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Analyzing Potential Age Cohort Effects in Car Ownership and Residential Location in the Metropolitan Region of Amsterdam

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Abstract

Previous research on car ownership has described ownership using a combination of socio-economic factors, demographics, individual preferences and residential factors. However, over the years people's attitudes towards car ownership have changed as new generations are being formed. A new generation of young adults has a different view on car ownership compared to the older generation when car ownership was still a display of status. In this research a first attempt is made to disentangle the effects of age on car ownership and residential location. A discrete choice modelling approach is used where we jointly model car ownership and residential location in the metropolitan region of Amsterdam. We will start from the multinomial logit model and from there try more complex models which capture correlation among alternatives, and introduce a cohort effect for people of a certain age using a nested panel model. The main result of the model shows that car ownership in the city shows more variation in age than car ownership outside of the city.

Keywords: Cohorts;joint choice;Discrete choice;panel model;car ownership;residential location

1. Introduction

Most urbanized cities benefit from a highly sophisticated multimodal transportation network, and are designed in such a way that they support transportation using different modalities. The purpose of this network is to transport many people over short distances using different public transit services. As a result, car ownership is generally discouraged in urbanized cities compared to rural areas since there is no need and space is limited. Depending on where someone lives, a person may have numerous options to travel to his destination. Someone living in the center

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of the city may have more transportation options available than a person living in the rural or suburban areas of the city. These differences in residential location can thus be important in predicting car ownership. In fact, many people select their residence based on their car ownership which is referred to as self-selection or residential sorting.

Apart from residential location, there are other factors that might influence car ownership. Maltha et al. [8] identifies five different influential factors in car ownership including economic, sociodemographic, spatial, attitudes and transportation factors. They also found that the influences of these influential factors changes over the years. Household income used to have a substantial influence but over the years it has decreased in favor of household size.

A study by Waard et al. [14] noted that car use in the Netherlands has levelled off in the period between 2000 and 2010. They observe that there is a generation of young adults which own a car at a later stage in their life than several years ago while the older generation grew up owning a car and are reluctant to give up their car. This result is possibly caused by the fact that this generation of young adult start a family in a later stage in their life than the older generation did. Additionally, they observe that working from home and home shopping may have substantial effects on car use although the effects of these developments remain unclear.

More recent studies investigated the ongoing trends among these young adults. Oakil et al. [10] investigated changes in a person his car ownership situation and whether there where residential, professional or demographic changes that might have influenced the decision for owning a car. The results showed indeed that changes in car ownership were observed as a person his households needs and aspirations changes. In his future work Oakil et al. [11] and Oakil et al. [12] further investigated these effects and identified several household structures and changes in household structures which affect the car ownership of an individual.

In a different work the older generations have been researched by means of cohort analysis. Bush [3] investigated travel behavior between the 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. This implies that satisfying future transportation needs requires the consideration of future generations and not only the current.

Some work has been done on the joint choice of car ownership and residential location, and some research has been done on cohort effects in transportation. However, These topics have as far as we know always been researched separately while it seems very likely that cohort effects can influence car ownership. In this paper we want to further investigate these differences in car ownership based on residential location and cohort effects. Therefore, an attempt is made to estimate both whether a person lives in the city or not and whether he owns a car or not based on cohort effects. In order to do this a mixed nested panel model is used where a cohort is created of individuals of a certain age, and the explanatories consists of socio-economic and other demographic variables.

In the first section, some literature will be discussed where car ownership, residential location and cohort effects have been researched. In the second section, the data that has been used in order to perform this research is described. The thirth section describes 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

Some work has been done in the past where car ownership and residential location were jointly estimated. Bhat & Guo [1] created a general methodology to correct for self-selection in their model. He used a joint mixed-multinomial logit-ordered response structure which incorporates both built environment characteristics and transportation network variables. The results of his model showed that the demographic and built environment attributes are influential in the decision for car ownership and residential location. The household variables however appear to be more dominant than the built environment attributes.

Mulalic et al. [9] researched the effects of a new metro network extension on residential choice and car ownership in the metropolitan region of Copenhagen. They used a multinomial logit to estimate the joint choice of car ownership and residential location. They however make a distinction between single-earners and dual-earner households and use two different model estimations. In their modelling procedure they assume that single-earner households are able to own no or one car, and dual earner households can own none, one, or two cars. The residential location is divided into 166 different regions where an individual can choose to live and for each of these area's variables are measured related to the accessibility, transportation and neighborhood characteristics. The results of the model showed that there was an increased interest in living close to the metro station mainly for dual-earner households with a high income.

Weinberger & Goetzke [16] researched whether car ownership preference changes as someone moves to or from a metropolitan region. They used a multinomial probit model in order to predict the joint choice of car ownership and residential location. Residential location is modelled in this paper as living inside the central city or outside the central city, while car ownership was modelled as either owning none, one or two cars. Their results show that moving from the central city to suburban residential location results in lower vehicle ownership compared to others living in the same suburban region. On the other hand moving to the central city and coming from a suburban region resulted in higher vehicle ownership compared to living in the central city area. This result implies that learned preferences from previous residential locations are influential in the decision of owning a car or not.

In a follow-up work Goetzke & Weinberger [5] used the results of their previous research to identify the impacts of both the endogenous effects and contextual effects on car ownership. They defined a two-stage probit model in which first endogenous effects were estimated using an ordinary least squares approach. The results of these model are then used as an instrumental variable in the second stage which estimated car ownership. Their overall results showed that car ownership is less likely in neighborhoods populating higher educated people, while car ownership is more likely to occur in neighborhoods with high concentrations of poor people

Guerra [6] examined the relation between income, car ownership and suburbanisation in the region of Mexico City. They used a joint mixed logit model with random error components to predict car ownership and residential location. residential location was incorporated in this model as an aggregated geographical unit, where each unit is either the city center or an urban ring around the center. Car ownership was modelled as an individual owning none, one or two cars. The results showed that suburbanisation and car ownership do not seem to be closely linked.

Kuwano et al. [7] used a dynamic generalized extreme value model which is able to capture multiple social interaction effects. Their main goal was to identify reference groups which could be relevant in predicting car ownership, and which social interactions were important. Their results show that social interactions effects exist on a household and neighborhood level of people with the same income. However, these social interaction effects from the society as a whole did not affect the household choice for car ownership, indicating the importance of reference groups in car ownership.

Pinjari et al. [13] did not only model the joint choice of car ownership and residential location, but he also included bicycle ownership and commute mode choice. They created their own framework in which commute mode and residential location is estimated by using a multinomial model, and bicycle and car ownership is estimated using an ordered logit. Each of these models have a common error structure which allows them to correct several important interdependencies including self-selection endogeneity and associative correlations. An important result of their research was that neglecting any of these effects resulted in an inflation in the estimated variables of the model.

In addition to capturing correlations between alternatives, as is mostly done in discrete choice modelling, Dugundji & Walker [4] is also interested in capturing correlations between individuals. They describe how interdependent residential location and socio-economic status can be incorporated in a discrete choice approach to modelling transportation mode choice. Several strategies are introduced to capture these effects, namely by either introducing generic feedback effects, unobserved group heterogeneity, alternative-specific dummy variables and random parameter feedback effects. The application results of their strategies prove to be significant compared to traditional methods of market segmentation. We apply the concept of unobserved group heterogeneity in the current research to model social interactions in age cohorts.

3. Data description

The data that has been used in this research originates from a national travel survey in the Netherlands that is conducted every year. For this paper, survey data of the years 2011 up to 2017 was aggregated. In this survey, people are questioned about their travel patterns on a specific day, and how they made these travels. Although the survey is conducted on a national scale, for the years 2011-2017 additional responses were collected of people living inside the metropolitan region of Amsterdam. For our research we are only interested in the people living inside the Metropolitan region of Amsterdam, and people who had any origin, destination or interchange in the city of Amsterdam. In some cases, the data contained either extremely high distances travelled or long travel times for a trip. These records were considered outliers and therefore people travelling more than 200 kilometres and having more than 6 hours of travel time were removed from the dataset. Additionally, people that did not have an identifiable household or were younger than 18 years old were removed from the dataset. After removing these outliers we ended up with a total of 9857 records to estimate our model.

The data contains a lot of information about different variables, but not all variables were used. The reason why some of them are not included is due to the fact that some of these variables showed significant correlation structures among variables. This correlation is not only caused by the fact that many explanatories are correlated with each other, but also because the data consists mostly out of categorical variables. As a result, the variables trip frequency, gender and education are considered only to have a residential effect and not a car ownership effect.

4. Modelling approach

The model that was used in this paper is a discrete choice model. These models come in a variety of specifications depending on the assumptions that are being made. The discrete choice models that we will be using are based on random utility theory. We will start our modelling procedure from the multinomial logit model from which we know it is able to find a unique solution. The results of the multinomial model will be used as a starting point for the Nested logit. Additionally, the results for the nested logit model will be used as a starting point for the mixed nested panel model in order to improve the estimation procedure. The software used to estimate these models is Bierlaire [2]. For the estimation procedure, the default parameter values were used except for the mixed nested panel model. Since we are using mixed effects, the choice was made to perform Halton draws instead of the default option for these models.

4.1 *Nested logit*

In the nested logit we are allowing correlation between nests. In our research two different nest structures were tested. In the first nesting structure, the alternatives were nested based on car ownership levels, meaning that people owning 0, 1 or 2 cars are nested. However, The results of this approach were insignificant and are therefore omitted from our analysis. The second nesting structure tested is where residential locations are nested, meaning that people belonging to an urban or rural residential area are nested. In our current work we are looking for correlations between residential location because this correlation structure was the most prevalent in our dataset.

4.2 *Panel model*

Multinomial, nested and mixed logit models have been used in previous literature and are known to most researchers. What might be new to some however might be the panel model which is used in this paper. The difference between a panel model and a Mixed Logit model is that a panel model allows the definition of cohorts. As a result, the panel model allows each cohort to have a different variance structure. This variance can be captured in either an alternative-specific variable or in an alternative specific constant. In our model we will try to capture variance in an alternative specific constant. We assume that our cohorts consist of people of the age between 18 and 95. As a result, our decision makers are individuals of the same age which make a sequence of choices, and are assumed to have a similar variance structure. In order to fully understand the effects of our cohorts, we estimate two mixed nested panel models. First, we estimate the model without the age variable as an explanatory and after that we will estimate the model including age as an explanatory variable. This way we can better distinguish the cohort effects from the explanatory effects in our model.

In order to properly normalize our panel model we follow Walker et al. [15] where model specifications for a mixed logit model are given. Our panel model does not only involve panel data, but also uses a nested structure. In Walker et al. [15] both these specifications require normalization of any one of the variance term. In our model normalization is done on the alternatives where no car is owned.

Table 1: Estimation results

	MNL	**NL**	**Panel-age**	**Panel+age**
Constant				
Rural + 1 car	-1.46 (-9.1)	-0.0872 (-1.4)	0.2 (4.83)	-0.0886 (-1.41)
Rural + 2 cars	-1.56 (-8.67)	-0.0974 (-1.48)	0.0738 (1.71)	-0.0307 (-0.42)
Urban + 1 car	0.0731 (0.55)	0.14 (1.2)	0.527 (6.53)	0.00872 (0.06)
Urban + 2 cars	-1.77 (-8.95)	-1.68 (-9.11)	-1.28 (-13.46)	-1.65 (-8.79)
Rural + 1 car				
Age	1.167 (7.79)	0.527 (6.36)		0.523 (6.18)
Couple + child	1.85 (22.78)	0.757 (14.74)	0.719 (14.22)	0.757 (14.73)
Transit daily	-0.429 (-5.15)	-0.291 (-9.5)	-0.326 (-10.6)	-0.292 (-9.47)
Transit weekly	-0.841 (-10.47)	-0.309 (-9.64)	-0.31 (-9.64)	-0.31 (-9.63)
Single + child	0.338 (2.84)	0.09 (2.37)	0.0454 (1.21)	0.0872 (2.28)
Rural + 2 cars				
Age	0.646 (2.4)	0.299 (3.3)		0.169 (1.54)
Couple + child	2.79 (30.69)	0.959 (16.39)	0.937 (16.12)	0.962 (16.33)
Transit daily	-1.27 (-11.93)	-0.482 (-12.56)	-0.543 (-13.47)	-0.514 (-12.77)
Transit weekly	-1.52 (-14.62)	-0.477 (-11.9)	-0.499 (-12.06)	-0.498 (-12.06)
Single + child	-0.0696 (-0.37)	0.0133 (0.27)	-0.0378 (-0.76)	-0.00882 (-0.17)
Male	0.326 (5.64)	0.0789 (3.31)	0.0771 (3.23)	0.0798 (3.32)
Education	0.562 (7.27)	0.139 (4.38)	0.108 (3.45)	0.144 (4.48)
Trip frequency	0.105 (0.61)	0.0852 (1.13)	0.0838 (1.12)	0.0862 (1.13)
Urban + 1 car				
Age	1.15 (6.62)	0.74 (4.79)		0.916 (4.38)
Couple + child	1.47 (20.35)	0.636 (10.15)	0.609 (9.51)	0.659 (10.19)
Transit daily	-1.32 (-17.08)	-1.12 (-16.16)	-1.14 (-16.19)	-1.09 (-15.51)
Transit weekly	-0.9 (-14.45)	-0.575 (-10.22)	-0.573 (-10.09)	-0.568 (-10)
Single + child	-0.0749 (-0.74)	-0.151 (-1.62)	-0.144 (-1.52)	-0.0921 (-0.97)
Urban + 2 cars				
Age	1.15 (3.67)	0.703 (2.34)		0.651 (2.11)
Couple + child	2.48 (23.95)	1.61 (16.71)	1.55 (16.77)	1.6 (16.65)
Transit daily	-2.1 (-12.49)	-1.84 (-11.31)	-1.9 (-11.83)	-1.85 (-11.33)
Transit weekly	-1.57 (-12.83)	-1.18 (-9.98)	-1.19 (-10.1)	-1.18 (-9.99)
Single + child	-0.535 (-2.05)	-0.619 (-2.4)	-0.679 (-2.64)	-0.625 (-2.42)
Male	0.0478 (0.91)	-0.0857 (-1.93)	-0.0849 (-1.9)	-0.0831 (-1.86)
Education	0.355 (5.24)	0.137 (2.33)	0.0816 (1.4)	0.137 (2.3)
Trip frequency	0.349 (2.24)	0.331 (2.58)	0.318 (2.47)	0.33 (2.56)
Rho-square	0.133	0.173	0.173	0.175
Nest parameter		4.91 (15.11)	4.90 (14.99)	4.87 (15.08)

5. Results

The results of the multinomial model, nested model and mixed nested panel models can be found in table 1. The table shows the weight of the variables along with the t-test statistic in parenthesis. The multinomial model shows high significance in most explanatory variables except for the male, education, and trip frequency of individuals living in an urban area. Additionally, if a person is single and has a child there is no significance in any of the alternatives, while people living as a couple with a child show some of the highest significance. Furthermore, the transit daily and transit weekly variables seem to be close in significance to each other in most cases but the impacts differ. The impact of daily transit usage is higher for people living in urban areas than the weekly transit usage, while in rural areas the weights are closer to each other.

When we look at the results for the nested logit model, we do not observe many differences. The only changes we see are in the error structure where only the constant of the 6th alternative is significant, and in some of the previously insignificant explanatory variables. The rho-square of the model however does improve from 0.135 to 0.173. This result makes sense since we mentioned that most of the explanatory variables that we are adding show some correlation with each other.

Finally we will look at the results for the mixed nested panel model. The results for the explanatory variables do not change a lot in significance in the panel-age model. The only thing that does change is the significance of the explanatory for single with a child living in a rural area, and our education explanatory for living in an urban area. However, the significance of the constants changed compared to the nested and multinomial logit. The fact that there are significant constant terms in the Panel-age model could mean that it is still possible to improve this model by adding explanatory variables to the model. The cause of this change might be in the interpretation of the constants. In the multinomial and nested models the constant term can be interpreted as a mean error over all individuals, while in the panel model there is an additional normal error term which is interpreted as the mean error over all age classes. Additionally, the rho-square did not improve the model compared to the nested logit where age was used as an explanatory.

If we look at the results of our Panel+age model we can observe that adding the age variable as an explanatory improves the rho-square. The significance of age as an explanatory variable remains roughly the same as in our previous nested logit model, except for individuals living in a rural area and owning two cars. However, The constant error terms become even more insignificant in two of our alternatives compared to our nested logit model while in our Panel-age model some of these constants became significant. This may be the result of adding additional explanatory power to the model improving the performance of the model.

Table 2: Normal error terms

Alternative	**Panel-age**	**Panel+age**
Rural + 1 car	0.0618 (4.14)	0.0161 (0.7)
Rural + 2 cars	0.0836 (5.05)	0.0778 (5.49)
Urban + 1 car	0.242 (6.28)	0.202 (6.38)
Urban + 2 cars	0.0114 (0.07)	-0.0391 (-0.35)

Table 3: Hypothesis testing

Comparison	$-2[L^R - L^U]$	**Degrees of freedom**	$\chi_{0.05}$	**Conclusion**
MNL vs NL	1402.23	1	3.84	reject MNL
NL vs Panel+age	66.69	4	9.49	reject NL
Panel-age vs Panel+age	52.78	4	9.49	reject Panel-age

The results for the normal error terms in table 2 tell us that the variance in age is most significant for people living inside of Amsterdam and owning one car. Additionally, the variance in age of individuals owning two cars and living inside of Amsterdam is not significant, indicating that there is no reason to believe that difference in age plays a role in this alternative. This result however might be biased due to the fact that the observations for this alternative is rather low. The variation in age for people living outside of Amsterdam seems to be lower compared to the people living inside of Amsterdam. However, as car ownership increases the variation does seem to increase. Overall we observe that there is more age variation in car ownership inside of Amsterdam than what we observe outside of Amsterdam.

The result of the normal error terms for the Panel+age model in table 2 show similar results as the Panel-age model, except for the alternative for living in a rural area and owning one car. Apparently the addition of age as an explanatory variable was enough to explain the variance in this alternative. Overall, the impact of variance terms seem to decrease as explanatory variables are added to the model. In order to determine which one of these models performs best, likelihood-ratio tests were conducted. In table 3 the results of the likelihood ratio test can be found. Unsurprisingly the results for the nested logit model outperform the results of the multinomial model. The Panel+age model however seems to both outperform the nested logit as well as the Panel-age model. In order to compare the nested logit model with the Panel-age model a non-nested hypothesis test has to be conducted. The test returned a p-value of 0.00035 which means that the nested logit model was rejected in favor of the Panel-age model

6. Discussion

In this paper a joint choice model with cohort effects was estimated using a nested mixed panel model. The results of the model showed that even when using a nested mixed panel model, the significance of the explanatory variables from the multinomial model remain unchanged. The addition of the correlation structure however did improve the model fit which likely has to do with the fact that the utilities have much in common with each other. The panel-age model did not seem to add any explanatory power compared to the nested logit. However, the results of the panel+age model did improve the results compared to both the nested logit and the panel-age model. Additionally the constant error terms pointed out that improvement was still possible in the panel-age model. These results imply that adding cohort effects to a model instead of explanatory variable may result in better estimation results. The estimation results presented here might change if age classes were defined broader and more evenly distributed.

The nested panel models provided insight on the sensitivity of age in different car ownership and residential settings. The most important finding is that in urban areas, the age of a person seems to be more variable than in a rural area. This might be caused by the fact that there are many different age groups living in Amsterdam while the people coming from outside of Amsterdam are close to the same age. This might also explain why adding age as an explanatory variable has a decreasing effect on the constant error term for people owning one car and living in a rural area. In order to further analyze these effects, future research should focus on age differences in different city districts. As is the case with residential self-selection in car ownership, people may choose to live in a certain part of the city depending on their age, or own a car depending in their age.

Additionally, as car ownership in Amsterdam increases the variation captured decreases indicating that multiple car ownership in Amsterdam might be something unique for a certain age group. The results for the t-test however proved to be insignificant meaning that we cannot be sure of this result. Further analysis of high car ownership in Amsterdam is required in order to support these findings.

In future research it might be interesting to investigate different cohorts consisting of income classes, household decomposition or a combination of the aforementioned. Previous research has already pointed out that income and household decomposition are important in car ownership and residential location modelling. The panel model provides the flexibility to define an individual as a fictional person with a certain income, household decomposition and/or age class where each fictional person has its own variance structure.

Although this panel model does a first step in analyzing age effects, two different specifications would be interesting to further investigate. First of all, as stated before, the cohorts can be defined in age clusters. Currently, the assumption is made that every year of age is its own cohort and has its own variance structure. Secondly, instead of capturing the variance as an alternative specific constant, one can try to capture the variance in an alternative-specific variable. In this specification, one can capture the variance of one of the explanatory variables.

Finally, we would like to point out that the results of the model might have been better if a more extensive dataset was used. The number of records and the representativity of the coverage of data in the travel survey is not sufficient to explain differences in different parts of the city at a detailed district level. An interesting dataset would be register data of the people living in Amsterdam or data from a Census. Additionally, adding explanatory variables related to the built environment may improve the performance of the model.

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