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ScienceDirect

Procedia Computer Science 201 (2022) 101–108

Procedia Computer Science

www.elsevier.com/locate/procedia

The 13th International Conference on Ambient Systems, Networks and Technologies (ANT)
March 22 - 25, 2022, Porto, Portugal

Yearly Development of Car Ownership in Urban and Rural Environments

Jullian van Kampen[a,b,*], Luk Knapen[a,c], Rob van de Mei[a,b], Eric Pauwels[a], Elenna Dugundji[b]

[a] *Centrum Wiskunde en Informatica, Science Park 123, 1098 XG Amsterdam, Netherlands*
[b] *Free University of Amsterdam, de Boelelaan 1018, 1018 HV Amsterdam, Netherlands*
[c] *UHasselt, Transportation Research Institute, Agoralaan , 3590 Diepenbeek, Belgium*

Abstract

The decision to own a car usually results from a mix of changes in socio-economics, residential location, demographics or preferences of the individuals. These changes do not directly influence car ownership but are lagged in time or sometimes occur on anticipation of future events. In this research we investigate how some of the most common predictors for car ownership change over the years and how much impact they actually have in their decision for owning a car. We make a distinction in impact for people living in an urban and people living in a rural environment. A multinomial logit was estimated in 4 separate years to assess the impact of changes in residential location, age and income. The results show that not only the impact of these common predictors is changing but also the relation that they have regarding car ownership. These results illustrates the complexity of car ownership and suggests a more dynamic approach for the prediction of car ownership in both urban and rural environments.

Keywords: car ownership; residential location; self-selection; discrete choice; multinomial logit; urban environment; rural environment

1. Introduction

The relation between car ownership and residential location has been studied for years in transportation research. Usually, it is assumed that self-selection or residential sorting takes place which means that people choose their residential location based on their car ownership level. Hence, people owning a car are more likely to live in more peripheral areas of the city and people not owning a car are more likely to live near the city center. Moreover, people living in central areas of the city are less inclined to own a car since these area's usually have plenty of travel alter-

* Corresponding author. Tel.: +31205924059
E-mail address: jullian.van.kampen@cwi.nl

10.1016/j.procs.2022.03.016

natives and amenities. This illustrates that residential location can be a determinant for car ownership but also that car ownership can be a determinant for residential location which has resulted in a vast amount of literature on the subject.

Although residential location is of importance for determining car ownership, Maltha et al.[7] identifies several other factors which can influence the decision for owning a car. Overall, They found that economic, socio-demographic, spatial, attitudes and transportation factors can potentially influence the decision for owning a car. Moreover, evidence was found that the influence of these factors is changing over the years. In particular, income used to have a substantial influence on car ownership but has decreased over the years in favor of household size.

The importance of household size on car ownership is further illustrated in Oakil et al.[9]. He investigated changes in car ownership situations and if there were residential, professional or demographic changes that influenced the situation. Results show that the needs and aspirations of a household change following a change in car ownership status. In their follow-up research Oakil et al. [10] [11] continue their research and identify several household structures and changes in household structures which affect the car ownership of an individual.

The results found in the study by Oakil are further confirmed by a study of Waard et al.[13]. He noted that in the period between 2000 and 2010 car use has levelled off in the Netherlands due to a generational effect. They observe that there is a generation of young adults which own a car at a later stage in their life compared to several years ago while older generations grew up owning a car and are reluctant to give up their car. They argue that young adults start a family at a later stage in their life and as a result, the necessity of a car comes at a later stage in their life. Moreover, they observe that working from home and home shopping can have substantial effects on car use although the effects of these developments remain unclear.

In a different work, Bush [2] researched the older generations by means of cohort analysis. She investigated travel behaviour between the current 65+ generation and the future 65+ generation in the United states. The results of the analyzes showed that current estimations for future travel demand might be biased due to different transportation needs of the future 65+ generation. Furthermore, they conclude that investments in transit could increase the 65+ transit usage propensities. This implies that satisfying future transportation needs requires the consideration of future generations and not only the current generation.

Some work has been done in the past where a joint choice is made for residential location and car ownership. In this work we further investigate the joint choice of residential location and car ownership and how their choice changes over time using a discrete choice model. For our work we have access to register data of the central bureau of statistics which allows us to track an individual his residential location and car ownership over the years 2010-2019. Our model will comprise of demographic, socio-economic and time-lagged residential location variables.

In the next section, some literature will be discussed where car ownership and residential location have been researched. Consequently, the data that has been used in order to perform this research is described. Afterwards, we describe the model used as well as the modelling procedure that has been used during this research. Finally, we will discuss the results of the models and discuss how to further improve the model.

2. Literature Review

Gonzalez et al. [4] researched to what extend transportation policies aimed at improving urban sustainability influence car ownership. They explain car ownership using socio-demographic characteristics, built-environment characteristics, transport network attributes and policy-related attributes which are calibrated in a multilevel ordered logit model. Their results show that socio-demographics like family structure and income have a positive impact on the number of cars owned. Furthermore, in neighborhoods with a substantial supply of public transit and public transit fare pass ownership car ownership rates are lower. Finally, they found that population and residential density further reduce car ownership in neighborhoods.

Yang et al. [14] investigated which built environment characteristics cause people to switch from driving to other commuting modes, and whether the effects of these built environment characteristics are spatially heterogenous across zones. For their research they estimated a multilevel probit model with sample selection using a full information maximum likelihood estimator. Their results showed that the effect of the built environment on travel mode choice is greater than its effect on car ownership. Moreover, based on the results they conclude that car dependency can be efficiently reduced by compact land use, high building density, narrow width street networks, and a good transit service with high bus route coverage.

Haustein [5] examined how car ownership changes over time and how this relates to free-floating car sharing (FFCS) membership, attitudinal and demographic factors. Her study is based on a longitudinal survey among FFCS users and non-FFCS users in Copenhagen which were surveyed 2 times over a period of 2.5 years. In their analysis 5 population segments were created showing similar attitudinal profiles which range from car dependent segments on the one end and car avoiders on the other hand. The segmentation showed that mainly young adults living in central areas with car ownership aspirations were likely to experience changes in their living situation. The regression results showed that these group of people most likely increase their car ownership as a result of increased household size.

Carrone et al. [3] examined how car ownership preferences of different age cohorts are changing over time using a joint discrete choice model for car ownership and household level. They estimate a multinomial logit model using time-varying coefficients to identify changes with respect to period, age and generation. They used multiple cross-sectional data collected over the years 2007-2017 to estimate their model. The results of their model show that young age cohorts are less likely to acquire a car compared to 10 years ago. On the other hand, older age cohorts are more likely to own two or more cars compared to 10 years ago. Moreover, their model results show that a fixed preference setting for the coefficients can lead to biased predictions for car ownership, and that preferences are slightly saturated over the time periods.

Heinonen et al. [6] performed a mixed-method analysis of car ownership in Reykjavik. Their study is focused on adults in the age categories 25-40 which are supposedly less car-oriented compared to older generations. Additionally, they put their findings in perspective by describing the historic development of Reykjavik. An important observation here is the fact that there are no rail services in Iceland which could compete with the car as a modality. Their results show that there is a deeply rooted car culture resulting from poor quality of the public transit network and a perpetuating car ownership tendency from previous generations. Moreover, they did find a weak impact of the built environment characteristics but only near the city center.

Yu et al. [15] examined mobility of chinese residents and discuss the efficiency of policies in the mobility of rural people. They used nationwide survey data from 119 rural towns for a total of 12524 respondents. They estimated travel frequency using a multi-level regression model including variables on the individual level and on the town environment level. Their results show that car ownership is one of the most crucial factors explaining increase in travel frequencies towards higher-order centres, and that other transport choices have a positive but weaker effect. Moreover, they suggest that in order to enhance transportation of rural towns investments have to be made in both the road infrastructure and the transit infrastructure to enhance mobility as a whole.

This research is an extension of our previous work performed in van Kampen et al. [12]. In this study we investigate the effect of age cohorts on car ownership and residential location. In order to find these effects, a nested panel logit model was estimated which is able to capture age cohort effects. Overall, we concluded that car owners in urban areas have more age variation than car owners in rural areas. This effect seems to decrease as car ownership increases indicating that higher levels of car ownership might be linked to one specific age group. However, due to lack of data it was not possible for us to confirm this. In this research we will be using a larger dataset which hopefully provides more insight in the effects of age on car ownership in urban environments.

3. Data

For our research we used register data provided by the Central Bureau of Statistics. This data contains information on an individual level over multiple years which allows us to track an individual over time. For this research we decided to track people who lived, or were living, in Amsterdam in the period between 2010-2019 and have changed their car ownership in this period. Thus, our data consists of 10 records for each individual over the years 2010-2019, where each record describes a residential location and a car ownership level. Consequently, we linked an individual his income, and age for each corresponding record year to the individual to see how changes in these variables affect car ownership.

3.1. Data preprocessing

In this research we are looking for explanations why people change their car ownership level. Therefore, our data requires some preprocessing in order to exhibit changes in their income, age or residential location. As a result the following measures were taken regarding income, age and residential location variables.

1. Income: we chose to implement the income variable as a continuous variable by computing a moving average using the current year and the past year.
2. Residential location: for residential location we decided to make separate dummy variables using lagged variables. The dummy variables FROM_AMSTERDAM1 and FROM_AMSTERDAM2 tells us whether the person was living in Amsterdam either 1 year or 2 years ago respectively. The dummy variables TO_AMSTERDAM1 and TO_AMSTERDAM2 tells us whether the person moved to Amsterdam either 1 year or 2 years ago, respectively.
3. Age: For age attempts were made to create 4 separate age groups ranging from 18-30, 31-49, 50-65 and 65+. However, During the modelling, many of these grouped variables were correlated and therefore age was left as a continuous variable for our models.

4. Methodology

For our research we will be using discrete choice models which are used to infer preferences and trade-offs of an individual. These models assume that an individual has a set of alternatives to choose from and that each alternative has a certain utility. The individual chooses the alternative which maximizes his utility. In this research we will be estimating joint choice models where an individual makes a choice between residential location and car ownership level. For residential locations it is possible to either live inside Amsterdam, outside of Amsterdam but inside the Metropolitan region of Amsterdam, or live outside Amsterdam and outside of the metropolitan region and Amsterdam. Car ownership levels are allowed to vary between 0, 1 and 2 or more cars. As a result, our joint choice model has 9 separate choices based on residential location and car ownership level. Table 1 shows how each of our alternatives are defined.

Table 1. Definition of alternatives

Alternative	Car ownership level	Residential location
0	no car	outside metropolitan region
1	one car	outside metropolitan region
2	at least 2 cars	outside metropolitan region
3	no car	inside metropolitan region
4	one car	inside metropolitan region
5	at least 2 cars	inside metropolitan region
6	no car	Amsterdam
7	one car	Amsterdam
8	at least 2 cars	Amsterdam

Additionally, our discrete choice model allows us to estimate alternative specific coefficients for each alternative. Therefore, since we are dealing with such a large dataset, we constantly attempt to create alternative specific coefficients for each explanatory variable corresponding to each alternative. When it turned out coefficients were correlated they were either removed or aggregated as one coefficient. We will briefly explain the multinomial logit model in the next subsection.

Initially, our plan was to exploit this data structure using a panel logit model. This model introduces an additional normal error term which allows us to correct for multiple observations of the same individual. However, introducing such an error term would require us to solve an integral in which our normal error terms are generated using simulation techniques. As a result, the panel logit model took several days to solve this integral since we were dealing with large amounts of data. Therefore, the decision was made to estimate 4 separate multinomial models for the years 2013, 2015, 2017, and 2019.

4.1. Multinomial model

$$U_{in} = V_{in} + \varepsilon_{in} \tag{1}$$

The utility function shown in equation 1 corresponding to an alternative i in the choice set C_n for an individual n is divided into two components where U_{in} is the total utility; V_j represents the systematic component of the utility (consist of a constant term and observed heterogeneity) and ε_j is the random part of the utility (also referred to as error term, which accounts for the unobserved heterogeneity). McFadden [8] shows that if ε_j follows an extreme value distribution function, the choice situation results in a multinomial logit model (MNL). The probability that an individual chooses an alternative is given by equation 2.

$$P(i|C_n) = \frac{exp\ V_{in}}{\sum_j exp\ V_{jn}} \tag{2}$$

For further mathematical details readers can refer to Ben-Akiva et al.[1].

5. Results

The results for the car ownership model can be found in table 1. In this table each columns refers to a year the model was estimated. Each value in the table refers to the value of the parameter followed by the t-test in parenthesis. The final row of the table shows us the rho-square of the model. Interestingly, as years progress we can see that the rho-square for the model seems to decrease, which indicates that the model fit with the current set of variables is getting worse. Overall, we notice that all of the t-tests have extreme high positive or extreme low negative values. This can be explained by the fact that we have a lot of data which can result in anything becoming significant as long as you have enough data. An important sidenote to make is that alternative 6 was selected as our baseline alternative meaning that most of the results discussed here are compared to alternative 6 where people own no car and live in Amsterdam.

5.1. Alternative specific constants

The alternative specific constants show that not owning a car and living in Amsterdam is one of the most likely alternatives for an individual. The only alternative which appears to be more likely is the alternative where an individual does not own a car and lives outside of the metropolitan region. Moreover, we can see that as time progresses the impact of the constants decreases as well as the significance of the constants.

5.2. Age

Alternative 0 and 3 show us that as age increases it becomes less likely that an individual does not own a car over all years. On the other hand we can see car ownership increases in likeliness as age increases for people living in Amsterdam. Additionally, in our models in 2019 we can see that our age variable has a negative impact for car owners outside Amsterdam while this used to be positive in previous years. Moreover, the impact of age on car owners in Amsterdam has decreased in 2019.

5.3. Residents moving from Amsterdam

For the people who have moved from Amsterdam 1 year ago we can see that people are more likely to own a car. Moreover, the impact of residential relocation on car ownership seems to be higher inside the metropolitan region of Amsterdam compared to the outer metropolitan region of Amsterdam. If we consider the people who have moved from Amsterdam 2 years ago we can draw the exact same conclusions. The impact of residential relocation 2 years ago seems to be stronger compared to the same coefficients 1 year ago. This shows that people who move from the city develop a tendency for car ownership which increases over the years. The impact of this variable has been decreasing over the years indication that this car ownership tendency is slowly decaying over the years.

Table 2. Multinomial logit results

Name	2013	2015	2017	2019
ASC_0	0.594 (30.1)	0.259 (12.5)	0.25 (11.4)	0.568 (24)
ASC_1	-3.08 (-115)	-2.56 (-97.7)	-1.63 (-65.2)	-0.411 (-17.3)
ASC_2	-6.49 (-76.3)	-6.02 (-72.5)	-4.9 (-65.5)	-3.37 (-51.1)
ASC_3	-0.834 (-39.2)	-0.846 (-40.4)	-0.494 (-22.8)	0.0606 (2.59)
ASC_4	-3.88 (-138)	-3.07 (-121)	-2.06 (-88.4)	-0.801 (-36.3)
ASC_5	-6.65 (-82.7)	-5.54 (-76.1)	-4.55 (-70.6)	-3.08 (-54.6)
ASC_7	-1.91 (-148)	-1.59 (-121)	-0.919 (-67.8)	-0.0377 (-2.59)
ASC_8	-4.51 (-148)	-4.28 (-137)	-3.64 (-116)	-2.91 (-90)
B_AGE_0	-5.98 (-96.7)	-4.7 (-80)	-4.12 (-72.5)	-4.28 (-75.1)
B_AGE_1	1.6 (25.6)	0.677 (11.3)	-0.751 (-13.2)	-2.4 (-45.2)
B_AGE_2	4.03 (23.5)	3.05 (18.3)	1.29 (8.4)	-0.836 (-5.99)
B_AGE_3	-2.6 (-43.1)	-2.01 (-36.8)	-2.32 (-43.8)	-3.08 (-57)
B_AGE_4	3.16 (52.5)	1.98 (36.3)	0.543 (10.8)	-1.17 (-24.9)
B_AGE_5	4.41 (27.9)	2.54 (16.9)	1.17 (8.75)	-0.822 (-6.91)
B_AGE_7	4.04 (138)	3.21 (112)	1.94 (67.6)	0.384 (13)
B_AGE_8	4.84 (79.5)	4.17 (68.3)	2.98 (49.1)	1.73 (28)
B_FROM_AMSTERDAM2_1	2.02 (77.1)	1.76 (66.5)	1.76 (76.9)	1.77 (83.1)
B_FROM_AMSTERDAM2_2	2.02 (24.6)	1.94 (24.5)	1.89 (28.4)	1.7 (28.5)
B_FROM_AMSTERDAM2_4	2.6 (108)	2.1 (88.3)	2 (95.9)	1.94 (99.1)
B_FROM_AMSTERDAM2_5	2.65 (41.2)	1.94 (27.8)	1.95 (34.5)	1.87 (38.6)
B_FROM_AMSTERDAM_1	1.86 (69.4)	1.76 (70.4)	1.74 (76.1)	1.64 (75.4)
B_FROM_AMSTERDAM_2	1.85 (21.6)	1.83 (23.1)	1.86 (28.1)	1.5 (23.5)
B_FROM_AMSTERDAM_4	2.44 (99.4)	2.14 (95.3)	2.05 (101)	1.88 (95.1)
B_FROM_AMSTERDAM_5	2.36 (33.8)	2 (31)	1.96 (35.6)	1.66 (31.9)
B_INCOME_0	0.357 (5.74)	0.435 (6.62)	0.202 (2.81)	-0.108 (-1.36)
B_INCOME_1	-1.09 (-7.39)	-0.815 (-6.23)	-0.92 (-7.64)	-1.11 (-10.3)
B_INCOME_2	-0.253 (-0.725)	-0.328 (-0.934)	-0.458 (-1.47)	-0.683 (-2.53)
B_INCOME_3	0.0963 (1.24)	-0.0132 (-0.163)	-0.00633 (-0.0802)	-0.0803 (-1.02)
B_INCOME_4	-1.29 (-8.13)	-1.37 (-9.02)	-1.51 (-11)	-1.67 (-13.9)
B_INCOME_5	-0.384 (-1.15)	-0.849 (-2.26)	-0.607 (-2.14)	-1.06 (-4)
B_INCOME_7	-0.68 (-11.4)	-0.615 (-10.3)	-0.72 (-11.9)	-0.738 (-12.6)
B_INCOME_8	-0.184 (-1.42)	-0.193 (-1.44)	-0.32 (-2.37)	-0.264 (-2.15)
B_TO_AMSTERDAM2_7	0.0318 (1.47)	0.0502 (2.35)	0.165 (8.12)	0.263 (12.2)
B_TO_AMSTERDAM2_8	-0.31 (-4.52)	-0.459 (-6.18)	-0.0778 (-1.28)	-0.0496 (-0.764)
B_TO_AMSTERDAM_7	0.141 (6.68)	0.191 (9.26)	0.281 (13.8)	0.468 (21)
B_TO_AMSTERDAM_8	-0.389 (-5.39)	-0.161 (-2.46)	-0.0982 (-1.56)	0.136 (2.09)
Rho square	0.33	0.299	0.259	0.222
Observations	347769	347763	346633	343855

5.4. *Residents moving to Amsterdam*

For people who have moved to Amsterdam 1 year ago we can see that they are still likely to own one car. Additionally, when we consider the people who have moved to Amsterdam 2 years ago we can still see a positive impact on car ownership. Additionally, we can observe that over the years the impact and significance of this variable has been increasing. Alternatively, people are less likely to own at least 2 cars when they have moved to Amsterdam 1 or 2 years ago although the impact is quite low. However, we can see that in 2019 people who have moved to Amsterdam 1 year ago have an increased likelihood of owning 2 cars. This result, along with the result that the impact and significance of owning 1 car is increasing, indicates that people who move to Amsterdam take their car with them or have a tendency to purchase a car when moving to Amsterdam.

5.5. Income

Our income variable tells us that as income increases the likelihood of owning a car decreases since all the alternatives concerning car ownership show a negative impact. Moreover, this negative impact perpetuates for car owners over the years. Finally, the results show that income has a negative impact on 2 or more car owners but gains in significance over the years. On the other hand, for people living outside of Amsterdam, income seems to have a positive impact on the probability to become a non car owner but this effect has decreased over the years and eventually disappears in 2019.

6. Discussion

In this research an attempt was made to estimate a joint choice model for car ownership and residential location for residents of the city of Amsterdam over the years 2010-2019. With the help of register data we are able to observe changes in an individual his demographics, socio-economics car ownership status and residential location. Overall, we observed that the rho-square of the model decreased from 0.33 in 2013 to 0.222 in 2019 which tells us that the model fit with our current set of variables is getting worse. This might be a consequence of the reduced impact of income and age in our model in 2019 and suggests that different variables might work better in explaining car ownership and residential location. The results of the model showed that previous residence has an impact on car ownership depending on whether the person lived in a city, in this case Amsterdam, the metropolitan region or somewhere else. Surprisingly, we found that people who have moved to Amsterdam seem to have a tendency to keep or purchase a car. This result strikes out since it shows that the concept of self-selection, which states that people choose their residence based on their car ownership level, does not apply to all people who move to Amsterdam. Moreover, it illustrates how car dependency still resonates through people who have lived in suburban neighborhoods and have moved to Amsterdam. Additionally, the impact of income shows a negative impact on car ownership which has been considered to have a positive effect for years in previous research. It shows that not only the impact of variables is subject to change over the years, but also the sign of the variable. Finally, the age variable shows an important trend in car ownership in 2019 for people in Amsterdam. In regions outside Amsterdam we can see that age has a negative impact on car ownership while this impact is positive in Amsterdam. This result suggests that as age increases car ownership increases in Amsterdam and thus car ownership might be prevalent among a certain age group. This is in line with our previous research in [12] where we suggested that owning 2 cars or more in urban environments might be associated with older age groups.

This study shows the potential and richness of register data and how it can contribute to research that has been done in the past. Obviously, multinomial logit models have been used for decades and the factors influencing car ownership and residential location have been known for some time now. However, the real contribution of this study lies in the fact that register data allows us to try different kind of modelling specifications based on complete knowledge of all individuals who own or have owned a car. Although the amount of variables used is limited in this research, each variable by itself shows interesting results which may not have been found using smaller datasets. Future researchers should attempt different variable setups and see how the model performs as time progresses.

Although we encourage the use of this kind of data there are some limitations. One of the main problems encountered when performing this research was the model estimation time. Preliminary tests on the dataset already showed us that increasing the quantity of data showed a linear trend on increase on computation time. However, adding complexity to the model in terms of adding explanatory variables showed an exponential increase in computation time. As a result, we were not able to try many model specifications since for even some of the simple multinomial logit models computation times were close to an hour per model. Moreover, since we were dealing with such high computation times we were not able to estimate some more complex models like mixed logit models or panel logit models. Finally, we only used a small selection of variables in this study while there are many other factors that influence car ownership and residential location. We hope this research encourages future researchers to develop and extend this kind of research as the results presented prove to be simple but insightful. Additionally, Future research should focus on other factors affecting car ownership or residential location and see whether they are able to find as surprising results as we did in this research. For example, it is likely that income is related to education level and that the impact found in this research is more due to education instead of income.

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