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The influence of parking on car ownership

A statistical analysis of the relationship between urban parking availability and household car ownership in the Netherlands

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By

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SUMMARY

The growing population of the Netherlands is putting pressure on the accessibility and liveability of Dutch cities. To address both challenges new mobility policies prioritise quiet, low-emission and space-efficient modes of transport. This changing perspective on urban mobility is thus increasingly in odds with the characteristics of the private car, as private (fuel-engine) cars are loud, polluting and space-inefficient compared to other sustainable modes of transport. To illustrate, a personal trip by private car in Amsterdam requires about 95m^2 of public space, of which 15m^2 is dedicated to parking. For this reason, cities in the Netherlands are looking at measures to reduce (extra) car mobility. They expect that parking regulations could be an effective instrument to reduce car ownership and improve the liveability of cities. But, evidence to support these claims is lacking as the effects of such policies are understudied in car ownership research, which mainly focus on socio-demographic and household characteristics to predict car ownership levels. Therefore, this study aims to address this knowledge gap in the current car ownership literature and support municipalities to substantiate policy interventions and in finding a good balance between car accessibility and liveability.

The study starts off by defining dimensions of urban parking availability, as parking availability is not only affected by the number of parking places but also by multiple regulations. This study identifies two main types of parking, namely; private parking on premises and public on-street parking. Parking regulations that could further influence the parking availability relate to the cost and availability of parking permits which subsidize the costs of parking for residents.

To explain the influence of parking availability on household car ownership a multinomial logistic regression (MNL) model is estimated. This statistical method is identified as the preferred method to explain the influence of household car ownership determinants by multiple comparison studies and provides extra flexibility over ordered-response mechanisms.

To estimate the MNL, travel data of 80,527 urban households was collected from three years of the Dutch National Traffic Survey (ODiN). In the traffic survey the number section of the households' postal code is recorded, allowing to include aggregated characteristics of the neighbourhood in the household cases and thus the MNL. From the identified dimensions of parking availability the number of on-street parking bays per household, parking places on premises per household and the maximum parking costs in the municipality could be operationalised considering data availability.

The outcomes of the multinomial logistic regression model show that the parking availability in a households' neighbourhood does influence car ownership. Based on the analysis, both parking types have a positive relationship with household car ownership. While higher maximum permit costs in a households' municipality (which can also be seen

as an indication of the strictness of the municipalities parking policies) decreases the probability of car ownership.

The next step in the study was to investigate the extent of the influence of parking availability on household car ownership, as parking policies based on a relatively minor influence are not likely to have a desired impact. Previous studies have identified household composition and income as the most influential determinants of car ownership and these determinants also have the highest overall explanatory power in the statistical analysis. That means that the composition of a household together with its financial status best explain the households' decision to own a certain number of cars. Especially the number of driving licenses in a household (which is closely correlated to the number of adults) has a high relative importance, followed by the households' disposable income. The latter having a similar relative importance as the number of parking bays in a neighbourhood. So, compared to the household characteristics the individual dimensions of parking availability have a smaller but still significant effect.

However, as parking policies should be a strategic combination of multiple interventions the dimensions of parking availability were also analysed together to investigate the influence of increasing levels of parking availability on car ownership. First, the household car ownership probabilities were compared between three existing neighbourhoods for two average households (a one driving license and a two driving license household). And secondly, car ownership levels of a potential new neighbourhood were predicted for three increasing levels of parking availability.

The first exploration shows that based on the analysis the probability of car ownership for an average one driving license household increases by 39 percentage points when comparing a very dense and well-connected neighbourhood in Amsterdam to a less-dense neighbourhood in Almere with ample parking. The second exploration shows that the total predicted number of cars of a possible population of Almere Pampus could increase by 49% from a low to high parking availability scenario. Comparing the parking supply in the different scenarios to the predicted number of cars shows that the low parking availability scenario can cause parking problems, while high parking availability can easily result in overcapacity. Highlighting the importance of a balanced parking strategy.

The discovered relationship between parking availability and household car ownership is of importance to policy makers as it can substantiate parking regulations to reduce car ownership. This study therefore recommends municipalities that aim to develop neighbourhoods with a low amount of parking and cars to create parking policies by combining the identified dimension of parking availability. The effect of such parking policies on a neighbourhoods' parking supply and car ownership levels can then be calculated to optimise the use of public space in a neighbourhood.

Future research efforts to gain more insight into both parking availability and car ownership could be directed towards proving causality, improving the spatial data and exploring more factors of car ownership and parking availability. The outcomes of the study have its limitations with regards to proving causality as the direction of causality between parking availability and household car ownership can't be established based on the statistical analysis. The study does however prove a statistical relation between the two. Furthermore, it is recommended for policy advice on specific parking norms to enhance the reliability of parking data by splitting residential parking bays from commercial parking lots in the parking bay data. Another recommendation for future research is to include attitudinal factors on car ownership. These perceptions towards car ownership could also be important car ownership determinants and a study that includes attitudinal factors could analyse the differences in preferences towards cars of households living in car-friendly or car-free neighbourhoods. Lastly, the influence of parking availability on car ownership was investigated for the two highest categories of urbanization in the Netherlands. That raises the question if these results could be generalised to rural parts of the Netherlands. It is expected that the direction of the relationship between parking availability and household car ownership is the same, but that the size of the effect will probably be smaller as parking in non-urban areas of the Netherlands is generally over-supplied and car dependency is also assumed to be higher. Further research could identify the possible differences and similarities between the outcomes of this study and car ownership in rural areas.

CONTENTS

1. INTRODUCTION

1.1 PROBLEM STATEMENT

The population of the Netherlands is expected to grow to 19 million in 2040 and this population growth will mainly affect the larger cities of the Netherlands, putting pressure on mobility, the public environment and citizens' living conditions (Jorritsma et al., 2023). The scarcity of public space together with environmental goals of municipalities translate to new visions on urban mobility that do not purely focus on accessibility but also on the liveability of cities (Gemeente Amsterdam, 2020; Gemeente Den Haag, 2021). Therefore, new mobility plans prioritise quiet, low-emission and space-efficient modes of transport. The changing perspective on urban mobility is thus increasingly in odds with the characteristics of the private car, as private (fuel-engine) cars are loud, polluting and space-inefficient compared to other sustainable modes of transport. To illustrate, a trip by private car requires 95m^2 of public space in the studied area of Amsterdam (of which 15m^2 is related to car parking) compared to 6m^2 for a trip by tram when accounting for the number of passengers (Figure 1). For these reasons, cities in the Netherlands are looking at measures to reduce the share of car mobility. Potential measures consist of alternative mobility-oriented approaches, such as the improvement of public transport and the encouragement of shared mobility usage. These measures are complimented by other spatial measures, such as the introduction of (partially) car-free areas and multiple parking regulations. Cities in the Netherlands expect that implementing parking regulations could be an effective instrument to reduce car ownership and improve the liveability of cities (Jorritsma et al., 2023). The city of Amsterdam even stated that it wants to repurpose at least 10 000 parking spots to become greenery, bicycle infrastructure or public play grounds before 2025 (Gemeente Amsterdam, 2020).

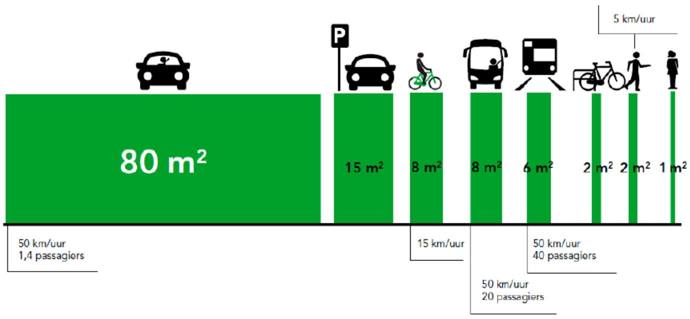

Figure 1. Land use per mode of transport.
Source: Gemeente Amsterdam (2020)

However, introducing such restrictive parking policies can be politically challenging as they often lead to resistance from car owners that fear for a higher parking pressure in their neighbourhood (Scheiner et al., 2020). The car centric attitude of residents could be attributed to previous mobility policies that were very accommodating to cars with low-cost residential parking permits that subsidize the cost of parking (Groote et al., 2016) and high minimum parking requirements (CROW, 2016) that result in an over-supply of parking (Christiansen et al., 2017). Making the car affordable and convenient. Therefore, when municipalities aim to reduce car ownership and parking space through parking regulations they should strike a good balance between inefficient land-use, when designing for overcapacity, and significant parking pressure or problems, when the parking supply is too low in a neighbourhood. To be able to substantiate such politically sensitive policies it is important for municipalities to be able to quantify the effects of parking measures before making substantial infrastructure investments. But, current models struggle with the increasing complexity of mobility (Snelder et al., 2021). Including parking availability in the estimation of car ownership can optimise the balance between parking supply and demand and thus better determine the amount of public space that must be dedicated to private parking.

1.2 KNOWLEDGE GAP IN CAR OWNERSHIP RESEARCH

To start off, car ownership is a well-studied subject in travel behaviour research as private cars play a vital role in the daily travel decisions of households (Anowar et al., 2014). Since the introduction of private cars, cars have steadily become a prominent part of our mobility system. This can also be seen in the Netherlands where currently 8.3 million households (CBS, 2024b) own 9.1 million private cars (CBS, 2024c). Sociological studies on car ownership explain these high levels of car ownership trough sociological and cultural phenomena and introduce the concept of (perceived) 'car dependency' (Sheller, 2004). Individuals increasingly are or feel that they are dependent on their car for work or transport in general due to culture norms and societal institutions. Sociologists therefore argue that structural change in travel behaviour can only be achieved through institutional and cultural change, but it is hard to define policy interventions based on these concepts (Cairns et al., 2014). Shove (2010) even argues the extent of which policy makers could actually influence and shape these social practices.

That is why transport policies are often based on behavioural studies that use individuals or households as the unit of analysis as, in principle, it is believed that behaviour could be changed and assessed on an individual level (Cairns et al., 2014). Most of the behavioural studies identify the household as the decision unit and identify socio-economic and household characteristics, such as income and household size, as key drivers of households' car ownership (Clark et al., 2016; Haque et al., 2019; Kitamura, 2009; Maltha, 2016). While these characteristics can be good predictors of car ownership, mobility policies typically focus on spatial- and accessibility-oriented policies. Therefore, this study focusses on the effects of such spatial policies on household car ownership levels. To be more specific, the influence of parking availability on car ownership as parking policies are shifting from 'a means to accommodate current and future desired vehicles' to 'a tool in the municipalities arsenal to influence levels of vehicle ownership' (Marsden, 2014).

The relationship between parking supply and car ownership has been studied in international literature and these studies found a (not always significant) positive relation between parking supply and car ownership (Antonson et al., 2017; Christiansen et al., 2017; Guo, 2013; McAslan & Sprei, 2023). However, parking availability is more complex than only monitoring the number of parking places in an area as the availability of these parking places is influenced by multiple regulations (Guo, 2013). These complexities have not been collectively studied in existing car ownership studies.

Guo (2013) argues that the relationship between residential parking and car ownership is understudied because parking supply is not often monitored by government agencies. This barrier is also present in the context of the Netherlands, where parking policies are decentralized through municipalities. The data barrier has been lowered by TNO that developed a data science method to estimate the parking supply in the Netherlands. These parking estimation methods have been used once to estimate a linear regression car ownership model by Snelder et al. (2021), but some of the parameters had counterintuitive directions as this linear model did not account for the complexities of parking availability. This study will therefore investigate how this parking data can be included reliably in a car ownership model together with regulations that impact parking availability to account for the the complexities of parking availability.

To conclude, this thesis adds to the body of car ownership literature by including and combining multiple dimensions of parking availability to better study the relationship between parking availability and car ownership in the Netherlands.

1.3 RESEARCH QUESTIONS

This thesis aims to quantify the effect of residential car parking measures by creating a car ownership model that includes parking availability in urban areas by asking the following research question:

To which extent does urban parking availability influence household car ownership in the Netherlands?

To be able to answer this main research question the influence of parking availability on car ownership will be explored through multiple sub-questions. These sub-questions are mostly procedural in nature and designed to, when answered, arrive at a car ownership model that will predict car ownership on a household level with which the main research question could be answered.
First, as parking availability is affected by multiple regulations this thesis aims to provide a more extensive definition of parking availability to include multiple policy options that relate to residential parking, such as parking norms and permit regulations. Therefore, the first sub-question is about the different *ways* that urban parking availability can be defined.

SRQ1. *Which dimensions define residential parking availability in urban areas?*

The second sub-question builds on the first sub-question as it asks how these different dimensions of parking availability, according to the literature overview, can be implemented as determinants in a car ownership model based on available data.

SRQ2. *How can parking availability be implemented per zone as a determinant of household car ownership levels, considering data availability?*

To answer this sub-question the *properties* of the available data need to be identified and discussed. These initial descriptives are key to a better understanding of the data and therefore also important to identify which elements of parking availability can be included in the car ownership model. By answering the first two sub-questions a foundation is created for further analysis in the next sub-question. The third sub-question is about analysing the different possible implementations of parking availability that arrived from the first sub-questions. This is done by comparing the effects on household car ownership levels of the different dimensions of residential parking availability.

SRQ3. *To which extent do the dimensions of residential parking availability influence household car ownership, when controlled for spatial and socio-demographic characteristics?*

1.4 RESEARCH METHODOLOGY

To analyse the effects of parking availability on household car ownership, data on Dutch households and parking supply were collected and combined. The base dataset for the analysis is the ODiN study carried out by Statistical Netherlands (CBS, 2023), which includes several household characteristics for a large number of households together with their level of car ownership. For this study the results of three consecutive ODiN years (2020-2022) where used, which resulted in a database of 80,527 households located in urban environments. The dimensions of urban parking availability were defined by examining Dutch reports on parking policies and strategies. These dimensions were operationalised based on data availability into multiple spatial determinants that were aggregated and linked to the households of the ODiN study through the postal code 4 specific locations.
The constructed households were then used to estimate a multinomial logistic regression model (MNL), as this specification should be the preferred specification to explain car ownership according to the studies of Bhat & Pulugurta (1998) and Potoglou & Susilo (2008). Lastly, to analyse the effects of parking availability on household car ownership the results of the statistical analysis were explored through a comparison of different neighbourhoods and a use-case of Almere Pampus.

1.5 THESIS OUTLINE

The thesis is divided into 6 chapters. Chapter 2 contains a literature review to identify the most important household car ownership determinants in car ownership literature and to define parking availability. The research methodology and the descriptives of the available data will be discussed in chapter 3 to determine which car ownership determinants can be included in the analysis and if so, how. In chapter 4 the results of the analysis are discussed and exemplified by comparing multiple neighbourhoods and predicting car ownership level changes for an expected population of Almere Pampus. To conclude, in chapter 5 and 6 the conclusion and the limitations of the study are discussed.

2. LITERATURE REVIEW

This chapter will discuss findings from the existing body of literature on car ownership and parking policies. The goal is to identify important determinants of car ownership and get a better understanding of current parking measures and availability. This will be done by discussing multiple papers on car ownership and parking policies followed by a discussion of various Dutch residential parking measures from policy reports and municipal parking strategies. The insights will be combined to form a conceptual model on which the analysis will be based.

2.1. SEARCH STRATEGY

To provide a first overview of the current academic literature on parking and car ownership modeling the Scopus database was used for the literature search. In order to get a complete overview of the existing literature on parking and car ownership, the literature search was divided into two different searches, each with its own results.

"car ownership" AND ("modelling" OR "spatial modeling")

("parking" or "parking policies" or "car-free or "car free") AND "car ownership"

Given the extensive body of travel behaviour research, these searches resulted in a total of 500 articles on car ownership modeling and 294 when adding parking to the search query. In order to start selecting relevant review articles for this literature review from all these results, the titles on the first results pages were analysed. After this initial selection, the number of citations of the paper and the abstract were read to further determine the relevance of the review articles.
To complement these review articles with other papers, the references in these review articles were used to broaden or strengthen different views.

To obtain a more detailed understanding of the current state of car ownership modelling efforts in the Netherlands these academic papers are supplemented with reports by Dutch agencies found using the Google search engine. These include reports from Kennisinstituut Mobiliteit Nederland (KiM), Plan Bureau voor de leefomgeving (PBL) and TNO to provide an overview of the current state of car ownership modeling in the Netherlands. Snowballing from these reports also resulted in insightful additions to the body of literature.

2.2 DETERMINANTS OF CAR OWNERSHIP

Travel behaviour research is extensive and this also includes models on car ownership, as private car ownership plays a vital role in the daily travel decisions of households (Anowar et al., 2014). The models that are widely used in the literature to explain travel behaviours, such as the decision of a household to own a car, are discrete choice models (Paredes et al., 2017). These models show which factors contribute to the choices made by people and are also used to project future demand estimates, which can be used for policy exploration (Paredes et al., 2017). In this chapter the main determinants of car ownership in existing literature will be discussed.

Early car ownership studies and models aimed to predict (national) car fleet sizes using aggregate car market models. These methods are still used in large car ownership models such as the SPARK model used in the Netherlands (PBL & Rijkswaterstaat WVL, 2023). These are economic supply and demand models that use car (use) costs and population statistics as inputs to predict the change of aggregate car fleet size over time (Jong et al., 2004). However, when aiming to identify factors that drive car ownership decisions, disaggregate car ownership models with different determinants are preferred (Jong et al., 2004). These models are based on the random utility theory and aim to explain differences in car ownership levels. Most studies focus on car ownership decisions on a household level, as the purchase of a car is a major decision and therefore expected to be made collectively (Witte et al., 2022). This also results in different explanatory determinants with a lower levels of co-linearity (Bhat & Pulugurta, 1998) than in the aggregate car ownership models.

2.2.1 SOCIO-DEMOGRAPHIC DETERMINANTS

A popular group of determinants in car ownership studies are social-demographic factors, such as age and gender (Witte et al., 2022). Witte et al. (2022) argues that this popularity is probably a result of the fact that these socio-demographic determinants are a standard question in travel surveys and easy to extract from population registries and future projections of the population. This makes them relatively easy to obtain and therefore popular for forecasting future car ownership. However, while these objective socio-demographic determinants can be good predictors of car ownership their explanatory power is low as they can be seen as indicators for other underlying factors on a household level. When age and gender are included in car ownership models these are often the age and gender of ‘the head of the household’, which is often identified as the individual with the highest income (Jong et al., 2004). For example age is an indication of life stage and after a qualitive analysis Witte et al. (2022) found that when controlling for other variables, such as driving licenses, amount of children and workers in a household, age has almost no explanatory power. Therefore, the next part of this chapter will discuss the multiple household characteristics that are identified in the body of car ownership literature to influence car ownership.

2.2.1 HOUSEHOLD CHARACTERISTICS

Clark et al. (2016) analysed panel data of the UK Household Longitudinal Study to identify the determinants of different levels of car ownership change. The results of the study can be found in Table 1. This table illustrates the directions of the identified relations quite well with similar results as found in other literature on car ownership. One of the important determinants of household car ownership is the composition of households. In Table 1 this is described as the 'Family biography' and has some of the strongest increases in odds of the whole table. For example, gaining a senior member in the family increases the odds of getting an (extra) car and losing a senior member increases the odds of a decrease of the car ownership level in a household. Attaining similar results to Haque et al. (2019) and Maltha (2016) who have identified household composition to be a great predictor of household car ownership. Also, the addition of driving licenses to the household has a strong influence on car ownership. This was also identified as the most influential determinant by Kitamura (2009) using Dutch panel data.

Table 1. Relations between life-events and car ownership (Clark et al., 2016)

Life event	0–1 car	1–2 car	2–1 car	1–0 car
Family biography				
Gain an adult	++	+++	–[a]	
Lose an adult			+++	++
Gain partner	++	++		–
Lose partner			+++	++
Had child	++		++	
Acquired driving licence	+++	++		–
Residential biography				
Residential relocation			+	++
Increase in number of bus stops				+[a]
Increase in pop dens		–[a]	+[a]	
Employment biography				
Gain employment	+	+		–
Switch employer		+		
Lose employment			+	++
Retire				++[a]

– Reduces odds; + increases odds and odds ratio < 2

++ Increases odds and odds ratio between 2 and 5; +++ increases odds and odds ratio > 5

[a] indicates significant at 90 % level compared to 95 % level for all other relationships

Next to the importance of household size Clark et al. (2016) has identified two other categories of determinants. Namely, the spatial context of the household and employment status. In the first category an increase in population density and an increase in bus stops in the area increase the likelihood of losing a car in the household, in line with the study of Potoglou & Kanaroglou (2008). However, the relationships are less significant than other relationships in the table. Indicating that these spatial relationships are harder to prove statistically. The employment status also relates to income, which is identified as the other main determinant next to household composition in multiple studies (Clark et al., 2016; Haque et al., 2019; Maltha, 2016). An interesting outcome in Table 1 is that losing employment has a stronger relationship with car ownership than gaining employment. This contradicts the believe that car ownership has a certain stickiness and therefore reacts more to rising than falling income (Weis et al., 2010; Witte et al., 2022). This could be attributed to the economic recession at the time of data collection, which where the first two waves of the UK Household Longitudinal Study in 2009-2011.

According to Haque et al. (2019) changes in car ownership levels are mostly triggered by life-events, such as a change in; income, household size, moving houses or changing jobs. These life-events can change your mobility needs or budget and studies in travel behaviour often see these as the important driving forces of owning a car. That is why most of the car ownership studies that use discrete choice models mainly focus on the influence of household and socio-economic characteristics on car ownership. In some studies these factors are supplemented with spatial characteristics of the living environment, such as the accessibility of mobility alternatives and proximity of amenities. A paper by Potoglou & Kanaroglou (2008) does include spatial (GIS) neighbourhood characteristics in their car ownership model studying Hamilton, Canada. They find that next to the influential household and socio-economic factors, mixed density and land-use diversity within walking distance do also influence household's decisions on car ownership.

So, over the years household composition (size, amount of driving licenses, etc.) and household income have been identified as the main determinants of household car ownership levels. Which one of the two categories is the most important determinant differs from study to study, as well as over time according to (Maltha, 2016). He studied the dynamics of determinants over the years and has seen a trend in the influence of income and household size on car ownership in the Netherlands. Throughout the years household size has become a greater predictor than income, which used to be the biggest predictor, as cars became more affordable. And thus removing part of the budget restraint, making car ownership more dependent on mobility needs.

2.3 DEVELOPMENT OF PARKING POLICIES

According to Marsden (2014) parking policy can be seen 'as a means to accommodate current and future desired vehicles' or 'as a tool to influence levels of vehicle ownership'. When studying literature on parking policies a shift in thinking of parking policies from accommodating to influencing car ownership emerges.

Parking policies have long been designed to only accommodate parking demand (Guo, 2013). This approach to parking leads to an oversupply of parking and less attractive living environments (Manville & Shoup, 2005), with the underlying assumption that neighbourhoods with fewer cars have better urban qualities and are therefore more desirable (Antonson et al., 2017). For the last few decades the parking supply of the Netherlands is also largely based on the expected parking demand (Kansen et al., 2018). The CROW provides parking guidelines to municipalities in the form of the expected demand of parking capacity per building type (CROW, 2016). Although the guidelines are general numbers designed to help municipalities determine the actual required or desired amount of parking spaces in their specific context, they are often directly translated to minimum parking requirements (Kansen et al., 2018). Minimum parking requirements often lead to an observable oversupply of parking and in cities with a big competition for land, unused parking spaces are a very inefficient use of this valuable land (McAslan & Sprei, 2023).
Another problem associated with minimum parking regulations are the costs related to parking in construction when applying high minimum parking norms (Shoup, 2021). For an affordable housing unit requiring one parking place per unit parking can amount to 12,5 percent of the cost of the house (Litman, 2011). Since these houses are inhabited by low income households with often lower car ownership they are essentially paying for someone else's parking (Litman, 2011). Decoupling the price of parking from house prices could mitigate this problem and create a free market between supply and demand, which could then possibly affect car ownership choices of residents. The problems of high construction costs due to high minimum parking requirements are also present in the Netherlands. A research conducted by the province of Zuid-Holland (2017), where more than a fifth of the Dutch population lives, estimates that about 20 percent less homes were build due to high minimum parking standards and multiple buildings that were completed have underutilised parking space. These problems caused by minimum parking standards have been a driving force to reevaluate these norms in cities where land is scarce.

Although minimum parking requirements are still often used to provide a desired amount of parking in development projects, the second part of Marsden (2014) view on parking policy 'as a tool to influence levels of vehicle ownership' starts to be more prominent in current parking policies and literature in the last decade. For example Guo & Ren (2013) find that a switch from minimum to maximum parking requirements for new developments in London resulted in 40 percent less parking (note: not car ownership). These parking approaches were often neglected by policy makers before, due to a lack of empirical evidence of these policies on car ownership and use (Guo, 2013). As discussed in chapter 2.2, household characteristics, such as income and size, are key determinants for household car ownership. Suggesting that car ownership is purely based on mobility needs and budget constraints and not influenced by land-use policies, such as lower parking requirements (Guo, 2013). If that is the case, then parking policies can only respond to parking demand and intervening by introducing maximum parking requirements can then create a spillover effect to other neighbourhoods (Marsden, 2014). This could result in a higher parking pressure in multiple neighbourhoods and could cause more congestion as well, due to cruising to find a parking spot. So, in order to confidently 'use parking policies as a tool to influence car ownership' the effects of different policies on car ownership should be analysed.

2.4 INFLUENCE OF PARKING POLICIES ON CAR OWNERSHIP

A limiting number of studies have discussed the influence of parking policies on car ownership. In this chapter the findings of the papers of Guo (2013), Antonson et al. (2017), Christiansen et al. (2017) and McAslan & Sprei (2023), will be discussed. The main logical thought process which is behind the expected relationship in these studies is that parking provides a convenience to car owners and encourages car use by increasing the utility of the car. And since car ownership and car use are heavily correlated in literature (Guo, 2013), decreasing car parking convenience or increasing costs is expected to influence the utility function of the car and thus car ownership.

The first question that is often asked in these studies is about the question if parking policies, such as lower parking regulations, actually influence car ownership levels. The short answer to that question is yes, there seems to be a relationship between parking policies and car ownership. Access to guaranteed or reserved parking at home does increase the likelihood of owning a car, as this convenience increases the utility of a private car (Christiansen et al., 2017; Guo, 2013). There are some caveats to this short answer however, as the studies also identify that parking can be quite complex and different parking types have different effects (Guo, 2013). Thus the next questions asked are; How much effect do residential parking policies have on car ownership compared to other factors? And what are the differences between the different types of residential parking (think of on- and off-street)? To address these questions, Guo (2013) has found that parking supply in neighbourhoods in New York outperforms household characteristics as predictors for household car ownership. However, this is the case for residential off-street parking, such as driveways and/or garages. A relationship between on-street parking and car ownership can't be statistically proven in this case study of New York. Christiansen et al. (2017) also analysed if systemic differences could be found in car ownership that could be linked to different parking norms and facilities in Norway. He found that access to private or reserved parking triples the likelihood of car ownership. Both find a clear and prominent relationship between private parking and car ownership, but can't say anything about non-reserved parking types.

Antonson et al. (2017) and McAslan & Sprei (2023) include these parking types by using different parking metrics than these previous studies. McAslan & Sprei (2023) used two parking metrics that are used in Swedish parking policies, namely the amount of parking spaces in the area per apartment or building area. The analysis of 56 Swedish municipalities shows a positive, yet not statistically significant, relationship between minimum parking requirements and car ownership. Antonson et al. (2017) also used minimum parking requirements as a determinant of car ownership in his study in Gothenburg, Sweden and found that lowering the minimum parking requirements did not significantly change car ownership or use in the city. It could be however, that the minimum parking requirements in the different neighbourhoods were not restrictive enough to test their hypothesis. The average parking norm in Gothenburg is 0.5 parking places per household, while car ownership in the city is at 38 percent. This means that people in more restrictive neighbourhoods with maximum parking regulations could easily find a spot in a neighbouring part of the city. This exemplifies the need of a truly citywide strategic parking policy where parking policies are combined with transport planning tailored to the local conditions of the neighbourhoods (Antonson et al., 2017).

The methodology used in these studies, comparing different households or zones and statistically analysing the differences in parking options and household car ownership levels, has its limitations with regards to proving causality. First off, the direction of causality can't be proven with this methodology (Christiansen et al., 2017; McAslan & Sprei, 2023). In other words; the analysis can identify a correlation between lower parking regulations and car ownership, but not if lower parking regulations directly reduce car ownership or that for example higher minimum parking regulations are in place due to a higher demand for parking as a result of existing high car ownership levels.
Another limitation that is existent in these studies, as well in multiple travel behaviour studies is the influence of residential self-selection. People who prefer to own a car will probably be drawn to a car-friendly neighbourhood with ample parking opportunities, while people with less of a preference to car use are maybe more drawn to the benefits of a mix-used environment with less cars. This also has an impact on causation, as the influence of the build environment on car ownership levels can also be a result of underlying attitudes towards car use (Ding et al., 2018). One way to solve this problem is to include more attitude and preference data in the analysis (Ding et al., 2018). Weinberger (2012) argues however that the problem of self-selection is a technical one and not important for policy considerations as from a policy perspective households with a strong preference to drive would 'waste' the resources of a transit rich, low parking area.

2.5 PARKING AVAILABILITY IN THE NETHERLANDS

As discussed by Guo (2013) residential parking supply is not monitored by most governments and affected by multiple regulations, creating barriers for analysing the effect of residential parking on car ownership levels. This chapter will dive deeper into the context of the Netherlands by exploring current and proposed parking policies in cities to get a better understanding of the regulations affecting parking availability.

In the beginning of 2020 the 8 million households in the Netherlands owned about 8,7 million private cars (Witte et al., 2022). Comparing these car ownership levels to that of its neighbours Germany and Belgium the Netherlands has less cars per capita, but when calculated per square kilometre of land the Netherlands has the highest spatial car density within the EU after the island of Malta (Zijlstra et al., 2022). This already indicates the pressure on public space caused by car ownership with around 19 million parking spaces in the Netherlands, spanning an area of 225 square kilometres (Zijlstra et al., 2022). This leaves the question on how the Netherlands accommodates or regulates al these cars trough policy.

In section 2.3 the shift in thinking of parking policies from accommodating to influencing car ownership was discussed and this shift can also be seen in Dutch cities that are trying to cope with the increase of car ownership. For the last few decades the parking supply of the Netherlands was largely based on the expected parking demand using CROW guidelines that were often translated to minimum parking requirements (Kansen et al., 2018). This is a good example of accommodating parking policies where for each building type a minimum amount of car parking needs to be realised. However, the new mobility plans of more and more Dutch cities are putting less emphasis on the car and follow the STOMP design principle for their urban planning (CROW, 2021). This is a list of design steps that prioritises sustainable mobilities, standing for; Stappen (Walking), Trappen (Biking), OV (Public transport), MaaS and the Private car. The private car is the last step in the design process and the space left in parts of the city for the car is therefore less than in older policies based on the minimum parking requirements. This doesn’t mean that there is no space for private cars and parking in Dutch cities, but that municipalities want to promote other modes through urban planning by prioritising them in the order of urban design. The space that is left for the car then differs per area type. For example, the space for cars in the city centre or around a train station will be more restrictive than that in a purely residential neighbourhood. These restrictions for different area types are then translated into parking regulations by municipalities.

So, high density municipalities in the Netherlands are designing more strict parking policies with the goal of limiting the share of (land dedicated to) private cars in comparison to the other more sustainable STOMP mobilities. These regulations can be divided in measures for destination parking, such as parking costs, and origin (residential) measures, such as residential minimum parking requirements. Both dimensions can have some overlap when using the same space, but do often serve a different purpose *with other results.* As discussed in section 2.4 measures at destination are often associated with limiting car use, while the residential parking measures are also associated with car ownership. Therefore the latter of the two will be discussed from insights out of the parking strategies of the Gemeente Den Haag (2021), Gemeente Zwolle (2023), Gemeente Amsterdam (2020), Gemeente Utrecht (2021) and the Province of Zuid-Holland (2017) to identify which dimensions define residential parking availability in urban areas.

- **Minimum / maximum parking regulations:** In international academic literature this is the most discussed residential parking measure. Lowering minimum parking regulations or even imposing strict maximum parking regulations are supposed to have a negative relation with car ownership. In the Netherlands Amsterdam is imposing maximum parking regulations in certain neighbourhoods (Gemeente Amsterdam, 2020) to limit cars in the city. This is coupled with investments in other modalities and introducing more greenery in the city. Only removing parking will probably anger residents, while coupling these strict parking measures with other liveability improvements can actually result in a more positive opinion of residents.

- **Permit costs:** Permit costs are a subsidy for the parking costs of car owners (Groote et al., 2016), as with a residential parking permit you're able to park in your residential neighbourhood without having to pay the daily tariffs. However, he space that is allocated to cars is quite expensive for the municipalities (Groote et al., 2016) and therefore cities such as Amsterdam and Utrecht want to influence all car ownership by steadily increasing the permit costs. Other cities such as The Hague heavily subsidize the first car with low permit costs, but want to influence the second or third car in a household by increasing the costs for these permits.

- **Permit maximum and permit waiting lists:** These two dimensions of residential parking regulations are often combined by municipalities. To start off, the maximum allowed permits in a zone also relates to the maximum parking regulations in a neighbourhood. In cities with scarce public space there could be a maximum of parking permits issued. Such hard stops are implemented in multiple neighbourhoods in Amsterdam and Utrecht. These neighbourhoods then also have a waiting list to get a permit if one becomes available again. The waiting lists duration can be months or sometimes even years where you have to pay the regular expensive parking tariffs in the meantime. According to the study of Groote et al. (2016) an extra year of waiting time reduces car ownership in the studied area of Amsterdam by 2 percent point.

All the measures listed above are expected to reduce car ownership in urban areas that contain accessible mobility alternatives from the first for STOMP letters. However, not all these expectations are supported by empirical evidence. Therefore, the aim of this thesis is to include these dimensions of parking availability in a statistical car ownership model.

2.6 CONCEPTUAL MODEL

The insights of the discussed international academic literature and different Dutch government (agency) reports are combined in a conceptual model. This model is presented in Figure 2 and includes the car ownership determinants that were identified in the literature overview and the direction of their expected relation with car ownership. The conceptual model will be the base of the further analysis.

The green coloured determinants are expected to have a positive effect on the level of car ownership while the red determinants are expected to have a negative effect according to the discussed literature. The socio-demographic determinants are also expected to have an effect on car ownership, but due to the nominal nature of these determinants they don't have a colour assigned to them in Figure 2. As discussed the multiple categories of determinants could also influence each other due to residential self-selection effects, attitudes and life-stages. This is also illustrated in the conceptual model below.

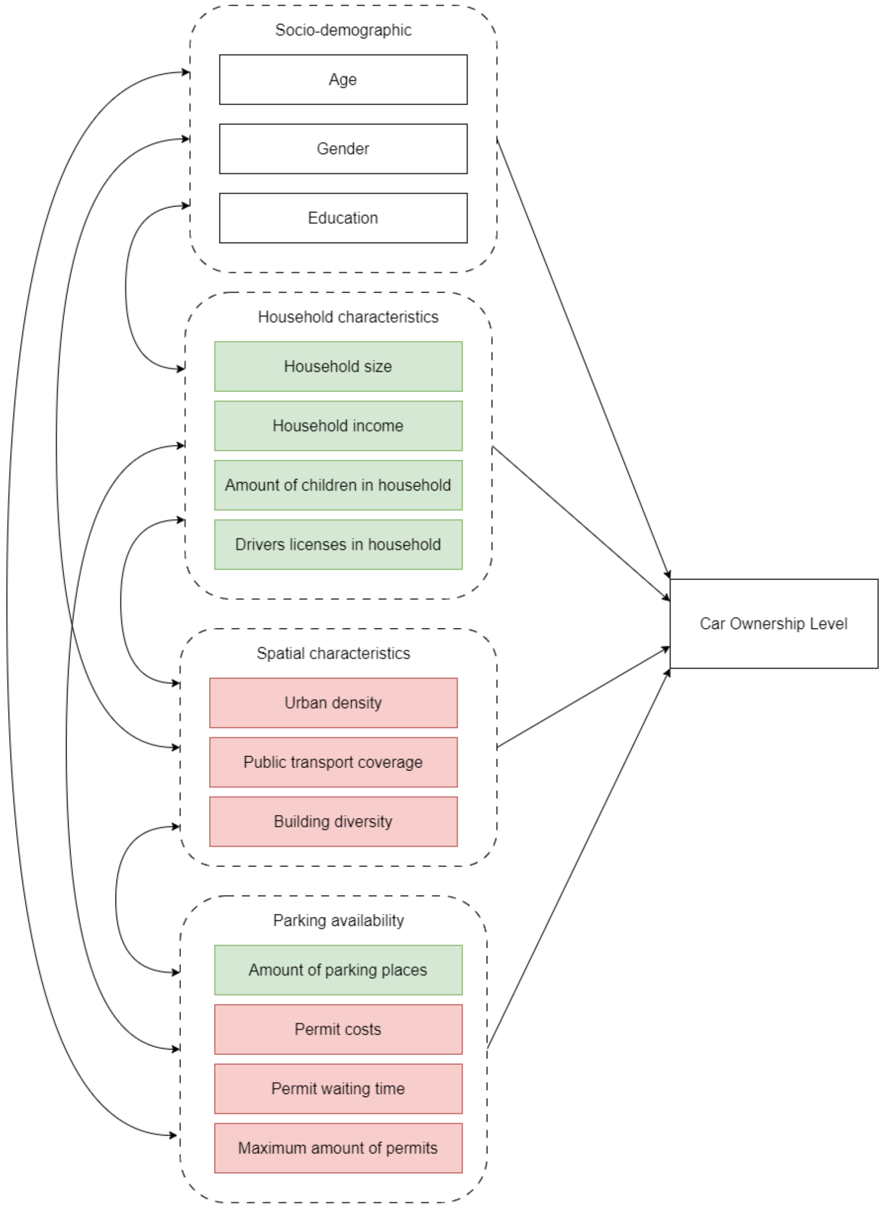

Figure 2. Conceptual model

3. METHODOLOGY

The literature review section ended with a conceptual model. The methodology chapter will explain how the conceptual model will be operationalised based on the available data sources. This contains the preparation of variables from the different data sources together with their assumptions and limitations to get an understanding of the variables used in the statistical modelling.

3.1 DATA SOURCES

According to Guo (2013) data retrieval is one of the biggest barriers for studies on the relation between residential parking regulations and car ownership, as parking supply is not often inventoried by government agencies. This is also the case for the Netherlands where parking is regulated on a municipal level. Due to the decentralized nature of parking policies there is a large difference in parking data collection between municipalities. Therefore, this research uses a method developed by TNO (Sterkenburg, 2021) to estimate the amount of different parking types in a zone.

Another research approach could have been to use extensive panel data on travel behaviour and car ownership to determine the influence of parking availability on car ownership, such as partly done by Clark et al. (2016). The most extensive mobility panel in the Netherlands is the Mobiliteitspanel Nederland (MPN), but after an initial data exploration the MPN data was not suitable to answer the research question. The panel is mostly focussed on travel behaviour and contained very few questions about the residential parking availability and its regards to car ownership. Also, of the roughly 3000 respondents of the MPN only about 20 respondents decreased the number of cars in the household and none caused by parking policies. Therefore, the MPN could only give insights in the household characteristics coupled with the number of private cars in their household. But, for this purpose another Dutch study into travel behaviour and car ownership would be preferable due to a substantial larger amount of respondents and more specific postal code information to merge spatial characteristics on, such as parking supply and public transport coverage. This is the ODiN dataset (CBS, 2023), which will be explained in more detail in the next subchapter 3.1.1 followed by chapters on the data sources available for spatial or parking characteristics that will be added using the household postal code information in ODiN.

3.1.1 ODiN

ODiN stands for ‘Onderweg in Nederland’, which roughly translate to ‘Netherlands in transit’. It is a study conducted by Statistics Netherlands (CBS) in collaboration with Rijkswaterstaat and the Dutch Institute for Transport Policy Analysis (KiM) (CBS, 2023). It is a survey study in which multiple questions are asked to a sample of the population about their movements and mode choices on a specific day. The resulting dataset also contains multiple socio-demographic and household characteristics of the respondent, such as household income and size, coupled with the number of private cars owned in the household. These characteristics of the dataset makes it a suitable base for the operationalisation of the determinants and car ownership from the conceptual model in Figure 2. For a larger sample size, the data gathered in the last three consecutive years are obtained from CBS.

- ODiN 2022 (61 953 respondents)
- ODiN 2021 (67 083 respondents)
- ODiN 2020 (62 940 respondents)

These datasets can be stacked as the ODiN sample is using a random sampling method every year, instead of the MPN which uses mostly the same panel every year. This resulted in a total of 191 976 cases to analyse. The years selected also correspond to the period in which the linked spatial data is collected.

3.1.2 SPATIAL CHARACTERISTICS

The ODiN dataset contains, next to household characteristics and corresponding car ownership, the location of the respondents' household. This location is specified on a 4-digit postal code, due to strict privacy regulations that the CBS must adhere to in it studies. The Netherlands is divided into 4070 of these postal code zones, which differ in area size depending on the density. These postal codes can be used to link the ODiN data to spatial datasets aggregated on PC-4 level.
The main spatial dataset used to this end is the 'Core numbers per postal code' data set of CBS (CBS, 2020). This is a useful dataset with socio-demographic and spatial information per zone, such as the number of amenities, the average distance to a train station and urban density. Next to the spatial zone information the aggregated demographic variables can also be used for the operationalisation of determinants from the conceptual model. An example of this is the amount of households in a zone, which in turn could be used to calculate metrics based on availabilities per household in a zone.

3.1.3 PARKING AVAILABILITY

In section 2.5 the dimensions of residential parking availability were discussed. To include these dimensions in the car ownership model that is based on the data gathered in the ODiN study parking data has to be collected and aggregated on postal code level. As parking policies are decentralized to the municipal level, data collection on parking is, if done, also mostly done by municipalities. On a national level such databases with parking data do not exist yet. Therefore TNO has developed a data science method to estimate the amount of parking places in the Netherlands. This currently results in a database with parking place estimated for three different types of parking. Each has its own characteristics and estimation method. These estimation methods will briefly be discussed in this chapter and next chapters will then further elaborate on the estimation methods and their implications.

- **Parking bays:** The total of parking bays per zone is deduced from the 'Basic Registration Large Scale Topography' (BGT) map. This is a detailed map of the Netherlands with the location of physical objects such as buildings, roads and water (BRON). If properly documented it also marks road polygons that contain a parking bay as *bgt_functie = parkeervak.* The polygon has a surface area and by dividing this service area by 11, which is the assumed area of a car parking space, you arrive at the number of parking spaces at that polygon. These parking bays consist mainly of outside parking places that are outlined, and therefore documented properly. Though multiple urban municipalities also document roads where you can park on-street without proper bay markings. This is the most reliable source of parking supply as it is not really estimated, but deduced from the BGT data.

- **Parking on premises (POET):** Data on parking on private residential property is not available. That is why TNO (Snelder, 2021) developed a method to (roughly) estimate which houses contain a driveway to park a car in the Netherlands. This is done using BAG data for the addresses and street names, BRK data for the plot area of houses and the BGT. This a thorough process that is properly documented in the 'Rapport A: Methode Urban Tools Next II' (Snelder, 2021), but to give a short and simplified summary; The method deduces the plot size of a house and determines if in the area between the street and the house a car could be parked.

- **Street parking:** The last estimation method is developed to estimate the parking places on the street that are not documented in the BGT data. The method is also well documented in the 'Rapport A: Methode Urban Tools Next II' (Snelder, 2021) and uses the National Road database (NWB) and OpenStreetMaps (OSM) to estimate the amount of on-street parking places. This is done by determining the streets on which there are no parking restrictions and filling them with parking places if they do not interfere with the already included parking bays and POET places. This method is the most unreliable source of parking places as it vastly overestimates parking places. This will be elaborated on further when discussing the implications of the estimation methods.

These methods are all focussed on accurately determine the amount of parking places available for residents in the Netherlands. One omission of the amount of parking places per zone is that the amount of parking places in underground parking garages under new development isn't documented or currently estimated. These will therefore not be included in the model.
As discussed in section 2.5 the parking availability is not just determined by the parking supply, but also depends on parking regulations. These mostly have to do with permit availability and costs to share the scarce (parking) space in cities between residents. As residential parking regulations are designed by municipalities we have contacted the municipalities connected to the XCARCITY project to obtain data on the dimensions discussed in section 2.5. However, the response was low and the municipalities that

responded mainly provided us with the costs of a residential parking permit in their municipality. This is a regulation used by all municipalities with paid parking to subsidize these costs for residents. In the small response, together with a sample of the parking reports by municipalities, a higher cost of a residential parking permit did also seem to indicate more strict residential parking regulations with permit maximums and waiting times. For example the municipalities with the highest permit costs, namely Amsterdam and Utrecht, also have a maximum of one residential parking permit and long waiting lists in multiple neighbourhoods (Gemeente Amsterdam, 2020; Gemeente Utrecht, 2021)

There were too limited responses by municipalities with permit costs to include in the model. Another time consuming method could be to obtain the permit costs for each municipality from their website, but a Dutch home owners association called 'Vereniging Eigen Huis' has already done this for 129 municipalities in the Netherlands (Vereniging eigen huis, 2024). The study documents the costs of the (first) residential parking permit for residents in zone 1 of the municipality. These costs can be added to the model, as ODiN also includes the municipality of the respondent.

3.2 CHOICE OF STATISTICAL MODEL

Future car fleet size can be predicted through the use of aggregate extrapolation models that model car ownership directly at the aggregate level, such as zonal or national level (Bhat & Pulugurta, 1998). This is the method used in the SPARK model that Rijkswaterstaat uses to predict changes in the national private car fleet (PBL & Rijkswaterstaat WVL, 2023). Another method that can predict car ownership levels are disaggregate models that use the household as a decision making unit, as it is assumed that the decision to buy or discard a car is made at the household level (Witte et al., 2022). These disaggregate models are structurally more behavioural and are therefore better able to capture the relationship between car ownership and its determinants (Bhat & Pulugurta, 1998). The study of Bhat & Pulugurta (1998) comparing disaggregate models demonstrates that the MNL specification is a superior disaggregate model to explain car ownership compared to order-response mechanisms. According to Potoglou & Susilo (2008) the results of the study of Bhat & Pulugurta (1998) didn't result in a consensus among researchers on the disaggregate model that best reflect households' car ownership decisions. Therefore, they also conducted a comparison study between multinomial logit, ordered logit and ordered probit models where they also found that the multinomial logit model (MNL) is the model to be preferred for modelling car ownership levels.

3.3 EXCLUSION OF NON-URBANIZED AREAS

The pressure on scarce public space and parking mainly exists in dense urban areas (Jorritsma, Jonkeren, et al., 2023). The main research question is thus also focussed on the relationship between urban parking availability and car ownership. This is one reason to

only focus on urban areaa and exclude less urbanized areas in the analysis, but initial data analysis also provides multiple other reasons to exclude non-urban areas in the model.
In the Netherlands urbanization is categorized in 5 categories based on the density of addresses in a zone, with 1 being the most urbanized and 5 being the least. The analysis in this thesis will only be done for cases in the first two urbanization categories provided in ODiN. Namely, because the aggregated spatial data in urban areas is a better representation than in the less urbanized zones according to the initial data analysis. This can be explained by the size of postal code zones, which span a smaller area in urbanized area's. The aggregation of spatial data is therefore more detailed and provides a more realistic representation of the area in the data. Also, the parking availability data is more accurate as more parking bays (which is the most accurate source of parking places) are documented and parking permits are more often used to influence car ownership than to fill a gap in the municipalities budget (Vereniging eigen huis, 2024).

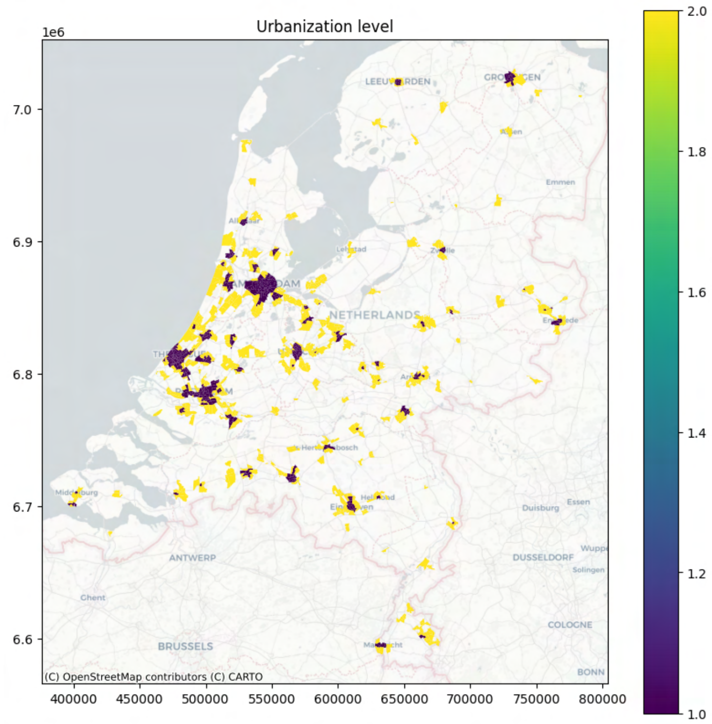

Figure 3. Included urban areas

This reasoning and assumptions lead to the exclusion of the lowest three categories of urbanization in the analysis. Selecting only the highest categories of urbanization leaves 68 138 ODiN cases for further analysis. These urbanized areas are depicted in Figure 3, with the highest density postal codes in purple.

3.4 DESCRIPTIVES ODiN

In this chapter the distributions of the ODiN variables are discussed. This is then paired with how they can be operationalised in the multinomial logit model, as not all relations with car ownership are linear.

3.4.1 CAR OWNERSHIP LEVELS IN ODiN

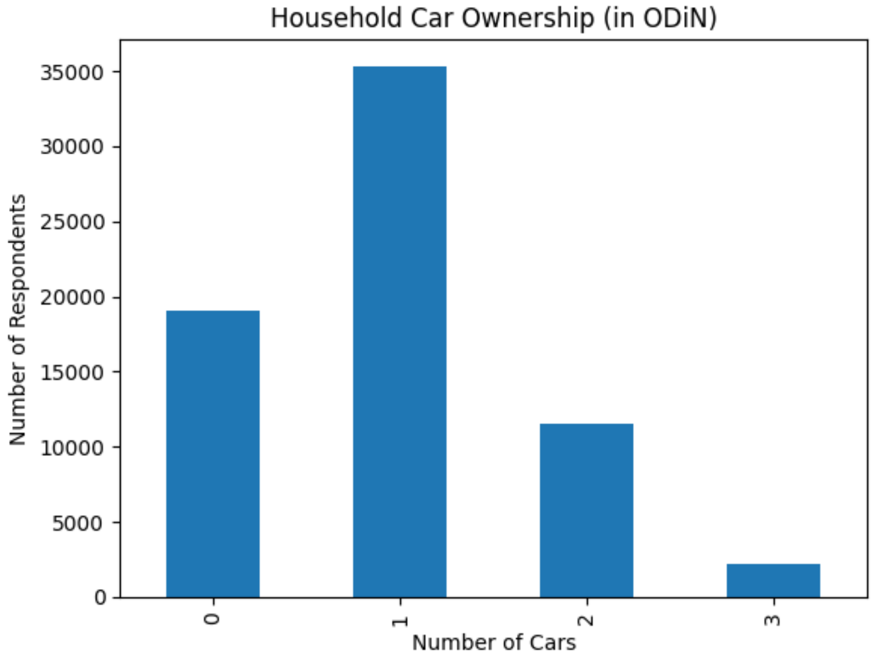

Figure 4. Car ownership levels in ODiN dataset

For each household the number of cars owned is measured in ODiN. This will be the dependent variable in the analysis. To get insights in the distribution of household car ownership levels in the ODiN dataset the distribution of household car ownership is plotted in Figure 4. Note: This is the ODiN data without the urbanization categories 3 to 5. So, the cases that will be used in the multinomial logit model. About half of the households in the sample own 1 car, followed by 25.1% with 0 cars, 20% with 2 cars and 4.7% with 3 or more cars. The last category is very small making it possibly harder to accurately predict these household car ownership levels. To be able to compare the determinants for each level of car ownership, zero cars will be included as the reference category in the MNL. The flexibility of the MNL makes it then possible to estimate and compare models for each level of car ownership.

3.4.2 PERSONAL CHARACTERISTICS

The ODiN survey includes the socio-demographic characteristics of the respondent, such as age and gender. However, these determinants will not be included in the multinomial logit model for the following two reasons. First, car ownership is measured at the household level and the socio-demographic variables on an individual level. These levels don't match and therefore caution should be applied when you want to include such individually measured socio-demographic variables. Secondly, as discussed by Witte et al. (2022) the socio-demographic determinants, although popular, are proxies for other underlying determinants when modelling car ownership. For example age could be seen as an indication of life stage and after a qualitive analysis Witte et al. (2022) found that when controlling for other variables, such as driving licenses, amount of children and workers in a household, age has almost no explanatory power. Therefore the aforementioned household characteristics in ODiN will be used as determinants to model household car ownership.

3.4.3 HOUSEHOLD CHILDREN

The conceptual model in Figure 2 includes a category with household characteristics (i.e. household size, income, the number of children and driving licenses) which can all be found in the ODiN survey. Household size and the number of children in a household are heavily correlated with each other, as the most common household composition is made up of two adults and the amount of children therefore mostly determents household size. The number of children in a household, combined with household income and the amount of driving licenses in the household, could thus be a better representation of household composition compared to household size.

The ODiN study doesn't directly measure the number of children in a household, but does directly measure the amount of household members in the following three age groups: younger than 6, 6 to 12 and 12 to 18. These three groups are combined in a new variable *hh_kids*. Children are thus household members younger than 18 that can only ride in a car as a passenger. For the analysis the households with more than 3 children are combined with the households with 3 children in one category; 3+ children.

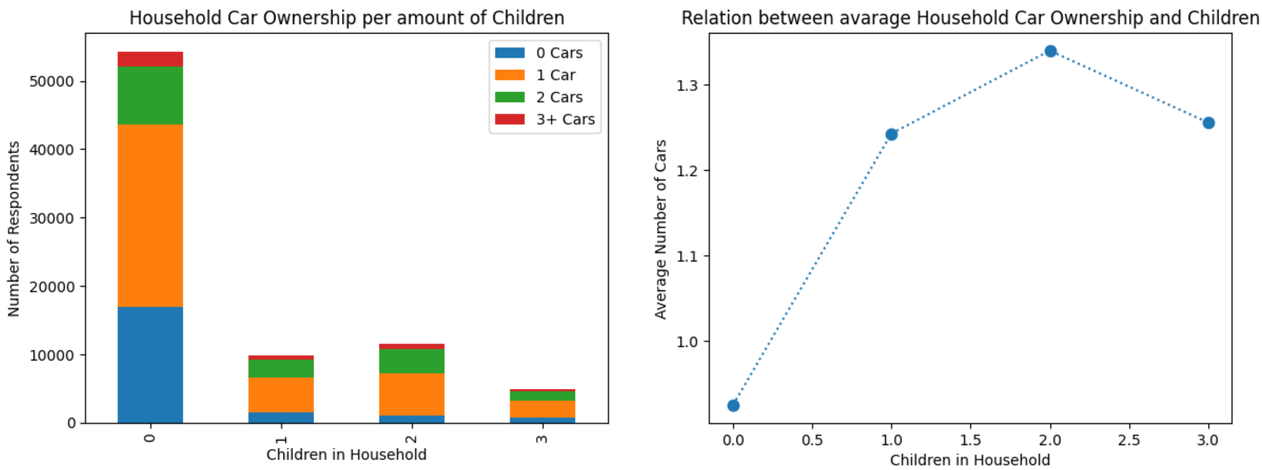

Figure 5. Relationship between household car ownership and the amount of children in a household

Figure 5 shows the distribution of children in a household in ODiN and the relationship between the number of children in a household and household car ownership. The majority of households are childless, followed by households 1 or 2 kid households. The last and least present category is 3 or more children. Every household with more than 3 children is combined in this category. When plotting the average household car ownership level for each number of children the relation seems to be non-linear, with household car ownership levels rising until 2 children. After this increase, more children in a household decreases the average household car ownership. Due to this non-linearity the household children variable will be implemented as a dummy variable in the multinomial logit model with 0, 1, 2 and 3+ categories.

3.4.4 HOUSHOLD INCOME

Household income is measured in ODiN through the disposable income groups of CBS (2022). All the households in the Netherlands are divided into 10 equal sized groups. These groups are shown in Table 2, which contains the groups together with the average and median disposable income of the income group. The definition of the disposable income is the gross income of the household, excluding taxes and (health and unemployment) benefits. Table 2 also shows that the higher disposable income groups have more members that generate some sort of income than households with a low income. Therefore the household income determinant could also contribute to the representation of household composition as a proxy of the amount of workers in a household. Together with the number of children and driving licenses you could start to shape a picture of the household composition.

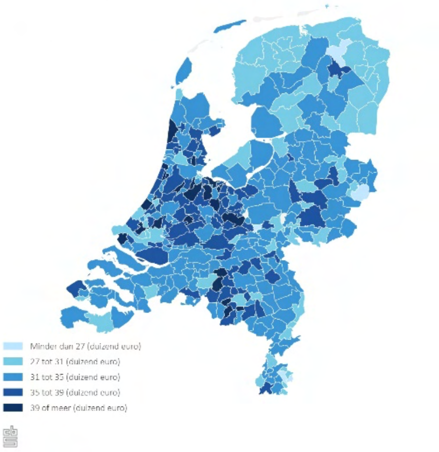

Figure 6. Distribution of household income

Table 2. Household income groups in the Netherlands

	Household members with income	Average income	Median income
	amount	x1 000 euro	x1 000 euro
1st 10%-group (low income)	1.1	12.2	14.9
2nd 10%-group	1.1	21.7	21.8
3rd 10%-group	1.3	26.7	26.7
4th 10%-group	1.4	32.0	32.0
5th 10%-group	1.5	38.2	38.1
6th 10%-group	1.8	45.8	45.7
7th 10%-group	2.0	54.8	54.8
8th 10%-group	2.2	65.2	65.1
9th 10%-group	2.5	79.2	78.7
10th 10%-group (high income)	2.8	133.2	108.4
Source: CBS			

Plotting the distribution of household income and its relationship with car ownership in Figure 2 illustrates that the high-income groups are overrepresented in the dataset. Although the number of households in each income group in the population is equal, the dataset has about twice the amount of respondents in income group 10 compared to group 1. This could result in a distorted distribution of car ownership levels in ODiN (as shown in Figure 4. Car ownership levels in ODiN dataset. It should be noted however that the rural parts of the Netherlands are excluded in the dataset and urban density does also have a correlation with household income in the Netherlands, as can be seen geographically in Figure 6. Distribution of household income. Thus excluding these areas can partly explain the skewed disposable household income variable, but for another part this is a limitation of the ODiN survey which has a lower response rate for low income households (CBS, 2023).

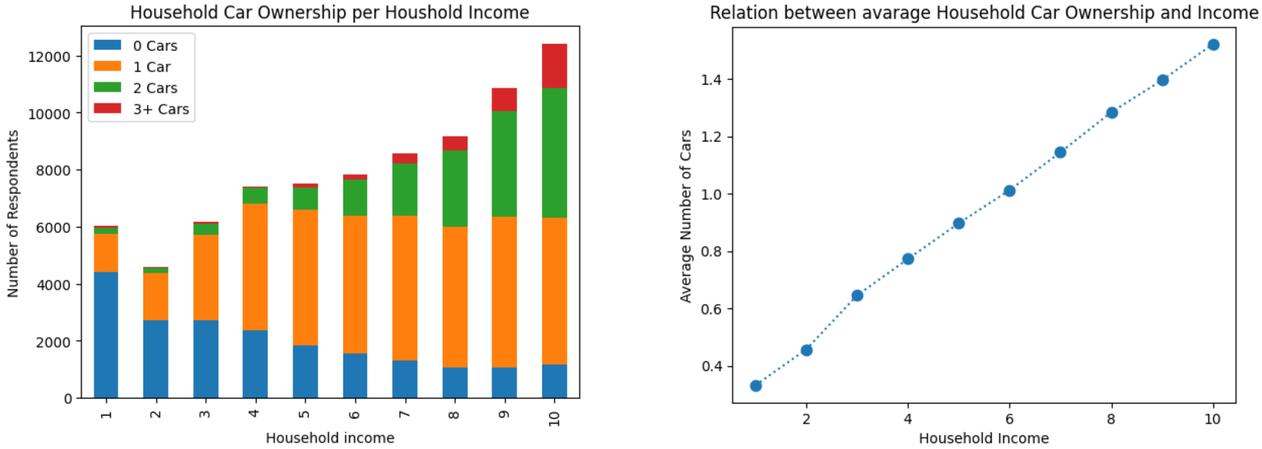

Figure 7. Relationship between household car ownership and household income

When plotting the relation between the income categories and the average car ownership level of each category in Figure 7 there exists a positive linear relation between the two. The household income variable will thus be incorporated with these categories in the multinomial logit model.

3.4.5 HOUSEHOLD DRIVING LICENSES

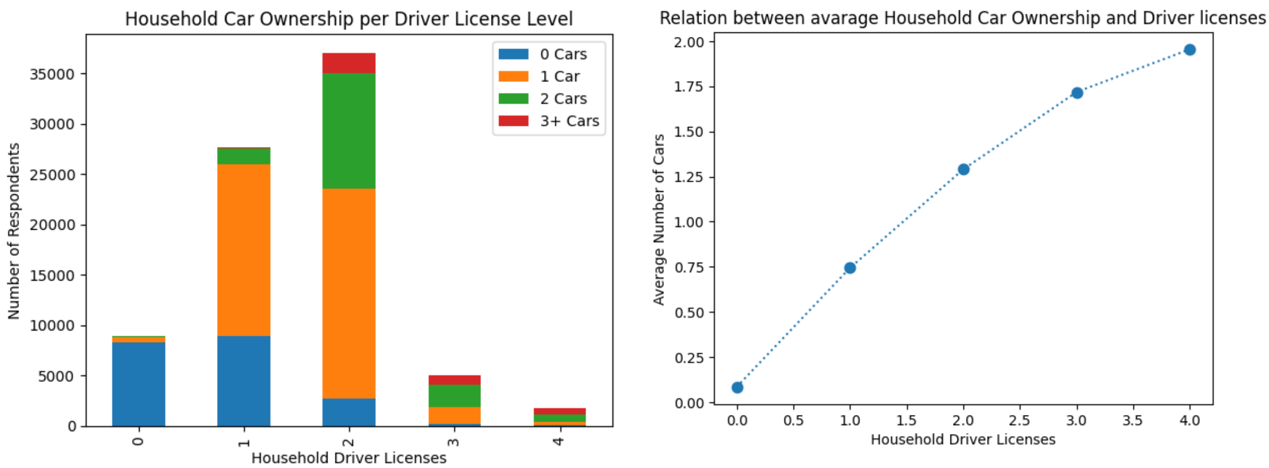

Figure 8. Relationship between household car ownership and the amount of household driving licenses

The remaining household characteristic from the conceptual model in Figure 2 is the amount of driving licenses in a household. According to the discussed literature on car ownership the amount of driving licenses is a major predictor of household car ownership. As without a driving license you are not allowed to drive a car, making it unattractive to own one. Having a driving license can also be an indication of your attitude to driving and your life stage. In ODiN the amount of driving licenses are directly measured and for the analysis the households with more than 4 driving licenses have been combined in category 4 together with the households with 4 licenses.

In Figure 8 the distribution of the amount of driving licenses per household is depicted. The majority of households have 1 or 2 drivers licenses and when the amount of driving licenses in a household increases the chance of owning a car also increases. Notable is that in the sample there is also a small portion of households with 0 driving licenses, but that do own 1 or 2 cars. The relation that is plotted in Figure 8 shows that the average number of cars increases in different steps for each increase in household driving licenses. Especially the step from 0 to 1 driving license in the household, which is essentially the step of not being allowed to drive a car to being able to drive and thus own a car. Therefore, the number of household driving licenses will be included as a dummy with the highest category being 3+ as the distribution of car ownership levels does not differ significantly between 3 and 4 driving licenses.

3.5 DESCRIPTIVES SPATIAL DATA

The conceptual model in Figure 2 contains spatial characteristics as determinants for car ownership. According to the study of Potoglou & Kanaroglou (2008) neighbourhoods' spatial characteristics, such as mixed land-use, influence car ownership. The postal code of the respondent that is recorded in the ODiN study could provide a connection to neighbourhood characteristics. CBS collects multiple spatial and demographic characteristics per postal code (CBS, 2020) that can easily be linked to the household characteristics. This chapter describes the way these characteristics will be added to the analysis.

3.5.1 URBAN DENSITY

In section 3.3 the exclusion of non-urbanized areas was discussed. By excluding low density areas the analysis only contains urban neighbourhoods. In these urban neighbourhoods CBS differentiates two categories of urban density: Very Urbanized and Very Strongly Urbanized. These two categories are based on the number of addresses in a square kilometre. With the cut-off point between the two lying at a surrounding address density 2500 addresses per square kilometre.

A higher urban density in the Netherlands is associated with lower car ownership levels in the Netherlands (Witte et al., 2022). Therefore the remaining two categories of urbanization will be added as a dummy variable in the analysis. Also, the urbanization level in the studied area of the Netherlands can be an indication of building diversity. For each zone the entropy can be calculated and used as a measure of land use mix (Zagorskas, 2016). The calculated entropies had a high correlation with the urban density levels of CBS (J. Rogier, personal communication). Therefore, a higher level of urbanization could also indicate a higher mix-use level.

3.5.2 PUBLIC TRANSPORT ACCESSIBILITY

The public transport accessibility data per postal code that is available for analysis is the average distance of a household to a train station. This is an average distance calculated for the entire postal code and thus a rough indication of the accessibility to the national railway. But, as only the two most urbanized categories are included in the dataset the size of the postal codes will be smaller and mainly contain one or few neighbourhoods. The average distance to a train station is therefore a more specific estimation than in the larger non-urbanized zones.

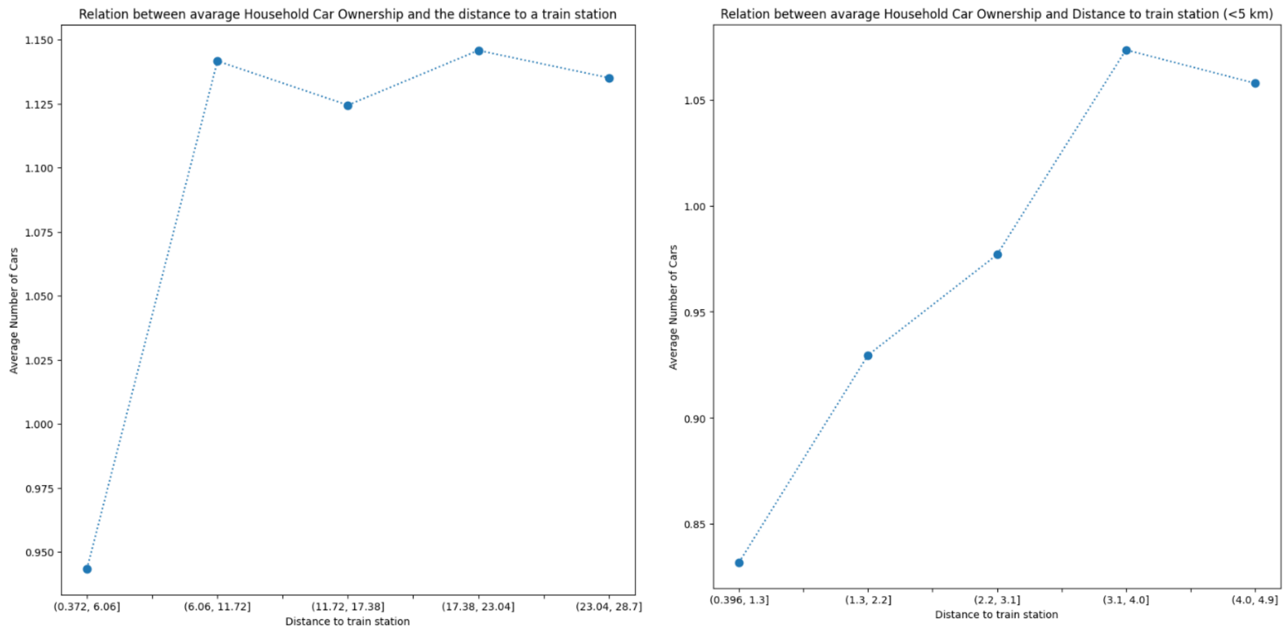

Figure 9. The relationship between the distance to a train station and average car ownership levels

When plotting the relationship between the average car ownership and the distance in to a train station in Figure 9 there is an increase in car ownership level until a distance of about 6 kilometres. After 6 kilometres the distance to a train station does not seem to influence the level of household car ownership. According to Jonkeren et al. (2018) the range of influence of a train station is a bikeable distance of about 5 kilometres. Plotting the distance for a range of 0 to 5 kilometres it is discovered that the cut-off point where distance to a train station does not influence the average car ownership is at about 4 kilometres. The distance to a train station will thus be included as a dummy variable in the multinomial logit model with 4+ as the highest dummy. The lowest category of the dummy variable is an average distance under 1,2 kilometres, as this is the radius defined as the main influence area of a train station (Provincie Zuid-Holland, 2023). This results in three categories with the most urban households in the reference category with an average distance to a train station of 1,2 to 4 kilometres.

3.6 DESCRIPTIVES OF PARKING DATA

The amount of parking places in a zone is deduced and estimated using multiple data science methods developed by TNO (Snelder, 2021). These methods each have assumptions and limitations that are relevant for the implementation and interpretation of the model regarding the parking supply variables. In Figure 10 the different types of parking are depicted in a neighbourhood in Delfgauw, which contains all three types of parking, namely parking bays (green), parking on premises (red or brown) and street parking (yellow). Comparing the datapoints with google maps and street view can already illustrate some of the limitations of the estimation methods used. In Figure 11 you can see the view from the circled junction in Figure 10. In this neighbourhood the methods used can correctly identify the amount of parking bays, as well as the houses that can park their car on the premise. However, you're not allowed to park at the yellow dots that indicate street parking. This estimation method overestimates street parking by a lot as it assigns a street parking place to every available part of road, which is not a realistic depiction of the amount of street parking in a zone. Therefore the street parking metric is not ready yet for implementation in the model and will be excluded. The remainder of this chapter will identify the assumptions, limitations and discusses the operationalisation of the other two parking types that will be used as determinants in the analysis, namely; Parking bays and Parking on premises.

Figure 10. Example of different parking types

Figure 11. Street view Delfgauw (Source: Google street view)

3.6.1 PARKING BAYS

The deduced amount of parking bays are expected to be a underestimation of the amount of parking places in a zone (Snelder, 2021). Initial analysis of the data shows that this could be the case for some older urban neighbourhoods, where the supply is not documented by the municipality. However the first analysis also identifies some cases of overestimation, which will be discussed in this chapter.

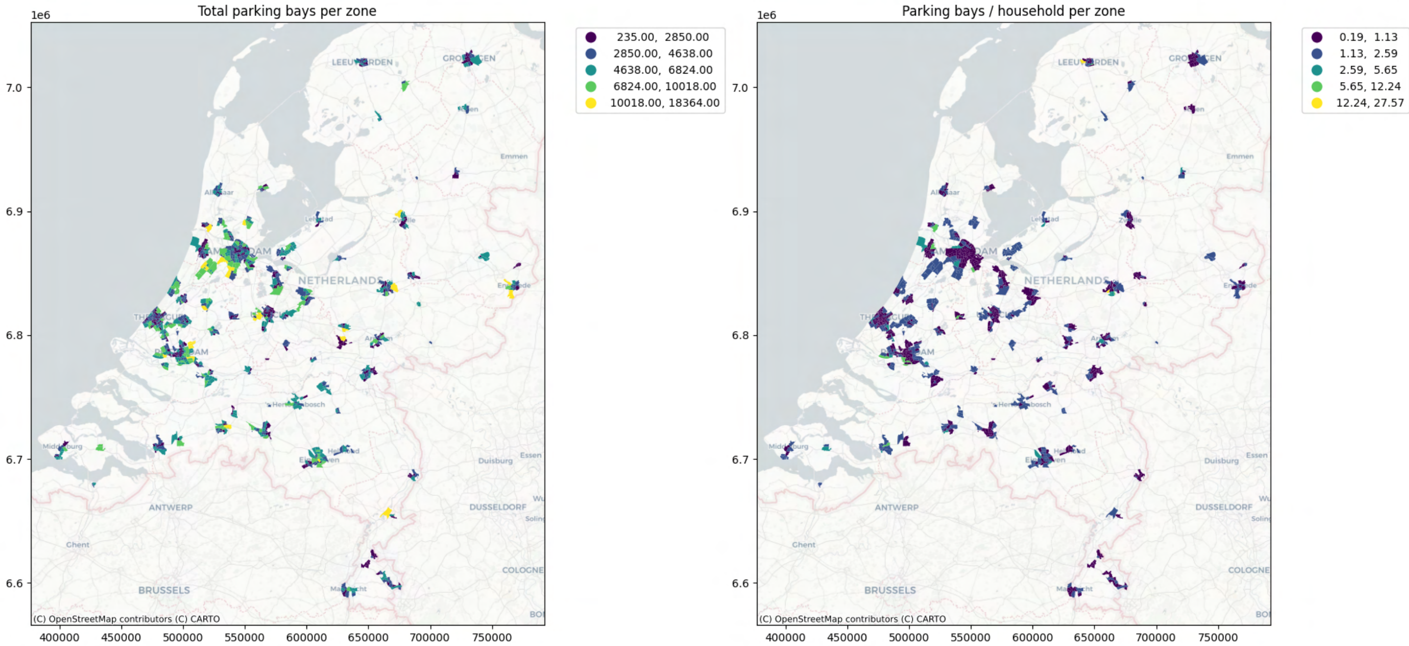

Figure 12. Parking bays per zone

In the initial data analysis the total of parking bays per urbanized zone is compared to the parking bays per household per zone. This is depicted in Figure 12 and in multiple of the zones with a high total of parking bays the high total can be explained by high numbers of households, as multiple of these areas have a low amount of parking bays per household. However, some of these areas still have a high parking bay to household ratio. When diving deeper into the parking bay data explanations can be found for these high parking bay per household numbers.

The main explanation of the high parking bay per household numbers in certain zones is that the totals of parking bays are aggregated by postal code and include all registered parking bays. An example of one of these zones is depicted in Figure 13. The area of land bordered by the two train lines and water is one postal code zone. Only the give or take three streets in the bottom left corner are residential streets with residential parking. The rest of the zone is filled with offices and commercial buildings with large parking plots that are not available for residential parking, but are added to the aggregated totals. The dataset contains more areas like these where the residential parking bays are a small section of the total amount of parking bays, affecting the parking bay per household variable.

This limitation of the dataset could be mitigated by determining if each parking bay is meant for residential (origin) use or destination parking at work for example. This could possibly be achieved by altering the algorithm used for deducing the amount of parking bays to also register the building functions next to a parking bay of a certain size. If this function is not residential these parking bays could then be marked at destination parking and excluded from the car ownership analysis. For this thesis there was not enough time to realise this. Therefore, area's with a high parking bay per household ratio are currently less reliable in the dataset. The way that is handled with these high outliers in the analysis is with the use of a dummy variable for the parking bay/household variable. In this manner the small over- or underestimation discrepancies when aggregating to postal code zone are less significant and the outliers, such as the neighbourhood in Figure 13, are also grouped together.

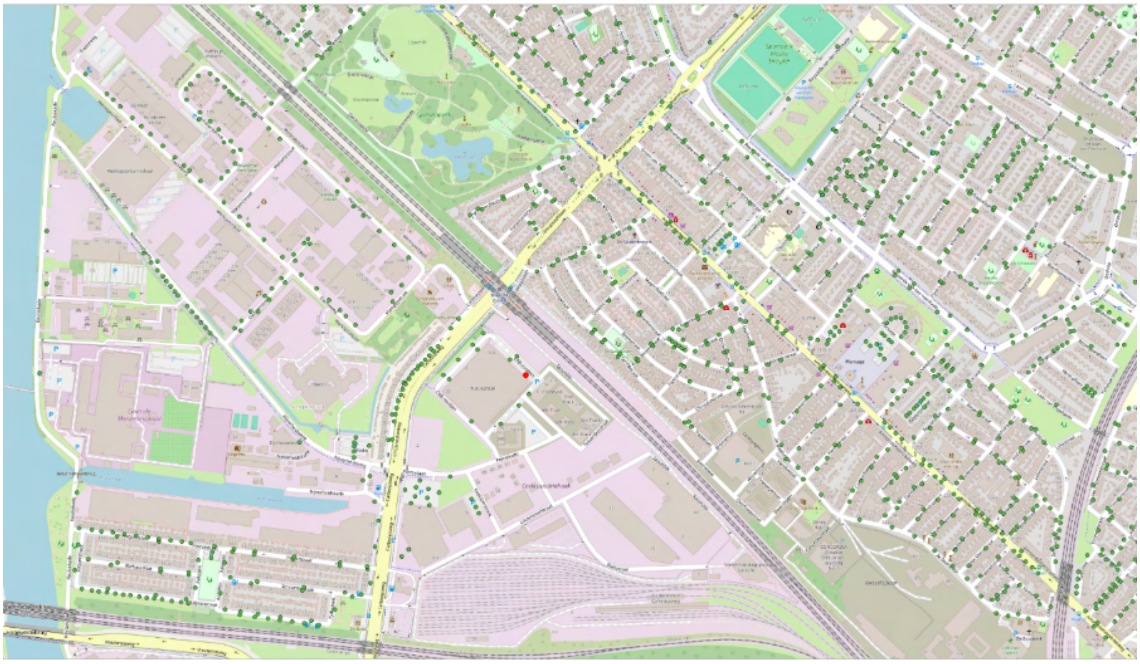

Figure 13. Example of a high parking bays per household postal code zone

In Figure 14 the relationship between parking bays per household against average car ownership is plotted. When grouping the households in 10 equal sized bins as shown in the left plot it is discovered that 90 percent of the households live in an area with less than 1,6 parking bays per household. The outliers, such as the neighbourhood from Figure 13, are all in this 10 percent group of households and will be included as the highest dummy category. The cut-off point of the highest dummy group is 1,5 parking bays per household as the right plot in Figure 13 illustrates that the average household car ownership of households does not seem to increase anymore after 1,5. For the other dummy categories groups with a width of 0,5 parking bays per household will be made. Resulting in the following groups; 0 to 0,5, 0,5 to 1, 1 to 1,5 and 1,5+ parking bays per household.

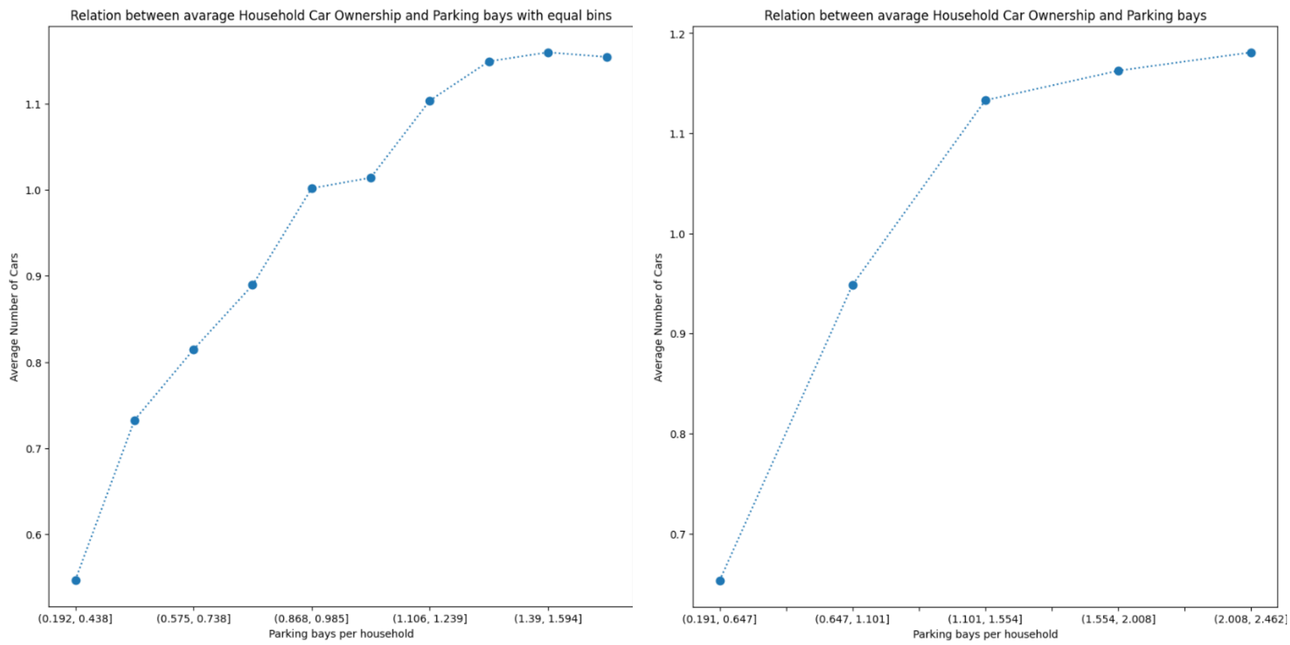

Figure 14. Relationship between household car ownership and parking bays per household

3.6.2 PARKING ON PREMISE (POET)

In contrast to the parking bays the POET data is expected to be a overestimation (Snelder, 2021). As the method can sometimes mislabel front gardens as driveways. While it is technically possible to park a car in a front garden it is not common practice to do this and destroy your plants at the same time. These assumptions were also cause for a deep dive into the POET data. This resulted in a few insights on the POET data. First, it is true that using this method some front gardens could be mislabelled as POET places leading to a small overestimation. However, when aggregating the POET places on postal code zone and comparing these zones with each other the values seem plausible. The dense centres of Amsterdam and Rotterdam for example have multiple postal codes with nearly 0 POET places per household, which could be confirmed by google maps. On the other side of the spectrum the postal code areas also contained big houses with large driveways. An example of this is a neighbourhood in Bussum depicted with the POET places in Figure 15. As you can see this is a neighbourhood with ample parking on premises, which can be confirmed by walking through the neighbourhood using google street view. Figure 16 shows the view from the Koningslaan, confirming the wide-stretched characteristics of the neighbourhood and the multiple driveways.

Figure 15. POET places Bussum

Figure 16. Street view Bussum (source: Google street view)

The range of POET places per household in a postal code zone ranges from 0 to 1 spaces per household. For the multinomial logit model 4 dummy's will be created, each spanning 0.25 POET places per household.

3.7 DESCRIPTIVES OF RESIDENTIAL PARKING PERMIT COSTS

The permit costs of the most central and often most expensive parking zone in the municipality is collected (Vereniging eigen huis, 2024). Due to a lack of more detailed data regarding parking these tariffs are applied to each neighbourhood in the municipality as an indication of the degree of parking policy implemented in the municipality.

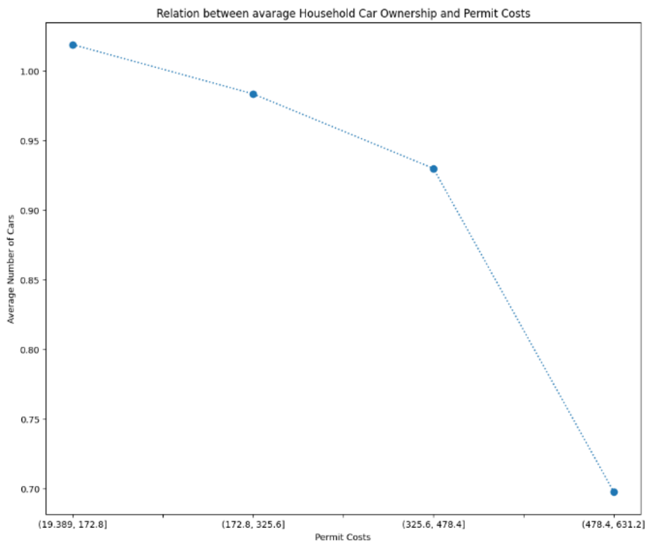

Figure 17. Relationship between household car ownership and permit costs

In Figure 17 the households are divided in 4 groups of permit costs and again plotted against the average car ownership levels of those groups. After examaning the line plotted through these four points the permit costs will be included as a continous variablein the MNL.

3.8 DATA PREPARATION

In the previous sections the available data sources and the operationalisation of the determinants in the conceptual model where discussed. A summary of the selected determinants and their operationalisation can be found in Table 3.

Table 3. Operationalisation of determinants

	Type	(Dummy) Range	Merged on
Household Income	Ordinal	{1, .., 10}	
# Driving licenses	Dummy	{0, .., 3+}	
# Kids in Household	Dummy	{0, .., 3}	
Distance to train-station	Dummy	{0, .., 1.2} -> 0 {1.2, .., 4} -> 1 {4, …, 28.7} -> 2	PC-4
Parking bays per household	Dummy	{0, .., 0.5} -> 0 {0.5, .., 1} -> 1 {1, …, 1.5} -> 2 {1.5, -> } -> 3	PC-4
POET places per household	Dummy	{0, .., 0.25} -> 0 {0.25, .., 0.5} -> 1 {0.5, …, 0.75} -> 2 {0.75, -> } -> 3	PC-4
Permit Costs	Continuous	Measured; {20,…,620 €}	Municipality
Urbanization level	Dummy	{1} -> 0 {2} -> 1	PC-4

The data preparation starts off with the ODiN dataset, as this dataset contains all the individual households and their characteristics coupled with their level of car ownership. The three years of ODiN are then combined into one big ODiN file spanning from the years 2020 till 2022. For each respondents ID the first of the three respondents' days is selected, as the mode choice information is not relevant for this study and otherwise each household will be included three times in the dataset.

The spatial (parking availability) characteristics are calculated per postal code 4 zone and merged with the ODiN dataset on the PC4 code that is present in both datasets. The permit costs collected on municipal level are merged on the households' municipality name. To achieve this there might exist a need to change some municipality names in one of the datasets to be able to match and merge the two. For example, Den Haag and ' s-Gravenhage can cause some semantic difficulties when merging on municipalities by name. The resulting data frame structure can be found in Table 4. This one case or household per row structure allows the data frame to be imported and analysed in SPSS.

Table 4. Input data frame structure

Id	Income	# Kids	# Driving licenses	PC-4	Distance to train	Parking bays/ hh	POET / hh	Urbanization	Munic.	Permit costs	# of Cars
Household characteristics				**Merge on:**	**Zonal characteristics**				**Merge on:**		**Dependent variable**
1											
…											
80.526											

4. RESULTS

In this chapter the results of the statistical analysis will be discussed. First, the results of the multinomial logit model generated using SPSS will be discussed and analysed by calculating the utility functions for the car ownership levels to exemplify the effects of parking availability on car ownership.

4.1 MULTINOMIAL LOGIT PARAMETERS

Table 5. Parameters multinomial logit model

	1 Car	Sig.	2 Cars	Sig.	3+ Cars	Sig.
Intercept	-0.174	<.001	-3.704	<.001	-6.328	<.001
Income	0.167	<.001	0.330	<.001	0.389	<.001
0 Driving licenses	-3.282	<.001	-2.865	<.001	-2.992	<.001
1 Driving license	0^b		0^b		0^b	
2 Driving licenses	0.959	<.001	2.370	<.001	2.763	<.001
3+ Driving licenses	1.005	<.001	3.294	<.001	4.791	<.001
Parking costs (€/100)	-0.106	<.001	-0.162	<.001	-0.173	<.001
0 Kids	0^b		0^b		0^b	
1 Kid	0.443	<.001	0.681	<.001	0.423	<.001
2 Kids	0.717	<.001	1.011	<.001	0.875	<.001
3+ Kids	0.588	<.001	0.838	<.001	0.775	<.001
0 - 1,2 Km to train station	-0.146	<.001	-0.219	<.001	-0.241	<.001
1,2 - 4 Km to train station	0^b		0^b		0^b	
4 + Km to train station	0.111	0,001	0.095	0,021	0.087	0,124
0 - 0,5 parking bays / household	-0.560	<.001	-0.813	<.001	-0.914	<.001
0.5 - 1 parking bays / household	0^b		0^b		0^b	
1 - 1.5 parking bays / household	0.251	<.001	0.401	<.001	0.562	<.001
1.5 + parking bays / household	0.227	<.001	0.453	<.001	0.567	<.001
0 - 0,25 POET / household	0^b		0^b		0^b	
0,25 - 0,5 POET / household	0.221	<.001	0.262	<.001	0.346	<.001
0,5 - 0,75 POET / household	0.401	<.001	0.660	<.001	0.578	<.001
0,75 + POET / household	0.751	<.001	1.034	<.001	1.142	<.001
Strongly Urban - Stedelijkheid = 1	0^b		0^b		0^b	
Urban - Stedelijkheid = 2	0.462	<.001	0.679	<.001	0.715	<.001

After the initial exploratory data analysis and preparation of the data as described in the methodology, a multinomial logit model was estimated to analyse the effects of the determinants on household car ownership levels. The resulting logit parameters of the multinomial logit model and their significance are depicted in Table 5. The full SPSS parameter output table can be found in APPENDIX A. Figure 18 contains the Pseudo R-square values of the MNL indicating a good model fit. For example, McFadden r^2 values of .2 to .4 represent an excellent model fit (McFadden, 1977). A McFadden r^2 of .274 therefore indicates a good model fit.

Pseudo R-Square

Cox and Snell	.470
Nagelkerke	.521
McFadden	.274

Figure 18. Pseudo R-square MNL

The logit parameters can be used to formulate utility functions (or logits) for each level of car ownership. An example of such function is partly shown in the first equation underneath. The chance of owning a certain number of cars based on the inputs for the explaining variables can be calculated with the help of the second formula. The logit for the reference scenario of zero cars is equal to 0. The chances of owning a certain number of cars as calculated with these formulas and the parameters of the MNL will be used to investigate and compare the effects of the determinants on household car ownership.

$$(1) \qquad logit_{(1\ car)} = Intercept + 0.167 * Income + \cdots + 0.462 * Urbanization_{level=2}$$

$$(2) \qquad P_{(1\ car)} = \frac{e^{logit_{(1\ car)}}}{e^{logit_{(0\ cars)}} + e^{logit_{(1\ car)}} + e^{logit_{(2\ cars)}} + e^{logit_{(3+\ cars)}}}$$

4.2 ANALYSIS OF MNL RESULTS

First, to analyse the influence of the explanatory variables on household car ownership (when controlling for the other variables) the probabilities of car ownership levels are calculated for the average of each variable. Secondly, the values of the explanatory variables will be systematically altered to measure the relative individual influence on household car ownership levels. This is done by taking the lowest and highest value for each variable to examine the effects of the full range of each determinant, while keeping the other variables constant at their average value. The range of outcomes is documented (APPENDIX B) and by analysing the Δ(min - max), Δ(min - avg) and Δ(avg - max) Table 6 is constructed. This table combines the insights of the directions of the different deltas and their relative size to those of other variables. This qualitive analysis of the effects better illustrates the relative explanatory power of each determinant. These results, together with those from Table 5 will be discussed in dept per category of determinants.

Table 6. Qualitive analysis MNL results

		$P_{(0\ cars)}$	$P_{(1\ car)}$	$P_{(2\ Cars)}$	$P_{(3+\ Cars)}$
Household characteristics	Income	- -	+ +	+ +	+
	Driving licenses	- - - -	+ + +	+ + + +	+ + +
	Children	-	+	+	
Spatial characteristics	Urbanization level	+	-	-	
	Distance to train station	-	+		
Parking availability	Parking bays / household	- -	+ +	+	
	POET/household	-	+	+	
	Permit costs	+	-	-	

4.2.1 HOUSEHOLD CHARACTERISTICS

First, the number of *driving licenses* has the highest explanatory power of the determinants in the MNL on the probability of a household owning a car. A driving license is a prerequisite of driving and thus owning a car. Therefore, when a household has no members with a driving license the probability of owning a car does decrease drastically in the multinomial logit model. For example, when keeping all other determinants at their average value a household with 3 driving licenses has a 96% chance of owning a car compared to 14% for a 0 car household. The probability is not zero as the logit is also influenced by the other determinants in the MNL and the multinomial logit model is based on the maximum utility principle, where the utility function with the highest utility is assumed to be chosen (Potoglou & Susilo, 2008). A probability of 14% will not be the highest percentage out of 4 categories. However, the individual probabilities can be a good measurement of the effects of the explanatory variables.

That the number of household driving licenses has the highest explanatory power in the multinomial logit model is in line with existing studies into household car ownership. Witte et al. (2022) argues that in the studied area of the Netherlands this can be explained by the large number of 11.5 million Dutch adults that have a driving license. Therefore, household driving licenses are assumed to mostly be a representation of the number of adults in a Dutch household, which is also a great predictor for household car ownership in international literature (Clark et al., 2016).
Another interesting insight from Table 5 is that from 2 to 3 driving licenses in a household the logit of owning one car does almost not differ. Compared to those of 2 or 3 cars where gaining an extra driving license (so going form 2 to 3) increases the probability of owning multiple cars. Indicating that the first driving license in the household is a condition for owning one car, which could be shared by multiple adults (with a driving license). More

driving licenses (and thus adults) in the household, that are assumed to be active users of the car, are then the biggest explanatory factor to obtain more cars in the household according to the analysis.

Secondly, the *number of children* in a household also relates to the composition of the household and life-stage of the adults. While they are not active users of the car (drivers) they can change the mobility needs of their parents and influence car ownership (Clark et al., 2016; Haque et al., 2019; Maltha, 2016). This can be seen in Table 5 where the logits for 1, 2 and 3+ cars increase if the number of children increase compared to 0 children. For each level of car ownership the logit increase for 3+ children is lower of that of 2 children in a household. This could be due to the increase in cost associated with 3 or more children compared to 2.
Also, the relative importance of the number of children in a household determinant is much smaller to that of driving licenses as they are no active users of the car.

The third household characteristic, and second biggest predictor according to the qualitive analysis of the MNL results (Table 6), is the *disposable income* of the household. The disposable income is correlated with the amount of paid workers in a household Table 2. Household income groups in the Netherlands (Table 2) and also slightly with the amount of driving licenses in a household. The correlation with the driving license variable is the largest correlation between explanatory variables in the analysis, but is not big enough for problematic multicollinearity. The disposable income has a positive influence on car ownership, as expected.

To summarize; the composition and income of a household (included in the analysis through the disposable income, driving license and children determinants) are identified as the greatest predictors of household car ownership levels (Table 6) in the analysis. These results are in line with current studies on car ownership and therefore provide a solid base to study the (relative) effects of parking availability on household car ownership levels.

4.2.2 SPATIAL CHARACTERISTICS

Another identified determinant is the spatial context of the household, as this could change the households mobility needs. According to the analysis this is the case in the Netherlands, but compared to the household characteristics the effects of urbanization and distance to the train station are relatively small (Table 6).

First, the *urbanization level* decreases the logit of 1 and 2 cars in the same magnitude as the increase from 0 to 1 child in the household (the relative smallest predictor of the household characteristics). Thus, for a household in a less urban area, which in the Netherlands is also associated with less mixed-use, the probability of owning a car increases with the same magnitude as it does for the first child of a household.

Secondly, the access to high quality public transport, translated to *the distance to a train station* has the relatively smallest influence on car ownership in the analysis. When living close to a train station (less than 1.2 kilometres) the probability of owning one or more cars decreases. If you live far from a train station the parameters of 4+ km for one or two cars are not statistically significant. This could be due to the unclear relation with car ownership compared to the reference group of 1.2 to 4 km as could also be seen in Figure 9. So statistically the change in car ownership levels can't be confidently argued from 4+ km compared to the reference category.

4.2.3 PARKING AVAILABILITY

The aim of this thesis is to study the influence of parking availability on household car ownership levels. The identified dimensions that could be implemented (due to data availability) are significant in the MNL analysis (Table 5) and do seem to influence household car ownership. To which (relative) extent these dimensions individually influence car ownership levels will be discussed in this chapter.

First, the *number of parking bays* and *POET places* per household in the households' neighbourhood increases the probability of a household owning one or more cars. But mainly, the absence of parking decreases the probability of car ownership.
For the *parking bays* per household determinant the largest group of households in the studied (urban) area lives in a neighbourhood with 0.5 to 1 parking bays per household, which is added as the reference category for the determinant in the MNL. The parameters for the parking bay determinant in Table 5 are twice as large for a decrease from the reference category of 0.5 to 1 than for an increase in parking bays per household. Showing that the decrease in parking has a larger effect on car ownership than an increase from the reference point. Also, the effect of 1 to 1.5 and that of 1.5+ parking bays per household does not differ significantly.
The *number of parking on premise places* per household has a positive effect on the probability of owning a car. It was expected due to the extra convenience that this effect would have a higher relative importance to that of parking bays in an area. But the influence of POET places on car ownership is lower than that of parking bays per household (Table 6). This could be a result of the also excellent accessibility of residential parking bays, as most households in the Netherlands can park their car within 10 metres of their front door with the average distance being 21 metres (Zijlstra et al., 2022). Therefore, that improved convenience might be overvalued in the assumptions made.

So, both the parking supply determinants do influence the probability of owning a car in the Netherlands according to the estimated multinomial logistic regression model. The relative explanatory power is lower compared to the most influential household characteristics, but the relative importance of the parking bays in the neighbourhood comes close to that of the disposable household income (Table 6).

The third dimension of parking availability included in the model next to both the parking supply variables, *permit costs,* has a negative influence on car ownership. Households in a municipality with high maximum parking permit costs have a lower probability to own a car.

4.3 COMPARISON OF NEIGHBOURHOODS

In section 4.2 the influences of individual determinants on household car ownership were discussed. However land-use policies should be a strategic combination of multiple accessibility measures (Antonson et al., 2017). To better illustrate the effects of the build environment, including parking availability, three neighbourhoods were selected on their increasing degree of parking availability and will be compared in this section.

Table 7. Selected neighbourhoods

	Density	Accessibility PT	Parking bays	POET	Permit costs
1011 - Amsterdam	High	High	Low	Low	High
1068 - Amsterdam	High	Medium	Medium	Low	High
1312 - Almere	Medium	High	High	High	Low

The selected neighbourhoods are depicted in Table 7. First, neighbourhood 1011 is selected to illustrate an existing high-density neighbourhood in the Netherlands with a very low parking availability. The next neighbourhood (1068) is selected to show how probabilities of car ownership can change in the same city with different neighbourhood characteristics and a slightly higher parking availability. The last neighbourhood is selected to illustrate the other side of the parking availability spectrum by selecting a neighbourhood in Almere which is close to Amsterdam.

For each neighbourhood the same two average households are taken. These are households in the disposable income group 6 with a child and 1 or 2 driving licenses. For each of these households the probabilities of owning a car are calculated based on the statistical analysis.

Table 8. Car ownership probabilities 1011

	One driving license household	Two driving license household
P (0)	**0.513**	0.258
P (1)	0.462	**0.606**
P (2)	0.023	0.124
P (3+)	0.002	0.012

1011 - Amsterdam

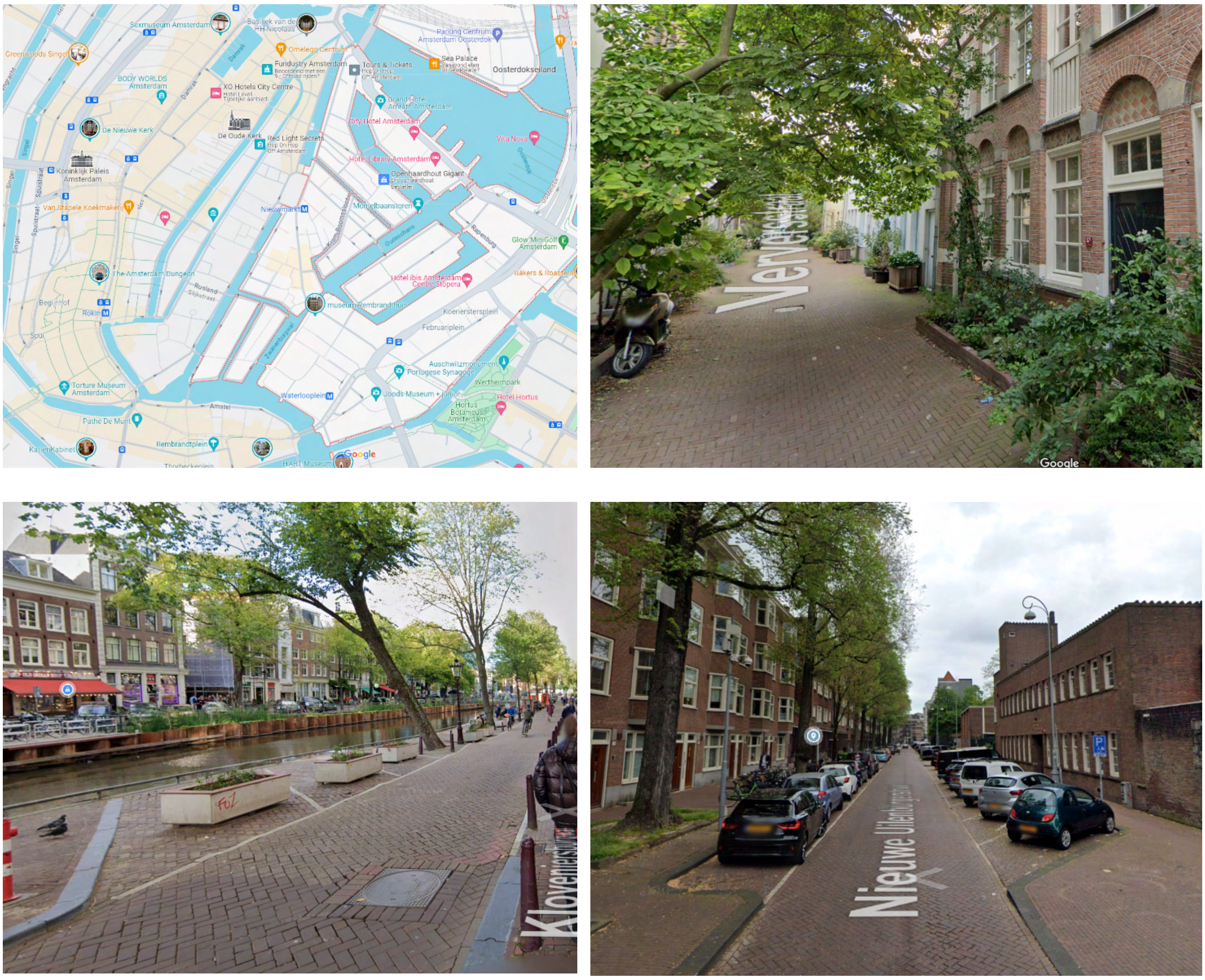

Figure 19. Illustration of postal code 1011. Source: Google maps

The first analysed neighbourhood is located in the center of Amsterdam (postal code 1011) with a high density and great accessibility to public transport. The map of the area and the view of three streets are depicted in Figure 19. Multiple streets in the neighbourhood are car-free and the neighbourhood also contains roads where parking bays are slowly being transferred into new street functions. The low supply of on-street parking together with strict permit policies (high permit costs of €631 per year coupled with long permit waiting lists) result in low parking availability in the neighbourhood.
Based on the statistical analysis the first, *one driving license,* household has a high probability of owning zero cars (Table 8). Adding one driving license (or adult according to Witte et al. (2022)) to the household shifts the probabilities resulting in the highest probability being that of 1 car. Illustrating that the household composition is still a very influential determinant of household car ownership.

1068 – Amsterdam

Figure 20. Illustration of postal code 1068. Source: Google maps

To identify the extent of the influence of parking availability on household car ownership the neighbourhood in the center of Amsterdam with low parking availability will be compared with another Amsterdam neighbourhood less than 10 kilometres to the west (Figure 20). This neighbourhood has the same high urban density, but is with an average of a 2 km distance further located to the nearest train station.

When looking at the dimensions of parking availability, the neighbourhood mainly sees an increase in parking bays from about 1 per 4 households to a bit more than 1 parking bay per 2 households in the neighbourhood. The increase of parking bays can be confirmed using Google street view (Figure 20). The permit costs in the model stay the same as in the other neighbourhood, as the maximum permit costs for each municipality are collected as a measure for the strictness of municipal parking policies (Vereniging eigen huis, 2024). However, the permit costs and measures in the 1068 neighbourhood are in reality less strict than those in the center district. This is a limitation of the model due to data accessibility, but in this case does allow to compare the effects of the residential parking supply on the household car ownership probabilities.

Table 9. Car ownership probabilities 1068

	One driving license household	Two driving license household
P (0)	0.338	0.138
P (1)	**0.616**	**0.655**
P (2)	0.043	0.187
P (3+)	0.003	0.021

The probabilities, depicted in Table 9, show that the probabilities for both households to own one or more cars do increase in comparison to the neighbourhood in the center. An average household in an area with less accessibility to national public transport and a higher on-street supply of parking bays will thus statistically be more likely to own a car than the same household in a well-connected area with a lower parking availability.

1312 - Almere

Figure 21. Illustration of postal code 1312. Source: Google maps

The third neighbourhood that will serve as a comparison is that with postal code 1312 in Almere (Figure 21). Almere is a city just outside of Amsterdam with a lower urban density where a lot of people live that work in the Amsterdam area, but choose Almere for its quitter character or more affordable housing. The neighbourhood has a train station close by from which you can be at both Amsterdam Zuid or Central station in half an hour. So, the neighbourhood has great accessibility to regional and national public transport.
When further analysing the neighbourhood it is revealed that the parking availability in the area is much higher than that of both Amsterdam neighbourhoods. The area has ample off- and on-street parking and Almere's maximum permit costs are a third of that of Amsterdam.

When comparing the same households from Amsterdam to those in Muziekwijk Noord in Almere their probabilities of owning one or more cars do increase even more according to the statistical analysis (Table 10). This shows that the neighbourhood characteristics, including density, accessibility to high quality public transport and parking availability, do influence household car ownership decisions. To put the extend of influence that parking availability has on car ownership in context, moving the one driving license household from neighbourhood 1011 in Amsterdam to 1312 in Almere statistically increases the probability of the household owning one of more cars by 39 percentage points. While, adding one more driving license to the Amsterdam household increases the households' probability to own one or more cars by 26 percentage points.

Table 10. Car ownership probabilities 1312

	One driving license household	Two driving license household
P (0)	0.128	0.038
P (1)	**0.763**	**0.596**
P (2)	0.100	0.320
P (3+)	0.010	0.046

4.4 USE CASE; ALMERE PAMPUS

To further analyse the effects of parking availability on household car ownership, the household car ownership levels for different degrees of parking availability are estimated. The analysis is based on a possible demographic scenario of Almere Pampus. This is a new proposed neighbourhood in Almere, just north of the (high parking availability) neighbourhood discussed in the previous chapter (Figure 21). So, Almere Pampus is a neighbourhood that does not exist yet and one of the use cases of the XCARCITY program, making it an interesting use case to experiment with.

Table 11. Parking availability scenarios

	Low	Mid	High
Parking bays / household	0.4	0.8	1.4
POET / household	0.1	0.1	0.4
Permit costs (€)	400	235	235

First, a population was created based on a possible demographic scenario of Almere Pampus (Appendix C). And secondly, the number of cars in Almere Pampus was estimated for the population using the probabilities of the multinomial logistic regression model. This is done for three scenarios of parking availability, namely; Low, Mid and High parking availability (Table 11). The *low parking availability* scenario has parking supply ratios per household that are in the lowest categories of parking bays and the parking on premise variables. The permit costs are defined as almost double the costs of the current permit costs in Almere. Together these measures result in a neighbourhood with a low parking availability. The other two scenarios increase the parking availability comparable to the increase in the neighbourhoods in section 4.3. The permit costs are fixed at the current maximum parking costs in the municipality of Almere. For the *medium parking availability* scenario the parking supply is comparable to that of the 1068 neighbourhood (Figure 20) and the *high parking availability* scenario to that of the neighbouring Muziekwijk Noord in Almere. The difference in estimated household car ownership levels between scenarios can be seen in Figure 22.

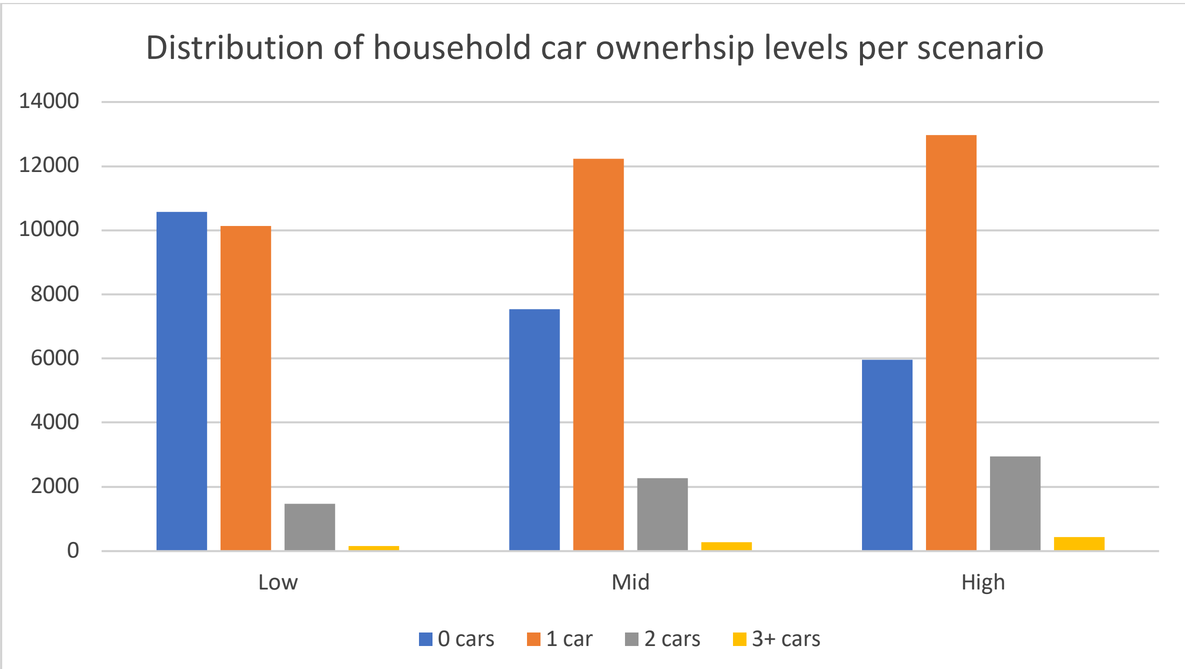

Figure 22. Distribution of car ownership levels Almere Pampus

Figure 22 shows that the parking availability scenarios influence the estimated distribution of household car ownership in Almere Pampus. In the low parking availability scenario the number of households that own one or zero cars are almost equal. When the parking availability increases the share of zero car households decreases by about 30% and 46% compared to the low parking availability scenario while the other car ownership categories increase. The total predicted number of cars increases by 49% from the low parking availability scenario to that of high parking availability, while the increase from mid to high parking availability only shows an increase in the number the number of cars of 15%.

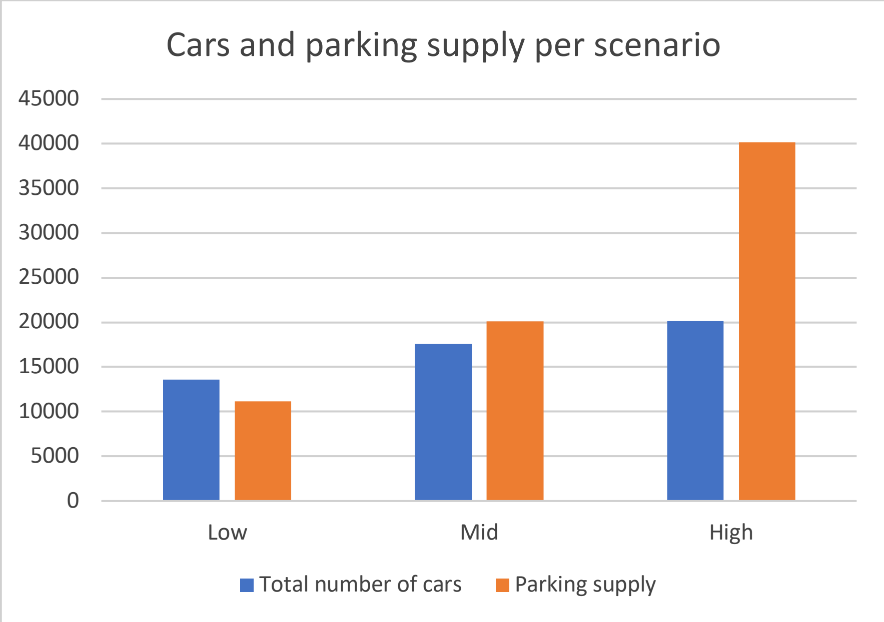

Figure 23. The parking supply and total number of cars

In Figure 23 the total number of estimated cars for each parking availability scenario is plotted together with the parking supply based on the ratios in Table 11. This shows that when you design a neighbourhood with a low parking availability the expected number of cars could be greater than the parking supply, possibly causing parking and accessibility problems. But, on the other side when designing for overcapacity as in the high parking availability scenario there could be about twice as much as residential parking supply compared to the expected number of cars. Essentially wasting valuable and scarce urban land. In the case of Almere Pampus with good accessibility to public transport and a high urbanization level the middle parking availability scenario seems to offer the best balance of household car ownership and residential parking availability based on the statistical analysis.

5. CONCLUSION

The growing population of the Netherlands is putting pressure on the accessibility and liveability of Dutch cities. To address both challenges new mobility policies prioritise quiet, low-emission and space-efficient modes of transport. This changing perspective on urban mobility is thus increasingly in odds with the characteristics of the private car, as private (fuel-engine) cars are loud, polluting and space-inefficient compared to other sustainable modes of transport. To illustrate, a personal trip by private car in Amsterdam requires about 95m^2 of public space, of which 15m^2 is dedicated to parking. For this reason, cities in the Netherlands are looking at measures to reduce (extra) car mobility. They expect that parking regulations could be an effective instrument to reduce car ownership and improve the liveability of cities. But, evidence to support these claims is lacking as the effects of such policies are understudied in car ownership research, which mainly focus on socio-demographic and household characteristics to predict car ownership levels. Therefore, this study aims to address this knowledge gap in the current car ownership literature and support municipalities to substantiate policy interventions and find a good balance between car accessibility and liveability by asking the following research question:

To which extent does urban parking availability influence household car ownership in the Netherlands?

To be able to answer the main research question the study started off by defining dimensions of urban parking availability, as parking availability is not only affected by the number of parking places but also by multiple regulations. The parking supply is largely defined by its size and parking type. This study identifies two main parking types, namely; private parking on premises and public on-street parking. Parking regulations that could further influence the parking availability relate to the cost and availability of parking permits which subsidize the costs of parking for residents.

To explain the influence of parking availability on household car ownership a multinomial logistic regression (MNL) model is estimated. This statistical method is identified as the preferred method to explain the influence of household car ownership determinants by multiple comparison studies and provides extra flexibility over ordered-response mechanisms.
To estimate the MNL, data on 80,527 urban households from three years of the Dutch National Traffic Survey (ODiN) was used. The numbers section of the households' postal code is collected in the traffic survey, allowing aggregated characteristics of the neighbourhood to be included in the household cases and thus the MNL. From the identified dimensions of parking availability the number of on-street parking bays per household, parking places on premises per household and the maximum parking costs in the municipality could be operationalised considering data availability.

The outcomes of the multinomial logistic regression model show that the parking availability in a households' neighbourhood does influence car ownership. Based on the analysis, both parking types have a positive relation with household car ownership. While higher maximum permit costs in a households' municipality (which can also be seen as an indication of the strictness of the municipalities parking policies) decreases the probability of car ownership.

Next, to substantiate possible parking interventions by municipalities the extent of the influence of parking availability on household car ownership is further investigated and compared to that of other determinants, as parking policies based on a relatively minor influence are not likely to have a desired impact. Previous studies have identified household composition and income as the most influential determinants of car ownership and these determinants also have the highest explanatory power in the statistical analysis. That means that the composition of a household together with its financial status best explain the households' decision to own a certain number of cars. Especially the number of driving licenses in a household (which is closely correlated to the number of adults) has a high relative importance, followed by the households' disposable income. The latter having a similar relative importance as the number of parking bays in a neighbourhood. So, compared to the household characteristics the individual dimensions of parking availability have a smaller but still significant effect.

However, as parking policies should be a strategic combination of multiple interventions the dimensions of parking availability were also analysed together to further investigate the extent of the relationship between urban parking availability and household car ownership. First, the household car ownership probabilities were compared between three existing neighbourhoods for two average households (a one driving license and a two driving license household). And secondly, car ownership levels of a potential new neighbourhood were predicted for three increasing levels of parking availability.

The first exploration shows that the build environment does influence the probability of a household to own a car. Based on the statistical analysis, the probability of car ownership increases by 39 percentage points when comparing a very dense and well-connected neighbourhood in Amsterdam to a less-dense neighbourhood in Almere with ample parking. To put the extent of these environmental factors in context, a two driving license (or adult) household in the centre of Amsterdam increases the households' probability to own one or more cars by 26 percentage points compared to that of an one driving license household. This shows that a high-density environment with low parking availability can significantly reduce the probability of household car ownership.

The combined influence of the dimensions of parking availability is further analysed by predicting car ownership levels for increasing levels of parking availability for the proposed neighbourhood of Almere Pampus. This analysis also shows that a higher level of parking availability increases the predicted number of cars. The total predicted number of cars of a possible population of Almere Pampus increases by 49% from the lowest to the highest parking availability scenario. Comparing the parking supply in the different scenarios to the predicted number of cars shows that low parking availability can cause parking problems, while high parking availability can easily result in overcapacity. Highlighting the importance of a balanced parking strategy.

To conclude, this study has shown that a neighbourhoods' parking availability does impact household car ownership levels to an extent that could substantiate parking policies. This adds to the body of car ownership literature as a households' decision to own a car is often considered to be mostly based on budget constraints and the mobility needs of its members by previous studies. While these factors still have a relative high influence on household car ownership, this study shows that parking availability in an urban residential neighbourhood could also significantly influence household car ownership.

So, the outcomes of the study show that parking regulations could be a tool of a municipality to influence car ownership. Therefore, this study recommends municipalities that aim to develop neighbourhoods with a low amount of parking and cars to create strategic parking policies out of the identified dimension of parking availability. The effect of such parking policies on a neighbourhoods' parking supply and car ownership levels can then be calculated to optimize the use of public space in a neighbourhood.

RECOMMENDATIONS FOR FUTURE RESEARCH

The discovered statistical relationship between a neighbourhoods' parking availability and car ownership is of importance to policy makers as it can substantiate parking regulations to reduce car ownership.. Further research efforts could provide even more insight in the implications of such car-oriented policies. This section highlights a few recommendations for such future research efforts that could provide more insight in car ownership and parking availability.

To start off, urban municipalities are also exploring other measures to make more efficient use of the scarce public space in cities and to reduce car ownership. The city of Amsterdam has investigated the replacement ratio of private cars when adding shared cars to different postal code 4 neighbourhoods. They have found that in certain neighbourhoods shared cars could replace about 5 private cars (Gemeente Amsterdam, 2023), leading to less public space that needs to be dedicated to car parking. Including shared mobilities in the analysis could therefore add to the parking availability and car ownership research.

Other determinants that could improve the car ownership analysis are attitude or preference data on car ownership, as a high perceived car dependency could also be an important driver for car ownership. Thus, a study that includes attitudinal factors could analyse the differences in preferences towards cars between households living in car-friendly or car-free neighbourhoods. This could provide more insights into the differences between neighbourhoods and mitigate biases caused by residential self-selection.

This study has focused (due to data availability) on ‘visible’ above ground parking. That will say, above ground parking that can be deduced from maps and other geographical data. However, the burden of realising residential parking is increasingly put on developers for larger residential developments in big cities. Residents of such newer developments are often not eligible for parking permits (Gemeente Den Haag, 2021), adding to the complexity of parking. Gathering data on private residential garages and including them in the analysis could therefore provide more insight in the different types of parking.

Lastly, the study did not make any distinction between or elaborate on accessibility between different groups in the population. However, car dependency may be higher for the elderly or certain other subgroups of the population. Before implementing restrictive parking policies that could influence their accessibility the implications on mobility poverty and potential social injustice of such policies should also be further investigated.

6. REFLECTION

Throughout the thesis limitations of the study were discussed. This chapter combines these insights and offers a reflection on the outcomes of this study by discussing the limitations of the study and the possible impact that these limitations could have on the outcomes.

First, regarding the research design. The methodology used in this study of statistically analysing the differences in household car ownership levels between neighbourhoods has its limitations with regards to proving causality. To start off, the direction of causality can't be proven with this research design. As the lower levels of household car ownership could be a result of low parking availability, but the low parking availability could as well be a result of an already low level of car ownership for which less parking has to be realised.
The second limitation related to causality is that of residential self-selection, as car centric households could prefer to live in a car-friendly neighbourhood with a high level of parking availability. This can create a bias in the data. The effect of self-reflection could be mitigated by including more attitude and preference data towards car ownership in the analysis. The limitations on causality should be considered when interpreting the outcomes of the study. Therefore, you cannot say based on this study that removing parking bays will directly reduce car ownership levels in an existing neighbourhood. However, when creating a new neighbourhood like that of Almere Pampus you could make predictions on car ownership levels for different levels of parking availability based on the statistical analysis. As this neighbourhood could, based on the analysis, 'statistically exist'.

Secondly, data retrieval barriers introduce limitations to the study. Accurate data on parking availability is difficult to collect as residential parking supply is not monitored by most governments and affected by multiple municipality specific regulations. Therefore, the supply of parking was deduced and estimated using data science methods developed by TNO and the only parking regulation that could be implemented in this study was the cost of a parking permit in the most expensive zone of the municipality. The supply of parking could be an overestimation in urban areas as the number of parking bays do not only include residential street parking but also larger office or commercial parking lots. Most of these errors are mitigated by including the number of parking bays per household as categories. Therefore, this study recommends for car ownership models that are currently being developed to include the aggregated parking supply determinants in categories to mitigate the small under- and over-estimations in certain areas. However, the impact of the overestimation could be substantial on the number of parking bays per household in a few neighbourhoods that contain few households and a lot of non-residential parking lots. But, as about 90 percent of the households in the analysis live in an urban neighbourhood with less than 1.5 parking bays per household the overestimation in a few neighbourhoods will not heavily impact the overall outcomes of the study but could cause a underestimation of the influence of 1.5+ parking bays per household on car ownership. Thus readers should be cautious when interpreting the results of this highest category. For further research using this parking data it is recommended to identify residential parking bays out of the parking data and thus exclude large commercial parking plots. This could possibly be achieved by analysing the surrounding building functions.

Another omission in the parking data are private residential parking garages and plots. In multiple larger new developments in big Dutch cities the developer is responsible for realising residential parking on or under the premise. These parking plots are mostly not included in the analysis. This could cause an underestimation of parking availability in cities and thus impact the outcomes.

Third, although the MNL did obtain a good model fit based on the r^2 values the predictive accuracy of the MNL was not externally validated. This could be done in further research by estimating the car ownership levels for a synthetic population of the Netherlands and compare the predicted number of cars to a recorded number of private cars for each neighbourhood. This could improve the validity of the outcomes but the data to perform the external validation was currently not available. Therefore, the outcomes of the predictive comparison parts of the study, such the outcomes of the Almere Pampus use case, could be underestimations of the number of cars as the MNL has strong preference to one car households over 2 and 3+ car households. However, half of the recorded households in the population are also one car households.

Lastly, the influence of parking availability on car ownership was investigated for the two highest categories of urbanization in the Netherlands. That raises the question if these results could be generalised to rural parts of the Netherlands. It is expected that the direction of the relationship between parking availability and household car ownership is the same, but that the size of the effect will probably be smaller as parking in non-urban areas of the Netherlands is generally over-supplied and car dependency is also assumed to be higher. Further research could focus on the relation between parking availability and car ownership in rural areas and their possible differences with urban areas.

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APPENDIX A

Table 12 contains the parameter estimates directly out of SPSS. For the dummy variables SPSS takes the highest value of the independent variable. Because the results of the MNL can be interpreted more clearly with other reference categories some of the variables are switched around, but properly labelled again in Table 5.

Table 12. SPSS parameter output

Parameter Estimates

HHAuto[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
1	Intercept	-0,174	0,032	29,321	1	0,000			
	p_beleid	-0,106	0,005	374,241	1	0,000	0,900	0,890	0,909
	HHBestInkG	0,167	0,004	1445,626	1	0,000	1,181	1,171	1,191
	[dum_station=.00]	-0,146	0,027	30,080	1	0,000	0,864	0,820	0,911
	[dum_station=1.00]	0,111	0,034	10,450	1	0,001	1,118	1,045	1,196
	[dum_station=2.00]	0[b]			0				
	[dum_vak=.00]	-0,560	0,031	324,024	1	0,000	0,571	0,537	0,607
	[dum_vak=1.00]	0,227	0,041	29,955	1	0,000	1,254	1,157	1,360
	[dum_vak=2.00]	0,251	0,029	74,705	1	0,000	1,285	1,214	1,360
	[dum_vak=3.00]	0[b]			0				
	[dum_poet=.00]	0,751	0,142	27,940	1	0,000	2,118	1,604	2,798
	[dum_poet=1.00]	0,211	0,035	36,771	1	0,000	1,235	1,154	1,322
	[dum_poet=2.00]	0,401	0,063	40,950	1	0,000	1,493	1,321	1,688
	[dum_poet=3.00]	0[b]			0				
	[dum_sted=.00]	0,462	0,032	212,941	1	0,000	1,586	1,491	1,688
	[dum_sted=1.00]	0[b]			0				
	[dum_kid=.00]	0,588	0,058	104,050	1	0,000	1,800	1,608	2,015
	[dum_kid=1.00]	0,443	0,040	124,149	1	0,000	1,557	1,441	1,683
	[dum_kid=2.00]	0,717	0,044	271,315	1	0,000	2,049	1,881	2,231
	[dum_kid=3.00]	0[b]			0				
	[dum_driver_ref1=.00]	-3,282	0,045	5256,882	1	0,000	0,038	0,034	0,041

	[dum_driver_ref1=1.00]	1,005	0,073	188,942	1	0,000	2,732	2,368	3,153
	[dum_driver_ref1=2.00]	0,959	0,026	1311,090	1	0,000	2,608	2,476	2,747
	[dum_driver_ref1=3.00]	0[b]			0				
2	Intercept	-3,704	0,053	4970,202	1	0,000			
	p_beleid	-0,162	0,007	471,400	1	0,000	0,851	0,838	0,863
	HHBestInkG	0,330	0,006	2875,663	1	0,000	1,391	1,374	1,408
	[dum_station=.00]	-0,219	0,036	37,548	1	0,000	0,803	0,749	0,862
	[dum_station=1.00]	0,095	0,041	5,335	1	0,021	1,099	1,014	1,192
	[dum_station=2.00]	0[b]			0				
	[dum_vak=.00]	-0,813	0,048	285,182	1	0,000	0,443	0,404	0,487
	[dum_vak=1.00]	0,453	0,049	85,190	1	0,000	1,573	1,429	1,732
	[dum_vak=2.00]	0,401	0,036	123,401	1	0,000	1,493	1,391	1,603
	[dum_vak=3.00]	0[b]			0				
	[dum_poet=.00]	1,034	0,152	46,512	1	0,000	2,811	2,089	3,784
	[dum_poet=1.00]	0,363	0,041	78,143	1	0,000	1,438	1,327	1,558
	[dum_poet=2.00]	0,660	0,070	89,236	1	0,000	1,934	1,687	2,218
	[dum_poet=3.00]	0[b]			0				
	[dum_sted=.00]	0,679	0,039	307,015	1	0,000	1,972	1,828	2,128
	[dum_sted=1.00]	0[b]			0				
	[dum_kid=.00]	0,838	0,065	164,604	1	0,000	2,312	2,034	2,628
	[dum_kid=1.00]	0,681	0,046	216,042	1	0,000	1,975	1,804	2,163
	[dum_kid=2.00]	1,011	0,048	436,284	1	0,000	2,749	2,500	3,023
	[dum_kid=3.00]	0[b]			0				
	[dum_driver_ref1=.00]	-2,865	0,114	630,112	1	0,000	0,057	0,046	0,071
	[dum_driver_ref1=1.00]	3,294	0,078	1786,026	1	0,000	26,943	23,126	31,390
	[dum_driver_ref1=2.00]	2,370	0,038	3960,048	1	0,000	10,701	9,939	11,520
	[dum_driver_ref1=3.00]	0[b]			0				
3	Intercept	-6,328	0,112	3168,202	1	0,000			
	p_beleid	-0,173	0,012	205,677	1	0,000	0,841	0,821	0,861
	HHBestInkG	0,389	0,011	1321,497	1	0,000	1,476	1,445	1,507
	[dum_station=.00]	-0,241	0,056	18,301	1	0,000	0,786	0,703	0,877
	[dum_station=1.00]	0,087	0,056	2,367	1	0,124	1,090	0,977	1,218

[dum_station=2.00]	0b			0				
[dum_vak=.00]	-0,914	0,090	102,045	1	0,000	0,401	0,336	0,479
[dum_vak=1.00]	0,567	0,068	68,837	1	0,000	1,762	1,541	2,015
[dum_vak=2.00]	0,562	0,053	111,962	1	0,000	1,754	1,580	1,946
[dum_vak=3.00]	0b			0				
[dum_poet=.00]	1,142	0,176	42,024	1	0,000	3,134	2,219	4,426
[dum_poet=1.00]	0,346	0,056	37,625	1	0,000	1,414	1,266	1,579
[dum_poet=2.00]	0,578	0,089	41,726	1	0,000	1,783	1,496	2,124
[dum_poet=3.00]	0b			0				
[dum_sted=.00]	0,715	0,056	164,054	1	0,000	2,045	1,833	2,281
[dum_sted=1.00]	0b			0				
[dum_kid=.00]	0,775	0,089	75,622	1	0,000	2,170	1,823	2,584
[dum_kid=1.00]	0,423	0,064	44,270	1	0,000	1,526	1,348	1,729
[dum_kid=2.00]	0,875	0,065	183,414	1	0,000	2,398	2,113	2,722
[dum_kid=3.00]	0b			0				
[dum_driver_ref1=.00]	-2,992	0,363	67,845	1	0,000	0,050	0,025	0,102
[dum_driver_ref1=1.00]	4,791	0,110	1900,387	1	0,000	120,423	97,087	149,368
[dum_driver_ref1=2.00]	2,763	0,086	1030,050	1	0,000	15,847	13,387	18,760
[dum_driver_ref1=3.00]	0b			0				

a. The reference category is: 0.

b. This parameter is set to zero because it is redundant.

APPENDIX B

The different ranges of the variables coupled with the three different intercepts make it hard to compare the parameters out of the MNL with each other and define their relative importance. Therefore, to get a better idea of the relative importance of the determinants an average household is created and the range of the determinants (Table 13) are tested while keeping all other determinants at their average value. The car ownership probabilities for the average values of the determinants are shown in Table 14.

Table 13. Range of variables

	Low	Average	High
Income (group)	1	**6**	10
Driving licenses	0	**1**	3+
Permit costs	20	**220**	620
Number of children	0	**1**	3
Distance to train station	0.4	**2.7**	28.7
Parking bays / household	0.19	**1**	9.67
POET / household	0	**0.2**	1
Urban Density	1	**1**	2

Table 14. Probabilities average values

P (0)	0.199
P (1)	0.721
P (2)	0.073
P (3+)	0.007

The outcomes of the high and low variations of the determinants are shown in Table 15. In this table you can compare how the determinants' ranges influence the probabilities of car ownership.

Table 15. Probabilities of low and high values

	Low				High			
	P(0)	**P(1)**	**P(2)**	**P(3+)**	**P(0)**	**P(1)**	**P(2)**	**P(3+)**
Income (group)	0.337	0.594	0.027	0.002	0.104	0.736	0.143	0.017
Driving licenses	0.863	0.118	0.018	0.001	0.040	0.400	0.396	0.164
Permit costs	0.165	0.742	0.084	0.008	0.279	0.663	0.054	0.005
Number of children	0.283	0.658	0.053	0.006	0.176	0.739	0.076	0.008
Distance to train station	0.224	0.703	0.066	0.006	0.182	0.738	0.074	0.007
Parking bays / household	0.366	0.591	0.040	0.003	0.201	0.714	0.078	0.007
POET / household	0.199	0.721	0.073	0.007	0.102	0.782	0.105	0.011
Urban Density	0.199	0.721	0.073	0.007	0.132	0.762	0.096	0.009

APPENDIX C

The Almere Pampus case is a use case of the XCARCITY program. Almere Pampus is a proposed neighbourhood in Almere which is still in its planning phase. To construct a population for the analysis a possible demographic scenario of Almere Pampus was used (Internal, confidential). From this possible demographic scenario 80 population groups were constructed. The assumptions that are made to create these groups are discussed in this appendix.

These are some of the assumptions made to create the population groups:

- **Small households** are expected to contain 1 or 2 people. 20% of the Dutch households are single person households and 50% are two person households (CBS, 2022a). Therefore, 40% of the small households will contain 1 person and *60%* will be 2 person households.
- **Driving licenses** are then the next division to create multiple groups. 80% of Dutch adults have a driving license (CBS, 2024a), so for example the group of two person households will be divided into three groups; 2 driving licenses (64%), 1 driving license (32%) and 0 driving licenses (0%). 50% of the population older than 75 years has a driving license, so for these groups the division will differ.
- **The household income** is divided in three categories in the potential scenario. This is the gross income of households, while the income variable in the analysis is the disposable income. Therefore the gross income will be multiplied by 0,59 for households under 75 years old and multiplied by 0,76 for older households, as these pay less taxes and premiums (CBS, 2022b). The groups are then compared to the groups in Table 2 to create inputs for the analysis.
- **The number of households' kids** in families will follow that of 1.5 as in the ODiN survey. That means that 2/3 of families will have 2 kids and 1/3 will have 1 kid. 3 children households will be neglected in the population. The parameter of 3 kids in a household lies between that of 1 and 2 kids, so this implementation is expected to be a good implementation of the amount of children.

With these assumptions 80 groups were created that are based on a possible demographic scenario of Almere Pampus.