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The impact of the built environment on car ownership in the Netherlands

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Abstract

This thesis discusses the effects of the built environment on car ownership in the Netherlands. Adding to existing literature this study also looks at individual's preferences towards cars. Firstly, previous literature is reviewed and discussed to look at what the effects of the built environment on car ownership are so far. Next, with the help of a self-administered survey sent out to households in the Netherlands, data has been gathered. Six models using OLS (ordinary least squares regression) were created with the number of cars in a household as the dependent variable. For some comparison a logistic regression has also been made. The results showed that households in the more rural areas tend to own more cars than households in very urban areas. Probably due to better public transport and having more activities nearby in urban areas. The preferences showed some unexpected signs. Most notably, a household where someone prefers to walk over taking the car owns more cars than a household where the car is preferred. This shows some evidence that preferences do not have a big influence on car ownership. Even though someone does not prefer a car they still might need it. Further analysis might be needed with a bigger sample size to confirm the found effects.

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1. Introduction

In 1885, the first modern automobile had been developed by Karl Benz. It was a simple three-wheeled vehicle which ran on gas and could only reach a speed of eight miles per hour. Since Benz's invention we have come a long way. Since then we have produced a huge number of cars, developed cars powered by other energy sources than gasoline such as batteries or hydrogen, and even developed self-driving cars. 125 years after the first modern automobile, in 2010, we reached 1 billion cars worldwide for the first time (OICA, 2017). This number consists of passenger cars and commercial vehicles in use worldwide. Dargay, Gately and Sommer (2007) projected that vehicle ownership will continue to increase in the upcoming years, especially for non-OECD countries with a high-income growth. China in particular will see a huge increase in vehicle ownership. According to Huo, Wang, Johnson and He (2007) China could have the largest amount of highway vehicles in the world by 2035.

It is safe to say that we can't imagine a life without motorized vehicles anymore. However, this dependence on cars also causes some problems for society. It already has some big effects nowadays, imagine the impact it will have on society if vehicle production will grow even bigger. One of the problems is the health risks that are caused by vehicles. It does not only have direct effects on health, such as traffic accidents. But vehicles also have indirect effects on health, such as obesity, cardiovascular diseases and damage inflicted by air pollution. Several studies showed that health risks are reduced when a mode shift from car to public transport or cycling occurs. Rojas-Rueda, Nazelle, Texidó and Nieuwenhuijsen (2012) for example estimated for Barcelona that 67.46 deaths will be avoided annually if travelers shift modes. Besides the health risks of traffic accidents, there are also some costs attached. Connelly and Supangan (2006) showed that for Australia road traffic crash casualties in 2003 cost roughly 2.3% of the gross domestic product. The World Health Organization (2004) states similar results. The costs of traffic accidents are approximately between 1% and 2% of a government's gross national product. Moreover, traffic accidents are the 11th leading cause of death, with over one million people killed annually.

Another negative effect from car use is pollution. According to IPCC (2014) the greenhouse gas emissions in 2010 are for 14% caused by transportation. Passenger cars are responsible for a large part of the pollution caused by transportation. For example, approximately 81.8% of land transport passenger-kilometers traveled in Europe is by passenger cars (Statista Research Department, 2020). Pollution is closely related to one more negative externality, namely congestion. Congestion has some negative impacts on society, for example vehicles use more fuel in a traffic jam since fuel is not being used efficiently (Treiber, Kesting & Thiemann, 2008). This inefficient use of fuel contributes to greenhouse gas emissions. Not only is congestion bad for the environment, it is also a waste of time and money, since people get stuck in traffic and thus productivity is lost. Congestion might also be a cause of more traffic accidents. A study done by Green, Heywood and Navarro (2016) on traffic accidents after a congestion charge had been introduced in London showed that traffic accidents were reduced in the area of the congestion charge and the adjacent areas. All in all, congestion has some serious negative effects on society.

There is much research done on solutions for the negative externalities of cars. As just discussed, Green, Heywood and Navarro (2016) have examined a possible solution for the increasing amount of car use. The solution they examined is the implementation of a congestion charge. For the case in London, this means that you are charged daily with a certain amount of money for driving a vehicle within the area that has been set as the charging zone. The government in Sweden also introduced a congestion charge in Stockholm in 2006 to examine the effects. Just like in London the congestion charge seemed to have a positive effect (Eliasson, Hultkrantz, Nerhagen & Rosqvist, 2009). Despite positive results, congestion charging also has some potential problems. Some people might be unhappy about the fact they have to pay extra to get to work, especially people who are already in the lower income classes. People might also be concerned about their privacy, since data could possibly be collected based on their location and time.

Another solution to tackle the problem of carbon emissions caused by vehicles is the use of gasoline taxes. Increasing the price of fuel and make it more expensive to consumers could possibly mean a decreased demand for fuel. Since it is increasing the price of using the car, people might change to other transport modes. Some studies on fuel taxes and its effect on fuel demand or on carbon emissions show that a fuel tax indeed has an effect. Sterner (2007) shows that a high fuel taxation policy leads to less demand for fuel. With respect to carbon emissions, according to Davis and Kilian (2011) vehicle emissions would decrease by approximately 1,5% in the US if the gasoline tax is increased with 10-cent per gallon. However, fuel taxation might not be the optimal solution for decreasing car ownership, since not all cars nowadays are as fuel dependent as they used to be. There are more electric vehicles than ever, and people might also just shift to diesel cars, since these are more fuel efficient than petrol cars.

Public transport is one of the transport modes available as a substitute for car use. However, public transport might not be as advanced in certain areas or even not available at all. This is why transit subsidies could help here and, in the end, reduce car use. Adler and Ommeren (2016) studied the so-called congestion relief benefit, which is basically the reduction of congestion due to public transport. They examined this effect by studying car speed during public transport strikes. They found that the congestion relief benefit does actually have a significant effect. This is also supported by Anderson (2014) who concludes that public transport systems actually have a much higher benefit on congestion relief than was previously found.

Every day, lots of people commute by car. However, you will see that most of them travel alone while this does not seem like the most efficient option. Less people per car means more cars on the road, which in the end leads to more traffic jams. Car sharing might be a good solution to this problem, especially for example to people who work at the same office but until now commute separately. According to a study conducted by Nijland and Meerkerk (2017) car ownership decreases by over 30% after their respondents started sharing cars as well as a decrease of kilometers traveled by car. This in its place has also led to a reduction of carbon emissions by the respondents. However, car sharing initiatives might lead to an increased car use for some individuals. Some carless people might consider sharing a car with a car owner.

The measures discussed above, such as gasoline taxes and congestion charging make owning a car relatively more expensive and might not seem like the optimal solution. However, if we want to solve the problems car use creates, we should limit car ownership, since car use and car ownership are often suggested to be related with each other. It seems that car use is higher on average in households that own one or more cars, than in households without a car (Dieleman, Dijst & Burghouwt, 2002). Nevertheless, car ownership takes different roles in various literature. Most of the time car ownership is used by researchers as an exogenous variable to explain car use (Schwanen, Dijst & Dieleman, 2002). While on the other hand it is also frequently used as an endogenous variable (Bhat & Guo, 2007). A few studies, however, combine these two methods and therefore car ownership takes on the form of a mediating variable between car use and built environment (Van Acker & Witlox, 2010; Ding, Wang, Liu, Zhang & Yang, 2017). This means that car ownership and built environment have a direct effect on car use. Furthermore, built environment also has an indirect effect on car use through car ownership. Sioui, Morency and Trépanier (2013) studied the effects of carsharing on car use. They discovered that households who are participating in a car sharing program, are less likely to use the car than households with one or more cars. All things considered, it can be assumed that car use and car ownership are related to each other and that owning a car can significantly increase car use.

In many planning initiatives over the last years, the relationship between travel behavior and urban form has been a key element. Travel demand can potentially be moderated by altering the built environment. Distance to the nearest public transport station, accessibility to certain areas, and the design of streets are some examples of elements used by urban planners. There is much research done regarding the built environment and its effect on travel behavior. Cervero and Kockelman (1997) for example, provided some justifications of why travel choices might be influenced by the built environment. They were the first to come up with the 3 D's, density, diversity and design. Destination accessibility and distance to transit were introduced later on by Ewing and Cervero (2001). In 2010, Ewing and Cervero (2010) conducted a meta-analysis on present built environment-travel literature up until 2009. It seemed that most studies over the years on this topic had similar results. Although individual built environment variables did not seem to have a significant impact on travel variables, some built environment variables combined could actually have quite a large effect.

The Netherlands is known to be one of the most bicycle-friendly countries in the world. This follows from the fact that it has a very flat landscape and it is a relatively small country, so distances between cities are not that big. Besides the geographical advantages, the Netherlands also has bicycle-friendly policies, planning and laws. However, we see that the number of cars is still increasing in the Netherlands. The number of passenger cars increased by approximately 1,9% in 2019 compared to 2018 (CBS, 2019). This shows us that although a bicycle is a very usable mode choice in the Netherlands, people are still buying cars. This might be explained by individual's preferences towards built environment and mode choice or habits regarding mode choice. These preferences and habits could also have played a role in residential choices of households.

The relationship between the built environment and travel behavior can be quite complex, since there are so many aspects to the built environment and to travel behavior. Travel behavior for example, can be defined by car ownership, travel mode choice, number of trips etc. While built environment can be defined different aspects such as distance to transit, land use mix, density etc. This study focuses on the relationship between the built environment and car ownership. This choice was based on the fact that car ownership is an important variable between attributes of the built environment and car use as shown by Van Acker and Witlox (2010) and Ding et al. (2017). And also, since car ownership in general seems to play an important role in society. We can't imagine a world without cars anymore and the negative externalities of cars are huge. Therefore, this paper aims to contribute to existing literature on the effects of the built environment on car ownership in the Netherlands and broaden the empirical research findings. The influence of the built environment on car ownership will be analyzed while also taking into account individual's preferences and characteristics. Therefore, the main research question of this paper is as follows:

What is the impact of the built environment on car ownership in the Netherlands?

There are many studies out there at the moment that investigate the relationship between the built environment and car ownership and many also account for residential self-selection. However, there are relatively few studies that have considered personal preferences which could influence the effect of built environment on car ownership. For example, individuals might just own a car not because they need to, but because they want to. One study that does implement preferences is a study by Cao, Mokhtarian and Handy (2007). They found in their cross-sectional model that when preferences are included in a model which explores the effects of the built environment on car ownership, the effects of the built environment become neglectable. However, this was not the case in their panel model. There is still much unknown on what the actual influence is of preferences in such a model. This study tries to broaden the knowledge on that topic.

In this study, car ownership will be described as the function of built environment characteristics while using socio-demographic variables as control variables. Car ownership being the dependent variable in this study and is described by the number of cars owned in a household. This research will mainly focus on using OLS (ordinary least squares regression) for analysis, but it will also use logit to compare some results. The data used in this study is collected by a self-administered survey send out to households in the Netherlands in the beginning of 2020.

Following this introduction, the existing literature will be reviewed. Next, the data and methodology will be covered. Followed by the discussion of the results. And finally, the conclusion and discussion will be given.

2. Literature review

This chapter analyzes and discusses the relevant literature on the built environment, residential self-selection, preferences and other relevant topics for this study. Lots of research has already been done in some areas of the built environment, but there are some topics that have only been touched a few times. First of all, the built environment in general will be shortly discussed. Next, some more in-depth topics on built environment and its effect on car ownership will be discussed.

2.1 Built environment

As previously discussed in the introduction, the built environment is likely to help reduce the negative externalities of car use. Since car use is considered to be related to car ownership, and car ownership can be influenced by the built environment. Van Acker and Witlox (2010) showed that car ownership and the built environment have a direct effect on car use. And also, the built environment has an indirect effect on car use through car ownership. So, it is important to understand how exactly the built environment can be used to alter individual's behavior.

2.1.1 The 'D' variables

So, what is the built environment actually, and how can it be measured? A short answer for this is that it is the space where individuals live, work and play. However, it covers much more than just that simple description. Urban design is a term often used when talking about the built environment. This usually refers to the process of designing a city and its physical features. How these physical features are placed within the city and how they appear to the public are very important for urban design. Design also often contains the characteristics of a street network (e.g. the number of intersections, average block size etc.). Next to design, land use is also an important element for the built environment. It is not very useful to place certain activities like stores all over the city. But it might be more convenient to place these all together in a certain area. The density of different activities should be right when considering land use. So, the way in which land is being used and in which activities are distributed over this area is something that should not be overlooked. Density in this case, is the variable of interest per unit of area. This could contain characteristics like population density, dwelling unit density, employment density etc. One could argue that denser areas are usually associated with lower rates of car ownership, since there is less space for parking facilities and such areas most often offer better public transport services. Something that should also be considered in land usage is the diversity of everything represented in a given area. A higher diversity in a neighborhood will most likely be associated with a lower probability of owning a car. A diverse neighborhood will most likely fulfill multiple needs for residents. For example, individuals in such a neighborhood will not have to go to other neighborhoods to do their groceries. Since multiple services are provided in that neighborhood there is less need to use a car, because walking and using a bicycle are also viable transport modes. Urban design, density, and diversity are three key elements in the theory behind the built environment. They were introduced back in 1997 by Cervero and Kockelman (1997) who called them the '3Ds' (Density, Diversity and Design). In their study they examined the effect of the '3Ds' on travel demand and came to the conclusion that although the elasticities were only modest to moderate, the 3Ds indeed have an effect on travel demand and should be considered in urban planning.

Later on, two other Ds were introduced, namely destination accessibility and distance to transit (Ewing & Cervero, 2001; Ewing, Greenwald, Zhang, Walters, Feldman, Cervero & Thomas, 2009). Destination accessibility is simply the easiness of reaching a destination. Although it is defined somewhat different in studies. In some studies, it refers to the distance to an economically important destination, such as a central business district. But in other studies, it might be considered as the number of attractions available in a certain radius (e.g. number of jobs within a one-hour drive). This description of destination accessibility is referred to as regional accessibility by Handy (1993). Destination accessibility might also be local accessibility. In this case, accessibility is referring to the distance from home to convenience establishments (e.g. supermarkets). Handy distinguishes these two types of definitions by defining regional accessibility as distance to large regional retail centers and local accessibility as distance to smaller 'local' shops. The large regional retail centers attract customers within a bigger range than the local shops. Distance to transit is simply an average of the distance from residences or workplaces to the nearest transit station. It can also be referred to as the density of transit stops per unit of area.

2.1.2 The effect of built environment on car ownership/use

One commonly researched topic regarding the built environment is the effect it has on travel behavior and/or car ownership. The main interest of this study is the effect on car ownership, so it is important to understand how exactly car ownership is influenced by the built environment, and what other variables we have to take into account. In most studies that are going to be discussed next, car ownership is described as the number of cars within a household. And it takes on the form of a continuous variable. In this study car ownership will be addressed the same.

As previously discussed, there has been an increasing interest in the relationship between land use and transportation. This is motivated by the possibility that with the help of policies the built environment can be used to manage an individual's travel behavior. And since vehicles are the cause of many negative externalities, this possibility of changing individual's travel behavior will be of use to decrease car ownership and thus car use.

In the past, a few studies have already tried to include the effects of urban physical features in their models when trying to explain car ownership. Holtzclaw (1994) for example, tried to estimate what the effects from different neighborhood characteristics were on car usage. Holtzclaw used residential density, transit accessibility, neighborhood shopping and pedestrian accessibility in his study to measure a neighborhood's features. This is much in line with the 5Ds introduced a few years later by Cervero and Kockelman (1997), Ewing and Cervero (2001) and Ewing et al. (2009). Other studies before Holtzclaw's study have also suggested that household density explains variations in car usage. When density increases, car ownership decreases. However, he extends these results by analyzing multiple different metropolitan areas, whereas the previous studies only analyzed one metropolitan area. Hereby, the results are more significant. It is also concluded from this study that accessibility of transit is significant as well as an explanatory variable for car usage. The other variables, however, were found not to be significant when also considering density and transit accessibility in the models. Cervero and Gorham (1995) also looked into the effects of neighborhood characteristics on car use, by comparing two different types of neighborhoods, transit-oriented and car-oriented. Transit-oriented neighborhoods were defined as neighborhoods which are primarily gridded with mainly four-way intersections, and which are built near a transit station. Car-oriented neighborhoods were defined as neighborhoods without transit stations in the surrounding area, and with random street patterns. The transit-oriented neighborhoods showed to have more trips by foot, bike and individuals shared their rides more than in car-oriented neighborhoods. These results are similar to the results of Baldwin Hess and Ong (2002) in their study for Portland, Oregon. They found that traditional neighborhoods, which are neighborhoods with better pedestrian connectivity and transit accessibility, are more likely to have individuals use alternatives to cars. The more homogeneous land use becomes, the more the probability of owning a car decreases. However, it is also acknowledged that residential self-selection might influence the results.

Soltani (2005) used travel data from the Adelaide Metropolitan region to explain the impacts of household and urban features on car ownership. He used socio-economic factors and elements of the built environment in his model to explain car ownership. Soltani showed that the most important factors for car ownership are income, household size and type, dwelling density, and land use mix. Individuals living in areas where public transport services were higher, were also less likely to own a car. He also found a positive relationship between owning a vehicle and neighborhoods with less pedestrian-friendly street designs. Thus, individuals living in the suburbs tend to own more cars than individuals living in pedestrian-friendly neighborhoods. Dwelling density and land use mix are the two built environment elements that were shown to be significant in Soltani's models. When dwelling density increases, car ownership decreases. This might be due to less parking spaces in the area. Soltani also acknowledges residential self-selection and claims that this problem should be investigated more. The results from his study show that although the built environment is important in a household's decision to own a car, it is not the only factor (socio-economic factors are also important determinants).

Zegras (2010) explored the relationship between the built environment and car ownership in the capital of Chile, Santiago. He considered both relative location of residents and the neighborhood characteristics. At the time of this study Santiago was a rapidly motorizing and developing city. This probably means that individuals are choosing whether to buy a car or not based on their income, and not so much on their neighborhood characteristics. Zegras finds out that income indeed plays the number one role in owning a car or not. However, he also finds a very strong relationship between the built environment and car ownership. This effect applies to a household's decision of owning a car and the effect gets stronger whenever a household is choosing to own even more vehicles. Zegras did not take residential self-selection into account as some results might indicate. Living in an apartment has a negative effect on the likelihood of owning a car, same counts for dwelling unit density. This might be due to less space for vehicle parking in such areas. And as just mentioned, because of self-selection, individuals might have moved to an apartment because they don't have the need to own one or more vehicles in the first place.

2.1.3 Car ownership as a mediating variable

In some studies car ownership is taken as a mediating variable between the built environment and travel behavior. In this case, car ownership as well as the built environment both have a direct effect on car use. In addition, built environment has an indirect effect on car use through car ownership. This means that these studies also analyze the effect of the built environment on car ownership. And what can also be concluded from this is that car ownership and car use are very much related to each other. Ding, Wang, Liu, Zhang and Yang (2017) analyzed the effects of the built environment on travel mode choice with car ownership as a mediating variable. They found that the built environment has a significant effect on car ownership, even after controlling for socio-demographic factors. A higher population density is associated significantly with a lower probability of owning a car. The same counts for a higher employment density. The results regarding land use mixture, however, show contrary results to other studies and what should be expected. It is positively associated with car ownership, which implies that more mixed land use increases car ownership. This is a strange result, since it should be expected that if land use mixture increases, origin and destination get closer to each other. And thus, walking and cycling become more viable options. However, this result can be explained by the average cost per trip decreasing since origin and destination are closer to each other. Therefore, making owning a car more attractive. The results of connectivity and accessibility indicate that neighborhoods with a good connectivity and accessibility are more likely to have less cars per households. And also, the further the distance to transit, the more likely individuals are to own a car.

Van Acker and Witlox (2010) tried the same as Ding et al. (2017) and conducted research on car ownership as a mediating variable between the built environment and travel behavior with data from travelers in Belgium. They found that car ownership is indeed a mediating variable between the built environment and travel behavior and should be considered when studying this relationship. This indicated that the built environment does have an effect on car ownership when also controlling for other variables, such as socio-economic and demographic variables. Van Acker and Witlox (2010) also found that neighborhoods with a higher density and a higher mixed land use are associated with lower car ownership per household.

Although there are several studies that point out that the built environment has a significant influence on car use/ownership, there are also some studies that indicate it only has a moderate effect. For example, Stead (2001) analyzed the relationships between the built environment, socio-economic variables, and travel behavior with data from travelers in Britain. Socio-economic variables consistently describe the variation in travel behavior more than the built environment variables. For example, socio-economic variables explain up to 55% of the variation, while the built environment variables only explain up to 27% (Stead, 2001). Some similar results are also found by Simma and Axhausen (2003) who conducted research on accessibility, personal characteristics and travel behavior. Their results indicate that car ownership is mainly influenced by personal characteristics such as gender. However, the built environment did show to have a moderate effect on car ownership and should not be neglected.

Nonetheless, based on most studies, it seems that the built environment still has a significant influence on car ownership. The studies that showed only a moderate effect, also acknowledged that land use planning might still have a significant effect on car ownership. Still, there might be some underlying causes that influence this relationship. For example, in the past years there has been a growing body of literature on residential self-selection and the built environment. Individuals might choose to live in a certain neighborhood according to their needs and preferences.

2.2 Residential self-selection

One of the first papers which studied the effects of built environment on car ownership whilst also controlling for residential self-selection was conducted by Bhat and Guo (2007). They used data of residents in the Alameda County in the San Francisco Bay area. They focused their study on car ownership levels and residential choice of individuals. Before this study it was assumed by most research that the relationship between built environment and car ownership was a one-way flow. Individuals move themselves to certain neighborhoods, and then the built environment influences their behavior with respect to owning a car. However, as already discussed before, this is most likely not the case. Most individuals move to a neighborhood that already fits their preferences. And thus, if this is not taken into account when analyzing the relationship between the built environment and car ownership, the results might lead to misinformed policies. Bhat and Guo (2007) controlled for self-selection by controlling for both demographic and unobserved household factors. They found that the built environment influences choice of residence and car ownership. Both built environment and demographics have an influence on car ownership. The effect of demographics, however, is stronger. Regarding residential self-selection, household income has the biggest influence. Households with a low income tend to live in neighborhoods with a higher density where costs of traveling are lower. A surprising result of Bhat and Guo's study is that after controlling for residential self-selection, a model that examines the influence of built environment characteristics on car ownership is adequate enough to explain car ownership.

With the help of both cross-sectional and quasi-panel research, Cao, Mokhtarian and Handy (2007) examined the relationship between the built environment and car ownership. They used data from residents in Northern California for their research. They find that socio-demographics are the most dominant in determining car ownership. The built environment does influence car ownership as well, but these effects are only marginal. Spaciousness is one of the characteristics which stands out from the results, whereas it has a positive relationship with car ownership. The more space someone has in their neighborhood, the more likely it is that they own one or more cars. The density of business types in the neighborhood has a negative relationship with car ownership. This could be explained by walking and cycling becoming a viable option to go from origin to destination since there are more businesses in the area. Similar results are found by Cao and Cao (2014) who conducted research on the influence of light rail transit, the built environment, and residential self-selection on car ownership in Minneapolis-St. Paul metropolitan area. Car ownership is affected by residential self-selection. While some neighborhood characteristics, such as spaciousness and density only have a marginal effect on car ownership. Again, more space increases car ownership, most likely since there is more room for parking. Although some results might be due to residential self-selection, Cao and Cao still acknowledge that neighborhood design should be considered in policymaking.

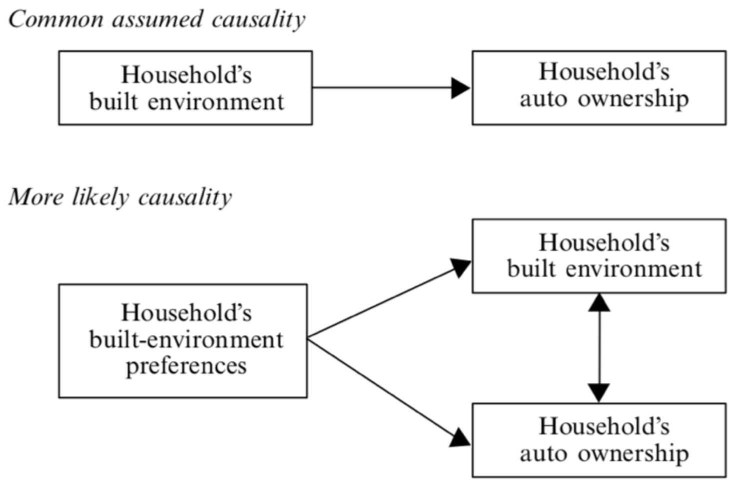
Cao, Mokhtarian and Handy (2009) examine residential self-selection by analyzing 38 studies and comparing their results. They also discuss the nine methodological categories these studies fall into and what the methods pros and cons are. They concluded, based on the results from the 38 studies, that the built environment does have an effect on travel behavior even after accounting for self-selection. It could be stated that if an individual who prefers walking moves to a neighborhood which encourages walking, this individual will most likely walk more.

This seems somewhat obvious. However, from the results we can also state that if an individual who prefers using the car moves to the same neighborhood, this individual is also likely to walk more.

2.3 Preferences

It seems most likely that individual's preferences and attitudes towards the built environment and car ownership play a role as well in this topic. Let's say an individual prefers the car over walking, because he likes the feeling of driving. This preference towards owning a car might confound the relationship between the built environment and car ownership. The same counts for preferences for certain built environment characteristics. The study previously discussed by Cao et al. (2007), also accounts for the preferences and attitudes of their respondents. What is most often assumed, is that the built environment has a direct effect on car ownership. However, it is more likely that individuals have preferences and attitudes, which also influence their decisions. Cao et al. (2007) used this figure to simply describe the relationships between these factors.

Figure 1 (Cao, Mokhtarian & Handy, 2007)



They created a survey for their study in which they asked the respondents for their neighborhood characteristics, preferences, attitudes towards travel, and finally some questions to find the sociodemographic variables. From their cross-sectional model appears that the built environment influences car ownership. However, when they include preferences in their model, these effects of the built environment become neglectable. Nevertheless, in their panel model preferences and attitudes don't change the outcome. And they point out that there is actually a causal relationship. The changes in attitudes were associated with changes in car ownership. If an individual perceived their neighborhood to be more spacious over time, car ownership also increased. And a higher density is related to a decrease in car ownership. They concluded that preferences for neighborhood characteristics and car ownership can be influenced over time, and thus urban design policies could possibly be used to alter car ownership.

2.4 Socio-economic and demographic factors

Empirical studies which analyze the relationship between the built environment and car ownership should also take socio-economic and demographic characteristics into account, since these characteristics have been shown to have an important impact on car ownership as well. Otherwise, the results will not be of significant use. In most studies previously discussed, it is found that socio-economic and demographic factors have a dominant influence on car ownership (Cao et al., 2007; Ding et al., 2017; Bhat & Guo, 2007. Probably one of the most important factors that influences car ownership decisions is income. Dargay (2001) examined the effect of income on car ownership and gave some insight on what happens when income increases or decreases. He points out that the relationship between income and car ownership shows signs of hysteresis. In this case this means that changes in car ownership are greater when income increases, than when income decreases. This can be explained by individuals getting used to their car when they have bought one. After a while, your car becomes a necessity. Next to income, household composition also seems to be one of the most important factors influencing car ownership. It seems obvious that factors such as the number of children or the number of people with a driver's license in a household have an impact on the number of cars in a household. Oakil, Manting and Nijland (2016) conducted research on young households in the Netherlands and what influenced their car ownership decisions. They concluded that household composition is indeed of importance when explaining car ownership. Car ownership is lower for singles than for couples. And households consisting of two parents and one or more children living at home are the group most likely to own a car. Various papers also examined the influences of the age of the household head on car ownership. According to Eakins (2013), when a household head's age is higher, it is more likely for that household to have more than one car. Similar results are found by Dargay (2002). Lastly, gender also seems to play a role in car ownership. Most often men are known to have more desire for a car than women. Matas and Raymond (2008) support this claim by showing that a household with a male head is more likely to own one or more cars than a household with a female head.

2.5 Table of variables from previous studies

In table 1, a summary of the most common variables influencing car ownership from previous research is given. The variables are shortly described and the expected sign/effect of the variable on car ownership is given. For example, if a variable has a "-" as an expected sign, an increase in this variable is associated with a decrease in car ownership.

Table 1. Variables influencing car ownership

Variables	Description	Expected sign
Density (residential density or employment density)	The variable of interest per unit of area	-
Design (urban design)	The characteristics of the area/neighborhood	-
Diversity (land use mix)	The extent to which a certain area provides a diverse range of activities	-
Destination accessibility	The ease of access to trip destinations	-
Distance to transit	The distance of a household to the nearest transit station	+

Neighborhood preference on accessibility	The extent to which an individual prefers a good accessibility in a neighborhood	-
Neighborhood preference on outdoor spaciousness	The extent to which an individual prefers spaciousness in the neighborhood (e.g. more parking supply)	+
Preference towards distance to transit	The extent to which an individual prefers to live close to a transit station	-
Preference towards car	The extent to which an individual is dependent on a car	+
Safety of a car	The perceived safety of a car by an individual	+
Household income	The average income of a household	+
Household size	The number of people within a household	+
Household composition	The composition of a household (e.g. singles, couples, parents, etc.)	+
Number of driving licenses	The number of driving licenses within a household	+
Age	The age of the household head	+
Gender (male)	The gender of the household head	+

3. Data and Methodology

In this chapter, the data and methodology used for this study will be discussed. First the dataset used will be discussed. Next, hypotheses will be formulated. Then, a description of the variables will be given. And finally, the methodology will be discussed.

3.1 Dataset

The dataset in this study consist of two sources. Most data came from a self-administered survey send out in the beginning of 2020 to households living in the Netherlands. Furthermore, some neighborhood statistics were retrieved from Statistics Netherlands (CBS). For example, the urban form and the population density of the respondent's neighborhoods were collected.

3.2 Survey

After the survey had been created it was distributed by an anonymous link where the receivers of the link were also free to forward the survey to other people. The questions in the survey were inspired by surveys used in previous research. It consisted of 20 questions where respondents are asked about their preferences towards certain characteristics of a neighborhood, preferences towards car use, and some socio-demographics. For the first question, respondents were asked to imagine a situation in which they are looking for a new place to live. Next, they had to rate the importance of six characteristics about their new potential neighborhood. For example, the first statement was that there has to be a supermarket within a 1-kilometer radius. The respondents could answer based on a four-point scale from 1 ('not important at all') to 4 ('very important'). These preferences can be used to support literature about how residential self-selection explains correlations between car ownership and the built environment. The survey continues with the question if the respondent owns a car. This way, data from respondents without a car, which are not of interest in this study, will be easily removed. Next, the respondents were asked to choose between two means of transportation. They were asked to imagine a situation where both options were feasible. For example, if the respondent had to choose between a car or a bike it is not feasible if the distance would be enormous. With these questions, the preference towards a car could be examined. For the second-last part of the survey, respondents were questioned about their car dependency. For example, if they could imagine a life without a car within the next 5 years. The last part consisted of some socio-demographic questions. These variables include number of people within the household, household composition, number of cars within the household, number of people with a driver's license within the household, age, gender, and household income. The respondent's four-digit zip code was also asked in the last question to be able to get data from CBS and complete the dataset.

The survey ended up getting 191 responses in total. However, 24 responses were removed since they were not usable. These responses were not fully completed and thus not usable for analysis. All in all, the number of respondents' data had been collected from is 167. This is a rather small sample size, which decreases the statistical power and could lead to some results not being significant. However, the results can still be of use.

3.3 Hypotheses

In this study the effect of the built environment on car ownership in the Netherlands will be analyzed while also taking preferences into account. Firstly, the effect of certain neighborhood characteristics will be analyzed. It is shown in previous studies that a better land-use mix, or in other words a higher diversity, in a neighborhood has a negative effect on car ownership. This can be explained by residents having everything they need nearby and thus not needing a car for their daily activities. Van Acker and Witlox (2010), for example showed this relationship between land use mix and car ownership. The built environment characteristics used in this study are urban form, population density, and whether there are certain activities in a 1km radius. These activities consist of supermarkets, primary schools, sports grounds, and public parks. These activities will simply be called "daily activities". It is expected that if the daily activities are within the 1km radius, this will have a negative effect on household car ownership. Therefore, the first hypothesis is as follows:

Hypothesis 1: Having daily activities within a 1km radius has a negative effect on household car ownership.

The second characteristic that seems to be important in car ownership is distance to transit. The greater the distance between a residence and a transit station, the more likely a household is to own one or more cars (Cervero & Gorham, 1995; Ding, et al., 2017). In this study data has been collected on whether there is a train station within a 5km radius. It is expected, according to previous research, that if there is a train station within a 5km radius households are more likely to own less cars than households where there is no train station present within a 5km radius. And thus, the second hypothesis will be:

Hypothesis 2: Having a train station within a 5km radius has a negative effect on household car ownership.

According to previous research, urban form and car ownership are related to each other. This relationship means that people living in more urban areas, and thus areas with a higher density, are less likely to own a car than people living in rural areas (Ding et al., 2017; Van Acker & Witlox, 2010). This could be explained by residents having all the daily needs in a close proximity and thus not needing a car. Urbanity in this study is described as to what extent a neighborhood is urban/rural. What is expected is the more urban a neighborhood, the more likely households own less cars. Therefore, the third hypothesis is as follows:

Hypothesis 3: A household living in a very urban area owns less cars than a household living in a very rural area.

The built environment seems to have a significant influence on car ownership, which is also shown by various studies (Bhat & Guo, 2007; Cao, Mokhtarian & Handy, 2009). However, is this still the case when the preferences towards cars of residents are taken into account. It seems to make sense that if a household prefers the car over other transport modes it will own more cars than a household that doesn't prefer the car. For this reason, the fourth hypothesis is formulated as follows:

Hypothesis 4: Preferences towards car use have a positive effect on household car ownership.

Cao et al. (2007) showed that when residential preferences are taken into account, actual land use mix in the neighborhood becomes insignificant when explaining the effect of the built environment on car ownership. If this is also the case in this study, it could lend some support to the theory that residential self-selection explains the relationship between car ownership and the built environment. Therefore, the fifth hypothesis is as follows:

Hypothesis 5: When taking preferences towards neighborhood characteristics into account the influence of neighborhood characteristics on car ownership is insignificant.

3.4 Description of the variables

The dependent variable used in this study is car ownership. Which in this study is described as the number of cars owned in a household. Therefore, in the survey, respondents were asked to report the number of cars available in their household. This variable is measured in the number of cars within a household and is called *hh_Car*. The number of cars ranges from 0 to 4, where 4 is equal to 4 or more cars. Since owning 4 or more cars is not very common in a household, this range had been chosen. Normally, *hh_Car* could be seen as an ordinal variable, since the values 0, 1 and 2 are the most frequent. However, in this study *hh_Car* will be used as a continuous variable so that OLS (ordinary least squares regression) can be used. The OLS is preferred over for example an ordered logit model, since it is relatively easy to analyze the data and it produces solutions that are easily interpretable. Also, the results given will be more or less the same as with an ordered logit model if there are more than 4 categories and if the distribution looks normal. *Hh_Car* has 5 categories, however it is not really normally distributed as can be seen in table 2. The values 1 and 2 have a frequency of 69 and 64 respectively. These two values together already amount up to 133 out of 167 in total. Another limitation is that the coefficients given by OLS are less meaningful. Since in real life the number of cars in a single household cannot increase with 0.5, while this could be the coefficient given by OLS.

Although results given by the OLS might be similar to a logit model, it is still interesting to take a look at those results. Hence, one model in this study will use car ownership as a binary variable, whether a household owns a car yes or no and a logistic regression will be used to analyze the data.

Table 2. Distribution of the dependent variable household car ownership (*hh_Car*)

Number of cars per household	Frequency	Percent	Cumulative
0	19	11.38	11.38
1	69	41.32	52.69
2	64	38.32	91.02
3	10	5.99	97.01
4 or more	5	2.99	100.00
Total	167	100.00	

The independent variables are classified into four groups: neighborhood characteristics, neighborhood preferences, preference towards car use, and socio-demographics. The data for these variables were collected by the survey and by using CBS. The remainder of this segment will present the four groups of variables.

3.4.1 Neighborhood characteristics and neighborhood preferences

In the survey respondents were asked to indicate how important certain neighborhood characteristics are for them if they were looking for a new place to live. They could choose between the following answers: not important at all, not important, important, and very important. This way, neighborhood preferences could be found out per respondent. The variable names for these preferences are: *Imp_Sup*, *Imp_School*, *Imp_Sport*, *Imp_Park*, *Imp_Train*, and *Imp_Parking*. All variables have been summarized in table 1 in Appendix A, where a short description and the numerical values are given. Next, data from the CBS had been collected on the actual neighborhood characteristics. The variable names for these characteristics are as follows: *km_Sup*, *km_School*, *km_Sport*, *km_Park*, *km_Train*, *num_Sup*, *num_School*. The variables starting with ”*km”* are explained by whether there is a certain activity available within a 1 kilometer radius. However, for the variable *km_Train*, a 5 kilometer radius is used, since the data provided by the CBS only had this information. It also sounds more reasonable to use this bigger radius, since a train station is something that is less common than a supermarket. Moreover, it seems that people are willing to travel a larger distance to go to a train station then to a supermarket. *Num_Sup* and *num_School* represent the number of supermarkets and primary schools there are available within a 1 kilometer radius. When comparing the actual neighborhood characteristics of respondents to their neighborhood preferences it indicates how well their current neighborhood meets their preferences.

The last three variables on neighborhood characteristics that were collected from the CBS are: *Urban*, *address_Density*, and *pop_Density*. *Urban* represents the urban form of a household. There are five categories to specify what urban form a neighborhood has. Namely, very urban, urban, moderate urban, rural, and very rural. This classification is based on address density in a neighborhood. The address density is the average number of addresses per km^2 within a 1 kilometer radius. Very urban means more 2500 or more addresses per km^2, urban 1500 to 2500 addresses per km^2, moderate urban 1000 to 1500 addresses per km^2, rural 500 to 1000 addresses per km^2, and rural less than 500 addresses per km^2. Since *Urban* and *address_Density* basically mean the same, *address_Density* will be left out of analysis. *Pop_Density* represents the population density in the neighborhood. It is measured by dividing the number of residents by the land area of the neighborhood.

3.4.2 Preference towards car use and car dependence

To measure the preference towards car use, the respondents were asked three questions in which they had to choose between two options. Each question, one of the two options was the car. They were asked to imagine a situation where both options were feasible modes of transport. With these questions, the preference of using a car over other modes can possibly be measured. For example, imagine that someone is going to a friend of theirs who lives only 1 kilometer away and has the option to take a bike or the car. If this person still decides to take the car it can be assumed that this person has a preference for the car. Since biking is a very viable option in this case. The three answers will be combined to make a new variable for preference towards the car in a whole (*Pref_Car*).

The survey also had two questions on car dependence or willingness to live with less or no cars. The respondents were asked to look at the next 5 years of their life and if they were willing to live with one car less in their household (if they owned two or more cars). The second question was if they were willing to live without a car. Willing to live without a car if someone owns a car at the moment is a very big change in their live. This probably means that they are not that dependent on a car, which in its place could relate to the number of cars in their household.

3.4.3 Socio-demographics

Finally, the survey also contained some socio-demographic questions that may help explain car ownership in households. Also, if the effect of the built environment on car ownership is analyzed, it is important to control for these variables. The list of socio-demographic variables includes *Gender*, *Age*, *hh_Pers*, *household*, *hh_License*, *hh_*Inc, and *Zip*. *Age* is divided into six categories: 18 to 25, 26 to 35, 36 to 45, 46 to 55, 56 to 65, and older than 65. Furthermore, *hh_Pers* indicates the number of people in a household, *hh_License* represents the number of people with a driver's license within a household, and *hh_Inc* is the household income. Household income is divided into four groups: less than modal, modal, higher than modal, and the option where respondents preferred not to answer. Modal income in the Netherlands in 2020 is approximately €36,500 gross per year. The last variable *Zip* (Zip code) was used to gather data from CBS about the respondent's neighborhoods. So, this variable is not of use in the analysis.

Some descriptive statistics of the most important variables can be found in Appendix A. For the continuous variables the mean, the standard deviation, the minimum, and the maximum can be found. And for the categorical variables the frequency is presented. Furthermore, some tables are given where the dependent variable *hh_Car* is presented with some important independent variables. This way, some quick links between variables can already me made.

3.5 Methodology

In most previously discussed studies car ownership is defined as the number of cars in a household. Also, in the survey the respondents were asked to give the number of cars owned in their household. Owning zero cars in a household only had a frequency of 19 out of 167 responses. Which might be on the low side for an analysis where car ownership is described as owning a car yes or no. Therefore, in this study the same definition is used, namely as the number of cars owned in a household. As previous studies have shown, the probability of owning a car is mainly a function of socio-economic variables and built environment elements. And thus, it can be described as a function of variables such as income, household size, land-use mix, urban form etc. This research is focused on the effects of the built environment on car ownership while also taking preferences into account. Hence, the function will consist of built environment characteristics while using socio-demographic variables as control variables. To estimate the effects of the built environment on car ownership this study will mainly use OLS (ordinary least squares regression). But also, one model using a logistic regression will be made to compare some results.

Some data in the dataset was not of use for the analysis and had to be emitted. In the survey, respondents were allowed to not answer certain questions such as their income. This information is somewhat private, and some people don't intend to share this kind of private information. For the variable *hh_Inc* the value 3 equaled "prefer not to answer". And for *Gender* the value 2 equaled "prefer not to answer". Furthermore, for the variable *Car_Less*, the value 2 indicated that the question did not apply since the respondent did not own more than one car. These values, which cannot be used in analysis have been changed to missing values.

Since some variables are categorical variables, dummy variables had to be created in order to interpret the results. This is the case for the following variables: *Imp_Sup*, *Imp_School*, *Imp_Sport*, *Imp_Park*, *Imp_Train*, *Imp_Parking*, *Age*, *household*, *hh_Inc*, and *Urban*. The reference categories for the dummy variables are as follows:

- For all the "*Imp_*" variables = the first value (not important at all)
- Age = 18-25 years old
- Household = single-person household
- Household income = Less than modal
- Urban form = very urban

To test for multicollinearity, a Pearson correlation matrix is made. This matrix can be found under table 15 in appendix B. If multicollinearity is the case, this means that there are very high intercorrelations among independent variables. If this problem is not solved, the data might not be reliable. The matrix does not show any correlation that should be a problem. The highest Pearson correlation coefficient (0.9118) is between *hh_Inc* and the dummy variable of income, *income 3*. This seems to be the case for a few other dummy variables and their normal variable. However, this will not cause any problems in the analysis, since only the dummy variables will be used.

The models used in this study start with the number of cars in a household as the dependent variable. For each hypothesis a different model with different independent variables is presented. Also, the models are being expanded with each hypothesis, meaning that one or more independent variables will be added every time. In the end, this will lead to a complete model. Below, the economic models for each hypothesis are presented.

Hypothesis 1:
hh_Car = f(Gender, Age, hh_Pers, household, hh_License, hh_Inc, km_Sup, km_School, km_Sports, km_Park)

Hypothesis 2:
hh_Car = f(Gender, Age, hh_Pers, household, hh_License, hh_Inc, km_Sup, km_School, km_Sports, km_Park, km_Train)

Hypothesis 3:
hh_Car = f(Gender, Age, hh_Pers, household, hh_License, hh_Inc, km_Sup, km_School, km_Sports, km_Park, km_Train, Urban, pop_Density)

Hypothesis 4:
hh_Car = f(Gender, Age, hh_Pers, household, hh_License, hh_Inc, km_Sup, km_School, km_Sports, km_Park, km_Train, Urban, pop_Density, Pref_CarBike, Pref_CarPT, Pref_CarWalk, Car_Less, Car_No)

Hypothesis 5:
hh_Car = f(Gender, Age, hh_Pers, household, hh_License, hh_Inc, km_Sup, km_School, km_Sports, km_Park, km_Train, Urban, pop_Density, Pref_CarBike, Pref_CarPT, Pref_CarWalk, Car_Less, Car_No, Imp_Sup, Imp_School, Imp_Sport, Imp_Park, Imp_Train, Imp_Parking)

Hypothesis 5 (without preferences towards car use)
hh_Car = f(Gender, Age, hh_Pers, household, hh_License, hh_Inc, km_Sup, km_School, km_Sports, km_Park, km_Train, Urban, pop_Density, Imp_Sup, Imp_School, Imp_Sport, Imp_Park, Imp_Train, Imp_Parking)

For the logit model the dependent variable *hh_Car* needed to be changed to a binary variable. The variable is renamed to *hh_Car_bin* to make it clear that from that moment on it is a binary variable. In table 3 below the distribution is given. As can be seen in table 3, the frequency of not owning a car is only 19, which is quite low compared to owning a car. This could lead to some problems analyzing the data since there is not much variability in the dependent variable.

Table 3. Distribution of the dependent variable household car ownership as a binary variable (*hh_Car_bin)*

Owns a car yes or no **0 = no** **1 = yes**	**Frequency**	**Percent**	**Cumulative**
0	19	11.38	11.38
1	148	88.62	100.00
Total	167	100.00	

4. Results

In this chapter the results for each model made for the hypotheses will be discussed. The overall results will also be treated. As mentioned in the previous chapter, this study builds OLS models for each different hypothesis to investigate the relationships between the variables. The economic model for each hypothesis will be given and after that the results and interpretation will be discussed.

4.1 Hypotheses testing

Another problem that can be encountered is if one of the models suffers from heteroskedasticity. If a model suffers from this, it means that there is a systematic change in the spread of the residuals and because of this there is a chance the results cannot be trusted. To test for heteroskedasticity in the models the Breusch-Pagan test was used. The results of this test can be found in appendix B, under table 16 to 21. The results show that model 4 suffers from heteroskedasticity, since p=0.000. To control for the heteroskedasticity in this model, the regressions are estimated with robust standard errors.

4.1.1 Daily activities

For the first hypothesis the effect of having daily activities nearby on household car ownership is being investigated. Daily activities in this study are defined by supermarkets, primary schools, sports grounds, and public parks.

Hypothesis 1: Having daily activities within a 1km radius has a negative effect on household car ownership.

This hypothesis is tested by trying to explain the number of cars in a household with having daily activities within a 1km radius, while also controlling for socio-demographic variables. The regression output can be found in appendix C, in table 22. All variables except for *hh_License*, *age2*, *age3*, *age4*, *age5*, and *age 6* were found to be insignificant. The model shows that if the number of driver's licenses in a household increases with 1, the number of cars owned will increase with 0.726. It makes sense that the number of driver's licenses in a household has a positive effect on household car ownership, since most people buy a car within the next few years after getting their license. *Age* also shows some expected results. People aged between 26 and 35 own 0.867 (significant at the 1% level) more cars than people aged between 18 and 25. People between the age of 18 and 25 might not have enough money yet to buy a car. They are possibly still studying or just started at a new job. That is probably why all the other age groups own significantly more cars than the youngest age group. The other variables being insignificant could be because of the small sample size. This does not mean that there is no relationship at all. Therefore, the results could still be of use. The correlations of daily activities with household car ownership, except for *km_Sports*, are as expected. Households having a supermarket, a primary school, and a public park within a 1km radius have 0.320, 0.485, and 0.385 fewer cars per household than households without these daily activities nearby. This makes sense, since having more daily activities and necessary facilities nearby means that owning a car is less needed. Households having a sports ground nearby however have 0.136 more cars per household than households with no sports ground nearby.

All in all, the first hypothesis is rejected. Although three out of four variables show the expected effect, they are all insignificant.

4.1.2 Distance to transit

Hypothesis 2: Having a train station within a 5km radius has a negative effect on household car ownership.

The model for this hypothesis is almost the same as the first model. The only thing that was added is the variable *km_Train*. This variable indicates having a train station within a 5km radius. The regression output for this model can be found in appendix C, table 23. The results are somewhat the same as the previous model, as expected since only one variable has been added. Again, most variables are insignificant, except for the age dummies, *hh_License*, and *km_School*. This time having a school within a 1km radius is significant (at the 10% level). A household that lives near a primary school owns 0.522 fewer cars than a household with no primary school nearby. This result is as expected, since a primary school is a necessity for parents with young kids. If a school is too far away, they might need a car to bring their kids to school. This is also partly supported by the data itself. As can be seen in table 4 down below, the frequency of households with the most cars is for couples and couples with kids. Although the other daily activity variables including *km_Train* are insignificant. They do show the expected correlation according to the literature (except again for *km_Sports*).

In short, hypothesis 2 is rejected. Having a train station within a 5km radius does show the expected correlation, but the result is not significant.

Table 4. Number of cars owned by each household composition

	Household composition				
Number of cars per household	**Single**	**Couple**	**Couple with kids**	**Single parent with kids**	**Total**
0	11	2	5	1	**19**
1	15	28	22	4	**69**
2	2	29	32	1	**64**
3	0	9	9	0	**10**
4 or more	0	3	3	1	**5**
Total	**28**	**61**	**71**	**7**	**167**

4.1.3 Urban form

Hypothesis 3: A household living in a very urban area owns less cars than a household living in a very rural area.

To test this hypothesis urban form and population density had been added to the model. Since urban form consisted of five categories a dummy variable had been created and added. The base category is *urbanity1* (very urban), so the results of *urbanity2* to *urbanity 5* are with respect to the base category. The regression output is presented in appendix C, table 24. Again, as in the first two models, the age dummies and *hh_License* are significant with approximately the same coefficients. Regarding the urban form dummies only *urbanity5* (very rural) is significant at the 5% level. The effect is in line with the expectations and literature. A household that lives in a very rural area owns 1.001 more cars than a household that lives in a very urban area. Although the other urban form dummies are insignificant, they show the same correlation as what was expected. As previously explained in the literature review, this is probably due to the density of activities and necessary facilities in a very urban area. Since everything is in a close proximity there is no need for a car. Most often also because public transport is very efficient in very urban areas. Very rural areas, however, are often located far away from all these facilities. And thus, households living there need a car to get their groceries or go to work.

In conclusion, the hypothesis cannot be rejected. There is a significant effect of urban form on car ownership. Although all the dummy variables showed the expected correlation, only one was actually significant.

4.1.4 Preferences and attitudes towards car use

Hypothesis 4: Preferences towards car use have a positive effect on household car ownership.

In this model the preferences and attitudes towards cars had been added to be able to test the hypothesis. The regression output can be found in appendix C, table 25. What is interesting to see is that the age dummies are not significant anymore. Instead, *income2*, *income3*, *km_School*, *km_Park*, *urbanity4* have become significant (first 4 at the 10% level and *urbanity4* at the 5% level). Of the newly added variables, *Pref_CarWalk* and *Car_Less* are significant (both at the 5% level). For the preferences, preferring the car is equal to 0 and preferring the second option is equal to 1. What the model suggests, is that a household that prefers to walk instead of taking the car owns 0.432 more cars than a household that prefers the car over walking. This result does not correspond with the expectations. However, in the survey respondents were asked to imagine a situation where both options were feasible. In the case of choosing between taking the car or walking, this is only feasible for a very short distance (e.g. going to a friend who lives nearby). Most daily activities, like going to work are most often not such a short distance where walking is also a feasible option. Hence the result from this variable. On the other hand, the other two preference variables show a negative correlation with car ownership. This is in line with the expectations. Someone who prefers taking public transport over taking the car owns 0.114 fewer cars than someone who prefers the car. However, these results are insignificant and cannot entirely be trusted.

When it comes to the attitudes towards car ownership there were two variables include, namely *Car_Less* and *Car_No*. For both variables, in the survey the respondents were asked to look 5 years into the future. *Car_Less* indicates whether the respondent could imagine a life with one car less in their household if they own 2 or more cars. And *Car_No* indicates whether the respondent is willing to live without a car. Both variables show a negative correlation with car ownership as expected. However, only *Car_Less* is significant. A household that is willing to live with one car less owns 0.307 fewer cars than a household that is not willing to live with one car less. This shows that people who are willing to live with fewer cars have a certain attitude towards car ownership. This attitude might already influence their current car ownership situation.

In conclusion, the hypothesis is rejected. Although two out of three variables with respect to preferences are indeed correlated with car ownership as expected, these are not significant. The variable that is significant however, does not show the expected effect. When it comes to the attitudes towards car ownership, they both show the expected correlation, but only one out of two variables is actually significant. The relationship between attitudes towards car ownership and car ownership is quite interesting and subject to future research.

4.1.5 Controlling for preferences

Hypothesis 5: When taking preferences towards neighborhood characteristics into account the influence of neighborhood characteristics on car ownership is insignificant.

To test this hypothesis, the importance variables with respect to having a supermarket, primary school, sports ground, public park, train station, and having enough parking space have been added to the model. The regression output of this model can be found in appendix C, table 26. In this model, *hh_License* lost its significance. the only variables which are significant are *income2*, *income3*, and *Pref_CarWalk* (*income2* and *Pref_CarWalk* at the 5% level and *income3* at the 10% level). Due to these results another model had been made where the preference and attitude variables had been left out. The regression output for this model is presented in appendix C, table 27. For this hypothesis, only the results regarding neighborhood characteristics are important and whether preferences towards these characteristics change the results.

In this model the age dummies are once again significant except for *age5* (age group 56-65). The effect of the number of drivers' licenses on car ownership is significant again too. As well as *urbanity5*, *impschool4*, *imppark2*, *imppark3*, *imppark4*, *impparking3*, and *impparking4*. With regards to urban form and its effect on household car ownership it is as follows. A household that lives in a very rural area owns 0.917 more cars than a household that lives in a very urban area. This is again in line with the expectations and literature. When it comes to the importance of having a primary school in a 1km radius the model can be interpreted as follows. A person in a household who thinks having a primary school within a 1km radius is very important, owns 0.527 more cars than a household where having a primary school within a 1km radius is not important at all. The same positive correlation with car ownership counts for the importance variables of having a public park within a 1km radius, which are also significant. This means that although this person prefers having necessary facilities nearby, he/she owns more cars than a person who does not prefer to have all facilities nearby. However, this is a preference which had been asked to the respondents in the survey by letting the respondents imagine a situation where they would be moving to a new neighborhood. Since these preferences are in contrast with the actual neighborhoods characteristics of where the respondents are living, these results do not support the effect of residential self-selection on car ownership.

The variables *km_Sup, km_School, km_Sports,* and *km_Park* do have the expected negative correlation with car ownership but are not significant. Most of the importance variables show positive correlation with car ownership. Two out of three importance variables of enough parking spaces are significant at the 10% level. The more important a person thinks having enough parking spaces in the neighborhood, the more cars they own compared to a person who does not think having enough parking spaces is important. For example, a person in a household who thinks that having enough parking spaces is very important owns 0.845 more cars in their household than a person who thinks enough parking spaces is not important at all. This makes sense, since having one or more cars requires enough parking spaces.

All in all, the hypothesis cannot be rejected. Although in the earlier models, the neighborhood characteristics were already insignificant (except for *km_School* in model 2 and 3 and *km_Park* in model 3), in this model including preferences they are still insignificant.

4.2 Logit model

In addition to the models made with OLS, a logit model will also be made to compare some results. However, certain variables cannot be used in this model, such as *Pref_CarBike, Pref_CarPT, Pref_CarWalk*. Since if the value for the dependent variable is 0 the data for these preferences is missing. Respondents could only answer the question about preferences if they answered yes on whether they own a car. Also, the variable which describe the importance factors of built environment elements cannot be used in the model. Possibly due to the small sample size or the low frequency of the value 0 for the dependent variable. Therefore, not all variables can be used in the logit model. However, there are still some elements of the built environment that can be analyzed. The economic model made for this analysis is similar to the one used for hypothesis 3 and is as follows:

hh_Car_bin = f(Gender, Age, hh_Pers, household, hh_License, hh_Inc, km_Sup, km_School, km_Sports, km_Park, Urban, pop_Density)

The output for this regression can be found in appendix C table 28. In this model only *age4* is significant. This means that people within the age range of 46-55 are 17.508 times more likely to own a car than people within the age range of 18-25. Which seems logical, since most often the older people are the more money they have to buy a car. Also, it is more likely for older people to have children. And owning a car is arguably easier with children then not owning a car. This result is comparable to the results in the models made with OLS. With OLS, the results showed that the older the person, the more cars he/she owns compared to someone from the youngest group (18-25 years old).

All other variables are insignificant. The variables *household4, km_School, km_Park, urbanity3,* and *urbanity5* have been omitted since these predict success perfectly. Most insignificant variables do show an expected correlation with car ownership. Owning a driver's license, for example, shows a positive correlation. And households living in more rural places are more likely to own a car than households in a very urban area. But since these results are insignificant, they cannot really be used.

4.3 Other results

In total, six models were estimated using OLS as discussed in the methodology. Each model added new variables to test the effects of the built environment on car ownership. Many variables in the models are insignificant, however this may be due to the small sample size this study used. Therefore, it might still be interesting to look at what the coefficients are for some variables. What most models have in common, except for model 4 and 5, is that age has a positive significant influence on car ownership. These results are in line with expectations and the literature. The older someone is the higher car ownership within their household is than someone from the youngest group (18-25 years old). This effect is always the strongest for the group of people between 26-35 years old. Which makes sense, since people between 18 and 25 years old are often still studying and do not have enough money yet to buy their own car. When in your late 20s or early 30s, people often have a stable life with a job and enough money. Gender is in all models insignificant and the effect is also very small, so it has no realistic influence. Income was measured by three dummy variables. The lowest income group (lower than modal) is used as the base category. In all models except for the last one, income showed a positive correlation with household car ownership. In model 4 and 5 the results are also significant. Which is in line with the expectations and literature, since having more money available results in being able to buy more. Lastly, in all models except for model 5, the number of drivers' licenses has a positive significant influence on the number of cars within a household. This is probably due to most people buying a car within a few years after getting their driver's license.

5. Conclusion

5.1 Conclusion

By using data from a self-administered survey and the CBS, this paper tried to develop a model that explains the impact of the built environment on car ownership in the Netherlands. Using an ordinary least squares regression with built environment characteristics, preferences, attitudes, and socio-demographics, the effects were estimated. Many of the results were found to be statistically insignificant, this may be due to the small sample size this study used. Although most results were insignificant, this does not mean that there is no relationship at all. Possibly because of this small sample size there is no sufficient evidence to prove the effects of the variables on household car ownership. The results that were found to be significant however, are quite interesting. Having a primary school within a 1km radius from a household showed to be statistically significant in two models. A household that has a primary school within a 1km radius owns 0.522 fewer cars than a household without a primary school nearby. This negative relationship is also shown by the other model where the coefficient was 0.455. Next, the urban form of a neighborhood also showed to have significant effects on household car ownership. The very urban areas were used as a base category. In each model where urbanity was included it showed significant results, except for the fifth model. In the final model for example, a household that lives in a very rural area owns 0.917 more cars than a household that lives in a very urban area. Similar results were found in the model where urban form was introduced. Although the variables for urban, moderate urban, and rural are not significant, they still share the same relationship. For households living in urban, moderate urban, rural, and very rural areas, they own 0.208, 0.072, 0.423, and 1.001 more cars per household than households in the very urban areas, respectively. Furthermore, this study tried to include preferences and attitudes towards cars when explaining household car ownership. Interestingly though, it was found that a respondent that prefers to walk instead of taking the car owns 0.432 more cars per household than a household that prefers the car over walking. Also, a household that is willing to live with one car less owns 0.307 fewer cars than a household that is not willing to live with one car less. The other variables were found to be insignificant. Finally, preferences towards neighborhood characteristics were also analyzed. Preferences towards having a primary school and a public park within a 1km radius and preferences towards having enough space to park in the neighborhood were found to be significant. Respondents that value the characteristics more important own more cars per household than respondents that value these characteristics as not important at all. People's preferences do not match their actual neighborhood characteristics, so these results do not lend support to residential self-selection.

In conclusion, most built environment characteristics, preferences and attitudes showed to be insignificant in this study. However, those that were significant, showed some interesting results. One result that stands out the most is that a household, where the respondent preferred to walk over taking the car, is likely to own more cars per household than a household that prefers the car over walking. This could be because even though people like to walk, they still need to own one or multiple cars for work or other activities. Further analysis with a bigger sample size is needed to be able to tell if there are some actual relationships between the insignificant variables and household car ownership.

5.2 Policy recommendations

From the results of this study a few policy recommendations can be made. Households in rural areas tend to own more cars than households in very urban areas. Probably due to a good public transportation network in urban areas and a big diversity of activities in a close proximity, causing a lower need to own a car. Having a primary school nearby also showed to have a negative effect on the number of cars owned in a household. This study also showed that a preference for walking over taking the car does not decrease the number of cars in a household. And thus, preferences might not be of interest for policy makers. The focus with future policies should be on the need for a car. For example, people who live in rural areas might need a car to get to work or bring their kids to school. Investing in a better public transport connection in these areas, especially being connected better to areas with a big diversity of activities such as primary schools, could decrease the need for a car.

5.3 Limitations and future research

However, this study had some limitations when it came to its analysis. The biggest limitation being the sample size, since the dataset only consisted of data from 167 respondents. This probably caused a lot of the results to be insignificant. Secondly, the study is only based on data in the Netherlands. The Netherlands is considered to be a very bike friendly country, especially compared to the United States. This means that the results of this study might not be applicable to some other countries. Future studies might include more countries at once, maybe the overall household car ownership in the European Union. Thirdly, the number of cars a household owns was considered as a continuous variable in this study. However, it only had a few frequent outcomes, mainly 1 and 2 cars per household. Because of this, the OLS did not give the most accurate estimates. An ordered logit model would have probably given better estimates.

Although individual's preferences and attitudes as well as the built environment influence household car ownership, it is also possible that the built environment plays an indirect role by influencing the preferences and attitudes over time. For example, someone who has moved from a rural to a very urban area, may cultivate a non-car-oriented lifestyle which changes his attitudes towards cars and this in its place ends up influencing car ownership decisions again. The relationship between changes of attitudes towards cars, the built environment, and car ownership is quite interesting and is a topic that should be of interest in the future.

6. References

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7. Appendix

Appendix A – Variable list

In this appendix an overview of the variables in the used dataset is given. Furthermore, some descriptive statistics of the variables are presented.

Table 1. Variable overview

Variable	Description	Values
hh_Car	Number of cars per household	0, 1, 2, 3, 4 4= 4 or more cars
hh_Pers	Number of people per household	1, 2, 3, 4, 5, 6 6= 6 or more people
hh_License	Number of people within the household with a driver's license	0, 1, 2, 3, 4, 5, 6 6= 6 or more
hh_Inc	Household income	0= less than modal 1= modal 2= higher than modal 3= prefer not to answer
household	Household composition	0= single 1= couple 2= couple with kids 3= single parent with kids
Gender	Gender of the respondent	0= female 1= male 2= prefer not to answer
Age	Age of the respondent	0= 18-25 1= 26-35 2= 36-45 3= 46-55 4= 56-65 5= older than 65
Urban	Urban form of a neighborhood	1= very urban 2= urban 3= moderate urban 4= rural 5= very rural
pop_Density	The number of residents per km²	-
Imp_Sup	The importance of having a supermarket within a 1km radius	1= not important at all 2= not important 3= important 4= very important
Imp_School	The importance of having a primary school within a 1km radius	

Imp_Sport	The importance of having a sports ground within a 1km radius	
Imp_Park	The importance of having a public park within a 1km radius	
Imp_Train	The importance of having a train station within a 5km radius	
Imp_Parking	The importance of having enough parking spaces in the neighborhood	
km_Sup	Indicates whether there is a supermarket within a 1km radius	0= no 1= yes
km_School	Indicates whether there is a primary school within a 1km radius	
km_Sport	Indicates whether there is a sports ground within a 1km radius	
km_Park	Indicates whether there is a public park within a 1km radius	
km_Train	Indicates whether there is a train station within a 5km radius	
num_Sup	Number of supermarkets within a 1km radius	-
num_School	Number of primary schools within a 1km radius	-
Pref_CarBike	If the respondent has the choice between the car or the bike, which will he/she choose	0= car 1= bike
Pref_CarPT	If the respondent has a choice between the car or public transport, which will he/she choose	0= car 1= public transport
Pref_CarWalk	If the respondent has the choice between the car or walking, which will he/she choose	0= car 1= walking
Car_Less	Whether the respondent can imagine a life with 1 car less in their household if they own 2 or more cars	0= no 1= yes

		2= does not apply (respondent does not have more than 1 car)
Car_No	Whether the respondent is willing to live without a car	0= no 1= yes

Table 2. Descriptive statistics *hh_Car*, *pop_Density*, *address_Density*, *hh_Pers*, and *hh_License*

Variable	Obs.	Mean	Std. Dev.	Min	Max
hh_Car	167	1.479042	0.8838465	0	4
pop_Density	160	4168.175	3151.773	93	20712
address_Density	160	1600.819	1378.877	110	9479
hh_Pers	167	2.742515	1.330685	1	6
hh_License	167	2.083832	0.880944	0	5

Table 3. Descriptive statistics *Gender*

Gender	Freq.	Percent	Cum.
Female	87	52.10	52.10
Male	79	47.31	99.40
Prefer not to answer	1	0.60	100.00
Total	167	100.00	

Table 4. Descriptive statistics *Age*

Age	Freq.	Percent	Cum.
18-25	22	13.17	13.17
26-35	29	17.37	30.54
36-45	17	10.18	40.72
46-55	39	23.35	64.07
56-65	44	26.35	90.42
Older than 65	16	9.58	100.00
Total	167	100.00	

Table 5. Descriptive statistics *household*

Household composition	Freq.	Percent	Cum.
Single	28	16.77	16.77
Couple	61	36.53	53.29
Couple with kids	71	42.51	95.81
Single parent with kids	7	4.19	100.00
Total	167	100.00	

Table 6. Descriptive statistics *hh_Inc*

Income	Freq.	Percent	Cum.
Less than modal	14	8.38	8.38
Modal	50	29.94	38.32
Higher than modal	84	50.30	88.62
Prefer not to answer	19	11.38	100.00
Total	167	100.00	

Table 7. Descriptive statistics *Urban*

Urbanity	Freq.	Percent	Cum.
Very urban	27	16.88	16.88
Urban	40	25.00	41.88
Moderate urban	12	7.50	49.38
Rural	74	46.25	95.63
Very rural	7	4.38	100.00
Total	160	100.00	

Table 8. Descriptive statistics *Car*

Does the respondent own a car	Freq.	Percent	Cum.
No	19	11.38	11.38
Yes	148	88.62	100.00
Total	167	100.00	

Table 9. Descriptive statistics *Lease*

Does the respondent own a lease car	Freq.	Percent	Cum.
No	128	86.49	86.49
Yes	20	13.51	100.00
Total	148	100.00	

Table 10. Descriptive statistics *Pref_CarBike*

Preference Car/Bike	Freq.	Percent	Cum.
Car	78	52.70	52.70
Bike	70	47.30	100.00
Total	148	100.00	

Table 11. Descriptive statistics *Pref_CarPT*

Preference Car/PT	Freq.	Percent	Cum.
Car	124	83.78	83.78
Public Transport	24	16.22	100.00
Total	148	100.00	

Table 12. Descriptive statistics *Pref_CarWalk*

Preference Car/Walk	Freq.	Percent	Cum.
Car	23	15.54	15.54
Walking	125	84.46	100.00
Total	148	100.00	

Table 13. Descriptive statistics *Car_Less*

Can the respondent imagine a life with one car less (if he/she owns 2 or more cars)	Freq.	Percent	Cum.
No	26	17.57	17.57
Yes	61	41.22	58.78
Does not apply	61	41.22	100.00
Total	148	100.00	

Table 14. Descriptive statistics *Car_No*

Can the respondent imagine a life without a car	Freq.	Percent	Cum.
No	119	80.41	80.41
Yes	29	19.59	100.00
Total	148	100.00	

Appendix B – Model assumption tests

Table 15. Pearson correlation matrix

	hh_Car	Pref_C~e	Pref_C~T	Pref_C~k	Car_Less	Car_No	Gender
hh_Car	1.0000						
Pref_CarBike	-0.1416	1.0000					
Pref_CarPT	-0.1239	0.3175	1.0000				
Pref_CarWalk	0.1592	0.3690	0.1887	1.0000			

Car_Less	-0.0599	0.2095	0.1728	0.1673	1.0000		
Car_No	-0.0546	0.1802	0.1985	0.1178	0.1155	1.0000	
Gender	0.0055	-0.0780	-0.0357	-0.0393	-0.1013	-0.0277	1.0000
Age	0.0913	0.1283	0.1434	0.0608	0.1888	0.0213	-0.0081
hh_Pers	0.4026	0.0137	-0.0112	0.1012	-0.0019	0.0411	0.1360
household	0.3531	0.0391	0.0273	0.1123	-0.0316	0.0011	0.0431
hh_License	0.5671	-0.0049	0.0175	0.1602	0.1289	-0.0643	0.1005
hh_Inc	0.2446	0.1734	0.1305	0.2265	0.0339	0.0413	0.1933
km_Sup	-0.0471	0.1831	-0.0147	0.1849	0.1490	0.0122	0.0023
km_School	-0.1610	0.0963	0.0125	0.0007	0.1124	0.0319	0.0773
km_Sports	0.0959	0.0206	-0.0967	0.0575	0.0425	-0.1165	0.0497
km_Park	-0.0818	0.0481	-0.0679	0.0809	0.0084	0.0734	0.0367
km_Train	-0.2095	0.0046	0.0482	0.0426	0.0424	0.1423	-0.1219
pop_Density	-0.2538	0.1326	0.0962	0.1595	0.0812	0.0911	-0.0145
urbanity1	-0.2225	0.0877	0.1762	0.1555	0.0961	0.1292	-0.0862
urbanity2	-0.0976	-0.1437	-0.0315	-0.1428	-0.1447	-0.0391	0.0111
urbanity3	-0.0722	0.1038	0.0029	-0.0217	-0.1565	-0.0244	-0.1711
urbanity4	0.2240	0.0211	-0.0866	0.0727	0.0831	0.0106	0.1778
urbanity5	0.1610	-0.0310	-0.0125	-0.0942	0.0882	-0.1138	-0.0773
impsup1	0.1276	0.1235	-0.0515	0.0502	0.1001	-0.0578	0.0053
impsup2	0.0218	-0.0399	-0.0797	0.0280	-0.0465	0.0590	-0.0954
impsup3	0.0139	-0.0199	0.0140	-0.0733	-0.1846	-0.0501	0.0809
impsup4	-0.0835	0.0410	0.1052	0.0531	0.2736	0.0141	0.0035
impschool1	-0.1305	0.1913	0.1149	0.0810	0.2484	-0.0708	-0.1341
impschool2	-0.1764	-0.0051	0.0411	-0.0153	0.0097	0.0506	0.0089
impschool3	0.1237	-0.1356	-0.0961	-0.1078	-0.2351	-0.0195	0.0750
impschool4	0.2440	-0.0017	-0.0435	0.0960	0.0809	0.0357	0.0362
impsport1	-0.0664	0.0637	0.1710	-0.0525	0.0533	0.1313	-0.1156
impsport2	-0.0653	0.0513	-0.0863	0.1449	-0.0376	-0.0244	-0.0615
impsport3	0.0609	-0.1079	-0.0212	-0.1459	-0.0633	-0.0543	0.1005
impsport4	0.1141	0.0476	0.0192	0.0802	0.1612	0.0019	0.0740
imppark1	-0.0955	0.0090	-0.0733	-0.0435	0.0704	0.0227	0.0438
imppark2	0.1068	-0.1499	-0.0201	0.0091	-0.1776	-0.0321	-0.0803
imppark3	-0.0697	0.0316	0.0010	-0.0587	-0.0225	-0.0914	0.0640
imppark4	0.0107	0.1340	0.0551	0.0875	0.2315	0.1523	-0.0105
imptrain1	0.1541	-0.0442	-0.1010	-0.0794	0.0809	-0.1244	0.0362
imptrain2	0.1442	-0.0620	-0.1620	-0.0397	-0.1338	-0.1217	-0.0579
imptrain3	-0.0866	0.1402	0.1415	0.0712	0.0198	0.1340	0.0123
imptrain4	-0.2376	-0.0933	0.1737	0.0412	0.1008	0.1384	0.0363
impparking1	-0.2629	.	.	.	.	.	-0.0711
impparking2	-0.1476	0.0558	-0.0633	0.0617	0.1234	0.0498	-0.0799
impparking3	0.0342	0.1758	0.0272	-0.0123	0.1031	0.0609	-0.0422
impparking4	0.1098	-0.1935	-0.0092	-0.0054	-0.1495	-0.0759	0.0993
age1	-0.2118	-0.0335	-0.0635	0.0591	0.0340	-0.0843	0.1256
age2	0.0378	-0.1121	-0.1189	-0.1737	-0.3484	-0.0211	0.0063

age3	0.0192	-0.1119	-0.1532	-0.0308	0.0427	0.1571	-0.1229
age4	0.1336	0.0781	0.2540	0.1184	0.1067	-0.0098	-0.1460
age5	0.0605	0.1541	-0.0330	0.0632	0.2509	-0.0464	0.0563
age6	-0.1077	-0.0549	0.0578	-0.0646	-0.1625	0.0272	0.0975
household1	-0.4077	-0.0866	-0.0435	-0.0794	-0.0205	0.0891	-0.0749
household2	0.0392	0.0026	-0.0212	-0.0697	0.0083	-0.0890	0.0363
household3	0.2747	0.1030	0.0847	0.1222	0.0577	0.0023	0.0295
household4	-0.0120	-0.1261	-0.0904	-0.0064	-0.1519	0.0711	-0.0199
income1	-0.2593	-0.0908	-0.0402	-0.1033	-0.2215	0.0688	-0.1342
income2	-0.0217	-0.1300	-0.1290	-0.1868	0.1672	-0.1312	-0.1046
income3	0.1738	0.1737	0.1458	0.2351	-0.0601	0.0897	0.1792

	Age	**hh_Pers**	**househ~d**	**hh_Lic~e**	**hh_Inc**	**km_Sup**	**km_Sch~l**
Age	1.0000						
hh_Pers	-0.1455	1.0000					
household	-0.0608	0.7744	1.0000				
hh_License	-0.0717	0.7071	0.5711	1.0000			
hh_Inc	0.0693	0.3217	0.3217	0.3034	1.0000		
km_Sup	-0.0210	0.0619	-0.0454	0.0831	-0.0468	1.0000	
km_School	0.0208	-0.0424	0.0136	-0.0119	-0.0590	0.1601	1.0000
km_Sports	0.0556	-0.0036	-0.0058	0.1466	-0.0436	0.2334	0.1039
km_Park	-0.0368	0.0422	0.0007	0.0146	0.0333	0.1275	0.1957
km_Train	-0.0751	-0.1247	-0.1548	-0.2400	0.0762	-0.0737	-0.1669
pop_Density	-0.0826	-0.1886	-0.2162	-0.1183	-0.0465	0.1263	0.0628
urbanity1	-0.1454	-0.0619	-0.1460	-0.1419	-0.0451	0.1340	-0.1484
urbanity2	-0.0574	-0.1470	-0.0444	-0.1263	-0.0941	-0.1981	0.0529
urbanity3	0.1514	-0.0152	-0.0306	-0.0301	-0.0764	0.0847	-0.0551
urbanity4	-0.0161	0.2405	0.2162	0.2556	0.1649	0.0923	0.1984
urbanity5	0.2321	-0.1421	-0.1264	-0.0571	-0.0186	-0.1601	-0.2530
impsup1	-0.0077	0.0629	-0.0468	0.1148	0.0048	0.0335	0.0241
impsup2	0.1456	0.0730	0.0908	-0.0562	-0.0227	0.0174	-0.0144
impsup3	-0.1665	-0.0482	-0.0418	0.0131	0.1213	-0.0280	-0.0629
impsup4	0.0537	-0.0411	-0.0386	0.0154	-0.1442	0.0070	0.0942
impschool1	0.1653	-0.2031	-0.1018	-0.1335	-0.1586	-0.0976	0.0213
impschool2	0.0015	-0.0221	0.0086	-0.0687	-0.0270	0.1189	-0.0382
impschool3	-0.1607	0.0114	-0.0385	0.0382	0.1062	-0.0098	-0.0265
impschool4	0.0455	0.2743	0.1776	0.2159	0.0627	-0.0459	0.0737
impsport1	0.1846	-0.0879	-0.0479	-0.0535	0.0310	-0.0890	-0.0551
impsport2	0.0116	-0.0103	-0.0097	-0.0790	0.0624	0.1107	-0.0332
impsport3	-0.1658	0.0461	0.0530	0.0762	-0.0847	-0.0881	0.0473
impsport4	0.1295	0.0375	-0.0420	0.0915	0.0084	0.0587	0.0422
imppark1	-0.0012	-0.0983	-0.2061	-0.0968	-0.1190	-0.2095	-0.1372
imppark2	-0.0939	0.0853	0.1521	0.0512	0.0595	0.0214	0.0582
imppark3	0.0231	-0.0256	-0.0257	-0.0211	-0.0581	0.0874	-0.0172

imppark4	0.0804	-0.0216	-0.0511	0.0119	0.0598	-0.0436	0.0181
imptrain1	-0.0803	0.1848	0.1529	0.0581	0.0142	0.0172	-0.1409
imptrain2	0.0965	0.0414	0.0576	0.1290	-0.0176	-0.0374	0.1746
imptrain3	-0.0430	-0.0538	-0.0539	-0.0180	0.1160	0.0957	-0.0808
imptrain4	-0.0072	-0.1579	-0.1524	-0.2274	-0.1723	-0.1030	-0.0159
impparking1	-0.0110	-0.0877	-0.1642	-0.1487	-0.2476	0.0476	0.0343
impparking2	-0.0242	-0.0945	-0.0890	-0.0880	0.0331	0.0587	0.0422
impparking3	0.1842	0.1318	0.1292	0.0693	0.0866	-0.0206	0.0662
impparking4	-0.1759	-0.0684	-0.0437	0.0125	-0.0313	-0.0176	-0.0961
age1	-0.6461	0.0623	-0.0333	0.1039	-0.0844	-0.0141	-0.0033
age2	-0.4691	-0.1374	-0.1359	-0.1157	-0.0955	0.0118	-0.0668
age3	-0.1306	0.2445	0.2516	-0.0547	0.0627	0.0283	0.0737
age4	0.1365	0.2031	0.1885	0.1890	0.0967	0.0090	-0.0209
age5	0.5279	-0.1401	-0.0681	0.0048	0.0823	0.0132	0.0529
age6	0.4941	-0.2282	-0.2145	-0.1932	-0.1046	-0.0613	-0.0360
household1	-0.1538	-0.5533	-0.7502	-0.5721	-0.3903	0.0768	0.0181
household2	0.3140	-0.3965	-0.3227	-0.1007	0.0638	-0.1131	-0.0323
household3	-0.1644	0.7695	0.7059	0.5661	0.2729	0.1168	-0.0015
household4	-0.0622	0.0856	0.4323	-0.0880	-0.0771	-0.1601	0.0458
income1	-0.0901	-0.2727	-0.2888	-0.3286	-0.7190	0.0972	0.0672
income2	0.0144	-0.1128	-0.0930	-0.0181	-0.5102	-0.0539	0.0000
income3	0.0395	0.2688	0.2594	0.2114	0.9118	-0.0055	-0.0393

	km_Spo~s	**km_Park**	**km_Train**	**pop_De~y**	**urbani~1**	**urbani~2**	**urbani~3**
km_Sports	1.0000						
km_Park	0.2264	1.0000					
km_Train	-0.2437	0.1000	1.0000				
pop_Density	-0.1241	0.0699	0.3453	1.0000			
urbanity1	-0.2838	0.0623	0.5874	0.5867	1.0000		
urbanity2	0.0436	0.0798	0.1899	0.0101	-0.2601	1.0000	
urbanity3	0.0359	0.0394	-0.1561	-0.0620	-0.1283	-0.1644	1.0000
urbanity4	0.1990	0.0358	-0.4866	-0.3576	-0.4179	-0.5356	-0.2641
urbanity5	-0.1039	-0.4210	-0.0905	-0.1441	-0.0964	-0.1235	-0.0609
impsup1	0.0425	0.0156	-0.0814	-0.0447	-0.0507	-0.0650	-0.0320
impsup2	-0.0379	0.0811	-0.0028	-0.1570	-0.0351	-0.0413	0.1046
impsup3	0.0525	-0.0273	0.0457	0.1947	0.0217	0.1239	0.0084
impsup4	-0.0384	-0.0640	-0.0334	-0.0621	0.0277	-0.0978	-0.1254
impschool1	-0.1165	-0.1742	0.1035	0.0237	0.0479	-0.0094	0.0508
impschool2	0.0348	0.1000	0.0026	0.0399	0.0253	0.0684	-0.0562
impschool3	0.0930	0.0101	-0.0077	-0.0010	0.0361	-0.0224	-0.0209
impschool4	-0.0537	0.0477	-0.1214	-0.0895	-0.1554	-0.0585	0.0558
impsport1	-0.1076	-0.1356	0.0437	-0.0570	0.0618	-0.1096	0.1892
impsport2	-0.0425	0.0444	0.2328	0.1517	0.0891	0.2670	0.0036
impsport3	0.0725	0.0171	-0.2601	-0.1642	-0.1582	-0.1699	-0.0838

impsport4	0.0746	0.0273	-0.0043	0.1021	0.0867	-0.1140	-0.0562
imppark1	-0.0407	-0.2400	-0.0544	-0.1138	-0.0809	-0.0207	0.0852
imppark2	-0.0322	0.0825	0.0467	0.0954	0.0725	-0.0164	-0.0081
imppark3	0.0237	-0.0375	-0.0321	-0.1256	-0.0784	0.0217	0.0297
imppark4	0.0249	0.0637	0.0130	0.1066	0.0560	-0.0000	-0.0687
imptrain1	0.0567	-0.1136	-0.1876	-0.0749	-0.0877	-0.0867	0.0712
imptrain2	0.1543	0.1129	-0.1612	-0.1591	-0.2657	0.1473	0.1066
imptrain3	-0.0097	-0.0792	0.0726	0.1279	0.1897	-0.1926	-0.0804
imptrain4	-0.2702	0.0507	0.3038	0.1158	0.1957	0.1450	-0.1045
impparking1	-0.0605	0.0221	0.2212	0.2009	0.2485	-0.0000	-0.0456
impparking2	-0.1243	0.0273	-0.0043	0.0885	-0.0011	0.0380	-0.0562
impparking3	-0.1293	-0.1173	-0.0525	-0.1712	-0.0573	-0.0951	0.0493
impparking4	0.2022	0.1028	-0.0163	0.0758	-0.0216	0.0829	-0.0136
age1	0.0412	0.0552	0.0931	0.1126	0.1108	0.0210	-0.1137
age2	-0.0820	-0.0607	-0.0099	0.0148	0.0643	0.0482	-0.0649
age3	0.0690	0.0477	-0.0360	-0.0988	-0.1012	0.0820	0.0558
age4	-0.1376	0.0785	0.0488	0.0367	0.1329	-0.0925	-0.0511
age5	0.0436	-0.1330	-0.0836	-0.0609	-0.1831	-0.0333	0.1096
age6	0.1216	0.0445	-0.0071	-0.0111	-0.0304	0.0124	0.0712
household1	-0.0249	0.0637	0.1861	0.1711	0.1438	0.0380	-0.0687
household2	0.0444	-0.0896	-0.0163	0.0616	-0.0216	0.0527	0.1350
household3	-0.0191	0.0256	-0.1431	-0.1582	-0.0498	-0.1168	-0.0528
household4	-0.0115	0.0296	0.0382	-0.0798	-0.0964	0.0882	-0.0609
income1	0.0367	0.0470	-0.0267	0.0259	0.0514	0.0885	0.0075
income2	0.0158	-0.1043	-0.0737	0.0331	0.0000	0.0228	0.0977
income3	-0.0366	0.0719	0.0859	-0.0468	-0.0300	-0.0735	-0.0975

	urbani~4	**urbani~5**	**impsup1**	**impsup2**	**impsup3**	**impsup4**	**impsch~1**
urbanity4	1.0000						
urbanity5	-0.1984	1.0000					
impsup1	0.0085	0.2510	1.0000				
impsup2	0.0011	0.0144	-0.0648	1.0000			
impsup3	-0.0781	-0.1222	-0.1280	-0.6847	1.0000		
impsup4	0.1011	0.0714	-0.0473	-0.2529	-0.4993	1.0000	
impschool1	-0.1436	0.2166	0.0919	0.0455	-0.1340	0.1002	1.0000
impschool2	0.0148	-0.1548	0.0368	0.0960	0.0060	-0.1350	-0.3369
impschool3	-0.0075	0.0265	-0.0857	-0.0628	0.1446	-0.0957	-0.3642
impschool4	0.1683	-0.0737	-0.0371	-0.1077	-0.0710	0.2378	-0.1575
impsport1	-0.1214	0.1711	0.1653	0.2666	-0.1769	-0.1299	0.3087
impsport2	-0.2893	-0.0279	0.0033	0.1409	-0.0379	-0.1193	0.1076
impsport3	0.3300	-0.0473	-0.0890	-0.2519	0.1254	0.1596	-0.2507
impsport4	0.0808	-0.0422	-0.0213	-0.1137	0.0359	0.0946	-0.0903
imppark1	-0.0946	0.3128	-0.0193	0.1376	-0.0621	-0.0754	0.1924
imppark2	-0.0121	-0.0582	-0.0658	0.1141	-0.0356	-0.0694	-0.0674

imppark3	0.0173	0.0172	0.1018	-0.0597	0.0307	-0.0004	-0.0052
imppark4	0.0346	-0.0985	-0.0494	-0.1177	0.0293	0.1167	-0.0013
imptrain1	0.0457	0.1409	0.1450	0.0282	-0.0309	-0.0353	-0.1060
imptrain2	0.0614	-0.1123	-0.0912	0.1809	-0.0269	-0.1542	0.0567
imptrain3	0.0341	0.0808	0.0279	-0.1475	0.0946	0.0406	-0.1068
imptrain4	-0.1855	-0.0785	-0.0394	-0.0816	-0.0733	0.2102	0.1762
impparking1	-0.1485	-0.0343	-0.0172	-0.0922	0.0555	0.0407	0.1307
impparking2	0.0148	-0.0422	-0.0230	-0.0548	-0.0014	0.0750	-0.0200
impparking3	0.0759	0.0577	0.0958	0.1255	-0.1128	-0.0264	0.0294
impparking4	-0.0357	-0.0315	-0.0835	-0.0770	0.0990	-0.0170	-0.0634
age1	-0.0064	-0.0854	-0.0429	-0.1889	0.0843	0.1257	0.0022
age2	-0.0163	-0.0964	0.0948	-0.0892	0.1704	-0.1533	-0.2145
age3	0.0056	-0.0737	-0.0371	0.0735	-0.0309	-0.0353	-0.1060
age4	0.0573	-0.1214	-0.0608	0.1929	-0.1265	-0.0418	0.0735
age5	0.0145	0.2293	0.0591	-0.0102	-0.0081	0.0056	0.2158
age6	-0.0833	0.1409	-0.0358	-0.0056	-0.0904	0.1408	-0.0463
household1	-0.0973	-0.0181	-0.0494	-0.0077	-0.0031	0.0283	0.1240
household2	-0.1927	0.2237	0.1451	-0.1054	0.0487	0.0173	0.0014
household3	0.2422	-0.1839	-0.0947	0.0753	-0.0200	-0.0352	-0.1185
household4	0.0467	-0.0458	-0.0230	0.0818	-0.0619	-0.0074	0.0578
income1	-0.0892	-0.0728	-0.0378	-0.0314	-0.0108	0.0671	-0.0225
income2	-0.1210	0.1154	0.0401	0.0707	-0.1565	0.1189	0.2499
income3	0.1676	-0.0674	-0.0160	-0.0489	0.1558	-0.1532	-0.2253

	impsch~2	**impsch~3**	**impsch~4**	**impspo~1**	**impspo~2**	**impspo~3**	**impspo~4**
impschool2	1.0000						
impschool3	-0.5603	1.0000					
impschool4	-0.2423	-0.2620	1.0000				
impsport1	-0.0355	-0.1463	-0.1018	1.0000			
impsport2	0.1353	-0.1868	-0.0494	-0.2936	1.0000		
impsport3	-0.0911	0.2805	0.0114	-0.2445	-0.7845	1.0000	
impsport4	-0.0711	-0.0175	0.2542	-0.0584	-0.1874	-0.1561	1.0000
imppark1	-0.0524	-0.0642	-0.0591	0.2004	-0.0299	-0.0701	-0.0339
imppark2	-0.1152	0.1234	0.0684	-0.0828	0.2627	-0.2054	-0.0424
imppark3	0.0831	0.0260	-0.1653	-0.0236	-0.0878	0.1580	-0.1442
imppark4	0.0488	-0.1509	0.1670	0.0378	-0.1790	0.0634	0.2579
imptrain1	0.0500	0.0240	0.0176	0.0411	0.0299	-0.0291	-0.0650
imptrain2	-0.0311	-0.0667	0.0838	0.0132	0.0492	-0.0218	-0.0945
imptrain3	-0.0131	0.1589	-0.0986	-0.0125	-0.0632	0.0531	0.0489
imptrain4	0.0205	-0.1621	0.0041	-0.0403	-0.0081	-0.0196	0.1335
impparking1	0.0524	-0.1219	-0.0527	-0.0474	-0.0737	0.0336	0.1802
impparking2	0.1015	-0.1011	0.0284	-0.0633	0.2155	-0.1691	-0.0404
impparking3	0.0147	-0.0459	0.0132	0.1325	0.0465	-0.0877	-0.0918
impparking4	-0.0740	0.1280	-0.0086	-0.0949	-0.1141	0.1499	0.0540

age1	-0.0563	0.0621	-0.0140	-0.1178	-0.0238	0.1197	-0.0752
age2	0.0701	0.1976	-0.1543	-0.0816	-0.0653	0.1144	-0.0036
age3	-0.0753	0.0240	0.2141	-0.1018	0.0695	0.0114	-0.0650
age4	0.1698	-0.1960	-0.0454	0.0884	0.0590	-0.0699	-0.1066
age5	-0.2012	-0.0168	0.0684	0.1134	0.0179	-0.1498	0.1767
age6	0.1089	-0.0435	-0.0423	0.0484	-0.0717	0.0282	0.0465
household1	0.0488	-0.0517	-0.1511	-0.0201	0.0134	-0.0349	0.0856
household2	-0.0477	0.1023	-0.0909	0.0846	0.0352	-0.0536	-0.0796
household3	-0.0315	-0.0196	0.2312	-0.0416	-0.0833	0.0976	0.0292
household4	0.1015	-0.1011	-0.0704	-0.0633	0.0959	-0.0468	-0.0404
income1	0.0275	0.0669	-0.1164	-0.0916	-0.0549	0.0859	0.0506
income2	0.0037	-0.2314	0.0563	0.0699	-0.0193	0.0124	-0.0744
income3	-0.0198	0.1814	0.0150	-0.0126	0.0509	-0.0625	0.0411

	imppark1	**imppark2**	**imppark3**	**imppark4**	**imptra~1**	**imptra~2**	**imptra~3**
imppark1	1.0000						
imppark2	-0.1051	1.0000					
imppark3	-0.1899	-0.6466	1.0000				
imppark4	-0.0788	-0.2684	-0.4852	1.0000			
imptrain1	0.0571	0.1583	-0.0461	-0.1511	1.0000		
imptrain2	0.0689	0.0577	-0.0892	0.0195	-0.2790	1.0000	
imptrain3	-0.0642	-0.1009	0.1251	-0.0186	-0.2620	-0.6450	1.0000
imptrain4	-0.0629	-0.0859	-0.0091	0.1421	-0.1206	-0.2969	-0.2789
impparking1	-0.0275	-0.0937	-0.0122	0.1394	-0.0527	-0.0501	-0.1219
impparking2	-0.0367	0.0106	-0.0463	0.0661	0.1272	-0.1125	-0.0395
impparking3	0.0820	0.0266	0.0195	-0.0948	-0.0668	0.1309	-0.0209
impparking4	-0.0603	-0.0020	0.0031	0.0257	0.0325	-0.0718	0.0767
age1	0.1394	0.0082	0.0051	-0.0800	-0.1311	-0.1066	0.0986
age2	-0.0805	0.0129	0.0118	0.0058	0.1593	-0.0260	-0.0307
age3	-0.0591	0.2032	-0.0859	-0.0981	0.2141	-0.0372	-0.0577
age4	-0.0970	-0.1052	0.0563	0.0932	-0.0922	0.0899	0.0084
age5	0.0544	0.0434	-0.0740	0.0227	-0.0215	0.0577	-0.0168
age6	0.0622	-0.1485	0.0970	0.0173	-0.1096	-0.0213	-0.0015
household1	0.2033	-0.0865	-0.0350	0.0560	-0.1511	-0.0457	-0.0517
household2	0.0127	-0.0585	0.0530	-0.0076	-0.0086	-0.0212	0.1280
household3	-0.1511	0.0631	0.0179	-0.0293	0.1111	0.0515	-0.0446
household4	-0.0367	0.1462	-0.1062	-0.0139	0.0284	0.0091	-0.1011
income1	0.0885	-0.0969	0.0200	0.0525	-0.1125	-0.0361	-0.0142
income2	0.0571	0.0367	0.0566	-0.1487	0.1194	0.0694	-0.1449
income3	-0.1068	0.0222	-0.0658	0.1109	-0.0475	-0.0449	0.1467

	imptra~4	**imppa~g1**	**imppa~g2**	**imppa~g3**	**imppa~g4**	**age1**	**age2**
imptrain4	1.0000						
impparking1	0.3139	1.0000					

impparking2	0.1133	-0.0328	1.0000				
impparking3	-0.1069	-0.1799	-0.2403	1.0000			
impparking4	-0.0368	-0.1188	-0.1587	-0.8714	1.0000		
age1	0.1392	0.1706	0.0069	-0.1972	0.1458	1.0000	
age2	-0.0647	-0.0718	0.0619	-0.1755	0.1775	-0.1786	1.0000
age3	-0.0583	-0.0527	0.0284	0.0931	-0.0909	-0.1311	-0.1543
age4	-0.0641	-0.0865	-0.1155	0.2233	-0.1542	-0.2150	-0.2530
age5	-0.0431	-0.0937	0.0106	0.0815	-0.0585	-0.2330	-0.2742
age6	0.1397	0.2151	0.0334	-0.0863	0.0066	-0.1268	-0.1492
household1	0.2935	0.2442	0.0661	-0.0948	-0.0076	0.1569	0.0905
household2	-0.1543	-0.1188	0.0275	-0.0678	0.0960	-0.1852	0.0790
household3	-0.1174	-0.0555	-0.0590	0.1372	-0.0990	0.0590	-0.1384
household4	0.1133	-0.0328	-0.0437	0.0011	0.0275	0.0069	-0.0170
income1	0.1975	0.2812	0.0367	-0.0351	-0.0618	0.1105	0.0731
income2	-0.0032	-0.0014	-0.0919	-0.0777	0.1202	-0.0187	0.0433
income3	-0.1136	-0.1648	0.0660	0.0949	-0.0783	-0.0475	-0.0845

	age3	**age4**	**age5**	**age6**	**househ~1**	**househ~2**	**househ~3**
age3	1.0000						
age4	-0.1858	1.0000					
age5	-0.2014	-0.3301	1.0000				
age6	-0.1096	-0.1797	-0.1947	1.0000			
household1	-0.0981	-0.0204	-0.1229	0.0173	1.0000		
household2	-0.2143	-0.2718	0.2803	0.3023	-0.3405	1.0000	
household3	0.2312	0.2697	-0.1569	-0.2799	-0.3860	-0.6524	1.0000
household4	0.1272	0.0258	-0.0573	-0.0681	-0.0939	-0.1587	-0.1799
income1	-0.0440	-0.0481	-0.1485	0.1210	0.3854	-0.1135	-0.2160
income2	-0.0333	-0.0759	0.0686	-0.0032	0.0695	0.0512	-0.1147
income3	0.0578	0.1009	0.0222	-0.0684	-0.2940	0.0182	0.2371

	househ~4	**income1**	**income2**	**income3**
household4	1.0000			
income1	0.0673	1.0000		
income2	0.0246	-0.2309	1.0000	
income3	-0.0632	-0.3703	-0.8183	1.0000

Table 16. Breusch-Pagan test model 1

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: Gender age2 age3 age4 age5 age6 hh_Pers household2 household3 household4 hh_License income2 income3 km_Sup km_School km_Sports km_Park
chi2(17) = 22.27
Prob > chi2 = 0.1746

Table 17. Breusch-Pagan test model 2

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: Gender age2 age3 age4 age5 age6 hh_Pers household2 household3 household4 hh_License income2 income3 km_Sup km_School km_Sports km_Park km_Train
chi2(18) = 21.89
Prob > chi2 = 0.2371

Table 18. Breusch-Pagan test model 3

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: Gender age2 age3 age4 age5 age6 hh_Pers household2 household3 household4 hh_License income2 income3 km_Sup km_School km_Sports km_Park km_Train urbanity2 urbanity3 urbanity4 urbanity5 pop_Density
chi2(23) = 32.27
Prob > chi2 = 0.0947

Table 19. Breusch-Pagan test model 4

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: Gender age2 age3 age4 age5 age6 hh_Pers household2 household3 household4 hh_License income2 income3 km_Sup km_School km_Sports km_Park km_Train urbanity2 urbanity3 urbanity4 urbanity5 pop_Density Pref_CarBike Pref_CarPT Pref_CarWalk Car_Less Car_No
chi2(28) = 90.01
Prob > chi2 = 0.0000

Table 20. Breusch-Pagan test model 5

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: Gender age2 age3 age4 age5 age6 hh_Pers household2 household3 household4 hh_License income2 income3 km_Sup km_School km_Sports km_Park km_Train urbanity2 urbanity3 urbanity4 urbanity5 pop_Density Pref_CarBike Pref_CarPT Pref_CarWalk Car_Less Car_No impsup2 impsup3 impsup4 impschool2 impschool3 impschool4 impsport2 impsport3 impsport4 imppark2 imppark3 imppark4 imptrain2 imptrain3 imptrain4 impparking2 impparking3 impparking4
chi2(45) = 46.17
Prob > chi2 = 0.4237

Table 21. Breusch-Pagan test model 6

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: Gender age2 age3 age4 age5 age6 hh_Pers hh_License household2 household3 household4 income2 income3 km_Sup km_School km_Sports km_Park km_Train urbanity2 urbanity3 urbanity4 urbanity5 impsup2 impsup3 impsup4 impschool2 impschool3 impschool4 impsport2 impsport3 impsport4 imppark2 imppark3 imppark4 imptrain2 imptrain3 imptrain4 impparking2 impparking3 impparking4
chi2(40) = 49.09
Prob > chi2 = 0.1535

Appendix C – Regression output

Table 22. Regression results model 1

hh_Car	Coef.	Std. Err.	P>t	
Gender	-.0776694	.1253004	0.536	
age2	.866531	.2143831	0.000	***
age3	.8077462	.2638497	0.003	**
age4	.632317	.2196006	0.005	**
age5	.6298595	.2122734	0.004	**
age6	.653574	.2573058	0.012	*
hh_Pers	.063537	.0976685	0.517	
household2	-.1923541	.2126277	0.367	
household3	-.410953	.3021788	0.176	
household4	-.2882873	.4039436	0.477	
hh_License	.7258746	.1229094	0.000	***
income2	.0701031	.2231823	0.754	
income3	.1749909	.2271103	0.442	
km_Sup	-.3198719	.2125592	0.135	
km_School	-.4845176	.2919768	0.100	
km_Sports	.1359711	.1939682	0.485	
km_Park	-.3849881	.4153532	0.356	
_cons	.3682281	.5188075	0.479	

* p<0.1; ** p<0.05; *** p<0.01

Number of observations = 141
R-squared = 0.5174
Adj. R-squared = 0.4507

Table 23. Regression results model 2

hh_Car	Coef.	Std. Err.	P>t	
Gender	-.0857481	.1264459	0.499	
age2	.8500443	.2169187	0.000	***
age3	.7950803	.2655128	0.003	**
age4	.6311099	.220217	0.005	**
age5	.6121425	.2151247	0.005	**
age6	.6367582	.259703	0.016	*
hh_Pers	.0690595	.0984178	0.484	
household2	-.1988558	.2135206	0.354	
household3	-.4384342	.3068379	0.156	

household4	-.3171763	.4082282	0.439	
hh_License	.7147818	.1247811	0.000	***
income2	.0835842	.225049	0.711	
income3	.1967156	.2309155	0.396	
km_Sup	-.3146374	.2133444	0.143	
km_School	-.5215227	.299919	0.085	*
km_Sports	.1146077	.1980942	0.564	
km_Park	-.3422954	.4232041	0.420	
km_Train	-.0764697	.1343936	0.570	
_cons	.4230954	.5291006	0.425	

* p<0.1; ** p<0.05; *** p<0.01

Number of observations = 141
R-squared = 0.5187
Adj. R-squared = 0.4477

Table 24. Regression results model 3

hh_Car	Coef.	Std. Err.	P>t	
Gender	-.0582494	.1250436	0.642	
age2	.8276317	.210281	0.000	***
age3	.7379381	.2570662	0.005	**
age4	.5972106	.2118872	0.006	**
age5	.4775099	.2123275	0.026	**
age6	.4814701	.2533285	0.060	*
hh_Pers	.0421567	.0961809	0.662	
household2	-.0848529	.2109531	0.688	
household3	-.2992743	.30282	0.325	
household4	-.2476154	.395991	0.533	
hh_License	.7038488	.1208977	0.000	***
income2	.0251059	.2188961	0.909	
income3	.0705676	.2291294	0.759	
km_Sup	-.1816527	.2150403	0.400	
km_School	-.3768872	.3019248	0.214	
km_Sports	.0652044	.1933722	0.737	
km_Park	.0751967	.4311629	0.862	
km_Train	.2202947	.1791479	0.221	
urbanity2	.208356	.2270802	0.361	
urbanity3	.071649	.3256765	0.826	
urbanity4	.4230178	.2718927	0.122	
urbanity5	1.001052	.4016989	0.014	**
pop_Density	-.0000232	.0000221	0.296	

_cons	-.3626985	.6186878	0.559	

* p<0.1; ** p<0.05; *** p<0.01

Number of observations = 141
R-squared = 0.5752
Adj. R-squared = 0.4917

Table 25. Regression results model 4

hh_Car	Coef.	Std. Err.	P>t	
Gender	-.1801508	.1477788	0.229	
age2	.1388707	.2924999	0.637	
age3	-.0252053	.4083082	0.951	
age4	-.0402789	.2665436	0.881	
age5	.2872165	.3130911	0.364	
age6	.205815	.3854604	0.596	
hh_Pers	.0404833	.146965	0.784	
household2	-.1933303	.2962982	0.517	
household3	-.397858	.3070712	0.202	
household4	-.3051679	1.071332	0.777	
hh_License	.436671	.1935107	0.029	**
income2	.5074236	.2644867	0.062	*
income3	.477532	.2571234	0.070	*
km_Sup	.1230145	.2558678	0.633	
km_School	-.4551634	.2463384	0.071	*
km_Sports	-.2074032	.1877258	0.275	
km_Park	.4443147	.2336122	0.064	*
km_Train	.189928	.2375513	0.428	
urbanity2	.371083	.2396971	0.129	
urbanity3	.1433357	.3572697	0.690	
urbanity4	.7536796	.3417764	0.033	**
urbanity5	.7239839	.4820227	0.140	
pop_Density	-.0000125	.0000379	0.743	
Pref_CarBike	-.0360068	.177054	0.840	
Pref_CarPT	-.1137581	.138277	0.415	
Pref_CarWalk	.4316559	.1867495	0.026	**
Car_Less	-.3072494	.1477689	0.043	**
Car_No	-.0056984	.178392	0.975	
_cons	.1744052	.5781862	0.764	

* p<0.1; ** p<0.05; *** p<0.01

Number of observations = 73
R-squared = 0.6788

Table 26. Regression results model 5

hh_Car	Coef.	Std. Err.	P>t	
Gender	-.1785019	.1954408	0.369	
age2	-.3255067	.419367	0.444	
age3	-.4404882	.5086727	0.394	
age4	-.2505798	.4307538	0.566	
age5	.0047078	.4215421	0.991	
age6	-.146258	.4463775	0.746	
hh_Pers	.2154663	.1840733	0.252	
household2	-.479999	.5253527	0.369	
household3	-1.280456	.7683323	0.107	
household4	-.7849906	1.022078	0.449	
hh_License	.2397548	.2454166	0.337	
income2	.8170948	.3222887	0.017	**
income3	.8470532	.450472	0.071	*
km_Sup	.1397039	.270945	0.610	
km_School	-.7265273	.4442604	0.114	
km_Sports	.078162	.298083	0.795	
km_Park	.2256112	.2891872	0.442	
km_Train	-.1550231	.3213874	0.633	
urbanity2	.4701952	.3922185	0.241	
urbanity3	-.0081048	.5428894	0.988	
urbanity4	.6378961	.4356457	0.155	
urbanity5	.8942381	.5744092	0.131	
pop_Density	-.0000144	.0000514	0.781	
Pref_CarBike	-.0980332	.2547157	0.703	
Pref_CarPT	-.3447413	.2517964	0.182	
Pref_CarWalk	.51703	.2479618	0.047	**
Car_Less	-.277163	.2076933	0.193	
Car_No	.1703021	.2405247	0.485	
impsup2	.4425017	.5754278	0.449	
impsup3	.6175525	.6041846	0.316	
impsup4	-.1431102	.5106529	0.781	
impschool2	-.4548174	.5043763	0.375	
impschool3	-.4146795	.582374	0.483	
impschool4	-.0509355	.3998089	0.900	
impsport2	.8329206	.7087236	0.250	
impsport3	.932968	.8336357	0.273	
impsport4	.909762	.880553	0.311	
imppark2	.6896011	.8862226	0.443	

imppark3	.7436472	.8739711	0.402	
imppark4	.7568937	.9992137	0.455	
imptrain2	-.1132843	.2449412	0.647	
imptrain3	-.2116927	.2784043	0.454	
imptrain4	.1282477	.307362	0.680	
impparking2	0	(omitted)		
impparking3	.5588823	.515064	0.287	
impparking4	.1885987	.4365306	0.669	
_cons	-1.044418	1.157516	0.375	

* p<0.1; ** p<0.05; *** p<0.01

Number of observations = 73
R-squared = 0.7704

Table 27. Regression results model 6

hh_Car	Coef.	Std. Err.	P>t	
Gender	-.0652326	.1243647	0.601	
age2	.5609701	.2169438	0.011	**
age3	.4473509	.251211	0.078	*
age4	.4571787	.2217528	0.042	**
age5	.2920388	.2162504	0.180	
age6	.6379777	.2589689	0.015	**
hh_Pers	.0001795	.0980479	0.999	
hh_License	.7190075	.1177449	0.000	***
household2	-.2882536	.2229567	0.199	
household3	-.5115943	.315694	0.108	
household4	-.3145456	.3988192	0.432	
income2	-.1166067	.2174969	0.593	
income3	-.0412351	.2235295	0.854	
km_Sup	-.0978473	.2142997	0.649	
km_School	-.3078556	.2960064	0.301	
km_Sports	-.0148843	.1979492	0.940	
km_Park	-.4414221	.4260013	0.303	
km_Train	.1925147	.1726202	0.267	
urbanity2	.101286	.2267586	0.656	
urbanity3	-.255287	.3197972	0.427	
urbanity4	.2137164	.2671642	0.426	
urbanity5	.916516	.3982552	0.023	**
pop_Density	-.0000303	.0000219	0.169	
impsup2	.0285655	.51626	0.956	

impsup3	-.0765188	.5134152	0.882	
impsup4	-.5699351	.5244708	0.280	
impschool2	-.2216215	.1903499	0.247	
impschool3	.1592446	.2023109	0.433	
impschool4	.5265899	.2384812	0.030	**
impsport2	.1925431	.2429774	0.430	
impsport3	.1963225	.2805104	0.486	
impsport4	.4837762	.410412	0.241	
imppark2	.8955205	.4140606	0.033	**
imppark3	.8207485	.4007149	0.043	**
imppark4	.7981003	.4251554	0.063	*
imptrain2	-.1907924	.2061525	0.357	
imptrain3	-.3388476	.2037789	0.100	
imptrain4	-.2973074	.2889722	0.306	
impparking2	.3070351	.498035	0.539	
impparking3	.7411144	.4408457	0.096	*
impparking4	.8449893	.4380949	0.057	*
_cons	-.6769229	.9741109	0.489	

* p<0.1; ** p<0.05; *** p<0.01

Number of observations = 141
R-squared = 0.7001
Adj. R-squared = 0.5760

Table 28. Logit model output

hh_Car_bin	Coef.	Std. Err.	P>z	
Gender	.9371022	2.31077	0.685	
age2	20.20442	10.53172	0.055	
age3	4.257838	3.36475	0.206	
age4	17.50762	8.227696	0.033	*
age5	4.517054	3.715403	0.224	
age6	-.5913452	5.30964	0.911	
hh_Pers	.3138816	1.652138	0.849	
household2	14.38571	7.767084	0.064	
household3	1.950582	5.542852	0.725	
household4	0	(omitted)		
hh_License	.364977	3.218668	0.910	
income2	1.137118	3.150696	0.718	
income3	-3.079967	3.323154	0.354	
km_Sup	5.433422	4.774156	0.255	
km_School	0	(omitted)		

km_Sports	9.989293	6.159742	0.105	
km_Park	0	(omitted)		
km_Train	2.272784	3.43688	0.508	
urbanity2	5.958099	4.104855	0.147	
urbanity3	0	(omitted)		
urbanity4	7.418915	5.326762	0.164	
urbanity5	0	(omitted)		
pop_Density	-.0007538	.0004129	0.068	
_cons	-21.46585	13.10645	0.101	

* p<0.1; ** p<0.05; *** p<0.01

Number of observations = 114
LR chi2 (18) = 64.84
Prob > chi2 = 0.0000
Pseudo R2 = 0.7303