeconomic variables as against subjective variables. These objective factors include, vehicle features, household features, and demographical features (Yamamoto and Kitamura, 2000; Bhat and Sen, 2006; Fang, 2008; Bhat et al., 2009; Adjemian et al, 2010).

However, since 2000s, scholars have redirected their interests; dwelling more on subjective factors of households in modelling and estimation of ownership of cars. Leading study in this direction is Choo and Mokhtarian (2004), though, others have since followed the path; including: Whelan (2007); Baltas and Saridakis (2013) and Fang et al, 2014). While Choo and Mokhtarian (2004) examined lifestyle, personality, attitude, travel liking and how individuals perceived kilometres of miles travelled, Collantes and Mokhtarian, (2007) examined how individuals perceived amount of miles travelled as against the actual miles travelled. So, their focus could be seen as psychological perception of travellers.

Similarly, Train and Winston (2007), who drew their motivation from the critique of the US vehicle manufacturers' market share over the past decade. The finding of their critique prompted them to propose a consumer-level model of vehicle choice to provide insights on the disappearance of the U.S. automobile manufacturers' market share over the past decade. They investigated the impact of vehicle attributes, brand

loyalty, product line features, and dealerships. They concluded that most of the erosion in market share for U.S. manufacturers could be analysed by changes in simple vehicle characteristics, i.e.: price, size, power, operating cost, transmission type, reliability, and body type. Their conclusion through their analysis shows that U.S. manufacturers have developed their vehicles' characteristics but not as much as Japanese and European manufacturers have developed the characteristics of their vehicles.

In addition, Cao et al. (2007) examined neighbourhood design (location) as an incremental contribution to vehicle ownership. Based on their proposed nested logit model; controlling for socio-demographic factors, it was concluded that an outdoor spaciousness measure (based on perceptions of yard sizes and off-street parking available) and commute distance affect vehicle type choice. Not long ago, Fang et al., 2014) examined the influences on promotion of pro-environmental travel behaviour within the medium-sized cities in China. They considered how households' characteristics, situational factors, and trip features impact on their travel mode choices.

Based on the foregoing, it can be said that other explanatory variables besides the objective variables also help to gain better insights into the determinants of car ownership. It is important to note that the change in direction in terms of focus between these periods is arguably a function change in the most pressing societal 'needs' of each time as well as the availability of better research approaches and methodologies. The direction, which commenced in 1980s was hugely motivated by energy and environmental apprehension, which became serious issues, whereas, this was not the burning issue three decades earlier. In addition, the availability of comprehensive data on household vehicle holdings assisted the developments of the 1980s' onwards.

Though, it has been significantly proven and accepted that economic factors are determinants of cars ownership generally (Train and Winston, 2007; Baltas and Saridakis, 2013; Saridakis and Balta, 2016), the availability of huge variation in engine size, engine power, fuel type, gear

type, and drive system through and within all car size segments in todays' car market (Brand et al., 2013) and variation in preferences, which are not always premised on Economics factors suggest that non-economic factors could also be significant determinants. Therefore, scholars need to give adequate attention to such non-economic factors if holistic understanding of the subject will be gained. Put differently, this holistic approach encourages reflection into the processes that precede the consumers' car buying decisions, which eventually translate into final purchases[2] (i.e. car ownership). While literature has not given serious attention to multi-discipline range of car ownership determinants, close reflection on this area could enrich the body of literature.

Going by the literature, extensive microeconomic evidence exists for features of real-world decision making that fails to uphold the axioms of rational choice (Avineri, 2012; Kahneman and Tversky, 2013). For instance, in relation to energy end-users, Gillingham et al. (2009) considered the following behavioural characteristics in their review; noting that: (i) consumers are loss-averse and thus respond asymmetrically to expected losses and gains (e.g., upfront costs and future cost savings); (ii) decisions are 'boundedly' rational in such that finding and processing information is costly and imperfect; (iii) decision making uses heuristic (short-cut) methods, which are non-optimizing (e.g., a habit heuristic – repeating previous action(s)) (Shogren and Taylor, 2008). Physical spending, which requires trading off an upfront cost against uncertain expectations for future cost savings, are predominantly premised on such behavioural characteristics.

Importantly, based on empirical research on the 'energy efficiency gap', it is observed that end-users do not adopt energy-efficient technologies only based on a cost-effectiveness condition (Gillingham et al., 2009). Generally, reasons and perspectives do vary, but majority usually suggests 'barriers' to otherwise cost-effective technology adoption decisions.

[2] such processes are usually the focus and considerations of other non-economic disciplines such as, Psychology, Sociology etc.

Furthermore, the intricacies of energy end-user behaviour are demonstrated by Mundaca et al. (2010), who reviewed empirical literature and observed that preferences for energy-efficient technologies are presented within a wide range of non-monetary characteristics and decisions are non-optimizing and premised on inaccurate information. While commenting on their discoveries, Mundaca et al. (2010) note that, 'the literature shows that . . . capital and operating costs . . . represent only a part of a great variety of determinants that drive consumers' energy-related decisions regarding technology choices . . . even in the presence of perfect information, a larger set of determinants can still lead to irrational . . . decisions' (p. 317, Mundaca et al., 2010).

In line with the foregoing, since car ownership decisions are included in many of the energy-related decisions involving households, it is not a surprise that these decisions do not always follow strict microeconomic rules majority of the times. Thus, the foregoing provide support to say that though economic perspective is important to the understanding of car ownership behaviour, particularly, determinants of the number of cars that households hold, scholars have suggested in various works shown above that it is important to recognise the fact that this perspective is not sufficient; highlighting that other perspectives help in explaining car ownership and its characteristics.

As most economic and car ownership studies in the literature failed to give attention to these other perspectives, it appears that scholars' conclusions cannot capture full insights of consumers' car ownership and their characteristics. It is on this premise that the inclusion of other perspectives in investigation of consumer decisions, including the determinants of cars becomes useful and gap filling. Different disciplines have theories on determinants of cars, which if properly incorporated into car ownership analysis will aid better understanding of the theme. In the light of this, the next section focused on non-economic approaches to car ownership analysis.

3.2 NON-ECONOMIC APPROACHES TO CAR OWNERSHIP

Though, the influence of economic factors is generally accepted in car ownership research (Ewing et al. 2014; Anowar, et al., 2015; Oakil et al, 2016), empirical evidence has shown the importance of different non-economic variables in the research (Whelan, 2007; Oakil et al 2014;2016; Jansson et al, 2017). Studies have shown that decision makers' attitudes, socio-demographical features, status and position within social networks are also significant in consumers' energy-related decisions and technology choices (of which car ownership is a part) (Axsen and Kurani, 2012; Jansson et al, 2017).

Studies have suggested the relevance of non-economic factors in car ownership investigation, particularly, socio-demographic features (such as gender, age, household structure, household composition, educational status and employment situations). For instance, studies confirmed that males and females possess varied attitudinal disposition towards car use and car ownership (Oakil et al, 2016). In respect of age of people, research indicates that young singles and married individuals, who settle down for family life late have less inclination for car ownership (Oakil et al, 2016). In respect of household structure or household composition (That is, in terms of number of children and adults in the family or the number of income earners in households) and car ownership, research indicates a positive correlation. That is, the higher the number of young children in a household the higher the number of cars in the household all things being equal (Nolan, 2010).

In addition, the level of education (i.e. primary, secondary and tertiary levels of education) impacts car ownership levels in households. Higher levels of education promote environmental issue and alter the attitudinal disposition in respect of vehicle ownership (Flamm, 2009). Moreover, studies on employment status of household members suggest that households with more members in full time employment usually have higher number of cars (Potoglou and Kanaroglou, 2008). Furthermore, research posited that spatial/land-use features determine the number of cars owned by household members, including the state of urbanization and

availability of transport infrastructure (Potoglou and Kanaroglou, 2008; Nolan, 2010; Oakil et al, 2016).

It was observed that households whose members live within highly developed urbanized environments are not likely to have a car, unlike when household members live within thinly populated environments and poorly developed urbanized environment in which having a car is of necessity. In the latter case, household members are more likely to own a car (Potoglou and Kanaroglou, 2008). Thus, access to good public transport system has positive correlation with the number of cars owned by households (Ceder et al, 2013;Chowdhury and Ceder, 2016).

Research has established that psychological factors, including household perceptions, attitudes and habits have attracted interests of research scholars, who studied their relationships with car ownership in households (Belgiawan et al, 2014). Remarkably, emerging research on psychological and sociological determinants on car ownership shows insightful findings that are capable of enriching car ownership research. For instance, recent literature revealed that mainly comfort, prestige and social orderliness impact on the non-car dependence trends among young and emerging generations of families (Belgiawan et al, 2011, Belgiawan et al, 2014; Zhang et al.,2016). In addition, the influence of environmental concern has gained increasing attention from researchers.

Research in this context has shown that environmental concerns by car owners has led to switching behaviour towards electric cars or other modes of transport, including public transport (Jong et al, 2004; Coad et al, 2009; Ceder et al, 2013). Similarly, transport research has also investigated the relationship and impact of average number of passengers and travel distances and car ownership (Wu, et al, 2016). It is important to note that these various investigations produced inconclusive findings; thus, requiring further investigations.

3.3 CAR OWNERSHIP DETERMINANTS: RELEVANCE OF PSYCHOLOGICAL FACTORS?

The relevance of psychological factors in car ownership research cannot be overemphasised. For instance, pro-environmental actions (e.g. reduction in number of car ownership in households), and a change of individual's daily practices and behaviours, are therefore highly necessary for decreasing problems associated to car ownership and to advance environmental sustainability. Thus, investigation of psychological factors which could be critical in determining why some households behave pro-environmentally and others do otherwise.

According to Stern (2007), environmentally significant behaviour from the stance of its influence on "the extent to which it changes the availability of materials or energy from the environment or alters the structure and dynamics of ecosystems or the biosphere itself" (p. 408). Talking of environmental protection, pro-environmental behaviour (PEB) could be defined as a behaviour carrying the intent to benefit the environment, while pro-environmental behavioural intention (PEBI) suggests the willingness to interact with environmental actions in the future. Intentions are thought to indicate an individual's level of motivation, while current or past behaviour is seen to be a measure of an individual´s habitual patterns of behaviour, which could aid or impede future behaviour (Stern, 2007; Gardner and Stern, 2008; Gifford, 2014) postulated that different causal variables appear to work in different ways in studying a host of variables in relation to behaviour within an environmental context; there is still no agreement as to which of these variables appear to be the strongest determinants of PEB. As psychological factors as determinants of car ownership are given less representation in car ownership analysis, this thesis spends more time to consider psychological factors as determinants in relation to PEB, for which car ownership decisions relate.

3.3.1 Values and attitudes

Several studies have studied the attitudinal effects on the impacts of the built environment on travel behaviour (Bohte et al., 2009; Cao et al., 2010; Lin et al., 2017) and the impacts of travel attitudes on travel satisfaction (St-Louis et al., 2014; Ye and Titheridge, 2017). Expansive studies have demonstrated an

existing relationship between individuals´ values, attitudes (environmental concern) and PEB (Nordlund, and Garvill, 2002; Steg et al, 2005) as well as positive relationship between values, attitudes (e.g. environmental concerns) and pro-environmental behavioural intentions (PEBI), (Honkanen and Verplanken, 2004). Studies have also revealed that attitudes towards private cars significantly impact on decisions about car ownership and car use (Steg, 2005; Zhu et al., 2012;Belgiawan et al., 2016; Acheampong and Cugurullo,2019).

Generally, values are overall preferences for ways of acting. They refer to cognitive images of abstract goals (e.g. a world of equality) or abstract means of acting (e.g. being unselfish) and constitutes guiding philosophies essential to an individual´s choices of actions (Schwartz, 1992; Rohan, 2000; Manfredo et al, 2016). The organisation of the human value system is viewed to be universal among all people and values are fairly stable over an individual´s life span (Stern,2000; Schwartz, 1994). In order to comprehend and forecast the underlying motivations of people´s behaviour theorists, seek to measure people´s priorities for different values (Rohan, 2000). Studies showed that the predictive power of a value orientation depends on which belief is being explained, which agree with other findings indicating that the relative significance of values in elucidating beliefs differs across various types of beliefs (Stern, 2000; Nordlund and Garvill, 2002; Nordlund and Garvill, 2003; Schultz, P. W. and Zelezny,1999; Thøgersen and Ölander, 2002).

Expansive body of environmental studies regarding values are premised on Schwartz´s Value Theory (Schwartz, 1992,1994). Schwartz proposed a wide model, the Schwartz Value Inventory Scale, for categorising two orthogonal value orientation dimensions: self-transcendence versus self-enhancement, openness to change versus conservatism. Two types of self-enhancement values (e.g. power and achievement) and two types of self-transcendence values (e.g. universalism and benevolence) have been demonstrated to be predominantly appropriate for understanding environmental beliefs and actions. Generally, individuals who strongly endorse self-enhancement values are less likely to have pro-environmental beliefs and norms and to act pro-environmentally, while the opposite is mostly true for those who strongly endorse self-transcendence values (Stern et al,1994; Nordlund and Garvill, 2003; Thøgersen and Ölander, 2002; Schultz et al, 2005).

3.3.2 Self-transcendence: universalism vs. benevolence

Self-transcendence is considered as a social-altruistic value orientation and involves two value types: universalism and benevolence. Universalism connotes a wider form of altruism having the motivational goal of the welfare of all people encompassing humankind, such as social justice, equality and peace of earth. On the other hand, benevolence is seen as altruism towards in-groups like loyalty, forgivingness and responsibility. The motivational goal of benevolence is the welfare of close others (Schwartz, 1992, 1994). While past studies concluded that universalism positively linked to pro-environmental attitudes and behaviours, only inconsistent associations were discovered between benevolence and pro-environmental attitudes and behaviours (Schultz and Zelezny, 1999; Thøgersen and Ölander, 2002).

3.3.3 Self-enhancement: power vs. achievement

Self-enhancement is viewed as an egoistic value orientation, embracing the value type's power and achievement. Thus, the motivational objective of power is on domination over people and resources. Examples of power include authority, social power and wealth and these are opposite to the goals of universalism in Schwartz´s (Schwartz,1992) value structure (Hansla et al, 2008a). In contrast, the motivational goal of achievement includes values such as success, capability, and ambition which are opposite to benevolence in the self-enhancement-to-self-transcendence continuum (Hansla et al, 2008a; Schwartz, 1992).

Furthermore, research has shown that individuals rating high on self-enhancement values are less willing to involve in PEB (Honkanen and Verplanken, 2004; Bardi and Schwartz, 2003; Gärling et al, 2003). Moreover, according to (Hansla et al, 2008a), the two value type's power and achievement have a negative relationship with pro-environmental attitudes and behaviour, even if the differences between them suggest that they may influence attitudes and behaviour differently. Overall, people or individuals holding values high in self-transcendence report favouring PEB, whereas those who tend to hold self-enhancement values see the environment as a source of resources to be consumed (Nordlund, and

Garvill, 2002, 2003; Nilsson et al, 2004; Kaiser and Byrka, 2011; Thielmann et. al, 2020).

3.3.4 Awareness-of-consequences beliefs (AC)

Within the value-belief-norm (VBN) theory (Stern, 2000; Stern et al, 1995, Stern et al, 1999), AC-beliefs are essential constructs denoting beliefs about adverse consequences of environmental problems, suggesting consequences that may never actually occur. The VBN theory in turn shapes theoretical accounts of Schwartz´s (Schwartz, 1997) moral norm-activation theory of altruism, the theory of personal values [Schwartz, 1992, 1994), and the New Environmental Paradigm (NEP) developed by Dunlap and Van Liere (Dunlap and Van Liere, 1978). In the VBN theory, beliefs mediate between values and norms impact behaviour. That means for example, that if people view other species very high, awareness of consequences for the biosphere (ACbio), they will be concerned about environmental circumstances that may threaten those highly valued species.

Likewise, individuals having high altruistic values, who care about other people, awareness of consequences for other humans (AChum), will be concerned about environmental circumstances that may impact negatively the well-being of other individuals, as well as individuals having egoistic values will be concerned about situations that may negatively impact themselves, awareness of consequences of oneself (ACself). In this way, the three values (ACself, AChum and ACbio) are the foundation for environmental concerns (ECs) if the individual believes that there are ACs for particular valued object/s. Premised on VBN theory, an individual is more expected to carry out PEB if he/she believes that environmental attributes will result to ACs for his/her valued object/s and that he/she could limit the negative impact and has personal norms for such behaviours. Beliefs concerning negative consequences for valued objects (AC) are demonstrated to initiate pro-environmental personal norms and are thus, associated to altruistic or self-transcendence value orientation, while self-enhancement has be shown to be weaker related to the AC-beliefs (Nordlund and Garvill, 2002; Steg et al, 2005; Stern et al, 1995; Nordlund

and Garvill, 2003; Schultz and Zelezny, 1999; Schultz et al, 2005; Steg and Nordlund, 2012).

3.3.5 Environmental-concern evaluations (EC)

Environmental concern is viewed as the personal evaluation of the seriousness of environmental difficulties. According to Schultz (2000, 2001), environmental concern is entrenched in an individual's value system, which implies that people are concerned about environmental difficulties when these difficulties threaten things they value. Schultz (2001) found strong evidence for the distinction between concern for oneself (ECself), concern for others (EChum) and concern for the biosphere (ECbio). Research has demonstrated the relationships between EC evaluations and the values adopted from Schwartz have demonstrated significant positive association between self-transcendence and biospheric environmental concern (ECbio) as well as between self-transcendence and altruistic concerns (EChum). Self-enhancement was found to be positively associated to egoistic concerns (ECself) but negatively related to altruistic (EChum) and biospheric concerns (ECbio) (Hansla et al, 2008a; Nordlund, and Garvill, 2002; Steg et al, 2005). Furthermore, biospheric environmental concern (ECbio) correlated positively with self-reported PEB (Schultz et al, 2005;Schultz , 2000). Several studies have shown that a strong environmental concern increase the likelihood of PEB (Bamberg, 2003; Thøgersen, 2000).

The psychological concepts discussed under section 3.3 so far could be described as moral elements.Several works have identified a moral element (psychological perspective) to car ownership (e.g. Yadav and Pathak, 2016; Lin and Wu, 2018el). Taking attitude, subjective norm and Perceived Behavioural Control (PBC) into consideration, moral norms offered clear analysis of determinants underlying several pro-environmental behaviours, including use of cars as well as other means of transportation (Belgiawan et al, 2017). Conversely, Bamberg and Möser (2007) found moral norm to be of less significance, showing it to have little impact on intention and no direct impact on behaviour. Bamberg and Schmidt (2003) examined personal norm in the context of Schwartz's (1977) norm activation theory.

Reviewing the literature, the significance of environmental concerns in predicting intention and behaviour is mixed. For instance, Tertoolen et al., (1998) demonstrated that although information regarding the negative environmental and economic impacts of personal car use raises public awareness, the information is always not sufficient to alter behaviour. Actually, whether people choose to drive or take public transport is not strongly associated to their knowledge regarding the environmentally damaging impacts of personal car ownership (Nilsson and Kuller, 2000). It was demonstrated that habitual behaviour can be more vital than environmental difficulty in determining transport mode choice (Verplanken et al., 2008). However, environmental difficulty offers additional theories that could enhance prediction and be targeted so as to alter behaviour.

Meanwhile, different works have indicated that perceptions of others' behaviours, known as descriptive norms offer a better conclusion of the social pressure impact on intentions (e.g. Donald and Cooper, 2001; Rivis and Sheeran, 2003). Often than not, this impact shows positive relationship with intentions. In other words; perception that others hold to exhibit a form of behaviour is associated with stronger intentions. However, Gardner and Abraham (2010), in a study of car use, found that descriptive norm had an inverse relationship with intentions. Participants in there study were less motivated to drive when they thought other people would be driving. This clearly highlights the need for further research to investigate how descriptive norm impacts on car ownership.

The degree to which the formation of intention takes place is a rational and thoughtful process, as assumed in the TPB. However, this has been criticised. In particular the role of habit is proposed as potentially important as providing an alternate pathway to intention and/or behaviour. Lastly, habit has been identified to show significant impact for behaviours that are performed on a regular basis, including pro-environmental behaviour (e.g., De Vries et al., 2011) and car ownership (Verplanken et al., 1998, 2008). The foregoing buttresses the notion that other perspectives, apart from economic perspective assist in understanding car ownership characteristics.

Reflecting on psychological perspective, it could be concluded that early proponents of consumer psychology were influenced hugely by their training or academic specialty. Thus, conspicuous approaches within the field included the mentalist approach (represented by experimental psychologists like: Wundt, James, and Titchener); mechanistic approach (represented by Watson and Thorndike); and the dynamic psychological approach (represented by Freud and McDougall) (Haugtvedt et al., 2012). It is important to stress that psychological perspectives are rooted in psychoanalytic interpretations, with main emphasis on unconscious motives.

So, unconscious motives become the bedrock of these perspectives. A simple assumption within these interpretations is that socially unacceptable needs are focused into acceptable outlets. Product purchase (product use) or product avoidance is motivated by unconscious forces, which are often determined during childhood. In a way, it is reasonable to assume that unconscious motives determine what people effectively purchase and use as held by Psychologists. It is interesting to note that psychological perspectives (especially, motivational research) to car ownership offer a great appeal, at least to some marketers for several reasons. Motivational research seems to be less expensive compared to large-scale research, requiring huge survey data since interviewing and data processing costs are usually small.

Nevertheless, the knowledge gained from motivational research could assist in the development of marketing communications that appeal to deep-seated needs; providing a more powerful hook to relate a product to consumers. It might help to note that even if results are not necessarily valid for all consumers within a target market; insights obtained could be valuable when adopted in an exploratory way. After all, the rich imagery that may be connected to a commodity can be used creatively during advertising.

However, motivational research (psychological perspectives) has been criticised for two quite different reasons. On one hand, social critics

attacked this school of thought for providing advertisers and marketers the power to manipulate consumers. Furthermore, a lot of consumer researchers are of the view that the research lacked sufficient rigour and validity, since interpretations were subjective and indirect. To them, since research within Psychology is always based on the analyst's own judgement and derived from discussions with a small number of people, some researchers are doubtful about the degree to which these results can be generalized to a large market. In addition, since the original motivational researchers were mainly influenced by orthodox Freudian theory, their interpretations and analyses commonly carried strong sexual overtones.

Many a times this position tends to ignore other plausible causes of behaviour. It is worth noting that such over-interpretations and disregard of the more mundane and obvious reasons are capable of misleading users of such research. Despite these issues, it is reasonable to agree that these psychological concepts help to explain the determinants of car ownership in individual consumer behaviours. To verify this assertion, empirical studies were carried out on car ownership in chapters 5 & 6 and psychological factors were incorporated in an estimating model used to investigate discipline based factors and car ownership in UK and US households. Findings and analyses are contained in the two chapters.

3.4 CAR OWNERSHIP DETERMINANTS: RELEVANCE OF SOCIOLOGICAL FACTORS?

Apart from the traditional economic factors such as: fuel prices, taxes and national income growth, the relevance of non-economic factors such as sociological factors in car ownership investigation cannot be overemphasised. Land-use planning (e.g. inner-city redevelopment), changes in demographic behaviours, personal preferences and life styles of people (e.g. delay of parenthood) are among non-economic factors that have been found relevant in car ownership literature (Goodwin and Van Dender, 2013; van der Waard et al., 2013; Duncan, 2016; Ding et al., 2017). Furthermore, car ownership research in different countries has lent support to the importance of demographic factors and urbanisation level for understanding car mobility determinants (Dargay, 2002; Golob, 1990; Bhat

and Guo, 2007; Nolan, 2010; Van Acker and Witlox, 2010; Oakil et al., 2014; Clark et al, 2016). Although, many of these studies could not clearly explain these determinants of car ownership, they at least, indicated the importance and relevance of non-economic factors in car ownership analysis.

Similarly, some car ownership studies indicated household members' location in terms of rural/city variations and child bearing decisions among young families as relevant determinants (Potoglou and Kanaroglou, 2008a; Kuhnimhof et al., 2011). Findings shows that car ownership among single individuals is reducing compared to households with children (Potoglou and Kanaroglou, 2008a; Oakil et al, 2016). This is reasonable considering the fact that with singles, there could be reduced household incomes compared to families, just like it is expected that the number of singles without jobs are likely to be more in comparison to parents without jobs. Other non-economic factors identified include huge student population in cities. It is argued that many cities house huge populations of students, who have access to public transport system (i.e. both paid access and free access) and as a result many of them cannot afford to possess a car. The situation is the same with other classes of individuals such as immigrants, who incline to adopt use of public transport system more than private cars (Gautier and Zenou, 2010; Blumenberg and Agrawal, 2014).

Furthermore, interactive impacts between household composition and urbanisation level have been identified as determinants of car ownership. Couples, families as well as young singles could witness various travel difficulties and opportunities based on their residential locations. For instance, result showed that couples residing within high density locations share more out-of-home household duties compared to couples residing within low density locations (Schwanen et al., 2007; Van Acker et al, 2014). In addition, mode of travel preferences could vary premised on household types/structure, which in turn could impact on car ownership level. The impact of urbanisation was found not huge for households, who own a car since it is their preferred mode of travel, regardless of what location they

reside (Cao et al., 2007; Van Acker et al, 2014; Macfarlane et al, 2015; Clark et al, 2016).

Lastly, finding shows that there is symbolic/affective meaning towards car ownership and this has been viewed as significant factor behind the following decisions: decision to get a driving license, decisions to select a transport mode choice and car purchase decisions among other decisions (Steg, 2005, Gatersleben, 2011; Belgiawan et al., 2014).

3.5 EXPLANATORY VARIABLES IN LITERATURE

Overall, it is clear that as research into determining factors of car ownership develops, scholars' horizon of explanatory variables also expands, from objective characteristics, such as vehicle features, household features and demographical features (of which many are traditional economic-based factors) into subjective factors such as, attitudes and lifestyle to explain car ownership. This is highlighted in various scholars' analyses. From Choo and Mokhtarian (2004) using household location characteristics, built environment attributes to (Bhat et al., 2009) using household head characteristics and (Baltas and Saridakis, 2013), who used purpose of car use, pre-purchase information source used, consumer's proneness towards buying an ecological car, consumer's involvement with cars, and consumer attachment to cars as explanatory variables.

Meanwhile, to integrate both economic (objective) and non-economic variables into estimating models, scholars have found disaggregate approach useful, though, such integrated approach is novel going by the current car ownership literature. An important benefit of disaggregate modelling approach is that it enables use of individual or households' data. Use of household information is considered good since car ownership decisions are typically seen as a characteristic of the entire household (Clark, 2009). Thus, scholars have consequently shown interests in examining other determining factors (besides traditional factors) in car ownership analysis.

For instance, Lane and Potter (2007); Flamm (2009) and Egbue and Long (2012)were among those that have examined psychological factors in car ownership models. Furthermore, there is huge evidence from the literature, which suggests that many people have considerations for non-economic reasons and to a great extent, are influenced by these considerations when taking car ownership decisions (See Coad et al., 2009; Wang et al, 2016). Meanwhile, Lane and Potter (2007) have argued that psychological factors are particularly, important not because they have an indirect influence on purchases, but because they are capable of mediating the effects of situational factors.

Thus, in order to better understand how socio-demographical factors identified by traditional approaches affect car ownership decisions, these factors should be investigated in models that integrate behavioural factors (that is, psychological factors, sociological factors, demographical factors and economic factors). Table 3.5-1 below highlights some economic and non-economic explanatory factors that have been used in the literature with each study's main findings incorporated. In Clark (2012), an alternative inductive approach was adopted in which respondents gave explanations in their own words in response to the prompt. For instance, respondents were prompted like this: ''please explain why the number of cars available to you changed at this time?''. Responding to the question, responses provided by respondents show that 65 % of the 102 attributed car ownership level and its changes to one or combination of these life circumstances: change in working condition; residential relocation; child birth; children attaining driving age and acquisition of driving licence.

Dissecting the respondents' responses, it is obvious that there is interplay of different discipline based determining factors in why households hold different level of car ownership. Essentially, working condition relates to economic determinants, while residential location and child birth (in terms of the number of children in households) suggests sociological determinants. Attainment of driving age, which is a psychological factor could suggest feeling of being able to drive that sets in especially, for

young people. Lastly, acquisition of driving licence connotes a demographical factor.

While it is easy to overlook driving licence as a determinant, critical reflection of it will ensure that it is accorded its necessary consideration. In fact, Van Acker and Witlox (2010) concluded that demographic factors such driving licences are more important determinants of car ownership than others. Thus, there is interrelationship of different discipline based factors in determining level of car ownership in households. This is the reason why the inclusion of these different discipline based determinants in an estimation model of car ownership research, as demonstrated in the estimating chapters: 5 and 6 of this thesis becomes necessary and long overdue.

Table 3.5-1: ***Summary of Explanatory Variables in Literature***

Reference	Data Location & Year	Sample Size	Model Type	Choice Examined	Vehicle Characteristics	Households Characteri-stics and/or primer driver's characteristics examined
van de Kamp (2020)	1406 zones within Dutch population	Survey of 1,487 respondents	multinomial logit choice models	examined what extent the forecasts of household car ownership in the Netherlands are affected by the inclu-sion of life events and built environment factors in a dynamic model.	car costs, car age, car availability,car age and initial number of car	Age, Household income, Household size, occupation
Main Findings: (a)The empirical findings confirmed much recent work, but also provided new insight into the nature of car ownership decisions. First of all, these findings provide a deeper insight into the impacts of a variety of life events on car transaction behaviour. For example by identifying multiple lead lag effects and by highlighting life events with a spatial component as well (relocation and job transitions). (b)Relocating increases the chance of all types of car transactions (acquisition, replacement and disposal). Furthermore, it has a delayed positive effect on car disposals, while an anticipated relocation results in more acquisitions. The latter was not found by other authors before. Job transitions mainly result in more car acquisitions, but also in more replacements. The latter is true as well for an anticipated work change, which confirms recent findings. Contrary to other research, a positive effect of retirement on car disposals and replacements in the same year was found. Next to that, changes in household composition were found to affect car transactions, but not as substantially as other authors found. (c) Finally, as expected, obtaining a licence has major positive effects on car acquisitions, which is also true for obtaining a licence in the years before and after car acquisition. (d)The main built environment factor with an effect on car transactions is the availability of free parking near the residential location: car acquisitions and replacements are more likely, while the chance of disposal is reduced when there is free parking.						
Zhoua and Wang (2019)	Travel diary sample survey conducted in 2016 in Beijing, China	800 households (involving 1884 individuals aged 12 or above)	Descriptive statistics, multiple-group modeling framework	Generational differences in attitudes towards private cars and their interactions with car ownership and car use	N/A. Rather,12 attitu-dinal dimen-sions in relation to car owner-ship and travel dispo-sitions were useed to mea-sure the gene-	Gender, marriage status, edu-cation attainment, persoanl annual income, employment status, Hukou status, drivinng licence, household car owner-ship, number of trips, House-hold

					rational differences	incomes, household size, persoanl annual income.
Main findings: (a) Significant differences among different generations in terms of attitudes towards cars and their influences on car ownership, holding a driver's license, and trips by cars. Young adults, in particular, show less favorable attitudes towards private cars and less prominent attitude-behavior associations than older groups do. They are also found to be less pragmatic about car use. (b)The study shed new lights on the psychological factors on car-related choices and the significant differences between different generations, which are relevant for policies targeting on reducing car dependency and promoting a more sustainable lifestyle.						
Joseph et. al (2017)	wellstructured Survey between May and July 2016 to Akure city households in Nigeria	1181 Akure households in Western region of Nigeria	Multinomial Logit Model	Investigated contributing factors to car ownership in Akure city, South West, Nigeria.	N/A	Academic Qualification, Income (in Naira), occupa-tion,licence holders, number of household members, employed household members
Main findings: (a) Model estimates depicts that the probability of owning a car increases with increase in income and reduces with increase in household members. (b)Sensitivity analysis was carried out with the model estimates to test different scenarios. The test results show that a 50% increase in income and Number of household members increases the number of cars owned in Akure metropolis by 51% and 0.8% respectively while a decrease in income and household members by 50% reduces the number of cars owned by 37% and 0.8% respectively. R-square value of 0.705 and P-value of 0.000 implies that the model gives a good prediction. (3)The study has shown that car ownership will increase with increase in earning capacity of households in Akure such as in the periods of economic boom while the reverse is the case in periods of recession.						
Weimer et al. (2018)	Two Swedish cities: Stockholm and Uppsala	468 household residents from Stockholm and Uppsala between 18 and 65 years whose records were obtained from personal register in Swe-den (SPAR).	structural equation modelling (SEM)	Pro-environmental behaviours and beha-vioural intentions. These are: The eight types of PEB and PEBI were: 1) using low-energy lighting in the residence, 2) buying garden grown vegetables, 3) using public transport, 4) using well-filled dish-washer and	the predictive power of value orientations, awareness of consequences, environmental concern, moral judgment competen-ce, locus of control and sense of coherence	Random sample of household residents. Age, educational level, relationships, national status, owner-occupied apartments, sex

				washing-machine, 5) avoiding air travel in the spare-time, 6) showering shortly, 7) recycling the household waste and 8) airing clothes instead of washing.		
Main findings:(a)Predictive power of value orientations, awareness of consequences, environmental concern, moral judgment competence, locus of control and sense of coherence examined on eight types of pro-environmental behaviours and behavioural intentions and the best fitting causal model confirms partly the hypothetical model. The study hypothesis tested says the predictive power of value orientations, awareness of consequences and environmental concern helps in explaining pro-environmental behaviours (actual lifestyle) and pro-environmental behavioural intentions (intentional lifestyle). (b)Values indirect and direct affect pro-environmental behaviours and behavioural intentions with awareness of consequences and environmental concern as intermediate or transmitting variables. (c) Neither pro-environmental behaviours nor behavioural intentions are affected by awareness of consequences, environmental concern, locus of control, moral judgement competence or sense of coherence. Thus, there is need for more environmentally specific measures of the predictors in relation to specific behaviours						
Belgiawan et. al (2016)	N/A	500 undergra-duate students from one univer-sity in Bandung, Indonesia	structural equation modelling (SEM)	Car Ownership	symbolic/affective, arrogant prestige, independence, comfort, and social/env. Care	Income, commuting distance, income, sex, age
Main findings:(a) Results suggest that primarily independence, arrogant prestige, and some socio-demographic variables significantly influence car purchase decisions. (b)Clearly with higher GDP and increasing income in southeast Asian countries, we expect the modal share of cars to increase. However, we find that attitudes are important determinants of car ownership and that attitudes such as the perception of whether the car is a prestige object and income are not significantly correlated, so that there might be some hope that rapid economic growth will not necessarily mean a motorization development as experienced in Western countries several decades ago. (c)We find that independence-related aspects are the most important factor for students' decision to purchase a car. The result suggests that in Bandung and generally in situations where there are insufficient convenient public transport options, such services need to be improved first before one in fact has a choice.						
Moeckel and Yang (2016)	2007-2008 TPB (Transportation Planning Board)/BMC (Baltimore Metropolitan Council)	Survey of 14365 households	Auto-ownership model linked between land use and trans-port	examined how owning a car affects travel behavior and location choice; and how the built environ-ment and	N/A	Household income, Drivers license, Household size, Number of workers, presence of children, household location choice, work location choice

			system	the transportation needs affect auto-ownership decisions.		
Main Findings: (a)Car ownership influences almost all aspects of travel behavior, including travel frequency, travel distances, mode choice and time-of-day choice. At the same time, car ownership affects residential location choices, as households owning cars are less likely to choose urban neighborhoods than households without cars. This paper describes a new microscopic auto-ownership model that has been estimated with survey data. The model is fully integrated with a land use and a transportation model to capture: (a) how owning a car affects travel behavior and location choice; and (b) how the built environment and the transportation needs affect auto-ownership decisions.						
McDonald, N.C., (2015)	US Department of Transportation's National Household Travel Survey (NHTS) 1995, 2001 and 2009.	31,490 in 1995, 41,902 in 2001, and 47,805 in 2009	Descriptive statistics and Regression model	Observed decrease in automobility among Millennials'	N/A	age, race, sex, and education, indicators of household formation and parenthood
Main Findings:The results confirm the previously reported declines in auto use but show little evidence of increased use of sustainable travel modes. In the US, decreases in auto travel have not been compensated by upticks in other modes. If not going nowhere, the Millennials are clearly not going as many places as previous generations. Among young adults, lifestyle-related demographic shifts between Millennials and Generation X (those born in the late 1960s to the late 1970s) contribute for 10% to 25% of the observed decline in automobility, while Millennial-specific factors such as different attitudes to mobility contribute 35% to 50% of the observed decline in auto use. The other 40% of the decline is associated to the general dampening of auto usage in the late 2000s that affected all Americans.						
Lave and Train (1979)	Seven U.S. cities in 1976	541 new car buyers	Multinomial logit model	Choice among 10 existing categories based on size and price	Purchase price, ope-rating cost, number of seats, weight, horse-power to weight, fuel efficiency	Income, number of household members, number of miles driven, number of vehicles, age, and educational level
Main findings: (a) Larger households are more likely to choose subcompact cars. (b) Households with more miles driven are more likely to choose large vehicles. (c) Older people tend to choose larger cars. (d) Households with high incomes are likely to choose large and expensive cars. (e)Vehicle price negatively affects the choice of each vehicle type. (f) Households owning more than two vehicles tend to choose smaller cars when they buy another.						
Manski and Sherman (1980)	Nationwide U.S. sample 1976	1200 households from a consumer panel survey	Multinomial logit model	Choice among 26 alternative vehicle types based on make, model, and vintage (single-	Purchase price, operating cost, number of seats, weight, luggage space, acceleration	Number of household members, number of workers, income, age, education, location of the household

				vehicle and two-vehicle households examined)	time, vehicle age, turning radius, braking distance, noise level, scrappage rate, search cost, country of origin	
Main findings: (a) Seating space and luggage space positively affect the vehicle type choices, especially in larger single-vehicle households. (b) Scrappage rate (a proxy for the probability of mechanical vehicle failure) has a negative impact on the vehicle choices. (c) When heads of the households are older than 45 years old, they are more likely to consider vehicle weight in their vehicle type choices. (d) Households with low incomes are less likely to choose vehicles with higher operating costs. (e) Acceleration time had a significant and positive impact on vehicle type choice						
Hocherman et al. (1983)	Israel in 1979	A sample of 500 households that did not buy a car and 800 households that bought a car in 1979	Nested logit model	Choice among 20 alternatives based on make, model, body type, and vintage (transaction type also examined (i.e., buying a first car or replacing an existing car)	Purchase price, operating cost, vehicle size, engine size, luggage space, horsepower to weight, transaction cost, vehicle age	Number of household members, income, number of vehicles, age
Main findings: (a) Purchase price and operating cost variables have negative effects on vehicle type choice, except in households where the heads of household are 45 or older. (b) Older people or buyers of higher incomes tend to choose more expensive cars. (c) People of the age 30–45 place higher values on horsepower and weight. (d) Vintage dummy variables have a highly significant and negative effect on the choice of each vehicle type. (e) Brand loyalty and the number of vehicles of the same make have a positive effect on the vehicle type choice. (f) For households without any vehicle, the households of higher incomes and/or households with members that travel long distances by bus are more likely to buy cars. (g) Attributes such as engine size and vintage of the currently owned vehicle affect the decision to replace a car						
Berkovec and Rust (1985)	Nationwide U.S. study in 1978	237 singlevehicle households	Nested logit model	Choice among 15 categories based on size and age-vintage	Purchase price, operating cost, number of seats, vehicle age, turning radius, horsepower to weight, manufacturer, transaction	Number of household members, income, and age

Main findings: (a) Purchase price, operating cost, and vehicle age have negative effects on the choice of each vehicle type. (b) Vehicle size negatively affects the choice of each vehicle type in urban as opposed to rural areas. (c) Horsepower has a higher value for the age group of 45 or younger. (d) Ford and foreign manufacturers are valued significantly positively; other domestic vehicle brands are valued significantly negatively						
Kitamura et al. (2000)	South Coast (Los Angeles)metropolitan area in 1993	1898 multi–vehicle households	Multinomial logit model	Choice among 6 categories based on body type (four-door sedan, two-door coupe, van/wagon, sports car, sport utility vehicle [SUV], and pickup truck)	N/A	Number of household mem-bers, number of workers, number of vehicles, income, type of household, and residence attributes such as accessibility and residen-tial density, age, gender, education, employment status, acquisition decision, commute distance.
Main findings: (a) Four-door sedans and vans/wagons are more likely to be chosen in areas with high transit accessibility, and sports cars are more likely to be chosen in areas with high residential density. (b) Males are more likely to use pickup trucks; and younger are more likely to use sports cars, SUVs, and pickup trucks. (c) People with college degrees or long-distance commuters are more likely to use four-door sedans. (d) Households with high incomes are more likely to use SUVs, whereas households with low incomes are more likely to use pickup trucks and two-door coupes. (e) Larger households are more likely to use vans/wagons.						
Brownstone et al. (2000)	California in 1993	Sample of 4747 households that successfully completed a vehicle-choice experiment	Compared multinomial logit and mixed logit models	Choice among 6 alternatives based on fuel type and body type (electric car or truck, natural gas car or truck, and methanol vehicle car or truck)	Vehicle range, purchase price, home and service station refuelling time, home and service station refuelling cost, service station availability, acceleration time, top speed, tailpipe emissions, vehicle size, luggage space.	Household structure, vehicle inventory, housing characteristics (including home-ownership), basic employment, income and commuting for all adults.
Main findings: (a) Revealed preference data appeared to be critical for obtaining realistic body type choice and scaling information, but multicollinearity and difficulties with measuring vehicle attributes were problems. (b) Stated preference data were critical for obtaining information about attributes which are not available in the market place. (c) Using stated preference models alone may provide implausible forecasts						

Mannering et al. (2002)	Nationwide U.S. household panel survey between 1993 and 1995	654 households that had bought new vehicles between 1993 and 1995	Nested logit model	Choice among 10 alternatives based on make and model (acquisition methods such as leasing, financing, and paying cash were also examined)	Purchase price, operating cost, passenger side airbag, horsepower, turning radius, vehicle reliability, vehicle residual value, vehicle size.	Income and brand loyalty characteristics (consecutive purchases, manufacturer)
Main findings: (a) Regardless of acquisition type, households are more likely to choose vehicles with higher brand loyalty and residual values. (b) When households decide to acquire vehicles by leasing, they tend to place high values on vehicle attributes such as passenger side airbags and horsepower and are more likely to choose larger vehicles and SUVs						
Nordlund and Garvill (2003)	Five Swedish cities of medium size (about 100 000 inhabitants)	The sample consisted of 2500 registered car owners in five Swedish cities of medium size.	Hierarchical model	Willingness to reduce personal car use	Effects of values, problem awareness, and personal norm	Random sample of registered car owner. Age, sex
Main findings: (a)Data supported the hypothesized model. The model predicted that personal norm, derived from values and activated by problem awareness, should mediate most of the effects of values and problem awareness on willingness to cooperate and the personal norm should positively influence willingness to reduce personal car use. (b)Values and problem awareness influenced personal norm, which in turn influenced willingness to reduce personal car use. (b)The results clearly showed the importance of personal norm for willingness to cooperate in a social dilemma.						
Choo and Mokhtarian (2004)	San Francisco Bay area in 1998	Sample of 1904 respondents	Multinomial Logit model	Choice among 9 alternatives based on size and body type	N/A	Travel attitude, personality, lifestyle, mobility, and demographic variables
Main findings: (a) Travel attitudes, personality, and lifestyle are important to vehicle type choice. (b) People who live in higher density urban areas are more likely to drive luxury cars or SUVs. (c) A dislike for travel in general is associated with driving a luxury car (a luxury car is chosen possibly to make an undesirable activity more pleasant). (d) People who think they engage in a great deal of long-distance travel are less likely to drive compact cars.						
Abrahamse et al (2009)	Three Canadian government ministries	500 govern-ment mini-stries' employ-	Hierarchical regression analyses	car use for commuting and intentions to reduce	N/A	Variables reflecting self-interest (i.e. from the theory of planned behaviour

		yees (a sample of Canadian office workers).		it.		(Ajzen, 1991)) and variables reflecting moral considerations (stemming from the norm-activation model; Schwartz, 1977) are compared as explanations. Age, sex, house-hold structure, distance between home and work are all included.
Main findings: (a)Normative influences on altruism. In L. Berkowitz (Ed.). Advances in experimental social psychology (Vol. 10, pp. 221–279). New York: Academic Press]) were able to explain self-reported car use for commuting and intentions to reduce it in a sample of Canadian office workers.(b) Car use for commuting was mostly explained by variables related to individual outcomes (perceived behavioural control and attitudes) whereas the intention to reduce car use was mostly explained by variables related to morality (personal norms).(c)The study also found that perceived behavioural control moderated the relation between personal norms and behavioural intentions: stronger personal norms were associated with stronger behavioural intentions, but only when perceived behavioural control was low. Some issues evoked by these results are discussed.						
Eriksson et al.(2010)	One Swedish city: Växjö (living 6 20 km from the city centre).	A sample of 1753 randomly selected car owners in the municipality of Växjö	Descriptive Analyses using with different scenarios	The expected car use reduction in response to one push measure (i.e. raised tax on fossil fuel), one pull measure (i.e. improved public transport), and a combination of the two measures.	N/A	Car owners with car fuelled by gasoline, sex, age
Main findings:(a)In line with expectations and previous studies, the largest expected car use reduction was found for the measure combining a raised tax and improved public transport, while no difference was found between the individual push and pull measures. Even after considering that the level of changes in prices and service were rather substantial in the present study, the expected car use reduction was larger compared to other studies. (b)Overall though, the demonstrated pattern, adds to the studies showing that packages of travel demand management (TDM) measures lead to larger behavioural responses compared to the individual TDM measures. Since the package makes both the cost for using the car higher as well as the cost for using alternative travel modes lower, more environmentally friendly travel modes become more favourable compared to if no measure or only one of the single measures would be implemented.(c)The analyses of car reducing strategies provide information as to how car users respond to different TDM measures. As expected, both trip chaining (on an annual basis) and changing travel mode (on an annual basis and in						

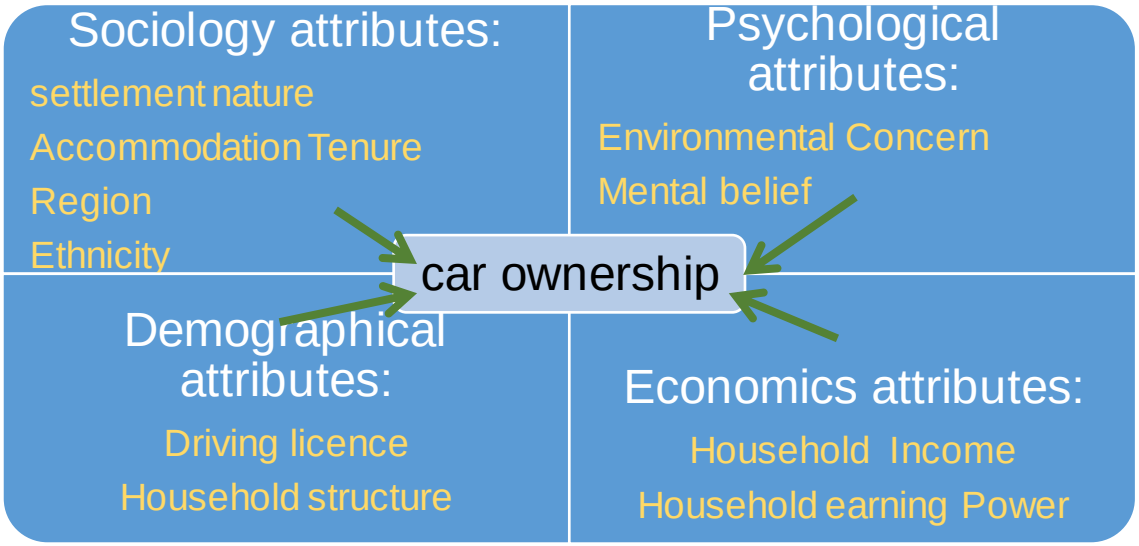
the weekly retrospective car diary) were commonly used strategies in response to the TDM measures (cf. Loukopoulos et al., 2006). However, different travel modes were chosen in response to the different TDM measures.						
Baltas and Saridakis (2013)	N/A	1622 consu-mers, exami-ning consu-mer buying behaviour and preferences in the car market	Multinomial choice model	12 vehicle type cate-gories: segment A (mini cars), segment B (super-mini cars), segment C (small family cars), segment D (medium- sized cars), segment E (large family cars), segment F (luxury cars), SUVs, MPVs, coupes, cabriolets, roadsters, and station wagons.	purchasing and operating costs, horsepower, and scrappage rate	Household structure, income, gender and age, (1) importance of composite car characteristics (x), (2) demographics (DM), (3) driver's characteristics (DC), (4) basic purpose of car use (PU), (5) pre-purchase information sources used (IS), (6) consumer involvement with cars (INV), and (7) consumer attachment to cars (ATC).
Main findings: The results provide clear evidence that variables such as purpose of car use, pre-purchase information source used, consumer's proneness towards buying an ecological car, consumer's involvement with cars, and consumer's attachment to cars, significantly affect car type choice. The empirical findings provide strong evidence in support of all relevant hypotheses regarding the impact of the chosen variables on car type choice. Factors such as purpose of car use, pre-purchase information source used, consumer's proneness towards buying an ecological car, consumer's involvement with cars, and consumer's attachment to cars, have significant effects on car type choice in ways that are relevant to various players in the automobile industry. Furthermore, our findings show that those who have a high social status involvement with cars are more likely to prefer luxury cars. A direct implication of this finding is that those drivers who consider cars as symbols of status will be less amenable to policies designed to curtail the consumption of transportation or fuel. Similarly, it was shown that there is a negative relationship between driving skills and propensity to drive smaller-sized cars. Evidently, newer car drivers are a better audience for policies targeted to reduce the problem of traffic congestion and energy consumption. Newer car drivers are expected to respond more positively to campaigns which promote the ownership of smaller-sized cars at the expense of larger and less fuel efficient body types.						

In view of the earlier research reviewed above, including those shown in the table 3.5-1above, one can hypothesize a correlated relationship between specific explanatory factors and the number of car ownership. This study assumes a relationship between disciplined based attributes and the number of car ownership in households. The demographical attributes (driving licence, household structure), psychological attributes (environmental concern and mental belief), sociological factors (settlement nature, accommodation tenure, region, ethnicity) and economic factors (household income and earning power). As outlined in figure 3.5-1, one can also hypothesize a correlated relationship of demographical factors, psychological factors, sociological factors and economic factors.

In sum, the aim of the present study is to explore the relationships of economic and non-economic factors (i.e. driving licence, household structure, environmental concern or mental belief, settlement nature, accommodation tenure, region, ethnicity, household income and earning power) as determinants of the number of car ownership in households.

Premised on the review of the literature, the following research analytical framework of the number of car ownership in the figure 3.5-1 below was proposed and adopted for the empirical analysis carried out in chapters 5 and 6 of this thesis. The decision for selecting the determinants was based on a number of reasons, including the objective of this study, current literature and the data available in databases used for this study.

Figure 3.5-1: Research analytical framework: Determinants of Car Ownership



Lawal (2021)

The figure 3.5-1 shows different factors mapped out of the literature; representing individual discipline based perspectives and combined to investigate car ownership in this study. From the discussion of Maslow hierarchical human needs in section 2.3-1, it appears that employment or sources of incomes, which is an example of safety needs in the hierarchy has some relationship with economists' perspective of car ownership determinant. Economists observe that there is a positive relationship between employment and the number of cars a household holds. Similarly, love or belonging needs in Maslow hierarchy of needs relate to demographical factors such as, household structure, which sociologists and marketers have used to investigate car ownership. Maslow opines that to belong to family setting constitutes a need that individuals aspire to meet. Similarly, ethnicity has been used by scholars to investigate car ownership in households. Therefore, Maslow hierarchy of needs provides theoretical relationship among different discipline based perspectives of investigating car ownership.

To this end, this study explored an approach that integrated these perspectives into a whole as it is believed that such holistic perspective is capable of offering better understanding to car ownership investigation in households. It is on the basis of this that the research analytical framework depicted in the figure 3.5-1 above was proposed. In other words, rather than for each discipline to investigate car ownership within its discipline area alone, integrating different perspectives into a whole will help in gaining better understanding of car ownership in households. This is the focus of this study.

3.6 CONCLUSION

Though, economic views of determinants of car ownership in general are rooted in rational, hedonistic and maximising principles, these views have been criticised as economists have argued that economic agents are not always in possession of accurate or complete information. Even, when they do possess the complete information, they do not always possess the necessary cognitive ability to handle the large number of decisions required to maximise their interest (Bollen, 2002; Crano et al., 2014). Thus, their decisions and choices are premised on inaccurate information and principles based on conscious and subconscious learning (Smith, 2003). This is the basis of the concept of *bounded rationality* developed by Simon (1982).

Similarly, reservations have been made on motivation in the acquisition of some goods and services. For example, it has been noted that a consumer may buy some products not because of any physical need, but in order to meet a psychological desire; perhaps, to project a particular position in the society or acquire people's esteem. This is considered as conspicuous consumption (Bannock et al., 1998; Hindess, 2014).

Furthermore, while economic perspectives, which deal with aspect of purchases, are important, all other perspectives which dwell on how and why these decisions to purchase are made should be accorded with importance, otherwise, researchers might not capture complete understanding of car ownership and their characteristics. This is the basis of inclusion of other perspectives in estimating models of car ownership studies, otherwise conclusion premised on full investigation will not be achieved. Meanwhile, as earlier stated, this chapter has only considered economic perspectives and adopted sociological perspective, demographical perspectives and psychological perspective as non-economic perspectives. The next chapter deals with model development of the study.

CHAPTER 4
FRAMEWORK DEVELOPMENT OF THE RESEARCH

4.0 INTRODUCTION

The literature documents various car ownership models that have been used in different vehicle ownership studies and these models are as diverse as different aims and objectives of different scholars that have used them. For instance, car producers adopt car models to estimate consumer assessment of attributes of cars towards meeting customers' market expectations. Similarly, national governments, in estimating tax revenue decision make use of car ownership models. In the same vein, different levels of government; national, regional and local governments make use of car ownership models to estimate transport use, energy usage and possible effect on government various policies.

In this chapter of the thesis, a brief review most of the different car ownership models adopted for different works is carried out, though more attention is given to area of modelling relevant to the purpose and objective of this study. Thereafter, the chapter developed and proposed modelling framework for estimating number of car ownership for UK and US households. The chapter discussed aggregate and disaggregate discrete choice modelling approaches. It provided review of various modelling approaches, highlighting Multinomial logit and Nested logit models. Lastly, it offered justification for why Multinomial logit model is selected for the empirical analysis carried out in the subsequent chapters.

4.1 DEVELOPMENT OF MODELLING APPROACHES

The development of car ownership and car usage models could be traced to as far back as to 1950s (Whelan, 2007). Then, car ownership modelling approaches began with models, which examined factors that affect consumer car purchases, with the principal focus on estimating market shares of car makes (e.g., Tanner, 1958). Thus, in the early stage of forecasting, scholars adopted aggregate methods, focussing on ownership at national, regional or local levels (Holtzclaw et al., 2002; Clark, 2007). Others were mainly based on time-series data (e.g. OHerlihy, 1967; Romilly

et al., 1998) whilst some adopted a union of the two earlier approaches (e.g. Bates et al., 1978; Dargay and Gately, 2007). The studies did not analyse the fundamental behavioural mechanisms that mainly dictate and rule the household decision making processes, making the accuracy of the models and their policy sensitivity when viewed in practical usage very inadequate (Kitamura and Bunch, 1990).

Another feature of the estimating approaches of the era is that they are usually premised on econometric models, which analysed car ownership or car use as a function of per-capita income (examples include: Tapio, 1996; Tapio and Hietanen, 2002). Microeconomic principles provided the bedrock upon which other disciplines have built over time. However, since the last four decades modelling approaches have taken a new direction with several works taken to disaggregate modelling approaches. Following the leading studies and with the availability of household databases, scholars started moving towards disaggregate choice data in modelling car ownership (See; Karlaftis and Golias, 2002; Whelan, 2007). The start of disaggregate modelling could be traced back to 1970s.

In this approach, the household or individual propensity to own or use cars is now associated to his or her socio-economic, locational and non-economic features, the price of ownership and the accessibility of other means of transport. Early studies in this area had inclinations for cross-sectional data analysis (examples include: Golob and Burns, 1978; Train, 1980; Ben-Akiva and Lerman, 1985), though the last two and half decades have witnessed a temporal dimension with the use of pooled time-series cross-sectional data (e.g. MVA Consultancy, 1996) or panel data (e.g. Nobile et al., 1996; Hanly and Dargay, 2000).

Generally, disaggregate data offer substantial variation in the behaviour of interest and in the determinants of that behaviour, allowing efficient estimation of model parameters. This is not the case with the aggregate approaches, which result in considerable loss in variability; thus requiring more data in order to derive same amount of model accuracy. Last but not the least, disaggregate models, if and when properly specified, produce un-

biased parameter estimates, while aggregate model estimates are known to produce biased (inaccurate) parameter estimates. In contrast, the aggregate approaches dwell mainly on statistical relationships among relevant variables at a level different from that of the decision maker. Thus, it is incapable of offering accurate and reliable estimates of the change in choice behaviour due changes in the population.

The disaggregate models have overcome problems and shortcomings of aggregate models like Multicollinearity (also Collinearity) across explanatory variables, huge standard errors of estimated parameters and aggregation bias. In addition, the widely use of disaggregate models is premised on their suitability for policy-sensitive analyses and suitability to modern day realities in transportation modelling (Miller et al., 1999). Meanwhile, it is important to note a few issues that characterised the emergence and development of disaggregate models in car ownership studies. First and foremost, the concern of the late 1970s and mid-1980s over increased traffic congestion and fuel efficiency, caused by increased interest in car use promoted new forecasting models. Thus, scholars started to use disaggregate models to examine the interrelated choice of car ownership and car use (e.g. Train and Lohrer, 1983; Mannering and Winston, 1985; Train, 1986; de Jong, 1990).

By mid 1990s there was apprehension among analysts concerning the fact that traditional causal forecasting models and approaches failed to capture the dynamic effect of the car ownership decisions and the interest of alternatively fuelled vehicles. Therefore, research started moving into this area. Studies in this area include analysis of market penetration of electric and LPG/CNG vehicles using disaggregate models (e.g. Batley et al., 2004) and vehicle holding decisions (e.g. Mannering and Winston, 1991; de Jong, 1996). Progressively, the last fifteen years have seen scholars increasingly using disaggregate models to investigate non-economic factors to analysis car ownership and car use. These include: consumer attitudes and lifestyles on choice of vehicle (Choo and Mokhtarian, 2004); impact of neighbourhood design as an incremental contribution to vehicle choice (Cao et al., 2007); influence of vehicle attributes, brand loyalty, product line features and dealerships on vehicle type (Train and Winston, 2007); employment

Attributes, built environment and transit Attributes (Guo, 2013) and environmental concern (Beck et al., 2013). In a recent study by Baltas and Saridakis (2013) developed a disaggregate model to examine impacts of purpose of car use, pre-purchase information source used, consumer proneness towards buying an ecological car, consumer involvement with cars, and consumer attachment to cars on choice of car type.

Furthermore, Roos et al. (2020) examined the influence of socio-demography, geography and personality on car driving and use of public transportation. In their study, they adopted sociodemographic factors such as, age, gender, income and education, while applying geographic factors through residential areas (e.g., rural and urban areas). Personality was studied using the Five-Factor-Model of personality—degree of Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.

With the development of disaggregate models, in which the elements of investigating car ownership are individual households, there appears to be reduction of several problems that constituted aggregate modelling approaches, offering a path for getting a more precise, detailed and policy relevant model results (De Jong et al, 2004; Fox et al, 2017). Thus, car ownership studies in recent time have dwelt on investigation of the car ownership decisions within disaggregate level (precisely, at household level). In view of the foregoing and in line with the objective of this study, disaggregate modelling approach was selected for the empirical analysis in chapters 5 & 6 of the thesis. Like every car ownership study, the choice of model structure and functional form used for this study are motivated by the objectives and context of the study (Brownstone and Golob, 2009; Anowar et al., 2014).

In a recent review of car ownership modelling approaches review, Anowar et al. (2014) presented different classifications of disaggregate household-level models. Summarising their review findings, they classified current models in the literature as follows:

i. Exogenous static models. These models forecast vehicle holding at a point in time without recognition of the dynamics of vehicle growth.
ii. Endogenous static models. These models jointly forecast vehicle ownership alongside other decision elements at a point in time arguing

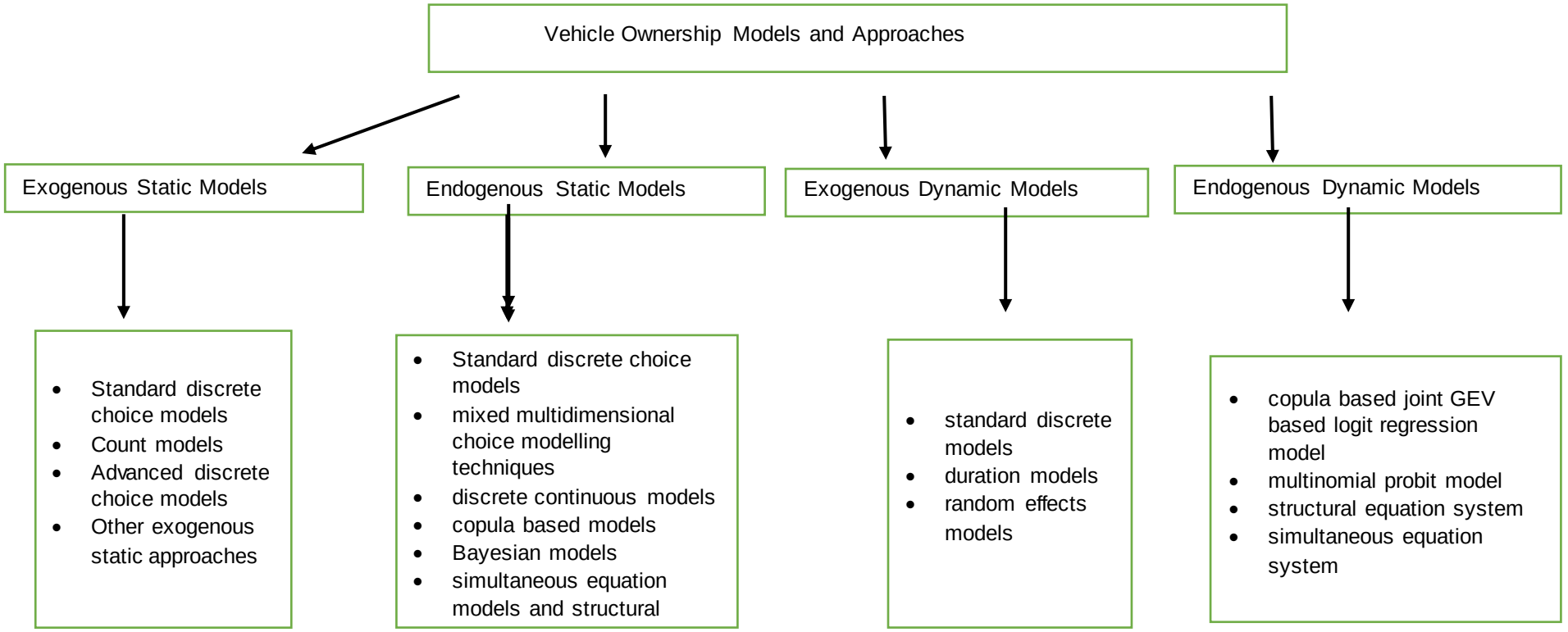
that a choice dimension (such as vehicle ownership or vehicle type) does not constitute an exogenous determinant (e.g. vehicle usage), rather, it is endogenous to the system.

iii. The exogenous dynamic models. These models investigate evolution in vehicle ownership decisions in households.

iv. The endogenous dynamic models. These include models in which both Endogeneity between household composition or usage decisions and dynamics linked with the vehicle acquisition.

Figure 4.1-1 below details the pictorial representation of the different categories of the models, followed by table 4.1-1, which provides suggestions of types of models suitable for different types of car ownership studies (For detailed explanations of each of the categories in figure 4.1-1 and table 4.1-1, see Anowar et al., 2014).

Figure 4.1-1: Vehicles Ownership Models and Approaches



Adapted from Anowar et al. (2014).

Table 4.1-1: Summary of suggested Models for different Car Ownership studies

Vehicle demand	Suggested Model			
	Exogenous static	**Endogenous static**	**Excogenous dynamic**	**Endogenous dynamic**
1. Vehicle count				
No Heteregeneity	Generalised ordered logit	Multidimensional choice modeling	—	Simultaneous equation model
Heteregeneity	Latent class multinomial logit	Mixed multidimensional choice modeling	Mixed Generalised ordered logit	—
2. Vehicle count and use	—	Multiple discrete continuous extreme value model	—	—
3. Vehicle type				
No Heteregeneity	Multinomial logit	—	—	Multinomial probit
Heteregeneity	Mixed multinomial logit	—	—	—
4. Vehicle type and use	—	Copula based joint multinomial discrete continuos model	—	Copula based joint GEV-based logit regression model
5. Vehicle ownership duration	—	—	Duration model (single Hazard)	—
6. Vehicle trnsaction	—	—	Duration model (Competing Hazard)	Hazard based simultaneous equation model
7. Vehicle transaction and type	—	—	Mixed parameter logit	—

Adapted from Anowar et al. (2014).

4.2 CAR OWNERSHIP: MODELLING REPRESENTATION

Representation of the ownership or use has been an interesting area within car ownership analysis literature and the purpose and objective of the study always dictate what representation the analyst adopts. Representation chosen by the analyst is informed by the methodological framework and the policy analysis elements of the study (Anowar et al., 2014). Meanwhile, the basic form of any vehicle representation decision processes relates to the decision of the number of vehicles at a particular point of time (See Bhat and Pulugurta, 1998; Potoglou and Susilo, 2008; Baltas and Saridakis, 2013). With the advent of modelling approaches that put emphasis on vehicular emission, different scholars have adopted diverse models to investigate household fleet composition, particularly,

using different classifications of vehicle body type, e.g. coupe, pickup truck, sports utility vehicle (See for example, Choo and Mokhtarian, 2004; Kitamura et al., 2000; Lave and Train,1979), make/model(See for example, Mannering and Mahmassani, 1985), fuel type (See for example, Brownstone et al., 2000; Baltas and Saridakis, 2013), body type and vintage (See for example, Mohammadian and Miller, 2003), and make/model and vehicle acquisition type (See for example, Mannering et al., 2002). This class of studies belongs to exogenous static models category i.e. studies that deal with vehicle ownership as independent of other decisions.

Furthermore, there has been another group of other modelling approaches, which focussed on investigation of impact of one element of vehicle ownership on another element of vehicle ownership. For example, it is reasonable that household that have unobserved predisposition for holding a large fleet of cars are likely to have a positively influencing unobserved element of higher incomes with it. Actually, an increasing body of studies in the literature show that unobserved factors (for instance, inclination towards a certain vehicle, environmental consciousness) impacts decisions of households on vehicle type. Similarly, investigation of vehicle ownership models show significant impact of land use, location and urban areas on household vehicle fleet decisions (Yamamoto, 2009; Zegras, 2010).

Nevertheless, recent research has shown that integrating land use, location and urban areas as ordinary exogenous factors is not accurate since households carry inherent preferences for residential location decisions creating self-selection (Pinjari et al., 2011; Anowar et al., 2014). Rather, impacts of other decisions processes on vehicle ownership decisions should be investigated as this creates dual basis for policy control. That is, if the dependent variable area cannot be controlled, independent variables aspect should be controllable. Meanwhile, there have been increasing interests to investigate the impact of other decision processes on vehicle ownership decisions. For instance, Baltas and Saridakis (2013) investigated household' decision on car types and these explanatory variables: car characteristics, demographics, driver's characteristics, purpose of car use, pre-purchase information source used, consumer's involvement with cars, and consumer's attachment to cars.

Other relevant study is Guo (2013), which considered the impact of residential parking supply on private car ownership, the relationship at the heart of the debate on whether residential parking regulations could be used as an ownership management strategy to influence travel behaviour. Thus, the framework of such modelling approaches, which integrate impact of additional elements accounts for impact of unobserved elements in the joint modelling of different elements of vehicle ownership. Based on the figure 4.1-1 above, such studies that adopt this methodological analytical approach are classified to belong to the endogenous static modelling groupings.

The above approaches are static in their presentations. However, household car ownership decisions do go through a number of stages over time, which include: purchasing stage, disposal stage or sale stage and replacement stage. Each of these stages could be affected by series of other processes and factors. For instance, the modifications to a household number of cars could be caused by several happenings like the birth of a child into the household, marital status changes necessitating vehicular requirements for the household. While scholars have tried to take into cognisance different circumstances to reflect dynamic inferences of car ownership analysis, majority of studies have always inclined to the use of static modelling analysis as it in this study.

This is more the case when impact of exogenous variables is investigated on vehicle ownership (as in the case of this particular study). In this study, in the empirical chapters, the proposed models were used to investigate the effects of discipline based factors on the number of car owned by UK and US households. Premised on the figure 4.1-1 and table 4.1-1 above and in line with the objective of this study; in that the number of car owned by each household could be estimated by behavioural factors (different household determinants, which are discipline based), the static analytical approach was selected. Importantly, there is an assumption of heterogeneity behind the different dependent variables used in the empirical chapters with each of them assumed different from the others.

Meanwhile, review of several studies indicated that standard discrete choice models are certainly the most generally adopted modelling approach in the

literature (See table 9-1 in appendices for updated list). Most of the works either adopted the ordered or the unordered response modelling approach. Based on literature, disaggregate models view car ownership observations (e.g. 0, 1, 2, 3 or more cars) as either ordinal nominal discrete variables or nominal discrete variables, offering two different types of choice models: the ordered and unordered, respectively. Within ordered structures like the ordered logit and ordered probit models, the choice of the number of household cars comes from a uni-dimensional latent index, which shows the probability of number of cars a household owns. Whereas, unordered response models are premised on the random utility maximization principle, with which a household links a utility value across diverse car ownership number and selects the one having the highest utility (Potoglou and Susilo, 2008; Zegras, 2010; Caulfield, 2012; Wong, 2013).

Nevertheless, two studies made comparison between the use of the ordered and unordered response modelling structures (Bhat and Pulugurta, 1998; Potoglou and Susilo, 2008) and premised on several yardsticks of data fit, these studies established that unordered response mechanisms such as MNL are more suitable for auto ownership modelling, informing the decision to select MNL model for the current study. The MNL and probit models are the main representations of the unordered response models, however, only the MNL has been used widely for its simple structure and low computational requirements (Potoglou and Susilo, 2008). In view of this, further discussion on modelling representation is now focussed on MNL models. Furthermore, in view of the foregoing review and in line with the objective of this study, static disaggregate car ownership models were adopted for the analysis. Table 4.2-1 above shows different car ownership model types and their individual recommended level of aggregation and data requirements among other relevant suitable conditionings.

Table 4.2-1: Classification of Vehicle Ownership Modelling Types

S/N	Model type	Level of aggregation	Static or dynamic	Long or short run forecasts	Car use	Car types	Data requirement
1	Aggregate time series models	Aggregate	dynamic	short, medium and long	not included	Not distin-guished	light
2	Aggregate cohort models	Aggregate	dynamic	medium and long	not included	none	light
3	Aggregate car model models	Aggregate	dynamic	short, medium and long	not included	limited	light
4	Heuristic simulation methods	Disaggregate	static	medium and long	can be included	limited	moderate
5	Static disaggregate car ownership models	Disaggregate	static	Long	included in some models via logsum	very limited	moderate
6	Indirect utility car ownership and car use models	Disaggregate	static	Long	included	often many (brand-model-age)	heavy
7	Static disaggregate car-type models	Disaggregate	static	Long	included in some models via logsum	very limited	heavy
8	Panel models	Disaggregate	dynamic	short and long	sometimes included in ad-hoc fashion	very limited	very heavy
9	Pseupanel models	Aggregate	dynamic	short and long	not included, but could be	very limited	moderate
10	Dynamic transaction models	Disaggregate	dynamic	short and medium	sometimes included in ad-hoc fashion	very limited in duration model, many in usage model	very heavy

Adapted from Fox et al., (2017)

4.3 EXOGENOUS STATIC MODELLING: MULTINOMIAL LOGIT (MNL) MODEL AND NESTED LOGIT (NL) MODEL

Generally, static disaggregate car ownership models could be segmented into two major decision approaches: ordered-response and unordered-response approaches (Guo and Bhat, 2007; Potoglou and Susilo, 2008). With ordered response modelling approaches, it is held that each household choice in terms of the number of cars to own is premised on a one-dimensional latent variable. However, with unordered response modelling approaches, the principle of random utility maximization is central and it is held that each household choice in terms of the number of cars to own is premised on their individual utility, assuming that individual will choose the choice having the highest utility (Baltas and Saridakis, 2013).Thus, the unordered multinomial discrete models do not obviously consider the ordinal element of the observed degree of car ownership. Rather, the mechanism is based on the random utility maximization (RUM) principle.

With RUM principle, each household associates a particular level of utility with a every car ownership level (a number of cars) and chooses the particular level that results the highest utility level (See Zegras, 2010; Caulfield, 2012; Wong, 2013; Baltas and Saridakis, 2013). The most frequently used model within the RUM framework is the multinomial logit (MNL) model. Meanwhile, Lerman and Ben-Akiva (1976) were the first to present a disaggregate modelling of the number of household vehicles in addition with the travel mode to work adopting the conditional multinomial logit (MNL) model (McFadden, 1974). MNL modelling approach has been considered as a major improvement in vehicle ownership modelling approaches when compared with aggregate modelling approaches because of numerous reasons. First and foremost, it deals individual households separately and this reduces aggregation bias (i.e. models are more consistent by so doing).

Furthermore, through estimation of model parameters at each household level, MNL modelling approach is able to attain a higher level of statistical accuracy, with a host of variables, giving room for more detailed explanations of decision-making processes. That is, the approach aids efficiency in modelling (Anowar, et al., 2015). In addition, the use of random utility method, which is the basis of the

MNL modelling approach, carries a robust behavioural base yielding a more intuitive model development by taking cognisance of a priori beliefs regarding human behaviour (Ben-Akiva and Lerman, 1985). As in the case of this study in which the dependent variable takes multiple discrete values, MNL model can be used to analyse the data with multiple discrete values. This is more the case when dealing with unordered multinomial data.

Assuming the random utility function be defined by

$$U_{ij} = V_{ij} + \varepsilon_{ij} \qquad 4.0$$

Where the subscript i is an index for the individual, the subscript j is an index for the alternative, V_{ij} is a nonstochastic utility function, and ε_{ij} is a random component (error) that captures unobserved elements of alternatives or individuals or both. In MNL models, the utility function is assumed to be linear, so that

$$V_{ij} = x'_{ij}\beta \qquad 4.1$$

In MNL modelling approach, independence of irrelevant alternatives (IIA), otherwise known as binary independence is assumed. In individual choice theory, IIA sometimes refers to Chernoff's condition implies, (say for example) if A is preferred to B among the choice set {A, B}, introducing a third option X, expanding the choice set to {A,B,X}, must not make B preferable to A. In other words, a household preferences for A or B should not be altered by the inclusion of X (That is, X is irrelevant to the choice between A and B). Within the conditional logit model, each for all is distributed independently and identically (IID) with the Type I extreme-value distribution, $\exp(-\exp(-\varepsilon_{ij}))$, otherwise called the Gumbel distribution.

Different works have used MNL models in car ownership estimation. For instance, Lave and Train (1979) used it in their investigation of vehicle type choice. They found significant impact on several explanatory variables, e.g. household attributes, vehicle attributes and gasoline prices on vehicle type choice was established. Thus, they identified these explanatory variables as determinants. Furthermore, Manski and Sherman (1980) built a MNL model of vehicle type choice. The study adopted a nationwide 1976 U.S survey. They attempted for the first time to bring the two elements of vehicle ownership

together (i.e. the number of vehicles owned and vehicle type choice). Their approach involved building separate vehicle type models for households; having one or two vehicles in their fleet. In order to capture the enhanced transportation accessibility and specialization of function that two vehicles offer, Manski and Sherman (1980) specified the utility of any vehicle pair as a function of the characteristics of each vehicle separately and on the characteristics of a fictitious composite vehicle joining the best of both real vehicles. Their study concluded that vehicle price, operating costs and transaction costs are all main determinants of vehicle utility, however, influence of price and operating cost varies considerably among socioeconomic and demographic groupings.

Similarly, Kitamura et al. (1999) developed a MNL model of vehicle type choice based on data from household survey in Southern California to study the impacts of automobiles and transit accessibility on vehicle holding, vehicle type choice and vehicle use. They focused on examination of primary driver's characteristics, type of household, and residence attributes as explanatory variables. The study adopted Household-based models developed for the total number of vehicles preferred by household, the number of vehicles per household member and per driver in the household, the choice of vehicle type for the most recently acquired vehicle and its use when annual mileage. Based on this study, in each model adopted, pointers of accessibility by auto and that by transit are used with residential density and other pointers of residential area and household features.

Furthermore, Mannering and Winston (1985) explored motivations that determine consumers' preference for leasing vehicles; using MNL model. They developed a model of vehicle acquisition decisions; estimating the type of vehicle to drive and whether to lease or purchase the vehicle. Their study concluded that consumers' increasing incentive to leasing comes from their ongoing desire to upgrade their vehicles—a trend of behaviour stimulated during the 1990s by an unprecedented income increase among the top twenty percent of US households. Study results show that leasing's recent popularity is mainly attributable to its role in facilitating vehicle upgrading through high income households.

In addition, Brownstone et al. (2000) compared MNL and mixed logit models using data on California households' revealed and stated preferences for various vehicles. Their studies note that the stated preference (SP) data showed households' preferences among gasoline, electric, methanol, and compressed natural gas vehicles with various attributes. They argue that mixed logit models are a general and practicable form of models suitable for joint RP/SP choice data, which could easily account for the scaling and unobserved error correlations usually found in RP/SP data applications. It is noted that their mixed logit models offered improved fits over logit that are highly significant and depicted large heterogeneity in respondents' preferences for alternative-fuel vehicles. Key findings from their work include: (i) stated preference data were found important to deriving information relating characteristics that are not readily obtainable from the market place; (ii) revealed preference data appeared important in deriving 'accurate' body type choice and scaling information, though, Multicollinearity among other problems remains part of issues with the data; (iii) adopting stated preference models without being supported by other models could yield unconvincing results.

In addition, Choo and Mokhtarian (2004) examined travel attitude, personality, lifestyle, and mobility factors that determine individuals' vehicle type choices (the type the respondent drives most often), adopting data from a 1998 mail-out/mail-back survey of 1,904 residents within three neighbourhoods in the San Francisco Bay Area. The study made use of MNL model for vehicle type choice to estimate the joint impact of main variables on the probability of selecting each vehicle type. Based on the tests of individual variables against vehicle type, using one-way ANOVA and chi-squared tests, all vehicle type groups (besides, the mid-sized car group) depicted unique features with respect to travel attitude, personality, lifestyle, mobility, and demographical variables. In contrast, no significant differences were found across vehicle types with respect to the commute time and commute distance variables.

Using European large household survey, Baltas and Saridakis (2013) developed disaggregate, compensatory MNL models to collectively investigate the impact of under-examined factors on consumer car type choice behaviour. As against most existing econometric forecasting models of vehicle type choice, which

usually focussed on objective measures, their study considered less investigated factors as determinants of vehicle type choice. Their proposed model considers 12 car-type alternatives and is successively expanded to allow for choice probability distortions emanating from individual heterogeneity across a set of 30 variables, associated to objective, behavioural and psychographic consumer features.

Furthermore, premised on revealed preference theory, which suggests that consumption preference of individual consumers could be revealed by their consumption behaviour, Fang et al. (2014) investigated the influences on citizens' travel decision; seeking to analyse the problems associated with promotion of pro-environmental travel behaviour within the medium-sized cities in China. The study was based on revealed preference (RP) theory and made use of the RP survey method and disaggregate model in its analysis in explaining how households' characteristics, situational factors, and trip features impact on their travel mode choices.

Tangshan City in China was used to collect the RP data. The study made use of an MNL model to explain the probability that a traveller chooses a particular travel mode among different alternatives. The results of the study exhibited that gender; occupation, trip purpose, and distance have impact on the travel mode choice. Importantly, their findings show that the male gender, high income, and business travel have a high correlation with carbon-intensive travel, while female gender and a medium income have higher propensity to promote pro-environmental travel modes (e.g. walking, cycling, and public transport).
In all of these studies and similar others, which adopted MNL models, IIA has been assumed.
The aim of the Multinomial Logit (MNL) model is to estimate a function that determines outcome probabilities. In this study, MNL model was used to investigate the relationships that exist between household factors and car ownership categories (no-car ownership category, one-car ownership category, two-car ownership category and three or more-car ownership category) in the the UK and the US. The probability of a car ownership is restricted to be between zero (0) and one (1). One car ownership category is selected as the reference category, typically the first, the last or the category with the

lowest or the highest frequency. It should be noted that by default, Stata normally chooses the most frequently occurring category to be the referent category So, in this study, Stata selected one-car category, the category with the highest frequency in the population. The probability of each category is compared to theprobability of referent category.

The IIA condition could be derived from the probability ratio of any two choices. For instance, it can be depicted that if the error terms ϵ_{ij} have standard Type I extreme value distributions with density,

$$f(\epsilon) = \exp\{-\epsilon - exp\{-\epsilon\}\} \qquad 4.2$$

Hence (See for instance, Maddala, 1983, pp 60–61)

$$\pi_{ij} = \frac{\exp\{n_{ij}\}}{\exp\{n_{ik}\}} \qquad 4.3a$$

$$\pi_{ij} = \frac{\exp\{n_{ij}\}}{\exp\{n_{ik}\}} = \Pr(Y = i) = \frac{\exp\{Z_i\}}{1 + \sum_{h=2}^{K} \exp\{Z_{hi}\}}\ , \qquad 4.3b$$

Which represents the standard equation capturing the MNL model.

Where,

$$\alpha_i + \sum_{h=I}^{H} \beta_{ih}\ X_{ih} = \ Z_i$$

For the reference category,

$$\Pr(Y = i) = \quad \frac{1}{\sum_{h=I}^{H} \beta_{ih}\ X_{ih} = \ Z_i} \qquad 4.3c$$

After rearranging equation (4.3b) and (4.3c), the MNL model can be written as follows:

$$\frac{\Pr(Y=i)}{\Pr(Y=I)} = \ \alpha_i + \sum_{h=I}^{H} \beta_{ih}\ X_{ih} = \ Z_i \qquad 4.3d$$

Where:

i = the number of ownership category

$\beta_{ih}\ X_{ih}$ = vectors of the estimated parameters and predictor variables respectively

$\frac{\Pr(Y=i)}{\Pr(Y=I)}$ the probability of each categories with the first category as reference.

The equation above expressed the logit (log odds) as a liner function of the independent factors (X_S). Therefore, equation (4.3d) allows for the interpretation of the logit weights for variables in the same way as in linear regressions.
In the special case in which $J = 2$, individual i will choose the first alternative if $\cup_{i1} - \cup_{i2} > 0$. If the random utilities $\cup_{ij}$ have independent extreme value distributions, their difference can be depicted to have a logistic distribution, and we derive the standard logistic regression model.

Luce (1959) derived Equation 4.3a starting from a simple requirement that the odds of choosing alternative j over alternative k should be independent of the choice set for all pairsj, k. This condition is the condition of IIA. Meanwhile, whether or not this assumption is realistic (and other alternatives are indeed irrelevant) depends on the nature of the choices. In choice situations, where IIA cannot be assumed other modelling approaches have been suggested (Brownstone and Golob, 2009; Anowar et al., 2014). For example, a classical example in which a MNL model does not work well is the case of the "red/blue bus" problem. It is important to stress that the IIA condition is beneficial on the basis of estimation and forecasting. For instance, it ensures that the prediction of choice for currently unavailable alternatives. If the IIA condition is suitable for the choice problem being considered, then estimation could be premised on the set of currently available alternatives and then the estimated model can be adopted to derive the probability that an individual would choose a new alternative not considered within the estimation procedure.

Nevertheless, the IIA condition is restrictive from the perspective of choice behaviour. That is, models that show that the IIA condition estimates that a change in the characteristics of one alternative alters the probabilities of the other alternatives uniformly such that the ratios of probabilities remain the same. Therefore, cross elasticities resulting to a change in the attributes of an alternative are equal for all alternatives. In settings where the analyst is of the view that IIA condition does not hold in the problem, another popular model used is nested logit model (NL) model.

4.3.1 NESTED LOGIT MODELS

In situations where the IIA condition is not realistic or not valid, the nested logit (NL) model structure has been recommended as a suitable generalization of the MNL model. NL model gives room for correlation between the utilities of alternatives within same nests (Koppelman and Sethi, 2008). To estimate the model, car ownership levels (The number of cars owned by households, for example) that are apparently similar or related to each other (because of unobserved preferences) are assembled into nests (See Mohammadian and Miller, 2003b; Cao et al., 2007; Guo, 2013; Cao, 2015; Fox et al., 2017). For example, in the number of car ownership estimation car fleet decision could be separated into two levels, using car availability (i.e. owning zero car versus owning car) as the first level, whereas, owning one car and owning two or more cars forming the second level and a two level NL model can be estimated (Kermanshah and Ghazi, 2001).

A lot of scholars have chosen nested logit models for their analyses. For example, Hocherman et al. (1983), the first set of scholars to study impact of vehicle and household characteristics on vehicle type choice for car market of Israel adopted a developed nested logit model. The study made use of household survey of 1300 households. In their study, a dynamic transaction model, which was embedded in a two-stage nested logit model of vehicle type choice conditioned on transaction type (i.e., buying a first car or replacing an existing car) was used. They found vehicle and household characteristics as determining factors for consideration in the vehicle type choice. Furthermore, Mannering et al (2002) presented a nested logit model of vehicle type choice conditional on vehicle acquisition methods such as leasing, financing, and paying cash.

They developed separate choice models for each vehicle acquisition method based on data from a nationwide U.S. household panel survey of 654 households that had bought new vehicles between 1993 and 1995. The study was based on 10 alternative vehicles; using the vehicles makes and models. Acquisition methods of the vehicles; for example, leasing, financing, and cash option were studied. Among others, major findings of the study are: (i) Irrespective of how the vehicles are acquired, households generally have higher

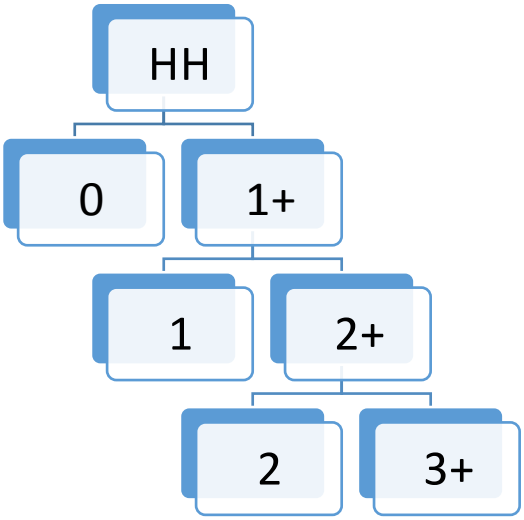
tendency to choose vehicles having higher brand loyalty and residual values; (ii) households that acquire vehicles through leasing option usually place high worth on vehicle characteristics, for examples, horsepower and passenger side airbags. Such households also have tendency to choose larger vehicles and sport utility vehicles (SUVs).

In addition, Cao et al. (2007) examined neighbourhood design as an incremental contribution to car choice. Their nested logit model suggested that an outdoor spaciousness (based on perceptions of yard sizes and off-street parking space) and commute distance also affect vehicle type choice after controlling for other socio-demographic and attitudinal factors. The specific aspects of the built environment that influence car choice, however, were not well-established. Similarly, in a recent Rand Europe study, which estimated national car ownership using 2011 as base year (Fox et al., 2017), nested logit models were used. Their approach involved building household-level disaggregate models of car ownership. Their approach allowed the effect of a range of socio-economic and other variables on car ownership to be integrated. The estimation approach used to investigate the household car ownership decision is modelled as a sequence of linked choices namely:

1. The choice between owning zero and one-plus cars (P1+)
2. The choice between one and two-plus cars (P2+)
3. The choice between two and three-plus cars (P3+).

Their model structure is as follows:

Figure 4.3.1-1: Nested Model Structure



Adapted from Fox et al. (2017)

From the top end, the first model estimates the binary choice between owning zero vehicle or one-plus vehicles. Should household (HH) chooses one-plus vehicles, then the second model estimates the binary choice between owning one vehicle or two-plus vehicles. Should two-plus cars be chosen, then the third model estimates the binary choice between owning two vehicles or three-plus vehicles. It is important to stress that the assignment of alternatives to different levels and positions within the nesting structure as well as the number of nesting levels is the sole prerogative of the analyst; and is informed by the purpose and assumptions guiding the analysis.

While the methodology provided in Fox et al. (2017) offers a valid approach to estimating car ownership, it is not suitable for my study for a number of reasons. First, this study seeks to promotes a MNL modelling structure developed to aid integration of different discipline based factors in a model so as to justify the benefit of holistic modelling in car ownership estimation. Two, the type of explanatory variables adopted in this study were selected based on the focus and motivation of the study, which then informed the literature review carried out and the determining factors mapped out. The years chosen for the data collection was to gain up-to-date understanding of declining growth being experienced in the households' car ownership. As shown in the introductory chapter,since the last decade,the growth in the number of cars associated to households is declining. Lastly, the data source used in this study cannot provide such modelling building blocks as highlighted in Fox et al. (2017).

Table 4.3.1-1 below highlights summary of previous studies on car ownership with MNL and NL models. Each study its data source, modelling approach and explanatory variables considered among other details.Nevertheless, the NL model holds the restrictions that alternatives within a shared nest possess equal cross-elasticities and alternatives not within a shared nest have cross-elasticities like the MNL model (Koppelman and Sethi, 2008). Reflecting on the structural modelling features highlighted above in relation to this research objective, the nature of the dependent variables investigated including the assumption that guide this current study and the purpose of this study as indicated in chapter 1 of this thesis, it is opined that the NL models are not suitable for this study, but MNL model. The IIA condition has been assumed in relation to the dependent alternatives. In view of this, the next section of the thesis presented the MNL models used for the empirical analysis in chapters 5 and 6.

Table 4.3.1-1: Summary of previous researches on Car ownership

					Variables Considered							
	Studies	**Data Source & Type**	**Modelling Approach**	**Vehicle Demand Form**	**Household Demographic**	**Individual Attributes**	**Employment Attributes**	**Life Cycle Attributes**	**Built Environment**	**Transit Attributes**	**Policy**	**Unobserved Effects**
S/N	**Exogenous Static (45)**											
1	Karlaftis and Golias (2002)	Greece roadside interviews	Binary logit	VO	√	—	—	√	√	√	√	—
2	Li et al. (2010)	China Household Survey	Binary logit	VO	√	√	√	√	√	√	—	—
3	Ma and Srinivasan (2010)	USA Census micro-data	Binary logit	VO	√	√	—	√	√	—	—	—
4	Whelan (2007)	Great Britain Travel Survey	Binary logit	VO	√	—	—	—	√	—	√	—
5	Bhat and Pulugurta (1998)	USA Activity Survey Netherlands Travel Survey	Ordered logit	VO	√	—	—	—	√	—	—	—
6	Hess and Ong (2002)	USA Activity and Travel Survey	Ordered logit	VO	√	√	—	—	√	√	—	—
7	Kim and Kim (2004)	USA Travel Survey	Ordered logit	VO	√	—	—	√	√	√	—	—
8	Potoglou and Susilo (2008)	USA, Netherlands, Japan Travel Survey	Ordered logit	VO	√	√	—	√	√	—	—	—
9	Potoglou and Kanaroglou (2008b)	Canada Internet Survey	Ordered logit	VO	√	—	√	√	√	√	—	—
10	Chu (2002)	USA Travel Survey	Ordered logit	VO	√	—	√	√	√	—	—	—
11	Cao et al. (2007)	USA Attitudinal Survey	Ordered logit	VO	√	√	—	—	√	—	—	√
12	Potoglou and Susilo (2008)	USA, Netherlands, Japan Travel Survey	Ordered logit	VO	√	√	—	√	√	—	—	—
13	Ma and Srinivasan (2010)	USA Census micro-data	Ordered logit	VO	√	√	—	√	√	—	—	—

14	Bhat and Pulugurta (1998)	USA Activity Survey Netherlands Travel Survey	Multinomial logit	VO	√	—	—	—	√	—	—	—
15	Wu et al. (1999)	China Stated Preference Survey	Multinomial logit	VT	√	√	√	√	√	√	√	—
16	Ryan and Han (1999)	USA Census micro - data	Multinomial logit	VO	√	—	—	—	√	—	—	—
17	Choo and Mokhtarian (2004)	USA Attitudinal Survey	Multinomial logit	VT	√	√	√	√	√	—	—	—
18	Bento et al. (2005)	USA Travel Survey	Multinomial logit	VO	√	√	—	√	√	√	√	—
19	Soltani (2005)	Australia Travel Survey	Multinomial logit	VO	√	—	—	√	√	√	—	—
20	Potoglou and Kanaroglou (2008b)	Canada Internet Survey	Multinomial logit	VO	√	—	√	√	√	√	—	—
21	Potoglou and Susilo (2008)	USA Netherlands Japan Travel Survey	Multinomial logit	VO	√	√	—	√	√	—	—	—
22	Potoglou (2008)	Canada Internet Survey	Multinomial logit	VT	√	√	—	√	√	—	—	—
23	Zegras (2010)	Chile OD Survey	Multinomial logit	VO	√	—	—	—	√	√	—	—
24	Caulfield (2012)	Ireland Census Data	Multinomial logit	VO	√	√	—	√	√	√	—	—
25	Wong (2013)	Macao Travel Survey	Multinomial logit	VO	√	—	—	√	√	—	—	—
26	McCarthy and Tay (1998)	USA Consumer Survey	Nested logit	VT	√	—	—	√	√	—	√	—
27	Kermanshah and Ghazi (2001)	Iran Travel Survey	Nested logit	VO	√	—	√	√	√	—	—	—
28	Mohammadian and Miller (2002)	Canada Retrospective Survey	Nested logit	VT	√	√	√	—	—	—	√	—
29	Mohammadian and Miller (2003b)	Canada Retrospective Survey	Nested logit	VT	√	√	√	—	—	—	√	—
30	Cao et al. (2006)	USA Attitudinal Survey	Nested logit	VT	√	√	—	√	√	—	—	—

31	Guo (2013)	USA Attitudinal Survey	Nested logit	VO	√	—	√	—	√	√	—	—
32	Potoglou (2008)	Canada Internet Survey	Random parameters logit	VT	√	√	—	√	√	—	—	—
33	Shay and Khattak (2011)	USA Travel Survey	Poisson regression	VO	√	—	—	—	√	—	—	—
34	Shay and Khattak (2005)	USA Travel Survey	Negative binomial regression	VO	√	—	—	—	√	—	—	—
35	Shay and Khattak (2007)	USA Travel Survey	Negative binomial regression	VO	√	—	—	—	√	√	—	—
36	Karlaftis and Golias (2002)	Greece Roadside Interviews	Poisson - lognormal model	VO	√	—	—	√	√	√	√	—
37	Anowar et al. (2014a)	Canada OD Survey	Latent class multinomial logit	VO	√	—	√	—	√	√	—	—
38	Beck et al. (2013)	Australia Interviewer Assisted Online Survey	Latent class multinomial logit	VT	√	—	—	—	—	—	√	—
39	Mohammadian and Miller (2002)	Canada Retrospective Survey	Artificial Neural Network	VT	√	√	√	—	—	—	√	—
40	Lave and Train (1979)	USA Attitudinal Survey	Multinomial logit	VO	√	√	—	√	√	√	—	—
41	Mannering and Winston (1985)	USA Vehicle Survey	Multinomial logit	VO	√	√	√	√	√	√	√	—
42	Kitamura et al. (2000)	USA Vehicle Survey	Multinomial logit	VO	√	√	—	√	√	√	—	—
43	Baltas and Saridakis (2013)	European Vehicle Survey	Multinomial logit	VT	√	√	—	—	√	√	√	—
44	Berkovec and Rust (1985)	USA Vehicle Survey	Nested logit	VT	√	—	—	√	√	—	√	—
	Note: VO = vehicle ownership; VT = vehicle type;											

(See table 9-1 in appendices for updated list)

Meanwhile, thorough investigation of table 9-1 of the appendices provides some instructive revelations. An immediate analysis of the table shows that about 90 studies presented dates back to 1990s and were grouped based on the four vehicle ownership representations in the figure 4.1-1 above. Table 9-1 gives details on the studies, which include data source, modelling approach, car ownership form, key variables considered, i.e. household demographics, individual, employment and life cycle attributes, built environment features, transit attributes, policy scenarios and unobserved effects. Furthermore, analysis of the table shows that over half of the studies are from the North America (50); basically, from US and Canada, while one quarter of the total studies are from European data. The remaining few studies are from the Asian (10 studies) countries, Australia (2 studies) and South American (1 study). In addition, in terms of model estimation, most of the studies (64 studies out of 93) used cross-sectional travel behaviour surveys as data.

Moreover, household demographical factors and built environment features (e.g. land use, location and availability of parking space) are the two most investigated exogenous variable groups. Lastly, based on the studies in table 4.3.1-1 above, vehicle ownership decisions have been mostly investigated as static exogenous choice adopting unordered choice modelling approaches with the most frequently model structural form being the multinomial logit (MNL) model. However, the review also shows that two modelling approaches were frequents, which are: MNL model and nested logit model or nested logit (NL) model. In the light of the objectives of this study, which influenced the type of modelling approach proposed in this study, the next section now discusses static exogenous choice modelling framework with the focus on MNL modelling approaches and NL modelling approaches.

4.4 MODEL STRUCTURE

Hitherto, this chapter has reviewed and specified different models that have been put forward by scholars to investigate car ownership determinants. Premised on the discussions and justification put forward for MNL model above, a special MNL model was developed and proposed to investigate determining factors for cars ownership among UK and US households. The

proposed model aimed at demonstrating that it is possible to incorporate several independent variables to represent each discipline in an estimating model.

Meanwhile, utility indicates value to an individual. Thus, it is assumed that utility being derived from the features of alternatives or collections of alternatives; for example, the total number of cars a household holds. According to the utility maximization condition, an individual will choose the alternative from his/her collection of available alternatives, which maximizes his or her utility. In addition, the condition means that there is a function containing features of alternatives and features of individuals that capture an individual utility valuation for each alternative. Following the justification put forward earlier in this chapter for why disaggregate MNL model is considered suitable for this study, a modified version MNL model developed by Baltas and Saridakis (2013) was used for the estimations carried out in chapters 5&6 of this thesis. Normally, the MNL could be seen as an unusual form of a standard model of utility maximization.

Thus, the utility function U has the condition that an alternative is selected if its utility is more than the utility of all remaining alternatives in the individual selection set, otherwise called, choice set. In other words, an alternative *i*, is selected among a set of alternatives, if and only if the utility of alternative, *i* is more than or equal to the utility of all alternatives[3], 'j', in the selection set C . Mathematically expressed as:

$$U\left(X_{I,}S_t\right) \geq U\left(X_{j,}S_t\right)\forall j \Rightarrow i \succ j \forall j \in C \qquad 4.4$$

Where:

U refers to the mathematical utility function,

$X_{I,}S_t$ refers to vectors of features describing alternatives *i* and *j*, respectively (e.g., household incomes and other relevant features of the available alternatives), S_t is a vector of features describing individual *t*, which impact on

[3] All *j* includes alternative *i*. The case of equality of utility is included to assume that the utility of *i* will be equal to the utility of *I* included in all *j*.

his/her choices among alternatives (*e.g.*, family type structure and other relevant features)

$i \succ j$ refers to the alternative or option to the left is preferred to the option to the right, and $\forall j$ refers to all the cases, j, in the selection set[4]

This means if the utility compnent of option i is more than or equal to the utility of all options; j, option i will be preferred and selected from the set of options C.

In this study, for every household i, a specific level of utility is derived from each of the number of cars associated to the households, such that, $\mathrm{U(option\ 0)} = \beta_0^1 x_{i0} + \varepsilon_{i0,} \ldots, \mathrm{U(option\ J)} = \beta_j^1 x_{ij} + \varepsilon_{ij}$. Restating again, under the utility maximization condition, household i will choose option j, if $U_I(\mathrm{option\ j}) > U_i(\mathrm{option\ k}) = \forall\ \mathrm{k} \neq \mathrm{j}$. It is presumed that the disturbances in the MNL model are IID, with similar extreme value distribution. Hence, the cumulative distribution function is

$$F(\varepsilon_{ij}) = \exp(-exp(-\varepsilon_{ij})) \qquad 4.5$$

Premised on equation (3.2), the choice likelihood (probability) of option j for household car ownership is given by

$$P_{ij} = \Pr(Y_i = j) = \Pr(U_j > U_m), \forall\ m \neq j = \frac{exp\beta_j x_{ij}}{\sum_{k=1}^{4} \exp(\beta_k x_{ik})}, j = 1, \ldots 4 \qquad 4.6$$

Here:

i represents a particular event (e.g. household, car category, etc.); $j, k\ and\ m$ represent the option choices; x represents the matrix of explanatory variables; and b represents each individual coefficient (Train, 2003; Train, 2009; Greene, 2012; Baltas and Saridakis, 2013). The model in (4.3c) is a multinomial logit (MNL) model[5]. Premised on Eq. (4.6), an integrated disaggregate, multinomial logit choice model to estimate the likelihood of making choice from mutually exclusive number of car categories was formulated. As noted earlier, most of the existing car ownership models have been focused on the examination of objective variables such as vehicle characteristics and demographical characteristics (see also Choo and Mokhtarian, 2004). In the light of this, at the start of the model development, a

[4] J is the union of all js or js are sub set of J.
[5] Nerlove and Press (1973).

baseline model was formulated to investigate the impact of composite household features on number of cars a household owns. Thus, by integrating Eq. (4.6), the likelihood of selecting number of cars j could be written as:

$$P_j = \frac{\exp(\alpha_j + \beta_{hj} X_{hij} + DM_{dj})}{\sum_{k=1}^{4} \exp(\alpha_k + \beta_{hk} X_{hik} + DM_{dk})}, \qquad j = 1, \ldots 4 \qquad 4.7$$

Where:

i remains as previously defined; $j\ and\ k$ represent the number of cars a household owns; α_j is an alternative-specific intercept; x represent the relative importance associated to respondent i to the number of car category feature h; β represents the individual associated coefficient, and DM represents an intercept, which gives room for choice likelihood distortions as a result of heterogeneity in demographical feature d among households. Thereafter, the baseline model (4.7) was then continually expanded to embrace the impact of other discipline based variables also relevant to the number of cars choice particularly, in line with objective of integrating different discipline based variables. Precisely, the baseline model (4.7) was first expanded to incorporate the impacts of sociological determinants, such as household/family structure and ethnic diversities. Thus, by expanding Eq. (4.7), the likelihood of selecting the number of cars j could be written

$$P_j = \frac{\exp(\alpha_j + \beta_{hj} X_{hij} + DM_{dj} + SF_{sj})}{\sum_{k=1}^{4} \exp(\alpha_k + \beta_{hk}\, x_{hik} + DM_{dk} + SF_{sk})}, j = 1, \ldots 4 \qquad 4.8$$

Where:

SF represents the impacts of sociological factors s on the likelihood of selecting option j.

Subsequently, model (4.8) was extended to incorporate the impacts of psychological factors characteristics. By the expansion of Eq.(4.8), the likelihood of selecting the number of cars j could be written as:

$$P_j = \frac{exp(\alpha_j + \beta_{hj} x_{hij} + DM_{dj} + SF_{sj} + PF_{pj})}{\sum_{k=1}^{4} \exp(\alpha_k + \beta_{hk}\, x_{hik} + DM_{dk} + SF_{sk} + PF_{pk})}, j = 1, \ldots 4 \qquad 4.9$$

Where:

PF represents the effect of Psychological factors p on the probability of choosing alternative j.

Subsequently, model (4.9) was extended to incorporate the impacts of economic factors. By extending Eq.(4.9), the likelihood of selecting the number of cars j could be written as:

$$P_j = \frac{exp(\alpha_j + \beta_{hj} x_{hij} + DM_{dj} + SF_{sj} + PF_{pj} + EF_{ej})}{\sum_{k=1}^{4} \exp(\alpha_k + \beta_{hk}\, x_{hik} + DM_{dk} + SF_{sk} + PF_{pk} + EF_{ek})}, j = 1, \ldots 4 \qquad 4.10$$

EF represents the effect of economic factors e on the likelihood of selecting option j. Altogether, four models were developed and that resulted in the above integrated specification Eq. (4.10).

Please note that these models as adopted did not integrate satiation effect due to the assumption of the study. Like many standard discrete choice (static) model, this study assumes no satiation effects. Furthermore, the study adopted standard discrete choice models with a linear utility specification. In other words, marginal utility of any number of cars chosen is independent of vehicle usage. This is more the case when using static modelling approach with cross sectional data. The reader is referred to Bhat (2005) and Bhat and Sen (2006) for further details. Results of the MNL model were compared with results derived from the Nested logit model, which was specified and discussed below.

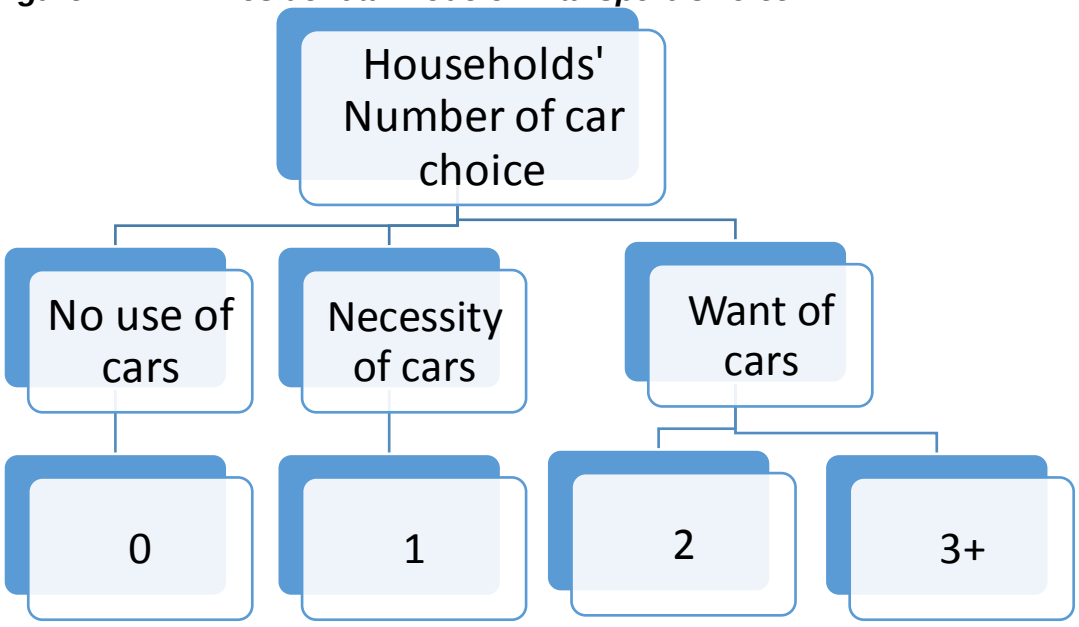
4.4.1 Nested logit Model structure

Meanwhile, whenever there is inter-related relationships among the alternatives of the dependent variables, the assumption of independence breaks down, yielding potentially biased parameter estimates. This is because some of the alternatives are more related to each other than others. Like every nested scenario, assume that there are three groups of households in the data collected. These are: (a) Households, which have no need for cars at all because of their conditions and peculiarities. It could because members of such households work from home or live close to rail station or access to other means of transportation; (b) Households, which have need for cars due to their peculiarities and therefore, hold one car. It could be because household members work far from home, need to move children to schools or because they do not have access to alternative modes of transportation; (c) Household, which have unbridled, 'want' desire for cars and therefore, end up holding two, three or more cars. Members of such households could enjoy luxurious lifestyle, in which case, they hold fleet of

cars. See figure 4.4.1-1 below for pictorial outlook of the nested tree of these three assumptions.

Thus, it is the relatedness among subsets of utilities that violates the MNL model assumption of independence. Nested logit (NL) models that explicitly account for interdependence among alternatives are preferred to MNL under such situations that have the above assumptions. Note: the bottom-level of the tree shows the number of cars associated to each nest of the tree. For 'No use of car' nest, there is 0 number of cars; 'Necessity of cars' nest, we have just one car associated to it and 'Want of cars' nest has $2 \text{ and } 3+$ cars associated to it. In this study there are four indices $(1,2,3,4)$ denoting three types of nests described above. So, $1 \text{ and } 2$ denote 'No use of car' and 'Necessity of cars' nests respectively, while, $3\ and 4$ indices denote 'Want of cars' nest.

Figure 4.4.1-1: Residential Mode of Transport Choice



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NL model, which carries out full information maximum-likelihood estimation, relaxes the assumption of independently distributed errors and the IIA inherent in MNL models by clustering related alternatives into nests. Normally, nlogit adopts a parameterization, which is consistent with RUM. In addition, it is important to stress that the Stata version used is RUM-consistent version and is based on a sound model of consumer behaviour. For detailed discussion of derivation of NL model under the assumption of

utility maximization see Amemiya (1985, chap. 9). Similarly, Hensher et al, (2005) offered similar details.

In this model, there is a set of unordered choices (number of cars) indexed by $1; 2; \ldots . J$. Thus, let $y_{ij}, j = 1; \ldots \ldots ; J$, be an indicator variable for the alternative actually selected by the ith individual (case). In other words, $y_{ij} = 1$ if individual i chose alternative j and $y_{ij} = 0$ otherwise. Furthermore, there are two forms of independent variables: alternative specific and case specific independent variables. While the alternative-specific variables vary among the alternatives (and also among cases), the case-specific variables vary among cases only. Assuming that there are p alternative-specific variables such that for case i we have a $J\ X\ p$ matrix,X_i. Additionally, assuming that there is a q case-specific variables such that there is a $1\ X\ q$ vector Z_i for case i. The random-utility model could then be represented as

$$\cup_i = X_i\beta + (Z_i A)^1 + \varepsilon_i \qquad 4.11$$

Where β is a $P\ X1$ vector of alternative-specific regression coefficients and $A = (\alpha_1, \ldots, \alpha_J)$ is a $q\ X\ J$ matrix of case-specific regression coefficients. The elements of the $J\ X1$ vector ε_i are independent Type I (Gumbel-type) extreme-value random variables with mean γ (the Euler–Mascheroni constant, approximately 0.577) and variance$\pi^2/6$. We must fix one of the α_j to the constant vector to normalize the location. We set $\alpha_k = 0$, where k is specified by the base alternative ( ) option. The vector $\cup_i$ quantifies the utility that the individual gains from the J alternatives. The alternative chosen by individual i is the one that maximizes utility.

MNL and conditional logit (clogit) models have been chosen for analysis in this study. Both models are used to analyse the choice of an individual among a set of J alternatives. The main difference between the two models could be specified very simply: MNL dwells on the individual as the unit of analysis and adopts the individual characteristics as explanatory variables; whereas, NL model focuses on the set of alternatives for each individual and the explanatory variables are characteristics of those alternative. Assuming X_i

stand for the characteristics of individual i and Z_i, for the characteristics of the jth

alternative for individual$i$, with the corresponding parameter vectors denoted by $\beta \ and \ \alpha$,respectively. Let J be the number of unordered alternatives (for the moment, assumed constant for all individuals) andP_i, the probability that individual i chooses alternative$j$. The choice probabilities in the MNL and asclogit models are:

$$\text{MNL:} \qquad P_{ij} = exp(X_i\beta_j) / \sum_{k=1}^{J} exp(X_i\beta_k), \qquad 4.12$$

$$NL: \qquad P_{ij} = exp(Z_{ij}\alpha) / \sum_{k=1}^{J} exp(Z_{ik}\alpha), \qquad 4.13$$

In the case of the UK, there are 2942 households and their choice set of four different categories of number of cars: Households with no cars (NocarHH), Households with one car (OnecarHH), Households with two cars (TwocarHH) and Households with three or more cars (Threeormorecars). From the nest tree, NoCarHH belongs to 'No use of cars' nest, while OnecarHH and TwocarHH belong to 'necessity of cars' nest. Lastly, ThreeormorecarHH belongs to 'Want of cars' nest. This study adopted approach in Heiss (2002) and proposed the decision tree in figure 4.4.1-2, which has two levels, with M alternatives at the upper level and a total of J alternatives at the bottom level.
Thus, in the UK analysis, the choice of the number of cars was modelled as a function of household income, the Household structure, ethnicity, household location (in terms of regions), mental belief on relationship of car to climate use, accommodation tenure and driving licence. Household income, Household structure, mental belief on relationship of car to climate use and driving licence are attributes of the Households' members, while ethnicity, household location (in terms of regions) and accommodation tenure are attributes of the alternative (the Households). That is, every household belongs to an ethnicity, is situated in a location and is accommodated in a particular form (e.g. rented apartment, mortgage etc.).

Similarly, in the case of the US analysis, there are 6342 households and their choice set of four different categories of number of cars: Households with no cars (NocarHH), Households with one car (OnecarHH), Households with two

cars (TwocarHH) and Households with three or more cars (Threeormorecars). From the nest tree, NoCarHH belongs to 'No use of cars' nest, while OnecarHH and TwocarHH belong to 'necessity of cars' nest. Lastly, ThreeormorecarHH belongs to 'Want of cars' nest. This study adopted approach in Heiss (2002) and proposed the decision tree in figure 4.4.1-2, which has two levels, with M alternatives at the upper level and a total of J alternatives at the bottom level.

Thus, in the UK analysis, the choice of the number of cars was modelled as a function of household income, the number of income earners in households, Household structure, ethnicity, mental belief on relationship of car to climate use, accommodation tenure and driving licence. Household income, the number of income earners in households, household structure, mental belief on relationship of car to climate use and driving licence are attributes of the households' members, while ethnicity, and accommodation tenure are attributes of the alternative (the Households). That is, every household belongs to an ethnicity and is accommodated in a particular form (e.g. rented apartment, mortgage etc.).

Based on random utility maximization (RUM), choosing alternative j, decision maker i obtains utility

$$\cup_{ij} = V_{ij} + \epsilon_{ij} = \alpha_j + X_{ij}\beta_j + z_i\gamma_j + \epsilon_{ij} \qquad 4.14$$

where V_{ij} is the deterministic part of utility and ϵ_{ij} is the random part. X_{ij} are alternative-specific variables and z_i are case-specific variables. The set of errors $\epsilon_{i1}, \ldots\ldots\ldots, \epsilon_{iJ}$ are assumed to follow the generalized extreme-value (GEV) distribution that constitutes a generalization of the type 1 extreme-value distribution, which allows for alternatives within nests of the tree structure to be correlated. Let ρ_m denote the correlation in nest m, and define the dissimilarity parameter $\tau_m = \sqrt{1-\rho_m}.\tau_m$=0 implies that the alternatives within nest m are perfectly correlated, while m=1 implies independence.

Note, the inclusive value for the mth nest corresponds to the expected value of the utility that decision maker i derives by choosing an alternative in nest m. Denote this value by IV_m:

$$IV_m = \ln \sum_{j \in B_m} exp(V_k/\tau_m \qquad 4.15$$

where B_m connotes the set of alternatives in nest m. With the inclusive values, it is possible to show that the probability that random-utility–maximizing (RUM) decision maker i chooses alternative$j$ is

$$Pr_j = \frac{\exp\{V_j/\tau(j)\}}{\exp\{IV(j)\}} \frac{\exp\{\tau(j)IV(j)\}}{\sum_m \exp(\tau_m IV_m)} \qquad 4.16$$

where $\tau(j)$ and $IV(j)$ are the dissimilarity parameter and inclusive value for the nest in which alternative j lies.

Consider two-level nested logit model for number of car choice for UK households. In this study, $= \{1,2,3\}$, which are the set of indices representing the three number of car categories and $R_1 = \{1\}$, $R_2 = \{2\}$ and $R_3 = \{3,4\}$ to be the set of indices representing each nest of the number of cars within type $t \in T$. Suppose C_1 and C_2 be the random variables that denote the choices made for the first level, number of cars type, and second level, car nests, of the hierarchy, where we observe the choices $C_1 = t, t \in T$, and $C_2 = j, j \in R_t$. Let z_t and x_{tj}, for $t \in T$ and $j \in R_t$, refer to the row vectors of explanatory variables for the first-level alternatives and bottom-level alternatives for one case, respectively. The utilities (latent utilities) could be written as $\cup_{tj} = z_t\alpha_t + X_{tj}\beta_j + \epsilon_{tj} = \eta_{tj} + \epsilon_{tj}$, where α_t andβ_j are column vectors and the ϵ_{tj} are random disturbances. When theX_{tj} xtj are alternative specific, we can drop the indices from β, where one coefficient is estimated for each alternative in $R_t, t \in T$.

When the random-utility framework is used to describe the choice behavior, the alternative that is chosen is the alternative that has the highest utility. Assume for the analysis of the number of cars in this study that we choose number of car type $t \in T$. For the RUM parameterization of nlogit, the conditional distribution, given choice of number of car type t is a multivariate version of Gumbel's extreme-value distribution,

$$F_{\frac{R}{T}}(\in | t) = \exp[-\{\sum_{m \in R_t} exp(\in_{tm}/\tau t)\}^{\tau t}] \qquad 4.17$$

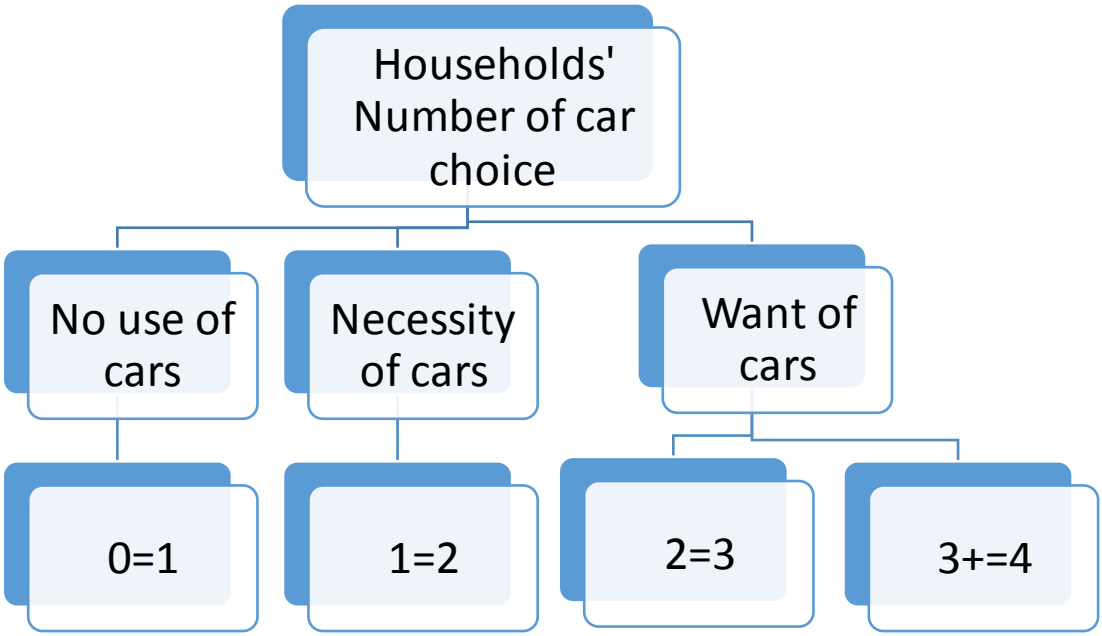
where it has been shown that the $\epsilon_{tj,} j \in R_t$ are exchangeable with correlation $1 - \tau_t^2$,for $\tau_t \in (0,1)$(Kotz and Nadarajah, 2000).

Generally, the probability of choosing any alternative that conform with RUM becomes;

$$\Pr(C_2 = j|C_1 = t) = \frac{\exp(X_{tj}\beta_j/\tau_t)}{\sum_{m\in R_t}\exp(X_{tm}\beta_m/\tau_t)} \qquad 4.18$$

Based on the discussion of the NL model described above., including the nested tree (which is relisted below) and its assumptions, the specifications and the approach adopted for the model are now described below. At the bottom of the tree is the individual number of cars categories, indicating that there are some random shocks that affect each household decision to choose a particular number of car category(s).

Figure 4.4.1-2: Residential Mode of Transport Choice



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Above the number of cars are the three types of the number of cars, connoting that other random shocks affect the type of number of cars chosen. As it is customary, when drawing decision trees at the top level is one box, demonstrating the household making the decision.

The following terms were used to describe nested logit models.

1. Decision level refers to the level or stage at which a decision is made. There are two levels in this study. In the first level, a type of the number of cars is chosen—'No use of cars' 'Necessity of cars', or 'Want of cars'—and in the second level, a specific number of cars is chosen. For instance, when 0 car is chosen, the household belongs to 1 category of the dependent variable.

2. The bottom level denotes the level at which the final decision is made. In this study, it is when households choose a specific number of car category.
3. The alternative set is the set of all possible alternatives at any given decision level.
4. The bottom alternative set is the set of all possible alternatives at the bottom level. The bottom alternative set is all four of the specific number of cars.
5. The alternative is a specific alternative in an alternative set. In this study, the first level- "No use of cars" is an alternative. In the second or bottom level, "3 category" is an alternative.
6. The chosen alternative refers to the alternative within an alternative set that is observed that someone has chosen.

Premised on the theoretical discussions of the different perspectives of car ownership in chapters 2 and literature review of chapter 3, empirical analysis in chapters 5 and 6 were carried out. In the analysis of the UK car ownership in chapter 5, the choice of the number of cars was modelled as a function of household income, the Household structure, ethnicity, mental belief on the relationship of car to climate use and driving licence, accommodation tenure in term of whether household members are tenants or owners of the property and location (in terms of city or village). Household income, the Household structure, ethnicity, mental belief on the relationship of car to climate use and driving licence, are attributes of the Households' members, while accommodation tenure in term of whether household members are tenants or owners of the property and location (in terms of city or village) could vary from households to households. For instance, every household belongs to a location.

Similarly, in the analysis of the US car ownership in chapter 6, the choice of the number of cars was modelled as a function of household income, number of income earners in households, the Household structure, ethnicity, mental belief on the relationship of car to climate use and driving licence and accommodation tenure in term of whether household members are tenants or owners of the property. Household income, the Household structure, ethnicity,

mental belief on the relationship of car to climate use and driving licence, are attributes of the Households' members, while accommodation tenure in term of whether household members are tenants or owners of the property could vary from households to households. For instance, every household belongs to a location.

In this study, a conditional logit model was fit to the study data. Because household income, Household structure, mental belief on the relationship of car to climate use and driving licence are constant within each are attributes of the household. In this study, two-level nested logit model was designed and used as shown in figure 4.4.-2. It is now described and specified below.
As NL models relax the independence assumption and ensure that the groupings for which unobserved shocks may have concomitant effects. In both the UK and US cases, it is assumed that number of cars should be grouped by 'No use of cars', 'necessity of cars' and 'Want of cars' categories.

Suffice to state in this chapter that two different datasets[6]; one from each country (UK and US) were used. In the UK data, 2942 households were involved with eight variables mapped out from the dataset; one dependent variable (number of cars associated to each household) and seven independent variables. Similarly, in the case of the US, 6342 households were involved with seven variables mapped out from the dataset; one dependent variable (number of cars associated to each household) and six independent variables. Further descriptions of the two data bases were made in chapters 5 &6.

4.5 CONCLUSION

This study takes its motivation from the critical analysis of the evolving development in car ownership research, particularly, the modelling approaches adopted by scholars. This chapter has discussed various car ownership models, starting from the aggregate models; highlighting its characteristics. Given that these forms of models are noted with some drawbacks, disaggregate soon became popular as scholars came up with

[6] Full description of the data was provided in chapter 5.

different versions of disaggregate models depending on the purpose and objectives of their studies. Furthermore, this chapter set out assumptions on which the empirical analysis were based. It also described the justification for MNL models considered suitable for the investigations carried out in subsequent chapters; proposing a version capable of investigating car ownership.

CHAPTER 5

THE DATA, MODEL ESTIMATIONS, RESULTS AND ANALYSIS OF UK NUMBER OF CAR HELD

5.0 INTRODUCTION

Premised on the background and objective of this study as specified in the introductory chapter, analysis and review of theories and the literature carried out in the chapters 1-3 and the model structure specified in the chapter 4, this chapter deals with the design and explanations of the data used for the study. The chapter also deals with the estimation, presentation and explanations of the results. Based on the baseline disaggregate multinomial choice model (MNL) of the number of cars, the impacts of different discipline based factors on the number of cars UK households own were estimated using two modelling approaches: MNL and NL models. These factors are: ethnicity, household location (in terms of regions), mental belief on the relationship of car to climate use, accommodation tenure, Household structure, driving licence, and household income.

Among others, the estimation methods adopted provided the opportunity to test if the proposed model offered more insights into the car ownership research compared to the existing approaches in the literature. Subsequent to derivation of results using the modelling approaches, findings were discussed. The remaining sections of the chapter are structured as follows. Section 5.1 deals with the design of the survey and data adopted for the study, while section 5.2, highlights the relevant data areas used in this study. The section also deals with explanations of dependent and independent variables, highlighting the justification of their inclusion in the model. Section 5.3 discusses the estimation results. Section 5.4 focuses on the explanation of results and analyses of different households and their possible association to different car ownership categories. The last section, section 5.5 dwells on the conclusions and limitations.

5.1 DESIGN OF THE DATA

This study made use of the British Social Attitude Survey (2016) for the UK analysis. The British Social Attitude Survey (2016) was based on UK

households and it normally reports socio-economic phenomena. These databases are considered suitable since it is relevant to the research objectives and questions focused on in this study. The British Social Attitude Survey is regularly undertaken by the Office for National Statistics and entails in-depth interviews with a sample of households all over the Great Britain. Its data is regularly updated yearly. The UK data for the present study comes from the 2016 edition of the British Social Attitude Survey, which contains responses of 2942 household samples used for the survey.

In common with majority of other Office for National Statistics (ONS) surveys, the Royal Mail Postcode Address File (PAF) of 'small users' is used as the frame from which the Opinions sample is derived. The PAF sampling frame included approximately 26 million addresses in Great Britain, without those that receive huge quantities of mail per day. Updated every three months, it can be said that the database is up-to-date and complete address database. One individual per household is chosen to respond to module questions. At the beginning of the interview, the interviewer determines the household composition and then he/she chooses the respondent from within all the over-16s. All interviews were carried out face-to-face (except for telephone reissues) by ONS interviewers who have been trained to carry out National Statistics surveys. There were no interviews by proxy. Advance letters were sent to all addresses, earlier to the interview, providing brief details of the survey. Interviewers visited all the chosen addresses, unless a refusal has been made beforehand in response to the advanced letter sent. The interviewer made up to eight calls at an address at different times of the day and the week prior coding the household as a non-contact.

5.2 DATA: DEPENDENT AND INDEPENDENT VARIABLES

It is the aim of this section to explain the variables mapped out from the survey and to describe suitable manner through which they have been combined to develop car ownership models. The dependent and independent variables used in this study are now discussed.

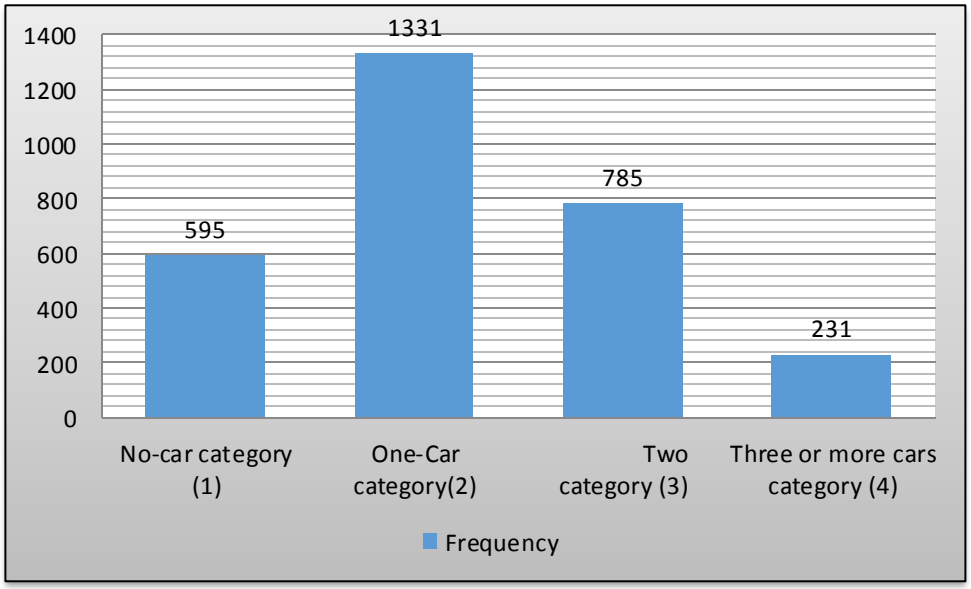
5.2.1 Dependent and Independent Variables

In the present study, the dependent variable of the number of cars choice model represents the number of car associated to each UK household captured in the sample. Each household in the UK owning car is examined, and is defined by 4 discrete values (1, 2, 3 and 4) representing car categories, namely, households with no car, households with one car, households with two cars and households with three or more cars respectively. This classification was adopted in order to operationalise the proposed model. Thus, in this study, a set of 4 categories was used to define the dependent variable for the car ownership choice model. Table 5.2.1-1 and figure 5.2.1.1 present the distribution of the number of cars categories within the household population.

Table 5.2.1-1: Number of Car Categories of the Households

Car Categories	Frequency	Percentage (%)	Cumulative %
No-car category (1)	595	20.22	20.22
One-Car category(2)	1331	45.24	65.46
Two category (3)	785	26.68	92.14
Three or more cars category (4)	231	7.85	100

Figure 5.2.1-1: Number of car ownership



As with any other economic good, we can specify the demand for number of cars as a function of their price and quality, the price and quality of competing

goods and income. Bearing this in mind and in line with the objective of this study, which is to combine economic and non-economic variables in a model, a systematic examination of the data were carried out and the following set of explanatory variables identified: ethnicity, household location (in terms of regions), mental belief on the relationship of car to climate use, accommodation tenure, Household structure, driving licence, and household income. Each of these variables is discussed one after the other in section 5.2.2 below, however, it is essential to note that the variables included within the analysis are simply those contained within the datasets referred to above. Though, some of these variables are similar to those commonly used within car ownership research, while others are not (See Anowar et al., 2014). It should be acknowledged that the household car ownership decision is clearly influenced by uncountable factors and arguably more detailed information could be accessed through a bespoke data collection exercise.

In total eight (8) major explanatory variables were combined in the final all-inclusive number of cars ownership model that were grouped into four relevant categories (code in parenthesis): (1) Demographical factors (DF), (2) Sociological factors (SF), (3) Psychological factors (PF), (4) Economic factors (EF). The table 5.2.1-2 below gives explanations of the variables, along with their operationalization.

Table 5.2.1-2: Variable Explanations

S/N	**Variable categories**	**Variable name**	**Variable description**
1	**Dependent variable**	Car ownership	Number of household cars available
	Independent variable		
2	Demographical factor	Household structure	This is the number of household members
3	Demographical factor	driving licence	1, if household respondent or any other adult has driving licence; 0, otherwise
4	Demographical factor	mental belief	Mental disbelief that car ownership impacts on climate change. 1= Total disbelief that climate change is taking place ,2= Minimum belief that climate change is taking place but not as a result of human actions such as car use,3= Absolute belief that climate change is taking place and it is a result of human actions such as car use
5	Sociological factor	accommodation tenure	This shows whether or not accommodation is owned, rented or under mortgage.1= outright ownership, 2= Mortgaged accommodation, 3= Shared ownership accommodation (e.g. part rent, part buy), 4 = Others.
6	Sociological factor	Ethnicity	Racial ethnic groups households belong.1= White origin,2=Caribbean origin,3= Indian origin,4=Pakistani origin,5=Chinese origin,6=Other Asian origin, 7= African origin,8=Mixed origins.
7	Sociological factor	Settlement nature	The place where the household lives in terms of whether it is rural or urban settlements.1= a big cit, 2= a small city or town, 3= a county or village,4= Others.

8	Sociological factor	Geographical Region	The region of the country in terms of geographical location the household. 1 =North East, 2= North West, 3 = Yorkshire and The Humber, 4=East Midlands, 5= West Midlands, 6=East of England,7 = H London, 8= South East,9=South West,= 10=Wales,11 =Scotland.
9	Economics factor	household income	The total income of your household from all sources before tax. 1 = Less than £590 pcm, 2=£591 -770 pcm, 3= £771 - 910 pcm, 4= £911 - 1,000 pcm, 5= £1,001 - 1,200 pcm, 6= £1,201 - 1,300 pcm,7= £1,301 - 1,500 pcm, 8=£1,501 - 1,700 pcm, 9= £1,701 - 1,900 pcm, 10= £1,901 - 2,200 pcm,11= £2,201 - 2,400 pcm,12= £2,401 - 2,700 pcm, 13= £2,701 - 3,000 pcm, 14= £3,001 - 3,300 pcm,15= £3,301 - 3,700 pcm,16= £3,701 - 4,200 pcm,17= £4,201 - 4,800 pcm, 18= £4,801 - 5,600 pcm,19= £5,601 - 7,200 pcm,20=£7,201 or more pcm

5.2.2 Independent variables explained

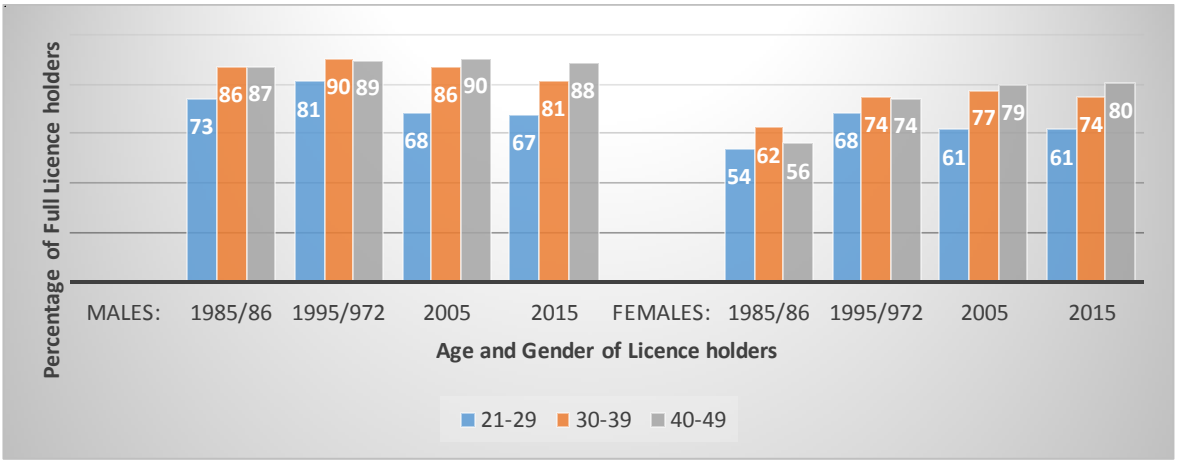
In this section, each of the independent variables used in the analysis is explained and its inclusion in the model also justified. A few of these variables have featured in the literature as established in the chapter 3. However, the study has carefully mapped out all of these variables from the British Social Attitude Survey (2016) in line with the gap, which it aimed at filling.

5.2.2.1 Driving licence

Generally, driving licence remains a compulsory requirement for driving in all countries and as such has correlation for number of cars a household holds. Inclusion of this variable is justified as rightly observed by Fox et al. (2017) that recent behavioural developments in car ownership, especially the decrease in young males owning driving licences (and a relative rise in female drivers) are not accounted for in the present model's approaches. Perhaps, the inclusion of this variable in this study could improve the forecasts or it creates opportunity to examine the current relationship of the variable with car ownership.

Obviously, the current trend in licence holding seems complex with decrease observed for young population of adults (especially, men), and growths recorded for older adult population (especially, women) (See figure 5.2.1-2 below for outlook of the trend). For instance, Williams and Jin (2013), in their analysis, observed from the 1981–2011 Census data that by 2011 the age bracket of 25–44years were more strongly concentrated in high-density locations. In view of the changing trend regarding UK licence holding, it is important to investigate if the variable is still relevant, particularly, in the integrated model proposed in this study.

Figure 5.2.1-2 : Percentage of UK Full license holders1985-2015 by age &Gender



Source: Transport statistics (2017)

5.2.2.2 Household structure

Generally, the number and ages of members of household units are important in determining the fleet of households' cars. The higher the number of members in a household, the more the propensity to engage in travelling and the more the number of cars needed for the travelling (Adjemian, et al; 2010; Fox et al., 2017). As only adults are allowed to drive and children being not allowed to drive, just as retired members currently have a lower likelihood to hold a driving license (Transport Statistics Great Britain, 2013), the more adults available in a household, the higher the probability of holding higher fleet of cars. Thus, it is reasonable to expect correlation between number of members of households and the number of cars held by households. However, to think of this alone might be wrong as the purchasing power is important in determining the number of cars a household can hold.

5.2.2.3 Ethnicity

There is a body of literature on residential location and travel demand (Newman and Kenworthy, 1989,1998; Waitt et. Al, 2016; Chatterton et al, 2016); nevertheless, little is documented regarding the relationships between the number car ownership and ethnic groups. For example, minority households tend to be concentrated in higher density areas of developed countries, inner city neighbourhood, which are characteristically well served by transit. The question is, then, how much does ethnicity define the number of car owned by households. Since there has not been any documented evidence, which

investigated this relationship, its inclusion within a model of car ownership is desirable for two reasons. From theoretical point of view, there is a relationship between culture and psychological perspectives and psychological reactions dictate outward actions, which include demand. It is posited that jobs are easily accessible by original citizens of a country compared to the immigrants or people who later settled in the country (Raphael and Stoll, 2003). If this postulation is still true, then citizens have higher purchasing power and higher ability to own cars compared to the immigrants or people who later settled in the country. For instance, empirical evidence from the US indicates that, relative to white workers, African American workers: (i) are less likely to own a car, (ii) experience higher unemployment rates and longer unemployment spells, (iii) earn lower wages, (iv) spend more time commuting to work, (v) travel less miles to go to their jobs, and (vi) search for jobs in a smaller area (Raphael and Stoll, 2003; Hu, 2015).

5.2.2.4 Accommodation tenure

As this variable has not been investigated before, there is scanty literature on its relationship with car ownership. Other related variable that has been investigated with car ownership is parking space and car ownership (De Groote et. al, 2016; Coelho et al, 2017). The possibility of having parking space provision or the size of the space could be a key factor on the fleet of cars a household might decide to hold. The conclusion was that the possibility of testing a term in the enhanced model specification should be considered, but this was caveated by the view that assembling Suffice to say that its inclusion is aimed at offering new area that could be investigated in car research.

Based on Microeconomic theory, purchasing power determines should dictate the number of car held by a household, suggesting that more money should create higher purchasing power. However, scale of preference could determine what household members decide to spend their money on. A family living in rented apartment could rank owning more cars as a top priority on its scale of preference as against securing mortgage or owning personal property. Whereas, another family that lives in a personal property might still rank owning more personal properties top on its scale of preference than increasing its fleet of cars. So, differences in choice and preference could be very important in

decisions relating to accommodation tenure and car ownership. The inclusion of this variable is to investigate popular preference of households in these relationships.

5.2.2.5 Mental Belief that Car Ownership impact on Climate Change

Generally, global process of urbanization within the last two centuries meant that 50% of the world population is already living in urban areas. Although growth rates vary all over regions, the United Nations noted that on average 74% of the population of developed countries and 43% of the population of less developed countries reside in urban areas (DESAPD, 2012). Transport system is a major aspect of urban life considering its impact on economic growth, social interaction and urban structure (Small, 2009) as well as climate change (Rockstro¨m et al., 2009;Barnosky et al., 2012; Pauliuk and Müller, 2014). Though, transport-related policies and projects are not, strictly speaking, health interventions, they do have potential impact on individual and collective health (McCarthy, 2005; Ogilvie et. al, 2006). Thus, urban transport policies and projects in relation to issues like car ownership need to be monitored and investigated to identify their social, economic and environmental costs towards defining strategies to improve the public health benefits of such interventions (Soria et al., 2017).

Other reason why this variable has been included in this model is because transportation is linked to environmental problems, economic losses and social inequalities and thus, transportation is viewed as a social and physical determinant of health. It is noted that motor vehicles are one of the main sources of environmental pollution, contributing 26% of carbon dioxide (CO2) emissions, as such, a major cause of global warming (Hansen and Sato, 2016), which in turn is responsible for changes in worldwide distribution patterns of infectious diseases such as, dengue fever and malaria (Khasnis, Nettleman,2005). Furthermore, the increased in number of vehicles and their associated increase in fuel consumption have been identified as source of danger to air, water and soil quality. Poor air quality is associated with respiratory disease (Bowatte et al., 2017), cardiovascular morbidity, mortality, premature deaths (Halonen et al., 2015). As this study aimed at gaining insights on the relationship between various independent variables and car ownership, inclusion of this a proxy to measure Psychological health condition of households in the model is

considered relevant. This is so as findings will provide basis for relevant policy makers.

5.2.2.6 Household Income

Generally, price of a product plays key role in its demand and as noted before, purchasing power of any economic agent determines his/her ability to pay price of the product. Thus, inclusion of household income in most car demand models is understandable. It is generally established that the bigger a household income (all things being equal), the higher the purchasing power, which in turn informs the number of cars the household can own (Oakil et al, 2014; Oakil et al, 2016). Households with higher numbers of working adults are more likely to have higher incomes compared to households with lower number of working adults. Since earning incomes, on many occasions involves having to travel outside homes, households with higher number of adults have greater overall need to travel, though, with likely higher living expenses. Therefore, income level of any households is significant to their overall purchasing power, which directly determines abilities to own small or large fleet of cars.

The inclusion of this variable in the model is premised on two reasons. First, car ownership is usually, seen as a yardstick of economic well-being and earnings are used as proxies for individuals' economic well-being (Norman, 2010). In other words, the ability of households to purchase and own a car is dependent on wealth and income; the greater the opportunities and needs for travel linked with a growing economy; and the fact that cars are seen as status symbol in society (Macintyre et al., 1998 and Gautier and Zenou, 2010). While scholars have examined the relationship between car ownership and income, none has integrated the variable in an all-embracing model as it is proposed in this study[7]. For instance, Storchmann (2005) studied the degree of correlation between car ownership and income per capital using the statistical data from different countries, while Dargay (2001, 2002) compared and examined the influence of asymmetry stemming from the change of car ownership with income and the difference in rural and urban areas with respect to car ownership.

[7] This study introduced household incomes in a model that has variables from diverse disciplines.

5.2.2.7 Settlement nature

The relationship of this variable and car ownership has been investigated by scholars (Goulias et al, 2012; Paleti et al., 2013; Lee, 2016), but conclusions have always been divergent; justifying its inclusion in this analysis. However, some scholars were able to establish the relationship between urbanisation level (which is related to location) and car ownership (Nolan, 2010; Oakil et al., 2014; Van Acker et al, 2014). In this study, the interest is to confirm or otherwise if there is a relationship between household location and car ownership. The inclusion of this study is premised on the emerging declining growth in car ownership as shown in figures 1.1 and 1.2 of the introductory chapter. People have argued that the nature of settlement of households could be one of the reasons responsible for the declining increase in the car ownership.

5.2.2.8 Geographical Region

Generally, literature has identified that there is a relationship between car ownership in households and geographical locations (Guerra, 2014,2015; Keller and Vance, 2013; Chatterton et al, 2016). The basis for including this variable is to verify whether the assertion is valid in the UK using current data and also to examine the nature of the relationship. It is expected that regions with developed public transport systems, households might not hold large fleet of cars and vice versa. Furthermore, it is opined that since each region has variation in terms of people, social classes, economic activities etc., there is a possibility that all these differences will translate into a certain outlook in terms of the relationship between the number of cars and geographical regions.

5.3 RESULTS

The results of the models were explained and compared in this section. In addition, how the independent variables were checked for significance was explained.

To specify the model using the data that are individual specific as in this study, approach of Greene, 2012, pp. 801-810 was adopted. For each sample, the data for each individual in the sample consist of the following:

1. **Number of car ownership:** 1 = No car, 2 = One car, 3 =Two cars, 4 = Three or more cars.

2. **Characteristics:** constant, driving licence, household structure, ethnicity, accommodation tenure, mental belief that car ownership impacts on climate change, household income, settlement nature and geographical regions.

5.3.1 Presentation of Results

In this section, the results of the multinomial logistic regression analyses are shown and explained. In addition, the NL regression results were shown and compared as well. The data were collected from 2942 households in the UK and are scored on various tests and indicators. The outcome measure in this analysis is the preferred categories of cars i.e. no-car category, one category, two category or three or more category- from which the results depict what form of relationships exists between UK household number of cars and ethnicity, household location (in terms of regions), mental belief on the relationship of car to climate use, accommodation tenure, Household structure, driving licence, and household income. In this study dependent variable, UK number of household ownership was treated as categorical variable under the assumption that the number of cars does not have natural ordering. Table 5.3.1-1 gives the data summary.

Table 5.3.1-1: Data summary

Variable	Obs	Mean	Std.Dev	Min	Max
Number of Cars	2942	2.221618	0.856899	1	4
Household structure	2942	2.310333	1.265726	1	11
Driving Licence	2942	0.709042	0.454282	0	1
Household Income	2942	4.167913	1.620072	1	6
Settlement Nature	2942	1.896669	0.744146	1	4
Accommodation Tenure:	2942	1.735894	0.975698	1	4
Mental belief	2917	2.789167	0.518961	1	3
Geographical regions	2942	6.060503	3.04166	1	11
Ethnic origins	2942	1.386472	1.411998	1	8

The results of the integrated model for each explanatory variable are analyzed (discussion by row of Table 5.3.1-2), focusing on its sign and magnitude for alternative vehicle ownership. Note: 1-car category is the referent category.

Table 5.3.1-2: **Regression results for MNL- four alternatives**

	0 Car	**2 cars**	**3+ cars**
Dependent variable: number of cars			
Driving Licence	-5.318	1.131	2.263
Household Size	-0.682	0.536	0.892
Accommodation Tenure:			
Mortgaged Properties	0.090	0.713	-14.603
Shared Property	1.184	-0.969	-1.181
Others	0.030	-0.687	-0.249
Settlement nature:			
small city	0.082	0.005	0.008
Village	-0.266	0.399	1.115
Others	-1.079	0.265	-14.532
Geographical regions:			
North West	-0.173	0.319	-0.071
Yorkshire and The Humber	-0.287	0.064	-0.223
East Midlands	-0.223	0.417	0.210
West Midlands	-0.661	0.618	0.416
East of England	-0.579	0.196	0.132
London	0.398	-0.495	-0.789
South East	-0.575	0.661	0.712
South West	-0.433	0.284	-0.316
Wales	-0.388	0.390	0.588
Scotland	-0.599	0.052	0.452
Mental Perception:			
Minimum belief	-0.358	0.005	1.388
Absolute belief	-0.336	0.270	1.038
Household Income	-0.205	0.282	0.470
Ethnic origins:			
Caribbean origin	0.360	-1.658	-14.400
Indian origin	0.818	-0.721	-15.417
Pakistani origin	-1.426	-0.582	-2.156
Chinese origin	-0.804	-1.315	-15.050
Other Asian origin	0.066	-0.667	-1.475
African origin	0.232	-1.001	-1.920
Mixed origins	-0.017	-0.024	-0.654
Obs.	2917.000		
Log-Likelihood	2917		
Pseudo-R^2	0.3645		
LR	2625.62		
_cons	3.157	-5.392	-11.409

The second category (households with one car) was automatically adopted as the referent category. Normally, Stata adopts category with the highest frequency as the referent category and this study did not alter this arrangement since it fits into the focus of this investigation. The study aimed at examining distribution of cars across different households in terms of how more or how less in relation to the selected disciplined based determinants. Therefore, one-car category adopted by Stata as referent category does fits into an analytical boundary of households who choose to own car(s) and those, who choose not to own any at all.

Furthermore, the MNL regression results was also used to obtain marginal effects (MEs). Marginal effects depict the level with which individual explanatory variable is sensitive to the predicted probabilities of mean choices. This is displayed under table 5.3.1-3 below. Marginal effects ensure that elasticity for each variable is derived.

Table 5.3.1-3: **Marginal effects**

dy/dx[a]	**NoCarHH**	**OneCarHH**	**TwoCarHH**	**ThreeormoreCarHH**
Driving licence	-0.284(0.007)**	0.038(0.022)*	0.141(0.025)**	0.105(0.025)**
Household structure	-0.040(0.003)**	-0.058(0.006)**	0.060(0.006)**	0.037(0.003)**
Accommodation Tenure: Mortgaged Properties	-0.003(0.045)	-0.085(0.108)	0.177(0.103)*	-0.089(0.006)**
Shared Property	0.073(0.009)**	0.091(0.019)**	-0.125(0.017)**	-0.039(0.010)**
Others	0.007(0.044)	0.089(0.092)	-0.102(0.079)	0.007(0.050)
Settlement nature: small city	0.004(0.019)	-0.004(0.021)	0.000(0.019)	0.000(0.011)
Village	-0.018(0.015)	-0.069(0.026)**	0.023(0.023)	0.064(0.015)**
Others	-0.060(0.044)	0.038(0.086)	0.085(0.076)	-0.064(0.009)**
Geographical regions: North West	-0.011(0.019)	-0.029(0.042)	0.053(0.039)	-0.014(0.025)
Yorkshire and The Humber	-0.015(0.022)	0.011(0.045)	0.018(0.041)	-0.014(0.025)
East Midlands	-0.015(0.023)	-0.045(0.047)	0.061(0.043)	-0.001(0.027)
West Midlands	-0.039(0.022)*	-'0.057(0.046)	0.091(0.043)**	0.005(0.028)
East of England	-0.032(0.022)	-0.000(0.044)	0.030(0.039)	0.002(0.025)
London	0.023(0.021)	0.057(0.046)	-0.051(0.041)	-0.029(0.027)
South East	-0.035(0.021)*	-0.074(0.042)*	0.085(0.038)**	0.025(0.025)
South West	-0.024(0.022)	-0.008(0.043)	0.056(0.039)	-0.025(0.024)
Wales	-0.023(0.024)	-0.046(0.049)	0.042(0.045)	0.027(0.029)

Scotland	-0.032(0.021)	0.006(0.045)	-0.004(0.041)	0.030(0.027)
Ethnicity: Caribbean origin	0.027(0.035)	0.216(0.097)**	-0.159(0.091)*	-0.084(0.005)**
Indian origin	0.047(0.028)*	0.097(0.060)	-0.060(0.055)	-0.084(0.005)**
Pakistani origin	-0.074(0.055)	0.181(0.095)*	-0.040(0.079)	-0.067(0.018)**
Chinese origin	-0.037(0.048)	0.245(0.097)**	-0.124(0.085)	-0.084(0.005)**
Other Asian origin	0.008(0.040)	0.108(0.088)	-0.065(0.078)	-0.051(0.032)
African origin	0.018(0.033)	0.143(0.068)**	-0.103(0.060)*	-0.059(0.025)**
Mixed origins	-0.000(0.024)	0.019(0.055)	0.016(0.053)	-0.034(0.033)
Mental Belief: Minimum belief	-0.019(0.019)	0.0206(0.046)	-0.036(0.045)	0.076(0.028)**
Absolute belief	-0.019(0.017)	0.040(0.040)	0.018(0.040)	0.041(0.021)**
Household income	-0.013(0.002)**	0.037(0.006)**	0.030(0.006)**	0.020(0.004)**
Obs.	2917			

[a] The estimated coefficient defines the effect of independent variable variation on each predicted probability. Values within brackets are error type for the individual estimated parameter. Coefficients having a* or ** refer to a 10% or a 5% parameter significance respectively.

Furthermore, as noted before, MEs reflect to what degree each independent variable is sensitive to the predicted probabilities of mean choices. For instance, marginal effect computations allow us to find the effect of an income increase on the aggregate share of each car ownership segment. Table 5.3.1-3 displays the predicted probabilities for each car ownership segment. These probabilities are derived for a fictive household individual, who has mean characteristics for each independent variable (mean household income, mean household structure, etc.). Within the setting of the table 5.3.1-3, the fictive household is viewed to have a 6 percent chance of choosing one-car option if household structure increases by 1 percent (i.e. if members of a household increase by 1percent). However, the imaginary household is viewed to have a 4 percent likelihood of selecting three or more- car option if members of a household increase by 1percent, and so forth.

To show the robustness of the MNL model, NL model was used on same dataset following the NL model specification described in section 4.4.1, and the result is displayed in table 5.3.1-4 below:

Table 5.3.1-4: Nested logit model for Number of cars

RUM-consistent nested logit regression				Number	of obs	11744
Case variable:family_id				Number	of cases	2936

Alternative variable: numberofcars				Alts per	case: min=	4
					avg =	4
					max =	4
				Wald	chi2(26)	=899.92
Log likelihood =	-2615.42			Prob	>chi2	=0.000
Dependent variable (Chosen)	**Coef.**	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf.**	**Interval]**
numberofcars						
Accommodation tenure	0.305	0.028	10.770	0.000	0.250	0.361
Location	-0.185	0.032	-5.780	0.000	-0.248	-0.122
type equations						
Nouseofcars						
Household income	-0.007	0.002	-3.620	0.000	-0.011	-0.003
Household structure	-0.595	0.070	-8.490	0.000	-0.732	-0.458
Driving licence	-5.336	0.257	-20.730	0.000	-5.840	-4.831
Mental belief	-0.018	0.091	-0.190	0.847	-0.197	0.162
Ethnicity-Africans	3.360	0.686	4.900	0.000	2.015	4.705
Ethnicity-Caribbean	3.377	0.741	4.560	0.000	1.925	4.830
Ethnicity-Indians	-0.022	0.821	-0.030	0.979	-1.632	1.588
Ethnicity-Pakistans	-1.710	1.071	-1.600	0.111	-3.809	0.390
Ethnicity-Chinese	0.304	1.247	0.240	0.807	-2.139	2.748
Ethnicity-OtherAsian~n	1.196	1.045	1.140	0.252	-0.852	3.244
Ethnicity-White	-0.556	0.656	-0.850	0.397	-1.841	0.730
Ethnicity-Mixedorigin	0.228	0.474	0.480	0.631	-0.701	1.156
Necessityofcars|						
Household income	(base)					
Household structure	(base)					
Driving licence	(base)					
Mental belief	(base)					
Ethnicity-Africans	(base)					
Ethnicity-Caribbean	(base)					
Ethnicity-Indians	(base)					
Ethnicity-Pakistans	(base)					
Ethnicity-Chinese	(base)					
Ethnicity-OtherAsian~n	(base)					
Ethnicity-White	(base)					
Ethnicity-Mixedorigin	(base)					
Wantofcars						
Household income	0.002	0.001	1.380	0.168	-0.001	0.004

Household structure	0.640	0.042	15.200	0.000	0.557	0.722
Driving licence	1.132	0.171	6.620	0.000	0.797	1.468
Mental belief	0.048	0.073	0.670	0.505	-0.094	0.191
Ethnicity-Africans	-305.238	384.709	-0.790	0.428	-1059.255	448.778
Ethnicity-Caribbean	-306.210	384.710	-0.800	0.426	-1060.228	447.807
Ethnicity-Indians	1.090	1.139	0.960	0.339	-1.143	3.322
Ethnicity-Pakistans	-0.268	0.637	-0.420	0.674	-1.517	0.981
Ethnicity-Chinese	-0.443	0.939	-0.470	0.637	-2.284	1.397
Ethnicity-OtherAsian~n	0.925	0.978	0.950	0.344	-0.993	2.843
Ethnicity-White	0.854	0.564	1.510	0.130	-0.252	1.960
Ethnicity-Mixedorigin	0.204	0.345	0.590	0.554	-0.473	0.881
dissimilarity parameters						
Type						
/Nouseofca~u	1	.			.	.
/Necessity~u	1	90694.77			177757.50	177759.50
/Wantofcar~u	434.039	555.019			-653.779	1521.857
LR test for IIA	(tau=1):		chi2(2)= 144.23		Prob>chi2=0	

5.3.2 Estimation method and explanations of results

The models specified in chapter 4; section 4.4 of this thesis relate to the utility of the number of cars by UK households, which in turn relate to demographical characteristics of the UK households, Psychological characteristics of the UK households, Sociological characteristics of the UK households and economic characteristic of the UK households. Stata results of the MNL models are shown under table 5.3.1-1, table 5.3.1-2 and table 5.3.1-3 above (See full Stata results under Appendix 2).

5.3.3 Models compared

As all models were nested under the integrated specification Equation (4.10), they were compared with each other with the use of the respective log-likelihood values. Table 5.3.3-1 depicts log-likelihood values and McFadden pseudo R-squared values for the successively integrated number of car model. As shown, the course of log-likelihood function increases as additional regressors were successively introduced. It is also obvious that there is a significant improvement in model fit (i.e. goodness of fit)[8], as the respective McFadden pseudo R-

[8] The measures of goodness of fit (e.g. McFadden pseudo R-squared) summarize the discrepancy between observed values and the values expected under the model in question. A thumb rule is that the adjustment of the model is excellent if $0.2 \leq McfaddenR^2 \leq 0.4$ (Joost and Kalbermatten, 2010).

squared value increases from the reduced models to the integrated specification. Therefore, one may conclude that the integrated model (Eq. 4.10) is the best specification. Therefore, one can easily answer with 'YES' to the research question 3, which seeks to know if the proposed 'number of cars ownership' estimating model reflect more insights into the households' car ownership; especially, in the light of its holistic approach. The question 3 is hereby resolved.

Table 5.3.3-1: Model calculations

Explanatory variables	**Model 1**	**Model 2**	**Model 3**	**Full Model**
Demographical characteristics : driving licence, household structure (Eq. (4.7))	√	√	√	√
Sociological characteristics: Accommodation Tenure, Regions, Settlement nature Ethnicity (Eq. (4.8))		√	√	√
Psychological characteristics: Mental belief (Eq. (4.9))			√	√
Economic variables: Household income (Eq. (4.10))				√
Log-Likelihood	-2571.96	-2361.03	-2342.57	-2289.24
Pseudo-R^2	0.2918	0.3499	0.3497	0.3645
LR	2119.17	2541.03	2518.95	2625.62

The McFadden pseudo R-square of the integrated model has a value of 0.3645, which is very satisfactory, taking into consideration the respective McFadden values of previous studies in the literature. For example, Kitamura et al. (2000) found a value of 0.249, whilst Baltas and Saridakis (2013) found a value of 0.245. Evidently, the proposed model did an excellent job in explaining number of car behaviour, compared to previous applications in the literature. In Table 5.3.1-2 above, the estimates of the proposed integrated number of car model ((Eq. (4.10) are presented. The results are mixed. Though, not all explanatory variables are statistically significant, the results are not only conceptually interpretable with low standard errors and expected signs, but also produced current realities of the relationship investigated. In the following sections, the results of the integrated model for each explanatory variable are analyzed (discussion by row of Table 5.3.1-2), focusing on its sign and magnitude for alternative vehicle ownership. (See full Stata results under Appendix 3).

5.3.4 Explanatory variables

The proposed choice model in Eq. (4.10) has explanatory power of four disciplines and two disciplines have more than one variable as their representatives in the model, while each of the remaining two has one variable representative. Using the multinomial logit model, comparison is to a base category, for which the alternative normalized to have coefficients equal to zero. In other words, the multinomial logit probabilities Eq. (4.6) in chapter 4 suggests that the conditional probability of observing alternative j given that either alternative j or alternative k is observed is:

$$P[y = j \mid y = jork] = \frac{p_j}{p_j + p_k} = \frac{exp\beta_j x_{ij}}{\exp(\beta_j x_{ij}) + exp(\beta_k x_{ik})} = \frac{exp\,(x_i(\beta_j - \beta_k))}{1 + exp(x_i(\beta_j - \beta_k))} \qquad 5.0$$

which is a binary logit model with coefficient $(\beta_j - \beta_k)$. Assume normalization is on alternative 1, so that $\beta_1 = 0$. In such case, then, Eq. (5.0) becomes

$$P[y = j \mid y = jor1] = \frac{exp\,(x_i\beta_j)}{1 + exp(x_i\beta_j)} \qquad 5.1$$

$and\ \beta_j$ can be interpreted in the same manner as the logit model coefficient for binary choice between alternatives j and 1. Likewise to the binary logit model[9], the probability of choosing alternative j rather than alternative 1 is $\left(\frac{P_r \mid y_1 = j \mid}{P_r \mid y_1 = 1 \mid}\right) = exp(x_i\beta_j)$ that could be simply converted to a linear model adopting the logit association, like this: $log\left(\frac{P_r \mid y_1 = j \mid}{P_r \mid y_1 = 1 \mid}\right) = x_i\beta_j$. Thus, β_j provides the difference in the log of odds whenever x_i alters with one unit. The analyses thus convert i in line with what option is normalized to possess zero coefficient. For this analysis to be actually beneficial, there is need for a natural base category (Cameron and Trivedi, 2005). Therefore, it is understandable, based on the perspective of the model predictive approach. The selection of the base category is random, in the light of interpretation of each category impacts, the selection of the base category could constitute a difference since impacts (i.e., coefficients) are construed for individual option vis-à-vis the selection of base category.

From the estimation results of this analysis, the two-car category of the dependent variable was selected as the reference category by Stata itself, obviously due to its highest frequency compared to other categories. As shown,

[9] See Cameron and Trivedi (2005) for more information on the binary logit model.

most independent variables were statistically significant with small standard errors. Premised on explanatory variables in table 5.2.1-2, the following estimation was made:

$$P_j = \frac{exp(\alpha_j+\beta_{hj}x_{hij}+drvlicn_{dj}+hhstru_{dj}+acctenurty_{sj}+apartstruty_{sj}+region_{sj}+ethnicorigins_{sj}+ccbeliev_{pj}+incomehh_{ej})}{\sum_{k=0}^{J}\exp(\alpha_k+\beta_{hk}x_{hik}+drvlicn_{dk}+hhstru_{dk}+acctenurty_{sk}+apartstruty_{sk}+region_{sk}+ethnicorigins_{sk}+ccbeliev_{pk}+incomehh_{ek})},$$

$$j = 1, \ldots\ldots J \qquad 5.2$$

Where:$\alpha_j + \beta_{hj}x_{hij}$,$\alpha_k + \beta_{hk}x_{hik}$, j, 1, and J remain as defined before, while $drvlicn_{dj}$,$hhstru_{dj}$,$acctenurty_{sj}$,$apartstruty_{sj}$,$region_{sj}$,$ethnicorigins_{sj}$,$ccbeliev_{pj}$, $incomehh_{ej}$ refer to driving licence, Household structure, accommodation tenure, settlement location, geographical regions, ethnicity, mental belief, household income respectively. See table 5.2.1-2 above for explanations of variables used in this estimation.

5.4 RESULTS AND FINDINGS

From the results summary presented in table 5.3.1-2, a significance of 0.000 which implies that the independent variables have a significant influence on the number of cars owned. The significance <0.05 implies that the model is a good fitting for the variables selected and therefore validates the model. Each category of disciplined based factors exhibits significant relationship with car ownership in UK households. Therefore, first research question is resolved in the estimates shown for the UK in table 5.3.1-2.

a list of results of significant variables is now presented in table 5.4.2-1 below. In this section, analyses of the results are presented. The analyses are based on the MNL model specified in E.q. (5.2). As presented in table 5.3.1-2, appreciable parts of the explanatory variables were statistically significant and theoretically interpretable, with low standard errors and expected signs. A few of the constants were found to be insignificant. However, they were included in the model to correct for sampling bias (Kassie et al., 2015). It is observed that the nested model results shown in table 5.3.1-4 above exhibit similar results observed using the MNL model when compared in terms of the variables found significant and those found insignificant. Furthermore, as shown in the full results displayed under appendix 2, implicit IIA assumption is valid.

5.4.1 Testing the IIA assumption

MNL modelling specifications are valid within the IIA assumption. Should this assumption be violated, then MNL model is not the suitable model structure, meaning an alternative model specification should be used. Premised on this background, the study tested whether the Independence from IIA assumption of the MNL model holds for the study modelling specification; using the Hausman–McFadden test (Hausman and McFadden, 1984; Greene, 2012). The Hausman and McFadden (1984) test connotes a variation of the Hausman (1978) test and dwells on the understanding that: (i) Within IIA, the parameters of the choice within a subset of different alternatives could be estimated with a MNL model on this subset or on the full set, however, the previous is less efficient in comparison to the latter, and (b) should IIA be not be valid, the parameter estimates of the full set are inconsistent, while those of the subset are consistent given that the subset is correctly selected (Hausman and McFadden, 1984). The following specifies Hausman–McFadden test:

$$Hausman - McFadden\ test = [\beta(r) - \beta(f)]'\,[\mathrm{V(r)\text{-}V(f)}]\ \text{-}1[\beta(r) - \beta(f)] \qquad 5.3$$

Where β represents an estimated coefficient vector, V refers to the estimated variance–covariance matrix of β, r means a restricted model, and $f\ refers\ to$ a full model. There is statistic of the chi-squared distribution, having degrees of freedom equal to the number of linearly independent restrictions required to gain the restricted model from the full one. The restrictions refer to estimating the model on only a subset of the alternatives. If IIA holds, the restricted model should be similar to the full one, and the test statistic should be small.

A huge test statistic calls for rejection of the null hypothesis that IIA holds (Cameron and Trivedi, 2005). The study carried out the test by estimating two multinomial logit models (a logit model on the full set of alternatives as well as a logit model on a random subset of alternatives – and the subsample with choices within this subset). Both the sets of parameter estimates were statistically similar to each other, implying that IIA holds. Essentially, the test could not be concluded because of (near) singularity of the $\mathrm{V}(r) - \mathrm{V(f)}$ matrix that is a usual empirical happening when IIA holds (Small and Hsiao, 1985). Small and Hsiao (1985) point out that if IIA holds, $\mathrm{V}(r)\ and\ \mathrm{V(f)}$ will of necessity

be the same to each other, and therefore their difference will be ‘‘close to zero’’ in a matrix sense, making the V(r) −V(f) matrix impossible to invert as necessary to reach the test statistic. Therefore, the statistical problems experienced in calculating the test are common.

In spite of the similarities within some number of cars modelled, it is not necessarily shocking since all of explanatory variables of the study are alternative-specific. Thus, giving room for a variable to be alternative-specific is suggested as one main solution to IIA violations of a MNL model as this approach limits correlations of the unobserved aspects of utility over a range of alternatives (Greene, 2012). As could be observed in the NL results (shown above and in appendix 2), in which explanatory variables were made to be alternative-specific, using LR test for IIA, correlations of the unobserved portions of the utility across a range of alternatives were limited.

5.4.2 Category-specific constants

The significant positive signs of the category-specific constants for the Two-car category (3) and Three or more-car category(4) imply that the average impact of all unmeasured variables tends to increase the probability of selecting these car categories. Conversely, for no-car category, the average impact of all unmeasured variables tends to reduce the probability of selecting this category (significant and negative category specific constants). In addition, the category-specific constant for no-car category (1), which was found to have produced the highest magnitude (absolute value) in comparison to those for the other number of car categories, implies that the selection probability of no-car category by UK households is least well-explained by the variables contained in the model proposed in this study.

Table 5.4.2-1: **Estimated parameter of Relative Risk Ratio (RRR) for MNL Regression**

Dependent Variables	NoCarHH	OneCarHH	TwoCarHH	ThreeormoreCarHH
Driving licence	0.005(0.001)**	***Ref***	3.098(0.546)**	9.613(4.032)**
Household structure	0.506(0.038)**	***Ref***	1.710(0.077)**	2.440(0.162)**
Accommodation Tenure: Mortgaged Properties	1.095(0.913)	***Ref***	2.039(1.228)	4.550(0.000)
Shared Property	3.267(0.578)**	***Ref***	0.379(0.126)**	0.307(0.070)**
Others	1.030(0.786)	***Ref***	0.503(0.301)	0.779(0.591)
Settlement nature: small city	1.086(0.220)	***Ref***	1.005(0.129)	1.008(0.223)
Village	0.766(0.266)	***Ref***	1.490(0.226)**	3.049(0.719)**
Others	0.340(0.276)	***Ref***	1.304(0.604)	4.880(0.000)
Geographical regions: North West	0.841(0.323)	***Ref***	1.375(0.371)	0.931(0.414)
Yorkshire and The Humber	0.750(0.321)	***Ref***	1.066(0.308)	0.800(0.372)
East Midlands	0.800(0.361)	***Ref***	1.518(0.450)	1.233(0.575)
West Midlands	0.516(0.220)	***Ref***	1.855(0.535)**	1.516(0.703)
East of England	0.560(0.244)	***Ref***	1.216(0.334)	1.141(0.491)
London	1.489(0.634)	***Ref***	0.61010(0.192)	0.454(0.251)
South East	0.563(0.235)	***Ref***	1.937(0.509)**	2.039(0.826)*
South West	0.648(0.272)	***Ref***	1.328(0.361)	0.729(0.324)
Wales	0.678(0.323)	***Ref***	1.476(0.456)	1.801(0.830)
Scotland	0.549(0.227)	***Ref***	1.053(0.306)	1.571(0.682)
Ethnicity: Caribbean origin	1.433(0.980)	***Ref***	0.190(0.203)	5.570(0.001)
Indian origin	2.266(1.272)	***Ref***	0.486(0.209)*	2.020(0.000)
Pakistani origin	0.240(0.240)	***Ref***	0.559(0.319)	0.116(1.133)*
Chinese origin	0.447(0.382)	***Ref***	0.268(0.218)*	2.910(0.000)
Other Asian origin	1.068(0.814)	***Ref***	0.513(0.386)	0.229(0.267)
African origin	1.262(0.806)	***Ref***	0.368(0.191)**	0.147(1.167)*
Mixed origins	0.983(0.463)	***Ref***	0.956(0.327)	0.520(0.403)
Mental Belief: Minimum belief	0.699(0.266)	***Ref***	1.005(0.309)	4.009(2.732)**
Absolute belief	0.715(0.236)	***Ref***	1.309(0.342)	2.823(1.807)*
Household income	0.815(0.038)**	***Ref***	1.326(0.052)**	1.600(0.125)**
Obs.	2917			
Log-Likelihood		-2289.24		
Pseudo-R^2		0.3645		
LR		2625.62		

Notes: Data in brackets present the error type for each estimated Relative Risk Ratio (RRR). Coefficients with a * or ** constitute a 10 or 5 percent parameter significant respectively.

The following sections now provide the explanations and descriptions of significant results for the alternative-specific constants $\propto_j$ and the explanatory variables using MNL approach (discussion by row is based on results in table 5.4.2-1).

5.4.3 Demographical factors

As explained before, the estimated coefficients derived for each category are interpreted vis-a-vis the selected reference category. Results show that most of the demographical variables were found significant for many different car categories, which was natural in view of the fact that the base alternative was the one-car category. Based on table 5.4.2-1, which shows the results of the explanatory variables with significant values, the model results show that the driving licence still has a significant effect on household number of car ownership in all the three categories. That is, after controlling for all other variables investigated, households with driving licences are more likely to choose owning cars than households without driving licences as expected. Furthermore, the relative probability of choosing no car option rather than one car is 99.5% less for households with driving licences than for households without driving licences. Whereas, the relative probabilities of choosing two car option and three or more car option rather than choosing one car alternative are 210% and 810% more respectively for households with driving licences than for households without driving licences.

Considering the enormous costs involved in getting driving licences, it is expected that households' members will acquire licences only once they are prepared to drive cars. So, this result is not strange. Furthermore, the results buttressed the conclusions of scholars that found driving licence as more important factor of car ownership than others (Van Acker and Frank, 2010; Clark et al, 2016; Fox et al., 2017)). In fact, Clark et al (2016) posited that acquisition of a driving licence most strongly increases the possibility of a household acquiring a first car, buttressing that driving licence acquisition entails a strong commitment to immediate car ownership; a position has been strongly supported by this result.

Holding other variables constant, the model results show that Household structure was significant in all the three categories relative to the base category. In other words, all else equal, it is found that the relative probability of choosing no car option rather than one car is 49.4% less for households with large Household structure than for households with small Household structure. In addition, the relative probability of choosing two-car option rather than choosing

one car option is 71% more for households with large Household structure than for households with small Household structure. Similarly, it is found that the relative probability of choosing three or more car option rather than choosing one car alternative is 144% more for households with large Household structure than for households with small Household structure. More specifically, all the two demographical variables were significant and intuitively signed in the model in all the three categories in relation to the base categories. This result confirms that these demographical factors investigated in this study remain relevant in explaining car ownership in the UK society.

Relating the results to previous empirical results (Fang, 2008; Bhat et al., 2009; Adjemian, et al; 2010; Fox et al., 2017), one can easily conclude that Household structure remains a key determinant of households' number of cars associated to different households. Large Household structure is significantly associated to higher probability of owning more cars as having more children of school age in a household and combined with more employees, all things being equal, is significantly associated with more car ownership, especially, when there are different household members working in different locations outside the homes.

Meanwhile, reflecting on the enduring nature of demographical factors, it could be said that demographical factors have produced consistent significant relationship with car ownership with long history dating back to four decades. For instance, investigating car ownership types, Baltas and Saridakis (2013) found other demographical variables to be significant in explaining car ownership. However, the findings from this study provided current insight into the reality of the UK households in terms of the number of cars held by individual households since the study used updated UK data.

Meanwhile, in their analysis of purpose why households acquire different types of cars, Baltas and Saridakis (2013), a number of purposes were identified including: Work-related purposes, entertainment/ social/ recreational-related purposes, and family-related purpose. A household that has more members working outside the home is likely to hold large fleet of cars and vice versa. Similarly, such family with large number of employees is likely to hold more driving licences. Thus, these two demographical factors provided additional

information to our understanding of the number of cars held by household members and may be useful background for decision makers and transportation planners, who develop transportation policies relevant to car ownership, traffic congestion, and energy consumption. For instance, investigating the Household structure in a locality or an area of a county is important for the development of effective traffic congestion policies, while the examination of number of adults with driving licences is important in order to identify the potential drivers and their likelihood of contributing to traffic congestion in the area.

The empirical findings provide evidence to support the notion gathered from the literature review that non-economic factors do determine car ownership in households and their inclusion in the empirical model help to reveal further insight into consumer characteristics. The two demographic factors included in the empirical analysis: driving licence and Household structure have significant effects on the number of cars held by household members in a way that is relevant to various stakeholders in the car industry. For instance, to the government tax agencies that might want to reflect on tax changes on households having over one car in their fleet, analysis provided in this study might offer some benefits.

Similarly, car marketers and manufacturers can also reflect on the price sensitivity of car buyers in their future market pricing. In addition, household members could also react to the results of the analysis by being proactive and defiling expectation of government agencies, perhaps, by reducing the number of cars in their fleet with the expectation that findings of this study are likely to make the government to levy higher tax rate on car owners with higher number of cars in their fleet.

5.4.4 Sociological factors

The model results show that UK geographical locations have a significant impact on household number of car ownership in the two of the three categories in relation to the base category. That is, after controlling for all other variables investigated, household members living in certain locations, specifically, South East and West Midlands are more likely to choose owning cars than households located in North East. In addition, holding other variables constant, the relative

probability of choosing two-car option rather than one-car alternative is 85.5% more for household members living in West Midlands than household members living in North East. Similarly, holding other variables constant, the relative probability of choosing two-car option rather than one-car alternative is 93.7% more for household members living in South East of the UK than household members living in North East. This result shows that there is an association between household locations in regional locations of the UK, particularly, the South East and the West Midlands locations and the number of cars held compared to North East of the country. This buttresses findings from other studies (Zegras, 2010; Keller and Vance, 2013; Guerra, 2014,2015; Chatterton et al, 2016). For instance, Chatterton et al (2016) found out that certain regions of the UK are likely to use more personal cars than others. They noticed that population predominately located within the denser central areas of London as well as other inner denser urban areas across the UK tend to use public transport to get to work, with lower car ownership. Thus, this study confirms variation in level of car ownership across the UK geographical locations as previously concluded by past studies.

Furthermore, holding all factors constant, the relative probability of choosing two-car option rather than choosing one car alternative is 63.2% less for household members of African origins than household members of white origin. As this is the only category that the relationship between African origins (in relation to white origin) is significant for the number of car ownership, the study further agrees with the notion the notion the places non-white ethnic communities at economic disadvantaged position compare to their white counterparts, a notion that has been proved from the existing literature. In their analysis, Klein and Smart (2017) observed very meaningful changes between racial/ethnic groups; indicating that all non-white groups (investigated in their study) have considerably lower access to cars, and higher unemployment.

Their findings also observed that those in employment are more expected to work in the accommodation, information and communication, financial as well as administrative related industries. Therefore, a lot of African origins end up holding low fleet of cars than holding large fleet of cars. Thus, this study buttressed the relationship between African origins in comparison to whites and

car ownership specifically, indicating variations in ethnicity and number of cars in many developed countries.

Premised on table 5.4.2-1, the model results depicts that shared properties has a significant effect on household number of car ownership in all the three categories in relation to the base category. That is, after controlling for all other variables investigated, household members living in shared properties (these include part-buy apartments and rented apartments) are more likely to choose owning cars than household members living in their outright owned properties. In addition, the relative probability of choosing no car option rather than one car is 227% more for household members living in shared properties (these include part-buy apartments, rented apartment) are more likely to choose owning cars than household members living in their outright owned properties.

Whereas, holding all factors constant, the relative probabilities of choosing two car option and three or more car option rather than choosing one car alternative are 62.1% and 30.7% more respectively for household members living in shared properties (these include part-buy apartments, rented apartment) than household members living in their outright owned properties. Expectedly, the trend of the results shows that household members that are living in shared properties have higher propensity to choose no car option rather than one car option relative to outright house owners, compared to household members that have two, three or more cars and living in shared properties. The variable is significant in all the three categories in relation to the base category.

Meanwhile, it is important to note that literature has no study that has investigated the relationship of this variable and car ownership. The closest, variable that has been investigated is built environment, including parking space (Guo, 2013; De Groote et. al, 2016; Coelho et al, 2017). However, the results follow similar pattern of various conclusions in these studies. For instance, Guo (2013), in his analysis, which focussed on the impact of residential parking supply in terms of driveway space and on-street parking on private car ownership, found out that driveway space availability has significant relationship with household car ownership decisions. In addition, Fang et al. (2014) concluded that an outdoor spaciousness measure (based on perceptions of yard

sizes and off-street parking available) and commute distance affect vehicle type choice. Thus, this result further strengthens existing results in the literature. In relation to accommodation tenure, which was investigated in this study, it is expected that someone sharing accommodation or renting apartment is not likely to own large space of parking space to hold fleet of cars unlike someone, who owns the entire property to his/her family. Therefore, the inclusion of this variable is not only justified, but provides insight for other determinant that could further help understand car ownership decisions in households.

In addition, holding other variables constant, the model results show that living in village was significant in two of the three categories relative to the base category. In other words, all else equal, it is found that the relative probability of choosing two-car option rather than one car option is 49.0% more for household members living in villages than for household members livings in big cities. In addition, holding other variables constant, the relative probability of choosing three or more cars option rather than choosing one-car option is 205% more for household members living in villages than for household members livings in big cities.

Relating this result to previous empirical results, household location in terms of urban areas and rural areas has been identified as determinants of car ownership (Macfarlane et al, 2015; Clark et al, 2016). The result does agree with conclusions from literature that household location has relationship with car ownership. In many big cities, because of developed transport network systems; including provision of other alternative transportation modes and congestion of road, many families will prefer to hold small fleet of cars.

Whereas, in villages and towns, such developed transportation systems might be difficult to come by, leaving population with few options to take. This is the reason why owning private cars is important in such places. Furthermore, it is opined that couples and household members, particularly, young singles will experience different travel difficulties and opportunities premised on their residential locations. For example, findings have confirmed that couples living within huge density locations share more out-of-home household duties in relation to couples residing within low density locations (Schwanen et al., 2007;

Van Acker et al, 2014; Haque et.al, 2019; Reimer et. al, 2020) and in addition to costs of running personal cars in the cities, congestion and lack of packing space might make such household members to prefer developed transport systems to holding personal cars.

Considering the results of all the sociological factors found to be significant, the empirical findings provide evidence to support the position highlighted in the literature review that non-economic factors, particularly, ethnicity, accommodation tenure, settlement nature (in terms of whether household location is a city, suburb or village; and geographical regions of the country do have some link with car ownership analysis and their inclusion in the empirical model help to gain further understanding into car ownership analysis. Meanwhile, the significance of this result is of relevance to various policy formulations that could be developed from it. For instance, to promote behavioural change towards ensuring less dependence on car use and achieving energy efficiency, the government might want to decide whether to promote alternative modes of transportation (e.g. cycling, walking etc.) among ethnicity groups.

It is of importance to note that African origin (premised on result from this study) has probability of holding large fleet of cars if other conditions are favourable for it. In other words, people are motivated to categorise themselves into groups, while dissociating from others. It appears that African origin derives some happiness in holding large fleet of cars. This finding is in line with Reimer et.al (2020), who found out that individuals are motivated to categorize themselves into some groups and out of others. Since this is the case, car ownership policies can be targeted at changing the focus of a group in the direction desired.Likewise, car marketers and manufacturers can also reflect on the price sensitivity of car buyers in their future market pricing. In particular, car manufacturers might want to direct their promotions and advertisements to different ethnic groups, different location and different settlement nature; depending on the objective aimed for by the policy makers. Lastly, comparing the findings from the literature and the findings from this study, it is important to note that accommodation tenure and settlement nature in this study are rarely examined in car ownership literature. So, their relationships with the number of

cars owned by households as determining factors, as reported in this study will go a long way to enrich the literature and further attract further studies towards directing interests on less investigated factors.

5.4.5 Psychological factor

Results show mental belief regarding the influence of car ownership on climate change has a significant effect on household number of car ownership in only the three-category. That is, after controlling for all other variables investigated, households, who hold minimum mental belief that car ownership impacts on climate change (as against those who do not believe that car ownership impacts on climate change) are more likely to owning more cars; suggesting positive relationship between car ownership and climate change. Ironically, households, who even hold minimum belief that car ownership impacts on climate change do not prefer low fleet of cars, rather they prefer to own three or more cars.

Furthermore, the relative probability of choosing three or more-car option as against one-car option is 103.9% more for households with minimum mental belief that car ownership impacts on Climate than for households without any mental belief that car ownership impacts on Climate. This suggests that psychological factors, particularly, mental believe in the relationship between car ownership and climate change might not reflect in the number of car ownership UK household hold.

The results support conclusions of scholars, which observed that moral norms offered clear analysis of determinants underlying several pro-environmental behaviours, taking attitude, subjective norm and Perceived Behavioural Control (PBC) into consideration (Belgiawan et al, 2017). Moral norms make consumer to react differently under same conditions to same products at different times. As argued in the literature that consumer behaviour will not always follow the same pattern and hence, cannot be accurately predictable. That a buyer exhibited a pattern of behaviour under a certain condition does not mean he/she will exhibit similar pattern of behaviour under similar condition.

Overall, the findings show that psychological factor investigated in this study does not really impact on the number of cars owned by UK households. Though, there has been conclusion that human activities have started to impact, even changing the global environment (Rockstro¨m et al., 2009; Barnosky et al., 2012; Pauliuk and Müller, 2014), results of this study show that there is no much evidence that confirms significance relationship between the mental believe in the relationship between car ownership and climate change; and the number of car ownership in the UK households.

On the contrary, Bamberg et al. (2010) found moral norm to be of less significance, showing it to have minimal effect on intention and no direct relationship on consumer behaviour. Therefore, findings of this study regarding relationship between psychological factors and car ownership, like previous findings call for more investigations. Out of the three categories related against the base, only one category is found to be significant in this study. Since the minimal mental belief is significant in this study, it suggests that some minimum mental belief that human actions impact on climate change is capable of affecting the fleet of cars held by UK households.

Therefore, the inclusion of the variable in car ownership research will reveal further understanding of car ownership and its determinants. For example, to promote energy efficiency behaviour among households, the government need to take cognisance that any policy directed at influencing psychological disposition of car users, particularly, erratic psychological tendencies of consumers must be considered. Other car stakeholders can have other means of influencing car users. For example, manufacturers might be able to influence adult groups of the society, who see access to means of transportation as means of measuring their wellbeing since transport-related factors, such as: having a driving license and individual assessments of public transport supply define the degree of unmet needs for ‘out-of-home’ activity (Nordbakke and Schwanen, 2015). In other words, in adults’ hierarchy of needs, access to transportation is considered primary, being measurement of their wellbeing.

5.4.6 Economic factors

The model results show that household income still has significant effect on households' number of car ownership in all the three categories. That is, after controlling for all other variables investigated, households with income are more likely to choose owning cars than households without income as expected. Furthermore, the relative probability of choosing no car option rather than one car is 18.5 % less for households with household income than for households without household income. Whereas, the relative probabilities of choosing two car option and three or more car option rather than choosing one car alternative are 32.6 % and 60.0 % more respectively for households with household income than for households without income.

Reviewing the model results of the economic factor investigated, household income under all the three categories was significant. Traditionally and as expected, the empirical findings gave credence to support the direct relationship between economic factors and the number of cars owned by households. Thus, the reaction of household income when integrated in an estimating model along with other non-economic factors still follow same pattern.

As confirmed from the literature, most economic factors and car ownership usually share direct relationship pattern for several years. For instance, individual household income grows; household members tend to travel more by private cars (Greene et al. 1995; Brownstone and Golob 2009; Rentziou et al. 2012; Fang et al, 2014; Ewing et al. 2014; Nolan, 2010; Oakil et al, 2014; Oakil et al, 2016). Thus, there is a direct relationship between income and the number of car. However, it is important to note that there is asymmetrical income elasticity in terms of the response levels of the consumers. For instance, there is a relative probability of choosing no car option rather than one car of 18.5 % less for households with household income than for households without household income.

Thus, income levels might not directly lead to smaller numbers of cars owned by households, but all things being equal; higher income levels will have higher propensity for households to own large fleet of cars (See the propensity percentage of 32.6 and 60.0 of choosing two car option and three or more car

option rather than choosing one car alternative). This is so since once a car has been bought; individuals become accustomed to car use and might not necessarily stop using a car. Thus, the disposal of a car is not easy when income falls (Dargay, 2001). For example, higher income levels positively affect car ownership levels, whereas lower levels of income, in a limited way, affect car ownership levels (Dargay, 2001, 2002). Based on findings from past studies, household income remains one of the most important variables that determine household car ownership (Dargay, 2002). Therefore, the relatively high and mainly significant values of income coefficients in the model suggest that there is a positive relationship between the income and the number of cars owned by a household. Therefore, research question 5 is hereby resolved.

5.5 CONCLUSION

This analysis has taken a novel approach to car ownership estimation. The main purpose of this thesis as noted in the introductory chapter could be split into three. Firstly, the investigation aimed at examining whether inclusion of discipline based determinants in an estimating number of car ownership model, mirroring number of cars individual households own is able to provide more insights into determinants of cars associated to different households in the UK. Secondly, the investigation aimed at estimating some rarely investigated car ownership determinants to further enrich the literature. Thirdly, the investigation, by adopting the two most frequently adopted modelling approaches in car ownership analysis on same set of data, this thesis further provided opportunity to confirm, validate or invalidate, the scholars' assertion regarding which of the two methodological approaches is better for analysis of car ownership.

The main research objectives were resolved in sections 5.4, 5.5 and 5.6 above. Essentially, the study made its contribution in validating and invalidating some previous findings. For example, it is evident through the findings that non-economic determinants are important in explaining car ownership in households. It was also observed that traditional economic factors, such as household income might not always follow strictly microeconomic law. That is, if household income drops, the household may not necessarily reduce the number of cars owned, at least, not at the immediate. Furthermore, the analysis contributed to literature in the areas of methodology, offering alternative modelling approach,

which integrated disciplined based determinants. Section 5.3.3 confirms that such integrated modelling approach does yields more insights into car ownership investigation.

In addition, the accuracy of the various predictions was shown to be in line with more popular and established techniques, given specific data constraints. For instance, McFadden pseudo R-square of the integrated MNL model has a value of 0.3645, which fits within established standard values. Furthermore, the novelty of this car modelling approach is not only because it proposes an estimating methodology, while allows integration of different discipline based factors, but the introduction and investigation of some factors, which are rarely investigated in car ownership research or not found in car ownership literature. These include: settlement nature, accommodation tenure, mental believe in the relationship between car ownership and climate change. It is believed that the inclusion of these factors in car ownership analysis will go a long way to enrich the literature; opening new perspectives on how vehicle determinants are modelled.

The results from the NL model and the results from the MNL of the number of cars owned by UK households; using same data offered rare opportunity to make comparative analysis between the two approaches. Based on the gap, which this thesis sets out to fill, there are key contributions that were identified in this empirical chapter and discussed. The overriding of these contribution being the opportunity created by the proposed modelling approach for integration of both economic and non-economic factors in an estimating model to analyse the number of cars owned by UK households. Furthermore, this study proposed methodology that allowed for the integration of different discipline based factors to be included in an estimating model. Thirdly, the use of a methodology that is based on micro data use is further promoted in this study.

The whole methodological approach adopted in this study; yielding the findings arrived at provides strong evidence to support the notion that understanding car ownership and its characteristics require more than investigating only economic factors, but also the non-economic variables. This is the direction that future investigations of car research will immensely benefit from. All of these results demonstrate the relevance of the variables to different players in the vehicle

industry. Particularly, the different results with their significant relationships in respect of the different variables show how various UK households are affected by these variables in terms of what type of UK households are likely to be associated to one-car category, two-car category and three or more car category.

CHAPTER 6
THE DATA, MODEL ESTIMATIONS, RESULTS AND ANALYSIS OF US NUMBER OF CAR HELD

6.0 INTRODUCTION

In line with the objective of this study, which is to estimate the impact of various discipline based determinants of car ownership on the number of cars owned by developed countries; using the UK and the US as representatives, this chapter compared the proposed models on US data set. It is of the opinion that there may be country-based peculiarities that could reflect in the functioning of the modelling approach in different countries. Thus, the consistency of the model is verified across the two countries by comparing the findings of this chapter with the findings arrived at in the previous chapter. So, this chapter offers opportunity to test the reliability of the modelling approach.

To this end, this chapter describes the design and explanations of the data used for the study. The chapter also deals with the estimation, presentation and explanations of the results. Based on the multinomial choice (MNL) and NL described in chapter 4, the impacts of different discipline based factors on the number of cars US households own were estimated. These factors are: ethnicity, mental belief on the relationship of car to climate use, accommodation tenure, Household structure, driving licence, number of household income earners and household income.

Among others, the estimation methods used in the study gave the opportunity to test if the proposed methodology offered more insights into the car ownership research compared to the existing approaches in the literature. Subsequent to derivation of results using the modelling approaches, findings were discussed and various policy implications to various transport stakeholders in both the UK and the US were highlighted. The remaining sections of the chapter are structured as follows.

The remaining sections of the chapter are structured as follows. Section 6.1 deals with the design of the survey and data adopted for the study, while section 6.2, highlights the relevant data areas used in this study. The section also deals with explanations of dependent and independent variables, highlighting the

justification of their inclusion in the model. Section 6.3 discusses the estimation results. Section 6.4 and 6.5 focus on the explanation of results and analyses of different households and their possible association to different car ownership categories. Section 6.6 presented policy implications of the study, its contribution and relevance to different stakeholders. The section also highlights and discusses comparable observation between the findings from the two study countries- the UK and the US. The last section, section 6.7, dwells on the conclusions, limitations and suggested areas for future research.

6.1 DESIGN OF THE CONSUMER EXPENDITURE SURVEY (CE)

The Consumer Expenditure Survey (CE) collects data from the US households, their buying behaviours (expenditures), household income, and the general household attributes. The advantage of the survey is that it ensures data users to relate the expenditures and income of consumers to the characteristics of those consumers(Consumer Expenditure Survey, Diary Survey, 2017). Generally, the CE is made up of two elements, namely: a quarterly Interview Survey and a weekly Diary Survey and each with its own questionnaire and sample. The CE program offers data on the buying behaviours of American consumers. Data collected from the CE are mainly used as measurements for the Consumer Price Index (CPI). CE offers the data to the research world in two forms. The first form uses tabulation of average and aggregate expenditures and income in news releases, databases, and tables.

The survey from which data for this study was derived, examined opinions of huge consumer units (CUs[10]). It is the aim of this section of the thesis to explain how data from this survey was used to investigate the impact of a range of explanatory variables on the households' car ownership decision and to identify

[10] According to Bureau of Labour Statistics (2017), a consumer unit is made up of any of these: '(1) all members of a particular household who are related by blood, marriage, adoption, or other legal arrangements; (2) a person living alone or sharing a household with others or living as a roomer in a private home or lodging house or in permanent living quarters in a hotel or motel, but who is financially independent; or (3) two or more persons living together who use their incomes to make joint expenditure decisions. Financial independence is determined by spending behavior with regard to the three major expense categories: housing, food, and other living expenses. To be considered financially independent, the respondent must provide at least two of the three major expenditure categories, either entirely or in part.' However, the terms consumer unit, family, and household are many a time used interchangeably because of convenience. For the purpose of this study, a consumer unit could be called a household.

a suitable manner through which they should be combined to develop car ownership models. One individual per household is chosen to respond to questions contained in the questionnaire. CE interview survey data are collected via Computer Assisted Personal Interview (CAPI) that is subsequently adopted by a Census Bureau field agent to carry out the interview. Individual household is interviewed during the period allocated for the exercise within each three months across five quarters.

6.2 DATA, DEPENDENT AND INDEPENDENT VARIABLES

It is the aim of this section to explain the data mapped out from CE (2016) and adopted to investigate the impact of a range of explanatory variables on the household's car ownership decision. From the composition of the CE (2016) described in section 6.1 above, a data set of 6342 consumer units (CU) was adopted and from this set; both the dependent and independent variables adopted for this study were mapped out. Thus, this section discusses how these explanatory variables have been combined within the proposed car ownership model proposed in the study. The dependent and independent variables used in this study are now discussed.

6.2.1 Dependent and Independent Variables

In this section, dependent and independent variables are explained.

6.2.1.1 Dependent variable

Within the choice model, the dependent variable refers to the number of car associated (owned) by each of the US households[11]. Thus, each CU (household) in the US owning car is defined by 4 discrete values 1, 2, 3 and 4 representing car categories, namely, households with no car, households with one car, households with two cars and households with three or more cars respectively. This classification was adopted to operationalise the proposed model. Therefore, a group of four sets was adopted to define the values of the dependent variable for the car ownership choice model. Table 6.2.1-1 and figure 6.2.1-1 present the distribution of preferences for cars ownership.

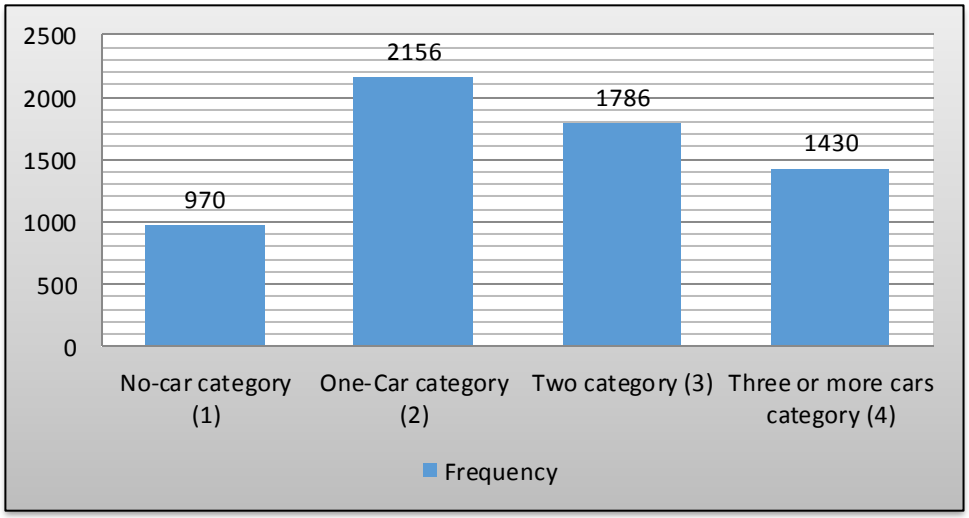
[11] Note, based on the US data set, consumer units refer to households

As noted earlier, table 6.2.1-1 below shows the distribution of the number of cars owned by different household based on the classification depicted in the table. From the table 6.2.1-1, 62.2% of the entire sample fall within either one-car category or two-car category; suggesting that the vast majority of the US population own cars (and vehicles in general) for functional purposes. Nevertheless, based on theoretical perspectives, car ownership is determined by a number of factors.

Table 6.2.1-1: Number of Car Categories of the Households

Car Categories	Frequency	Percentage (%)	Cumulative %
No-car category (1)	970	15.3	16.5
One-Car category (2)	2156	34.0	49.3
Two category (3)	1786	28.2	77.5
Three or more cars category (4)	1430	22.5	100

Figure 6.2.1-1 Number of car ownership



To the economists, the consumer preferences for a car could be specified as a function of its price, price and quality of competing cars, household income among others. Bearing this in mind, and in line with the objective of this study, which is to combine economic and non-economic determinants of car ownership within a specific a model, the following set of dependent and independent variables, listed in table 6.2.1-2 were mapped out. Each of these variables is further discussed one after the other in section 6.2.2 below, however, It is essential to understand that the variables integrated in the models of the analysis are those available in the selected database-CE (2016), which was earlier discussed in section 6.1 above.

While some of these variables are similar to those usually examined in car ownership research, others have not been used at all (See de Jong et al., 2004; Nayum et al, 2013; Anowar et al., 2014 for update literature). Furthermore, it is crucial to bear in minds that household car ownership decision is clearly determined by a host of factors and arguably more detailed information could be accessed through a bespoke data collection exercise. From the database, eight (8) variables were selected; containing one (1) dependent variable and seven (independent variables). To explain the sole dependent variable of the model-VEHQ (Car), seven (7) dependent variables were mapped out in the final proposed car ownership specified choice model and these 7 dependent variables could be grouped into four relevant categories (code in parenthesis): (1) Demographical factors (DF), (2) Sociological factors, (3) Psychological factors (PF), (4) Economic factors (EF). The Table 6.2.1-2 below gives explanations of the variables, along with their operationalization.

Table 6.2.1-2: Variable Explanations

	Variable categories	**Variable name**	**Variable description**
1	**Dependent variable**	Car ownership	Number of household cars available
	Independent variables		
2	Demographical factors	House-hold structure	This is the number of household members
3	Demographical factors	driving licence	1, if household respondent or any other adult has driving licence; 0, otherwise.
4	Psychological factors	mental belief	Mental disbelief that car ownership impacts on climate change. 1= Total disbelief that climate change is taking place, 2= belief that climate change is taking place but not as a result of human actions such as car use,3= Belief that clima-te change is taking place and it is as a result of human act-ions such as car use, 4=Absolute belief that climate change is taking place and it is a result of human actions such as car use, 5= Most absolute belief that climate change is taking place and it is a result of human actions such as car use
5	Sociological factors	Acco-mmodation tenure	This shows whether or not accommodation is owned, rented or under mortgage.1= outright ownership, 2= Mortgaged accommodation, 3= Shared ownership accommodation (e.g. part rent, part buy), 4 = Others.
6	Sociological factors	ethnicity	Racial ethnic groups households belong.1= White,2= Black, 3= Nativeamericans, 4= Asians,5= Pacificislander, 6= Multi-race.
7	Economics factors	Number of earners	This is the number of members in a household, who are earning income.
8	Economics factors	household income	The total annual income of your household from all sources before tax. 1 = Less than $5,000, 2= $5,000 to $9,999, 3= $10,000 to $14,999, 4= $15,000 to $19,999, 5= $20,000 to $29,999, 6= $30,000 to $39,999,7= $40,000 to $49,999, 8= $50,000 to $69,999, 9= $70,000 and over.

6.2.2 Independent variables

All the included variables have already been explained in chapter 5, except the 'number of earners' that was not part of the variables included in chapter 5 analysis. So, the 'number of earners' is now explained in this section. As earlier stated a few of these variables have featured in the literature as established in the chapter three, while additional ones will enrich the literature. However, this study has carefully mapped out all of these variables from the CE (2016) database based on the objectives of the study.

6.2.2.1 Number of earners in Households

Obviously, there is a strong relationship between income and employment. Households with higher number of individuals in income earners category, all things being equal, are likely to own higher number of cars unlike households with small number of individuals as income earners. To take account of impact that employment has on car ownership, over and above the income associated effects, the number of people in employment (be it self-employment or being employed) is investigated. Similarly, it is expected that households that have more members offering more hours to work (in comparison to those that offer less hours to work) are expected to access more earnings, which could indicate a higher number of car ownership. However, the investigation of this variable in this study is limited to the number of income earners in each household.

Meanwhile, as part of the criteria to get work, the ages of household members could be important factor. Households, whose members are old enough to work are likely to earn more compared to those whose members are too young to work and this in turn could dictate the number of cars such household members could hold. Thus, it is expected that, households in which majority of its adults are within employment groups have higher probabilities to earn more incomes compared to others, which are populated by dependent children. All things being equal, there is a direct relationship between level of earnings and number of cars acquisition in households. Similarly, all things being equal, a household, whose majority of its members fall within retirement age bracket should have lower earnings and this in turn, should impact negatively on propensity for

owning large fleet of cars. In this study, the number of income earners in households ranged from 0 to 7 (i.e. 0 being households where there is no income earners and 7 being households where there are seven members earning incomes).

6.3 RESULTS

The results of the models were explained and compared in this section. In addition, how the independent variables were checked for significance was explained.

To specify the model using the data that are individual specific as in this study, approach of Greene, 2012, pp. 801-810 was adopted. For each sample, the data for each individual in the sample consist of the following:

1. **Number of car ownership:** 1 = No car, 2 = One car, 3 =Two cars, 4 = Three or more cars.
2. **Characteristics:** constant, driving licence, household structure, ethnicity, accommodation tenure, mental belief that car ownership impacts on climate change, household income and number of income earners in household.

6.3.1 Presentation of Results

In this section, the results of the multinomial logistic regression analyses are shown and explained. The outcome measure in this analysis is the preferred categories of cars- no-car category, one category, two category or three or more category- from which the results depict what form of relationships exists between US household's number of cars and ethnicity, mental belief on relationship of car to climate use, accommodation tenure, Household structure, driving licence, number of household income earners and household income. In this study dependent variable, category of cars owned by US households was treated as categorical variable under the assumption that the number of cars does not have natural ordering, and the 2nd category (households with one car) was used as referent category. Table 6.3.1-1 gives the data summary. The following represents results from the model specification.

Table 6.3.1-1: Data Summary

Variable	Obs.	Mean	Std. Dev.	Min	Max
Number of Cars	6342	1.796121	1.496744	0	21
Household Structure	6342	2.441659	1.470839	1	12
Driving Licence	6342	0.8481552	0.358899	0	1
Accommodation Tenure	6342	2.423841	1.335096	1	6
Ethnic origins	6342	1.337118	0.896931	1	6
Mental Perception	6342	1.230211	0.726619	1	5
Household Income	6342	6.664775	2.435262	1	9
Number of earners in Households(Earning power)	6342	1.255913	0.967836	0	7

The results of the integrated model for each explanatory variable are analyzed (discussion by row of Table 6.3.1-2). The results summary was presented in table 6.3.1-2. A significance of 0.000 which implies that the independent variables have a significant influence on the number of cars owned. The significance <0.05 implies that the model is a good fitting for the variables selected and therefore validates the model. Each category of disciplined based factors exhibits significant relationship with car ownership in the US households. Therefore, first research question is resolved in the estimates shown for the US.

Table 6.3.1-2: Regression results for MNL- four alternatives

Dependent variable: number of cars	0 Car	2 cars	3+ cars
Driving Licence	-0.035	-0.088	-0.200
Household Size	-0.059	0.292	0.354
Accommodation Tenure:			
Ownerswithoutmortgage	0.334	0.267	0.258
Tenants	0.855	-0.822	-1.836
Others	1.285	-0.184	-0.752
ethnicity:			
Black	0.595	-0.404	-0.873
Nativeamericans	1.019	1.107	1.188
Asians	0.505	-0.332	-1.230
Pacificislander	0.339	0.491	0.003
Multi-race	0.186	-0.106	-0.298
Mental Perception:			
Minimum belief	-0.105	0.242	-0.020
Believe	-0.149	-0.083	0.485
Absolute belief	-0.111	0.149	-0.093

most absolute belief	0.142	0.217	0.726
Household Income	-0.595	0.392	0.734
earningpower	0.208	0.698	0.995
Obs.	6342		
Log-Likelihood	-7223.625		
Pseudo-R2	0.1546		
LR	2641.52		
_cons	-0.393	-2.481	-3.915

Furthermore, from the regression results, marginal effects of the independent variables were calculated. Meanwhile, the marginal effects (ME) depict the level with which individual explanatory variable is sensitive towards the predicted likelihood of mean choices. This is shown in table 6.3.1-3 below. Marginal effects ensure that elasticity for each variable is derived.

For instance, ME calculations ensure that we derive the impact of a rise in income on the total share of individual car ownership category. Table 6.3.1-3 displays the predicted likelihood for individual car ownership category. The likelihoods (probabilities) are obtained for an imaginary household individual that possess mean characteristics for individual explanatory variable (mean household income, mean household structure, etc.). Within the setting of the table 6.3.1-3, the fictive household is viewed to possess a two percent likelihood of selecting No-car option if household structure increases by 1 percent (i.e. if members of a household increase by 1percent). Whereas, the fictive household is viewed to have a 4 percent likelihood of selecting one-car option if members of a household increase by 1percent, and so forth.

Table 6.3.1-3: **Marginal effects**

dy/dx[a]	**NoCarHH**	**OneCarHH**	**TwoCarHH**	**ThreeormoreCarHH**
Driving licence	0.001(0.012)	0.020(0.016)	0.000(0.015)	0.022(0.013)*
Household structure	-0.019(0.003)**	-0.039(0.005)**	0.029(0.004)**	0.029(0.004)**
Accommodation Tenure: Ownerswithoutmortgage	0.015(0.010)	-0.052(0.015)**	0.022(0.015)	0.015(0.014)
Tenants	0.146(0.011)**	0.115(0.015)**	-0.067(0.014)**	-0.194(0.011)**
Others	0.167(0.035)**	-0.021(0.043)	-0.022(0.049)	-0.123(0.044)**
Ethnicity: Black	0.099(0.014)**	0.030(0.019)	-0.034(0.019)*	-0.096(0.016)**
Nativeamericans	0.047(0.060)	-0.180(0.063)**	0.070(0.087)	0.063(0.079)
Asians	0.087(0.023)**	0.046(0.029)	0.000(0.025)	-0.133(0.017)**
Pacificislander	0.019(0.070)	-0.063(0.091)	0.090(0.097)	-0.047(0.080)

Multi-race	0.027(0.036)	0.013(0.052)	-0.002(0.051)	-0.037(0.045)
Mental Belief: Minimum belief	-0.017(0.017)	-0.014(0.024)	0.052(0.024)**	-0.021(0.020)
Believe	-0.020(0.032)	-0.014(0.046)	-0.051(0.045)	0.085(0.045)*
Absolute belief	-0.015(0.022)	-0.001(0.030)	0.040(0.030)	-0.024(0.024)
most absolute belief	-0.003(0.043)	-0.065(0.056)	-0.026(0.058)	0.094(0.057)*
Household income	-0.084(0.006)**	-0.032(0.009)**	0.032(0.010)**	0.083(0.010)**
Earning power	-0.011(0.012)	-0.124(0.014)**	0.048(0.012)**	0.086(0.010)**

[a] The estimated coefficient underlines the impact of independent variable variation on the predicted probability. Data into brackets present the error type for each estimated parameter. Coefficients with a * or ** constitute a 10 or 5 percent parameter significant respectively. Note: dy/dx for factor levels is the discrete change from the base level

To show the robustness of the MNL model, NL model was used on same dataset following the NL model specification described in section 4.4.1 and the result is displayed in table 6.3.1-4 below:

Table 6.3.1-4: Nested logit model for Number of car ownership

RUM-consistent nested logit regression				Number	of obs	25368
Case variable:family_id				Number	of cases	6342
Alternative variable: numberofcars				Alts per	case: min=	4
					avg =	4.0
					max =	4
				Wald	chi2(26)	.
Log likelihood =	-5442.4975			Prob	>chi2	.
Dependent variable(chosen)	**Coef.**	**Std .Err.**	**z**	**P>|z|**	**[95% Conf.**	**Interval]**
numberofcars						
Accommodation Tenure	0.196	0.028	6.940	0.000	0.140	0.251
type equations						
nouseofcars						
Household income	1.448	58.730	0.020	0.980	-113.662	116.557
Earning power	0.353	59.715	0.010	0.995	-116.687	117.392
Driving Licence	-78.583	57265.140	0.000	0.999	-112316.200	112159.000
Household Size	0.988	63.758	0.020	0.988	-123.975	125.950
Mental Belief	1.488	79.766	0.020	0.985	-154.849	157.826
Whiteblack	33.482	56950.240	0.000	1.000	-111586.900	111653.900
NativeAmeri	33.833	57260.050	0.000	1.000	-112193.800	112261.500
Asians	2.974	14106.160	0.000	1.000	-27644.580	27650.530
Pacimultirac	0.351	1448.105	0.000	1.000	-2837.883	2838.585

necessityofcars|						
Household income	(base)	(base)	(base)	(base)	(base)	(base)
Earning power	(base)	(base)	(base)	(base)	(base)	(base)
Driving Licence	(base)	(base)	(base)	(base)	(base)	(base)
Household Size	(base)	(base)	(base)	(base)	(base)	(base)
Mental Belief	(base)	(base)	(base)	(base)	(base)	(base)
Whiteblack	18.013	(base)	(base)	(base)	(base)	(base)
NativeAmeri	0.673	10.653	0.060	0.950	-20.207	21.553
Asians	-11.469	7.169	-1.600	0.110	-25.519	2.581
Pacimultirac	20.184	13.713	1.470	0.141	-6.694	47.061
wantofcars						
Household income	0.346	0.014	24.250	0.000	0.318	0.374
Earning power	-0.015	0.037	-0.390	0.694	-0.087	0.058
Driving Licence	-16.233	55518.470	0.000	1.000	-108830.400	108798.000
Household Size	-0.002	0.024	-0.100	0.920	-0.050	0.045
Mental Belief	0.026	0.041	0.640	0.522	-0.054	0.107
Whiteblack	-35.160	55517.160	0.000	0.999	-108846.800	108776.500
NativeAmeri	16.983	55518.200	0.000	1.000	-108796.700	108830.700
Asians	-24.521	15.700	-1.560	0.118	-55.292	6.250
Pacimultirac	-5.413	3.121	-1.730	0.083	-11.530	0.705
dissimilarity parameters						
Type						
/nouseofca~u	1.00	32928.11			-64536.90	64538.90
/necessity~u	1.00	43729.68			-85707.60	85709.60
/wantofcar~u	36.04	20.83			-4.78	76.85

6.3.2 ESTIMATION METHOD AND EXPLANATION OF RESULTS

The models specified in chapter 4; section 4.4 of this thesis relate to the utility of the number of cars by US households, which in turn relate to the demographical characteristics of the US households, the Psychological characteristics of the US households, the Sociological characteristics of the US households and the economic characteristic of the US households. Stata results of the MNL models are shown under table 6.3.1-2, while table 6.3.1-3 depicts the results of the marginal effects. Since results of the NL are considered similar to MNL results, analysis of results is only provided for MNL model (See full Stata results under Appendix 3).

6.3.3 Model comparison

As all models were nested under the integrated specification Equation (4.10), they were compared with each other with the use of the respective log-likelihood values. Table 6.3.3-1 below depicts log-likelihood values and McFadden pseudo R-squared values for the successively integrated the number of cars model. As shown, the course of log-likelihood function increases as additional regressors were successively introduced. It is also obvious that there is a significant improvement in model fit (i.e. goodness of fit), as the respective McFadden pseudo R-squared value increases from the reduced models to the integrated specification. Therefore, one may conclude that the integrated model (Equation (4.10) is the best specification. Like the UK case, one can easily answer with affirmation. 'YES' to research question 3, which seeks to know if the proposed 'number of cars ownership' estimating model reflect more insights into the households' car ownership; especially, in the light of its holistic approach. The question 3 is hereby resolved.

The McFadden pseudo R-square of the integrated model shows a value of 0.1546 and this is very good, taking cognisance of various McFadden values of studies in the literature. For example, Lave and Train (1979) found a pseudo R-square value of 0.126; Kitamura et al. (2000) found a value of 0.249, whilst Choo and Mokhtarian (2004) found a value of 0.177. Evidently, the proposed model does an excellent job in explaining vehicle type choice behaviour, compared to previous applications in the literature. In Tables 6.3.1-1 and 6.3.1-2 data summary and the estimates of the proposed integrated vehicle type choice model (Equation (4.10) are presented. All explanatory variables are statistically significant and conceptually interpretable, with low standard errors and expected signs.

Table 6.3.3-1: Model Comparison

Explanatory variables	Model 1	Model 2	Model 3	Full Model
Demographical characteristics : driving licence, household structure	√	√	√	√
Sociological characteristics: Accommodation Tenure, Ethnicity		√	√	√
Psychological characteristics: Mental belief			√	√
Economic variables: Household income, number of earners				√
Log-Likelihood	-8162.4	-7535.8	-7529.43	-7223.625
Pseudo-R^2	0.0447	0.118	0.1188	0.1546
LR	763.97	2017.16	2029.9	2641.52

Table 6.3.3-1 depicts an increase to the predictive power of the integrated model in the light of a stepwise integration of the four groups of variables.

6.3.4 Explanatory variables

The proposed choice model in Eq. (4.10), has explanatory power of four disciplines and each discipline has at least one variable as its representatives in the model. Using the multinomial logit model, comparison is to a base category, which the alternative normalized to have coefficients equal to zero. In other words, the multinomial logit probabilities Eq. (7.3) above suggests that the conditional probability of observing alternative j given that either alternative j or alternative k is observed is:

$$P[y = j \mid y = jork] = \frac{p_j}{p_j + p_k} = \frac{exp\beta_j x_{ij}}{\exp(\beta_j x_{ij}) + exp(\beta_k x_{ik})} = \frac{exp(x_i(\beta_j - \beta_k))}{1 + exp(x_i(\beta_j - \beta_k))} \qquad 6.0$$

which is a binary logit model with coefficient $(\beta_j - \beta_k)$. Assume normalization is on alternative 1, so that $\beta_1 = 0$. In such case, then, Eq. (7.8) becomes

$$P[y = j \mid y = jor1] = \frac{exp(x_i\beta_j)}{1 + exp(x_i\beta_j)} \qquad 6.1$$

$and\ \beta_j$ can be interpreted in the same manner as the logit model coefficient for binary choice between alternatives j and 1. Likewise to the binary logit model[12], the probability of choosing alternative j rather than alternative 1 is $\left(\frac{P_r \mid y_1 = j \mid}{P_r \mid y_1 = 1 \mid}\right) = exp(x_i\beta_j)$ that could be simply converted to a linear model adopting the logit association, like this: $log\left(\frac{P_r \mid y_1 = j \mid}{P_r \mid y_1 = 1 \mid}\right) = x_i\beta_j$. Thus, β_j provides the difference in the log of odds whenever x_i alters with one unit. The analyses thus convert i in line with what option is normalized to possess zero coefficient. For this analysis

[12] See Cameron and Trivedi (2005) for more information on the binary logit model.

to be actually beneficial, there is need for a natural base category (Cameron and Trivedi, 2005). Therefore, it is understandable, based on the perspective of the model predictive approach. The selection of the base category is random, in the light of interpretation of each category impacts, the selection of the base category could constitute a difference since impacts (i.e., coefficients) are construed for individual option vis-à-vis the selection of base category.

From the estimation results of this analysis, the two-car category of the dependent variable was selected as the reference category by Stata itself, obviously due to its highest frequency compared to other categories. As shown, most independent variables were statistically significant with small standard errors. Premised on explanatory variables in table 5.2.1-2, the following estimation was made:

$$P_j = \frac{exp(\alpha_j + \beta_{hj}x_{hij} + drvlicn_{dj} + hhstru_{dj} + acctenurty_{sj} + ethnicorigins_{sj} + ccbeliev_{pj} + nuofearners_{ej} + incomehh_{ej})}{\sum_{k=1}^{J}\exp(\alpha_k + \beta_{hk}x_{hik} + drvlicn_{dk} + hhstru_{dk} + acctenurty_{sk} + ethnicorigins_{sk} + ccbeliev_{pk} + nuofearners_{ek} + incomehh_{ek})}, \quad j = 1, \ldots \ldots J \qquad 6.3$$

Where: $\alpha_j + \beta_{hj}x_{hij}$, $\alpha_k + \beta_{hk}x_{hik}$, j, 0, and J remain as defined before, while $drvlicn_{dj}, hhstru_{dj}, acctenurty_{sj}, ethnicorigins_{sj}, ccbeliev_{pj}, nuofearners, incomehh_{ej}$ refer to driving licence, Household structure, accommodation tenure, ethnicity, mental belief, number of earners and household income respectively. See table 5.2.1-2 in chapter 5 above for explanations of variables used in this estimation and section 6.4 below for explanations of results of the variables used in this estimation.

6.4 RESULTS AND FINDINGS

Model results are presented; highlighting the significant variables with necessary analysis. Most of the independent variables exhibited statistical significance with small standard errors. It was observed that only few of the constants were insignificant in different car-number categories. Nevertheless, they were still incorporated with the model specifications to avoid sampling bias (Alem et al., 2016). It is observed that the nested model results shown in table 6.3.1-4 above exhibit similar results observed using the MNL model, when compared in terms of the variables found significant and those found insignificant. Therefore, the following sections now provide the explanations and descriptions of significant results for the alternative-specific constants $\propto_j$ and the explanatory variables

using MNL approach (discussion by row is premised on results displayed in Table 6.4-1). Lastly, the same approach used in chapter 5, section 5.4.1 to test IIA condition was still adopted in the US analysis.

Table 6.4-1: **Estimated parameter of Relative Risk Ratio (RRR) for MNL Regression**

Dependent Variables	NoCarHH	OneCarHH	TwoCarHH	ThreeormoreCarHH
Driving licence	0.965(0.110)	***Ref***	0.916(0.088)	0.819(0.087)*
Household structure	0.506(0.038)	***Ref***	1.339(0.038)**	1.425(0.045)**
Accommodation Tenure: Ownerswithoutmortgage	1.396(0.197)**	***Ref***	1.306(0.118)**	1.294(0.123)**
Tenants	2.352(0.285)**	***Ref***	0.440(0.038)**	0.160(0.017)**
Others	3.614(0.907)**	***Ref***	0.832(0.240)	0.472(0.183)**
Ethnicity: Black	1.814(0.193)**	***Ref***	0.067(0.079)**	0.418(0.065)**
Nativeamericans	2.771(1.732)*	***Ref***	3.024(1.759)*	3.281(0.079)*
Asians	1.656(0.288)**	***Ref***	0.717(0.115)**	0.292(0.062)**
Pacificislander	1.404(1.003)	***Ref***	1.634(0.905)	1.003(0.699)
Multi-race	1.204(0.403)	***Ref***	0.899(0.283)	0.742(0.280)
Mental Belief: Minimum belief	0.900(0.159)	***Ref***	1.273(0.182)*	0.980(1.167)
Believe	0.862(0.300)	***Ref***	0.920(0.283)	1.625(0.509)
Absolute belief	0.895(0.206)	***Ref***	1.161(0.208)	0.910(0.188)
most absolute belief	1.153(0.515)	***Ref***	1.242(0.479)	2.066(0.829)*
Household income	0.551(0.032)**	***Ref***	1.480(0.086)**	2.083(0.157)**
Earning power	1.231(0.146)**	***Ref***	2.010(0.164)**	2.704(0.240)**
Obs.	**6342**			
Log-Likelihood		**-7223.625**		
Pseudo-R^2		**0.1546**		
LR		**2641.52**		

Notes: Values within brackets are error type for the individual estimated parameter of Relative Risk Ratio (RRR). Coefficients having a* or ** refer to a 10% or a 5% parameter significance respectively

6.4.1 Significance of category-specifics

The inference from the significant positive signs associated to the category-specific constants of the two-car household segment and three or more-car category is that the typical impact of the entire unestimated variables usually grow the likelihood of selecting both car categories. Conversely, for no-car household category, the typical impact of the entire unestimated variables appears to reduce the likelihood of selecting this category. In addition, the category-specific constant in respect of the no-car category that yielded the largest value (in terms of absolute value) in relation to the values for other car categories suggests that the choice likelihood of no-car category by the US

households is hardly fully-accounted for by the variables within the model proposed in this research.

6.4.2 Demographical factors

Holding other variables constant, the model results show that Household structure was significant in two of the three categories relative to the base category. That is, all else equal, it is found that the relative probability of choosing two-car option rather than one-car is 33.9% more for households with large Household structure than for households with small Household structure. Similarly, it is found that the relative probability of choosing three or more car option rather than choosing one car alternative is 42.5% more for households with large Household structure than for households with small Household structure. Specifically, the explanatory variable was significant. This result confirms that Household structure; in terms of the number of household members as investigated in this study remains relevant in explaining car ownership in many developed countries.

Meanwhile, car research in different societies confirms the relevance and relationship of household characteristics and the level of car ownership (Bhat and Guo, 2007; Oakil et al., 2014; Adjemian, et al; 2010; Fox et al., 2017). For instance, it is not uncommon to observe that the level of car ownership by singles appears small in comparison to married couples with children, necessitating need for different activities and programmes if this pattern should be corrected (Potoglou and Kanaroglou, 2008). This observable variation could be due to the fact that singles earn small incomes compared to married families, it could also be because singles having lower different activities, daily travels and programmes in comparison to families with children. The variation could also be because singles being jobless more frequently unlike family parents. All of these and many more could create such variations between the two groups, which could define the level of car ownership between them.

Furthermore, there are some journeys and actions carried out by couples with children, which are more controlled and planned in periods as well as in place in comparison to other household activities (Kitamura, 1983). Case in point, it was observed that child-related journeys and activities make it impossible to

circumvent using roads during busy hours (Oakil et al., 2015), explaining why parents with children will prefer to hold high level of car ownership in comparison to singles and barren couples. This is not always the case for singles without schooling children. Thus, one can easily conclude that Household structure remains a key determinant of household car ownership.

Large Household structure is significantly associated to higher likelihood of owning more cars as having large number of schooling children in a household and combined with more employees, all things being equal, is significantly linked with large number of car ownership, especially, when there are different household members working in different locations outside the homes. Thus, the empirical results give support the notion gathered from the literature review that non-economic factors do determine car ownership in households and their inclusion in the empirical model help to reveal further insight into consumer characteristics.

6.4.3 Sociological factors

Different accommodation tenures, including being accommodation owners without mortgage, being tenants in properties and other accommodation tenure were found significant, holding all factors constant. For instance, it is found that the relative probabilities of choosing no-car option, two-car option and three or more cars respectively rather than one-car option are 39.6%, 30.6% and 29.4%more for household members living in ‘accommodation without mortgage’ rather than for household members livings in their outright owned properties(or properties owned with mortgage). Being ‘owners without mortgage’ was found significant in all the three categories. For instance, were found for being ‘accommodation owners without mortgage for rather than choosing one car alternative.

In addition, holding other factors constant, the relative probability of choosing no car option rather than one car is 135.2% more for household members living in shared properties rather than household members living in their outright owned properties. Whereas, holding all factors constant, the relative probabilities of choosing two-car option and three or more car option rather than choosing one car alternative are 56.0% and 84.0% less respectively for household members

living in shared properties than household members living in their outright owned properties.

Furthermore, holding all factors constant, the relative probability of choosing no-car option rather than choosing one car alternative is 261.4% more for household members living in 'others' forms of properties (e.g. properties occupied without rent payments, student housing) than household members living in their outright mortgaged properties. However, all factors held constant, the relative probabilities of choosing two-car option and three or more cars alternative rather than choosing one car alternative are 56.0% and 52.8% less for household members living in 'others' forms of properties (e.g. properties occupied without rent payments, student housing) than household members living in their outright mortgaged properties. Expectedly, the trend of the results indicates that household members that live in shared properties as against living in mortgaged properties or properties without mortgage have higher propensity to choose no car option rather than one car option. Whereas, household members that have two, three or more cars and living in shared properties were less likely to choose no-car option.

Therefore, accommodation tenure as an explanatory variable is not only significant in all the three categories in relation to the base category; the results also give interpretations that fit into the realities. For instance, individual living in mortgaged properties or outright owned properties is expected to have spaces in his apartment, which readily accommodates large fleet of cars, This is not the case for someone staying in rented apartment, for which such large space is not always available. Literature has investigated the relationship between vehicle ownership and built environment; including parking space (Guo, 2013; Guerra 2014; Schwanen and Wang 2014; De Groote et. al, 2016; Coelho et al, 2017) and scholars have mostly concluded positive correlation.

That is, all other factors held constant, the more spaces available, the more the number of cars held by household members. This is why it is becoming popular for families to consider parking spaces before moving into apartments as cars are not luxury to many homes. In their study, Yang et al. (2017) found correlation between level of car ownership and built-up area. In addition, Fang et

al. (2014) concluded that the size of available parking space and distance impact on level of car ownership and vehicle type choice. Therefore, this result further buttresses current findings in the literature. Therefore, the inclusion of this variable is not only justified, but provides insight for other determinant that could further help understand car ownership decisions in households.

Moreover, holding all other factors constant, the study found black and Asians significant among all the ethnicities investigated in all the three categories. For instance, holding all factors constant, the relative probabilities of choosing no-car option rather than choosing one car alternative are 81.4% and 65.6% more for household members of African origins and Asian origin respectively than household members of white origin. On the other hand, holding other variables constant, the relative probabilities of choosing two-car option rather than choosing one car alternative are 33.3% and 28.5% less for household members of African origins and Asian origin respectively than household members of White origin.

Similarly, holding other variables constant, the relative probabilities of choosing three or more car option rather than choosing one car alternative are 58.2% and 70.8% less for household members of African origins and Asian origin respectively than household members of White origin. Meanwhile, in their analysis, Klein and Smart (2017) found very meaningful changes between racial/ethnic groups; suggesting that all non-white groups (investigated in their study) have considerably lower access to cars, and higher unemployment. They observed that non-white groups in their study, who are in any employment, are more likely to work in the accommodation, information and communication, financial as well as administrative related industries.

However, since the usual locations of such organisations and jobs are in cities, where there are developed transport systems, a lot of African and Asian origins tend to hold low fleet of cars than holding large fleet of cars. This means as the non- white groups gain employment and start to earn incomes, they are more likely to cars. Whereas, Whites living in predominant-white living areas may not need to wait to start earning incomes before they start driving cars. Therefore, this study confirms the correlation between African origins in comparison to

whites and car ownership; specifically, suggesting disparity in ethnicity and the level of cars ownership in many developed countries.

6.4.4 Psychological factors

Model results show mental belief regarding the influence of car ownership on climate change to be insignificant on household number of car ownership in all the three-categories. However, when the significant level is raised to 10%, mental belief regarding the influence of car ownership on climate change is significant at two-car category and at three or more-car category. That is, after controlling for all other variables and after significant level is increased to 10%, the probability of households, who hold minimum mental belief that car impacts on climate change, but humans are not responsible of choosing two-car option as against one-car option is 27.3% more. Whereas, the probability of households with most absolute belief that car impacts on climate change and humans are responsible of choosing three or more-car option as against one-car option is 106.6% more.

Paradoxically, these two categories of households, who hold minimum belief or absolute belief do not prefer low fleet of cars, rather they prefer to hold either two cars or three or more cars as against one car. Furthermore, the relative probability of choosing three or more-car option as against one-car option is 106.6% more for households with most absolute belief that car impacts on climate change and humans are responsible. This suggests that psychological factors, particularly, mental believe in the relationship between car ownership and climate change might not make US household to hold small number of cars.

This results agree with postulations that attitudes towards private cars hold important determinants of car ownership and car use (Steg, 2005; Zhu et al., 2012; Belgiawan et al., 2016). Attitudes have been recognized as an important determinant of travel behaviour as well as other life choices. Thus, the results support conclusions of scholars, which observed that moral norms offered clear analysis of determinants underlying several pro-environmental behaviours, taking attitude, subjective norm and Perceived Behavioural Control (PBC) into consideration (Belgiawan et al, 2017). Moral norms make consumer to react differently under same conditions to same products at different times. As argued

in the literature that consumer behaviour will not always follow same pattern and hence, cannot be accurately predictable. That a buyer exhibited a pattern of behaviour under a certain condition does not mean he/she will exhibit similar pattern of behaviour under similar condition. For instance, in their study, which examined psychographic factors, such as purpose of car use, prepurchase information sources used, consumer's proneness towards buying an ecological car, consumer's involvement with cars, and consumer's attachment to cars, Baltas and Saridakis (2013) found most of the factors significant.

Generally, unlike conclusion reached by Baltas and Saridakis (2013), the findings of the psychological factor investigated in this study- that car impacts on climate change will not really affect the number of cars owned by US households. Though, there has been conclusion that human activities have started to impact, even changing the global environment (Barnosky et al., 2012; Pauliuk and Müller, 2014), results of this study show that there is no much evidence that confirms significance relationship between the mental believe in the relationship between car ownership and climate change; and the number of car ownership of the US households.

If people have mental belief that climate is changing and human activities are responsible, irrespective of the degree to which human are responsible and yet, people do not see reason why this belief should lead to holding low fleet of cars, then there is need for more awareness within the population on the significance and contribution of car use in climate change issue. In addition, to promote energy efficiency behaviours among households, the government need to take cognisance that any policy directed at influencing psychological disposition of car users, particularly, erratic psychological tendencies of consumers must be considered. Other car stakeholders can have other means of influencing car users.

6.4.5 Economic factors

As expected, the model results exhibited that household income has significant impact on number of car ownership in all the three categories. In other words, after controlling for all other variables investigated, households earning more income are more likely to choose owning cars than households, who are earning

less income. In addition, the relative probability of choosing no car option rather than one car alternative is 44.9 % less for households earning more income than for households without income or earning less. However, the relative probabilities of choosing two car option and three or more car option rather than preferring one car alternative are 48.0 % and 110.0 % more respectively for households with income than for households without income.

Similarly, holding other variables constant, the model results show that household earning power in term of the number of income earners in households was significant in two of the three categories relative to the base category. In other words, all else equal, it is found that the relative probability of choosing two car option rather than one car is 110.0% more for households with more members earning incomes than for households with small household members earning incomes. In addition, the relative probability of choosing two-car option rather than choosing one car option is 170.0% more for households with more members earning incomes than for households with small household members earning incomes.

Expectedly, the model results of the two economic factors examined were significant, an indication that household income and earning power in terms of number of earners in households are still relevant to the explanation of car ownership level. The empirical findings support the direct relationship between economic factors and the number of cars owned by households. Therefore, the reaction of household income and number of earners in households, when incorporated in an estimating model along with other non-economic factors still follow same pattern. As confirmed from the literature, economic factors and car ownership usually share direct relationship pattern for several years (Ewing et al. 2014; Anowar, et al., 2015; Oakil et al, 2016). For instance, individual household income grows; household members tend to travel more by private cars (Oakil et al, 2016).

Therefore, there is a direct relationship between income and the number of car. Nevertheless, it is of significance to note that there is asymmetrical income elasticity in terms of the degree of the consumers' responses. For instance, there is a relative probability of choosing no car option rather than one car of

44.9 % less for households with household income than for households without household income. Whereas, the relative probabilities of choosing two car option and three or more car option rather than preferring one car alternative are 48.0 % and 110.0 % more respectively for households with income than for households without income.

Hence, income levels might not directly lead to smaller numbers of cars owned by households, but all things being equal; higher income levels will have higher propensity for households to own large fleet of cars (See the propensity percentage of 48.0 % and 110.0 % of choosing two car option and three or more car option rather than choosing one car alternative). This is so since once a car has been bought; individuals become accustomed to car use and might not necessarily stop using a car even when his/her income drops. Thus, the disposal of a car is not easy when income falls (Dargay, 2001). The reason for this might not be unconnected to the reason provided in Anowar, et al. (2015), who noted observed that both medium and high income earners are negatively correlated with temporal flexibility, suggesting that household members belonging to these households are less expected to take part in planned or impulsive activities, apparently reflecting their time constraints due job commitment issues. So, premised on the findings from this study and literature, household income remains one of the most important variables that determine household car ownership (Dargay, 2002; Train, 2009; Ji et al, 2017) and same assertion can easily be put forward for number of earners in households. Therefore, research question 5 is hereby resolved.

6.5 RESULTS AND DISCUSSION OF DISCIPLINE BASED FACTORS

In this section, variables examined in the two countries, the UK and US were further analysed, highlighting the similarities and variations observed in the findings. Essentially, analysis in this section is based on the explanatory variables with significant results. The study used 11 to perform our statistical work. In this section, direct impacts estimate the effect of one variable on another without mediation. That is, direct effects connotes how the different discipline based variables directly affect the likelihood that a household chooses to hold or not hold a certain number of cars.

Considering the direct effects (Columns 4 and 7 of Table 6.5-1), it is observed that the direct effect of household income is essential within in both the UK and US; in that higher income households are less expected to be willingly live without car. This effect is larger in US RRR's impact ranged from -44.9% to 110% than in the UK RRR's impact ranged from -18.5% to 60%. However, Household structure of household indicates different pattern and mixed. While the Household structure is significant for the UK in all the three categories in relation to the base category, it is only significant in two categories (two-car and three or more car category in the car) in the case of US. In addition, the effect is larger for the UK than for US. The UK RRR impact ranged from 49.4% to 144.0%), whereas, the US RRR's impact ranged from 33.9% to 42.5%). Perhaps, this might be because US has more dependents; of which many of them are children. However, the children need various trips to attend various activities.

Table 6.5-1: Comparison of US and UK Results

	UK Results			US Results		
Number of Cars	**P>z**	**Relative Risk Ratios(RRR)**	**Impact of RRR on base category**	**P>z**	**Relative Risk Ratios(RRR)**	**Impact of RRR on base category**
NocarHH					**NocarHH**	
Driving Licence	0.000	0.005	-99.5%			
Household structure	0.000	0.506	-49.4%			
Accommodation Tenure:						
Ownerswithoutmortgage				1.396	0.018	39.6%
Shared Property /tenant	0.000	3.267	226.7%	2.352	0.000	135.2%
Others				3.614	0.000	261.4%
Household Income	0.000	0.8149071	-18.5%	0.551	0.000	-44.9%
Ethnic origins:						
African origin				1.814	0.000	81.4%
Asian origin				1.656	0.004	65.6%
OnecarHH (Base Outcome)		**OnecarHH (Base Outcome)**				
TwocarHH				**TwocarHH**		
Driving Licence	0.000	3.09789	210%			
Household structure	0.000	1.709567	71.0%	1.339	0.000	33.9%
Accommodation Tenure:						

Ownerswithoutmortgage				1.306	0.003	30.6%
Shared Property /tenant	0.000	0.3793475	-62.1%	0.440	0.000	-56.0%
Settlement nature:						
Village	0.009	1.489649	49.0%			
Geographical regions:						
West Midlands	0.032	1.85472	85.5%			
South East	0.012	1.936513	93.7%			
Household Income	0.000	1.326262	32.6%	1.480	0.000	48.0%
Earningpower				2.010	0.000	10.1%
Ethnic origins:						
African origin	0.054	0.3675768	-63.2%	0.667	0.001	-33.3%
Asian origin				0.717	0.038	
ThreeormorecarHH						
Driving Licence	0.000	9.612767	861.3%			
Household structure	0.000	2.439586	144.0%	1.425	0.000	42.5%
Accommodation Tenure:						
Ownerswithoutmortgage				1.294	0.007	29.4%
Shared Property /tenant	0.000	0.3069378	-69.3%	0.160	0.000	-84.0%
Others				0.472	0.052	-52.8%
Ethnicity						
Black				0.418	0.000	-58.2%
Asians				0.292	0.000	
Settlement nature:						
Village	0.000	3.049437	205.0%			
Mental belief:						
Minimum belief	0.042	2.038571	103.9%			
Household Income	0.000	1.600131	60.0%	2.083	0.000	108.3%
Earningpower				2.704	0.000	170.4%

Note: 5 percent parameter of significance was adopted in the table.

This finding supports the Kühne et al., (2018), who found similar pattern of the relationship in terms of car ownership and Household structure between Germany and California. Nevertheless, this result contradicts Kuhnimhof et al. (2012), who identified a reducing trend in car ownership within Millennials in Germany.

Based on the demographic variables investigated- households size and driving licences (Columns 4 and 7 of Table 6.5-1, the study observed that Household structure is important in both the UK and US; however, driving licence was only found significant in the UK. This suggests that ownership of driving licence in the US does not place higher impact on the US household car ownership as it does in the UK. Furthermore, results from the two countries suggest similar pattern of accommodation tenure for both the UK and the US. For instance, the RRR impact of accommodation is not only significant in all the three categories for the two study countries, the RRR statistic for both countries are close. In addition, the two countries have similar pattern of accommodation tenure. For instance, being in shared property or a tenant is significant for both the UK and US in all the three categories in relation to the base category.

In addition, the effect is larger for the UK than for US in the no-car category and two-car category, while the effect is larger for US in the three or more car category. The UK RRR impact were 226.7% and -62.1% for no-car category and two-car category, whereas, US had -84.0% for the three or more car category as against 69.3% for the UK for the same category. Such variable accommodation tenure could better be described as variable that brings indirect effect on car ownership (Kühne et al., 2018). The results of accommodation tenure confirm the presence of residential self-selection as the variable can be partly explained using socio-economic and demographic variables in both countries. First and foremost, as their income increases, both the UK and the US households are more likely to reside in locations with higher population and employment densities and hold large fleet of cars. In addition, having children as well as adults of any generation, or employed individuals is likely to make households hold large fleet of cars.

Furthermore, ethnicity of household suggests different patterns and similar relationship in both countries. For instance, Black and Asians are significant in all the three categories of the US African (Black) is only significant in the second category (two-car category) of the UK study in relation to the base category. In addition, the effect is both countries is similar for the UK and the US. The UK RRR impact (at two-car category) is 63.2%), whereas, US RRR impact for Blacks was 81.4%, -33.3% and -58.2% for no-car category, two-car category

and three or more car category respectively. In addition, US RRR impact for Asians was 65.6%, -28.3% and -70.8% for no-car category, two-car category and three or more car category respectively.

Thus, the results agree with Klein and Smart (2017), who found very meaningful changes between racial/ethnic groups and car ownership; suggesting that all non-white groups (investigated in their study) have considerably lower access to cars, and higher unemployment. Non-white groups are usually located in cities for obvious reasons- greener pasture, which is the main reason many of them have moved into these developed countries-US and the UK. Meanwhile, in cities, where they reside, they have access to developed transport systems and as soon as they get settled in employment and their earnings get stable, they can decide to relocate to places far away from access to developed transport system and start using cars for their movements. Thus, research question 6 is resolved.

6.6 ANALYSIS OF DIFFERENT HOUSEHOLDS AND RELATIONSHIP TO DIFFERENT NUMBER OF CAR CATEGORIES

In this section, significant variables were further analysed premised on different number of car categories and concomitant characteristics of households, who normally choose each car category. It is instructive to note that this analysis depict attributes associated to both the UK and the US.

6.6.1 Households that are likely to prefer no-car category (Category 1)

The likelihood of household members to prefer no-car category (Category 1) is higher for households, whose members are not earning incomes because they are not gainfully employed. This is reasonable as owning a car comes with costs. Similarly, and expectedly, there is a high propensity for households, who earn low annual incomes to stick to no-car category. After all, the bigger the household income (all things being equal), the higher the purchasing power, which in turn informs the capacity to purchase a car. Similarly, there is a propensity for households with small members to prefer no-car category as such households engage in less travelling. The propensity of households to prefer no-car category is higher when households' mental belief is not given to purchasing

products. In other words, such households are given to minimalism (i.e. not given to purchasing material things).

While the foregoing should be the expectation for households with the description given, there are emerging sociodemographic trends, which inform that even with employment, household members can still be without any car. For instance, 'Generation X' households, which depicts a description of individuals that were born from 1965 to 1980 (the age of this group would be 35 to 50 years old as of 2015) might not conform to the analysis given. This group in the population of the developed countries is relatively small, being of the Great Depression era. This group was rarely studied compared to the generation called, Millennials and always describe as a generation of transition.

Studies note that members of Generation X are less car dependent compared to their parents when they were in their ages (Kamga, 2015). This observation has been associated with the decline in car travel, suggesting declining attractiveness of cars among the young generation (e.g. Kuhnimhof et al., 2012a; Van der Waard et al, 2013; McDonald, 2015). Other factors identified for the Generation X is the adoption of information and communication technologies (ICTs) (Mans et al. 2012). It has been posited that, Generation X is the first generation that has more inclination for telecommuting as a potential car trip replacement (Mans et al., 2012). This is not impossible for the young adults living in modern cities with developed public transport system. Thus, scholars have established the role of young people's attitudes in contributing to changes in car ownership among different generations of people (Delbosc and Currie, 2013; McDonald, 2015; Zhou and Wang, 2019).

6.6.2 Households that are likely to prefer two-car category (Category 3)

The propensity of individuals to prefer two-car category (Category 3) is higher for households whose members earn higher incomes. This is reasonable since purchasing power is an important consideration for purchasing cars as well as maintaining their running costs. For instance, in both countries, the higher the number of cars a household owns, the higher the running costs it bears. In addition and expectedly, households with large members can require the use of more than one car in travelling around. This is likely to be the case if the

members of the households are gainfully employed; requiring movements to different places of work.

Furthermore, the willingness to prefer two-car category is higher for household members, who take pleasure in material possections based on their mental belief of material goods. Literature has various theories and conclusions on consumers' psychological perception and car ownership (Fujiwara and Nagasawa, 2015). Several social factors have been identified as what could make individuals hold such psychological perception (Miura, 2013). These include: Bandwagon effect, Snob effect, and Veblen effect, just to name a few. For instance, individuals who associate with hedonists given to car beauty could be caught up with Bandwagon effect.

6.6.3 Households that prefer three or more-car category (Category 4)

Like category 3, the propensity of household members to prefer three or more car category (Category 4) is higher for households whose members are gainfully employed and earn more annual incomes. This is reasonable since purchasing power is an important factor for maintaining large fleet of cars. Being employed suggests that household members have to travel to work, especially, if they work outside their homes. To own three or more cars implies that such household members can only reside in certain accommodation. It is definitely not convenient to have such members living in small terrace apartments as there will not be enough parking spaces to park such large number of cars. Thus, such household members might be found in manor houses or mansions. Again, this confirms that such households must have access to huge annual incomes as the higher the number of cars a household owns, the higher the running costs associated to it.

Similarly, such households should have big number of members, hence, the fleet of three or more cars available for the use of household members. In addition, the willingness to prefer three or more-car category is higher for household members, who desire to engage in material possessions based on their mental belief of material goods. It is important to note that such individuals can acquire cars for social pleasure other than for necessity purposes. Therefore, research question 4 is now resolved.

6.7 CONCLUSION

As in other developed countries, level of car ownership among US and the UK households is still rising as highlighted in the chapter 1 of this thesis. While so many factors have been identified as determinants of level of car ownership in households, discipline-base approaches have always dominated Scholars' analyses and this limits gaining holistic view of the subject matter. This analysis, using a MNL modelling approach, estimated the impact of discipline based factors, namely: ethnicity, mental belief on the relationship of car to climate change, accommodation tenure, Household structure, driving licence, number of household income earners and household income, on the number of cars owned in US households. The main objective of the chapter was to see whether by integrating different discipline based factors in a model to estimate number of in US households will provide more insight into car ownership decision making in US households.

Premised on the model results, it is confirmed that most of the factors investigated still possess huge influence on level of US car ownership. Thus, the analyses suggest great benefits to the US households. Furthermore, as proposed in this analysis, integration of discipline based modelling approach can help gain more insights into household car ownership decisions among US households and as such, similar non-economic factors should be encouraged in future car ownership investigations. As highlighted in this chapter, beyond the traditional economic factors that used to dominate car ownership investigation, non-economic factors hold major relevance to car ownership decisions among the US households and this further confirms why inclusion of the later should not be subjected to optional methodological approaches, but compulsory investigative tool if holistic perspectives of car ownership research are to be attained. This is valid for the two cases: the UK and the US. Thus, the research question 3 is hereby resolved.

Meanwhile, the analysis suggests different observations, which are of importance to transport policy decisions as well as car ownership research. First and foremost, findings establish that policies should be directed at demographical elements of US households towards effecting desirable level of

car ownership among people. For instance, based on this research finding, it is of interest to note that Household structure could exert more effect on a household car ownership level than effect of household income. For example, that a household start experiencing decline in its incomes does not mean that such a household will immediately respond by decreasing the level of its car ownership if the number of children and amount of associated journeys has not declined. This raises important reflection to general stakeholders. For instance, it might be more potent for policy makers to look beyond the traditional factors in gaining understanding of car ownership decisions in US households.

Secondly, findings of this investigation connotes a huge implication for future car ownership in households, depending on what target or objective stakeholders set out to achieve. In their work, Goodwin and Van Dender (2013) highlighted three situations, namely: temporary decline, fullness, and car peak that a country could go through in terms of car ownership. Their conclusion is that a country is likely to experience any of the three scenarios. Though, there is still a sustained growth in the trend of US car ownership (See the opening chapter), it is not yet known which of the three scenarios the US households are currently going through. However, US can successfully determine what will be the future of its car ownership through investigation that incorporates holistic perspectives in its methodological analysis. Current demographical trends expect a continued growth in singlehood and late marriages and voluntary bareness.

The demographical trends also suggest further delays in parenthood in youthful generations with accompanying low car ownership rate among the youths (Kuhnimhof et al., 2012). All of these have future potential implications on car ownership. Many of these youths live in cities, earn incomes and yet still choose to hold low level of car ownership, suggesting that only traditional factors like household incomes cannot explain car ownership in households. Hence, inclusive approach as adopted in this study is considered preferable.

CHAPTER 7

CONCLUSIONS, SUMMARY OF FINDINGS, IMPLICATIONS AND RECOMMENDATIONS AND FURTHER RESEARCH

7.0 Conclusions and finding summary

As investigation of car ownership determinants continues to attract scholars of diverse disciplines for its numerous relevance and benefits, this analysis has taken a novel approach to investigate the number of car ownership choices of UK and US households, using the two countries as representatives of developed nations. Drawing from data set gathered from two huge surveys of household consumers, the study makes case for a novel approach in the investigation of car ownership in households. Furthermore, apart from the determinants that have featured in car ownership literature, the novelty of this study is premised on the rarely-investigated determinants, which were examined. These factors include: accommodation tenure, settlement nature and mental belief. Other factors investigated include: ethnicity, geographical regions, household structure, driving licence, number of income earners and household income. Mapping out both the dependent and independent variables from the data sets, an integrated disaggregate, compensatory choice model for the number of cars ownership was developed to estimate the joint impact of different main determinants on the possibility of not owning a car, owning one car, owning two cars or choosing three or more cars.

Using two countries to represent developed countries, number of car ownership of UK and US households was examined. Statistics show that there is a growing trend of car ownership in both the two countries, which has been attributed to a number of different determinants across range of different disciplines. Scholars have also adopted different models to estimate impact of these determinants on car ownership.

The main objective of the thesis was to estimate the impact of various discipline based determinants of car ownership on the number of cars owned in UK and US households. Scholars' investigative approaches, as against the approaches proposed in this study have always been too focussed on each scholar's discipline area (e.g. Economics, Marketing, Sociology, Psychology etc.). Therefore, scholars tend to be restrictive in their investigations. This approach cuts across qualitative research, quantitative research and empirical work

among others. Thus, this restricted approach yields a limited understanding in consumer analysis. The thesis, in an attempt to bridge this gap proposed and adopted a multinomial logit model (MNL) approach in two substantive chapters; with each empirical chapter focussed on each country. The proposed MNL modelling approach was compared with the Nested logit model (NL) results using sets of data from British Household Survey and the US Consumer Expenditure Survey. Analysis was conducted in Stata version 11 applying survey commands to account for the complex sample design.

Using two countries to represent developed countries, number of car ownership of UK and US households was examined. Statistics show that there is a growing trend of car ownership in both the two countries, which has been attributed to a number of different determinants across range of different disciplines. Scholars have also adopted different models to estimate impact of these determinants on car ownership.

As models were integrated to produce a final model used in chapter 5 and chapter 6; representing four discipline areas namely: demographical area, psychological area, sociological area and economic area, it was confirmed that integration of these factors in a model is not only possible but also yielded avenue for gaining further understanding of household behaviours as well as differences characterised car ownership decision making in the two countries.

The findings show that UK and US households, regardless of their car ownership status, view large number of cars preferable to small number of cars in all respects. In addition, comparing the findings from the two countries, model consistency can be established as most of the discipline based variables follow similar pattern. Furthermore, it is confirmed that all the different discipline based factors investigated have strong influence on the number of car ownership in these countries. Thus, the study contributes towards the growing literature in the area of household's number of car ownership decisions through the analysis of discipline based determining factors, namely: demographical factors, sociological factors, psychological factors and economic factors. The four discipline based determining factors examined in this thesis are of benefit for policy decision making and urban transportation planning decision purposes.

The analysis results show that several individual and household socio-demographic features as embedded in different discipline based factors

influence the number of car ownership in individual households. For instance, it was observed that driving licence was significant in the UK model results, whereas, in US model results, it was not the case. Furthermore, the psychological factor like the mental belief investigated did not really impact on household decisions regarding the number of car ownership level. For example, findings reveal that households, in spite of their mental belief that human actions, including car ownership impact on climate change are still inclined to hold higher number of cars.

Generally, the findings offered opportunity to enrich the literature the area of modelling framework, particularly, in its choice of analytical modelling premised on choice of data, aims and objective of the study and relevant assumptions of the study. The proposed modelling approach can be adapted to further examine other rarely investigated determining factors to gain further understanding of car ownership decisions. Therefore, research question 6 is hereby resolved.

7.1 Implications and recommendations

Certainly, the research results as analysed under chapters 5 and 6 exhibited crucial and significant inferences for car ownership researchers, business sector (e.g. car producers), and household sector as well as the government agencies. First and foremost, the study offers fascinating insights on modelling approach suitable for integrating non-economic determinants and economic determinants in an investigation of car ownership research. For instance, the use of MNL model and NL model on same set of data and comparison of results of both methodologies, while juxtaposing what is revealed in the set of results with objectives of the study, researchers are able to choose the better method of investigation. As revealed in the chapter 4 of the thesis, both MNL and NL approaches have been found as the most suitable methodological approaches when static exogenous choice framework is assumed (See table 4.1-1 in chapter 4).

So, using the two approaches on the same database, it appears that MNL approach reveals more insights into car ownership determinants. This approach further buttresses scholars' argument that through estimation of model parameters at each household level, MNL modelling approach is able to attain a

higher level of statistical accuracy, with a host of variables, giving room for more detailed explanations of decision-making processes (Bhat and Guo, 2007; Potoglou and Susilo, 2008; Anowar et al., 2014).Thus, the study offers methodological contribution.

Furthermore, it is important to note that analysis and insights provided in this study is specifically helpful to car businesses. For instance, car company managers, in their bid to initiate attractive marketing mix and gain market hedge/ product positioning strategies premised on the household features/ profiles will find the study useful. For instance, based on study results, car businesses are better informed of the geographical locations of the country associated with likelihood of holding large fleet of cars. Results reveal that the West Midlands and the South East of the UK have preference to holding two cars as against one car. Similar results were found for households located in villages; found to prefer two cars and three or more cars as against one car alternative. It was also observed that households of African origin do prefer two cars than one car.

Similarly, African and Asians in the US also prefer higher level of cars. All of these suggest that car businesses could find these different groups of households as potential buyers that should be given more attention. The businesses might want to set up their car sale garages and showrooms locations in African origin mostly dominated areas. The car businesses might want to reach out to villages with attractive car deals.

In addition, empirical results and their analyses can be easily construed in a manner that is useful to government agencies; including transport department agencies of different levels of government. Good reflection of the association between determining factors such as, those investigated in this study and car-category selection constitutes a useful working tool to different stakeholders. These stakeholders include transport decision makers and city transportation planners, who make strategies, policies and plans in respect of car use /choice, environmental and energy use. For instance, it is observed that Household structure shares positive relationship with higher car category (i.e. the higher the Household structure, the higher the number of cars households is likely to have).

Similarly, it is observed that mental belief has positive relationship with higher car category (i.e. the more households give favourable mental disposition to car ownership, the higher number of cars the households are likely to have). Such revelation suggests households with favourable disposition for large fleet of cars or more cars may not be positively associated with desire to reduction of energy use in cars. Thus, the government might need to engage drastic policy option to dissuade such households in these categories in order to achieve desired energy efficiency.

In addition, the findings of the study indicated that households who earn more income have a positive relationship with higher car category (i.e. the higher the household members earn incomes, the higher the number of cars the households is likely to have). Such revelation suggests that households with more members working are possibly a good target for car promotions and adverts. Such class of households might also be the focus of government increased taxes in order to achieve less use of car towards energy efficiency or other government policies. Furthermore, car producers are forward-thinking, coming up with alternative energy-friendly cars of different models. These moves appear to support the development of small and energy-efficient cars by car producers. In addition, as innovative auto technologies are captivating across the vehicle industry around the globe, it appears that there is likely to be continuous growth in car ownership in spite of the global energy efficiency problem.

Based on the study results, ordinary punitive measures might not produce a necessary desire in terms of energy efficiency, but drastic actions/policies that result in lower number of cars used by UK and US households. Literature implies that car producers could demand price premium for their greener car models as tax rates are changing and growing car ownership in households (Hur et al., 2015). Case in point, Honda and Toyota have brought hybrid cars into the market.

Similarly, another example is the dual-fuel Fiat Panda designed to use both natural gas and petrol, thereby reducing CO2 emissions drastically up to a level of 42% when juxtapose to the normal standard Fiat Panda petrol car. In general,

an extensive research is on-going to provide different fuel technologies capable of offering energy efficiency, such as zero-emission electric cars (Steenberghen and López, 2008; Ziegler, 2012). However, the energy efficiency being gained through the technologies and eco-friendly vehicles is lost to increasing car ownership and population increase.

Therefore, this study offers basis for good reflection concerning policy options of UK and US household car ownership. The above impacts of the selected variables on the number of car owned could dictate the strategy and formulation of transport policies to influence households and their car use in a manner that limits the adverse implications of excessive car use, including traffic bottleneck, energy inefficiency and air contamination. Nevertheless, besides the individual results of this investigation, the overall supposition is that subsequent car modelling can be more interesting with the inclusion of variables like those considered in this study.

Moreover, it is believed that this study will encourage market researchers and economists to evolve car ownership estimating models that integrate objective factors and different discipline based factors, such as those analysed in this study. Such all-embracing forecasting models can offer new understanding into car ownership analysis and innovative approaches to model and explain car ownership relationships. The research question 2 is hereby resolved.

7.2 Limitations of the research

Like every other study, this study is not without its own drawbacks. First and foremost, the data sources used does not include any information that suggests that car holding by each household is premised on the car type. It is possible that the type of cars held by household determines how large or small the fleet of cars associated to the household. In their car investigation Bhat and Sen (2006) noted that households adjust to cost structures, socioeconomic dynamics and environmental influence, taking cognizant of their choices. Bhat and Sen (2006) opine that the types of vehicles selected by households are sometimes determined by the amount of miles the households expect the vehicles to be driven (Bhat and Sen, 2006). For instance, many households hold more than one car type; each for varied purposes. If the data used has been modelled to

reflect types of cars held, it would result in relaxing the restrictive assumptions of mutually exclusive alternatives, which is characteristic of multinomial discrete choice methods.

Secondly, this study focused on the investigation of both the UK and the US car sectors (the two countries are developed nations). It will be interesting and enriching if same proposed model is tested on other country representatives of developing nations. Meanwhile, in spite of the identified limitations, the study offer great benefits to different stakeholders and different purposes.

7.3 Future research

In view of the identified methodological limitations, many fascinating ideas could be considered in future studies in this area of research. For instance, as noted in chapter 4 of this thesis, there are two main types of disaggregate, compensatory choice models that have widely gained popularity in the literature as far as analysis of vehicle type choice decisions is concerned, these are: MNL and nested logit models. One idea is to create choice models with alternative functional forms and stochastic specifications that seek to avoid the restrictive IIA implications, which are features of the existing multinomial car type logit models. Another idea is to allow the restrictive IIA implications. Furthermore, it would be fascinating to reproduce this study to other continents and regions (e.g., Asia, Australia, etc.) and to find any variance among various cultural contexts embedded in different continents and countries. This study has demonstrated how the future number of cars choice models can become more powerful with the addition of discipline based determinants such as those investigated in this study. In spite of the highlighted limitations and gap for further future studies, this novel attempt in the area of number of car ownership modelling should be seen as a demonstration of the future work that may be developed with the appropriate motivation and innovation.

Since PEB like number of car ownership investigated in the present study had focus on individual household consumption behaviours within the private-sector (behaviours are examined at the level of households), it may be plausible that the factors not confirmed as having effects according to the hypothetical model (ethnicity, accommodation tenure, settlement nature, mental belief, geographical regions, household structure, driving licence, number of household income

earners and household income) are more important determinants of such behaviour are more related to individuals interests within a household.

An advantage of this study is that the sample adopted was representative as it was randomly drawn from the population survey, and not from a subset of the population survey, which is mostly the case in this type of research. Therefore, the sample adopted for this study will perhaps ensure an adequate variation in responses, which also contribute to a greater generality in reaching conclusions.

Future research in this area of study should therefore prefer investigating behaviour of each member of households as against individual households, which is the case in this study. This approach might present different pattern of outcomes in relation to some of the factors investigated in this study. For instance, investigation of psychological factors will probably offer different outcomes if individual members of households' responses are considered as against each household.

Like every study, this research is not without its drawbacks. First and foremost, since the research data were sourced from secondary sources; necessitating use of proxies in the proposed model, getting accurate proxies for some variables was challenging. This is more of the case for psychological variables. Precision of results could have been improved if access to actual data set for proxied variables was possible. Moreover, this study did not make use car data based on their years of acquisition or their acquisition history. Models that consider this will add insights to the findings in terms of car ownership decision in both countries. This could be incorporated in future study.

Furthermore, this study focused on car holding by households, in terms of number of cars a household has. It is possible to arrive at different number of cars in different households if actual cars in terms of models of cars are analyzed.

This study did not classify growth in household car ownership based on young and adult populations, however, if such classification has been adopted, it would have produced more insights to further enrich car ownership literature. So, future studies could focus on this area. In addition, as there are factors examined in this analysis, such as ethnicity and accommodation tenure that have link with urbanisation status of household location, future research could investigate the relationship between car ownership and urbanisation.

8.0 REFERENCES

Abrahamse, W., and Steg, L.(2013) Social influence approaches to encourage resource conservation: a meta-analysis. Global Environmental Change, 23, pp. 1773-1785.

Abrahamse, W., Steg, L., Gifford, R., and Vlek, C. (2009) Factors influencing car use for commuting and the intention to reduce it: a question of self-interest or morality? Transportation Research Part F, pp. 317-324

ACEA, (2008) acea (Association des Constructeurs Européens d'Automobiles - European Automobile Manufacturers Association) The Automobile Industry Pocket Guide acea, Brussels (2008)

Acheampong, R.A. and Cugurullo, F., (2019) Capturing the behavioural determinants behind the adoption of autonomous vehicles: Conceptual frameworks and measurement models to predict public transport, sharing and ownership trends of self-driving cars. Transportation research part F: traffic psychology and behaviour, 62, pp.349-375.

Adjemian, M.K., Lin, C.Y.C., Williams, J. (2010) Estimating spatial interdependence in automobile type choice with survey data. Transportation Research Part A: Policy and Practice, 44, 661–675.

Alem, Y., Beyene, A.D., Köhlin, G. and Mekonnen, A., (2016) Modeling household cooking fuel choice: A panel multinomial logit approach. Energy Economics, 59, pp.129-137.

Amemiya, Takeshi, (1985) Advanced Econometrics Harvard University,Press, Cambridge

Anowar, S., Eluru, N., and Miranda-Moreno, L. F., (2014) Alternative Modeling Approaches Used for Examining Automobile Ownership: A Comprehensive Review. Transport Reviews, (ahead-of-print), 1-33.

Anowar, S., Eluru, N., Miranda-Moreno, L.F. and Lee-Gosselin, M., (2015) Joint Econometric Analysis of Temporal and Spatial Flexibility of Activities, Vehicle Type Choice, and Primary Driver Selection. Transportation Research Record: Journal of the Transportation Research Board, (2495), pp.32-41.

Asplund, D. and Pyddoke, R., (2019) Optimal pricing of car use in a small city: a case study of Uppsala.

Axsen, J. and Kurani, K.S., (2012) Social influence, consumer behaviour, and low-carbon energy transitions. Annual Review of Environment and Resources, 37, pp.311-340.

Avineri, E. (2012) On the use and potential of behavioural economics from the perspective of transport and climate change. Journal of Transport Geography, 24, 512-521.

Bagozzi, R., Gurhan-Canli, Z. and Priester, J., (2002) The social psychology of consumer behaviour. McGraw-Hill Education (UK).

Bagozzi, R.P., (2017) Consumer action. *Review of Marketing Research: Volume 2*, p.1.

Baltas, G., and Saridakis, C. (2013) An empirical investigation of the impact of behavioural and psychographic consumer characteristics on car preferences: an integrated model of car type choice. Transportation Research Part A: Policy and Practice, 54, 92-110.

Bamberg, S. (2003) How does environmental concern influence specific environmentally related behaviours? A new answer to an old question, Journal of Environmental Psychology, 23, pp. 21-32.

Bamberg, S., and Möser, G. (2007) Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour. Journal of environmental psychology, 27(1),14-25.

Bamberg. S., S. Fujii, M. Friman and T. Gärling. (2010) Behaviour theory and soft transport policy measures, Transport Policy 18, 228-235.

Bamberg, S. and Schmidt, P.,(2003) Incentives, morality, or habit? Predicting students' car use for university routes with the models of Ajzen, Schwartz, and Triandis. Environment and behavior, 35(2), pp.264-285.

Bannock, G., Baxter, R. E., and Davis, E. (1998) The Penguin Dictionary of Economics. London, UK: Penguin.

Bardi, A., and Schwartz, S. H. (2003) Values and behaviour: strength and structure of relations. Personality and Social Psychology Bulletin, 29, pp. 1207-1220.

Barnosky, A.D., Hadly, E.A., Bascompte, J., Berlow, E.L., Brown, J.H., Fortelius, M., Getz, W.M., Harte, J., Hastings, A., Marquet, P.A., Martinez, N.D., Mooers, A., Roopnarine, P., Vermeij, G., Williams, J.W., Gillespie, R., Kitzes, J., Marshall, C., Matzke, N., Mindell, D.P., Revilla, E., Smith, A.B. (2012) Approaching a state shift in Earth's biosphere. Nature 486, 52–58.

Barten, A., (1966) "Theorie en emperie van een volledig stelsel van vraagvargelijkingen, Doctoral Dissertation, University of Rotterdam, Rotterdam.

Bates, J.J., Gunn, H., Roberts, M., (1978) A disaggregate model of car ownership. DOE/DTp Research Report Number 20 London, HMSO.

Batley, R.P., Toner, J.P. and Knight, M.J., (2004) A mixed logit model of UK household demand for alternative-fuel vehicles. International Journal of Transport Economics/Rivista internazionale di economia dei trasporti, pp.55-77.

Beck, M.J., Rose, J.M. and Hensher, D.A., (2013) Environmental attitudes and emissions charging: An example of policy implications for vehicle choice. Transportation Research Part A: Policy and Practice, 50, pp.171-182.

Belgiawan, P.F., Schmöcker, J.D. and Fujii, S., (2011) December. Psychological determinants for car ownership decisions. In Proceedings of the 16th International Conference of Hong Kong Society for Transportation Studies (HKSTS), Hong Kong (pp. 17-20).

Belgiawan, P., Schmocker, J.-D., Abou-Zeid, M., Walker, J., Lee, T.-C., Ettema, D., Fujii, S., (2014) Car ownership motivations among undergraduate students in China, Indonesia, Japan, Lebanon, Netherlands, Taiwan, and USA. Transportation 41, 1227–1244.

Belgiawan, P.F., Schmöcker, J.D., Abou-Zeid, M., Walker, J. and Fujii, S., (2017) Modelling social norms: Case study of students' car purchase intentions. Travel Behaviour and Society, 7, pp.12-25.

Belgiawan, P.F., Schmöcker, J.D., Fujii, S., (2016) Understanding car ownership motivations among Indonesian students. Int. J. Sustain. Transport. 10 (4), 295–307.

Ben-Akiva, M. E., and Lerman, S. R. (1985) Discrete choice analysis: theory and application to travel demand (Vol. 9). MIT press.

Bento, A., M. Cropper, M. Mobarak and K. Vinha (2005) "The Effects of Urban Spatial Structure on Travel Demand in the US," Review of Economics and Statistics 87:466-478.

Berkovec, J. and Rust, J., (1985) A nested logit model of automobile holdings for one vehicle households. Transportation Research Part B: Methodological, 19(4), pp.275-285.

Bhat, C. R. (2005) A multiple discrete–continuous extreme value model: formulation and application to discretionary time-use decisions. Transportation Research Part B: Methodological, 39(8), pp.679-707.

— (2008) The multiple discrete–continuous extreme value (MDCEV) model: role of utility function parameters, identification considerations, and model extensions Transportation Research Part B, 42 (3) (2008), pp. 274-303.

Bhat, C.R. and Guo, J.Y., (2007) A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels. Transportation Research Part B: Methodological, 41(5), pp.506-526.

Bhat C.R, and Koppelman FS (1993) An endogenous switching simultaneous equation system of employment, income, and car ownership. Transp. Res. A 27 (6), 447-459.

Bhat, C. R., and Pulugurta, V. (1998) A comparison of two alternative behavioral choice mechanisms for household auto ownership decisions. Transportation Research Part B: Methodological, 32(1), 61–75.

Bhat, C.R. and Sen, S., (2006) Household vehicle type holdings and usage: an application of the multiple discrete-continuous extreme value (MDCEV) model. Transportation Research Part B: Methodological, 40(1), pp.35-53

Bhat, C.R., Sen, S., Eluru, N., (2009) The impact of demographics, built environment attributes, vehicle characteristics, and gasoline prices on household vehicle holdings and use. Transportation Research Part B: Methodological 43, 1–18.

Blackorby, C. and Russell, R.R., (1989) Will the real elasticity of substitution please stand up? (A comparison of the Allen/Uzawa and Morishima elasticities) Am. Econ. Rev., 79, pp. 882-888.

Blumenberg, E. and Agrawal, A.W., (2014) Getting around when you're just getting by: Transportation survival strategies of the poor. Journal of Poverty, 18(4), pp.355-378.

Bohte, W., Maat, K., Van Wee, B., (2009) Measuring attitudes in research on residential self-selection and travel behaviour: a review of theories and empirical research. Transp. Rev. 29 (3), 325–357.

Bollen, K.A., (2002) Latent variables in psychology and the social sciences. Annual review of psychology, 53(1), pp.605-634.

Bowatte, G., Lodge, C.J., Knibbs, L.D., Lowe, A.J., Erbas, B., Dennekamp, M., Marks, G.B., Giles, G., Morrison, S., Thompson, B. and Thomas, P.S., (2017) Traffic-related air pollution exposure is associated with allergic sensitization, asthma, and poor lung function in middle age. Journal of Allergy and Clinical Immunology, 139(1), pp.122-129.

Brand, C., Anable, J. and Tran, M., (2013) Accelerating the transformation to a low carbon passenger transport system: The role of car purchase taxes, feebates, road taxes and scrappage incentives in the UK. Transportation Research Part A: Policy and Practice, 49, pp.132-148.

Brewer, Marilynn B. (1999) “The Psychology of Prejudice: Ingroup Love or Outgroup Hate?” Journal of Social Issues, 55 (3), 429–44.
British Social Attitudes (2016) NatCen Social Research, accessed 1 October 2016, https://www.bsa.natcen.ac.uk/media/39198/bsa34-questionnaire.pdf

Buehler, R., Pucher, J., Gerike, R. and Götschi, T., (2016) Reducing car dependence in the heart of Europe: lessons from Germany, Austria, and Switzerland. Transport Reviews, pp.1-25.

Bureau of Labour Statistics (2017) Consumer Expenditure Survey. Frequently Asked Questions (FAQs) https://www.bls.gov/cex/csxfaqs.htm(Accessed, 26/02/2017).

Bureau of Transportation Statistics (2014) U.S. Passenger-Miles (Millions)" US Department of Transportation.

Bray, J. (2008) Consumer Behaviour Theory: Approaches and Models”, available: http://eprints.bournemouth.ac.uk/10107/1/.

Brownstone, D., Bunch, D. S., and Train, K. (2000) Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transportation Research Part B: Methodological, 34(5), 315-338.

Brownstone, D. and Golob, T.F., (2009) The impact of residential density on vehicle usage and energy consumption. Journal of Urban Economics, 65(1), pp.91–98.

Cameron, A.C., Trivedi, P.K., (2005) Microeconometrics: Methods and Applications. Cambridge University Press, New York.

Campbell, C. (1991) Consumption: the new wave of research in the humanities and social sciences. Journal of Social Behaviour and Personality, 6(6), 57-74.

Cao, X.Y., Mokhtarian, P.L., Handy, S.L., (2006) Neighborhood design and vehicle type choice: evidence from Northern California. Transp. Res. D 11 (2), 113–145.

Cao, X.; Mokhtarian, P.L.; Handy, S.L. (2007) Cross-Sectional and Quasi-Panel explorations of the connection between the built environment and auto ownership. Environ. Plan, 39, 830–847.

Cao, X., (2015) Examining the impacts of neighborhood design and residential self-selection on active travel: a methodological assessment. Urban Geogr. 36
(2), 236–255. http://dx.doi.org/10.1080/02723638.2014.956420.

Cao, X.J., Xu, Z., Fan, Y., (2010) Exploring the connections among residential location, self-selection, and driving: propensity score matching with multiple treatments. Transport. Res. Part A: Policy Pract. 44 (10), 797–805.

Carlson, R.L., (1978) Seemingly unrelated regression and the demand for automobiles of different sizes, 1965-75: A disaggregate approach. Journal of Business, pp.243-262.

Caulfield, B., (2012) An examination of the factors that impact upon multiple vehicle ownership: The case of Dublin, Ireland. Transport Policy, 19(1), pp.132-138.

Caves, D.W., Christensen, L.R., (1980) Global properties of flexible functional forms. American Economic Review, 70, 422-432.

Ceder, A., Chowdhury, S., Taghipouran, N. and Olsen, J., (2013) Modelling public-transport users' behaviour at connection point. Transport Policy, 27, pp.112-122.

Central Statistics Office, (2020) Vehicle licensed for the first time. https://www.cso.ie/en/search/?addsearch=vehicles%20licensed%20for%20the%20first%20time%20january%20-december (Accessed, 23/12/2020).

Chatterton, T., Anable, J., Cairns, S. and Wilson, R.E., (2016) Financial implications of car use and the drive to work: A social and spatial distributional analysis using income data and area classifications.

Choo, S., and Mokhtarian, P. L. (2004) What type of vehicle do people drive? The role of attitude and lifestyle in influencing vehicle type choice. Transportation Research Part A: Policy and Practice, 38(3), 201-222.

Chowdhury, S. and Ceder, A.A., (2016). Users' willingness to ride an integrated public-transport service: A literature review. Transport Policy, 48, pp.183-195.

Circella, G., Alemi, F., Berliner, R., Tiedeman, K., Lee, Y., Fulton, L., Handy, S. and Mokhtarian, P.L., (2017) The Multimodal Behavior of Millennials: Exploring
245
Differences in Travel Choices between 1 Young Adults and Gen Xers in California 2 (No. 17-06827).

Citroën, A., (1929) L'avenir de la construction automobile. Revue politique et parlementaire, 10, p.232.

Collantes, G. O., and Mokhtarian, P. L. (2007) Subjective assessments of personal mobility: What makes the difference between a little and a lot? Transport Policy, 14(3), 181192.

Christensen, L.R., Jorgenson, D.W. and Lau, L.J., (1975) Transcendental logarithmic utility functions. The American Economic Review, 65(3), pp.367-383.

Chu, Y.-L., (2002) Automobile ownership analysis using ordered probit models Transportation Research Record 1805, 60–67.

Clark, S., (2007) Estimating local car ownership models. J. Transport Geogr. 15 (3), 184–197. Clark, S., 2009. Charactering and predicting car ownership using rough sets. Transport. Res. Part C: Emerg. Technol. 17 (4), 381–393.

Clark, B., (2009) Charactering and predicting car ownership using rough sets. Transport. Res. Part C: Emerg. Technol. 17 (4), 381–393.

Clark, B., (2012) Understanding how household car ownership changes over time (Doctoral dissertation, University of the West of England).

Clark, B., Lyons, G. and Chatterjee, K., (2016) Understanding the process that gives rise to household car ownership level changes. Journal of Transport Geography, 55, pp.110-120.

Clark, B., Chatterjee, K. and Melia, S., (2016) Changes in level of household car ownership: the role of life events and spatial context. Transportation, 43(4), pp.565-599.

Coad, A., de Haan, P., Woersdorfer, J., (2009) Consumer support for environmental policies:an application to purchases of green cars. Ecological Economics 68, 2078–2086.

Coelho, V.N., Coelho, I.M., Coelho, B.N., de Oliveira, G.C., Barbosa, A.C., Pereira, L., de Freitas, A., Santos, H.G., Ochi, L.S. and Guimarães, F.G., (2017) A communitarian microgrid storage planning system inside the scope of a smart city. Applied Energy, 201, pp.371-381.

Consumer Expenditure Survey, Diary Survey (2017) U.S Department of Labour, Bureau of Labour Statistics.

Countryeconomy.com(2020) United States - New motor vehicle registrations. https://countryeconomy.com/business/car-registrations/usa(Accessed, 26/08/2020).

Crano, W.D., Brewer, M.B. and Lac, A., (2014) Principles and methods of social research. Routledge.

Dargay, J., (2001) The effect of income on car ownership: evidence of asymmetry Transpo. Res. A – Pol., 35, pp. 807-821.

—. (2002) Determinants of car ownership in rural and urban areas: a pseudo-panel analysis Transp. Res. E – Log., 38 (2002), pp. 351-366

Dargay, J., Gately, D., (1999) Income's effect on car and vehicle ownership, worldwide: 1960–2015. Transport. Res. Part A: Policy Pract. 33 (2), 101–138.

Dargay, J., Gately, D. and Sommer, M., (2007) Vehicle ownership and income growth, worldwide: 1960-2030. The Energy Journal, pp.143-170.

Dargay, J.M. and Vythoulkas, P.C., (1999). Estimation of a dynamic car ownership model: a pseudo-panel approach. Journal of Transport Economics and Policy, pp.287-301.

Davis, S.C., Diegel, S.W. ,Boundy, R.G. (2013) Transportation Energy Data Book (32nd ed.)Oak Ridge National Laboratory, Oak Ridge.

Davis, G. C., and Gauger, J. (1996) Measuring substitution in monetary-asset demand systems. Journal of Business and Economic Statistics, 14(2), 203–208

Deaton, A. and Muellbauer, J., (1980) An almost ideal demand system. The American economic review, 70(3), pp.312-326.

Deaton, A., (1986) Life-cycle models of consumption: Is the evidence consistent with the theory?.

De Groote, J., Van Ommeren, J. and Koster, H.R., (2016) Car ownership and residential parking subsidies: Evidence from Amsterdam. Economics of Transportation, 6, pp.25-37.

De Jong (1990) An indirect utility model of car ownership and private care use. European Economic Review, 34, 971-985.

De Jong (1996) A disaggregate model system of vehicle holding duration, type choice and use Transportation Research Part B: Methodological, 30 (4), pp. 263-276

De Jong, G., Fox, J., Pieters, M., Daly, A.J., Smit, R., (2004) Comparison of car Ownership models. Transport Rev. 24 (4), 379–408.

Delbosc, A., Currie, G., (2013) Causes of youth licensing decline: a synthesis of evidence. Transp. Rev. 33 (3), 271–290.

Deshmukh, S.A., (2018) Impact of ride-sharing on mobility trends and vehicle stock (Doctoral dissertation, Massachusetts Institute of Technology).

De Vries, P., Aarts, H., and Midden, C. J. H. (2011) Changing simple energy-related consumer behaviors: How the enactment of intention is thwarted by acting and non-acting habits. Environment and Behavior, 43, 612-633.

Ding, C., Wang, D., Liu, C., Zhang, Y. and Yang, J., (2017) Exploring the influence of built environment on travel mode choice considering the mediating effects of car ownership and travel distance. Transportation Research Part A: Policy and Practice, 100, pp.65-80.

Diewert, W.E., (1974) Applications of duality theory. In: Intriligator, M., Kendrick, D. (Eds.), Frontiers in Quantitative Economics, vol. 2. North-Holland, Amsterdam.

Dissanayake, D., Kurauchi, S., Morikawa, T. and Ohashi, S., (2012) Inter-regional and inter-temporal analysis of travel behaviour for Asian metropolitan cities: Case studies of Bangkok, Kuala Lumpur, Manila, and Nagoya. Transport Policy, 19(1), pp.36-46.

Donald, I., and Cooper, S. R. (2001) A facet approach to extending the normative component of the theory of reasoned action. British Journal of Social Psychology, 40, 599-621.

Duncan, M., (2016) How much can trip chaining reduce VMT? A simplified method. Transportation, 43(4), pp.643-659.

Dunlap, R. E., and Van Liere, K. D. (1978) The new environmental paradigm: A proposed measuring instrument and preliminary results. Journal of Environmental Education, 9, pp. 10-19.

Egbue, O. and Long, S., (2012) Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. Energy policy, 48, pp.717-729.

Ekebas-Turedi, C., Cilingir Uk, Z., Basfirinci, C. and Pinar, M., (2020) A Cross-Cultural Analysis of Gender-Based Food Stereotypes and Consumption Intentions among Millennial Consumers. *Journal of International Consumer Marketing*, pp.1-17.

Eluru, N. and Bhat, C.R., (2007) A joint econometric analysis of seat belt use and crash-related injury severity. Accident Analysis and Prevention, 39(5), pp.1037-1049.

Eluru, N., Bhat, C.R., Pendyala, R.M. and Konduri, K.C., (2010) A joint flexible econometric model system of household residential location and vehicle fleet composition/usage choices. Transportation, 37(4), pp.603-626.

Eriksson, L., Nordlund, A.M. and Garvill, J., (2010) Expected car use reduction in response to structural travel demand management measures. Transportation research part F: traffic psychology and behaviour, 13(5), pp.329-342.

European Automobile Manufacturer's Association (ACEA) (2012) "Electric vehicles: turning buzz into reality", available at: www.acea.be/news/news_detail/electric_vehicles_turning_buzz_into_reality/ (21Agustus 2016).

Ewing, R., Meakins, G., Hamidi, S. and Nelson, A.C., (2014) Relationship between urban sprawl and physical activity, obesity, and morbidity–update and refinement. Health & place, 26, pp.118-126.

Fang, H.A., (2008) A discrete–continuous model of households' vehicle choice and usage, with an application to the effects of residential density. Transportation Research Part B: Methodological, 42, 736–758.

Fang, X., Xu, Y., and Chen, W. (2014) Understanding attitudes towards pro-environmental travel: an empirical study from tangshan city in China. Computational intelligence and neuroscience.

Federal Highway Administration (FHWA), Highway Statistics (2012) Highway Finance Data Collection https://www.fhwa.dot.gov/policyinformation/statistics/2012/ (21August, 2017).

Federal Highway Administration (FHWA), Highway Statistics (2017) Highway Finance Data Collection https://www.fhwa.dot.gov/policyinformation/pubs/hf/pl11028/chapter4.cfm (21August, 2017).

Flamm, B., (2009) The impacts of environmental knowledge and attitudes on vehicle ownership and use. Transportation research part D: transport and environment, 14(4), pp.272-279.

Fox, J., Patruni, B., Daly, A. and Lu, H., (2017) Estimation of the National Car Ownership Model for Great Britain.

Fujiwara, K. and Nagasawa, S.Y., (2015) Analysis of psychological factors that influence preference for luxury food and car brands targeting Japanese people. American Journal of Industrial and Business Management, 5(09), p.590.

Gärling, T., Fujii, S., Gärling, A., and Jakobsson, C. (2003) Moderating effects of social value orientation on determinants of pro-environmental behaviour intention. Journal of Environmental Psychology, 23, pp. 1-9.

Gatersleben, B., (2011) The car as a material possection: Exploring the link between materialism and car ownership and use. In Auto motives: Understanding car use behaviours (pp. 137-148). Emerald Group Publishing Limited.

Gautier, P.A. and Zenou, Y., (2010) Car ownership and the labor market of ethnic minorities. Journal of Urban Economics, 67(3), pp.392-403.

Gardner, B., and Abraham, C. (2010) Going Green? Modelling the impact of environmental concerns and perceptions of transportation alternatives on decisions to drive. Journal of Applied Social Psychology, 40, 831-849.

Gardner, G. T., and Stern, P. C. (2008)The short list: the most effective actions U.S. households can take to curb climate change. Environment, 50, pp. 12-25.

Gifford, R. (2014) Environmental psychology matters. Annual Review of Psychology, 65, pp. 541-579.

Gilbert, C. C., (1992) A duration model of automobile ownership. Transportation Research Part B: Methodological, 26(2), 97-114.

Gillingham, K., Newell, R.G. and Palmer, K., (2009) Energy efficiency economics and policy. Annu. Rev. Resour. Econ., 1(1), pp.597-620.

Giuliano, C, Dargay, J. ,(2006) Car ownership, travel and land use: a comparison of the US and Great Britain. Transportation Research Part A, 40, 106-124.

Goldman, L., Giles, H. and Hogg, M.A., (2014) Going to extremes: Social identity and communication processes associated with gang membership. Group Processes & Intergroup Relations, 17(6), pp.813-832.

Golob, T.F (1990) The dynamics of household travel time expenditures and car ownership decisions. Transp. Res. Part A Gen. 24, 443–463.

Golob, T.F., (1996) A Model of Household Demand for Activity Participation and Mobility. Institute of Transportation Studies, University of California, Irvine,
Irvine, CA.

Golob, T.F. and Burns, L.D., (1978) Effects of transportation service on automobile ownership in an urban area. Transportation Research Record, 673, pp.137-145.

Golob, T.F., Bunch, D.S. and Brownstone, D. (1997) 'A vehicle use forecasting model based on revealed and stated vehicle type choice and utilization data', Journal of Transport Economics and Policy 31(1), pp. 69–92

Goodwin, P., Van Dender, K. (2013) 'Peak Car'—Themes and Issues. Transp. Rev. 33, 243-254.

Gorman, W. (1980) “A Possible Procedure for Analyzing Quality Differentials in the Egg Market.” Review of Economic Studies 47(5), 843-856.

Greene, D.L., Chin, S.-M. and Gibson, R., (1995) Aggregate vehicle travel forecasting model, Oak Ridge National Lab., TN (United States).

Greenman, J.V., (1996) The car park: diffusion models revisited. Energy Economics, 18(1), pp.107-128.

Greene, W.H., (2012) Econometric Analysis: International Edition (7th Edition). New York:Pearson Education.

Gruenspecht, H.K., (1982) Differentiated regulation: The case of auto emissions standards. The American Economic Review, 72(2), pp.328-331.

Guerra, E., (2014) The built environment and car use in Mexico City: is the relationship changing over time? J. Plan. Educ. Res. 34, 394–408.
Guerra, E., (2015) The geography of car ownership in Mexico City: a joint model of households’ residential location and car ownership decisions. Journal of Transport Geography, 43, pp.171-180.

Guo, J.Y.; Bhat, C.R.(2007) Operationalizing the concept of neighborhood: Application to residential location choice analysis. J. Transp. Geogr, 15, 31–45.

Guo, Z., (2013) Residential street parking and car ownership: a study of households with off-street parking in the New York City region. Journal of the American Planning Association, 79(1), pp.32-48.

Habitat, U.N., (2013) State of the world's cities 2012/2013: Prosperity of cities. Routledge.

Halonen, J.I., Hansell, A.L., Gulliver, J., Morley, D., Blangiardo, M., Fecht, D., Toledano, M.B., Beevers, S.D., Anderson, H.R., Kelly, F.J. and Tonne, C., (2015) Road traffic noise is associated with increased cardiovascular morbidity and mortality and all-cause mortality in London. European heart journal, 36(39), pp.2653-2661.

Hanly M., Dargay J. (2000) Car ownership in Great Britain: Panel data analysis Transportation Research Record: Journal of the Transportation Research Board (1718) pp. 83-89

Hansen, J. and Sato, M., (2016) Regional climate change and national responsibilities. Environmental Research Letters, 11(3).

Hansla, A., Gamble, A., Juliusson, A. and Gärling, T. (2008a) The relationships between awareness of consequences, environmental concern, and value orientations. Journal of Environmental Psychology, 28, pp. 1-9.

Haque, M.B., Choudhury, C., Hess, S. and dit Sourd, R.C., (2019) Modelling residential mobility decision and its impact on car ownership and travel mode. Travel behaviour and society, 17, pp.104-119.

Haugtvedt, C.P., Herr, P. and Kardes, F. eds., (2012) Handbook of consumer psychology. Psychology Press.

Heiss, F. (2002) Structural choice analysis with nested logit models. Stata Journal 2: 227–252.

Hensher, D. A., J. M. Rose, and W. H. Greene. (2005) Applied Choice Analysis: A Primer. New York: Cambridge University Press.

Hess, D.B. and Ong, P.M. (2002) Traditional Neighborhoods and Automobile Ownership, Transportation Research Record 1805, pp. 35-44.

Hess, M. and Yeung, H.W.C., (2006) Whither global production networks in economic geography? Past, present, and future.

Hindess, B., (2014) Choice, Rationality and Social Theory (RLE Social Theory). Routledge.

Holtzclaw, J., Clear, R., Dittmar, H., Goldstein, D. and Haas, P., (2002) Location efficiency: Neighborhood and socioeconomic characteristics determine auto ownership and use-studies in Chicago, Los Angeles and San Francisco. Transportation planning and technology, 25(1), pp.1-27.

Hocherman, I., Prashker, J.N. and Ben-Akiva, M., (1983) Estimation and use of dynamic transaction models of automobile ownership (No. 944).

Hogg, M. A. (2006) “Social Identity Theory,” in Contemporary Social Psychological Theories, Peter J. Burke, ed. Stanford, CA: Stanford University Press, 111–36.

Honkanen, P., and Verplanken, B. (2004) Understanding attitudes towards genetically modified food.: the role of values and attitude strength. Journal of Consumer Policy, 27, (4), pp. 401-420.

Hopkins, D., and Stephenso, J. (2016) The replication and reduction of automobility: Findings from Aotearoa New Zealand, Volume 56, pages 92-101. doi:https://doi.org/10.1016/j.jtrangeo.2016.09.005

Hidrue MK, Parsons GR, Kempton W, Gardner MP. (2011) Willingness to pay for electric vehicles and their attributes. Resour. Energy Econ. 33:686–705.

Hur, W.M., Woo, J. and Kim, Y., (2015). The role of consumer values and socio-demographics in green product satisfaction: The case of hybrid cars. Psychological reports, 117(2), pp.406-427.

Hurwicz, L., Uzawa, H., (1971) On the integrability of demand functions. In: Chipman, J., Hurwicz, L., Richter, M., Sonnenschein, H. (Eds.), Preferences, Utility, and Demand. Harcourt Brace, Jovanovich, New York.

Jevons, W.S. (1970) Theory of utility. In R.D. Collison Clark (Ed.), The theory of political economy (p.102). Harmondsworth: Penguine Books.

Jiang, S., Scott, N. and Ding, P., (2015) Using means-end chain theory to explore travel motivation: An examination of Chinese outbound tourists. Journal of vacation marketing,21(1), pp.87-100.

Joost, S., Michael Kalbermatten (2010) EPFL-ENAC-LASIG, March 2010.

Joseph, O.O., Eromietse, E.J., Emmanuel, D.S. and Olufunke, A., (2017) Multinomial Logit Model Estimation of Household Characteristics Influencing Car Ownership in Akure, South West, Nigeria. International Journal for Traffic & Transport Engineering, 7(2), pp.203-215.

Jansson, J., Marell, A. and Nordlund, A., (2010) Green consumer behaviour: determinants of curtailment and eco-innovation adoption. Journal of consumer marketing, 27(4), pp.358-370.

Jansson, J., Pettersson, T., Mannberg, A., Brännlund, R. and Lindgren, U., (2017) Adoption of alternative fuel vehicles: Influence from neighbors, family and coworkers. Transportation Research Part D: Transport and Environment, 54, pp.61-73.

Jong, G. D., Fox, J., Daly, A., Pieters, M., and Smit, R. (2004) Comparison of car ownership models. Transport Reviews, 24(4), 379-408.

Kahneman, D. and Tversky, A., (2013) Prospect theory: An analysis of decision under risk. In HANDBOOK OF THE FUNDAMENTALS OF FINANCIAL DECISION MAKING: Part I(pp. 99-127).

Kaiser, F.G. and Byrka, K., (2011) Environmentalism as a trait: Gauging people's prosocial personality in terms of environmental engagement. International Journal of Psychology, 46(1), pp.71-79.

Kamga, C., (2015) Emerging travel trends, high-speed rail, and the public reinvention of U.S. transportation. Transport Policy, 37, pp.111–120.

Keller, R. and Vance, C., (2013) Landscape pattern and car use: Linking household data with satellite imagery. Journal of Transport Geography, 33, pp.250-257.

Kim, H.S., Kim, E., (2004) Effect of public transit on automobile ownership and use in households of the USA. Review of Urban and Regional Development Studies 16 (3), 245–262.

Karlaftis, M. and Golias, J., (2002) Automobile ownership, households without automobiles, and urban traffic parameters: are they related?. Transportation Research Record: Journal of the Transportation Research Board, (1792), pp.29-35.

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M. and Erenstein, O., (2015) Production risks and food security under alternative technology choices in Malawi: Application of a multinomial endogenous switching regression. Journal of Agricultural Economics, 66(3), pp.640-659.

Kermanshah, M. and Ghazi, F., (2001) Modeling automobile ownership decisions: A disaggregate approach.

Khasnis, A.A. and Nettleman, M.D.,(2005) Global warming and infectious disease. Archives of medical research, 36(6), pp.689-696.

Kitamura, R., (1983) Serve passenger trips as a determinant of travel behaviour. Recent Advances in Travel Demand. Gower, Aldershot, UK.

Kitamura, R., (2009) The effects of added transportation capacity on travel: a review of theoretical and empirical results Transportation, 36, pp. 745-762

Kitamura, R., Golob, T. F., Yamamoto, T., and Wu, G. (1999) Accessibility and auto use in a motorized metropolis. Center for Activity Systems Analysis.

Kitamura, R., Golob, T.F., Yamamoto, T., Wu, G. (2000) Accessibility and auto use in a motorized metropolis. Paper presented at the 79th Transportation Research Board Annual Meeting, Washington, DC.

Kitamura R and Bunch DS (1990) Heterogeneity and state dependence in household car ownership: A panel analysis using ordered-response probit models with error components. In: Koshi M (ed.)Transportation and Traffic Theory (pp. 477–496). Amsterdam, The Netherlands: Elsevier Science Publishers, B.V.

Klein, N.J. and Smart, M.J., (2017) Millennials and car ownership: Less money, fewer cars. Transport Policy, 53, pp.20-29.

Koppelman, F.S., Sethi, V., (2008) Closed-form discrete choice models. In: Hensher, D.A., Button, K.J. (Eds), Handbook of Transport Modelling, 2nd edition. Ch. 13, 211-225, Elsevier Science.

Kotler, P. and Armstrong, G., (2008) Principiile marketingului, Teora Publishing House, Bucharest

Kotz, S., and S. Nadarajah. (2000). Extreme Value Distributions: Theory and Applications. London: Imperial College Press.

Kühne, K., Mitra, S.K. and Saphores, J.D.M., (2018) Without a ride in car country a comparison of carless households in Germany and California. Transportation research part A: policy and practice, 109, pp.24-40.

Kuhnimhof, T., Buehler, R., Dargay, J., (2011) A new generation: Travel Trends among Young Germansand Britons. Transport. Res. Rec. 2230, 58-67.

Kuhnimhof, T., Armoogum, J., Buehler, R., Dargay, J., Denstadli, J. M., and Yamamoto, T. (2012) Men shape downward trend in car use among young adults — Evidence from six industrialised countries. Transport Reviews, 32(6), 761–780.

Lancaster, K.J., (1966) A new approach to consumer theory. Journal of political economy, 74(2), pp.132-157.

Lane, B. and Potter, S., (2007) The adoption of cleaner vehicles in the UK: exploring the consumer attitude–action gap. Journal of cleaner production, 15(11-12), pp.1085-1092.

Lave, C.A. and Train, K.E., (1979) A disaggregate model of auto-type choice. Transportation Research Part A: Policy and Practice, Vol. 13, pp. 1-9.

Lerman, S.,and M. E. Ben-Akiva. (1976) A Behavioral Analysis of Automobile Ownership and Mode of Travel, Vol. 2. Technical Summary. U.S. Department of Transportation Washington, D.C.

Liao, F., Molin, E., Timmermans, H. and van Wee, B., (2020) Carsharing: the impact of system characteristics on its potential to replace private car trips and reduce car ownership. Transportation, 47(2), pp.935-970.

Lin, T., Wang, D., Guan, X., (2017) The built environment, travel attitude, and travel behaviour: residential self-selection or residential determination? J. Transp. Geogr. 65, 111–122.

Lin, B. and Wu, W., (2018) Why people want to buy electric vehicle: An empirical study in first-tier cities of China. Energy Policy, 112, pp.233-241.

Lisciandra, C.,(2018) The role of psychology in behavioral economics: The case of social preferences. Studies in History and Philosophy of Science Part A, 72, pp.11-21.

Liu, T., Ceder, A., Bologna, R. and Cabantous, B., (2016) Commuting by customized bus: a comparative analysis with private car and conventional public transport in two cities. Journal of Public Transportation, 19(2), p.4.

Liu, Y. and Cirillo, C., (2016) Small area estimation of vehicle ownership and use. Transportation research part D: transport and environment, 47, pp.136-148.

Luce, R. D. (1959) Individual choice behavior: A theoretical analysis. New York: Wiley.

Louviere, J.J., Hensher, D.A. and Swait, J.D., (2000) Stated choice methods: analysis and applications. Cambridge university press.

Ma, L. and Srinivasan, S., (2010) Impact of individuals' immigrant status on household auto ownership. Transportation research record, 2156(1), pp.36-46.

Macfarlane, G.S., Garrow, L.A. and Mokhtarian, P.L., (2015) The influences of past and present residential locations on vehicle ownership decisions. Transportation research part A: policy and practice, 74, pp.186-200.

Maddala, G.S., (1983) Limited-dependent and qualitative variables in econometrics (No. 3). Cambridge university press.

Manfredo, M.J., Teel, T.L. and Dietsch, A.M., (2016) Implications of human value shift and persistence for biodiversity conservation. Conservation Biology, 30(2), pp.287-296.

Mankiw, N.G., (2014) Principles of macroeconomics. Cengage Learning.

Mannering, F. and Mahmassani, H., (1985) Consumer valuation of foreign and domestic vehicle attributes: econometric analysis and implications for auto demand. Transportation Research Part A: General, 19(3), pp.243-251.

Mannering, F. and Winston, C., (1985) A dynamic empirical analysis of household vehicle ownership and utilization. The RAND Journal of Economics, pp.215-236.

—. (1991) Brand Loyalty and the Decline of American Automobile Firms, Brookings Papers on Economic Activity, Microeconomics, pp. 67–114.

Mannering, F., Winston, C., Starkey, W., (2002) An exploratory analysis of automobile leasing by US households. Journal of Urban Economics 52, 154–176.

Mans, J., Interrante, E., Lem, L., Mueller, J. and Lawrence, M., (2012) Next generation of travel behavior: potential impacts related to household use of information and communication technology. Transportation Research Record: Journal of the Transportation Research Board, (2323), pp.90-98.

Manski, C. F., and Sherman, L. (1980) An empirical analysis of household choice among motor vehicles. Transportation Research Part A: General, 14(5), 349-366.

Manting, D., (2014) Ruimtelijk beleid kan niet zonder demografische analyse.

Maslow, A.H., (1970) Religious Aspects of peak-experiences.

Maslow, A.H. (1999). Towards a Psychology of Being. (3rd ed.). New York, NY: John Wiley & Sons.

McCarthy, P.S., (2005) Alcohol, Public Policy, and Highway Crashes: A Time–series Analysis of Older–driver Safety. Journal of Transport Economics and Policy (JTEP), 39(1), pp.109-126.

McCarthy, P.S. and Tay, R.S., (1998) New vehicle consumption and fuel efficiency: a nested logit approach. Transportation Research E, Vol. 34 No. 1, pp. 39-51.

McDonald, N.C., (2015) Are Millennials Really the “Go-Nowhere” Generation? Journal of the American Planning Association, pp.1–14.

McFadden, D., (1974) The measurement of urban travel demand. Journal of public economics, 3(4), pp.303-328.

McFadden, D., (1981) Econometric models of probabilistic choice. Structural analysis of discrete data with econometric applications, 198272.

McFadden, D.L., (1984) Econometric analysis of qualitative response models. Handbook of econometrics, 2, pp.1395-1457.

McFadden, D. (2000) Disaggregate behavioural travel demand’s RUM side. Travel Behaviour Research, 17-63.

Mehta, N. and Chugan, P.K., (2019) Visual Merchandising and Consumer Demography: The Impact on Impulse Buying Behavior. Business, Economy and Environment: Corporate Perspectives”, Eds. Parag Rijwani, Samik Shome and Deepak Danak, Himalaya Publishing House, Mumbai for Institute of Management, Nirma University, Ahmedabad, pp.253-268.

Miller, E.J., Kriger, D.S. and Hunt, J.D., (1999) Integrated urban models for simulation of transit and land use policies: guidelines for implementation and use (Vol. 50). Transportation Research Board.

Miura, T. (2013) Are Japanese Consumers Tough Consumers? Their Cultural and Modernistic Attributes and Marketing Strategy. Yuhikaku, Tokyo, 43-69.

Moeckel, R. and Yang, D., (2016) Car ownership and the impact of built environment, demographics and transport systems. Journal of Civil Engineering and Architecture, 10(5), pp.587-595

Mohammadian, A. and Miller, E., (2002) Nested logit models and artificial neural networks for predicting household automobile choices: comparison of performance. Transportation Research Record: Journal of the Transportation Research Board, (1807), pp.92-100.

Mohammadian, A., and E. J. Miller, (2003a) An Empirical Investigation of Household Vehicle Type Choice Decisions. Transportation Research Record, 1854: 99-106.

Mohammadian, A., and E. J. Miller, (2003b) Dynamic Modeling of Household Automobile Transactions. Transportation Research Record, 1831: 98-105.

Mohammadian, A. and Rashidi, T., (2007) Modeling household vehicle transaction behavior, competing risk duration approach. Transportation Research Record: Journal of the Transportation Research Board, (2014), pp.9-16.

Mogridge, M.J., (1989) The prediction of car ownership and use revisited: the beginning of the end?. Journal of Transport Economics and Policy, pp.55-74.

Moore, Henry Ludwell. (1914) Economic Cycles: Their Law and Cause. New York: Macmillan.

Morikawa, T., Ben-Akiva, M. and McFadden, D., 2002. Discrete choice models incorporating revealed preferences and psychometric data. In Advances in Econometrics (pp. 29-55). Emerald Group Publishing Limited.

Mundaca, L., Neij, L., Worrell, E. and McNeil, M., (2010) Evaluating energy efficiency policies with energy-economy models. Annual review of environment and resources, 35, pp.305-344.

MVA Consultancy, (1996) Improved Car Ownership Models, Report prepared for the Department of Transport, March 1996.

National statistics (2015). Statistics information on licensed and unlicensed vehicles, and MOT testing. https://www.gov.uk/government/collections/vehicles-statistics. (Accessed 8 January 2015).

Nayum, A., Klöckner, C.A. and Prugsamatz, S., (2013) Influences of car type class and carbon dioxide emission levels on purchases of new cars: A retrospective analysis of car purchases in Norway. Transportation Research Part A: Policy and Practice, 48, pp.96-108.

Nerlove, M. and Press, S.J., (1973) Univariate and multivariate log-linear and logistic models (Vol. 1306). Santa Monica: Rand.

Newman, Peter WG, and Jeffrey R. Kenworthy. "Gasoline consumption and cities: a comparison of US cities with a global survey." Journal of the American planning association 55, no. 1 (1989): 24-37.

Newman, P.G. and Kenworthy, J.R., (1989) Cities and automobile dependence: An international sourcebook.

NEWMAN, P. and J. KENWORTHY (1998) Sustainability and Cities: Overcoming Automobile Dependence. Washington, DC: Island Press.

Nilsson, A., von Borgstede, C., and Biel, A. (2004) Willingness to accept climate change strategies: the effect of values and norms. Journal of Environmental Psychology, 24, pp. 267-277.

Nilsson, M., and Kuller, R. (2000) Travel behaviour and environmental concern. Transportation Research, 5D, 211-234.

Nobile, A., Bhat, C., Pas, E., (1996) A Random Effects Multinomial Probit Model of Car Ownership Choice, Research paper of Duke University and University of Massachusetts at Amherst.

Nolan, A., (2010) A dynamic analysis of household car ownership. Transportation research part A: policy and practice, 44(6), pp.446-455.

Nordbakke, S. and Schwanen, T., (2015) Transport, unmet activity needs and wellbeing in later life: exploring the links. Transportation, 42(6), pp.1129-1151.

Nordlund, A. M., and Garvill, J. (2002) Value structures behind pro-environmental behavior. Environment and Behavior, 34, pp. 740-756.

Nordlund, A. M.,and Garvill, J. (2003) Effects of values, problem awareness and personal norm on willingness to reduce personal car use. Journal of Environmental Psychology, 23, pp. 339-347.

Oakil, A.T.M., Ettema, D., Arentze, T., Timmermans, H.J.P., (2014) Changing household car ownership level and life cycle events: an action in anticipation or an action on occurrence. Transportation 41, 889-904.

Oakil, A.T.M., Nijland, L., Dijst, M., (2015) Rush hour commuting in the Netherlands: Gender-specific household activities and personal attitudes towards responsibility sharing. Travel Behav. Soc.

Oakil, A.T.M., Manting, D. and Nijland, H., (2016) Determinants of car ownership among young households in the Netherlands: The role of urbanisation and demographic and economic characteristics. Journal of transport geography, 51, pp.229-235.

OHerlihy, C .St. J., (1967) Demand for cars in Great Britain. Applied Statistics 14, 162–195.

Ogilvie, D., Mitchell, R., Mutrie, N., Petticrew, M. and Platt, S., (2006) Evaluating health effects of transport interventions: methodologic case study. American journal of preventive medicine, 31(2), pp.118-126.

Palan, K.M., (2001) Gender identity in consumer behavior research: A literature review and research agenda. Academy of Marketing Science Review, 2001, p.1.

Paleti, R., Bhat, C., Pendyala, R. and Goulias, K., (2013) Modeling of household vehicle type choice accommodating spatial dependence effects. Transportation Research Record: Journal of the Transportation Research Board, (2343), pp.86-94.

Paleti, R., Bhat, C. and Pendyala, R., 2013. Integrated model of residential location, work location, vehicle ownership, and commute tour characteristics. Transportation Research Record: Journal of the Transportation Research Board, (2382), pp.162-172.

Pauliuk, S. and Müller, D.B., (2014) The role of in-use stocks in the social metabolism and in climate change mitigation. Global Environmental Change, 24, pp.132-142.

Paleti, R., Pendyala, R.M., Bhat, C.R. and Konduri, K.C., (2011) A joint tour-based model of tour complexity, passenger accompaniment, vehicle type choice, and tour length.

Pauliuk, S. and Müller, D.B., (2014) The role of in-use stocks in the social metabolism and in climate change mitigation. Global Environmental Change, 24, pp.132-142.

Peters, A., de Haan, P. and Scholz, R.W., (2015) Understanding car-buying behavior: psychological determinants of energy efficiency and practical implications. International Journal of Sustainable Transportation, 9(1), pp.59-72.

Puentes, R., (2013) Have Americans Hit Peak Travel? ITF Round Tables Long-run Trends in Car Use, 152, p.91.

Pinjari, A.R., Pendyala, R.M., Bhat, C.R. and Waddell, P.A., (2011) Modeling the choice continuum: an integrated model of residential location, auto ownership, bicycle ownership, and commute tour mode choice decisions. Transportation, 38(6), p.933.

Potoglou D, Kanaroglou PS. (2007) Household demand and willingness to pay for clean vehicles. Transp. Res. D 12:264–74

Potoglou, D. (2008) Vehicle-type choice and neighbourhood characteristics: An empirical study of Hamilton, Canada. Transportation Research Part D: Transport and Environment, 13(3),177-186.

Potoglou, D., and Kanaroglou, P. S. (2008a) Disaggregate demand analyses for conventional and alternative fueled automobiles: A review. International Journal of Sustainable Transportation, 2(4), 234-259.

Potoglou, D., and Kanaroglou, P. S. (2008b). Modelling car ownership in urban areas: a case study of Hamilton, Canada. Journal of Transport Geography, 16(1), 42-54.

Potoglou, D., and Susilo, Y. (2008). Comparison of vehicle-ownership models. Transportation Research Record: Journal of the Transportation Research Board, 2076, 97-105.

Raphael, S. and Stoll, M.A., (2003) Modest progress: The narrowing spatial mismatch between blacks and jobs in the 1990s. Brookings Institution Center on Urban and Metropolitan Policy.

Rashidi, T.H., Mohammadian, A. and Koppelman, F.S., (2011) Modeling interdependencies between vehicle transaction, residential relocation and job change. Transportation, 38(6), p.909.

Reimer, N.K., Schmid, K., Hewstone, M. and Al Ramiah, A., (2020) Self-categorization and social identification: Making sense of us and them.

Rentziou, A., Gkritza, K. and Souleyrette, R.R., (2012) VMT, energy consumption, and GHG emissions forecasting for passenger transportation. Transportation Research Part A: Policy and Practice, 46(3), pp.487-500.

Reynolds, T.J. and Gutman, J., (1988) Laddering theory, method, analysis, and interpretation. Journal of advertising research, 28(1), pp.11-31.

Richarme, M., (2007) Consumer Decision-Making Models, Strategies, and Theories, Oh My!(Decision Analyst). Available from the Data Analyst website: http://www. decisionanalyst. com/Downloads/ConsumerDecisionMaking. pdf (accessed on 27 December, 2016).(IJACSA) International Journal of Advanced Computer Science and Applications, Review of Retail, Distribution and Consumer Research, 7(4), pp.311-337.

Rivis, A., and Sheeran, P. (2003) Descriptive norms as an additional predictor in the theory of planned behaviour: A meta-analysis. Current Psychology: Developmental, Learning, Personality, Social, 22, 218-233.

Rockstro¨m, J., Steffen, W., Noone, S., Persson, A˚ , (2009) A safe operating space for humanity. Nature 461, 472–475.

Rohan, M.J. (2000) A rose by any name? The values construct. Personality and social psychology review, 4(3), pp.255-277.

Romilly, P., Song, H.,and Liu, X. (1998) Modelling and forecasting car ownership in Britain: a cointegration and general to specific approach. Journal of Transport Economics and Policy, 165-185.

Roos, J.M., Sprei, F. and Holmberg, U., (2020) Sociodemography, geography, and personality as determinants of car driving and use of public transportation. Behavioral Sciences, 10(6), p.93.

Rosen, S., (1974) Hedonic prices and implicit markets: product differentiation in pure competition. Journal of political economy, 82(1), pp.34-55.

Rota, M.F., Carcedo, J.M. and García, J.P., (2016) Dual approach for modelling demand saturation levels in the automobile market. The Gompertz curve: Macro versus micro data. Investigación económica, 75(296), pp.43-72.

Ryan, J.M.,Han,G.(1999) Vehicle-ownership model using family structure and accessibility application to Honolulu, Hawaii. Transportation Research Record 1676, 1–10.

Saridakis, C. and Baltas, G., (2016) Modeling price-related consequences of the brand origin cue: An empirical examination of the automobile market.Marketing Letters, 27(1), pp.77-87.

Schwanen, T., Ettema, D., Timmermans, H., (2007) If you pick up the children, I'll do the groceries: spatial differences in between-partner interactions in out-of-home household activities. Environ. Plan. A 39, 2754-2773.

Schwanen, T., Wang, D., (2014) Well-being, context, and everyday activities in space and time. American Geographers]–>Ann. Assoc. Am. Geogr. 104, 833–851.

Schultz, P. W. (2000) Empathizing with nature: The effects of perspective taking on concern for environmental issues. Journal of Social Issues, 56, pp. 391-406.

Schultz, P. W. (2001) The structure of environmental concern: Concern for self, other people, and the biosphere. Journal of Environmental Psychology, 21, pp. 327-339.
Schultz, P. W. and Zelezny, L. (1999) Values as predictors of environmental attitudes: Evidence for consistency across 14 countries. Journal of Environmental Psychology, 19, pp. 255-265.

Schwartz, S. H. (1992) Universals in the content and structure of values: Theoretical advances and empirical tests in 20 countries. In M. Zanna (Ed.), Advances in Experimental Social Psychology, vol. 25 Orlando, FL: Academic Press, pp. 1-65.

Schwartz, S. H. (1994) Are there universal aspects in the structure and contents of human values? Journal of Social Issues, 50, (4), pp. 19-45.

Schwartz, S. H. (1997) Normative influences on altruism. In L. Berkowitz (Ed.), Advances in experimental social psychology vol. 10, New York: Academic Press, pp. 221-279.

Schultz, P. W., Gouveia, V. V., Cameron, L. D., Tankha, G., Schmuck, P. and Franek, M. (2005) Values and their Relationship to Environmental Concern and Conservation Behavior. Journal of Cross-Cultural Psychology, 36, pp. 457-475.

Schwartz, S. H. (1977) Normative influences on altruism. Advances in experimental social psychology, 10, 221-279.

Shankarmahesh, Mahesh N. (2006) “Consumer Ethnocentrism: An Integrative Review of Its Antecedents and Consequences,” International Marketing Review, 23 (2), 146–72.

Shephard, R. W., (1953) “Cost and Production Functions," Princeton Univ. Press, Princeton.

Shogren, J.F., Taylor, L.O., (2008) On behavioral-environmental economics. Rev. Environ. Econ. Policy 2 (1), 26–44

Simon, H.A., (1982) Models of bounded rationality: Empirically grounded economic reason (Vol. 3).

Sirkeci, I. and Bára Magnúsdóttir, L., (2011). Understanding illegal music downloading in the UK: a multi-attribute model. Journal of Research in Interactive Marketing, 5(1), pp.90-110.

Sivak, M., (2015) Has Motorization in the US Peaked? Part 7 Update through 2013: University of Michigan Transportation Research Institute, Report no. UMTRI-2015-10. March. Available from: www. umich. edu/~ umtriswt/PDF/UMTRI-2015-10_Abstract_English. pdf [Accessed 28 Mar 2017].

Sivak, M. and Schoettle, B., (2011) Recent changes in the age composition of US drivers: Implications for the extent, safety, and environmental consequences of personal transportation.Traffic Injury Prevention, 12(6), pp.588-592.

Smith, V.L., (2003) Constructivist and ecological rationality in economics. American economic review, 93(3), pp.465-508.

Soria Lara, J.A., Miralles-Guasch, C. and Marquet, O., (2017) The influence of lifestyle and built environment factors on transport CO2 emissions: the case study of Autonomous University of Barcelona. ACE: architecture, city and environment, 12(34), pp.11-28.

Steenberghen, T., López, E., (2008) Overcoming barriers to the implementation of alternative fuels for road transport in Europe. Journal of Cleaner Production 16, 577–590.

Steg, L., (2005) Car use: lust and must instrumental, symbolic and affective motives for car use. Transportation Research A 39, 147–162.

Steg, L., Dreijerink, L., and Abrahamse, W. (2005) Factors influencing the acceptability of energy policies: a test of VBN theory. Journal of Environmental Psychology, 25, pp. 415-425.

Steg, L., and Nordlund, A. (2012) Models to explain environmental behaviour. In L. Steg, A. E. van den Berg, and J. I. M. De Groot (Eds.), Environmental Psychology: An Introduction, Wiley-Blackwell, pp. 185-194.

Stern, P. C., and Dietz, T. (1994) The value basis of environmental concern. Journal of Social Issues, 50, (3), pp. 65-84.

Stern, P. C., Dietz, T., Kalof, L., and Guagnano, G. A. (1995) Values, beliefs, and pro-environmental action: Attitude formation toward emergent attitude objects. Journal of Applied Social Psychology, 25, pp. 1611-1636.

Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., and Kalof, L. A (1999) Value-Belief-Norm theory of support for social movements: The case of environmentalism. Human Ecology, Review,6, pp. 81-95.

Stern, P. C. (2000) Toward a coherent theory of environmentally significant behavior. Journal of Social Issues, 2000, 56, pp. 407-424.

St-Louis, E., Manaugh, K., van Lierop, D., El-Geneidy, A., (2014) The happy commuter: a comparison of commuter satisfaction across modes. Transport. Res. Part F: Traff. Psychol. Behav. 26, 160–170.

Stone, R., (1954) Linear expenditure systems and demand analysis: an application to the pattern of British demand. The Economic Journal, 64(255), pp.511-527.

TAE HOON OUM II, W.G., YONG, J.S. and Waters, W.G., (1992) CONCEPTS OF PRICE ELASTICITIES OF TRANSPORT DEMAND AND RECENT EMPIRICAL ESTIMATES: AN INTERPRETATIVE SURVEY. Journal of Transport Economics and Policy.

Tajfel, Henri (1974) "Social Identity and Intergroup Behavior," Social Science Information, 13 (2), 65–93.

Tajfel and John C. Turner (1986), "The Social Identity Theoryof Intergroup Behavior," in Psychology of Intergroup Relations, S. Worchel and W. Austin, eds. Chicago: Nelson Hall,7–24.

Tajfel and John C. Turner (2004), "The Social Identity Theory of Intergroup Behavior," in Political Psychology: Key Readings, J.T.Jost, ed. New York: Psychology Press, 276–93.

Tanner, J.C., (1958) An analysis of increases in motor vehicles in Great Britain. Research Note RN/1631, Road Research Laboratory, Harmondsworth.

Tapio, P., (1996) From technocracy to participation? Positivist, realist and pragmatist paradigms applied to traffic and environmental policy futures research. Futures 28 (5), 453–470.

Tapio, P., Hietanen, O., (2002) Epistemology and public policy: using a new typology to analyse the paradigm shift in Finnish transport futures studies. Futures 34 (7), 597–620.

Tertoolen, G., van Kreveld, D., and Verstraten, B. (1998) Psychological resistance against attempts to reduce private car use. Transportation Research, 32A, 171-181.

Thielmann, I., Spadaro, G. and Balliet, D., (2020) Personality and prosocial behavior: A theoretical framework and meta-analysis. Psychological Bulletin, 146(1), p.30.

Thøgersen, J. (2000) Psychological determinants of paying attention to eco-labels in purchase decisions: model development and multinational validation. Journal of Consumer Policy, 23, pp. 285-313.

Thøgersen, J., and Ölander, F. (2002) Human values and the emergence of a sustainable consumption pattern: a panel study. Journal of Economic Psychology, 23,pp. 605-630.

Thomas, E.F., McGarty, C. and Mavor, K., (2016) Group interaction as the crucible of social identity formation: A glimpse at the foundations of social identities for collective action. Group Processes & Intergroup Relations, 19(2), pp.137-151.

Theil, H., (1965). "The Information Approach of Demand Analysis", Econometrica 33:67-78.

Train, K. (1980) The potential market for non-gasoline-powered automobiles. Transp. Res. A 14:405–14.

— (1986) Qualitative choice analysis: Theory, econometrics, and an application to automobile demand (Vol. 10). MIT press.

— (2003) Discrete Choice Methods with Simulation, New York: Cambridge University Press.

Train, K., M. Lohrer (1983) Vehicle ownership and usage: an integrated system of disaggregate demand models Cambridge Systematics, Berkeley, California

Train, K. E., and Winston, C. (2007) Vehicle choice behaviour and the declining market share of us automakers. International Economic Review, 48(4), 1469-1496.

Train, K.E., (2009) Discrete choice methods with simulation. Cambridge university press.

Transport Statistics Great Britain (2003) Department for Transport, HMSO, London.

Turner, John, C. (2010) "Towards a Cognitive Redefinition of the Social Group," in Social Identity and Intergroup Relations, Henri Tajfel, ed. Cambridge, UK: Cambridge University Press, 15–40.

Turnheim, B., Berkhout, F., Geels, F., Hof, A., Mcmeekin, A., Nykvist, B. and Van Vuuren, D. (2015) Evaluating sustainability transitions pathways: Bridging analytical approaches to address governance challenges. Global Environmental Change, 35, 239-253.

United Nations Department of Economic and Social Affairs (UNDESA). (2012). "World Urbanization Prospects: The 2011 Revision". (9211514932), New York: UNDESA Population Division.

Van Acker, V., Mokhtarian, P.L. and Witlox, F., (2014) Car availability explained by the structural relationships between lifestyles, residential location, and underlying residential and travel attitudes. Transport Policy, 35, pp.88-99.

van der Waard, J., Jorritsma, P., Immers, B. (2013) New drivers in mobility; what moves the Dutch in 2012? Transp. Rev. 33, 343-359.

van de Kamp, M., (2020) Dynamic modelling of household car ownership: Including the effect of life events and built environment factors.

Verlegh, Peeter W.J. (2007) "Home Country Bias in Product Evaluation: The Complementary Roles of Economic andSocio-Psychological Motives," Journal of International BusinessStudies, 38 (3), 361–73.

Verplanken, B., Aarts, H., van Knippenberg, A., and Moonen, A. (1998). Habit versus planned behaviour: A field experiment. British Journal of Social Psychology, 37,111-128.

Verplanken, B., Walker, I., Davis, A., and Jurasek, M. (2008) Context change and travel mode choice: Combining the habit discontinuity and self-activation hypotheses. Journal of Environmental Psychology, 28(2), 121-127.

Small, K., (2009) Urban transportation policy. Making cities work: Prospects and policies for urban America, R. Inman, ed., Princeton University Press, Princeton, NJ, pp.63-93.

Solomon, M., Bamossy, G., Askegaard, S., and Hogg, M. (2010). Consumer behavior: A European perspective (4th Edition). Essex: Pearson Education Limited.

Spissu, E., Pinjari, A.R., Pendyala, R.M., Bhat, C.R., (2009) A copula-based joint multinomial discrete–continuous model of vehicle type choice and miles of travel Transportation, 36 (4), pp. 403-422.

Van Acker, V. and Witlox, F., (2010) Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship. Journal of Transport Geography, 18(1), pp.65-74.

Waitt, G., Kerr, S.M. and Klocker, N., (2016) Gender, ethnicity and sustainable mobility: A governmentality analysis of migrant Chinese women's daily trips in Sydney. Applied Mobilities, 1(1), pp.68-84.

Wall, R., Devine-Wright, P., and Mill, G. A. (2007) Comparing and combining theories to explain pro-environmental intentions: The case of commuting-mode choice. Environment and Behavior, 39, 731-753.

Wang, S., Fan, J., Zhao, D., Yang, S. and Fu, Y., (2016) Predicting consumers' intention to adopt hybrid electric vehicles: using an extended version of the theory of planned behavior model. Transportation, 43(1), pp.123-143.

Weimer, K., Ahlström, R. and Lisspers, J., (2018) Challenges in evaluating intervention effects of feedback on residential energy conservation in a field setting.

Wheaton, W.C., (1982) The long-run structure of transportation and gasoline demand. The Bell Journal of Economics, pp.439-454.

Whelan, G., (2007) Modelling car ownership in Great Britain. Transportation Research Part A: Policy and Practice, 41, 205–219.

Williams, I. and Y. Jin (2013) The Impacts of Urban Densification of Transport, slide presentation, European Transport Conference, Frankfurt.

Woldeamanuel, M.G., Cyganski, R., Schulz, A., Justen, A., (2009) Variation of households' car ownership across time: application of a panel data model. Transportation 36, 371–387.

Wong, K.I., (2013) An analysis of car and motorcycle ownership in Macao. International Journal of Sustainable Transportation, 7(3), pp.204-225.

Wu, G., Yamamoto, T., Kitamura, R., (1999) Vehicle ownership model that incorporates the causal structure underlying attitudes toward vehicle ownership. Transp. Res. Rec. 1676, 61–67

Wu, N., Zhao, S., Zhang, Q., (2016) A study on the determinants of private car ownership in China: findings from the panel data. Transp. Res. A: Policy Practice 85, 186–195. http://dx.doi.org/10.1016/j.tra.2016.01.012.

Yadav, R. and Pathak, G.S., (2016) Young consumers' intention towards buying green products in a developing nation: Extending the theory of planned behavior. Journal of Cleaner Production, 135, pp.732-739.

Yamamoto, T. and Kitamura, R., (2000) An analysis of household vehicle holding durations considering intended holding durations. Transportation Research Part A: Policy and Practice, 34, 339–351.

Yamamoto, T., (2009) Comparative analysis of household car, motorcycle and bicycle ownership between Osaka metropolitan area, Japan and Kuala Lumpur, Malaysia. Transportation 36 (3), 351–366.

Yang, Z., Jia, P., Liu, W. and Yin, H., (2017) Car ownership and urban development in Chinese cities: A panel data analysis. Journal of transport geography, 58, pp.127-134.

Ye, R., Titheridge, H., (2017) Satisfaction with the commute: The role of travel mode choice, built environment and attitudes. Transport. Res. Part D: Transport Environ. 52, 535–547.

Zanoli, R. and Naspetti, S., (2002) Consumer motivations in the purchase of organic food: a means-end approach. British food journal, 104(8), pp.643-653.

Zegras, C., (2010) The built environment and motor vehicle ownership and use: Evidence from Santiago de Chile. Urban Studies, 47(8), pp.1793-1817.

Zhang, D., Schmöcker, J.D., Fujii, S. and Yang, X., (2016) Social norms and public transport usage: empirical study from Shanghai. Transportation, 43(5), pp.869-888.

Zhou, M. and Wang, D., (2019) Generational differences in attitudes towards car, car ownership and car use in Beijing. Transportation Research Part D: Transport and Environment, 72, pp.261-278.

Zhu, C., Zhu, Y., Lu, R., He, R., Xia, Z., (2012) Perceptions and aspirations for car ownership among Chinese students attending two universities in the Yangtze Delta, China. J. Transp. Geogr. 24, 315–323.

Ziegler, A., (2012) Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: a discrete choice analysis for Germany. Transportation Research Part A: Policy and Practice 46, 1372–1385

9.0 APPENDICES

APPENDIX 1

Table 9-1: Summary of previous studies on vehicle ownership

					Variables Considered							
	Studies	**Data Source & Type**	**Modelling Approach**	**Vehicle Ownership Form**	**Household Demographic**	**Individual Attributes**	**Employment Attributes**	**Life Cycle Attributes**	**Built Environment**	**Transit Attributes**	**Policy**	**Unobserved Effects**
S/N	**Exogenous Static**											
1	Karlaftis and Golias (2002)	Greece roadside interviews	Binary logit	VO	√	—	—	√	√	√	√	—
2	Li et al. (2010)	China Household Survey	Binary logit	VO	√	√	√	√	√	√	—	—
3	Ma and Srinivasan (2010)	USA Census micro-data	Binary logit	VO	√	√	—	√	√	—	—	—
4	Whelan (2007)	Great Britain Travel Survey	Binary logit	VO	√	—	—	—	√	—	√	—
5	Bhat and Pulugurta (1998)	USA Activity Survey Netherlands Travel Survey	Ordered logit	VO	√	—	—	—	√	—	—	—
6	Hess and Ong (2002)	USA Activity and Travel Survey	Ordered logit	VO	√	√	—	—	√	√	—	—
7	Kim and Kim (2004)	USA Travel Survey	Ordered logit	VO	√	—	—	√	√	√	—	—
8	Potoglou and Susilo (2008)	USA, Netherlands, Japan Travel Survey	Ordered logit	VO	√	√	—	√	√	—	—	—
9	Potoglou and Kanaroglou (2008b)	Canada Internet Survey	Ordered logit	VO	√	—	√	√	√	√	—	—
10	Chu (2002)	USA Travel Survey	Ordered logit	VO	√	—	√	√	√	—	—	—
11	Cao et al. (2007)	USA Attitudinal Survey	Ordered logit	VO	√	√	—	—	√	—	—	√
12	Potoglou and Susilo (2008)	USA, Netherlands, Japan Travel Survey	Ordered logit	VO	√	√	—	√	√	—	—	—
13	Ma and Srinivasan (2010)	USA Census micro-data	Ordered logit	VO	√	√	—	√	√	—	—	—
14	Bhat and Pulugurta (1998)	USA Activity Survey Netherlands Travel Survey	Multinomial logit	VO	√	—	—	—	√	—	—	—

15	Wu et al. (1999)	China Stated Preference Survey	Multinomial logit	VT	√	√	√	√	√	√	√	—
16	Ryan and Han (1999)	USA Census micro - data	Multinomial logit	VO	√	—	—	—	√	—	—	—
17	Choo and Mokhtarian (2004)	USA Attitudinal Survey	Multinomial logit	VT	√	√	√	√	√	—	—	—
18	Bento et al. (2005)	USA Travel Survey	Multinomial logit	VO	√	√	—	√	√	√	√	—
19	Soltani (2005)	Australia Travel Survey	Multinomial logit	VO	√	—	—	√	√	√	—	—
20	Potoglou and Kanaroglou (2008b)	Canada Internet Survey	Multinomial logit	VO	√	—	√	√	√	√	—	—
21	Potoglou and Susilo (2008)	USA Netherlands Japan Travel Survey	Multinomial logit	VO	√	√	—	√	√	—	—	—
22	Potoglou (2008)	Canada Internet Survey	Multinomial logit	VT	√	√	—	√	√	—	—	—
23	Zegras (2010)	Chile OD Survey	Multinomial logit	VO	√	—	—	—	√	√	—	—
24	Caulfield (2012)	Ireland Census Data	Multinomial logit	VO	√	√	—	√	√	√	—	—
25	Wong (2013)	Macao Travel Survey	Multinomial logit	VO	√	—	—	√	√	—	—	—
26	McCarthy and Tay (1998)	USA Consumer Survey	Nested logit	VT	√	—	—	√	√	—	√	—
27	Kermanshah and Ghazi (2001)	Iran Travel Survey	Nested logit	VO	√	—	√	√	√	—	—	—
28	Mohammadian and Miller (2002)	Canada Retrospective Survey	Nested logit	VT	√	√	√	—	—	—	√	—
29	Mohammadian and Miller (2003b)	Canada Retrospective Survey	Nested logit	VT	√	√	√	—	—	—	√	—
30	Cao et al. (2006)	USA Attitudinal Survey	Nested logit	VT	√	√	—	√	√	—	—	—
31	Guo (2013)	USA Travel Survey	Nested logit	VO	√	—	√	—	√	√	—	—

32	Potoglou (2008)	Canada Internet Survey	Random parameters logit	VT	√	√	—	√	√	—	—	—
33	Shay and Khattak (2011)	USA Travel Survey	Poisson regression	VO	√	—	—	—	√	—	—	—
34	Shay and Khattak (2005)	USA Travel Survey	Negative binomial regression	VO	√	—	—	—	√	—	—	—
35	Shay and Khattak (2007)	USA Travel Survey	Negative binomial regression	VO	√	—	—	—	√	√	—	—
36	Karlaftis and Golias (2002)	Greece Roadside Interviews	Poisson -lognormal model	VO	√	—	—	√	√	√	√	—
37	Anowar et al. (2014a)	Canada OD Survey	Latent class multinomial logit	VO	√	—	√	—	√	√	—	—
38	Anowar et al. (2014a)	Canada OD Survey	Latent class multinomial logit	VO	√	—	√	—	√	√	—	—
39	Beck et al. (2013)	Australia Interviewer Assisted Online Survey	Latent class multinomial logit	VT	√	—	—	—	—	—	√	—
40	Mohammadian and Miller (2002)	Canada Retrospective Survey	Artificial Neural Network	VT	√	√	√	—	—	—	√	—
41	Dissanayake and Morikawa (2002)	Thailand Travel Survey	Nested logit	VO	√	√	√	√	—	—	—	√
42	Salon (2009)	USA Travel Survey	Multinomial logit	VO	√	—	—	√	√	√	√	√
43	Weinberger and Goetzke (2010)	USA Census Micro-Data	Multinomial logit	VO	√	√	—	√	√	—	—	√
44	Bhat and Guo (2007)	USA Travel Survey	Mixed multidimensional choice modelling	VO	√	—	—	—	√	√	—	√
45	Yamamoto (2009)	Japan, Malaysia Trip Survey	Trivariate binary probit	VO	√	—	—	—	√	√	—	√
46	Pinjari et al. (2011)	USA Travel Survey	Mixed multidimensional choice modelling	VO	√	√	—	√	√	√	√	√
47	Konduri et al. (2011)	USA Travel Survey	Probit-based joint discrete continuous model	VT	√	√	—	√	√	—	—	√
48	Anastasopoulos et al. (2012)	Greece Travel Survey	Random parameters bivariate ordered	VO	√	√	√	—	√	√	—	√

49	Paleti et al. (2013a)	USA Travel Survey	Mixed multidimensional choice modelling	VO	√	—	—	√	√	—	—	√
50	Paleti et al. (2013c)	USA Travel Survey	Bivariate multinomial probit	VO	√	—	√	√	√	—	—	√
51	Bhat and Sen (2006)	USA Travel Survey	Mixed multiple continuous extreme value model	VT&VU	√	—	—	√	√	—	√	√
52	Ahn et al. (2008)	South Korea, Face-to-face,Interview	Mixed multiple continuous extreme value model	VO&VU	—	—	—	—	—	—	√	√
53	Bhat et al. (2009)	USA Travel Survey	Joint nested multiple discrete continuous extreme value model	VT&VU	√	√	—	√	√	√	√	√
54	Vyas et al. (2012)	USA Travel Survey	Joint nested multiple discrete continuous extreme value model	VT&VU	√	√	—	√	√	—	—	√
55	Spissu et al. (2009)	USA Travel Survey	Copula based joint multinomial discrete-continuous model	VT&VU	√	√	—	√	√	√	—	√
56	Fang (2008)	USA Travel Survey	Bayesian multivariate ordered probit and tobit model	VO&VU	√	√	—	√	√	—	—	√
57	Brownstone and Fang (2009)	USA Travel Survey	Bayesian multi-variate ordered probit and tobit multivariate ordered probit and tobit	VO & VU	√	√	—	√	√	√	—	√
58	Schimek (1996)	USA Travel Survey	Two-equation system simultaneous equation model	VO & VU	√	√	—	√	√	√	—	√
59	Chen et al. (2008)	USA Travel Survey	Two-equation system simultaneous equation model	VO & VU	√	√	—	√	√	√	√	√
60	Bhat and Koppelman (1993)	Netherlands Travel Survey	Endogenous switching simultaneous equation model	VO	√	√	—	—	√	—	—	√
61	Golob et al. (1996)	USA Telephone Survey & SP Survey	Cross-sectional structural equation model	VT & VU	√	√	√	√	—	—	√	√

62	Golob et al. (1997)	USA Telephone Survey & SP Survey	Cross-sectional structural equation model	VT & VU	√	√	√	√	—	—	√	√
63	Giuliano and Dargay (2006)	USA Great Britain Travel Surve	Cross-sectional structural equation model	VO & VU	√	√	√	√	√	√	—	√
64	Cao et al. (2007)	USA Attitudinal Survey	Structural equation model	VO	√	√	—	√	—	—	—	√
65	Gao et al. (2008)	USA Census Tract Data	Cross-sectional structural equation model	VO	√	√	√	—	—	—	—	√
66	Senbil et al. (2009)	Japan Malaysia Travel Survey	Cross-sectional structural equation model	VO	√	√	—	—	√	√	√	√
67	van Acker and Witlox (2010)	Belgium Travel Behaviour Survey	Cross-sectional structural equation model	VO & VU	√	√	√	—	√	—	—	√
68	de Abreu e Silva et al. (2012)	Canada OD Survey	Cross-sectional structural equation model	VO & VU	√	√	√	√	√	—	—	√
69	Aditjandra et al. (2012)	Great Britain Quasi-longitudinal Data	Quasi-longitudinal structural equation model	VO	√	√	—	—	√	—	—	√
	Exogenous Dynamic											
70	Prillwitz et al. (2006)	Germanay Panel Waves	Binary probit	VO	√	√	√	√	√	—	—	—
71	Yamamoto (2008)	Japan Panel Survey	Multinomial logit	VTR	√	—	—	√	√	√	—	—
72	Pendyala et al. (1995)	Netherlands Mobility Panel Survey	Ordered probit	VO	√	—	—	—	√	√	—	—
73	Matas and Raymond (2008)	Spain Pseudo -Panel	Ordered probit	VO	√	√	—	√	√	√	—	—
74	Anowar et al. (2014 b)	Canada Pseudo - Panel	Scaled generalized ordered logit	VO	√	—	—	√	√	√	—	√
75	de Jong (1996)	Netherlands Vehicle Panel Survey	Single hazard duration model	VOD	√	√	—	—	—	—	√	√
76	Yamamoto and Kitamura (2000)	USA Panel Survey	Single hazard duration model	VOD	√	√	√	—	—	—	—	√
77	Gilbert (1992)	USA Panel Survey	Competing hazards duration model	VTR	√	√	√	√	—	—	—	—
78	Yamamoto et el. (1999)	USA Panel Survey	Competing hazards duration model	VTR	√	—	√	√	—	—	—	—

79	Mohammadian and Rashidi (2007)	Canada Retrospective Survey	Competing hazards duration model	VTR	√	√	√	√	√	—	√	√
80	Yamamoto (2008)	France Panel Survey	Competing hazards duration mode	VTR	√	—	—	√	√	√	—	—
81	Kitamura and Bunch (1990)	Netherlands Mobility Panel Survey	Random effects ordered probit	VO	√	√	—	√	—	√	—	√
82	Nobile et al.(1996)	Netherlands Mobility Panel Survey	Random effects multinomial probit mode	VO	√	—	—	√	√	—	—	√
83	Mohammadian and Miller (2003a)	Canada Retrospective Survey	Mixed parameter logit	VTR&VT	√	—	—	—	—	—	√	√
84	Bjorner and LethPetersen (2007)	Denmark Panel Survey	Random effects multinomial logit model	VO	√	√	√	—	√	—	√	√
85	Woldeamanuel et al. (2009)	Germanay Panel Survey	Random effects regression	VO	√	—	—	—	√	√	√	√
86	Nolan (2010)	Ireland Panel Survey	Random effects binary probit	VO	√	√	—	√	√	—	—	√
87	Anow ar et al. (2014b)	Canada Pseudo-Panel	Mixed generalized ordered logit	VO	√	—	—	√	√	√	—	√
	Endogenous Dynamic											
88	Eluru et al. (2010)	USA Travel Survey	Copula based joint GEV-based logitregression model	VT & VU	√	—	—	√	√	√	—	√
89	Paleti et al. (2011)	USA Vehicle Survey	Copula based joint GEV-based logitregression model	VT & VU	√	√	—	√	√	—	√	√
90	Paleti et al. (2013b)	USA Travel Survey	Multinomial probit model	VT	√	√	√	√	√	—	—	√
91	Golob (1990)	Netherlands Mobility Panel Survey	Longitudinal structural equation model	VO	√	—	—	√	√	—	—	√
92	Kitamura (2009)	Netherlands Mobility Panel Survey	Three equation simultaneous equation model	VO	√	√	—	√	√	√	—	√
93	Rashidi and Mohammadian (2011)	USA Travel Panel Survey	Hazard based Simultaneous equation model	VTR	√	√	—	—	√	√	—	√
	Note: VO = vehicle ow nership; VT = vehicle type; VU = vehicle use; VOD = vehicle ow nership duration; VTR = vehicle transaction; OD = origin-destination											

Anowar et al. (2014).

APPENDIX 2- FULL STATA RESULTS: UK MNL MODEL/NL MODEL

```
. tabulate  hhstru
```

hhstru	Freq.	Percent	Cum.
1	850	28.89	28.89
2	1,134	38.55	67.44
3	414	14.07	81.51
4	364	12.37	93.88
5	125	4.25	98.13
6	39	1.33	99.46
7	11	0.37	99.83
8	2	0.07	99.90
9	2	0.07	99.97
11	1	0.03	100.00
Total	2,942	100.00	

```
.
. tabulate  drvlicn
```

drvlicn	Freq.	Percent	Cum.
0	856	29.10	29.10
1	2,086	70.90	100.00
Total	2,942	100.00	

```
.
. tabulate  acctenur
```

acctenur	Freq.	Percent	Cum.
1	1,093	37.15	37.15
2	771	26.21	63.36
3	18	0.61	63.97
4	316	10.74	74.71
5	228	7.75	82.46
6	34	1.16	83.62
7	12	0.41	84.02
8	5	0.17	84.19
9	36	1.22	85.42
10	391	13.29	98.71
11	11	0.37	99.08
97	15	0.51	99.59
98	4	0.14	99.73
99	8	0.27	100.00
Total	2,942	100.00	

```
. tabulate  apartstru
```

apartstru	Freq.	Percent	Cum.
1	304	10.33	10.33
2	648	22.03	32.36
3	1,372	46.63	78.99
4	495	16.83	95.82
5	93	3.16	98.98
7	24	0.82	99.80
8	3	0.10	99.90
9	3	0.10	100.00
Total	2,942	100.00	

```
.
. tabulate  region
```

region	Freq.	Percent	Cum.
1	169	5.74	5.74
2	381	12.95	18.69
3	245	8.33	27.02
4	208	7.07	34.09
5	233	7.92	42.01
6	304	10.33	52.35
7	272	9.25	61.59
8	400	13.60	75.19
9	313	10.64	85.83
10	165	5.61	91.43
11	252	8.57	100.00
Total	2,942	100.00	

```
.
. tabulate  ccbeliev
```

ccbeliev	Freq.	Percent	Cum.
1	150	5.14	5.14
2	315	10.80	15.94
3	2,452	84.06	100.00
Total	2,917	100.00	

```
. tabulate  ethnicity
```

ethnicity	Freq.	Percent	Cum.
1	41	1.39	1.39
2	23	0.78	2.18
3	1	0.03	2.21
4	51	1.73	3.94
5	23	0.78	4.72
6	5	0.17	4.89
7	18	0.61	5.51
8	27	0.92	6.42
9	2,689	91.40	97.82
10	32	1.09	98.91
11	26	0.88	99.80
98	2	0.07	99.86
99	4	0.14	100.00
Total	2,942	100.00	

```
. recode  ethnicity(9=1 White)(2=2 Caribbean)(4=3 Indians)(5=4 Pakistans)(7=5 Chinese) (8=6 OtherAsianorigin)(1=7 Africans)(3 6 98 99 10/11=8 Mi
> ), gen (ethnicorigins)

. tabulate  ethnicity ethnicorigins
```

ethnicity	RECODE of ethnicity								
	White	Caribbean	Indians	Pakistans	Chinese	OtherAsia	Africans	Mixedorig	T
1	0	0	0	0	0	0	41	0	
2	0	23	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	1	
4	0	0	51	0	0	0	0	0	
5	0	0	0	23	0	0	0	0	
6	0	0	0	0	0	0	0	5	
7	0	0	0	0	18	0	0	0	
8	0	0	0	0	0	27	0	0	
9	2,689	0	0	0	0	0	0	0	2
10	0	0	0	0	0	0	0	32	
11	0	0	0	0	0	0	0	26	
98	0	0	0	0	0	0	0	2	
99	0	0	0	0	0	0	0	4	
Total	2,689	23	51	23	18	27	41	70	2

RECODE of ethnicity	Freq.	Percent	Cum.
White	2,689	91.40	91.40
Caribbean	23	0.78	92.18
Indians	51	1.73	93.92
Pakistans	23	0.78	94.70
Chinese	18	0.61	95.31
OtherAsianorigin	27	0.92	96.23
Africans	41	1.39	97.62
Mixedorigin	70	2.38	100.00
Total	2,942	100.00	

```
. summarize ethnicorigins
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ethnicorig~s	2942	1.386472	1.411998	1	8

```
.
. summarize i.ethnicorigins
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ethnicorig~s					
2	2942	.0078178	.0880871	0	1
3	2942	.0173351	.130539	0	1
4	2942	.0078178	.0880871	0	1
5	2942	.0061183	.0779931	0	1
6	2942	.0091774	.0953745	0	1
7	2942	.0139361	.1172457	0	1
8	2942	.0237933	.1524307	0	1

```
. describe  hhstru drvlicn acctenur apartstru region ccbeliev hhinco ethnicorigins
```

variable name	storage type	display format	value label	variable label
hhstru	byte	%8.0g		
drvlicn	byte	%8.0g		
acctenur	byte	%8.0g		
apartstru	byte	%8.0g		
region	byte	%8.0g		
ccbeliev	byte	%8.0g		
hhinco	byte	%8.0g		
ethnicorigins	byte	%16.0g	ethnicorigins	RECODE of ethnicity

```
. summarize  hhstru drvlicn acctenur apartstru region ccbeliev hhinco ethnicorigins
```

Variable	Obs	Mean	Std. Dev.	Min	Max
hhstru	2942	2.310333	1.265726	1	11
drvlicn	2942	.7090415	.4542816	0	1
acctenur	2942	4.219918	9.512831	1	99
apartstru	2942	2.848402	1.048045	1	9
region	2942	6.060503	3.04166	1	11
ccbeliev	2917	2.789167	.5189607	1	3
hhinco	2942	30.93168	36.73859	1	98
ethnicorig~s	2942	1.386472	1.411998	1	8

```
.
. recode  acctenur (1 2 =1 owners) (3=2 shared) (4/11=3 rent) (97/99=4 others), gen (acctenurty
(1849 differences between acctenur and acctenurty)
. tabulate  acctenur  acctenurty
```

acctenur	RECODE of acctenur owners	shared	rent	others	Total
1	1,093	0	0	0	1,093
2	771	0	0	0	771
3	0	18	0	0	18
4	0	0	316	0	316
5	0	0	228	0	228
6	0	0	34	0	34
7	0	0	12	0	12
8	0	0	5	0	5
9	0	0	36	0	36
10	0	0	391	0	391
11	0	0	11	0	11
97	0	0	0	15	15
98	0	0	0	4	4
99	0	0	0	8	8
Total	1,864	18	1,033	27	2,942

```
. tabulate  acctenurty
```

RECODE of acctenur	Freq.	Percent	Cum.
owners	1,864	63.36	63.36
shared	18	0.61	63.97
rent	1,033	35.11	99.08
others	27	0.92	100.00
Total	2,942	100.00	

```
.
. recode  apartstru(1 2=1 bigcity) (3=2 smallcity) (4 5=3 village) (7/9=4 others), gen (apartstruty)
(2638 differences between apartstru and apartstruty)

.
. tabulate  apartstru  apartstruty
```

apartstru	RECODE of apartstru bigcity	smallcity	village	others	Total
1	304	0	0	0	304
2	648	0	0	0	648
3	0	1,372	0	0	1,372
4	0	0	495	0	495
5	0	0	93	0	93
7	0	0	0	24	24
8	0	0	0	3	3
9	0	0	0	3	3
Total	952	1,372	588	30	2,942

```
. tabulate  apartstruty
```

RECODE of apartstru	Freq.	Percent	Cum.
bigcity	952	32.36	32.36
smallcity	1,372	46.63	78.99
village	588	19.99	98.98
others	30	1.02	100.00
Total	2,942	100.00	

```
.
. summarize i. apartstruty
```

Variable	Obs	Mean	Std. Dev.	Min	Max
apartstruty					
2	2942	.4663494	.4989512	0	1
3	2942	.199864	.399966	0	1
4	2942	.0101971	.1004818	0	1

```
.
. summarize i.  ccbeliev
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ccbeliev					
2	2917	.1079877	.310418	0	1
3	2917	.8405896	.3661211	0	1

```
.
. recode  hhinco (1/3=1 verypoor)(4/6=2 poor) (7/9=3 avergae) (10/12=4 rich) (13/20=5 veryrich) (97 98=6 undisclosed), gen(inco
(2856 differences between hhinco and incomehh)
```

```
. tabulate  hhinco  incomehh
```

hhinco	RECODE of hhinco verypoor	poor	avergae	rich	veryrich	undisclos	Total
1	86	0	0	0	0	0	86
2	107	0	0	0	0	0	107
3	88	0	0	0	0	0	88
4	0	114	0	0	0	0	114
5	0	112	0	0	0	0	112
6	0	88	0	0	0	0	88
7	0	0	121	0	0	0	121
8	0	0	115	0	0	0	115
9	0	0	111	0	0	0	111
10	0	0	0	161	0	0	161
11	0	0	0	124	0	0	124
12	0	0	0	82	0	0	82
13	0	0	0	0	105	0	105
14	0	0	0	0	89	0	89
15	0	0	0	0	114	0	114
16	0	0	0	0	125	0	125
17	0	0	0	0	114	0	114
18	0	0	0	0	101	0	101
19	0	0	0	0	123	0	123
20	0	0	0	0	183	0	183
97	0	0	0	0	0	447	447
98	0	0	0	0	0	232	232
Total	281	314	347	367	954	679	2,942

```
. tabulate  incomehh
```

RECODE of hhinco	Freq.	Percent	Cum.
verypoor	281	9.55	9.55
poor	314	10.67	20.22
avergae	347	11.79	32.02
rich	367	12.47	44.49
veryrich	954	32.43	76.92
undisclosed	679	23.08	100.00
Total	2,942	100.00	

```
. summarize i.incomehh
```

Variable	Obs	Mean	Std. Dev.	Min	Max
incomehh					
2	2942	.1067301	.3088223	0	1
3	2942	.117947	.3226002	0	1
4	2942	.1247451	.3304858	0	1
5	2942	.3242692	.4681807	0	1
6	2942	.2307954	.4214134	0	1

```
. summarize carnum hhstru drvlicn incomehh apartstruty acctenurty ccbeliev region ethnicorigins
```

Variable	Obs	Mean	Std. Dev.	Min	Max
carnum	2942	2.221618	.8568989	1	4
hhstru	2942	2.310333	1.265726	1	11
drvlicn	2942	.7090415	.4542816	0	1
incomehh	2942	4.167913	1.620072	1	6
apartstruty	2942	1.896669	.7441458	1	4
acctenurty	2942	1.735894	.9756975	1	4
ccbeliev	2917	2.789167	.5189607	1	3
region	2942	6.060503	3.04166	1	11
ethnicorig~s	2942	1.386472	1.411998	1	8

```
. mlogit carnum drvlicn hhstru, baseoutcome(2)

Iteration 0:   log likelihood = -3631.5476
Iteration 1:   log likelihood = -2777.6462
Iteration 2:   log likelihood = -2613.5868
Iteration 3:   log likelihood = -2573.8277
Iteration 4:   log likelihood = -2571.9744
Iteration 5:   log likelihood = -2571.9625
Iteration 6:   log likelihood = -2571.9625

Multinomial logistic regression                 Number of obs   =       2942
                                                LR chi2(6)      =    2119.17
                                                Prob > chi2     =     0.0000
Log likelihood = -2571.9625                     Pseudo R2       =     0.2918

------------------------------------------------------------------------------
      carnum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1            |
     drvlicn |  -5.261256   .2540755   -20.71   0.000    -5.759235   -4.763277
      hhstru |  -.5651518   .0660628    -8.55   0.000    -.6946325   -.4356712
       _cons |   2.170559   .1640284    13.23   0.000     1.849069    2.492049
-------------+----------------------------------------------------------------
2            |  (base outcome)
-------------+----------------------------------------------------------------
3            |
     drvlicn |   1.236384   .1682617     7.35   0.000     .9065971    1.566171
      hhstru |   .4661513   .0395838    11.78   0.000     .3885684    .5437342
       _cons |  -2.761443   .2055091   -13.44   0.000    -3.164234   -2.358653
-------------+----------------------------------------------------------------
4            |
     drvlicn |   2.531718   .4140607     6.11   0.000     1.720174    3.343262
      hhstru |   .7208444   .0566588    12.72   0.000     .6097952    .8318935
       _cons |  -5.973931   .4695989   -12.72   0.000    -6.894328   -5.053534
------------------------------------------------------------------------------

.
. mlogit carnum drvlicn hhstru i. acctenurty i. apartstruty i.region i.ethnicorigins, baseoutcome(2

Iteration 0:   log likelihood = -3631.5476
Iteration 1:   log likelihood = -2630.7449
Iteration 2:   log likelihood =  -2420.266
Iteration 3:   log likelihood = -2364.1521
Iteration 4:   log likelihood = -2361.1927
Iteration 5:   log likelihood = -2361.0712
Iteration 6:   log likelihood = -2361.0422
Iteration 7:   log likelihood =  -2361.036
Iteration 8:   log likelihood = -2361.0347
Iteration 9:   log likelihood = -2361.0344
Iteration 10:  log likelihood = -2361.0344
Iteration 11:  log likelihood = -2361.0343

Multinomial logistic regression                 Number of obs   =       2942
                                                LR chi2(75)     =    2541.03
                                                Prob > chi2     =     0.0000
Log likelihood = -2361.0343                     Pseudo R2       =     0.3499

------------------------------------------------------------------------------
      carnum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1            |
     drvlicn |  -5.318927   .2654019   -20.04   0.000    -5.839105   -4.798749
      hhstru |  -.7346733   .0755037    -9.73   0.000    -.8826578   -.5866888
             |
   acctenurty |
           2 |   .0431358   .8087187     0.05   0.957    -1.541924    1.628195
           3 |   1.294031   .1736167     7.45   0.000     .9537489    1.634314
           4 |   .1586025   .7073459     0.22   0.823     -1.22777    1.544975
             |
  apartstruty |
           2 |   .1216765    .198245     0.61   0.539    -.2668766    .5102296
           3 |   -.222346   .2887827    -0.77   0.441    -.7883496    .3436577
           4 |  -.6962861   .7373481    -0.94   0.345    -2.141462    .7488897
```

region						
2	-.1250687	.3785733	-0.33	0.741	-.8670587	.6169213
3	-.2011555	.4219889	-0.48	0.634	-1.028238	.6259275
4	-.2068427	.4469029	-0.46	0.643	-1.082756	.6690708
5	-.6252905	.4213026	-1.48	0.138	-1.451028	.2004475
6	-.5743897	.4254202	-1.35	0.177	-1.408198	.2594186
7	.240286	.4203346	0.57	0.568	-.5835546	1.064127
8	-.6439026	.4080376	-1.58	0.115	-1.443641	.1558363
9	-.5222334	.4158238	-1.26	0.209	-1.337233	.2927663
10	-.5641621	.4691585	-1.20	0.229	-1.483696	.3553716
11	-.7088056	.4049803	-1.75	0.080	-1.502552	.0849411
ethnicorig~s						
2	.2436356	.6874711	0.35	0.723	-1.103783	1.591054
3	.8042516	.5639549	1.43	0.154	-.3010797	1.909583
4	-1.088375	1.045106	-1.04	0.298	-3.136745	.959995
5	-.8984173	.8370061	-1.07	0.283	-2.538919	.7420845
6	.2172105	.7246779	0.30	0.764	-1.203132	1.637553
7	.2315355	.6398753	0.36	0.717	-1.022597	1.485668
8	-.1224571	.4542785	-0.27	0.787	-1.012827	.7679124
_cons	2.14083	.3729474	5.74	0.000	1.409867	2.871794
2	(base outcome)					
3						
drvlicn	1.096703	.1730709	6.34	0.000	.7574905	1.435916
hhstru	.5920776	.0442658	13.38	0.000	.5053182	.6788369
acctenurty						
2	.7472718	.5900743	1.27	0.205	-.4092527	1.903796
3	-1.151425	.1231181	-9.35	0.000	-1.392732	-.9101175
4	-.2596753	.5574592	-0.47	0.641	-1.352275	.8329247
apartstruty						
2	.0243535	.1256235	0.19	0.846	-.2218641	.2705711
3	.3972903	.1487018	2.67	0.008	.1058401	.6887406
4	.2333941	.4578059	0.51	0.610	-.663889	1.130677
region						
2	.2686498	.2646048	1.02	0.310	-.2499661	.7872658
3	-.0072884	.2837379	-0.03	0.980	-.5634044	.5488277
4	.2844049	.2895291	0.98	0.326	-.2830618	.8518716
5	.5121841	.2825899	1.81	0.070	-.0416819	1.06605
6	.1814622	.2699267	0.67	0.501	-.3475844	.7105089
7	-.3922318	.3115054	-1.26	0.208	-1.002771	.2183077
8	.661023	.2583004	2.56	0.010	.1547636	1.167282
9	.306505	.2670938	1.15	0.251	-.2169893	.8299993
10	.3997351	.304177	1.31	0.189	-.1964409	.9959112
11	.0656439	.2857885	0.23	0.818	-.4944913	.6257791
ethnicorig~s						
2	-1.554777	1.063631	-1.46	0.144	-3.639456	.5299026
3	-.7937023	.423704	-1.87	0.061	-1.624147	.0367422
4	-.8804661	.5524002	-1.59	0.111	-1.963151	.2022184
5	-1.48158	.8126743	-1.82	0.068	-3.074392	.1112327
6	-.7086316	.5999061	-1.18	0.238	-1.884426	.4671627
7	-.986239	.523612	-1.88	0.060	-2.0125	.0400217
8	-.0315783	.3331468	-0.09	0.924	-.6845341	.6213774
_cons	-2.953905	.3180359	-9.29	0.000	-3.577244	-2.330566
4						
drvlicn	2.206332	.4207361	5.24	0.000	1.381705	3.03096
hhstru	.9525903	.0654722	14.55	0.000	.8242671	1.080913
acctenurty						
2	-14.86213	1645.391	-0.01	0.993	-3239.77	3210.045
3	-1.471401	.2233277	-6.59	0.000	-1.909115	-1.033686
4	.0472326	.7552385	0.06	0.950	-1.433008	1.527473

apartstruty						
2	.0125921	.2190082	0.06	0.954	-.4166562	.4418403
3	1.081827	.2324005	4.66	0.000	.6263303	1.537323
4	-14.82161	1271.014	-0.01	0.991	-2505.964	2476.321
region						
2	-.2263338	.4369987	-0.52	0.605	-1.082836	.6301679
3	-.3624679	.4574874	-0.79	0.428	-1.259127	.534191
4	.0068058	.4560341	0.01	0.988	-.8870046	.9006161
5	.1974683	.4543573	0.43	0.664	-.6930557	1.087992
6	.0017013	.4231622	0.00	0.997	-.8276814	.831084
7	-.7696641	.5468558	-1.41	0.159	-1.841482	.3021534
8	.6482743	.3974202	1.63	0.103	-.130655	1.427204
9	-.3363902	.4383529	-0.77	0.443	-1.195546	.5227656
10	.5197809	.4528282	1.15	0.251	-.367746	1.407308
11	.3946275	.4261225	0.93	0.354	-.4405572	1.229812
ethnicorig~s						
2	-14.61137	1544.729	-0.01	0.992	-3042.225	3013.002
3	-15.93784	869.1813	-0.02	0.985	-1719.502	1687.626
4	-2.503899	1.129638	-2.22	0.027	-4.717949	-.2898488
5	-15.83455	1457.051	-0.01	0.991	-2871.602	2839.933
6	-1.649869	1.164585	-1.42	0.157	-3.932413	.632675
7	-1.817026	1.121424	-1.62	0.105	-4.014976	.3809242
8	-.6184546	.7666229	-0.81	0.420	-2.121008	.8840986
_cons	-6.21811	.6123859	-10.15	0.000	-7.418364	-5.017856

```
. mlogit, rrr

Multinomial logistic regression                 Number of obs   =       2942
                                                LR chi2(75)     =    2541.03
                                                Prob > chi2     =     0.0000
Log likelihood = -2361.0343                     Pseudo R2       =     0.3499
```

carnum	RRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
drvlicn	.004898	.0012999	-20.04	0.000	.0029114	.0082401
hhstru	.4796621	.0362162	-9.73	0.000	.413682	.5561658
acctenurty						
2	1.04408	.8443668	0.05	0.957	.2139691	5.094673
3	3.647461	.6332601	7.45	0.000	2.595421	5.125939
4	1.171872	.8289189	0.22	0.823	.2929451	4.687854
apartstruty						
2	1.129389	.2238957	0.61	0.539	.7657676	1.665674
3	.8006383	.2312105	-0.77	0.441	.4545944	1.410096
4	.498433	.3675186	-0.94	0.345	.117483	2.114651
region						
2	.8824363	.3340668	-0.33	0.741	.4201856	1.853214
3	.8177853	.3450963	-0.48	0.634	.3576364	1.86998
4	.8131476	.363398	-0.46	0.643	.3386608	1.952422
5	.535106	.2254415	-1.48	0.138	.2343292	1.221949
6	.5630484	.2395322	-1.35	0.177	.2445836	1.296176
7	1.271613	.5345028	0.57	0.568	.5579117	2.898306
8	.5252386	.2143171	-1.58	0.115	.2360666	1.168635
9	.5931942	.2466643	-1.26	0.209	.2625712	1.34013
10	.5688366	.2668745	-1.20	0.229	.2267979	1.426711
11	.4922318	.1993442	-1.75	0.080	.2225614	1.088653
ethnicorig~s						
2	1.275879	.8771302	0.35	0.723	.3316142	4.908921
3	2.235023	1.260452	1.43	0.154	.7400188	6.750273
4	.3367633	.3519533	-1.04	0.298	.0434239	2.611683
5	.4072136	.3408403	-1.07	0.283	.0789517	2.100309
6	1.242606	.9004888	0.30	0.764	.3002523	5.142571
7	1.260534	.8065846	0.36	0.717	.3596596	4.417916
8	.8847438	.4019201	-0.27	0.787	.3631909	2.155262
2	(base outcome)					

3						
drvlicn	2.994278	.5182224	6.34	0.000	2.132917	4.203493
hhstru	1.80774	.0800211	13.38	0.000	1.657513	1.971583
acctenurty						
2	2.111232	1.245784	1.27	0.205	.6641464	6.711324
3	.316186	.0389282	-9.35	0.000	.2483959	.4024769
4	.771302	.4299694	-0.47	0.641	.2586511	2.300036
apartstruty						
2	1.024652	.1287205	0.19	0.846	.8010242	1.310713
3	1.487788	.2212368	2.67	0.008	1.111644	1.991206
4	1.262879	.5781535	0.51	0.610	.5148452	3.097754
region						
2	1.308197	.3461553	1.02	0.310	.7788272	2.19738
3	.9927381	.2816774	-0.03	0.980	.5692677	1.731222
4	1.328971	.3847758	0.98	0.326	.7534732	2.34403
5	1.668932	.4716234	1.81	0.070	.9591748	2.903887
6	1.198969	.3236338	0.67	0.501	.7063924	2.035027
7	.6755475	.2104367	-1.26	0.208	.3668614	1.24397
8	1.936773	.5002691	2.56	0.010	1.167382	3.213249
9	1.358668	.3628919	1.15	0.251	.8049386	2.293317
10	1.49143	.4536586	1.31	0.189	.8216499	2.70719
11	1.067846	.3051782	0.23	0.818	.6098811	1.869702
ethnicorig~s						
2	.2112366	.2246778	-1.46	0.144	.0262666	1.698767
3	.4521676	.1915852	-1.87	0.061	.1970797	1.037426
4	.4145896	.2290194	-1.59	0.111	.1404153	1.224115
5	.2272784	.1847033	-1.82	0.068	.0462177	1.117655
6	.4923174	.2953442	-1.18	0.238	.1519162	1.595461
7	.3729768	.1952951	-1.88	0.060	.1336542	1.040833
8	.968915	.3227909	-0.09	0.924	.5043252	1.86149
4						
drvlicn	9.082344	3.82127	5.24	0.000	3.981684	20.71711
hhstru	2.592416	.1697312	14.55	0.000	2.280209	2.947371
acctenurty						
2	3.51e-07	.0005777	-0.01	0.993	0	.
3	.2296037	.0512769	-6.59	0.000	.1482115	.3556934
4	1.048366	.7917663	0.06	0.950	.2385902	4.606521
apartstruty						
2	1.012672	.2217834	0.06	0.954	.6592475	1.555567
3	2.950064	.6855962	4.66	0.000	1.870733	4.652122
4	3.66e-07	.0004647	-0.01	0.991	0	.
region						
2	.7974519	.3484854	-0.52	0.605	.3386339	1.877926
3	.6959566	.3183914	-0.79	0.428	.2839018	1.706067
4	1.006829	.4591483	0.01	0.988	.4118877	2.461119
5	1.218314	.5535501	0.43	0.664	.5000457	2.968309
6	1.001703	.4238828	0.00	0.997	.4370615	2.295806
7	.4631686	.2532864	-1.41	0.159	.1585823	1.352769
8	1.912238	.7599621	1.63	0.103	.8775205	4.16703
9	.7143443	.3131349	-0.77	0.443	.3025387	1.686686
10	1.681659	.7615026	1.15	0.251	.692293	4.084943
11	1.483831	.6322939	0.93	0.354	.6436777	3.420587
ethnicorig~s						
2	4.51e-07	.000697	-0.01	0.992	0	.
3	1.20e-07	.0001041	-0.02	0.985	0	.
4	.0817656	.0923655	-2.22	0.027	.0089335	.7483767
5	1.33e-07	.0001935	-0.01	0.991	0	.
6	.1920751	.2236877	-1.42	0.157	.0195963	1.88264
7	.1625084	.1822407	-1.62	0.105	.0180434	1.463637
8	.5387764	.4130383	-0.81	0.420	.1199107	2.420801

```
. mlogit carnum drvlicn hhstru i. acctenurty i. apartstruty i.region i.ethnicorigins i.ccbeliev, baseoutcome(2)

Iteration 0:   log likelihood = -3602.0454
Iteration 1:   log likelihood = -2611.0005
Iteration 2:   log likelihood = -2401.8009
Iteration 3:   log likelihood = -2345.6867
Iteration 4:   log likelihood = -2342.7281
Iteration 5:   log likelihood = -2342.6079
Iteration 6:   log likelihood = -2342.5792
Iteration 7:   log likelihood =  -2342.573
Iteration 8:   log likelihood = -2342.5718
Iteration 9:   log likelihood = -2342.5715
Iteration 10:  log likelihood = -2342.5714
Iteration 11:  log likelihood = -2342.5714

Multinomial logistic regression                 Number of obs   =       2917
                                                LR chi2(81)     =    2518.95
                                                Prob > chi2     =     0.0000
Log likelihood = -2342.5714                     Pseudo R2       =     0.3497
```

carnum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
drvlicn	-5.301443	.2662352	-19.91	0.000	-5.823254	-4.779632
hhstru	-.7253313	.0756597	-9.59	0.000	-.8736215	-.577041
acctenurty						
2	.112693	.8071227	0.14	0.889	-1.469238	1.694624
3	1.292121	.1746124	7.40	0.000	.9498868	1.634355
4	-.1671047	.7513092	-0.22	0.824	-1.639644	1.305434
apartstruty						
2	.1194454	.1993034	0.60	0.549	-.2711821	.510073
3	-.2388597	.2913412	-0.82	0.412	-.8098779	.3321585
4	-1.033979	.8098804	-1.28	0.202	-2.621315	.5533573
region						
2	-.1380248	.3802405	-0.36	0.717	-.8832824	.6072328
3	-.1821817	.4241487	-0.43	0.668	-1.013498	.6491344
4	-.1886597	.4476777	-0.42	0.673	-1.066092	.6887725
5	-.6482325	.4244321	-1.53	0.127	-1.480104	.183639
6	-.591042	.4290829	-1.38	0.168	-1.432029	.2499451
7	.2133431	.4223594	0.51	0.613	-.6144661	1.041152
8	-.5909878	.4132311	-1.43	0.153	-1.400906	.2189302
9	-.5077951	.4174099	-1.22	0.224	-1.325903	.3103132
10	-.5720872	.4702705	-1.22	0.224	-1.493801	.3496261
11	-.7102173	.4091988	-1.74	0.083	-1.512232	.0917976
ethnicorig~s						
2	.2514524	.6885437	0.37	0.715	-1.098069	1.600973
3	.8149486	.562052	1.45	0.147	-.2866531	1.91655
4	-1.137761	1.015635	-1.12	0.263	-3.128369	.8528478
5	-.8611109	.8367059	-1.03	0.303	-2.501024	.7788025
6	.0839574	.7553894	0.11	0.912	-1.396579	1.564493
7	.1742859	.639667	0.27	0.785	-1.079438	1.42801
8	-.1481371	.4584606	-0.32	0.747	-1.046703	.7504291
ccbeliev						
2	-.3329451	.3779709	-0.88	0.378	-1.073754	.4078642
3	-.3510469	.3280368	-1.07	0.285	-.9939872	.2918935
_cons	2.448567	.4835672	5.06	0.000	1.500793	3.396341
2	(base outcome)					
3						
drvlicn	1.081469	.174484	6.20	0.000	.7394867	1.423451
hhstru	.581016	.0443475	13.10	0.000	.4940964	.6679355
acctenurty						
2	.744265	.5862865	1.27	0.204	-.4048354	1.893365
3	-1.140596	.1238241	-9.21	0.000	-1.383286	-.8979048
4	-.4760581	.5914265	-0.80	0.421	-1.635233	.6831166
apartstruty						
2	.0114796	.1262884	0.09	0.928	-.2360412	.2590004
3	.3765066	.1492499	2.52	0.012	.0839822	.6690311
4	.2202489	.4621423	0.48	0.634	-.6855334	1.126031
region						
2	.2477566	.2653533	0.93	0.350	-.2723263	.7678395
3	-.0012198	.2840953	-0.00	0.997	-.5580363	.5555968
4	.3003869	.290296	1.03	0.301	-.2685828	.8693567
5	.5147309	.2830415	1.82	0.069	-.0400203	1.069482
6	.1546105	.2703896	0.57	0.567	-.3753433	.6845644
7	-.4137684	.31231	-1.32	0.185	-1.025885	.1983479
8	.6651305	.258841	2.57	0.010	.1578116	1.17245
9	.2935293	.2675829	1.10	0.273	-.2309235	.8179821
10	.3944081	.3044948	1.30	0.195	-.2023908	.9912069
11	.0435459	.2860118	0.15	0.879	-.5170269	.6041188

```
ethnicorig~s |
           2 |   -1.55243   1.065097    -1.46   0.145    -3.639982    .5351229
           3 |  -.7157487   .4256754    -1.68   0.093    -1.550057    .1185597
           4 |  -.8478433   .5591788    -1.52   0.129    -1.943814     .248127
           5 |  -1.514073   .8114125    -1.87   0.062    -3.104412    .0762663
           6 |  -.6957088   .5993672    -1.16   0.246    -1.870447    .4790292
           7 |  -.9734679   .5220138    -1.86   0.062    -1.996596    .0496605
           8 |    -.00315   .3360457    -0.01   0.993    -.6617874    .6554874
             |
     ccbeliev |
           2 |  -.0222713   .3036707    -0.07   0.942     -.617455    .5729124
           3 |   .2816579   .2585606     1.09   0.276    -.2251116    .7884273
             |
       _cons |  -3.137149    .402671    -7.79   0.000    -3.926369   -2.347928
-------------+----------------------------------------------------------------
4            |
     drvlicn |   2.207796   .4196348     5.26   0.000     1.385327    3.030265
      hhstru |   .9479925   .0657807    14.41   0.000     .8190646     1.07692
             |
  acctenurty |
           2 |  -14.95942   1593.072    -0.01   0.993    -3137.324    3107.405
           3 |  -1.476032   .2245667    -6.57   0.000    -1.916175   -1.035889
           4 |   .0796777   .7495077     0.11   0.915     -1.38933    1.548686
             |
 apartstruty |
           2 |   .0122987   .2194449     0.06   0.955    -.4178054    .4424028
           3 |   1.072734   .2328614     4.61   0.000     .6163336    1.529134
           4 |  -14.96461    1360.54    -0.01   0.991    -2681.574    2651.644
             |
      region |
           2 |  -.1870374   .4383671    -0.43   0.670    -1.046221    .6721464
           3 |  -.3479865   .4586308    -0.76   0.448    -1.246886    .5509134
           4 |   .0397988   .4576846     0.09   0.931    -.8572465     .936844
           5 |   .2617317   .4558474     0.57   0.566    -.6317128    1.155176
           6 |   .0208587   .4241441     0.05   0.961    -.8104486    .8521659
           7 |  -.7418284    .549056    -1.35   0.177    -1.817958    .3343015
           8 |    .695437   .3992089     1.74   0.082    -.0869981    1.477872
           9 |  -.3210814   .4398191    -0.73   0.465    -1.183111    .5409482
          10 |   .5616877   .4544935     1.24   0.217    -.3291031    1.452478
          11 |   .3999694   .4278315     0.93   0.350     -.438565    1.238504
             |
ethnicorig~s |
           2 |  -14.57767   1555.304    -0.01   0.993    -3062.917    3033.762
           3 |  -15.72394   865.0849    -0.02   0.985    -1711.259    1679.811
           4 |  -2.458839   1.133611    -2.17   0.030    -4.680676   -.2370026
           5 |  -15.82594   1453.269    -0.01   0.991    -2864.182     2832.53
           6 |  -1.578852   1.169146    -1.35   0.177    -3.870336    .7126322
           7 |  -1.941103   1.153671    -1.68   0.092    -4.202256    .3200494
           8 |  -.6039811   .7690541    -0.79   0.432    -2.111299    .9033371
             |
     ccbeliev |
           2 |   1.353016   .6758333     2.00   0.045     .0284069    2.677625
           3 |   1.069584   .6350047     1.68   0.092     -.175002    2.314171
             |
       _cons |   -7.30214   .8712384    -8.38   0.000    -9.009736   -5.594544
------------------------------------------------------------------------------

. mlogit carnum drvlicn hhstru i. acctenurty i. apartstruty i.region i.ccbeliev i.ethnicorigins incomehh, baseoutcome(2)

Iteration 0:   log likelihood = -3602.0454
Iteration 1:   log likelihood = -2576.7817
Iteration 2:   log likelihood = -2353.3826
Iteration 3:   log likelihood =  -2292.631
Iteration 4:   log likelihood = -2289.3983
Iteration 5:   log likelihood = -2289.2746
Iteration 6:   log likelihood = -2289.2456
Iteration 7:   log likelihood = -2289.2391
Iteration 8:   log likelihood = -2289.2377
Iteration 9:   log likelihood = -2289.2375
Iteration 10:  log likelihood = -2289.2374
```

Multinomial logistic regression

Number of obs	2917
LR chi2(84)	2625.62
Prob > chi2	0.0000
Pseudo R2	0.3645

Log likelihood = -2289.2374

carnum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
drvlicn	-5.317679	.2684646	-19.81	0.000	-5.843859	-4.791498
hhstru	-.6819308	.0760199	-8.97	0.000	-.8309271	-.5329346
acctenurty						
2	.0903755	.8336853	0.11	0.914	-1.543618	1.724369
3	1.183886	.1767875	6.70	0.000	.8373885	1.530383
4	.0302465	.7626068	0.04	0.968	-1.464435	1.524928
apartstruty						
2	.0821738	.202472	0.41	0.685	-.3146641	.4790117
3	-.2662339	.2953822	-0.90	0.367	-.8451723	.3127046
4	-1.07896	.8110734	-1.33	0.183	-2.668634	.5107148
region						
2	-.1728009	.3837013	-0.45	0.652	-.9248415	.5792398
3	-.2874732	.4281901	-0.67	0.502	-1.12671	.5517639
4	-.2226889	.4510182	-0.49	0.621	-1.106668	.6612905
5	-.6607809	.4256396	-1.55	0.121	-1.495019	.1734573
6	-.5792482	.4353139	-1.33	0.183	-1.432448	.2739514
7	.3981394	.4256221	0.94	0.350	-.4360646	1.232343
8	-.5750393	.4171069	-1.38	0.168	-1.392554	.2424752
9	-.4331484	.4201136	-1.03	0.303	-1.256556	.390259
10	-.3881918	.4767149	-0.81	0.415	-1.322536	.5461522
11	-.5989772	.4137219	-1.45	0.148	-1.409857	.2119029
ccbeliev						
2	-.3583536	.380775	-0.94	0.347	-1.104659	.3879518
3	-.3356541	.3302858	-1.02	0.310	-.9830024	.3116942
ethnicorig~s						
2	.3597775	.6842178	0.53	0.599	-.9812648	1.70082
3	.8179882	.5614883	1.46	0.145	-.2825086	1.918485
4	-1.425664	.9975965	-1.43	0.153	-3.380917	.5295896
5	-.8044503	.8529938	-0.94	0.346	-2.476287	.8673868
6	.0655905	.7621927	0.09	0.931	-1.42828	1.559461
7	.2324806	.6384174	0.36	0.716	-1.018794	1.483756
8	-.0168039	.4705363	-0.04	0.972	-.9390382	.9054303
incomehh	-.2046812	.0469711	-4.36	0.000	-.2967429	-.1126195
_cons	3.156814	.5172436	6.10	0.000	2.143035	4.170592
2	(base outcome)					
3						
drvlicn	1.130721	.1763693	6.41	0.000	.7850439	1.476399
hhstru	.5362399	.0450054	11.92	0.000	.448031	.6244488
acctenurty						
2	.7125419	.6020848	1.18	0.237	-.4675226	1.892606
3	-.9693025	.1260191	-7.69	0.000	-1.216295	-.7223096
4	-.6872813	.598401	-1.15	0.251	-1.860126	.4855632
apartstruty						
2	.0053329	.1278445	0.04	0.967	-.2452377	.2559035
3	.3985407	.1514867	2.63	0.009	.1016321	.6954492
4	.2652991	.4633638	0.57	0.567	-.6428773	1.173476
region						
2	.3187847	.2700577	1.18	0.238	-.2105186	.848088
3	.0636113	.2889208	0.22	0.826	-.5026631	.6298856
4	.4174079	.2962012	1.41	0.159	-.1631358	.9979515
5	.617734	.2883831	2.14	0.032	.0525135	1.182954
6	.1958832	.2745218	0.71	0.476	-.3421697	.7339361
7	-.4945417	.3156194	-1.57	0.117	-1.113144	.1240609
8	.6608887	.2628661	2.51	0.012	.1456806	1.176097
9	.2835549	.271906	1.04	0.297	-.2493711	.8164808
10	.3896347	.3089872	1.26	0.207	-.2159691	.9952384
11	.0517339	.2902258	0.18	0.859	-.5170983	.620566
ccbeliev						
2	.0053065	.3072424	0.02	0.986	-.5968775	.6074905
3	.2695217	.2614088	1.03	0.303	-.24283	.7818735

ethnicorig~s						
2	-1.658221	1.065997	-1.56	0.120	-3.747537	.4310949
3	-.7205375	.4306349	-1.67	0.094	-1.564566	.1234913
4	-.5816187	.570741	-1.02	0.308	-1.70025	.5370131
5	-1.314932	.8126033	-1.62	0.106	-2.907606	.2777409
6	-.6665141	.6047682	-1.10	0.270	-1.851838	.5188097
7	-1.000823	.5194838	-1.93	0.054	-2.018993	.0173465
8	-.0244271	.3350535	-0.07	0.942	-.6811198	.6322656
incomehh	.2823642	.0391351	7.22	0.000	.2056608	.3590677
_cons	-4.390819	.4487917	-9.78	0.000	-5.270435	-3.511204
4						
drvlicn	2.263092	.4194271	5.40	0.000	1.44103	3.085154
hhstru	.8918284	.0665658	13.40	0.000	.7613618	1.022295
acctenurty						
2	-14.60329	1315.889	-0.01	0.991	-2593.698	2564.492
3	-1.18111	.227304	-5.20	0.000	-1.626618	-.7356023
4	-.2491781	.7595064	-0.33	0.743	-1.737783	1.239427
apartstruty						
2	.0080133	.2216273	0.04	0.971	-.4263684	.4423949
3	1.114957	.2358441	4.73	0.000	.6527111	1.577203
4	-14.53226	1114.636	-0.01	0.990	-2199.178	2170.113
region						
2	-.0711059	.4449717	-0.16	0.873	-.9432345	.8010226
3	-.223155	.4647701	-0.48	0.631	-1.134088	.6877777
4	.2097563	.4665549	0.45	0.653	-.7046746	1.124187
5	.4158554	.4635918	0.90	0.370	-.4927678	1.324479
6	.1320626	.429934	0.31	0.759	-.7105925	.9747177
7	-.788503	.5522055	-1.43	0.153	-1.870806	.2937999
8	.7122493	.4050939	1.76	0.079	-.0817202	1.506219
9	-.3162834	.4450875	-0.71	0.477	-1.188639	.5560721
10	.5882942	.4610734	1.28	0.202	-.3153931	1.491982
11	.4520145	.4336781	1.04	0.297	-.397979	1.302008
ccbeliev						
2	1.388456	.6814327	2.04	0.042	.0528727	2.72404
3	1.037971	.6398323	1.62	0.105	-.216077	2.292019
ethnicorig~s						
2	-14.40025	1238.07	-0.01	0.991	-2440.972	2412.172
3	-15.41678	718.1454	-0.02	0.983	-1422.956	1392.122
4	-2.15566	1.150326	-1.87	0.061	-4.410257	.0989373
5	-15.05014	1219.372	-0.01	0.990	-2404.976	2374.876
6	-1.475167	1.168127	-1.26	0.207	-3.764654	.8143207
7	-1.920034	1.136358	-1.69	0.091	-4.147255	.3071857
8	-.6536489	.7747111	-0.84	0.399	-2.172055	.864757
incomehh	.4700854	.0779166	6.03	0.000	.3173716	.6227991
_cons	-9.488948	.9732099	-9.75	0.000	-11.3964	-7.581492

```
. mlogit, rrr
```

Multinomial logistic regression — Number of obs = 2917; LR chi2(84) = 2625.62; Prob > chi2 = 0.0000; Log likelihood = -2289.2374; Pseudo R2 = 0.3645

carnum	RRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
drvlicn	.0049041	.0013166	-19.81	0.000	.0028976	.0083
hhstru	.5056397	.0384387	-8.97	0.000	.4356452	.5868802
acctenurty						
2	1.094585	.9125396	0.11	0.914	.2136069	5.608979
3	3.267044	.5775724	6.70	0.000	2.310326	4.619944
4	1.030709	.7860253	0.04	0.968	.2312085	4.594814
apartstruty						
2	1.085644	.2198126	0.41	0.685	.7300341	1.614478
3	.7662599	.2263395	-0.90	0.367	.4294833	1.367118
4	.339949	.2757235	-1.33	0.183	.0693469	1.666482
region						
2	.8413051	.3228098	-0.45	0.652	.3965943	1.784681
3	.7501566	.3212096	-0.67	0.502	.3240977	1.736313
4	.8003638	.3609786	-0.49	0.621	.3306588	1.937291
5	.5164479	.2198207	-1.55	0.121	.2242443	1.18941
6	.5603194	.2439149	-1.33	0.183	.2387238	1.315151
7	1.489052	.6337732	0.94	0.350	.646576	3.429256
8	.5626827	.2346989	-1.38	0.168	.24844	1.2744
9	.6484642	.2724286	-1.03	0.303	.2846326	1.477363
10	.6782822	.3233472	-0.81	0.415	.2664587	1.726597
11	.5493733	.2272878	-1.45	0.148	.2441781	1.236028

ccbeliev						
2	.698826	.2660955	-0.94	0.347	.3313239	1.473959
3	.7148703	.2361115	-1.02	0.310	.374186	1.365737
ethnicorig~s						
2	1.433011	.9804914	0.53	0.599	.3748367	5.478437
3	2.265937	1.272297	1.46	0.145	.7538901	6.810633
4	.2403489	.2397712	-1.43	0.153	.0340163	1.698235
5	.4473337	.3815729	-0.94	0.346	.0840547	2.380681
6	1.067789	.8138613	0.09	0.931	.2397209	4.756256
7	1.261726	.8055078	0.36	0.716	.3610299	4.409475
8	.9833365	.4626955	-0.04	0.972	.3910037	2.472996
incomehh	.8149071	.0382771	-4.36	0.000	.7432351	.8934906
2	(base outcome)					
3						
drvlicn	3.09789	.5463727	6.41	0.000	2.192503	4.377154
hhstru	1.709567	.0769397	11.92	0.000	1.565227	1.867217
acctenurty						
2	2.039168	1.227752	1.18	0.237	.6265526	6.636644
3	.3793475	.047805	-7.69	0.000	.2963259	.4856294
4	.5029416	.3009608	-1.15	0.251	.155653	1.62509
apartstruty						
2	1.005347	.1285281	0.04	0.967	.7825185	1.291628
3	1.489649	.2256621	2.63	0.009	1.106976	2.004609
4	1.303821	.6041435	0.57	0.567	.5257774	3.23321
region						
2	1.375455	.3714522	1.18	0.238	.8101639	2.335178
3	1.065678	.3078966	0.22	0.826	.6049176	1.877396
4	1.518022	.4496398	1.41	0.159	.8494759	2.712719
5	1.85472	.53487	2.14	0.032	1.053917	3.264003
6	1.216385	.3339242	0.71	0.476	.7102277	2.083264
7	.6098503	.1924806	-1.57	0.117	.3285244	1.132085
8	1.936513	.5090435	2.51	0.012	1.156827	3.241696
9	1.327842	.3610481	1.04	0.297	.7792907	2.262524
10	1.476441	.4562014	1.26	0.207	.8057602	2.705369
11	1.053095	.3056355	0.18	0.859	.5962482	1.85998
ccbeliev						
2	1.005321	.3088771	0.02	0.986	.550528	1.835819
3	1.309338	.3422725	1.03	0.303	.7844048	2.185563
ethnicorig~s						
2	.1904775	.2030485	-1.56	0.120	.0235757	1.538942
3	.4864907	.2094999	-1.67	0.094	.2091787	1.13144
4	.5589928	.3190401	-1.02	0.308	.1826378	1.710889
5	.2684925	.2181779	-1.62	0.106	.0546063	1.320144
6	.5134954	.3105457	-1.10	0.270	.1569484	1.680027
7	.3675768	.1909502	-1.93	0.054	.1327892	1.017498
8	.9758688	.3269682	-0.07	0.942	.50605	1.881869
incomehh	1.326262	.0519034	7.22	0.000	1.228336	1.431994
4						
drvlicn	9.612767	4.031855	5.40	0.000	4.225046	21.87084
hhstru	2.439586	.1623931	13.40	0.000	2.14119	2.779567
acctenurty						
2	4.55e-07	.0005985	-0.01	0.991	0	.
3	.3069378	.0697682	-5.20	0.000	.1965934	.4792167
4	.7794412	.5919905	-0.33	0.743	.1759099	3.453634
apartstruty						
2	1.008045	.2234104	0.04	0.971	.6528758	1.55643
3	3.049437	.719192	4.73	0.000	1.920741	4.841396
4	4.88e-07	.0005443	-0.01	0.990	0	.
region						
2	.9313632	.4144303	-0.16	0.873	.3893664	2.227818
3	.7999908	.3718118	-0.48	0.631	.3217155	1.98929
4	1.233377	.5754384	0.45	0.653	.4942694	3.077714
5	1.515667	.7026507	0.90	0.370	.6109331	3.760225
6	1.14118	.4906319	0.31	0.759	.491353	2.650419
7	.4545247	.250991	-1.43	0.153	.1539995	1.341515
8	2.038571	.8258129	1.76	0.079	.9215298	4.509647
9	.7288529	.3244033	-0.71	0.477	.3046356	1.743809
10	1.800914	.8303535	1.28	0.202	.729502	4.445897
11	1.571475	.6815143	1.04	0.297	.6716761	3.676672
ccbeliev						
2	4.008657	2.73163	2.04	0.042	1.054295	15.24177
3	2.823483	1.806556	1.62	0.105	.8056733	9.8949
ethnicorig~s						
2	5.57e-07	.0006899	-0.01	0.991	0	.
3	2.02e-07	.0001448	-0.02	0.983	0	.
4	.1158268	.1332385	-1.87	0.061	.0121521	1.103997
5	2.91e-07	.0003548	-0.01	0.990	0	.
6	.2287406	.2671981	-1.26	0.207	.0231756	2.257642
7	.1466019	.1665922	-1.69	0.091	.0158078	1.359593
8	.5201444	.4029616	-0.84	0.399	.1139432	2.374429
incomehh	1.600131	.1246768	6.03	0.000	1.373513	1.864139

```
. mlogit carnum drvlicn hhstru, baseoutcome(2)

Iteration 0:   log likelihood = -3631.5476
Iteration 1:   log likelihood = -2777.6462
Iteration 2:   log likelihood = -2613.5868
Iteration 3:   log likelihood = -2573.8277
Iteration 4:   log likelihood = -2571.9744
Iteration 5:   log likelihood = -2571.9625
Iteration 6:   log likelihood = -2571.9625

Multinomial logistic regression                 Number of obs   =       2942
                                                LR chi2(6)      =    2119.17
                                                Prob > chi2     =     0.0000
Log likelihood = -2571.9625                     Pseudo R2       =     0.2918
```

carnum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
drvlicn	-5.261256	.2540755	-20.71	0.000	-5.759235	-4.763277
hhstru	-.5651518	.0660628	-8.55	0.000	-.6946325	-.4356712
_cons	2.170559	.1640284	13.23	0.000	1.849069	2.492049
2	(base outcome)					
3						
drvlicn	1.236384	.1682617	7.35	0.000	.9065971	1.566171
hhstru	.4661513	.0395838	11.78	0.000	.3885684	.5437342
_cons	-2.761443	.2055091	-13.44	0.000	-3.164234	-2.358653
4						
drvlicn	2.531718	.4140607	6.11	0.000	1.720174	3.343262
hhstru	.7208444	.0566588	12.72	0.000	.6097952	.8318935
_cons	-5.973931	.4695989	-12.72	0.000	-6.894328	-5.053534

```
. mlogit carnum i. acctenurty i. apartstruty i.region, baseoutcome(2)

Iteration 0:   log likelihood = -3631.5476
Iteration 1:   log likelihood = -3352.8927
Iteration 2:   log likelihood = -3331.0573
Iteration 3:   log likelihood = -3330.5863
Iteration 4:   log likelihood = -3330.4788
Iteration 5:   log likelihood = -3330.4549
Iteration 6:   log likelihood = -3330.4495
Iteration 7:   log likelihood = -3330.4487
Iteration 8:   log likelihood = -3330.4486
Iteration 9:   log likelihood = -3330.4486

Multinomial logistic regression                 Number of obs   =       2942
                                                LR chi2(48)     =     602.20
                                                Prob > chi2     =     0.0000
Log likelihood = -3330.4486                     Pseudo R2       =     0.0829
```

carnum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
acctenurty						
2	.9464473	.6555155	1.44	0.149	-.3383394	2.231234
3	1.23539	.1064779	11.60	0.000	1.026697	1.444083
4	1.144252	.5086455	2.25	0.024	.1473247	2.141178
apartstruty						
2	.0009101	.1233301	0.01	0.994	-.2408124	.2426326
3	-.5413407	.1864135	-2.90	0.004	-.9067044	-.175977
4	-.2479811	.5477246	-0.45	0.651	-1.321502	.8255394
region						
2	-.125645	.232112	-0.54	0.588	-.5805761	.3292861
3	-.3379211	.2580435	-1.31	0.190	-.8436771	.1678349
4	-.0607963	.2714801	-0.22	0.823	-.5928875	.4712949
5	-.316133	.2645155	-1.20	0.232	-.8345739	.2023078
6	-.9476498	.2674047	-3.54	0.000	-1.471753	-.4235462
7	-.0748943	.2480663	-0.30	0.763	-.5610954	.4113068
8	-.6622052	.2543548	-2.60	0.009	-1.160731	-.1636789
9	-.6895364	.2566128	-2.69	0.007	-1.192488	-.1865846
10	-.3413929	.3044366	-1.12	0.262	-.9380777	.2552918
11	-.2391007	.2548917	-0.94	0.348	-.7386794	.2604779
_cons	-1.036768	.2153782	-4.81	0.000	-1.458901	-.6146341
2	(base outcome)					
3						
acctenurty						
2	.6244838	.5502272	1.13	0.256	-.4539417	1.702909
3	-.984038	.1125297	-8.74	0.000	-1.204592	-.7634839
4	-.3515256	.5218016	-0.67	0.501	-1.374238	.6711867
apartstruty						
2	.0348073	.1182152	0.29	0.768	-.1968902	.2665048
3	.3266879	.1411782	2.31	0.021	.0499838	.603392
4	.0862791	.4276421	0.20	0.840	-.751884	.9244422
region						
2	.3033474	.2483209	1.22	0.222	-.1833526	.7900475
3	.119657	.2657657	0.45	0.653	-.4012341	.6405482
4	.2983942	.2728806	1.09	0.274	-.236442	.8332304
5	.4799485	.2648936	1.81	0.070	-.0392335	.9991304
6	.168714	.2539185	0.66	0.506	-.3289572	.6663852
7	-.2529826	.2872861	-0.88	0.379	-.8160531	.3100878
8	.6687329	.2420922	2.76	0.006	.194241	1.143225
9	.3373025	.2508021	1.34	0.179	-.1542605	.8288656
10	.3233642	.2872367	1.13	0.260	-.2396094	.8863379
11	.0962856	.268744	0.36	0.720	-.430443	.6230142
_cons	-.6396202	.2281481	-2.80	0.005	-1.086782	-.1924581
4						
acctenurty						
2	-13.50894	789.0513	-0.02	0.986	-1560.021	1533.003
3	-1.164036	.2013783	-5.78	0.000	-1.55873	-.769342
4	.0024532	.685867	0.00	0.997	-1.341821	1.346728
apartstruty						
2	.0619861	.2049787	0.30	0.762	-.3397648	.4637369
3	.9828164	.2152446	4.57	0.000	.5609448	1.404688
4	-13.6028	605.582	-0.02	0.982	-1200.522	1173.316
region						
2	-.1837447	.4094544	-0.45	0.654	-.9862606	.6187712
3	-.1153597	.4248554	-0.27	0.786	-.948061	.7173417
4	-.0185044	.4256029	-0.04	0.965	-.8526707	.815662
5	.0859875	.4232108	0.20	0.839	-.7434904	.9154654
6	.019242	.391954	0.05	0.961	-.7489737	.7874577
7	-.6331354	.510127	-1.24	0.215	-1.632966	.3666952
8	.6233671	.3683657	1.69	0.091	-.0986165	1.345351
9	-.223741	.4079743	-0.55	0.583	-1.023356	.575874
10	.3994694	.4179556	0.96	0.339	-.4197084	1.218647
11	.3953349	.395484	1.00	0.317	-.3797996	1.170469
_cons	-1.85354	.3609511	-5.14	0.000	-2.560991	-1.146089

TEST OF IIA ASSUMPTION

```
. xtreg carnum drvlicn  hhstru acctenur apartstru region ccbeliev hhinco ethnicity, fe

Fixed-effects (within) regression               Number of obs      =      2917
Group variable: incomehh                        Number of groups   =         6

R-sq:  within  = 0.3963                         Obs per group: min =       278
       between = 0.1859                                        avg =     486.2
       overall = 0.0745                                        max =       953

                                                F(8,2903)          =    238.24
corr(u_i, Xb)  = -0.9176                        Prob > F           =    0.0000

------------------------------------------------------------------------------
      carnum |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     drvlicn |   .9390494   .0266081    35.29   0.000     .8868768     .991222
      hhstru |   .1628268   .0092312    17.64   0.000     .1447264    .1809273
    acctenur |  -.0029359   .0012365    -2.37   0.018    -.0053603   -.0005115
   apartstru |   .1099187   .0109567    10.03   0.000      .088435    .1314025
      region |   .0060683   .0036923     1.64   0.100    -.0011714     .013308
    ccbeliev |   .0247009   .0217495     1.14   0.256    -.0179452     .067347
      hhinco |   .0400965   .0076384     5.25   0.000     .0251192    .0550738
   ethnicity |   .0065466   .0031344     2.09   0.037     .0004008    .0126925
       _cons |   -.509966   .2416017    -2.11   0.035    -.9836942   -.0362378
-------------+----------------------------------------------------------------
     sigma_u |  1.3956385
     sigma_e |   .59918366
         rho |   .84436591   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(5, 2903) =    47.13                 Prob > F = 0.0000

. estimates store fixed


. xtreg carnum drvlicn  hhstru acctenur apartstru region ccbeliev hhinco ethnicity,re

Random-effects GLS regression                   Number of obs      =      2917
Group variable: incomehh                        Number of groups   =         6

R-sq:  within  = 0.3900                         Obs per group: min =       278
       between = 0.9473                                        avg =     486.2
       overall = 0.4740                                        max =       953

Random effects u_i ~ Gaussian                   Wald chi2(8)       =   2620.11
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
      carnum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     drvlicn |   1.040413   .0261699    39.76   0.000     .9891214    1.091705
      hhstru |   .1982881   .0092238    21.50   0.000     .1802097    .2163664
    acctenur |  -.0035034   .0012831    -2.73   0.006    -.0060183   -.0009885
   apartstru |   .1074905    .011368     9.46   0.000     .0852097    .1297714
      region |   .0094208    .003826     2.46   0.014      .001922    .0169197
    ccbeliev |   .0589608   .0224731     2.62   0.009     .0149144    .1030073
      hhinco |   .0012994   .0003189     4.08   0.000     .0006744    .0019243
   ethnicity |   .0076166   .0032546     2.34   0.019     .0012377    .0139955
       _cons |   .4074874   .0789537     5.16   0.000     .2527411    .5622338
-------------+----------------------------------------------------------------
     sigma_u |           0
     sigma_e |   .59918366
         rho |           0   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. hausman fixed ., sigmamore

Note: the rank of the differenced variance matrix (5) does not equal the number of coefficients being tested (8); be sure this is what you expect, or
      there may be problems computing the test.  Examine the output of your estimators for anything unexpected and possibly consider scaling your
      variables so that the coefficients are on a similar scale.
```

	Coefficients (b) fixed	(B) .	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
drvlicn	.9390494	1.040413	-.101364	.0089039
hhstru	.1628268	.1982881	-.0354612	.0026259
acctenur	-.0029359	-.0035034	.0005675	.0000603
apartstru	.1099187	.1074905	.0024282	.0005827
region	.0060683	.0094208	-.0033525	.0002751
ccbeliev	.0247009	.0589608	-.0342599	.0023496
hhinco	.0400965	.0012994	.0387971	.0079291
ethnicity	.0065466	.0076166	-.00107	.0001059

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 218.32
Prob>chi2 = 0.0000
(V_b-V_B is not positive definite)

```
. describe

Contains data
  obs:        11,768
 vars:            10
 size:       353,040 (99.3% of memory free)
```

variable name	storage type	display format	value label	variable label
family_id	int	%8.0g		
numberofcars	str16	%16s		
chosen	byte	%8.0g		
income	byte	%8.0g		
size	byte	%8.0g		size
drive	byte	%8.0g		
ccbeliev	byte	%8.0g		
tenure	byte	%8.0g		
location	byte	%8.0g		
ethnicity	byte	%8.0g		

```
Sorted by:
     Note:  dataset has changed since last saved

.
. list family_id  numberofcars chosen size drive ccbeliev tenure location ethnicity in 1/25, sepby(fam)abbrev(10)
```

	family_id	numberofcars	chosen	size	drive	ccbeliev	tenure	location	ethnicity
1.	1	NocarHH	0	4	0	2	3	1	9
2.	1	OnecarHH	1	4	0	2	2	2	9
3.	1	TwocarHH	0	4	0	2	4	3	9
4.	1	ThreeormorecarHH	0	4	0	2	1	4	9
5.	2	NocarHH	0	2	1	3	2	2	9
6.	2	OnecarHH	1	2	1	3	1	3	9
7.	2	TwocarHH	0	2	1	3	3	4	9
8.	2	ThreeormorecarHH	0	2	1	3	4	1	9
9.	3	NocarHH	0	3	1	3	1	1	9
10.	3	OnecarHH	0	3	1	3	2	2	9
11.	3	TwocarHH	1	3	1	3	3	3	9
12.	3	ThreeormorecarHH	0	3	1	3	4	4	9
13.	4	NocarHH	0	3	1	3	1	2	9
14.	4	OnecarHH	0	3	1	3	2	3	9
15.	4	TwocarHH	1	3	1	3	3	4	9
16.	4	ThreeormorecarHH	0	3	1	3	4	1	9
17.	5	NocarHH	0	1	1	1	1	1	11
18.	5	OnecarHH	1	1	1	1	2	2	11
19.	5	TwocarHH	0	1	1	1	3	3	11
20.	5	ThreeormorecarHH	0	1	1	1	4	4	11
21.	6	NocarHH	1	1	0	3	3	3	9
22.	6	OnecarHH	0	1	0	3	4	4	9
23.	6	TwocarHH	0	1	0	3	1	1	9
24.	6	ThreeormorecarHH	0	1	0	3	2	2	9
25.	7	NocarHH	0	2	1	3	3	2	9

```
. nlogitgen type = numberofcars (Nouseofcars: NocarHH, Necessityofcars: OnecarHH, Wantofcars: TwocarHH | ThreeormorecarHH)
new variable type is generated with 3 groups
label list lb_type
lb_type:
           1 Nouseofcars
           2 Necessityofcars
           3 Wantofcars


.
. nlogittree numberofcars type, choice(chosen)

tree structure specified for the nested logit model

 type         N      numberofcars  N    k
------------------------------------------
 Nouseofcars  2942 -- NocarHH      2942  595
 Necessityo~s 2942 -- OnecarHH     2942 1331
 Wantofcars   5884 -- ThreeormorecarHH 2942  231
                   L- TwocarHH     2942  785
------------------------------------------
                          total  11768 2942

k = number of times alternative is chosen
N = number of observations at each level


.
. qui nlogitgen type = numberofcars (Nouseofcars: NocarHH, Necessityofcars: OnecarHH, Wantofcars: TwocarHH | ThreeormorecarHH)
type already defined
r(110);


.
. generate Africans=1 if ethnicity<=1
(11604 missing values generated)


.
. replace Africans=0 if ethnicity>1
(11604 real changes made)


.
. tab Africans

  Africans |      Freq.     Percent        Cum.
-----------+-----------------------------------
          0 |     11,604       98.61       98.61
          1 |        164        1.39      100.00
-----------+-----------------------------------
      Total |     11,768      100.00
```

```
. generate Caribbean=0

. replace Caribbean=1 if ethnicity>=2
(11604 real changes made)

. tab Caribbean
```

Caribbean	Freq.	Percent	Cum.
0	164	1.39	1.39
1	11,604	98.61	100.00
Total	11,768	100.00	

```
. generate Otherblacks=0

. replace Otherblacks=1 if ethnicity>=3
(11512 real changes made)

. tab Otherblacks
```

Otherblacks	Freq.	Percent	Cum.
0	256	2.18	2.18
1	11,512	97.82	100.00
Total	11,768	100.00	

```
. generate Indians=0

. replace Indians=1 if ethnicity>=4
(11508 real changes made)

. tab Indians
```

Indians	Freq.	Percent	Cum.
0	260	2.21	2.21
1	11,508	97.79	100.00
Total	11,768	100.00	

```
. generate Pakistans=0

. replace Pakistans=1 if ethnicity>=5
(11304 real changes made)

. tab Pakistans
```

Pakistans	Freq.	Percent	Cum.
0	464	3.94	3.94
1	11,304	96.06	100.00
Total	11,768	100.00	

```
. generate Chinese=0

. replace Chinese=1 if ethnicity>=7
(11192 real changes made)

. tab Chinese
```

Chinese	Freq.	Percent	Cum.
0	576	4.89	4.89
1	11,192	95.11	100.00
Total	11,768	100.00	

```
. generate OtherAsianorigin=0

. replace OtherAsianorigin=1 if ethnicity>=8
(11120 real changes made)
```

```
. tab OtherAsianorigin
```

OtherAsianorigin	Freq.	Percent	Cum.
0	648	5.51	5.51
1	11,120	94.49	100.00
Total	11,768	100.00	

```
.
. generate White=0

.
. replace White=1 if ethnicity>=9
(11012 real changes made)

.
. tab White
```

White	Freq.	Percent	Cum.
0	756	6.42	6.42
1	11,012	93.58	100.00
Total	11,768	100.00	

```
.
. generate Mixedorigin=0

.
. replace Mixedorigin=1 if ethnicity>=10 & ethnicity<=11
(232 real changes made)

.
. tab Mixedorigin
```

Mixedorigin	Freq.	Percent	Cum.
0	11,536	98.03	98.03
1	232	1.97	100.00
Total	11,768	100.00	

```
. nlogit chosen tenure location || type: income size drive ccbeliev Africans Caribbean Indians Pakistans Chinese OtherAsianorigin White
> (Necessityofcars)|| numberofcars:, noconstant case(family_id )
```

```
RUM-consistent nested logit regression          Number of obs      =      11744
Case variable: family_id                        Number of cases    =       2936

Alternative variable: numberofcars              Alts per case: min =          4
                                                               avg =        4.0
                                                               max =          4

                                                  Wald chi2(26)    =     899.92
Log likelihood = -2615.4235                       Prob > chi2      =     0.0000
```

chosen	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
numberofcars						
tenure	.3050261	.0283135	10.77	0.000	.2495326	.3605195
location	-.1851974	.0320403	-5.78	0.000	-.2479951	-.1223996
type equations						
Nouseofcars						
income	-.0068573	.0018928	-3.62	0.000	-.0105673	-.0031474
size	-.5949797	.0701154	-8.49	0.000	-.7324034	-.4575559
drive	-5.335573	.2573893	-20.73	0.000	-5.840047	-4.8311
ccbeliev	-.0176033	.0914319	-0.19	0.847	-.1968065	.1615999
Africans	3.360104	.6862514	4.90	0.000	2.015076	4.705132
Caribbean	3.377342	.7412484	4.56	0.000	1.924522	4.830162
Indians	-.0219442	.8212206	-0.03	0.979	-1.631507	1.587619
Pakistans	-1.709642	1.071359	-1.60	0.111	-3.809466	.3901826
Chinese	.3044622	1.246859	0.24	0.807	-2.139336	2.748261
OtherAsian~n	1.195942	1.044903	1.14	0.252	-.8520306	3.243914
White	-.5556901	.6560017	-0.85	0.397	-1.84143	.7300496
Mixedorigin	.2277865	.4737949	0.48	0.631	-.7008344	1.156407
Necessityofcars|						
income	(base)					
size	(base)					
drive	(base)					
ccbeliev	(base)					
Africans	(base)					
Caribbean	(base)					
Indians	(base)					
Pakistans	(base)					
Chinese	(base)					
OtherAsian~n	(base)					
White	(base)					
Mixedorigin	(base)					
Wantofcars						
income	.001812	.0013136	1.38	0.168	-.0007626	.0043865
size	.6399391	.0421027	15.20	0.000	.5574194	.7224589
drive	1.132488	.1711388	6.62	0.000	.7970624	1.467914
ccbeliev	.048391	.0725071	0.67	0.505	-.0937204	.1905023
Africans	-305.2384	384.7094	-0.79	0.428	-1059.255	448.7781
Caribbean	-306.2102	384.7098	-0.80	0.426	-1060.228	447.8072
Indians	1.089593	1.138916	0.96	0.339	-1.142642	3.321827
Pakistans	-.2679483	.6374079	-0.42	0.674	-1.517245	.9813482
Chinese	-.4433907	.9391367	-0.47	0.637	-2.284065	1.397283
OtherAsian~n	.9251312	.9784938	0.95	0.344	-.9926814	2.842944
White	.8537745	.5643959	1.51	0.130	-.2524212	1.95997
Mixedorigin	.2041762	.3452601	0.59	0.554	-.4725212	.8808736
dissimilarity parameters						
type						
/Nouseofca~u	1	.			.	.
/Necessity~u	1	90694.77			-177757.5	177759.5
/Wantofcar~u	434.039	555.0191			-653.7785	1521.857

LR test for IIA (tau = 1): chi2(2) = 144.23 Prob > chi2 = 0.0000

APPENDIX 3- FULL STATA RESULTS: US MNL MODEL/NL MODEL

```
. tabulate  carnum
```

carnum	Freq.	Percent	Cum.
0	963	15.18	15.18
1	2,141	33.76	48.94
2	1,784	28.13	77.07
3	784	12.36	89.44
4	364	5.74	95.18
5	155	2.44	97.62
6	73	1.15	98.77
7	34	0.54	99.31
8	19	0.30	99.61
9	10	0.16	99.76
10	7	0.11	99.87
11	2	0.03	99.91
12	1	0.02	99.92
13	1	0.02	99.94
14	2	0.03	99.97
15	1	0.02	99.98
21	1	0.02	100.00
Total	6,342	100.00	

```
.
. tabulate  hhstru
```

hhstru	Freq.	Percent	Cum.
1	1,945	30.67	30.67
2	2,074	32.70	63.37
3	930	14.66	78.04
4	775	12.22	90.26
5	368	5.80	96.06
6	153	2.41	98.47
7	57	0.90	99.37
8	25	0.39	99.76
9	9	0.14	99.91
10	3	0.05	99.95
11	2	0.03	99.98
12	1	0.02	100.00
Total	6,342	100.00	

```
.
. tabulate hhinco
```

hhinco	Freq.	Percent	Cum.
1	258	4.07	4.07
2	219	3.45	7.52
3	394	6.21	13.73
4	408	6.43	20.17
5	725	11.43	31.60
6	657	10.36	41.96
7	556	8.77	50.73
8	826	13.02	63.75
9	2,299	36.25	100.00
Total	6,342	100.00	

```
.
. tabulate noofearners
```

noofearners	Freq.	Percent	Cum.
0	1,515	23.89	23.89
1	2,351	37.07	60.96
2	1,971	31.08	92.04
3	375	5.91	97.95
4	107	1.69	99.64
5	20	0.32	99.95
6	2	0.03	99.98
7	1	0.02	100.00
Total	6,342	100.00	

```
. tabulate  drvlicn
```

drvlicn	Freq.	Percent	Cum.
0	963	15.18	15.18
1	5,379	84.82	100.00
Total	6,342	100.00	

```
. tabulate  acctenur
```

acctenur	Freq.	Percent	Cum.
1	2,214	34.91	34.91
2	1,743	27.48	62.39
4	2,267	35.75	98.14
5	104	1.64	99.78
6	14	0.22	100.00
Total	6,342	100.00	

```
. tabulate  ccbeliev
```

ccbeliev	Freq.	Percent	Cum.
1	5,598	88.27	88.27
2	370	5.83	94.10
3	86	1.36	95.46
4	234	3.69	99.15
5	54	0.85	100.00
Total	6,342	100.00	

```
. tabulate ethnic
```

ethnic	Freq.	Percent	Cum.
1	5,212	82.18	82.18
2	700	11.04	93.22
3	30	0.47	93.69
4	300	4.73	98.42
5	22	0.35	98.77
6	78	1.23	100.00
Total	6,342	100.00	

```
. describe carnum
```

variable name	storage type	display format	value label	variable label
carnum	byte	%8.0g		

```
. recode  carnum (0=1 NocarHH) (1=2 OnecarHH) (2=3 TwocarHH) (3/21=4 ThreeormorecarHH), gen (carnumHH)
(5978 differences between carnum and carnumHH)
. tabulate  carnum carnumHH
```

carnum	RECODE of carnum				
	NocarHH	OnecarHH	TwocarHH	Threeormo	Total
0	963	0	0	0	963
1	0	2,141	0	0	2,141
2	0	0	1,784	0	1,784
3	0	0	0	784	784
4	0	0	0	364	364
5	0	0	0	155	155
6	0	0	0	73	73
7	0	0	0	34	34
8	0	0	0	19	19
9	0	0	0	10	10
10	0	0	0	7	7
11	0	0	0	2	2
12	0	0	0	1	1
13	0	0	0	1	1
14	0	0	0	2	2
15	0	0	0	1	1
21	0	0	0	1	1
Total	963	2,141	1,784	1,454	6,342

```
. tabulate  carnumHH
```

RECODE of carnum	Freq.	Percent	Cum.
NocarHH	963	15.18	15.18
OnecarHH	2,141	33.76	48.94
TwocarHH	1,784	28.13	77.07
ThreeormorecarHH	1,454	22.93	100.00
Total	6,342	100.00	

```
. describe  hhstru drvlicn acctenur ccbeliev hhinco
```

variable name	storage type	display format	value label	variable label
hhstru	byte	%8.0g		
drvlicn	byte	%8.0g		
acctenur	byte	%8.0g		
ccbeliev	byte	%8.0g		
hhinco	byte	%8.0g		

```
. summarize carnum
```

Variable	Obs	Mean	Std. Dev.	Min	Max
carnum	6342	1.796121	1.496744	0	21

```
. summarize  hhstru drvlicn acctenur ccbeliev hhinco
```

Variable	Obs	Mean	Std. Dev.	Min	Max
hhstru	6342	2.441659	1.470839	1	12
drvlicn	6342	.8481552	.3588987	0	1
acctenur	6342	2.423841	1.335096	1	6
ccbeliev	6342	1.230211	.7266191	1	5
hhinco	6342	6.664775	2.435262	1	9

```
. tabulate  carnum
```

carnum	Freq.	Percent	Cum.
0	963	15.18	15.18
1	2,141	33.76	48.94
2	1,784	28.13	77.07
3	784	12.36	89.44
4	364	5.74	95.18
5	155	2.44	97.62
6	73	1.15	98.77
7	34	0.54	99.31
8	19	0.30	99.61
9	10	0.16	99.76
10	7	0.11	99.87
11	2	0.03	99.91
12	1	0.02	99.92
13	1	0.02	99.94
14	2	0.03	99.97
15	1	0.02	99.98
21	1	0.02	100.00
Total	6,342	100.00	

```
. recode  acctenur (1=1 Ownerswithmortgage) (2=2 Ownerswithoutmortgage) (4=3 Tenants) (5 6=4 Others), gen (acctenurHH)
(2385 differences between acctenur and acctenurHH)

. tabulate  acctenur  acctenurHH
```

acctenur	RECODE of acctenur				
	Ownerswit	Ownerswit	Tenants	Others	Total
1	2,214	0	0	0	2,214
2	0	1,743	0	0	1,743
4	0	0	2,267	0	2,267
5	0	0	0	104	104
6	0	0	0	14	14
Total	2,214	1,743	2,267	118	6,342

```
. tabulate  acctenurHH
```

RECODE of acctenur	Freq.	Percent	Cum.
Ownerswithmortgage	2,214	34.91	34.91
Ownerswithoutmortgage	1,743	27.48	62.39
Tenants	2,267	35.75	98.14
Others	118	1.86	100.00
Total	6,342	100.00	

```
. recode  ethnic(1=1 White) (2=2 Black) (3=3 Nativeamericans) (4=4 Asians)(5=5 Pacificislander)(6=6  Multi-race), gen (ethnicity)
(0 differences between ethnic and ethnicity)

. tabulate  ethnic ethnicity
```

ethnic	RECODE of ethnic						
	White	Black	Nativeame	Asians	Pacificis	Multi-rac	Total
1	5,212	0	0	0	0	0	5,212
2	0	700	0	0	0	0	700
3	0	0	30	0	0	0	30
4	0	0	0	300	0	0	300
5	0	0	0	0	22	0	22
6	0	0	0	0	0	78	78
Total	5,212	700	30	300	22	78	6,342

```
. tabulate  ethnicity
```

RECODE of ethnic	Freq.	Percent	Cum.
White	5,212	82.18	82.18
Black	700	11.04	93.22
Nativeamericans	30	0.47	93.69
Asians	300	4.73	98.42
Pacificislander	22	0.35	98.77
Multi-race	78	1.23	100.00
Total	6,342	100.00	

```
.
. summarize i. ethnicity
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ethnicity					
2	6342	.1103753	.3133817	0	1
3	6342	.0047304	.0686202	0	1
4	6342	.0473037	.2123044	0	1
5	6342	.0034689	.0588001	0	1
6	6342	.012299	.1102253	0	1

```
.
. summarize i.  ccbeliev
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ccbeliev					
2	6342	.0583412	.234406	0	1
3	6342	.0135604	.115666	0	1
4	6342	.0368969	.1885235	0	1
5	6342	.0085147	.0918885	0	1

```
.
. recode  hhinco (1/3=1 verypoor)(4/6=2 poor) (7/9=3 avergae) (10/12=4 rich) (13/20=5 veryrich) (97 98=6 undisclosed), gen(hhincoty)
(6084 differences between hhinco and hhincoty)

.
. tabulate  hhinco  hhincoty
```

hhinco	RECODE of hhinco verypoor	poor	avergae	Total
1	258	0	0	258
2	219	0	0	219
3	394	0	0	394
4	0	408	0	408
5	0	725	0	725
6	0	657	0	657
7	0	0	556	556
8	0	0	826	826
9	0	0	2,299	2,299
Total	871	1,790	3,681	6,342

```
. tabulate  hhincoty
```

RECODE of hhinco	Freq.	Percent	Cum.
verypoor	871	13.73	13.73
poor	1,790	28.22	41.96
avergae	3,681	58.04	100.00
Total	6,342	100.00	

```
.
. summarize i. hhincoty
```

Variable	Obs	Mean	Std. Dev.	Min	Max
hhincoty					
2	6342	.2822453	.4501276	0	1
3	6342	.5804163	.4935298	0	1

```
.
. recode  noofearners (0 1=1 veryfew)(2 3=2 few) (4 5=3 avergae) (6 7=4 large), gen(earningpower)
(2020 differences between noofearners and earningpower)

.
. tabulate  noofearners  earningpower
```

noofearners	RECODE of noofearners				
	veryfew	few	avergae	large	Total
0	1,515	0	0	0	1,515
1	2,351	0	0	0	2,351
2	0	1,971	0	0	1,971
3	0	375	0	0	375
4	0	0	107	0	107
5	0	0	20	0	20
6	0	0	0	2	2
7	0	0	0	1	1
Total	3,866	2,346	127	3	6,342

```
. do "C:\Users\talawal\AppData\Local\Temp\STD07000000.tmp"

. mlogit carnumHH drvlicn hhstru, baseoutcome(2)

Iteration 0:   log likelihood = -8544.3852
Iteration 1:   log likelihood = -8168.7315
Iteration 2:   log likelihood = -8162.4188
Iteration 3:   log likelihood = -8162.3989
Iteration 4:   log likelihood = -8162.3989

Multinomial logistic regression                 Number of obs   =       6342
                                                LR chi2(6)      =     763.97
                                                Prob > chi2     =     0.0000
Log likelihood = -8162.3989                     Pseudo R2       =     0.0447
```

carnumHH	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NocarHH						
drvlicn	-.0508087	.1095681	-0.46	0.643	-.2655583	.1639409
hhstru	-.1500976	.0374614	-4.01	0.000	-.2235206	-.0766745
_cons	-.4672828	.1231394	-3.79	0.000	-.7086316	-.2259339
OnecarHH	(base outcome)					
TwocarHH						
drvlicn	-.0748816	.092679	-0.81	0.419	-.2565291	.1067659
hhstru	.4402054	.0255475	17.23	0.000	.3901332	.4902777
_cons	-1.157281	.1037956	-11.15	0.000	-1.360716	-.953845
Threeormor~H						
drvlicn	-.2069114	.0969408	-2.13	0.033	-.3969119	-.016911
hhstru	.5319017	.026441	20.12	0.000	.4800784	.5837251
_cons	-1.518241	.1093106	-13.89	0.000	-1.732486	-1.303996

```
. mlogit carnumHH drvlicn hhstru i. acctenurHH i.ethnicity, baseoutcome(2)

Iteration 0:   log likelihood = -8544.3852
Iteration 1:   log likelihood = -7614.6074
Iteration 2:   log likelihood = -7536.8268
Iteration 3:   log likelihood = -7535.8049
Iteration 4:   log likelihood = -7535.8041

Multinomial logistic regression                 Number of obs   =       6342
                                                LR chi2(30)     =    2017.16
                                                Prob > chi2     =     0.0000
Log likelihood = -7535.8041                     Pseudo R2       =     0.1180
```

carnumHH	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NocarHH						
drvlicn	-.0623229	.1122429	-0.56	0.579	-.2823149	.1576691
hhstru	-.1158957	.0361859	-3.20	0.001	-.1868188	-.0449725
acctenurHH						
2	.5394776	.1376684	3.92	0.000	.2696525	.8093027
3	1.089307	.118195	9.22	0.000	.8576493	1.320965
4	1.738907	.2437448	7.13	0.000	1.261176	2.216638
ethnicity						
2	.6271787	.1037476	6.05	0.000	.4238372	.8305202
3	1.12968	.6170154	1.83	0.067	-.0796482	2.339008
4	.437659	.1685846	2.60	0.009	.1072393	.7680788
5	.3181632	.7166211	0.44	0.657	-1.086388	1.722715
6	.194984	.3297842	0.59	0.554	-.4513812	.8413493
_cons	-1.461334	.1632645	-8.95	0.000	-1.781327	-1.141341
OnecarHH	(base outcome)					
TwocarHH						
drvlicn	-.0367539	.0949403	-0.39	0.699	-.2228336	.1493257
hhstru	.4514906	.0263778	17.12	0.000	.399791	.5031902
acctenurHH						
2	-.0146595	.0855555	-0.17	0.864	-.1823452	.1530261
3	-1.013051	.0825301	-12.27	0.000	-1.174808	-.8512954
4	-.5962413	.2802839	-2.13	0.033	-1.145588	-.0468949
ethnicity						
2	-.4694979	.1159624	-4.05	0.000	-.6967799	-.2422159
3	.9464385	.5711837	1.66	0.098	-.173061	2.065938
4	-.2446024	.1584621	-1.54	0.123	-.5551823	.0659775
5	.3868401	.5554428	0.70	0.486	-.7018079	1.475488
6	-.1441973	.3100294	-0.47	0.642	-.7518437	.4634492
_cons	-.7890707	.1193272	-6.61	0.000	-1.022948	-.5551938
Threeormor~H						
drvlicn	-.1378599	.1025701	-1.34	0.179	-.3388935	.0631738
hhstru	.5774584	.028795	20.05	0.000	.5210213	.6338955
acctenurHH						
2	-.1665954	.0884721	-1.88	0.060	-.3399975	.0068068
3	-2.11647	.1058735	-19.99	0.000	-2.323979	-1.908962
4	-1.394537	.3728006	-3.74	0.000	-2.125213	-.6638615
ethnicity						
2	-.9635607	.1527556	-6.31	0.000	-1.262956	-.6641651
3	.9987304	.6036577	1.65	0.098	-.1844169	2.181878
4	-1.090477	.2104945	-5.18	0.000	-1.503039	-.6779159
5	-.2352644	.6912371	-0.34	0.734	-1.590064	1.119536
6	-.299459	.3653891	-0.82	0.412	-1.015609	.4166905
_cons	-.958867	.1280232	-7.49	0.000	-1.209788	-.7079462

```
. mlogit carnumHH drvlicn hhstru i. acctenurHH i.ethnicity i.ccbeliev, baseoutcome(2)

Iteration 0:   log likelihood = -8544.3852
Iteration 1:   log likelihood = -7608.6102
Iteration 2:   log likelihood = -7530.4718
Iteration 3:   log likelihood = -7529.4339
Iteration 4:   log likelihood = -7529.4332
Iteration 5:   log likelihood = -7529.4332

Multinomial logistic regression                 Number of obs   =       6342
                                                LR chi2(42)     =    2029.90
                                                Prob > chi2     =     0.0000
Log likelihood = -7529.4332                     Pseudo R2       =     0.1188
```

carnumHH	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NocarHH						
drvlicn	-.0637359	.1122886	-0.57	0.570	-.2838176	.1563458
hhstru	-.1167856	.0362208	-3.22	0.001	-.1877771	-.0457941
acctenurHH						
2	.5384876	.1377068	3.91	0.000	.2685872	.808388
3	1.088316	.1182502	9.20	0.000	.8565496	1.320082
4	1.735357	.2438579	7.12	0.000	1.257405	2.21331
ethnicity						
2	.628557	.1038093	6.05	0.000	.4250946	.8320194
3	1.12431	.6173302	1.82	0.069	-.085635	2.334255
4	.4402353	.1686742	2.61	0.009	.10964	.7708306
5	.3067949	.7176666	0.43	0.669	-1.099806	1.713396
6	.1980763	.3301655	0.60	0.549	-.4490363	.8451888
ccbeliev						
2	-.0666128	.173254	-0.38	0.701	-.4061844	.2729588
3	-.1439106	.3402711	-0.42	0.672	-.8108297	.5230086
4	-.1238008	.2284902	-0.54	0.588	-.5716334	.3240318
5	.0704209	.4425306	0.16	0.874	-.7969231	.9377649
_cons	-1.448726	.1641591	-8.83	0.000	-1.770472	-1.12698
OnecarHH	(base outcome)					
TwocarHH						
drvlicn	-.0409358	.0949942	-0.43	0.667	-.2271211	.1452494
hhstru	.4522814	.0263951	17.14	0.000	.4005479	.504015
acctenurHH						
2	-.0155645	.0856303	-0.18	0.856	-.1833968	.1522678
3	-1.011225	.0826429	-12.24	0.000	-1.173202	-.8492481
4	-.5963628	.2806083	-2.13	0.034	-1.146345	-.0463807
ethnicity						
2	-.4661334	.1160483	-4.02	0.000	-.693584	-.2386829
3	.9520495	.5714797	1.67	0.096	-.1680302	2.072129
4	-.2492557	.1586062	-1.57	0.116	-.5601181	.0616067
5	.3824594	.5551466	0.69	0.491	-.705608	1.470527
6	-.1364009	.31047	-0.44	0.660	-.744911	.4721092
ccbeliev						
2	.2357145	.140319	1.68	0.093	-.0393057	.5107347
3	-.156044	.3055113	-0.51	0.610	-.7548352	.4427471
4	.1658724	.1753667	0.95	0.344	-.17784	.5095847
5	.2144453	.381552	0.56	0.574	-.5333829	.9622735
_cons	-.8086359	.1201954	-6.73	0.000	-1.044215	-.5730573
Threeormor~H						
drvlicn	-.1362222	.1027043	-1.33	0.185	-.3375189	.0650745
hhstru	.5787709	.0288252	20.08	0.000	.5222746	.6352673
acctenurHH						
2	-.169954	.0885596	-1.92	0.055	-.3435276	.0036195
3	-2.124017	.1060682	-20.03	0.000	-2.331907	-1.916128
4	-1.40041	.3728168	-3.76	0.000	-2.131117	-.6697021
ethnicity						
2	-.9602833	.1529166	-6.28	0.000	-1.259994	-.6605723
3	1.009024	.6042335	1.67	0.095	-.1752516	2.1933
4	-1.101359	.2107285	-5.23	0.000	-1.514379	-.6883385
5	-.2446189	.6900728	-0.35	0.723	-1.597137	1.107899
6	-.3273084	.3659321	-0.89	0.371	-1.044522	.3899053
ccbeliev						
2	-.0125782	.1647703	-0.08	0.939	-.3355221	.3103656
3	.3597029	.3040888	1.18	0.237	-.2363002	.955706
4	-.0494645	.1983313	-0.25	0.803	-.4381867	.3392578
5	.6735011	.3918265	1.72	0.086	-.0944646	1.441467
_cons	-.9695452	.1290516	-7.51	0.000	-1.222482	-.7166087

```
. mlogit carnumHH drvlicn hhstru i. acctenurHH i.ethnicity i.ccbeliev hhincoty earn

Iteration 0:   log likelihood = -8544.3852
Iteration 1:   log likelihood = -7356.1174
Iteration 2:   log likelihood = -7226.2632
Iteration 3:   log likelihood = -7223.6279
Iteration 4:   log likelihood = -7223.6247
Iteration 5:   log likelihood = -7223.6247

Multinomial logistic regression                 Number of obs   =       6342
                                                LR chi2(48)     =    2641.52
                                                Prob > chi2     =     0.0000
Log likelihood = -7223.6247                     Pseudo R2       =     0.1546
```

carnumHH	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NocarHH						
drvlicn	-.0353089	.1143554	-0.31	0.758	-.2594414	.1888235
hhstru	-.0588265	.038364	-1.53	0.125	-.1340186	.0163655
acctenurHH						
2	.3338714	.1409947	2.37	0.018	.0575269	.6102159
3	.8554196	.1213232	7.05	0.000	.6176305	1.093209
4	1.284889	.2509387	5.12	0.000	.7930581	1.77672
ethnicity						
2	.5953321	.106122	5.61	0.000	.3873369	.8033273
3	1.019322	.6248216	1.63	0.103	-.2053056	2.24395
4	.5046692	.1736493	2.91	0.004	.1643228	.8450157
5	.338982	.7147325	0.47	0.635	-1.061868	1.739832
6	.185689	.3346594	0.55	0.579	-.4702314	.8416094
ccbeliev						
2	-.1049519	.1764356	-0.59	0.552	-.4507595	.2408556
3	-.1488272	.3483848	-0.43	0.669	-.8316488	.5339945
4	-.1112902	.2307943	-0.48	0.630	-.5636386	.3410582
5	.14203	.4472185	0.32	0.751	-.7345021	1.018562
hhincoty	-.595235	.0579461	-10.27	0.000	-.7088073	-.4816626
earningpower	.2078126	.1184786	1.75	0.079	-.0244012	.4400263
_cons	-.3927981	.2150683	-1.83	0.068	-.8143242	.028728
OnecarHH	(base outcome)					
TwocarHH						
drvlicn	-.0880208	.0966719	-0.91	0.363	-.2774941	.1014526
hhstru	.2920017	.0285074	10.24	0.000	.2361282	.3478753
acctenurHH						
2	.2673014	.0900335	2.97	0.003	.090839	.4437638
3	-.8215679	.0855927	-9.60	0.000	-.9893265	-.6538094
4	-.1841654	.2884437	-0.64	0.523	-.7495046	.3811738
ethnicity						
2	-.4044542	.1179895	-3.43	0.001	-.6357092	-.1731991
3	1.10665	.5815828	1.90	0.057	-.0332313	2.246531
4	-.3321183	.1604456	-2.07	0.038	-.646586	-.0176507
5	.4911708	.5538162	0.89	0.375	-.594289	1.576631
6	-.1061596	.3142553	-0.34	0.736	-.7220886	.5097694
ccbeliev						
2	.2415601	.1431807	1.69	0.092	-.039069	.5221892
3	-.0834333	.3075569	-0.27	0.786	-.6862337	.5193671
4	.1492054	.1793514	0.83	0.405	-.202317	.5007278
5	.2166391	.3859039	0.56	0.575	-.5397187	.9729968
hhincoty	.3922914	.0577563	6.79	0.000	.2790912	.5054916
earningpower	.6980676	.0816831	8.55	0.000	.5379717	.8581635
_cons	-2.481192	.1888262	-13.14	0.000	-2.851284	-2.111099
Threeormor~H						
drvlicn	-.199915	.1065156	-1.88	0.061	-.4086817	.0088517
hhstru	.3544857	.0317483	11.17	0.000	.2922601	.4167112
acctenurHH						
2	.2578653	.0953055	2.71	0.007	.0710701	.4446606
3	-1.835605	.1092339	-16.80	0.000	-2.049699	-1.62151
4	-.7516479	.387482	-1.94	0.052	-1.511099	.0078029
ethnicity						
2	-.8726004	.1567496	-5.57	0.000	-1.179824	-.5653769
3	1.188057	.6338093	1.87	0.061	-.0541864	2.4303
4	-1.230211	.2131689	-5.77	0.000	-1.648014	-.8124076
5	.0026424	.6973895	0.00	0.997	-1.364216	1.369501
6	-.2981771	.3770271	-0.79	0.429	-1.037137	.4407825
ccbeliev						
2	-.0197318	.1705011	-0.12	0.908	-.3539077	.3144442
3	.4854299	.3135207	1.55	0.122	-.1290595	1.099919
4	-.0934595	.2060176	-0.45	0.650	-.4972466	.3103275
5	.7255862	.4012739	1.81	0.071	-.0608963	1.512069
hhincoty	.7339096	.0751869	9.76	0.000	.586546	.8812733
earningpower	.9947142	.0888083	11.20	0.000	.8206531	1.168775
_cons	-3.914989	.2363148	-16.57	0.000	-4.378158	-3.45182

```
. mlogit, rrr

Multinomial logistic regression                 Number of obs   =       6342
                                                LR chi2(48)     =    2641.52
                                                Prob > chi2     =     0.0000
Log likelihood = -7223.6247                     Pseudo R2       =     0.1546
```

carnumHH	RRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NocarHH						
drvlicn	.9653072	.1103881	-0.31	0.758	.7714824	1.207828
hhstru	.9428703	.0361723	-1.53	0.125	.8745738	1.0165
acctenurHH						
2	1.396364	.1968798	2.37	0.018	1.059214	1.840829
3	2.352361	.285396	7.05	0.000	1.854528	2.983833
4	3.614266	.9069591	5.12	0.000	2.210145	5.910436
ethnicity						
2	1.813633	.1924663	5.61	0.000	1.473053	2.232958
3	2.771316	1.731578	1.63	0.103	.8143984	9.430508
4	1.656438	.2876393	2.91	0.004	1.178595	2.328014
5	1.403518	1.00314	0.47	0.635	.3458092	5.696386
6	1.204048	.4029459	0.55	0.579	.6248577	2.320098
ccbeliev						
2	.9003678	.158857	-0.59	0.552	.6371441	1.272337
3	.861718	.3002095	-0.43	0.669	.4353309	1.705732
4	.8946791	.2064868	-0.48	0.630	.5691344	1.406435
5	1.152611	.515469	0.32	0.751	.4797442	2.76921
hhincoty	.551433	.0319534	-10.27	0.000	.4922309	.6177554
earningpower	1.230982	.1458451	1.75	0.079	.9758941	1.552748
OnecarHH	(base outcome)					
TwocarHH						
drvlicn	.9157419	.0885265	-0.91	0.363	.75768	1.106777
hhstru	1.339105	.0381745	10.24	0.000	1.266337	1.416056
acctenurHH						
2	1.306434	.1176228	2.97	0.003	1.095093	1.558562
3	.4397416	.0376387	-9.60	0.000	.371827	.5200609
4	.8317982	.2399269	-0.64	0.523	.4726006	1.464002
ethnicity						
2	.667341	.0787392	-3.43	0.001	.5295598	.8409702
3	3.02421	1.758829	1.90	0.057	.9673148	9.454883
4	.7174024	.1151041	-2.07	0.038	.5238311	.9825042
5	1.634228	.9050621	0.89	0.375	.5519549	4.838625
6	.8992811	.2826038	-0.34	0.736	.4857367	1.664907
ccbeliev						
2	1.273234	.1823026	1.69	0.092	.9616844	1.685714
3	.9199525	.2829377	-0.27	0.786	.5034687	1.680964
4	1.160911	.2082111	0.83	0.405	.816836	1.649922
5	1.241896	.4792524	0.56	0.575	.5829122	2.645862
hhincoty	1.480369	.0855006	6.79	0.000	1.321928	1.6578
earningpower	2.009865	.164172	8.55	0.000	1.71253	2.358825
Threeormor~H						
drvlicn	.8188003	.087215	-1.88	0.061	.6645257	1.008891
hhstru	1.425447	.0452556	11.17	0.000	1.339451	1.516964
acctenurHH						
2	1.294164	.1233409	2.71	0.007	1.073656	1.559961
3	.159517	.0174247	-16.80	0.000	.1287736	.1976001
4	.4715888	.1827322	-1.94	0.052	.2206674	1.007833
ethnicity						
2	.4178635	.0654999	-5.57	0.000	.3073328	.568146
3	3.280701	2.079338	1.87	0.061	.9472555	11.36229
4	.2922309	.0622945	-5.77	0.000	.1924316	.4437883
5	1.002646	.6992348	0.00	0.997	.255581	3.933387
6	.7421699	.2798182	-0.79	0.429	.3544682	1.553923
ccbeliev						
2	.9804616	.1671697	-0.12	0.908	.7019398	1.369498
3	1.624873	.5094315	1.55	0.122	.8789217	3.003923
4	.9107749	.1876356	-0.45	0.650	.608203	1.363872
5	2.065942	.8290086	1.81	0.071	.9409208	4.536105
hhincoty	2.083209	.15663	9.76	0.000	1.797768	2.413971
earningpower	2.703951	.2401333	11.20	0.000	2.271983	3.218049

```
. describe

Contains data
  obs:        25,368
 vars:            10
 size:       761,040 (98.5% of memory free)
```

variable name	storage type	display format	value label	variable label
family_id	int	%8.0g		
numberofcars	str16	%16s		
income	byte	%8.0g		
drive	byte	%8.0g		
size	byte	%8.0g		
ccbeliev	byte	%8.0g		
noofearners	byte	%8.0g		
ethnicity	byte	%8.0g		
tenure	byte	%8.0g		
chosen	byte	%8.0g		

```
Sorted by:
     Note:  dataset has changed since last saved

.
. list family_id  numberofcars chosen tenure size drive ccbeliev ethnicity noofearners in 1/16, sepby(fam)abbrev(10)
```

	family_id	numberofcars	chosen	tenure	size	drive	ccbeliev	ethnicity	noofearn~s
1.	1	NocarHH	0	2	4	1	1	1	2
2.	1	OnecarHH	1	1	4	1	1	2	2
3.	1	TwocarHH	0	3	4	1	1	3	2
4.	1	ThreeormorecarHH	0	4	4	1	1	4	2
5.	2	NocarHH	0	2	1	1	1	1	1
6.	2	OnecarHH	0	1	1	1	1	2	1
7.	2	TwocarHH	0	3	1	1	1	3	1
8.	2	ThreeormorecarHH	1	4	1	1	1	4	1
9.	3	NocarHH	0	2	3	1	1	1	0
10.	3	OnecarHH	1	1	3	1	1	2	0
11.	3	TwocarHH	0	3	3	1	1	3	0
12.	3	ThreeormorecarHH	0	4	3	1	1	4	0
13.	4	NocarHH	0	1	2	1	1	1	1
14.	4	OnecarHH	0	2	2	1	1	2	1
15.	4	TwocarHH	0	3	2	1	1	3	1
16.	4	ThreeormorecarHH	1	4	2	1	1	4	1

```
. nlogitgen type = numberofcars (nouseofcars: NocarHH, necessityofcars: OnecarHH, wantofcars: TwocarHH | ThreeormorecarHH)
new variable type is generated with 3 groups
label list lb_type
lb_type:
           1 nouseofcars
           2 necessityofcars
           3 wantofcars

.
. generate Whiteblack=1 if ethnicity<=1
(19026 missing values generated)

.
. replace Whiteblack=0 if ethnicity>1
(19026 real changes made)

.
. tab Whiteblack
```

Whiteblack	Freq.	Percent	Cum.
0	19,026	75.00	75.00
1	6,342	25.00	100.00
Total	25,368	100.00	

```
.
. generate NativeAmeri=0

.
. replace NativeAmeri=1 if ethnicity>=2
(19026 real changes made)

.
. tab NativeAmeri
```

NativeAmeri	Freq.	Percent	Cum.
0	6,342	25.00	25.00
1	19,026	75.00	100.00
Total	25,368	100.00	

```
.
. generate Asians=0

.
. replace Asians=1 if ethnicity>=3
(12684 real changes made)

.
. tab Asians
```

Asians	Freq.	Percent	Cum.
0	12,684	50.00	50.00
1	12,684	50.00	100.00
Total	25,368	100.00	

```
.
. generate Pacimultirac=0

.
. replace Pacimultirac=1 if ethnicity>=4
(6342 real changes made)


. tab Pacimultirac
```

Pacimultirac	Freq.	Percent	Cum.
0	19,026	75.00	75.00
1	6,342	25.00	100.00
Total	25,368	100.00	

```
.
. nlogit chosen tenure|| type: income noofearners drive size ccbeliev Whiteblack NativeAmeri Asians Pacimultirac, base(necessityofcars) || numberofcars:,
>  noconstant case(family_id )
```

```
tree structure specified for the nested logit model

 type           N       numberofcars  N    k
──────────────────────────────────────────────
 nouseofcars   6342 ─── NocarHH      6342  963
 necessityo~s  6342 ─── OnecarHH     6342 2141
 wantofcars   12684 ─┬─ ThreeormorecarHH 6342 1454
                     └─ TwocarHH     6342 1784
──────────────────────────────────────────────
                               total  25368 6342

k = number of times alternative is chosen
N = number of observations at each level
note: the model specified for level 1 has collinear variables; convergence may not be achieved
note: clogit model failed; null likelihood is invalid
note: the LR test for IIA will not be computed

Iteration 0:   log likelihood = -6669.4102
Iteration 1:   log likelihood = -6619.7768  (backed up)
Iteration 2:   log likelihood = -6426.2832  (backed up)
Iteration 3:   log likelihood = -6194.7573  (backed up)
Iteration 4:   log likelihood = -6052.5564  (backed up)
Iteration 5:   log likelihood = -5923.6051  (backed up)
Iteration 6:   log likelihood = -5867.3342  (backed up)
Iteration 7:   log likelihood = -5845.2212
Iteration 8:   log likelihood = -5834.1431  (backed up)
Iteration 9:   log likelihood = -5773.0176  (backed up)
Iteration 10:  log likelihood = -5714.1764  (backed up)
Iteration 11:  log likelihood = -5566.8922
Iteration 12:  log likelihood = -5531.1861
Iteration 13:  log likelihood = -5493.3129
Iteration 14:  log likelihood = -5483.1862
Iteration 15:  log likelihood = -5458.9044
Iteration 16:  log likelihood = -5457.0113
Iteration 17:  log likelihood = -5452.2201
Iteration 18:  log likelihood = -5451.3419
Iteration 19:  log likelihood = -5449.5621
Iteration 20:  log likelihood = -5449.3905
Iteration 21:  log likelihood = -5449.3381
Iteration 22:  log likelihood = -5449.3122
Iteration 23:  log likelihood = -5449.0391
Iteration 24:  log likelihood = -5446.6875
Iteration 25:  log likelihood = -5444.9998
Iteration 26:  log likelihood = -5443.8491
Iteration 27:  log likelihood = -5443.1454
Iteration 28:  log likelihood = -5442.6942
Iteration 29:  log likelihood = -5442.5389
Iteration 30:  log likelihood = -5442.5288
Iteration 31:  log likelihood = -5442.5251
Iteration 32:  log likelihood = -5442.5136
Iteration 33:  log likelihood = -5442.5038
Iteration 34:  log likelihood = -5442.5006
Iteration 35:  log likelihood = -5442.4994
Iteration 36:  log likelihood = -5442.4993
Iteration 37:  log likelihood = -5442.4993
Iteration 38:  log likelihood = -5442.4986
Iteration 39:  log likelihood = -5442.4982
Iteration 40:  log likelihood = -5442.4982
Iteration 41:  log likelihood = -5442.4981
Iteration 42:  log likelihood = -5442.4976
Iteration 43:  log likelihood = -5442.4975
```

RUM-consistent nested logit regression — Number of obs = 25368
Case variable: family_id — Number of cases = 6342

Alternative variable: numberofcars — Alts per case: min = 4
avg = 4.0
max = 4

Wald chi2(21) = .
Log likelihood = -5442.4975 — Prob > chi2 = .

chosen	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
numberofcars						
tenure	.1956995	.0282006	6.94	0.000	.1404272	.2509717
type equations						
nouseofcars						
income	1.447577	58.73049	0.02	0.980	-113.6621	116.5572
noofearners	.3526036	59.71493	0.01	0.995	-116.6865	117.3917
drive	-78.58348	57265.14	-0.00	0.999	-112316.2	112159
size	.9876726	63.75752	0.02	0.988	-123.9748	125.9501
ccbeliev	1.488259	79.7656	0.02	0.985	-154.8494	157.826
Whiteblack	33.48188	56950.24	0.00	1.000	-111586.9	111653.9
NativeAmeri	33.83313	57260.05	0.00	1.000	-112193.8	112261.5
Asians	2.973786	14106.16	0.00	1.000	-27644.58	27650.53
Pacimultirac	.3507325	1448.105	0.00	1.000	-2837.883	2838.585
necessityofcars|						
income	(base)					
noofearners	(base)					
drive	(base)					
size	(base)					
ccbeliev	(base)					
Whiteblack	18.0125	.	.	.	.	.
NativeAmeri	.6731494	10.65333	0.06	0.950	-20.20699	21.55329
Asians	-11.46866	7.168537	-1.60	0.110	-25.51874	2.581412
Pacimultirac	20.18358	13.71313	1.47	0.141	-6.693652	47.06081
wantofcars						
income	.3464735	.0142885	24.25	0.000	.3184686	.3744784
noofearners	-.0145625	.0370752	-0.39	0.694	-.0872287	.0581036
drive	-16.23311	55518.47	-0.00	1.000	-108830.4	108798
size	-.0024353	.0243177	-0.10	0.920	-.0500972	.0452265
ccbeliev	.0264563	.0412876	0.64	0.522	-.0544658	.1073785
Whiteblack	-35.15975	55517.16	-0.00	0.999	-108846.8	108776.5
NativeAmeri	16.98324	55518.2	0.00	1.000	-108796.7	108830.7
Asians	-24.52134	15.6998	-1.56	0.118	-55.29239	6.249703
Pacimultirac	-5.412696	3.121166	-1.73	0.083	-11.53007	.7046774
dissimilarity parameters						
type						
/nouseofca~u	1	32928.11			-64536.9	64538.9
/necessity~u	1	43729.68			-85707.6	85709.6
/wantofcar~u	36.03514	20.82571			-4.782504	76.85278

```
. tabulate  hhstru
```

hhstru	Freq.	Percent	Cum.
1	850	28.89	28.89
2	1,134	38.55	67.44
3	414	14.07	81.51
4	364	12.37	93.88
5	125	4.25	98.13
6	39	1.33	99.46
7	11	0.37	99.83
8	2	0.07	99.90
9	2	0.07	99.97
11	1	0.03	100.00
Total	2,942	100.00	

```
.
. tabulate  drvlicn
```

drvlicn	Freq.	Percent	Cum.
0	856	29.10	29.10
1	2,086	70.90	100.00
Total	2,942	100.00	

```
.
. tabulate  acctenur
```

acctenur	Freq.	Percent	Cum.
1	1,093	37.15	37.15
2	771	26.21	63.36
3	18	0.61	63.97
4	316	10.74	74.71
5	228	7.75	82.46
6	34	1.16	83.62
7	12	0.41	84.02
8	5	0.17	84.19
9	36	1.22	85.42
10	391	13.29	98.71
11	11	0.37	99.08
97	15	0.51	99.59
98	4	0.14	99.73
99	8	0.27	100.00
Total	2,942	100.00	

```
. tabulate  apartstru
```

apartstru	Freq.	Percent	Cum.
1	304	10.33	10.33
2	648	22.03	32.36
3	1,372	46.63	78.99
4	495	16.83	95.82
5	93	3.16	98.98
7	24	0.82	99.80
8	3	0.10	99.90
9	3	0.10	100.00
Total	2,942	100.00	

```
.
. tabulate  region
```

region	Freq.	Percent	Cum.
1	169	5.74	5.74
2	381	12.95	18.69
3	245	8.33	27.02
4	208	7.07	34.09
5	233	7.92	42.01
6	304	10.33	52.35
7	272	9.25	61.59
8	400	13.60	75.19
9	313	10.64	85.83
10	165	5.61	91.43
11	252	8.57	100.00
Total	2,942	100.00	

```
.
. tabulate  ccbeliev
```

ccbeliev	Freq.	Percent	Cum.
1	150	5.14	5.14
2	315	10.80	15.94
3	2,452	84.06	100.00
Total	2,917	100.00	

```
. tabulate  ethnicity
```

ethnicity	Freq.	Percent	Cum.
1	41	1.39	1.39
2	23	0.78	2.18
3	1	0.03	2.21
4	51	1.73	3.94
5	23	0.78	4.72
6	5	0.17	4.89
7	18	0.61	5.51
8	27	0.92	6.42
9	2,689	91.40	97.82
10	32	1.09	98.91
11	26	0.88	99.80
98	2	0.07	99.86
99	4	0.14	100.00
Total	2,942	100.00	

```
. recode  ethnicity(9=1 White)(2=2 Caribbean)(4=3 Indians)(5=4 Pakistans)(7=5 Chinese) (8=6 OtherAsianorigin)(1=7 Africans)(3 6 98 99 10/11=8 Mixedorigin
> ), gen (ethnicorigins)

. tabulate  ethnicity ethnicorigins
```

ethnicity	RECODE of ethnicity								
	White	Caribbean	Indians	Pakistans	Chinese	OtherAsia	Africans	Mixedorig	Total
1	0	0	0	0	0	0	41	0	41
2	0	23	0	0	0	0	0	0	23
3	0	0	0	0	0	0	0	1	1
4	0	0	51	0	0	0	0	0	51
5	0	0	0	23	0	0	0	0	23
6	0	0	0	0	0	0	0	5	5
7	0	0	0	0	18	0	0	0	18
8	0	0	0	0	0	27	0	0	27
9	2,689	0	0	0	0	0	0	0	2,689
10	0	0	0	0	0	0	0	32	32
11	0	0	0	0	0	0	0	26	26
98	0	0	0	0	0	0	0	2	2
99	0	0	0	0	0	0	0	4	4
Total	2,689	23	51	23	18	27	41	70	2,942

RECODE of ethnicity	Freq.	Percent	Cum.
White	2,689	91.40	91.40
Caribbean	23	0.78	92.18
Indians	51	1.73	93.92
Pakistans	23	0.78	94.70
Chinese	18	0.61	95.31
OtherAsianorigin	27	0.92	96.23
Africans	41	1.39	97.62
Mixedorigin	70	2.38	100.00
Total	2,942	100.00	

```
. summarize ethnicorigins
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ethnicorig~s	2942	1.386472	1.411998	1	8

```
.
. summarize i.ethnicorigins
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ethnicorig~s					
2	2942	.0078178	.0880871	0	1
3	2942	.0173351	.130539	0	1
4	2942	.0078178	.0880871	0	1
5	2942	.0061183	.0779931	0	1
6	2942	.0091774	.0953745	0	1
7	2942	.0139361	.1172457	0	1
8	2942	.0237933	.1524307	0	1

```
. describe  hhstru drvlicn acctenur apartstru region ccbeliev hhinco ethnicorigins
```

variable name	storage type	display format	value label	variable label
hhstru	byte	%8.0g		
drvlicn	byte	%8.0g		
acctenur	byte	%8.0g		
apartstru	byte	%8.0g		
region	byte	%8.0g		
ccbeliev	byte	%8.0g		
hhinco	byte	%8.0g		
ethnicorigins	byte	%16.0g	ethnicorigins	RECODE of ethnicity

```
. summarize  hhstru drvlicn acctenur apartstru region ccbeliev hhinco ethnicorigins
```

Variable	Obs	Mean	Std. Dev.	Min	Max
hhstru	2942	2.310333	1.265726	1	11
drvlicn	2942	.7090415	.4542816	0	1
acctenur	2942	4.219918	9.512831	1	99
apartstru	2942	2.848402	1.048045	1	9
region	2942	6.060503	3.04166	1	11
ccbeliev	2917	2.789167	.5189607	1	3
hhinco	2942	30.93168	36.73859	1	98
ethnicorig~s	2942	1.386472	1.411998	1	8

```
.
. recode  acctenur (1 2 =1 owners) (3=2 shared) (4/11=3 rent) (97/99=4 others), gen (acctenurty)
(1849 differences between acctenur and acctenurty)
. tabulate  acctenur  acctenurty
```

acctenur	RECODE of acctenur owners	shared	rent	others	Total
1	1,093	0	0	0	1,093
2	771	0	0	0	771
3	0	18	0	0	18
4	0	0	316	0	316
5	0	0	228	0	228
6	0	0	34	0	34
7	0	0	12	0	12
8	0	0	5	0	5
9	0	0	36	0	36
10	0	0	391	0	391
11	0	0	11	0	11
97	0	0	0	15	15
98	0	0	0	4	4
99	0	0	0	8	8
Total	1,864	18	1,033	27	2,942

```
. tabulate  acctenurty
```

RECODE of acctenur	Freq.	Percent	Cum.
owners	1,864	63.36	63.36
shared	18	0.61	63.97
rent	1,033	35.11	99.08
others	27	0.92	100.00
Total	2,942	100.00	

```
.
. recode  apartstru(1 2=1 bigcity) (3=2 smallcity) (4 5=3 village) (7/9=4 others), gen (apartstruty)
(2638 differences between apartstru and apartstruty)

.
. tabulate  apartstru  apartstruty
```

apartstru	RECODE of apartstru bigcity	smallcity	village	others	Total
1	304	0	0	0	304
2	648	0	0	0	648
3	0	1,372	0	0	1,372
4	0	0	495	0	495
5	0	0	93	0	93
7	0	0	0	24	24
8	0	0	0	3	3
9	0	0	0	3	3
Total	952	1,372	588	30	2,942

```
. tabulate  apartstruty
```

RECODE of apartstru	Freq.	Percent	Cum.
bigcity	952	32.36	32.36
smallcity	1,372	46.63	78.99
village	588	19.99	98.98
others	30	1.02	100.00
Total	2,942	100.00	

```
.
. summarize i. apartstruty
```

Variable	Obs	Mean	Std. Dev.	Min	Max
apartstruty					
2	2942	.4663494	.4989512	0	1
3	2942	.199864	.399966	0	1
4	2942	.0101971	.1004818	0	1

```
.
. summarize i.  ccbeliev
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ccbeliev					
2	2917	.1079877	.310418	0	1
3	2917	.8405896	.3661211	0	1

```
.
. recode  hhinco (1/3=1 verypoor)(4/6=2 poor) (7/9=3 avergae) (10/12=4 rich) (13/20=5 veryrich) (97 98=6 undisclosed), gen(incomehh)
(2856 differences between hhinco and incomehh)
```

```
. tabulate  hhinco  incomehh
```

hhinco	RECODE of hhinco						
	verypoor	poor	avergae	rich	veryrich	undisclos	Total
1	86	0	0	0	0	0	86
2	107	0	0	0	0	0	107
3	88	0	0	0	0	0	88
4	0	114	0	0	0	0	114
5	0	112	0	0	0	0	112
6	0	88	0	0	0	0	88
7	0	0	121	0	0	0	121
8	0	0	115	0	0	0	115
9	0	0	111	0	0	0	111
10	0	0	0	161	0	0	161
11	0	0	0	124	0	0	124
12	0	0	0	82	0	0	82
13	0	0	0	0	105	0	105
14	0	0	0	0	89	0	89
15	0	0	0	0	114	0	114
16	0	0	0	0	125	0	125
17	0	0	0	0	114	0	114
18	0	0	0	0	101	0	101
19	0	0	0	0	123	0	123
20	0	0	0	0	183	0	183
97	0	0	0	0	0	447	447
98	0	0	0	0	0	232	232
Total	281	314	347	367	954	679	2,942

```
.
. tabulate  incomehh
```

RECODE of hhinco	Freq.	Percent	Cum.
verypoor	281	9.55	9.55
poor	314	10.67	20.22
avergae	347	11.79	32.02
rich	367	12.47	44.49
veryrich	954	32.43	76.92
undisclosed	679	23.08	100.00
Total	2,942	100.00	

```
. summarize i.incomehh
```

Variable	Obs	Mean	Std. Dev.	Min	Max
incomehh					
2	2942	.1067301	.3088223	0	1
3	2942	.117947	.3226002	0	1
4	2942	.1247451	.3304858	0	1
5	2942	.3242692	.4681807	0	1
6	2942	.2307954	.4214134	0	1

```
.
. summarize carnum hhstru drvlicn incomehh apartstruty acctenurty ccbeliev region ethnicorigins
```

Variable	Obs	Mean	Std. Dev.	Min	Max
carnum	2942	2.221618	.8568989	1	4
hhstru	2942	2.310333	1.265726	1	11
drvlicn	2942	.7090415	.4542816	0	1
incomehh	2942	4.167913	1.620072	1	6
apartstruty	2942	1.896669	.7441458	1	4
acctenurty	2942	1.735894	.9756975	1	4
ccbeliev	2917	2.789167	.5189607	1	3
region	2942	6.060503	3.04166	1	11
ethnicorig~s	2942	1.386472	1.411998	1	8

```
. mlogit carnum drvlicn hhstru, baseoutcome(2)

Iteration 0:   log likelihood = -3631.5476
Iteration 1:   log likelihood = -2777.6462
Iteration 2:   log likelihood = -2613.5868
Iteration 3:   log likelihood = -2573.8277
Iteration 4:   log likelihood = -2571.9744
Iteration 5:   log likelihood = -2571.9625
Iteration 6:   log likelihood = -2571.9625

Multinomial logistic regression                 Number of obs   =       2942
                                                LR chi2(6)      =    2119.17
                                                Prob > chi2     =     0.0000
Log likelihood = -2571.9625                     Pseudo R2       =     0.2918

------------------------------------------------------------------------------
      carnum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1            |
     drvlicn |  -5.261256   .2540755   -20.71   0.000    -5.759235   -4.763277
      hhstru |  -.5651518   .0660628    -8.55   0.000    -.6946325   -.4356712
       _cons |   2.170559   .1640284    13.23   0.000     1.849069    2.492049
-------------+----------------------------------------------------------------
2            |  (base outcome)
-------------+----------------------------------------------------------------
3            |
     drvlicn |   1.236384   .1682617     7.35   0.000     .9065971    1.566171
      hhstru |   .4661513   .0395838    11.78   0.000     .3885684    .5437342
       _cons |  -2.761443   .2055091   -13.44   0.000    -3.164234   -2.358653
-------------+----------------------------------------------------------------
4            |
     drvlicn |   2.531718   .4140607     6.11   0.000     1.720174    3.343262
      hhstru |   .7208444   .0566588    12.72   0.000     .6097952    .8318935
       _cons |  -5.973931   .4695989   -12.72   0.000    -6.894328   -5.053534
------------------------------------------------------------------------------

.
. mlogit carnum drvlicn hhstru i. acctenurty i. apartstruty i.region i.ethnicorigins, baseoutcome(2)

Iteration 0:   log likelihood = -3631.5476
Iteration 1:   log likelihood = -2630.7449
Iteration 2:   log likelihood =  -2420.266
Iteration 3:   log likelihood = -2364.1521
Iteration 4:   log likelihood = -2361.1927
Iteration 5:   log likelihood = -2361.0712
Iteration 6:   log likelihood = -2361.0422
Iteration 7:   log likelihood =  -2361.036
Iteration 8:   log likelihood = -2361.0347
Iteration 9:   log likelihood = -2361.0344
Iteration 10:  log likelihood = -2361.0344
Iteration 11:  log likelihood = -2361.0343

Multinomial logistic regression                 Number of obs   =       2942
                                                LR chi2(75)     =    2541.03
                                                Prob > chi2     =     0.0000
Log likelihood = -2361.0343                     Pseudo R2       =     0.3499

------------------------------------------------------------------------------
      carnum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1            |
     drvlicn |  -5.318927   .2654019   -20.04   0.000    -5.839105   -4.798749
      hhstru |  -.7346733   .0755037    -9.73   0.000    -.8826578   -.5866888
             |
  acctenurty |
           2 |   .0431358   .8087187     0.05   0.957    -1.541924    1.628195
           3 |   1.294031   .1736167     7.45   0.000     .9537489    1.634314
           4 |   .1586025   .7073459     0.22   0.823     -1.22777    1.544975
             |
 apartstruty |
           2 |   .1216765    .198245     0.61   0.539    -.2668766    .5102296
           3 |   -.222346   .2887827    -0.77   0.441    -.7883496    .3436577
           4 |  -.6962861   .7373481    -0.94   0.345    -2.141462    .7488897
```

region						
2	-.1250687	.3785733	-0.33	0.741	-.8670587	.6169213
3	-.2011555	.4219889	-0.48	0.634	-1.028238	.6259275
4	-.2068427	.4469029	-0.46	0.643	-1.082756	.6690708
5	-.6252905	.4213026	-1.48	0.138	-1.451028	.2004475
6	-.5743897	.4254202	-1.35	0.177	-1.408198	.2594186
7	.240286	.4203346	0.57	0.568	-.5835546	1.064127
8	-.6439026	.4080376	-1.58	0.115	-1.443641	.1558363
9	-.5222334	.4158238	-1.26	0.209	-1.337233	.2927663
10	-.5641621	.4691585	-1.20	0.229	-1.483696	.3553716
11	-.7088056	.4049803	-1.75	0.080	-1.502552	.0849411
ethnicorig~s						
2	.2436356	.6874711	0.35	0.723	-1.103783	1.591054
3	.8042516	.5639549	1.43	0.154	-.3010797	1.909583
4	-1.088375	1.045106	-1.04	0.298	-3.136745	.959995
5	-.8984173	.8370061	-1.07	0.283	-2.538919	.7420845
6	.2172105	.7246779	0.30	0.764	-1.203132	1.637553
7	.2315355	.6398753	0.36	0.717	-1.022597	1.485668
8	-.1224571	.4542785	-0.27	0.787	-1.012827	.7679124
_cons	2.14083	.3729474	5.74	0.000	1.409867	2.871794
2	(base outcome)					
3						
drvlicn	1.096703	.1730709	6.34	0.000	.7574905	1.435916
hhstru	.5920776	.0442658	13.38	0.000	.5053182	.6788369
acctenurty						
2	.7472718	.5900743	1.27	0.205	-.4092527	1.903796
3	-1.151425	.1231181	-9.35	0.000	-1.392732	-.9101175
4	-.2596753	.5574592	-0.47	0.641	-1.352275	.8329247
apartstruty						
2	.0243535	.1256235	0.19	0.846	-.2218641	.2705711
3	.3972903	.1487018	2.67	0.008	.1058401	.6887406
4	.2333941	.4578059	0.51	0.610	-.663889	1.130677
region						
2	.2686498	.2646048	1.02	0.310	-.2499661	.7872658
3	-.0072884	.2837379	-0.03	0.980	-.5634044	.5488277
4	.2844049	.2895291	0.98	0.326	-.2830618	.8518716
5	.5121841	.2825899	1.81	0.070	-.0416819	1.06605
6	.1814622	.2699267	0.67	0.501	-.3475844	.7105089
7	-.3922318	.3115054	-1.26	0.208	-1.002771	.2183077
8	.661023	.2583004	2.56	0.010	.1547636	1.167282
9	.306505	.2670938	1.15	0.251	-.2169893	.8299993
10	.3997351	.304177	1.31	0.189	-.1964409	.9959112
11	.0656439	.2857885	0.23	0.818	-.4944913	.6257791
ethnicorig~s						
2	-1.554777	1.063631	-1.46	0.144	-3.639456	.5299026
3	-.7937023	.423704	-1.87	0.061	-1.624147	.0367422
4	-.8804661	.5524002	-1.59	0.111	-1.963151	.2022184
5	-1.48158	.8126743	-1.82	0.068	-3.074392	.1112327
6	-.7086316	.5999061	-1.18	0.238	-1.884426	.4671627
7	-.986239	.523612	-1.88	0.060	-2.0125	.0400217
8	-.0315783	.3331468	-0.09	0.924	-.6845341	.6213774
_cons	-2.953905	.3180359	-9.29	0.000	-3.577244	-2.330566
4						
drvlicn	2.206332	.4207361	5.24	0.000	1.381705	3.03096
hhstru	.9525903	.0654722	14.55	0.000	.8242671	1.080913
acctenurty						
2	-14.86213	1645.391	-0.01	0.993	-3239.77	3210.045
3	-1.471401	.2233277	-6.59	0.000	-1.909115	-1.033686
4	.0472326	.7552385	0.06	0.950	-1.433008	1.527473

apartstruty						
2	.0125921	.2190082	0.06	0.954	-.4166562	.4418403
3	1.081827	.2324005	4.66	0.000	.6263303	1.537323
4	-14.82161	1271.014	-0.01	0.991	-2505.964	2476.321
region						
2	-.2263338	.4369987	-0.52	0.605	-1.082836	.6301679
3	-.3624679	.4574874	-0.79	0.428	-1.259127	.534191
4	.0068058	.4560341	0.01	0.988	-.8870046	.9006161
5	.1974683	.4543573	0.43	0.664	-.6930557	1.087992
6	.0017013	.4231622	0.00	0.997	-.8276814	.831084
7	-.7696641	.5468558	-1.41	0.159	-1.841482	.3021534
8	.6482743	.3974202	1.63	0.103	-.130655	1.427204
9	-.3363902	.4383529	-0.77	0.443	-1.195546	.5227656
10	.5197809	.4528282	1.15	0.251	-.367746	1.407308
11	.3946275	.4261225	0.93	0.354	-.4405572	1.229812
ethnicorig~s						
2	-14.61137	1544.729	-0.01	0.992	-3042.225	3013.002
3	-15.93784	869.1813	-0.02	0.985	-1719.502	1687.626
4	-2.503899	1.129638	-2.22	0.027	-4.717949	-.2898488
5	-15.83455	1457.051	-0.01	0.991	-2871.602	2839.933
6	-1.649869	1.164585	-1.42	0.157	-3.932413	.632675
7	-1.817026	1.121424	-1.62	0.105	-4.014976	.3809242
8	-.6184546	.7666229	-0.81	0.420	-2.121008	.8840986
_cons	-6.21811	.6123859	-10.15	0.000	-7.418364	-5.017856

```
. mlogit, rrr

Multinomial logistic regression                 Number of obs   =       2942
                                                LR chi2(75)     =    2541.03
                                                Prob > chi2     =     0.0000
Log likelihood = -2361.0343                     Pseudo R2       =     0.3499
```

carnum	RRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
drvlicn	.004898	.0012999	-20.04	0.000	.0029114	.0082401
hhstru	.4796621	.0362162	-9.73	0.000	.413682	.5561658
acctenurty						
2	1.04408	.8443668	0.05	0.957	.2139691	5.094673
3	3.647461	.6332601	7.45	0.000	2.595421	5.125939
4	1.171872	.8289189	0.22	0.823	.2929451	4.687854
apartstruty						
2	1.129389	.2238957	0.61	0.539	.7657676	1.665674
3	.8006383	.2312105	-0.77	0.441	.4545944	1.410096
4	.498433	.3675186	-0.94	0.345	.117483	2.114651
region						
2	.8824363	.3340668	-0.33	0.741	.4201856	1.853214
3	.8177853	.3450963	-0.48	0.634	.3576364	1.86998
4	.8131476	.363398	-0.46	0.643	.3386608	1.952422
5	.535106	.2254415	-1.48	0.138	.2343292	1.221949
6	.5630484	.2395322	-1.35	0.177	.2445836	1.296176
7	1.271613	.5345028	0.57	0.568	.5579117	2.898306
8	.5252386	.2143171	-1.58	0.115	.2360666	1.168635
9	.5931942	.2466643	-1.26	0.209	.2625712	1.34013
10	.5688366	.2668745	-1.20	0.229	.2267979	1.426711
11	.4922318	.1993442	-1.75	0.080	.2225614	1.088653
ethnicorig~s						
2	1.275879	.8771302	0.35	0.723	.3316142	4.908921
3	2.235023	1.260452	1.43	0.154	.7400188	6.750273
4	.3367633	.3519533	-1.04	0.298	.0434239	2.611683
5	.4072136	.3408403	-1.07	0.283	.0789517	2.100309
6	1.242606	.9004888	0.30	0.764	.3002523	5.142571
7	1.260534	.8065846	0.36	0.717	.3596596	4.417916
8	.8847438	.4019201	-0.27	0.787	.3631909	2.155262
2	(base outcome)					

3						
drvlicn	2.994278	.5182224	6.34	0.000	2.132917	4.203493
hhstru	1.80774	.0800211	13.38	0.000	1.657513	1.971583
acctenurty						
2	2.111232	1.245784	1.27	0.205	.6641464	6.711324
3	.316186	.0389282	-9.35	0.000	.2483959	.4024769
4	.771302	.4299694	-0.47	0.641	.2586511	2.300036
apartstruty						
2	1.024652	.1287205	0.19	0.846	.8010242	1.310713
3	1.487788	.2212368	2.67	0.008	1.111644	1.991206
4	1.262879	.5781535	0.51	0.610	.5148452	3.097754
region						
2	1.308197	.3461553	1.02	0.310	.7788272	2.19738
3	.9927381	.2816774	-0.03	0.980	.5692677	1.731222
4	1.328971	.3847758	0.98	0.326	.7534732	2.34403
5	1.668932	.4716234	1.81	0.070	.9591748	2.903887
6	1.198969	.3236338	0.67	0.501	.7063924	2.035027
7	.6755475	.2104367	-1.26	0.208	.3668614	1.24397
8	1.936773	.5002691	2.56	0.010	1.167382	3.213249
9	1.358668	.3628919	1.15	0.251	.8049386	2.293317
10	1.49143	.4536586	1.31	0.189	.8216499	2.70719
11	1.067846	.3051782	0.23	0.818	.6098811	1.869702
ethnicorig~s						
2	.2112366	.2246778	-1.46	0.144	.0262666	1.698767
3	.4521676	.1915852	-1.87	0.061	.1970797	1.037426
4	.4145896	.2290194	-1.59	0.111	.1404153	1.224115
5	.2272784	.1847033	-1.82	0.068	.0462177	1.117655
6	.4923174	.2953442	-1.18	0.238	.1519162	1.595461
7	.3729768	.1952951	-1.88	0.060	.1336542	1.040833
8	.968915	.3227909	-0.09	0.924	.5043252	1.86149
4						
drvlicn	9.082344	3.82127	5.24	0.000	3.981684	20.71711
hhstru	2.592416	.1697312	14.55	0.000	2.280209	2.947371
acctenurty						
2	3.51e-07	.0005777	-0.01	0.993	0	.
3	.2296037	.0512769	-6.59	0.000	.1482115	.3556934
4	1.048366	.7917663	0.06	0.950	.2385902	4.606521
apartstruty						
2	1.012672	.2217834	0.06	0.954	.6592475	1.555567
3	2.950064	.6855962	4.66	0.000	1.870733	4.652122
4	3.66e-07	.0004647	-0.01	0.991	0	.
region						
2	.7974519	.3484854	-0.52	0.605	.3386339	1.877926
3	.6959566	.3183914	-0.79	0.428	.2839018	1.706067
4	1.006829	.4591483	0.01	0.988	.4118877	2.461119
5	1.218314	.5535501	0.43	0.664	.5000457	2.968309
6	1.001703	.4238828	0.00	0.997	.4370615	2.295806
7	.4631686	.2532864	-1.41	0.159	.1585823	1.352769
8	1.912238	.7599621	1.63	0.103	.8775205	4.16703
9	.7143443	.3131349	-0.77	0.443	.3025387	1.686686
10	1.681659	.7615026	1.15	0.251	.692293	4.084943
11	1.483831	.6322939	0.93	0.354	.6436777	3.420587
ethnicorig~s						
2	4.51e-07	.000697	-0.01	0.992	0	.
3	1.20e-07	.0001041	-0.02	0.985	0	.
4	.0817656	.0923655	-2.22	0.027	.0089335	.7483767
5	1.33e-07	.0001935	-0.01	0.991	0	.
6	.1920751	.2236877	-1.42	0.157	.0195963	1.88264
7	.1625084	.1822407	-1.62	0.105	.0180434	1.463637
8	.5387764	.4130383	-0.81	0.420	.1199107	2.420801

```
. mlogit carnum drvlicn hhstru i. acctenurty i. apartstruty i.region i.ethnicorigins i.ccbeliev, baseoutcome(2)

Iteration 0:   log likelihood = -3602.0454
Iteration 1:   log likelihood = -2611.0005
Iteration 2:   log likelihood = -2401.8009
Iteration 3:   log likelihood = -2345.6867
Iteration 4:   log likelihood = -2342.7281
Iteration 5:   log likelihood = -2342.6079
Iteration 6:   log likelihood = -2342.5792
Iteration 7:   log likelihood =  -2342.573
Iteration 8:   log likelihood = -2342.5718
Iteration 9:   log likelihood = -2342.5715
Iteration 10:  log likelihood = -2342.5714
Iteration 11:  log likelihood = -2342.5714

Multinomial logistic regression                 Number of obs   =       2917
                                                LR chi2(81)     =    2518.95
                                                Prob > chi2     =     0.0000
Log likelihood = -2342.5714                     Pseudo R2       =     0.3497
```

carnum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
drvlicn	-5.301443	.2662352	-19.91	0.000	-5.823254	-4.779632
hhstru	-.7253313	.0756597	-9.59	0.000	-.8736215	-.577041
acctenurty						
2	.112693	.8071227	0.14	0.889	-1.469238	1.694624
3	1.292121	.1746124	7.40	0.000	.9498868	1.634355
4	-.1671047	.7513092	-0.22	0.824	-1.639644	1.305434
apartstruty						
2	.1194454	.1993034	0.60	0.549	-.2711821	.510073
3	-.2388597	.2913412	-0.82	0.412	-.8098779	.3321585
4	-1.033979	.8098804	-1.28	0.202	-2.621315	.5533573
region						
2	-.1380248	.3802405	-0.36	0.717	-.8832824	.6072328
3	-.1821817	.4241487	-0.43	0.668	-1.013498	.6491344
4	-.1886597	.4476777	-0.42	0.673	-1.066092	.6887725
5	-.6482325	.4244321	-1.53	0.127	-1.480104	.183639
6	-.591042	.4290829	-1.38	0.168	-1.432029	.2499451
7	.2133431	.4223594	0.51	0.613	-.6144661	1.041152
8	-.5909878	.4132311	-1.43	0.153	-1.400906	.2189302
9	-.5077951	.4174099	-1.22	0.224	-1.325903	.3103132
10	-.5720872	.4702705	-1.22	0.224	-1.493801	.3496261
11	-.7102173	.4091988	-1.74	0.083	-1.512232	.0917976
ethnicorig~s						
2	.2514524	.6885437	0.37	0.715	-1.098069	1.600973
3	.8149486	.562052	1.45	0.147	-.2866531	1.91655
4	-1.137761	1.015635	-1.12	0.263	-3.128369	.8528478
5	-.8611109	.8367059	-1.03	0.303	-2.501024	.7788025
6	.0839574	.7553894	0.11	0.912	-1.396579	1.564493
7	.1742859	.639667	0.27	0.785	-1.079438	1.42801
8	-.1481371	.4584606	-0.32	0.747	-1.046703	.7504291
ccbeliev						
2	-.3329451	.3779709	-0.88	0.378	-1.073754	.4078642
3	-.3510469	.3280368	-1.07	0.285	-.9939872	.2918935
_cons	2.448567	.4835672	5.06	0.000	1.500793	3.396341
2	(base outcome)					
3						
drvlicn	1.081469	.174484	6.20	0.000	.7394867	1.423451
hhstru	.581016	.0443475	13.10	0.000	.4940964	.6679355
acctenurty						
2	.744265	.5862865	1.27	0.204	-.4048354	1.893365
3	-1.140596	.1238241	-9.21	0.000	-1.383286	-.8979048
4	-.4760581	.5914265	-0.80	0.421	-1.635233	.6831166
apartstruty						
2	.0114796	.1262884	0.09	0.928	-.2360412	.2590004
3	.3765066	.1492499	2.52	0.012	.0839822	.6690311
4	.2202489	.4621423	0.48	0.634	-.6855334	1.126031
region						
2	.2477566	.2653533	0.93	0.350	-.2723263	.7678395
3	-.0012198	.2840953	-0.00	0.997	-.5580363	.5555968
4	.3003869	.290296	1.03	0.301	-.2685828	.8693567
5	.5147309	.2830415	1.82	0.069	-.0400203	1.069482
6	.1546105	.2703896	0.57	0.567	-.3753433	.6845644
7	-.4137684	.31231	-1.32	0.185	-1.025885	.1983479
8	.6651305	.258841	2.57	0.010	.1578116	1.17245
9	.2935293	.2675829	1.10	0.273	-.2309235	.8179821
10	.3944081	.3044948	1.30	0.195	-.2023908	.9912069
11	.0435459	.2860118	0.15	0.879	-.5170269	.6041188

ethnicorig~s						
2	-1.55243	1.065097	-1.46	0.145	-3.639982	.5351229
3	-.7157487	.4256754	-1.68	0.093	-1.550057	.1185597
4	-.8478433	.5591788	-1.52	0.129	-1.943814	.248127
5	-1.514073	.8114125	-1.87	0.062	-3.104412	.0762663
6	-.6957088	.5993672	-1.16	0.246	-1.870447	.4790292
7	-.9734679	.5220138	-1.86	0.062	-1.996596	.0496605
8	-.00315	.3360457	-0.01	0.993	-.6617874	.6554874
ccbeliev						
2	-.0222713	.3036707	-0.07	0.942	-.617455	.5729124
3	.2816579	.2585606	1.09	0.276	-.2251116	.7884273
_cons	-3.137149	.402671	-7.79	0.000	-3.926369	-2.347928
4						
drvlicn	2.207796	.4196348	5.26	0.000	1.385327	3.030265
hhstru	.9479925	.0657807	14.41	0.000	.8190646	1.07692
acctenurty						
2	-14.95942	1593.072	-0.01	0.993	-3137.324	3107.405
3	-1.476032	.2245667	-6.57	0.000	-1.916175	-1.035889
4	.0796777	.7495077	0.11	0.915	-1.38933	1.548686
apartstruty						
2	.0122987	.2194449	0.06	0.955	-.4178054	.4424028
3	1.072734	.2328614	4.61	0.000	.6163336	1.529134
4	-14.96461	1360.54	-0.01	0.991	-2681.574	2651.644
region						
2	-.1870374	.4383671	-0.43	0.670	-1.046221	.6721464
3	-.3479865	.4586308	-0.76	0.448	-1.246886	.5509134
4	.0397988	.4576846	0.09	0.931	-.8572465	.936844
5	.2617317	.4558474	0.57	0.566	-.6317128	1.155176
6	.0208587	.4241441	0.05	0.961	-.8104486	.8521659
7	-.7418284	.549056	-1.35	0.177	-1.817958	.3343015
8	.695437	.3992089	1.74	0.082	-.0869981	1.477872
9	-.3210814	.4398191	-0.73	0.465	-1.183111	.5409482
10	.5616877	.4544935	1.24	0.217	-.3291031	1.452478
11	.3999694	.4278315	0.93	0.350	-.438565	1.238504
ethnicorig~s						
2	-14.57767	1555.304	-0.01	0.993	-3062.917	3033.762
3	-15.72394	865.0849	-0.02	0.985	-1711.259	1679.811
4	-2.458839	1.133611	-2.17	0.030	-4.680676	-.2370026
5	-15.82594	1453.269	-0.01	0.991	-2864.182	2832.53
6	-1.578852	1.169146	-1.35	0.177	-3.870336	.7126322
7	-1.941103	1.153671	-1.68	0.092	-4.202256	.3200494
8	-.6039811	.7690541	-0.79	0.432	-2.111299	.9033371
ccbeliev						
2	1.353016	.6758333	2.00	0.045	.0284069	2.677625
3	1.069584	.6350047	1.68	0.092	-.175002	2.314171
_cons	-7.30214	.8712384	-8.38	0.000	-9.009736	-5.594544

```
. mlogit carnum drvlicn hhstru i. acctenurty i. apartstruty i.region i.ccbeliev i.ethnicorigins incomehh, baseoutcome(2)

Iteration 0:   log likelihood = -3602.0454
Iteration 1:   log likelihood = -2576.7817
Iteration 2:   log likelihood = -2353.3826
Iteration 3:   log likelihood =  -2292.631
Iteration 4:   log likelihood = -2289.3983
Iteration 5:   log likelihood = -2289.2746
Iteration 6:   log likelihood = -2289.2456
Iteration 7:   log likelihood = -2289.2391
Iteration 8:   log likelihood = -2289.2377
Iteration 9:   log likelihood = -2289.2375
Iteration 10:  log likelihood = -2289.2374
```

Multinomial logistic regression

Number of obs	2917
LR chi2(84)	2625.62
Prob > chi2	0.0000
Log likelihood = -2289.2374	
Pseudo R2	0.3645

carnum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
drvlicn	-5.317679	.2684646	-19.81	0.000	-5.843859	-4.791498
hhstru	-.6819308	.0760199	-8.97	0.000	-.8309271	-.5329346
acctenurty						
2	.0903755	.8336853	0.11	0.914	-1.543618	1.724369
3	1.183886	.1767875	6.70	0.000	.8373885	1.530383
4	.0302465	.7626068	0.04	0.968	-1.464435	1.524928
apartstruty						
2	.0821738	.202472	0.41	0.685	-.3146641	.4790117
3	-.2662339	.2953822	-0.90	0.367	-.8451723	.3127046
4	-1.07896	.8110734	-1.33	0.183	-2.668634	.5107148
region						
2	-.1728009	.3837013	-0.45	0.652	-.9248415	.5792398
3	-.2874732	.4281901	-0.67	0.502	-1.12671	.5517639
4	-.2226889	.4510182	-0.49	0.621	-1.106668	.6612905
5	-.6607809	.4256396	-1.55	0.121	-1.495019	.1734573
6	-.5792482	.4353139	-1.33	0.183	-1.432448	.2739514
7	.3981394	.4256221	0.94	0.350	-.4360646	1.232343
8	-.5750393	.4171069	-1.38	0.168	-1.392554	.2424752
9	-.4331484	.4201136	-1.03	0.303	-1.256556	.390259
10	-.3881918	.4767149	-0.81	0.415	-1.322536	.5461522
11	-.5989772	.4137219	-1.45	0.148	-1.409857	.2119029
ccbeliev						
2	-.3583536	.380775	-0.94	0.347	-1.104659	.3879518
3	-.3356541	.3302858	-1.02	0.310	-.9830024	.3116942
ethnicorig~s						
2	.3597775	.6842178	0.53	0.599	-.9812648	1.70082
3	.8179882	.5614883	1.46	0.145	-.2825086	1.918485
4	-1.425664	.9975965	-1.43	0.153	-3.380917	.5295896
5	-.8044503	.8529938	-0.94	0.346	-2.476287	.8673868
6	.0655905	.7621927	0.09	0.931	-1.42828	1.559461
7	.2324806	.6384174	0.36	0.716	-1.018794	1.483756
8	-.0168039	.4705363	-0.04	0.972	-.9390382	.9054303
incomehh	-.2046812	.0469711	-4.36	0.000	-.2967429	-.1126195
_cons	3.156814	.5172436	6.10	0.000	2.143035	4.170592
2	(base outcome)					
3						
drvlicn	1.130721	.1763693	6.41	0.000	.7850439	1.476399
hhstru	.5362399	.0450054	11.92	0.000	.448031	.6244488
acctenurty						
2	.7125419	.6020848	1.18	0.237	-.4675226	1.892606
3	-.9693025	.1260191	-7.69	0.000	-1.216295	-.7223096
4	-.6872813	.598401	-1.15	0.251	-1.860126	.4855632
apartstruty						
2	.0053329	.1278445	0.04	0.967	-.2452377	.2559035
3	.3985407	.1514867	2.63	0.009	.1016321	.6954492
4	.2652991	.4633638	0.57	0.567	-.6428773	1.173476
region						
2	.3187847	.2700577	1.18	0.238	-.2105186	.848088
3	.0636113	.2889208	0.22	0.826	-.5026631	.6298856
4	.4174079	.2962012	1.41	0.159	-.1631358	.9979515
5	.617734	.2883831	2.14	0.032	.0525135	1.182954
6	.1958832	.2745218	0.71	0.476	-.3421697	.7339361
7	-.4945417	.3156194	-1.57	0.117	-1.113144	.1240609
8	.6608887	.2628661	2.51	0.012	.1456806	1.176097
9	.2835549	.271906	1.04	0.297	-.2493711	.8164808
10	.3896347	.3089872	1.26	0.207	-.2159691	.9952384
11	.0517339	.2902258	0.18	0.859	-.5170983	.620566
ccbeliev						
2	.0053065	.3072424	0.02	0.986	-.5968775	.6074905
3	.2695217	.2614088	1.03	0.303	-.24283	.7818735

ethnicorig~s						
2	-1.658221	1.065997	-1.56	0.120	-3.747537	.4310949
3	-.7205375	.4306349	-1.67	0.094	-1.564566	.1234913
4	-.5816187	.570741	-1.02	0.308	-1.70025	.5370131
5	-1.314932	.8126033	-1.62	0.106	-2.907606	.2777409
6	-.6665141	.6047682	-1.10	0.270	-1.851838	.5188097
7	-1.000823	.5194838	-1.93	0.054	-2.018993	.0173465
8	-.0244271	.3350535	-0.07	0.942	-.6811198	.6322656
incomehh	.2823642	.0391351	7.22	0.000	.2056608	.3590677
_cons	-4.390819	.4487917	-9.78	0.000	-5.270435	-3.511204
4						
drvlicn	2.263092	.4194271	5.40	0.000	1.44103	3.085154
hhstru	.8918284	.0665658	13.40	0.000	.7613618	1.022295
acctenurty						
2	-14.60329	1315.889	-0.01	0.991	-2593.698	2564.492
3	-1.18111	.227304	-5.20	0.000	-1.626618	-.7356023
4	-.2491781	.7595064	-0.33	0.743	-1.737783	1.239427
apartstruty						
2	.0080133	.2216273	0.04	0.971	-.4263684	.4423949
3	1.114957	.2358441	4.73	0.000	.6527111	1.577203
4	-14.53226	1114.636	-0.01	0.990	-2199.178	2170.113
region						
2	-.0711059	.4449717	-0.16	0.873	-.9432345	.8010226
3	-.223155	.4647701	-0.48	0.631	-1.134088	.6877777
4	.2097563	.4665549	0.45	0.653	-.7046746	1.124187
5	.4158554	.4635918	0.90	0.370	-.4927678	1.324479
6	.1320626	.429934	0.31	0.759	-.7105925	.9747177
7	-.788503	.5522055	-1.43	0.153	-1.870806	.2937999
8	.7122493	.4050939	1.76	0.079	-.0817202	1.506219
9	-.3162834	.4450875	-0.71	0.477	-1.188639	.5560721
10	.5882942	.4610734	1.28	0.202	-.3153931	1.491982
11	.4520145	.4336781	1.04	0.297	-.397979	1.302008
ccbeliev						
2	1.388456	.6814327	2.04	0.042	.0528727	2.72404
3	1.037971	.6398323	1.62	0.105	-.216077	2.292019
ethnicorig~s						
2	-14.40025	1238.07	-0.01	0.991	-2440.972	2412.172
3	-15.41678	718.1454	-0.02	0.983	-1422.956	1392.122
4	-2.15566	1.150326	-1.87	0.061	-4.410257	.0989373
5	-15.05014	1219.372	-0.01	0.990	-2404.976	2374.876
6	-1.475167	1.168127	-1.26	0.207	-3.764654	.8143207
7	-1.920034	1.136358	-1.69	0.091	-4.147255	.3071857
8	-.6536489	.7747111	-0.84	0.399	-2.172055	.864757
incomehh	.4700854	.0779166	6.03	0.000	.3173716	.6227991
_cons	-9.488948	.9732099	-9.75	0.000	-11.3964	-7.581492

```
. mlogit, rrr
```

Multinomial logistic regression

Number of obs	2917
LR chi2(84)	2625.62
Prob > chi2	0.0000
Pseudo R2	0.3645

Log likelihood = -2289.2374

carnum	RRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
drvlicn	.0049041	.0013166	-19.81	0.000	.0028976	.0083
hhstru	.5056397	.0384387	-8.97	0.000	.4356452	.5868802
acctenurty						
2	1.094585	.9125396	0.11	0.914	.2136069	5.608979
3	3.267044	.5775724	6.70	0.000	2.310326	4.619944
4	1.030709	.7860253	0.04	0.968	.2312085	4.594814
apartstruty						
2	1.085644	.2198126	0.41	0.685	.7300341	1.614478
3	.7662599	.2263395	-0.90	0.367	.4294833	1.367118
4	.339949	.2757235	-1.33	0.183	.0693469	1.666482
region						
2	.8413051	.3228098	-0.45	0.652	.3965943	1.784681
3	.7501566	.3212096	-0.67	0.502	.3240977	1.736313
4	.8003638	.3609786	-0.49	0.621	.3306588	1.937291
5	.5164479	.2198207	-1.55	0.121	.2242443	1.18941
6	.5603194	.2439149	-1.33	0.183	.2387238	1.315151
7	1.489052	.6337732	0.94	0.350	.646576	3.429256
8	.5626827	.2346989	-1.38	0.168	.24844	1.2744
9	.6484642	.2724286	-1.03	0.303	.2846326	1.477363
10	.6782822	.3233472	-0.81	0.415	.2664587	1.726597
11	.5493733	.2272878	-1.45	0.148	.2441781	1.236028

ccbeliev						
2	.698826	.2660955	-0.94	0.347	.3313239	1.473959
3	.7148703	.2361115	-1.02	0.310	.374186	1.365737
ethnicorig~s						
2	1.433011	.9804914	0.53	0.599	.3748367	5.478437
3	2.265937	1.272297	1.46	0.145	.7538901	6.810633
4	.2403489	.2397712	-1.43	0.153	.0340163	1.698235
5	.4473337	.3815729	-0.94	0.346	.0840547	2.380681
6	1.067789	.8138613	0.09	0.931	.2397209	4.756256
7	1.261726	.8055078	0.36	0.716	.3610299	4.409475
8	.9833365	.4626955	-0.04	0.972	.3910037	2.472996
incomehh	.8149071	.0382771	-4.36	0.000	.7432351	.8934906
2	(base outcome)					
3						
drvlicn	3.09789	.5463727	6.41	0.000	2.192503	4.377154
hhstru	1.709567	.0769397	11.92	0.000	1.565227	1.867217
acctenurty						
2	2.039168	1.227752	1.18	0.237	.6265526	6.636644
3	.3793475	.047805	-7.69	0.000	.2963259	.4856294
4	.5029416	.3009608	-1.15	0.251	.155653	1.62509
apartstruty						
2	1.005347	.1285281	0.04	0.967	.7825185	1.291628
3	1.489649	.2256621	2.63	0.009	1.106976	2.004609
4	1.303821	.6041435	0.57	0.567	.5257774	3.23321
region						
2	1.375455	.3714522	1.18	0.238	.8101639	2.335178
3	1.065678	.3078966	0.22	0.826	.6049176	1.877396
4	1.518022	.4496398	1.41	0.159	.8494759	2.712719
5	1.85472	.53487	2.14	0.032	1.053917	3.264003
6	1.216385	.3339242	0.71	0.476	.7102277	2.083264
7	.6098503	.1924806	-1.57	0.117	.3285244	1.132085
8	1.936513	.5090435	2.51	0.012	1.156827	3.241696
9	1.327842	.3610481	1.04	0.297	.7792907	2.262524
10	1.476441	.4562014	1.26	0.207	.8057602	2.705369
11	1.053095	.3056355	0.18	0.859	.5962482	1.85998
ccbeliev						
2	1.005321	.3088771	0.02	0.986	.550528	1.835819
3	1.309338	.3422725	1.03	0.303	.7844048	2.185563
ethnicorig~s						
2	.1904775	.2030485	-1.56	0.120	.0235757	1.538942
3	.4864907	.2094999	-1.67	0.094	.2091787	1.13144
4	.5589928	.3190401	-1.02	0.308	.1826378	1.710889
5	.2684925	.2181779	-1.62	0.106	.0546063	1.320144
6	.5134954	.3105457	-1.10	0.270	.1569484	1.680027
7	.3675768	.1909502	-1.93	0.054	.1327892	1.017498
8	.9758688	.3269682	-0.07	0.942	.50605	1.881869
incomehh	1.326262	.0519034	7.22	0.000	1.228336	1.431994
4						
drvlicn	9.612767	4.031855	5.40	0.000	4.225046	21.87084
hhstru	2.439586	.1623931	13.40	0.000	2.14119	2.779567
acctenurty						
2	4.55e-07	.0005985	-0.01	0.991	0	.
3	.3069378	.0697682	-5.20	0.000	.1965934	.4792167
4	.7794412	.5919905	-0.33	0.743	.1759099	3.453634
apartstruty						
2	1.008045	.2234104	0.04	0.971	.6528758	1.55643
3	3.049437	.719192	4.73	0.000	1.920741	4.841396
4	4.88e-07	.0005443	-0.01	0.990	0	.
region						
2	.9313632	.4144303	-0.16	0.873	.3893664	2.227818
3	.7999908	.3718118	-0.48	0.631	.3217155	1.98929
4	1.233377	.5754384	0.45	0.653	.4942694	3.077714
5	1.515667	.7026507	0.90	0.370	.6109331	3.760225
6	1.14118	.4906319	0.31	0.759	.491353	2.650419
7	.4545247	.250991	-1.43	0.153	.1539995	1.341515
8	2.038571	.8258129	1.76	0.079	.9215298	4.509647
9	.7288529	.3244033	-0.71	0.477	.3046356	1.743809
10	1.800914	.8303535	1.28	0.202	.729502	4.445897
11	1.571475	.6815143	1.04	0.297	.6716761	3.676672
ccbeliev						
2	4.008657	2.73163	2.04	0.042	1.054295	15.24177
3	2.823483	1.806556	1.62	0.105	.8056733	9.8949
ethnicorig~s						
2	5.57e-07	.0006899	-0.01	0.991	0	.
3	2.02e-07	.0001448	-0.02	0.983	0	.
4	.1158268	.1332385	-1.87	0.061	.0121521	1.103997
5	2.91e-07	.0003548	-0.01	0.990	0	.
6	.2287406	.2671981	-1.26	0.207	.0231756	2.257642
7	.1466019	.1665922	-1.69	0.091	.0158078	1.359593
8	.5201444	.4029616	-0.84	0.399	.1139432	2.374429
incomehh	1.600131	.1246768	6.03	0.000	1.373513	1.864139

```
. mlogit carnum drvlicn hhstru, baseoutcome(2)

Iteration 0:   log likelihood = -3631.5476
Iteration 1:   log likelihood = -2777.6462
Iteration 2:   log likelihood = -2613.5868
Iteration 3:   log likelihood = -2573.8277
Iteration 4:   log likelihood = -2571.9744
Iteration 5:   log likelihood = -2571.9625
Iteration 6:   log likelihood = -2571.9625

Multinomial logistic regression                 Number of obs   =       2942
                                                LR chi2(6)      =    2119.17
                                                Prob > chi2     =     0.0000
Log likelihood = -2571.9625                     Pseudo R2       =     0.2918
```

carnum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
drvlicn	-5.261256	.2540755	-20.71	0.000	-5.759235	-4.763277
hhstru	-.5651518	.0660628	-8.55	0.000	-.6946325	-.4356712
_cons	2.170559	.1640284	13.23	0.000	1.849069	2.492049
2	(base outcome)					
3						
drvlicn	1.236384	.1682617	7.35	0.000	.9065971	1.566171
hhstru	.4661513	.0395838	11.78	0.000	.3885684	.5437342
_cons	-2.761443	.2055091	-13.44	0.000	-3.164234	-2.358653
4						
drvlicn	2.531718	.4140607	6.11	0.000	1.720174	3.343262
hhstru	.7208444	.0566588	12.72	0.000	.6097952	.8318935
_cons	-5.973931	.4695989	-12.72	0.000	-6.894328	-5.053534

```
. mlogit carnum i. acctenurty i. apartstruty i.region, baseoutcome(2)

Iteration 0:   log likelihood = -3631.5476
Iteration 1:   log likelihood = -3352.8927
Iteration 2:   log likelihood = -3331.0573
Iteration 3:   log likelihood = -3330.5863
Iteration 4:   log likelihood = -3330.4788
Iteration 5:   log likelihood = -3330.4549
Iteration 6:   log likelihood = -3330.4495
Iteration 7:   log likelihood = -3330.4487
Iteration 8:   log likelihood = -3330.4486
Iteration 9:   log likelihood = -3330.4486

Multinomial logistic regression                 Number of obs   =       2942
                                                LR chi2(48)     =     602.20
                                                Prob > chi2     =     0.0000
Log likelihood = -3330.4486                     Pseudo R2       =     0.0829
```

carnum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
acctenurty						
2	.9464473	.6555155	1.44	0.149	-.3383394	2.231234
3	1.23539	.1064779	11.60	0.000	1.026697	1.444083
4	1.144252	.5086455	2.25	0.024	.1473247	2.141178
apartstruty						
2	.0009101	.1233301	0.01	0.994	-.2408124	.2426326
3	-.5413407	.1864135	-2.90	0.004	-.9067044	-.175977
4	-.2479811	.5477246	-0.45	0.651	-1.321502	.8255394
region						
2	-.125645	.232112	-0.54	0.588	-.5805761	.3292861
3	-.3379211	.2580435	-1.31	0.190	-.8436771	.1678349
4	-.0607963	.2714801	-0.22	0.823	-.5928875	.4712949
5	-.316133	.2645155	-1.20	0.232	-.8345739	.2023078
6	-.9476498	.2674047	-3.54	0.000	-1.471753	-.4235462
7	-.0748943	.2480663	-0.30	0.763	-.5610954	.4113068
8	-.6622052	.2543548	-2.60	0.009	-1.160731	-.1636789
9	-.6895364	.2566128	-2.69	0.007	-1.192488	-.1865846
10	-.3413929	.3044366	-1.12	0.262	-.9380777	.2552918
11	-.2391007	.2548917	-0.94	0.348	-.7386794	.2604779
_cons	-1.036768	.2153782	-4.81	0.000	-1.458901	-.6146341
2	(base outcome)					
3						
acctenurty						
2	.6244838	.5502272	1.13	0.256	-.4539417	1.702909
3	-.984038	.1125297	-8.74	0.000	-1.204592	-.7634839
4	-.3515256	.5218016	-0.67	0.501	-1.374238	.6711867
apartstruty						
2	.0348073	.1182152	0.29	0.768	-.1968902	.2665048
3	.3266879	.1411782	2.31	0.021	.0499838	.603392
4	.0862791	.4276421	0.20	0.840	-.751884	.9244422
region						
2	.3033474	.2483209	1.22	0.222	-.1833526	.7900475
3	.119657	.2657657	0.45	0.653	-.4012341	.6405482
4	.2983942	.2728806	1.09	0.274	-.236442	.8332304
5	.4799485	.2648936	1.81	0.070	-.0392335	.9991304
6	.168714	.2539185	0.66	0.506	-.3289572	.6663852
7	-.2529826	.2872861	-0.88	0.379	-.8160531	.3100878
8	.6687329	.2420922	2.76	0.006	.194241	1.143225
9	.3373025	.2508021	1.34	0.179	-.1542605	.8288656
10	.3233642	.2872367	1.13	0.260	-.2396094	.8863379
11	.0962856	.268744	0.36	0.720	-.430443	.6230142
_cons	-.6396202	.2281481	-2.80	0.005	-1.086782	-.1924581
4						
acctenurty						
2	-13.50894	789.0513	-0.02	0.986	-1560.021	1533.003
3	-1.164036	.2013783	-5.78	0.000	-1.55873	-.769342
4	.0024532	.685867	0.00	0.997	-1.341821	1.346728
apartstruty						
2	.0619861	.2049787	0.30	0.762	-.3397648	.4637369
3	.9828164	.2152446	4.57	0.000	.5609448	1.404688
4	-13.6028	605.582	-0.02	0.982	-1200.522	1173.316
region						
2	-.1837447	.4094544	-0.45	0.654	-.9862606	.6187712
3	-.1153597	.4248554	-0.27	0.786	-.948061	.7173417
4	-.0185044	.4256029	-0.04	0.965	-.8526707	.815662
5	.0859875	.4232108	0.20	0.839	-.7434904	.9154654
6	.019242	.391954	0.05	0.961	-.7489737	.7874577
7	-.6331354	.510127	-1.24	0.215	-1.632966	.3666952
8	.6233671	.3683657	1.69	0.091	-.0986165	1.345351
9	-.223741	.4079743	-0.55	0.583	-1.023356	.575874
10	.3994694	.4179556	0.96	0.339	-.4197084	1.218647
11	.3953349	.395484	1.00	0.317	-.3797996	1.170469
_cons	-1.85354	.3609511	-5.14	0.000	-2.560991	-1.146089