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The dynamic effects of car ownership determinants in the Netherlands

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Preface

After four years and a few months, my student years are over. A period in which I learned very much and met a lot of interesting and inspiring people. First I finished my Bachelor of Economics and Business Economics at the Erasmus University. Now this thesis concludes my Master Urban, Port and Transport Economics. This was a truly inspiring and interesting year, with many useful lectures, field trips and assignments. I would like to thank every professor and student who was a part of this year. Especially, I would like to thank Jan-Jelle Witte, my supervisor for all his advice, tips, feedback and time he put into this project. Also, I would like to thank my family and friends, for their advice, patience and motivational support.

Abstract

This thesis discusses the dynamics of some main household car ownership determinants in the Netherlands between 2005 and 2015. First of all, a literature review is made to look for existing relationships and dynamic effects. Next, three models were created with household car ownership as dependent variable. The models were formed around the three main determinants: income, urban form and household composition. Adding a interaction between the determinant of interest and the year of observation, the dynamic effects were estimated with the pooled ordinary least squares method. The graphs show a dynamic effect for both income and household composition, where the income effect seems to follow the business cycle. Household composition showed decreasing importance in determining household car ownership. In contradiction, urban form showed no significant dynamic effect between 2005 and 2015. The author recommends further analysis with some model improvements to confirm found effects and find possible causes for the trends found. Also, other car ownership determinants might be interesting to check for dynamic effects. For example, parking supply and psychological variables regarding car ownership.

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1. Introduction

The number of cars is rapidly increasing throughout the world. In 2000 there were around 700 million light-duty road vehicles (LDV's) around the world (World Business Council for Sustainable Development, 2004). This category consists of cars, light trucks, minivans and sport utility cars. The World Business Council for Sustainable Development (2004) also made a extrapolated forecast for these light-duty vehicle stocks of different regions. According to this forecast, there will be approximately 1.3 billion LDV's in 2030 and just over 2 billion in 2050. The growth is primarily caused by developing countries. For example, the car stock in China expanded 2.9 times between 2000 and 2005 (Han & Hayashi, 2008). Nowadays the car stock is causing a lot of problems already. First of all, traffic congestion is a major problem for society. According to Winston and Langer (2006) traffic congestion led to around 700 million person hours of delay per year in the 80's, around 2 billion in the 90's and almost 3.5 billion person hours of delay in 2000. Moreover, they estimate the yearly cost of congestion around $50 billion a year for motorists, truck operators and shippers combined.

Another externality of car use is pollution. The transport sector is responsible for 14% of the total Greenhouse Gas Emissions (GGE). The major part of this is caused by road transport of both freight and passengers (Hensher, 2008). For example, in Australia the transport sector was responsible for 76.2 Mt (mega tonnes) of CO_2, which is 13.5% of the total emissions of Australia. Only the energy sector is more polluting. Passenger transport is the largest part, accounting for 41.7 Mt CO_2. Furthermore, the pollution of road transport is strengthened by traffic congestion. The stop-and-go driving associated with congestion increases the CO_2 emissions (Barth & Boriboonsomsin, 2008).

Furthermore there is a problem regarding road accidents. Elvik (2000) states a rule of thumb that road accidents cost the national economy 1% of its gross national income. Moreover, road accidents cause a lot of health issues and fatalities. In 2002 about 1.18 million people died in road accidents, this accounted for 2.1% of the total mortalities around the globe (Anderson, 2009).

Congestion, pollution and road accidents are some examples of negative effects related to car use. The magnitudes of these problems emphasise the importance of reducing car use. Basically, it is necessary to reduce the Vehicle Miles Transport (VMT). This is how car use is often measured and used in literature. VMT can be reduced by reducing car use itself or by reducing car ownership. These two are related, which will be discussed later in this section.

There is much research done regarding solutions for the externalities of cars. Basso, Guevara, Gschwender and Fuster (2011) analysed if congestion pricing, transit subsidies and dedicated bus lanes are sufficient solutions for reducing congestion. Parry (2002) examined the efficiency of congestion taxes on freeways, transit fare subsidy and gasoline tax in reducing traffic congestion. Arnott, De Palma and Lindsey

(1991) researched if route guidance and information systems can reduce traffic congestion. Also platooning, synchronized movement of multiple vehicles with similar speed and very little distance between them, is analysed in potentially reducing both traffic congestion and pollution (Mitra & Mazumdar, 2007). Fullerton and West (2002) analysed different forms of taxes on cars and/or mileage in order to reduce pollution. Also, some cities are banning old diesel cars in their inner city in order to improve their air quality. All these proposed solutions have the possibility to reduce car use, but also reduce car ownership. Measures like congestion pricing, gasoline taxes and transit subsidies make owning a car relatively more expensive. For example, Bento, Goulder, Jacobsen and Von Haefen (2009) found that an increase of one cent per gallon in gasoline decreases the gasoline consumption by 0.2 percent. Also, an increase of 25 cents gasoline tax reduces the vehicle fleet by about 0.5 percent.

Research suggest that car ownership and car use are related. The relation of these two variables is analysed very often in literature, which claims different roles for car ownership. First of all, car ownership is stated to be an exogeneous variable, which together with spatial and socio-economic variables describe car use (Bagley & Mokhtarian, 2002). Other researches try to explain car ownership as an endogenous variable, which is described by spatial- and socioeconomic variables (Dargay, 2002). Interestingly, there are some researches that describe car ownership as mediating variable in the relation between the built environment and car use or travel behaviour. According to van Acker and Witlox (2010), car ownership and the built environment directly influence travel behaviour, but the built environment also influences car ownership. The built environment indirectly influences travel behaviour via car ownership, which is thus a mediating variable. In practice, the influence of car ownership on travel behaviour is also noticeable. If someone owns a car it is very easy and tempting to use the car for every trip, even if it could easily be done with, for example, the bike. Also, the marginal costs of using the car are relatively small if you own one. Car sharing programs strengthen this finding by showing the opposite. When people do not own a car themselves they consider each individual trip more. Meijkamp (1998) found that car sharing schemes reduce the average mileage by cars with 33%, from 8450 kilometres per year to 5660 kilometres per year. For the subgroup 'substituters', who owned a car before the sharing program, it is even a 65% reduction. This can be explained by the reduced availability of the car, users need to make a calculated decision when they need the car and make a reservation. So, this only occurs when they really need it.

Some research findings suggest that VMT and car ownership is partly reducing without interference. For example, the decreased preference for cars amongst younger generations, the millennials. Klein and Smart (2017) found that American millennials own, on average, 13% less cars than older cohorts. In their research this is mainly caused by lower income, decreased employment and less wealth. However, Jorritsma, Harms and Berverling (2014) of the KiM (Kennisinstituut mobiliteit) claim that young adults delay their car ownership instead of not owning a car at all. The young adults more often live in cities and study longer, which means the need for a car is less. The questionnaire of the study found that having children is an important reason to own a car and also the young adults (age 17- 24) stated they will take a car when they start a family. However, it is hard to say how this will be for the next generations.

Probably related to decreased car ownership among younger cohorts, is the idea of "peak car". Since younger generations own less cars or buy a car later in their lives, the car stock stops increasing. Some literature claims that we have reached "peak car", at least in some countries. Peak car refers to decreasing growth, levelling or even decline in car use/ownership in especially developing countries (Goodwin & van Dender, 2013). According to Newman and Kenworthy (2011) peak car is present in cities of developed countries and is caused by: technological limits, the fast growth in transit and re-urbanisation, the cutback in car use of older and younger generations due to urbanism and the growth of fuel prices.

Above some possible solutions for the negative externalities of car use and some relativities were discussed, while some solutions might reduce some of the externalities, it is far from sufficient. More research is needed to fully understand how VMT can be reduced. As described above, the influence of car ownership on car use might be a key factor in actually reducing VMT: why do people use and own cars, and how can households be stimulated to own less cars?

Looking at the cross-sectional literature regarding this topic, lots of research tried to find and estimate the determinants of car ownership and car travel. The effect of income is intensively analysed in different settings (Dargay, 2001; Dargay, 2007) and is almost incorporated in every model trying to explain car ownership. Also, economic development (Pongthanaisawan & Sorapipatana, 2010; Medlock & Soligo, 2002), parking supply (Guo, 2013; Weinberger, Seaman & Johnson, 2009; Tam & Lam, 2004), life-course events, such as changing household composition, (Prillwitz, Harms & Lanzendorf, 2006; Oakil, Ettema, Arentze & Timmermans, 2014) and urban form (Li, Walker, Srinivasan, & Anderson, 2010) are examined. Obviously, household characteristics, individual characteristics and socio-demographic variables have been incorporated or controlled for in most models. These cross-sectional analyses describe which variables explain car ownership, but only at one specific point in time. To estimate the actual effects of certain variables, time series are necessary. Also, the difference in importance of the variables over time can be estimated with time series. So, while the cross-sectional findings give interesting insights, for more precise effects and the dynamics of the variables over time we need dynamic models. However, if variables that only change over time are included panel data is required to estimate the actual effects. For this research time series are essential, because this is the best method to find and describe the changing importance of the car ownership determinants.

Interestingly, far less of these dynamic analyses regarding car ownership exist in former research. Dynamic models of car ownership determinants are very interesting for current and future car ownership trends. Most dynamic models focused the changing effects of income on car ownership (Dargay & Vythoulkas, 1999; Dargay & Gately, 1999). Oakil, Manting, & Nijland (2016) analysed the trend of decreasing car ownership among young adults. Other trends such as car-sharing, autonomous driving and/or a combination of these two might have a major influence on the amount of cars or whether people will still own a car. Well, the effects of these trends are hard to estimate right now, it is interesting to look how determinants of car ownership change over time. Lots of parties need to anticipate what car ownership will do. For example, parking supply is a major component of urban planning (Mingardo, van Wee & Rye, 2015). If car ownership decreases, should cities reshape existing parking facilities to other purposes or will parking facilities have new functions?

This paper wants to broaden the few empirical research findings regarding the dynamics of car ownership determinants. Looking at the most established determinants of car ownership, their influence will be analysed through time. Which factors are becoming more or less important? Using data from OViN (Onderzoek Verplaatsingen in Nederland) the main variables influencing car ownership will be analysed for different years with the pooled Ordinary Least Squares method.

How is the effect of different determinants of car ownership changing over time? And how can this be used to stimulate households to own less cars?

There is one recent study, which conducted similar research. Maltha, Kroesen, Van Wee and van Daalen (2017) analysed the changing influence of factors explaining household car ownership levels in the Netherlands. The goal and data of their study are similar to this research, however the execution is different. First of all, the time span is different. Maltha et al. (2017) analysed the factors between 1987 and 2014, whereas the focus of this study is between 2005 and 2015. Furthermore, the model will be different. Maltha et al. (2017) used an Ordered Logistic Regression, whereas this study will used Pooled Ordinary Least Squares using time dummies. This study will also be more careful with concluding dynamic effects. Dynamic effect are most likely to be caused by Omitted Variable Bias (OVB). OVB occurs when a variable has an influence but is not included in the model. So, this missing variables influence both included variables and the dependent variable, biasing the estimates of the independent variables. For example, the changing effect of income over time could be the consequence of not controlling for the economic crisis. Basically this study tries to describe the time effect more precisely.

In the next part the literature review will be covered, followed by the case study and methodology. Next, the results will be discussed.. Finally, the conclusion and discussion will be given.

2. Literature Review
With all the interesting developments and current or upcoming trends, discussed in the introduction, car ownership determinants is a very interesting topic. Lots of research already has been conducted, trying to estimate the determinants of why people own cars. First of all, the effects of car ownership will be shortly discussed. Also, the existing literature regarding the determinants of car ownership will be discussed.

2.1 Effects car ownership
As already discussed in the introduction, car ownership and car use are related. These variables are linked in literature in different ways. Some of them, describe car ownership as a mediating variable (Van Acker & Witlox, 2010). They claim, that car ownership directly influences travel behaviour, but also indirectly via the built environment. Moreover, car ownership increases car use significantly, meaning not only car use but also car ownership should be discouraged to reduce VMT (Van Acker & Witlox, 2010). Apparently, if people own a car they will use it more. Car sharing programs show similar results. If people do not own a car, they will only use the car when it is really necessary. For example, Meijkamp (1998) found a reduction of 33% of the average mileage of cars for a car sharing scheme. A more recent study in Montreal found that households, who are part of a car sharing program, use the car significantly less than households owning one or multiple cars (Sioui, Morency, & Trépanier, 2013). The results above, show that owning a car significantly increases the usage of a car. More car usage, or higher VMT, increases the negative externalities of using a car for transport.

Based on the above, car ownership increases car use. This means car ownership indirectly accounts for the negative externalities of car use. Probably the most well-known and most frustrating externality of car use is congestion. With the massive growth of car use, the capacity of the roads is barely holding. Basically, the car stock is growing faster than road capacity. Especially in peak times the capacity is far from sufficient. In the United States congestion caused yearly 700 million person hours delay in the 80's, approximately 2 billion in the 90's and almost 3.5 billion person hours delay in 2000 (Winston & Langer, 2006). Besides the time loss, congestion also increases the costs of a lot of parties influenced by the traffic congestion.

Another negative externality of car use is pollution. According to Kittelson (1998), road transport is one of the main sources of primary particular matter (PM) and the combustion of fuel is the primary cause of precursor gases like Carbon Monoxide (CO) and Nitrogen Oxides (NO_x) in the environment. Henser (2008) even claims that road transport is responsible for 14% of total Greenhouse Gas Emissions. Moreover, several studies showed the negative association of PM with health outcomes, like for instance Pope et al. (2002).

Road accidents is also a big negative externality of car use. Road accidents cost the national economy about 1% of its gross national income (Elvik, 2000). Road accidents are also responsible for a lot of health issues and fatalities. In 2002 about 1.18 million people died in road accidents, this accounted for 2.1% of the total mortalities around the globe (Anderson, 2009).

The externalities are not just bad themselves, they also sometimes strengthen each other. Pollution of cars becomes worse when driving in congestion. The stop-and-go driving associated with congestion increases the CO_2 emissions (Barth & Boriboonsomsin, 2008). Also, road accidents are often the cause of traffic congestion or worsen traffic congestion.

2.2 Car ownership determinants

Lots of research regarding car ownership is conducted already. In this section these determinants and former researches will be discussed.

2.2.1 Income

One of the most examined variables is income. Income is one of the main determinants of car ownership. To illustrate, in 1995 about 41% of the households in the UK of the lowest income decile owned a car, while in the highest decile it was 91% (Dargay, 2001). Dargay (2001) also looked at the car per person, which was 0.16 and 0.83 for the lowest and highest decile, respectively.

National level

First of all, income on the national level will be discussed. Dargay and Gately (1999) tried to estimate these effects worldwide. They used annual data between 1960 and 1992 of 26 countries, which are OECD countries and developing economies like China, India and Pakistan. The interest of their research was to estimate a econometric model that describes the growth of car ownership as a function of income (per-capita). The model is stated dynamically to both describe short- and long term income elasticities of car ownership. By plotting the number of cars per 1000 inhabitants and the annual growth rate of cars, considerable differences were found. The number of cars per 1000 inhabitants ranged from 2 to 560 and the annual growth rate from 1.2% to 18%. With the larger growth rates primarily found in fast growing economies like South Korea and Taiwan. In the figure below the ownership levels of 1970 and 1992 are plotted against the absolute number of cars. It becomes clear that countries with the lowest car ownership levels in 1970 experienced the highest percentage increase, for example: China, South Korea and more.

Figure 1

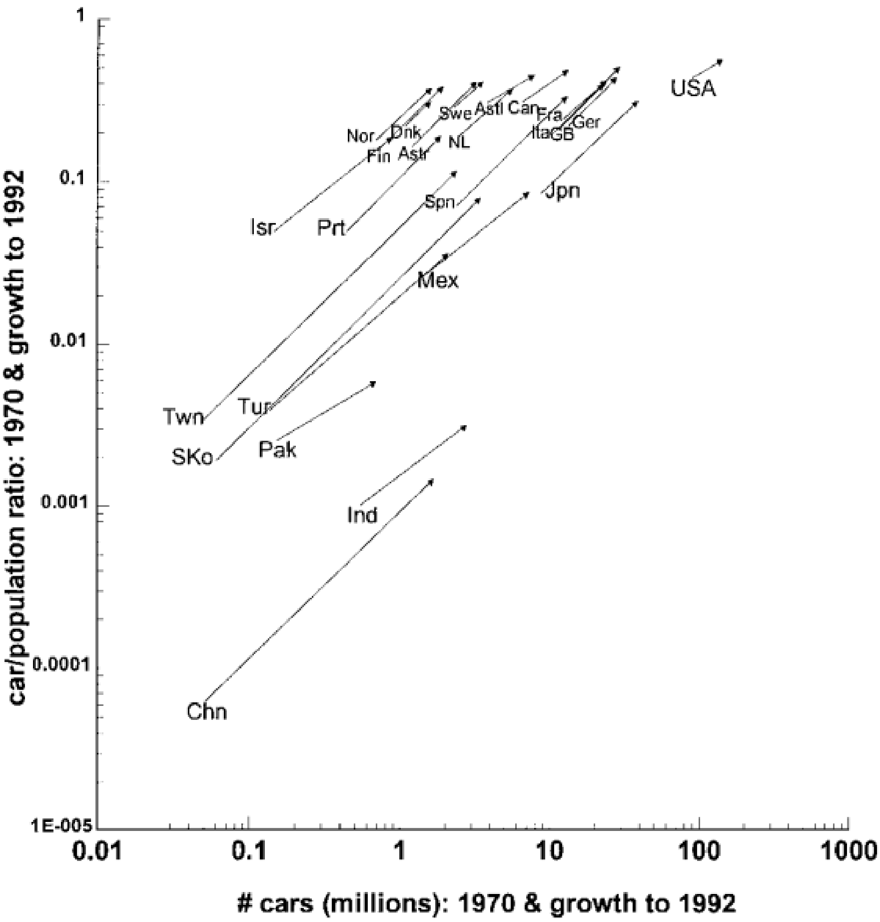
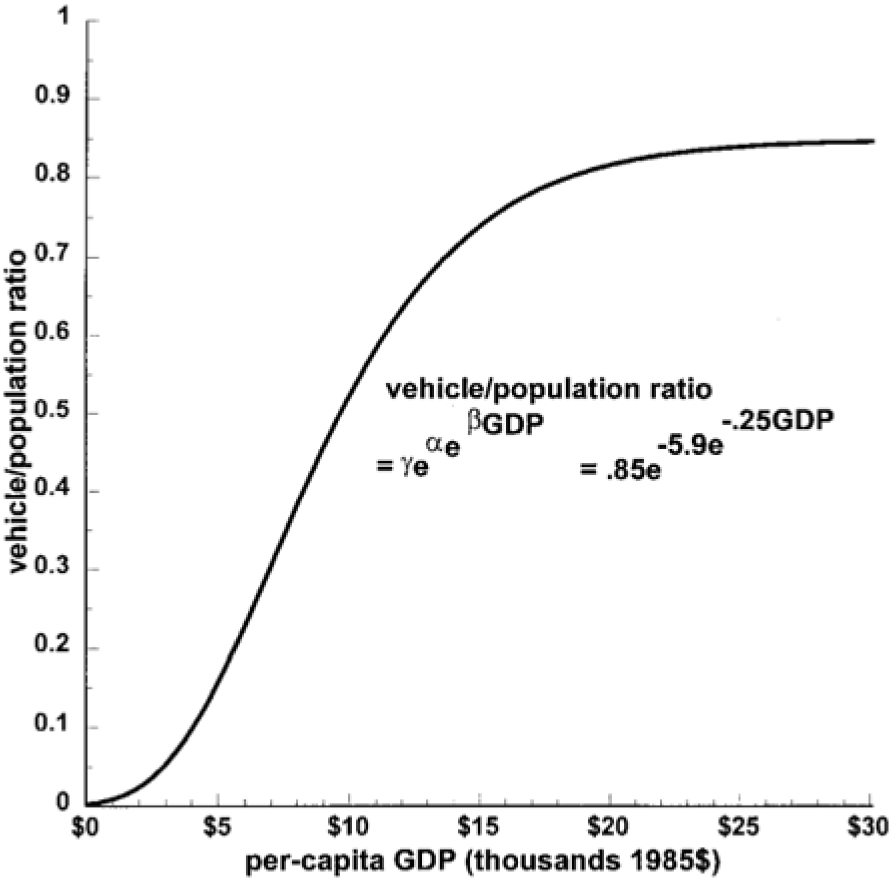


Figure 1 (Dargay & Gately, 1999)

Dargay and Gately (1999) used this and other figures to describe the relationship between vehicle ownership and per-capita income. Car ownership increases very gently at the lowest income levels, then increases very fast at higher income levels and finally the growth is flattening out at the highest levels when the saturation point is reached, leaving a sort of S-shape function. After some trial and error they describe the relationship with the Gompertz model, as can be seen in the figure below:

Figure 2: Vehicle Population Ratio



(Dargay & Gately, 1999)

Basically, Dargay and Gately (1999) found that the relationship between vehicle ownership and per-capita income is S-shaped as a Gompertz function, like the figure above. Were the largest growth in vehicles is in low income countries, which have an high increase in income. This work is extended by Dargay, Gately and Sommer (2007) by implementing unique saturation points for each country instead of one saturation point for every country, extending the dataset till 2002, adding 19 (mostly non-OECD) countries in the sample and including asymmetry with respect to falling and rising income in the model. The results were similar, again the Gompertz function described the relation between per-capita income and car ownership the best.

Individual level

While these results are interesting, the effect of income on the individual level tells more about the actual effects of income on car ownership. First of all, Dargay (2001) claimed that income elasticity is not constant throughout time. Income will increase car ownership, but this effect will decrease over time. Dargay (2001) also found hysteresis in the relation between income and car ownership, meaning that the elasticity with rising income is significantly larger compared to the elasticity regarding decreasing income. Probably it is easier to buy a car when your income increases, than dispose your car when your income falls. Once you own a car, it becomes a necessity. Dargay (2007) conducted similar research, analysing the effects influencing household car travel and car ownership. Using household income, prices of cars and fuels the car

travel and car ownership were estimated. Dargay (2007) found results similar to his results of Dargay (2001). The asymmetry of the household income effect was again highly significant, meaning significantly higher elasticity of rising income to car ownership than decreasing income.
It is obvious that income elasticity with respect to car ownership is central in the former discussed researches. Dargay and Vythoulkas (1999) also looked into this using a pseudo-panel approach. This approach combines the responses of independent samples of cross-sections from the population throughout a time span. Using this method they found that car ownership increases with income, as expected. Moreover, income elasticity decreases with increasing income and car ownership until middle income. From middle income on it remains constant.

Dynamics
Pendyala, Kostyniuk and Goulias (1995) also examined the relationship between car ownership and income, but especially how it changes over time. They analysed the sensitivity of car ownership with respect to income, the symmetry of the income elasticity and if the elasticity differ across various household types. They used panel data from 1984 through 1989 of the Dutch National Mobility Panel Survey. In order to estimate the effects and elasticities. Pendyala, Kostyniuk and Goulias made ordered-response probit models of car ownership at six different time points. They found that the number of drivers in the household and income were the most important variables in estimating car ownership. Both variables were highly significant at all six points in time.

From all the above, it becomes clear that income is one of the most important determinants of car ownership. Income is analysed a lot. Especially, the elasticity of income with respect to car ownership has been examined with different settings and different methods. Basically, all the results are similar. There is asymmetry in the elasticity, elasticity with rising income is significantly larger compared to the elasticity regarding decreasing income. Furthermore, there is the Gompertz function, the S-shaped relation between per-capita income and vehicle ownership. Important to notice, is that changing importance of income throughout time could also be caused by Omitted Variable Bias. For example, changing preferences regarding car ownership might have a dynamic effect. First, people only own cars if their income is sufficient. This implies a strong effect of income on car ownership. Next, people decide to not own a car, even when their income is sufficient, because of changing preferences. This weakens the effect of income on car ownership.

2.2.2 Household Composition and Life-cycle events
Besides income, household composition is also a well-known determinant of car ownership. The number of adults, the number of people with a driver’s license and the number of children all might have an influence on the number of cars owned by a household. Besides the composition itself, the changing composition of a household might be of interest as well. For instance, does the birth of a child influence the number of cars in a household? In this part, the effect of household composition and life-cycle events on car ownership will be discussed.

Household Composition
Household composition is an important determinant of household car ownership. First of all, the number of people is already of great influence on the number of cars in a household. Moreover, the composition influences the number of cars. The number of children, aged under 12, and the number of adults is both associated with increased chance of household car ownership (Nolan, 2010). Potoglou and Kanaroglou (2008) found that the household compositions: couple, couple with children and extended family all had a significant increased probability of owning two cars.

Decreasing car ownership young adults
The trend of decreasing car ownership among young adults is very interesting topic. Goodwin and Van Dender (2013) named possible factors responsible for this trend: expanded urbanisation, increasing singlehood, the forthcoming of e-communication, increased car mobility charges, higher economic uncertainty and the altering of life styles. Oakil, Manting and Nijland (2016) examined this trend as well by analysing car ownership of young Dutch adults for different values of household composition, urbanisation, income, employment situation and ethnic background. First of all, they state that car ownership declined from 30% to 25% for young adults between 20 and 25 years and from 52% to 46% for young adults between 25 and 30 years old, both trends were between 2000 and 2013. They used pooled data of vehicle registration and a Social Statistical Dataset and filtered on young households. Only young adults living as a single, couple, single-parent and two-parent household were included. According to their data, 60% of young adults do not own a car, 70% live in (high) urbanised areas and 68% of young adults is single. The second model also showed that household composition has an influence on household car ownership. Young single adults and single-parent families have to lowest change of owning a car, while two-parent families have the highest odds of owning a car (Oakil, Manting and Nijland, 2016). Finally, the second model also confirms that within the group of young adults, the oldest households are more likely to own a car than the younger households. Basically, urbanisation and the postponement of parenthood are partly responsible for this trend.

While this is an interesting trend, it is probably not an independent determinant influencing car ownership. If the model would control for all other determinants influencing car ownership (socio-demographics, income, urbanisation, household composition and all other possible determinants) their still should be a young adult effect. Frequently, remaining undescribed effects are assigned to preferences in economic models. However, I think it is likely this effect is still caused by variables, which are not included in the model. Basically, this would imply that decreased car ownership by young adults is possibly just a trend and not an independent determinant influencing car ownership.

Life-cycle events
Goodwin (1989) was one of the first to analyse the effect of life-cycle changes on car ownership using panel data. This consisted of marriage, childbirth, children growing up, children leaving home and retirement. His results show very small to no effect of these events on car ownership.

Clark, Chatterjee and Melia (2016) also looked in to life-cycle events. More precisely, they analysed which life-cycle event caused what car ownership level change (zero to one, one to two, etc). Acquiring the first car in a household is most likely to occur after cohabitation and child birth. The transition to a non-car owning household is associated the most by losing an adult, by children becoming an adult and moving out or by losing a partner. If an adult leaves the household the odds of losing a car rises with a factor of almost four (Clark, Chatterjee, & Meila, 2016). Gaining an adult in the household, by for example gaining a partner, has the strongest increase in moving from a single car to a two car household. Last, changing from a two car household to a single or non-car household is most likely caused by losing an adult, this increases the odds of losing a car by a factor of almost seven. Also, having a child increases the like hood of disposing a car (Clark, Chatterjee, & Meila, 2016). Household are likely to change the two cars for one bigger family car.

Dargay and Hanly (2007) used dynamic panel data models to compare car ownership levels of households. They found households that experienced a change in household composition had a greater chance of changing household car ownership levels in comparison to households that did not experience a life-cycle event. An adult leaving the household causes a 33.8% chance of the household reducing the car ownership level. If the number of adults increases in a household, there is a 30.5% chance the number of cars owned by that household will increase (Dargay & Hanly, 2007).

Dynamics

The importance of household composition and life-cycle events could change over time. In most cases, changing importance of determinants means the model suffers Omitted Variables Bias as described earlier. For household composition, children under the age of 12 are of great influence (Nolan, 2010). Especially, households with baby's seem to own and use cars more. For them, the car seems to be the safest and mostly the most convenient way to travel with their children. If public transport would become more safe and convenient to take prams along, this would weaken the effect of having kids on car ownership.

2.2.3 Urban Form

The third determinant of car ownership that will be discusses is urban form. The urban form of where the household lives might have an influence on whether or not they own one or multiple cars. For example, someone living in the inner-city is probably less likely to own and need a car, because this person lives close to all his basic needs.

Potoglou and Kanaroglou (2008) analysed the influence of urban forms on household car ownership in the metropolitan area of Hamilton, Canada. They found that higher density areas along with residences, located within walking distance from other transport modes, decrease the car ownership levels (Potoglou & Kanaroglou, 2008). Moreover, they claim that car ownership is mainly a requirement for households with members that do not live close to their work. This is similar with the results of Mata, Raymond and Roig (2009) for their Barcelona and Madrid case study. They found that urban structure, especially the public transport structure with respect to time costs for accessing jobs is very important in determining car ownership. Increasing this structure leads to a reduction of car ownership of 32.1% to 19.1% (Mata, Raymond and Roig, 2009).

Density

Li, Walker, Srinivasan and Anderson (2010) analysed the impact of urban form on car ownership in 36 megacities in China. They were interested in this effect in developing areas. China had a very high increase in private cars and urbanization, so was the perfect setting. They found a negative significant relation between population density and car ownership. Interestingly, they also found that in cities, households owning cars rather live in the inner-city than on the edge of the city (Li, Walker, Srinivasan and Anderson, 2010). Multiple researches focused the effect of urban density on car ownership. Caulfield (2012) for example found that people living in rural areas, so low dense areas, are significantly more likely to own cars. This is also found by: Dargay and Hanley (2007); Oakil, Manting and Nijland (2016) and Whelan (2007). The effect of urbanisation is strengthened by household composition, these two determinants are interacting. According to Oakil, Manting and Nijland (2016), the effect of urbanisation on car ownership varies for different household compositions. For example, in higher density areas, the young families are significantly owning more cars than young singles or couples.

Dynamics

The changing importance of urban form throughout time could be caused by omitting related variables in the model. For example, the accessibility of public transport. People living in cities might not need a car as much as people living in rural areas, because public transport facilities and accessibility are much better. If the model does not include public transport infrastructure this might influence the importance of urban form. If public transport improves throughout time, while not being controlled for, the effect of urban form on car ownership might increase through the same time span.

2.2.4 Parking supply

Another interesting possible determinant of car ownership is parking supply. Especially, local governments that want to reduce cars in their cities are interested in whether residential parking regulations can be used to decrease car ownership and travel behaviour. Guo (2013) found that parking supply has a strong significant effect on car ownership, while controlling for the endogeneity between the two variables. Moreover, different types of parking have different effects. For off-street parking, driveway parking is the most important for car ownership, but garage spaces were also significant (Guo, 2013). Garage spaces are probably less important, because garage spaces are often used for storage off things other than cars. Also, off-street parking has a positive significant effect on car ownership (Jiang, Gu, Chen, he, & Mao, 2017). Tam and Lam (2004) found in their case study of Hong Kong, that residential parking supply has a positive significant effect on owning multiple cars per household. So, according to them parking supply is more important if a household owns more than one car than for owning one car.

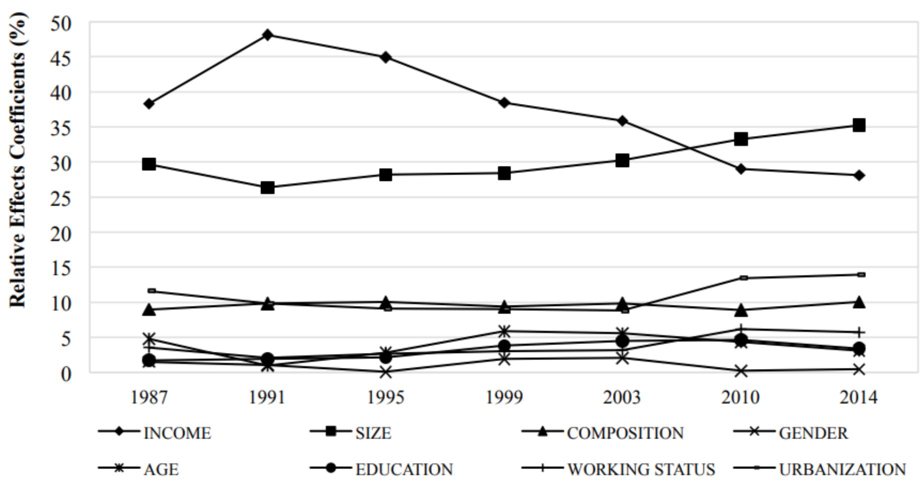
Dynamics

The effect of parking supply could change over time. This could be caused again by not controlling for all possible determinants of car ownership in the model. Parking policy of cities could be one of them, for example. If a city decides to ban cars in their inner-city this could affect both car ownership and the effect of parking supply on car ownership.

2.2.5 Dynamic analysis car ownership determinants

The main interest of this study is the dynamics of car ownership determinants. How does the influence of these variables change over time, if they change at all. There is very little research done regarding the changing influence of these determinants. Maltha, Kroesen, Van Wee and van Dalen (2017) made an ordered logistic regression of the determinants with data for the Netherlands between 1987 and 2014. Income, the most researched determinant, showed interesting results. The relative effect of income on car ownership declined from 38% in 1987 to 28% in 2014. This might be caused by hysteresis, as explained in 2.2.1. In contradiction, household size has gained importance. The contribution of household size to the total effect increased from 29% in 1987 to 35% in 2014. Furthermore, gender decreased from 1.5% in 1987 to 0.4% in 2014 and age from 4.8% in 1987 to 3.1% in 2014. Working status, educational level and urbanisation were more or less constant over time. In the figure below the relative importance of the determinants regarding car ownership throughout time are presented.

Figure 3: Relative effects determinants car ownership



(Maltha, Kroesen, Van Wee, & van Daalen, 2017)

3. Case Study and methodology

In this section the data and methodology used for this research will be discussed. First, the construction of the dataset will be showed together with the case study and formation of the hypotheses. Secondly, the methodology will be discussed alongside the regression models used to answer the hypotheses.

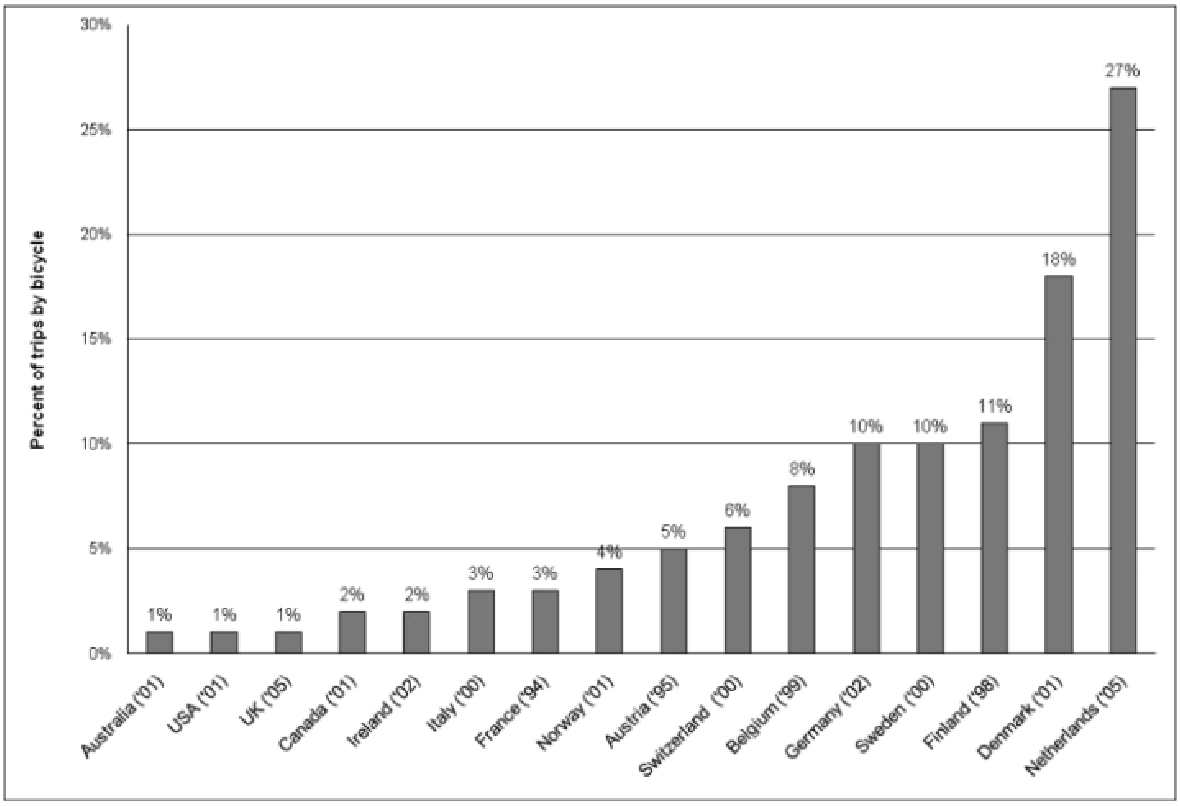
3.1 Dataset

The data used for this research is extracted from a dataset created by Onderzoek Verplaatsingen in Nederland (OVin). The goal of OViN is to provide sufficient information about the mobility of Dutch citizens (CBS, 2016). The data is collected on behalf of the Ministry of Infrastructure and Environment and for other research institutions. Random sampling is used to select respondents, who are asked to describe their mobility on one selected day in the year. So, where they are going, for what reason, which transport mode they use and how long it took (CBS, 2016). Furthermore, some socio-demographic and basic information is asked. Also, every year a new random sample is created, meaning this dataset is not panel data. The total dataset consists of the years 1978 till 2017. For this research the years 2005 till 2017 will be used, because for earlier years the data is less complete.

3.2 Case Study

In this part the case specific influences will be discussed. Mainly, doing this research for another region or timespan might not yield the same results, because of these case specific influences. This research studies car ownership determinants for Dutch citizens between 2005 and 2015. First of all, the Netherlands is well-known for its bicycle use. Pucher and Buehler (2008) analysed levels of cycling in different countries and regions and how their policies regarding transport influence these levels. It becomes clear, the Netherlands has a very high bicycle use. About 27% of the trips in 2005 were made by bike, while for example in the United Kingdom it was only 1%. The figure below shows the percent of trips made by bicycle in different countries.

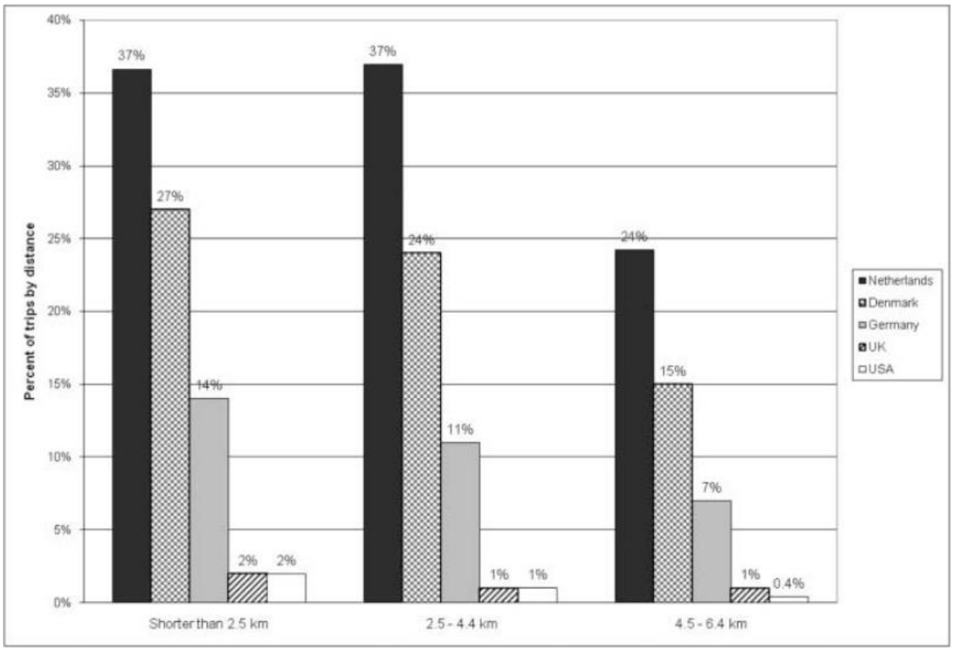
Figure 4: Bicycle trips made (%) per country



(Pucher & Buehler, 2008)

The figure shows the Netherlands has by far the highest percentage of trips made by bike. Some argue the Netherlands has on average shorter trip distances than for example the USA, but even after controlling for trip distance the Dutch make much more trips by bike than American people. For trips shorter than 2.5 kilometres, 37% of the trips are made by bike in the Netherlands. Americans only take the bike for 2% of the trips shorter than 2.5 kilometres. See the figure below for more details.

Figure 5: Bicycle trips made(%) by distance



(Pucher & Buehler, 2008)

The bike-loving behaviour might be in the genes of Dutch citizens, but it could also be the result of policy. Pucher and Buehler (2008) claim that part of the cause of this phenomenon is the created safety, convenience and attractiveness of cycling. Also, integration with public transport, education and training and promotional campaigns are partly responsible for this extensive bike use. However, this observation should be taken into account by the interpretation of this specific data. This high bicycle use in the Netherlands, could potentially influence the results of this research that would differ significantly when the research was done somewhere else. Specifically, it probably reduces car use and/or ownership through increased bicycle use.

3.3 Hypotheses

For this study of the Netherlands between 2005 and 2015 car ownership determinants will be analysed throughout this timespan. Especially the three main determinants discussed in the literate review will be studied. First of all, the effect of income on car ownership will be tested. Is the effect of income stable over this timespan, is income becoming more or less important or might there be variables missing that cause an de- or increase of the effect? Former research showed there are indications that the effect of income on car ownership is not constant throughout time (Dargay, 2001) . Therefore, the first hypothesis is formulated as follows:

H_1: The effect of income on car ownership is not constant between 2005 and 2015

The second determinant is household composition. In the literature review some interesting effects and trends were discussed like the postponement of parenthood and decreased car ownership of young adults. While I doubted if that were independent factors effecting car ownership, it is however interesting to see how household composition changes over time. There are no indications that household composition has a changing effect on car ownership in former research. For this reason, the second hypothesis will be:

H_2: The effect of household composition on car ownership is constant between 2005 and 2015

The third determinant of car ownership is urban form. According to literature, urban form is related to car ownership. Meaning, people living in higher dense areas or in cities are less likely to own a car compared to people living in rural areas (Caulfield (2012); Dargay and Hanley (2007); Oakil, Manting and Nijland (2016) and Whelan (2007)). There is however no indication for a changing effect of urban form over time. This study will try to find out if this effect is constant over time, trying to avoid Omitted Variable Bias as much as possible. The third hypothesis is formulated as follows:

H_3: The effect of urban form on car ownership is constant between 2005 and 2015

3.4 Description of the variables

The model of this research uses *hhCar* as dependent variable. This variable describes the number of cars a household owns. The number of cars are described from 0 till 8, a 9 means 9 or more cars and a 10 denotes the missing values, so the number of cars is unknown. These values of 10 will be dropped out, because they will give incorrect and misleading outcomes. Furthermore, this variable will be used as a continuous variable in this research. Strictly, *hhCar* is an ordinal variable, because only a few values are frequent (0,1 and 2 cars). However, for this research OLS is preferred over ordinal logit regression. First of all, the result are for more straightforward to interpret in comparison with an ordered logit model. Also, the results of OLS and ordered logit regression are often comparable if the dependent variable consists of more than 4 categories and the distribution is normal. However, this is questionable for this research. As can be seen in table 1 from Appendix A, the distribution is far from normal, because the first three values (0,1 and 2) are far more common than the others. Using OLS for this analysis is slightly a limitation, because it can be assumed OLS is not giving us the best estimates. Also, the interpretation of the coefficients are slightly less meaningful. For example, an unit increase of an independent variable could lead to an increase of 0.05 cars per household.

The independent variables used in this model are: *household*, *Urban, inc_proxy, hhAge1*, *hhAge2*, *hhAge3*, hhAge4, *Gender*, *Age* and *Year*. *Household,* is a proxy for the composition of the household, so for example a single-person household, a single-parent household with kid(s) or other compositions. The dataset did not include the household composition before 2010, so a proxy is created to define the household composition. The variables indicating how many persons per age range are present in the household and how many persons the household consists of in total are combined to make this proxy of household composition. All the compositions are described in table 1. *Urban,* describes the urban form of the households' address. For every address the density (of addresses) in a one kilometre radius is determined. Next for every municipality the average of all the address' densities are calculated and categorized. The five categories are based on the number of addresses per km². Starting from very urban, 2500 addresses or more, urban, 1500 till 2500 addresses, moderate urban, 1000 till 1500, rural, 500 till 1000 and very rural, less than 500 addresses per km². Again the numerical values of these categories can be found in table 1 below. *HHBestInk* is the variable indicating the disposable income of the households. It is determined by subtracting income transfers, income insurance premiums, health insurance premiums, tax expenses on income and property from their gross income. Important to notice, income was measured on the individual level in the dataset until 2010 and on the household level from 2010 on. To unify these two variables, an income proxy is created. *Inc_proxy* has four values, which all roughly presents an income group. One, describes approximately the lowest 15% of the incomes (both individual as household), Two stands for roughly the next 20%, Three for about the next 40% (basically the middle-income group) and four denotes approximately the top 25% of the incomes. *hhAge1, hhAge2, hhAge3* and *hhAge4* describe how many persons in that age range are part of the household. These categories range from 0 till 9 persons and 10 means ten or more persons. *hhAge1* are kids younger than 6 years old, *hhAge2* are kids from 6 till 12 years old, *hhAge3* resembles kids from 12 till 18 years old and *hhAge4* describes the number of people older than 18 in the household. *Gender* denotes the gender, with a 1 for males and a 2 for females. *Age* gives the age of the respondent from 0 till 98 and 99 denotes 99 or older. Finally the variable *Year,* which simply defines the year of the observation. The table below gives an overview of all the variables and their values/ categories.

Table 1: Overview variables

Variable	Description	Values
hhCar	Number of cars per household	0….9
hhpers	Number of persons household	1…9 10= 10 or more
household	Proxy for the household composition	1= single-person household 2= 2 adults 3= single-parent + 1 kid 4= single-parent + 2 kids 5= single-parent + 3(+) kids 6= 2 adults + 1 kid 7= 2 adults + 2 kids 8= 2 adults + 3(+) kids
Urban	Urban form	1= very urban 2= urban 3= moderate urban 4= rural 5= very rural

Inc_proxy	Proxy, unifying individual and household income to one variable	1= 0 - 15% 2= 15 – 35% 3= 35 – 75% 4= 75 – 100% (note this is a very rough proxy)
hhAge1	Household members below 6 years	0…9 10= 10 or more
hhAge2	Household members between 6 and 12 years	0…9 10= 10 or more
hhAge3	Household members between 12 and 17 years	0…9 10= 10 or more
hhAge4	Household members older than 18 years	0…9 10= 10 or more
Gender	Gender	1= male 2= female
Age	Age of respondent	0…98 99= 99 or older
year	Year of observation	-

Some descriptive statistics can be found in Appendix A. First of all the standard descriptive statistics like: mean, standard deviation, minimum and maximum can be found for the continuous variables and the frequency for the categorical variables in tables 5 through 10. Also, Appendix A consists three tables, where the dependent variable, *hhCar*, is displayed against the three main determinants of this study (*Inc_proxy*, *Urban* and *household).* This is presented in table 2,3 and 4. These tables give some good impressions of what the relation could be. For example, the percentage of the households of the lowest income group that own no cars is 35.86% compared to 2.45% of the highest income group (Table 2). While the significance is not tested yet, it gives an impression of income positively effecting car ownership. Also, 26.04% of the household living in a very urban environment do not own cars, compared to only 5.59% of the households located in very rural areas (Table 3). So, strong indications for a negative association between urban form and car ownership.

Next, the completeness of the variables is checked. If there are too much variables missing or there is a pattern in the missing values, this might be problematic. First of all, table 11 in Appendix A presents the missing values per variable. The table shows that for only two variables missing values are present. The income proxy and the household composition proxy are both missing almost 20% of their values. For the income proxy this is most likely, because people do not want to state their income. They find this information too private. This holds for all income classes, so no problems regarding these missing values. The household composition proxy misses some values, because not all composition are included. As can be seen in table 1 the compositions consist of 1 or 2 adults with or without kid(s), so it leaves out the composition with 3 or more adults. This means when a household consists of 3 adults or more, the value for the household proxy will be missing. This might be problematic, because the missing values are not random. However, *household* is an independent variable, so it would not be of a problematic influence on the results. Although, it does mean the results of this research are not applicable to these missing household compositions. Table 13 in Appendix B shows the household compositions in the Netherlands, which consists of at least 3 adults. It shows that for 2010, the middle of the time span of this research, 727.166 households have at least 3 adult members (CBS, 2018a). In 2010, the Netherlands counted 7.386.144 households in total (CBS, 2018b), which means 9,85% of the households consisted of at least 3 adults. This shows the missing data does not represent a major household composition, but it is important to keep in mind that the results are not applicable for this group.

3.5 Methodology

This research will use pooled ordinary least squares regression to estimate the changing effects of the determinants on car ownership. Interactions of time dummies with the main determinants show how the effect changes throughout different years. These coefficients will be graphed to visually show the dynamics. The graphs will also display the 95% confidence interval of these coefficients. When the confidence interval does not intersect with zero, it shows the coefficient is significantly different from zero on the 5%-significance level. The time span of the research is between 2005 and 2015, the year dummies are made for every 2 years. These dummies will indicate when the importance of the determinants changes, so this can be further analysed. When a significant change occurs, it is most likely these years suffer omitted variable bias. These points or trends will be analysed deeper, trying to indicate what possible causes for this change could be, which might be interesting for new studies to analyse. It also might be changing perceptions of people in what is most important to them for owning one or multiple cars.

Before describing the model, a Pearson correlation matrix is made, to test for multicollinearity. This matrix is given in Appendix B, table 12. The table shows a very high Pearson correlation coefficient between *hhAge4* and *hh1*, r = -0.8052. *hhAge4* denotes the number of persons of 18 years and older in the household and *hh1* is the dummy for single-person household. It makes sense these two are highly associated, because a single-person household will almost always be someone of 18 year or older. This means the assumption of no multicollinearity is violated. Basically, this means one independent variable can be linearly predicted from other independent variables, with significant preciseness. In order to not violate the assumption and to improve the model, *hhAge4* will be left out the model. This will not be a problem, because the number of adults a household consists of is already integrated in the household composition proxy. *hhAge1, hhAge2,* and *hhAge3* will still be included in the model, while the presence of kids is partly included in the household proxy. It is still interesting to see the different effects between age categories of children, because especially the youngest category seemed to have a significant influence on car ownership (Nolan, 2010). The model will control for socio-demographic variables like: age and gender. Below the economic model is given. The economic model is favoured over the econometric model, because that model would be very long and unclear to read.

Basically, the base model for $\boldsymbol{H_1}$ will be:

(1) *hhCar = f(hhAge1, hhAge2, hhAge3, Age, Gender, Urban, Household, inc_proxy, Year, inc_proxy*Year)*

Where:

inc_proxy*Year is the interaction effect between income and the year of observation

The base categories for the dummy variables are:

Year = 2005
Income = Income group 1 (so lowest 15% of incomes)
Urban form = very Urban
household = single-person household
Gender = Male

All the base categories are checked on the frequency in the database to check for under- or over representation. The frequency and percentage of the base categories can be checked in the descriptive statistics tables 6 through 10 in Appendix A.

The models for $\boldsymbol{H_2}$ and $\boldsymbol{H_3}$ will be similar, but then the time dummies will be applied on *Sted* and *Household*, respectively.

Also, in Appendix D an example of the base model is displayed. In this example, the average number of cars for the average Dutch household are modelled and graphically visualised.

4. Results

In this section the main results of the different models will be discussed, along with the outcomes of the hypotheses testing. Prior to the interpretation of the three models, the presence of heteroskedasticity is checked. A model suffers heteroskedasticity when the standard errors of a variable are not constant. If the assumption of no heteroskedasticity fails, the standard errors of the regression coefficients are biased. This makes the individual significance of the coefficients unreliable. The Breusch-Pagan test was used to check for heteroskedasticity, the results of this test are presented in tables 14, 15 and 16 form Appendix B. The tables show all three models suffer heteroskedasticity (p=0.000). To control for this, all the regression are estimated with White-Huber standard errors.

4.1 Main results

Before discussing the outcomes of the hypotheses, the general outcomes of the models will be discussed. Three models were estimated as discussed in the methodology. The regression outcomes of all models are presented in Table 2 below. The interaction effects, specific for each hypothesis, are left out in this table. The complete regression outputs can be found in Appendix C. It becomes clear from table 2 that the models are very close. The only difference between them, is the interaction between the year and the main variable for each hypothesis (1=income, 2=urban form and 3=household composition), which are not given in this table for a clearer overview. The output shows no real significant difference between the coefficients of the three models worth mentioning. There are some differences in the coefficients, but most of them are smaller than 0.1 car, which has no real world meaning. The variables do show some interesting outcomes. For example, the variables for the number of children of different age categories show a negative effect on car ownership. For the number of children between 0 and 6 years old, the coefficient is approximately -0.06 (significant at the 1% level) in all models. This is in contradiction with the literature and expectations of this relationship, because the presence of small kids are a main reason to own a car according to existing literature. This is the same for kids between 6 and 12 years. For the third category, kids between 12 and 18, the coefficient is around -0.055 (significant at the 1% level) for all models. For this category the association makes more sense, because kids of these ages are becoming more independent. For example, they are old enough to bike or take the bus to school. So, less reliant on their parents owning a car. The variable *Age*, indicating the age of the respondent, has a value of approximately -0.003 (significant at the 1% level). Again this effect is so small, it has no real world meaning.

Next, the income effect on car ownership is as expected. The income proxy shows increased car ownership for higher income groups. The first model, which includes the interactions of income and year, visualises this. The base category used in this model is the lowest income group, so the lowest 15% of incomes. The model shows the second income group own 0.0209 (significant at the 10% level) more cars than the lowest income group. This difference is so small, it has no real world meaning. Even though the difference is significant, owning 0.02 more cars has no real interpretation. However the other two groups do have a significant and real world difference. The third income group owns 0.249 (significant at the 1% level) cars more than households of the lowest income group. For the highest income group the difference is 0.443 (significant at the 1% level) cars. Meaning the difference between the lowest income group and the highest group is almost half a car. This effect is expected, as already stated in the literature review, income is of the most important determinants for car ownership.

Urban form has some interesting results as well. This dummy variable, describing how dense the living area of the household is, shows the effect with respect to the base category. The base category used in these models is very urban, this is the category with the most addresses per km², so the most dense category. For this interpretation the second model of table 2 is used, since this regression includes the time interactions of urban form. As expected and in line with the literature, car ownership increases with decreasing density of living environment. Households living in an urban environment own 0.171 (significant at the 1% level) more cars than household in very urban areas. For moderate urban, rural and very rural living environments this is 0.246, 0.302 and 0.349 (all significant at the 1% level) more cars per household than very urban living households, respectively. As described earlier, this is probably due to having all necessary facilities close to home and a better public transport network in very urban living environments.

Next, the household compositions all show a significant effect, at the 1% level, on household car ownership. The effects are with respect to the base category, single person household. For this interpretation model three is used, since this is the model with the interaction for household composition. The model shows a difference between household compositions with two adults and single parent households. The households with two adults, two adults with one kid, two adults with two kids and two adults with three or more kids own 0.566, 0.734, 0.842 and 0.869 more cars than a single person household, respectively. This is in line with the expectations and literature, since two adults are often owning more cars than a single person household. In addition, having kids increases the household car ownership level. The single parent households with one kid, two kids and 3 or more kids have 0.234, 0.285 and 0.496 (significant at the 1% level) more cars than a single person household, respectively. These effects are lower than for two adult households, since probably only one person in the household can drive a car and a single parent with kids has less money available for a car than two adult households.

The remaining variables are not very interesting, since they are not significant or have no real world effect. *Gender*, for example is only significant in the first two models, but again so small (-0.00738 & -0.00401) that it has no realistic influence. Leaves the variable *year*, which shows very small effects for the first two models (with varying significance). The third model shows that from 2010 till 2017 households own between 0.13 and 0.2 cars per household more than in 2005, which is the base year. Furthermore, the constant in this model is significant at the 1% level, but has no real meaning.

Table 2: Results regression models

VARIABLES	(1) hhCars	(2) hhCars	(3) hhCars
hhAge1	-0.0601***	-0.0611***	-0.0616***
	(0.00805)	(0.00805)	(0.00772)
hhAge2	-0.0494***	-0.0497***	-0.0478***
	(0.00801)	(0.00800)	(0.00767)
hhAge3	-0.0574***	-0.0569***	-0.0550***
	(0.00821)	(0.00821)	(0.00786)
Age	-0.00315***	-0.00318***	-0.00352***
	(6.14e-05)	(6.13e-05)	(6.29e-05)
Urban form			
Urban	0.191***	0.171***	0.192***
	(0.00318)	(0.0108)	(0.00317)
Moderate Urban	0.266***	0.246***	0.267***
	(0.00340)	(0.0111)	(0.00340)
Rural	0.332***	0.302***	0.333***
	(0.00334)	(0.0113)	(0.00333)
Very Rural	0.374***	0.349***	0.375***
	(0.00376)	(0.0119)	(0.00376)
Female	-0.00738***	-0.00401***	0.000176
	(0.00205)	(0.00202)	(0.00203)
Household composition			
2 Adults	0.475***	0.485***	0.566***
	(0.00285)	(0.00274)	(0.00767)
Single parent + 1 kid	0.125***	0.128***	0.234***
	(0.0109)	(0.0109)	(0.0283)
Single parent + 2 kids	0.169***	0.174***	0.285***
	(0.0178)	(0.0178)	(0.0356)
Single parent + 3(+) kids	0.192***	0.201***	0.496***
	(0.0261)	(0.0261)	(0.0662)
2 adults + 1 kid	0.625***	0.634***	0.734***
	(0.00911)	(0.00907)	(0.0150)
2 adults + 2 kids	0.703***	0.715***	0.842***
	(0.0163)	(0.0163)	(0.0184)
2 adults + 3(+) kids	0.727***	0.739***	0.869***
	(0.0262)	(0.0261)	(0.0288)
Year			
2006	0.0431***	-0.00429	0.00849
	(0.0147)	(0.0129)	(0.00875)
2007	0.0795***	0.0344***	0.0366***
	(0.0154)	(0.0133)	(0.00897)
2008	0.0644***	0.00384	0.00334
	(0.0174)	(0.0146)	(0.00944)
2009	0.128***	0.0280*	0.0116
	(0.0194)	(0.0156)	(0.00993)
2010	-0.0107	0.0185	0.180***
	(0.0134)	(0.0128)	(0.01000)
2011	-0.00269	0.0389***	0.185***
	(0.0131)	(0.0127)	(0.00986)
2012	0.0180	0.0415***	0.194***
	(0.0136)	(0.0129)	(0.00991)
2013	-0.0284**	0.0130	0.194***
	(0.0132)	(0.0127)	(0.0102)
2014	-0.0314**	0.0102	0.175***
	(0.0130)	(0.0125)	(0.00932)
2015	-0.0254*	0.0157	0.184***
	(0.0136)	(0.0118)	(0.00980)
2016	-0.0543***	-0.00521	0.154***
	(0.0146)	(0.0120)	(0.00989)

2017	-0.0668***	-0.0123	0.139***
	(0.0147)	(0.0119)	(0.00964)
Inc_proxy			
2	0.0209*	0.0651***	0.0957***
	(0.0110)	(0.00362)	(0.00376)
3.	0.249***	0.274***	0.309***
	(0.0106)	(0.00357)	(0.00378)
4.	0.443***	0.525***	0.561***
	(0.0119)	(0.00396)	(0.00417)
Constant	0.464***	0.438***	0.325***
	(0.0106)	(0.0101)	(0.00809)
Observations	382.800	382.800	382.800
R-squared	0.295	0.294	0.297

Robust standard errors in parantheses
***p<0.01 **p<0.05 *p<0.1

4.2 Hypotheses testing

In this part the results of the hypotheses testing is discussed. First of all, the basic results are discussed. Also, the results are compared with the analysis of Maltha, Kroesen, Van Wee and van Daalen (2017). Their analysis had the same goal, so it is interesting to compare the results with each other.

4.2.1 Income

The first hypothesis tries to state the dynamic effect of income on car ownership:

H_1: The effect of income on car ownership is not constant between 2005 and 2015

The complete regression output is displayed in Appendix C, Table 17. In this figure all the interaction coefficients are included. To give a more clear view of the results, a graph is made for each income group with their dynamic effect between 2005 and 2015. Important to notice, the coefficients are the effects with respect to the first income group in 2005. Also, the 95% confidence interval of the coefficients is added in the graphs with dotted lines. This confidence interval distinct whether a coefficient is significantly different from zero (on the 5% level). That is, if the dotted line does not intersect with zero. So, if the confidence interval lies completely above zero, the effect is significantly different form zero and positive. If the confidence interval is completely below zero, then the effect is significantly different from zero and negative. Moreover, for the combined graph in figure 9, if two confidence intervals are not intersecting it means their respective coefficients are significantly different from each other.

The Figures 6, 7 and 8 show the dynamics of the income coefficients for the second, third and fourth income group, respectively.

Figure 6: Dynamic effect income group 2

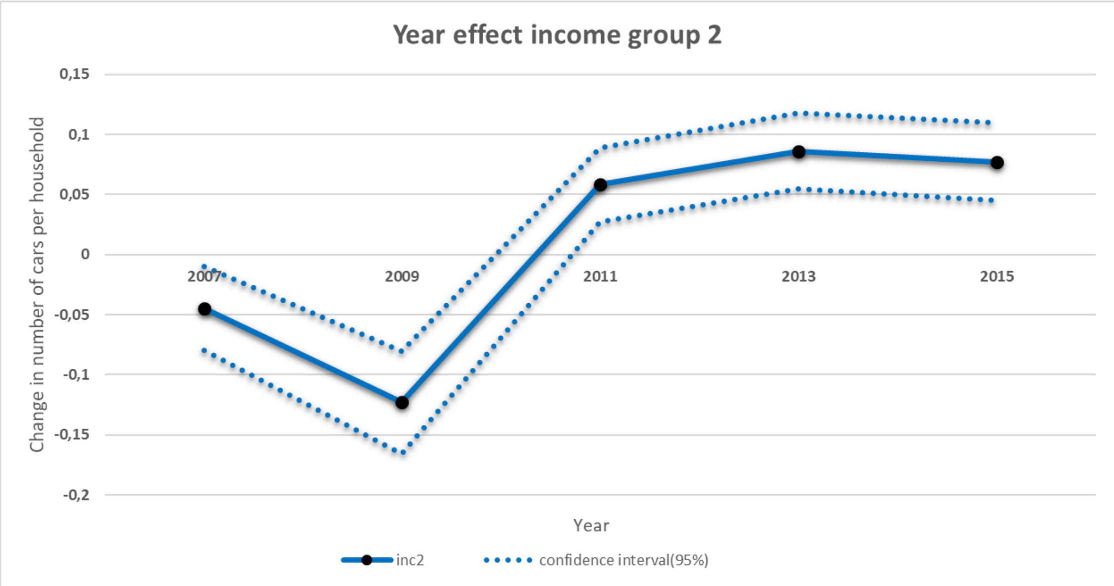


Figure 6 shows that all coefficients of the second income group of the proxy are significantly different from zero. This means, that for this income group, we cannot reject the first hypothesis. Income seems to have a dynamic effect on car ownership. The magnitude of the changes, are between -0.12 and +0.09 cars per household with respect to the lowest income group in 2005. In real world terms this is a rather small effect.

Figure 7: Dynamic effect income group 3

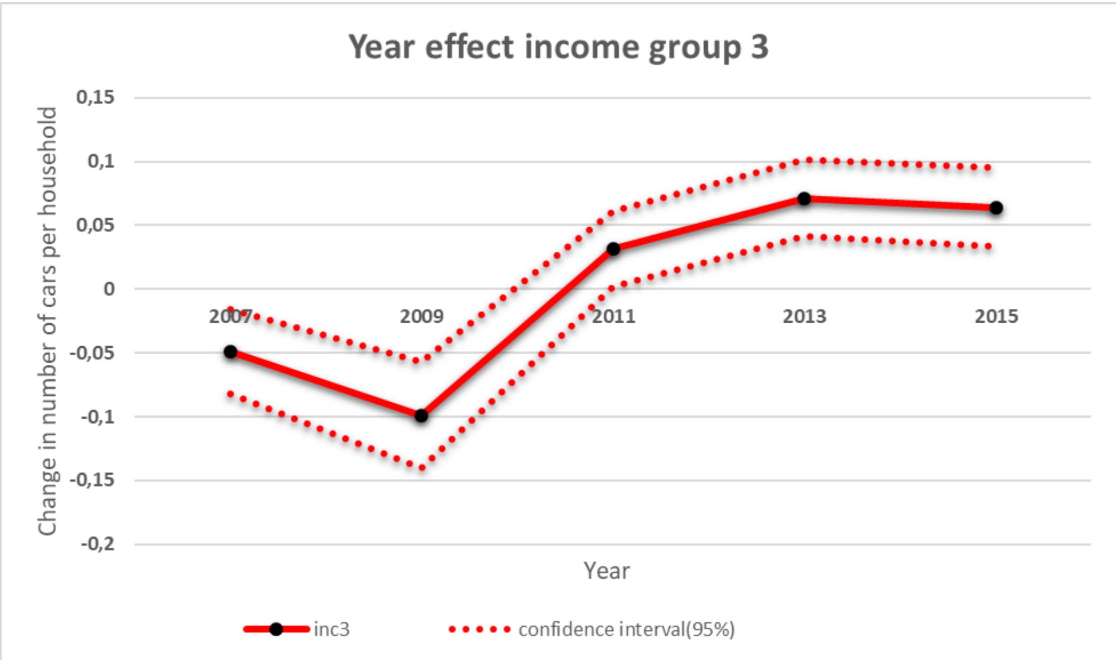


Figure 7 shows a similar trend as figure 6. All the coefficients are significantly different from zero, so also for this income group the first hypothesis cannot be rejected. Again, the real world meaning is minimal, as the coefficients lay between -0.1 and +0.07 cars per household in comparison with the lowest income group in 2005.

Figure 8: Dynamic effect income group 4

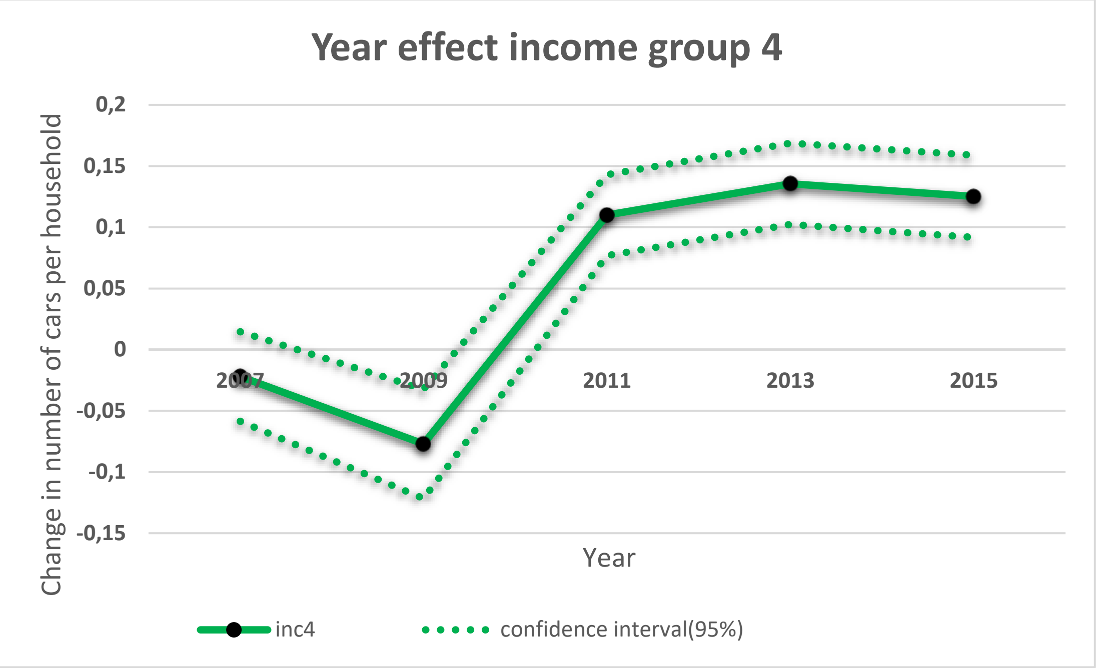
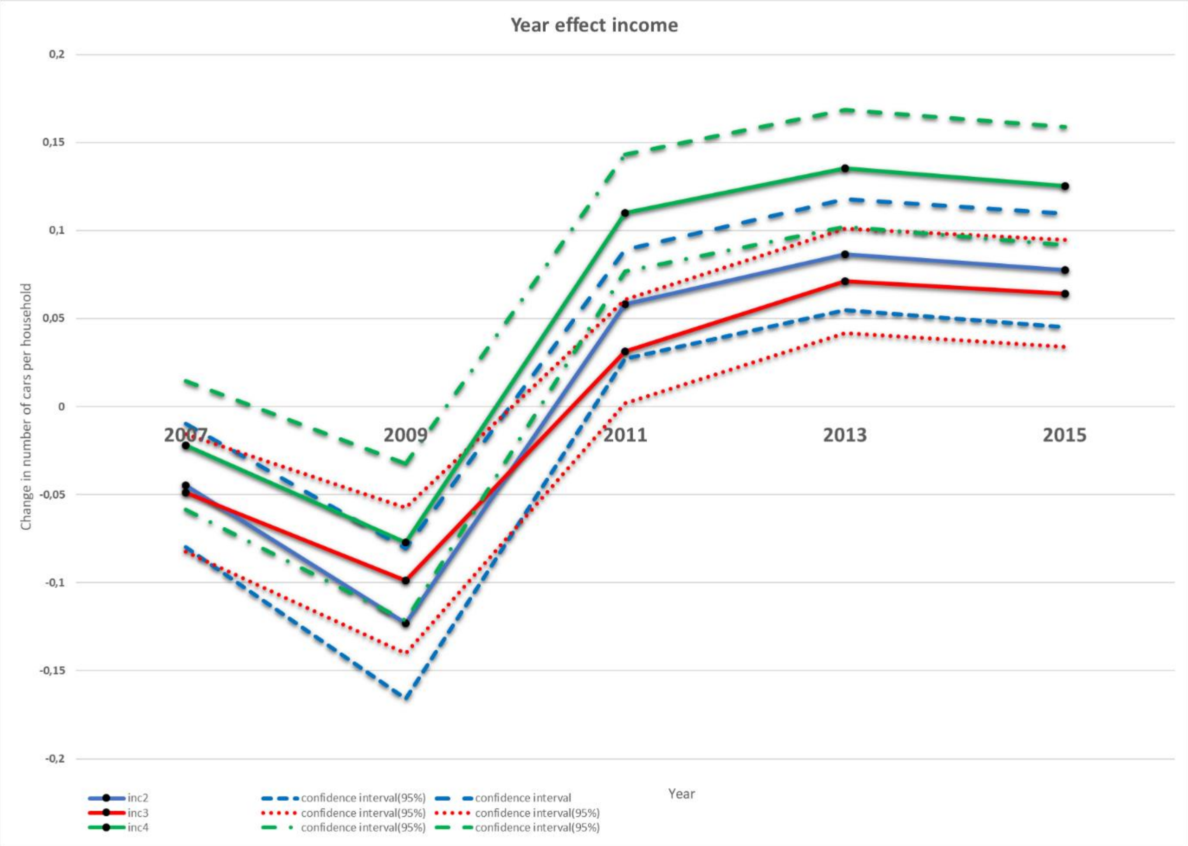


Figure 8 shows that for all the years, except 2007, the coefficients are significantly different from zero. So, also for the highest income group we cannot reject the first hypothesis. Just as for the first two income groups, the real world impact is very small with the coefficients ranging from -0.07 till +0.14 cars per household with respect to the lowest income group in 2005.

In figure 9, all three income groups are combined in one graph. None of the confidence intervals is strictly above or beneath another confidence interval. This means, the income groups and their coefficients are not significantly different from each other with respect to the lowest income group in 2005.

Concluding, the first hypothesis cannot be rejected. There is a significant dynamic effect of income on car ownership. This is in line with the expectations and former research. However, the magnitude of the effect is minimal in terms of real world meaning. Changes between approximately -0.12 and 0.14 cars per household, are no big changes. Looking at the figures, the trend seems to follow the business cycle a bit. For example, the effect of income became less important around 2008/2009, which was the time of the economic depression. This is only hypothetical, but is however interesting for future research.

Figure 9: Dynamic effect all income groups



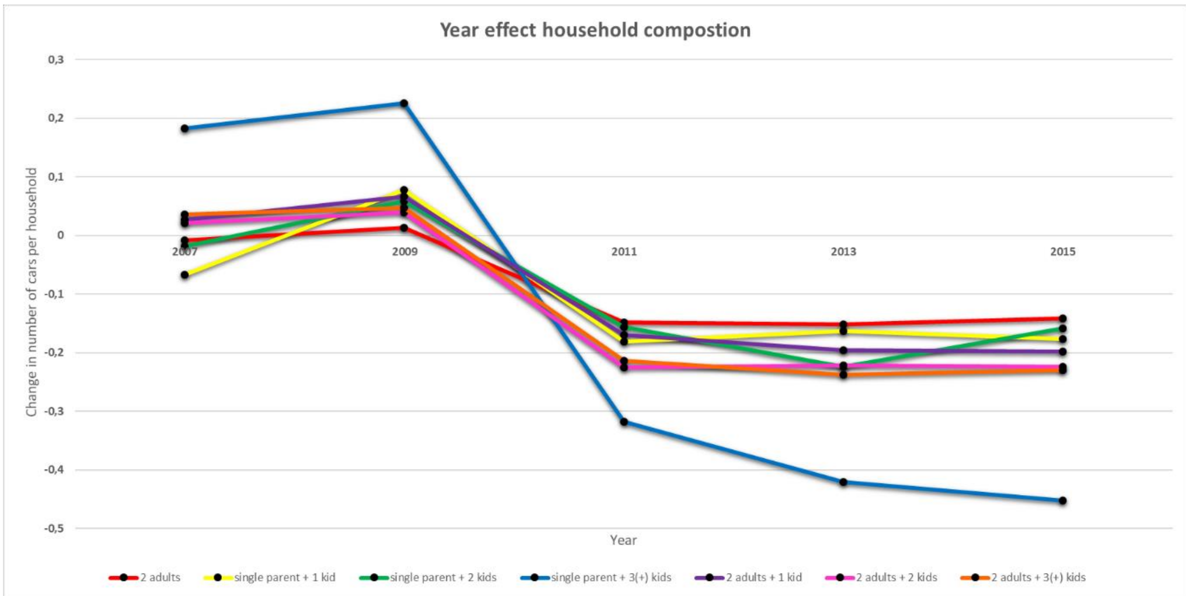
4.2.2 Household composition

The second hypothesis regards the possible dynamic effect of household composition on household car ownership.

H$_2$: The effect of household composition on car ownership is constant between 2005 and 2015

To test this hypothesis, interaction terms between the household composition dummy and the year of observation were included. The complete regression output is displayed in Appendix C, table 19. Also, the graphs for each individual household composition is displayed in Appendix C (figure 1 through 7). For these coefficients the effects is with respect to a single person household in 2005, which is the base category. From table 19 and the figures 1 through 7 of Appendix C it becomes clear, almost all the coefficients are significantly different from zero (on the 5% level). Only the year 2007 has no significant effect and for the households: two adults, single parent with 1 child, single parent with two kids, two adults with three or more kids, the 2009 coefficient is not significantly different from zero either. In figure 10 below, all the coefficient graphs are combined. The confidence intervals are left out, to ensure the readability of the graph. Figure 10 shows all the household compositions have similar trends and effects with respect to the base category, except for single parents with 3 or more kids. This category shows more extreme differences with single person households in 2005. Single parents with 3 or more kids, have 0.31 (2011), 0.42 (2013) and 0.45 (2015) less cars per household with respect to the base category. This is a substantial significant difference. For the other categories, this effects is approximately between 0.15 and 0.25 less cars per household with respect to single person households in 2005.

Figure 10: Dynamic effect household composition



In conclusion, the second hypothesis is rejected. The effect of household composition is not constant between 2005 and 2015. Especially, from 2011 onwards it seems household composition has become less important in the decision for owning one or multiple cars for a household. It remains unknow, whether there is a missing variable in the model causing this effect or household composition is really becoming less important in the car ownership determination. This is definitely an interesting result and subject for other studies to further analyse this outcome.

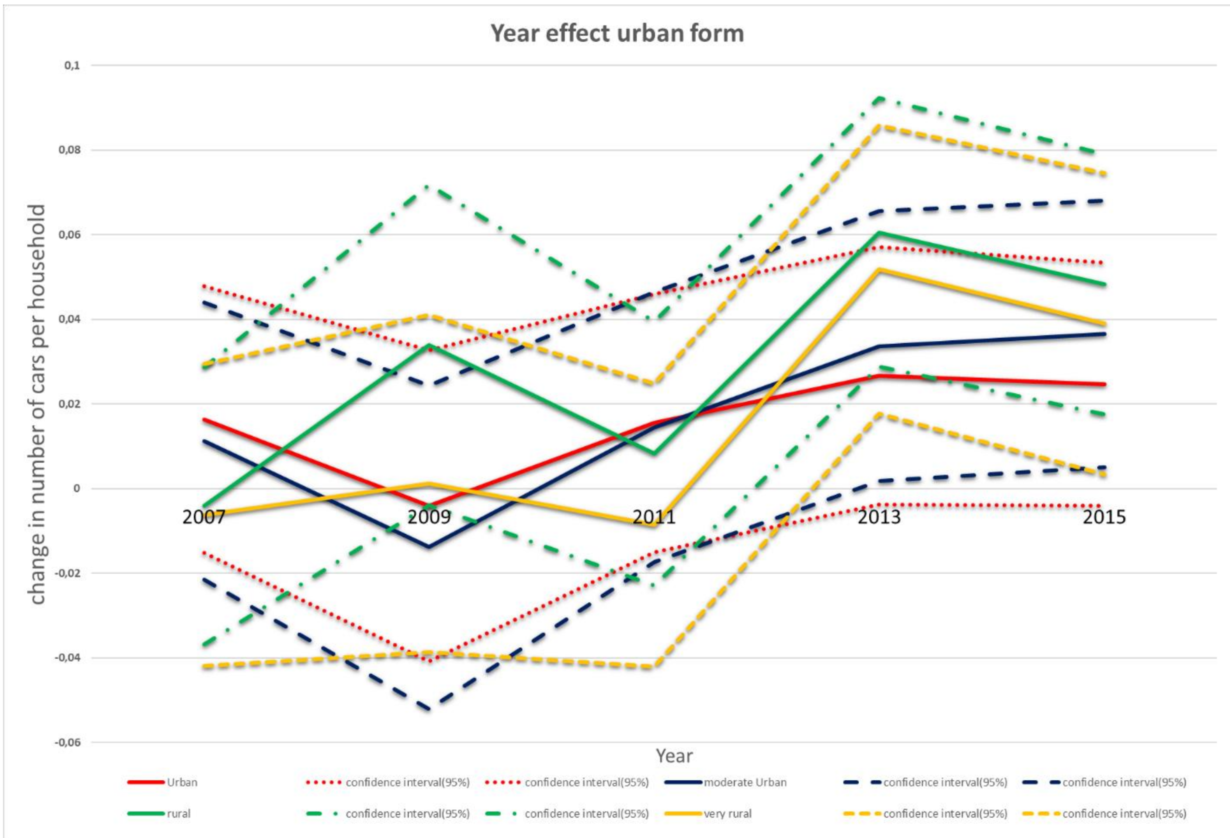
4.2.3 Urban form

The last hypothesis stated the association between urbanity of household living locations and car ownership.

H_3: The effect of urban form on car ownership is constant between 2005 and 2015

This hypothesis was tested by adding interactions between the urbanity dummy and the year of observation. The complete regression output can be found in Appendix C, table 18. Again, a graph is made to visualise the dynamic effect. Figure 11 shows the dynamic effect of the different urban forms with respect to the highest urban category in 2005, which is the base category. The figure below might be a bit hard to read, but it instantly shows the coefficient are not significantly different from each other. The confidence intervals of each coefficient overlaps with the other ones, so no significant difference between them. Moreover, most coefficient's confidence intervals spread around zero, meaning no significant dynamic effect at all. For the category, urban, there is no significant difference with the base category at all. The other three categories only have a significant effect for 2013 and 2015. However, these effects are less than 0.06 cars per household. This effect is so minimal, it is almost negligible.

Figure 11: dynamic effect urban form



In conclusion, the last hypothesis cannot be rejected. The coefficients shows no statistical significant or no significant, in real world terms, dynamic effect of urban form on household car ownership. This means the association between urban form and household car ownership can be considered constant throughout this timespan.

4.3 Former research

As described earlier this research is similar to that of Maltha, Kroesen, Van Wee and van Daalen (2017). They tried to estimate the dynamic effects of car ownership determinants as well. They used the same dataset, but then for the years 1987, 1991, 1995, 1999, 2003, 2010 and 2014. Their timespan is quite longer than the one used for this research. Another difference is the model they used. Using ordered logistic regression (OLR), in which they specify household car ownership into levels of: zero, one, two and three or more cars. This is an advantage over ordinary least squares. However, these models are pretty inflexible. ORL relies on a single latent variable. More interesting is to compare the results with this research. Important to notice, Maltha et al. (2017) measured the dynamic effects relatively to the total effect on car ownership. First of all, they found income has become relatively less important between 2003 and 2014 (36% to 28%), while in this research income seems to follow the business cycle (figure 9). For urbanisation level, they found a relative stable importance, which is in line with the findings in figure 11. Also, for household composition a relatively stable dynamic effect on household car ownership is found. This is in contradiction with the results from figure 10, where a significant dynamic effect is observed from 2011 onwards. The results are for some variables similar and for others contradicting. This might be caused by the difference in methodology and primarily by the model used. Also, the timespan might be of influence. It is interesting both analyses found dynamic effects with different models and implementation of the models. Both, Maltha et al. (2017) and this analysis give an interesting base for further research. Basically, these are one of the first to discover these possible dynamic effects. For both analyses there are some points of improvement, to better capture the dynamic effect of determinants on household car ownership. However, the start is there.

5. Conclusion & discussion

5.1 Conclusion

This research tried to find and describe the dynamic effect of determinants for car ownership between 2005 and 2015 in the Netherlands. Using a pooled ordinary least squares regression with interaction effects between the year of observation and the determinant of interest, the dynamic effects were graphically displayed. First of all, some basic effects were already interesting. For example, the presence of small kids had a statistically significant negative effect on car ownership. While in literature, having small kids is one of the main reasons to own a car. However the real world meaning is very small, a coefficient of -0.06. The base effect of income was as expected, a positive significant effect. While the difference between the second and first income group was negligible, the third and fourth showed a real difference. Someone from the third income group owns 0.249 more cars than someone from the lowest income group. For the highest income group the difference is 0.443 cars with respect to someone from the lowest income group. For household compositions the model showed a difference between household compositions with two adults and single parent households. The households with two adults, two adults with one kid, two adults with two kids and two adults with three or more kids own 0.566, 0.734, 0.842 and 0.869 more cars than a single person household, respectively. The single parent households with one kid, two kids and 3 or more kids have 0.234, 0.285 and 0.496 more cars than a single person household, respectively. This is all in line with expectations and former research. The association of urbanisation level had similar results as found in the literature. The most dense urban category was used as the base category. The lower the urbanisation, the higher the car ownership. Urban, moderate urban, rural and very rural living areas for households, leads to 0.171, 0.246, 0.302 and 0.349 more cars per household with respect to highest urban category, respectively.

However, the main interest of this study is the dynamics of the determinants: income, urbanisation level and household composition. First of all, income showed a significant dynamic effect, which seems to follow the business cycle. However, the actual changes were around maximum ± 0.15 cars per household, which is not that substantial. Next, urban form showed no significant dynamic effect at all. This is in line with the literature, where no dynamic effect was suspected. Household composition did have a substantial dynamic effect. From 2011 onwards, household composition seemed to become less important in the decision for owning one or multiple cars. Single parents with 3 or more kids, have 0.31 (2011), 0.42 (2013) and 0.45 (2015) less cars per household with respect to single person households in 2005. This is a substantial significant difference. For the other categories, this effects is approximately between 0.15 and 0.25 less cars per household with respect to single person households in 2005. It remains unclear, whether this is caused by omitted variable bias or this actually becoming less important in household car ownership determination.

In conclusion, income and household composition showed dynamic effects between 2005 and 2015. In contradiction, urban form showed no dynamic effect in this timespan. Further analysis is needed to confirm these effects and find their possible causes, before this information can be used to stimulate households in reducing household car ownership.

5.2 Limitations and future research

This research had some interesting findings, but as any study there were some limitations regarding this analysis. First of all, income is measured with a very rough proxy. Before 2009, income was measured on the individual level. From 2010 onwards it was measured as household income. These two are combined in the income proxy, in which the incomes are divided in 4 classes. To improve the findings, data for income should be collected on the household level for the whole timespan. The variable representing the household composition is not flawless as well. Before 2010, this variable was not included in the dataset. To reconstruct this variable for these years, a proxy is made. In this proxy the variables, that denoted the number of persons and the number of kids a household consists of, were combined. This household proxy showed missing values, which were not at random. Household consisting of 3 or more adults were not represented by this proxy, so the results are not applicable to these households (table 13, Appendix B). Next, the dependent variable, indicating the number of cars per household, was considered as a continuous variable. Strictly, this variable is an ordinal variable. The number of cars a household owns, has only a few frequent outcomes (0,1,2 and 3 cars). The dataset showed the distribution of the dependent variable was indeed not normally distributed, but far more frequent values for 0,1 and 2 cars. For this reason, the ordinary least square regression will not give the best estimates. Basically, an ordered logit model might have been a good alternative for this research. Also, the results of this study should be applied with care to other regions as the Netherlands. As mentioned in the case study, the Netherlands has a significant higher bicycle usage. This could reduce car use and car ownership significantly.

However, this analysis has provided a good base for future research. First of all, it is hard to tell whether the found dynamic effects are due to omitted variable bias or real changing preference with respect to the car ownership determinants. It is interesting to further analyse the found effects. Especially, the dynamic effect of income has drawn the attention. This effect seems to follow to business cycle, as the drop in importance followed the economic crisis of 2008/2009. After the crisis, the importance recovered, as did the economy. It might be interesting to further analyse if this is really the case. Also, the dynamics of other determinants might be interesting to analyse. For example, parking supply. Parking supply, is a hot topic for urban planners nowadays. Cities are looking for car free inner cities, so the dynamic of this determinant might be interesting for them. Also, psychological determinants of car ownership could be of interest, as these preferences regarding car ownership might change as well.

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7. Appendix

Appendix A: Descriptive statistics and missing values

In this appendix the descriptive statistics of the variables are presented. Also, the three main variables are combined in a table with the dependent variable, *hhCars.*

Table 1: Distribution of the dependent variable, *hhCars*

Number of cars per household	Freq.	Percent	Cum.
0	64,993	11.39	11.39
1	296,860	52.00	63.39
2	182,152	31.91	95.30
3	20,864	3.66	98.96
4	4,295	0.75	99.71
5	944	0.17	99.87
6	256	0.04	99.92
7	117	0.02	99.94
8	44	0.01	99.95
9 or more	309	0.05	100.00
Total	570,834	100.00	

Table 2: Percentage of people per income group that own *x* cars

	Number of cars per household										
inc_ proxy	0	1	2	3	4	5	6	7	8	9	Total
1	19,735	25,673	8,060	1,206	244	52	20	8	4	38	55.040
%	35.86	46.64	14.64	2.19	0.44	0.09	0.04	0.01	0.01	0.07	100.00
2	20,254	62,666	14,821	1,619	342	76	21	17	4	41	99.861
%	20.28	62.75	14.84	1.62	0.34	0.08	0.02	0.02	0.00	0.04	100.00
3	11,206	104,391	59,945	5,280	965	219	59	24	14	119	182.222
%	6.15	57.29	32.90	2.90	0.53	0.12	0.03	0.01	0.01	0.07	100.00
4	3,059	46,653	62,669	9,605	2,188	491	142	58	19	103	124.987
%	2.45	37.33	50.14	7.68	1.75	0.39	0.11	0.05	0.02	0.08	100.00
Total	54,254	239,383	145,495	17,710	3,739	838	242	107	41	301	462.110
%	11.74	51.80	31.48	3.83	0.81	0.18	0.05	0.02	0.01	0.07	100.00

Table 3: Percentage of people per urban form that own *x* cars

Urban form	Number of cars per household 0	1	2	3	4	5	6	7	8	9	Total
Very Urban	21,900	44,769	15,829	1,259	223	52	21	9	5	48	84,115
%	26.04	53.22	18.82	1.50	0.27	0.06	0.02	0.01	0.01	0.06	100.00
Urban	19,563	83,911	44,949	4,172	791	164	58	22	6	69	153,705
%	12.73	54.59	29.24	2.71	0.51	0.11	0.04	0.01	0.00	0.04	100.00
Moderate Urban	9,930	60,159	38,787	4,134	797	179	36	26	5	65	114,118
%	8.70	52.72	33.99	3.62	0.70	0.16	0.03	0.02	0.00	0.06	100.00
Rural	8,933	67,465	50,368	6,643	1,473	320	84	34	17	76	135,413
%	6.60	49.82	37.20	4.91	1.09	0.24	0.06	0.03	0.01	0.06	100.00
Very Rural	4,667	40,556	32,219	4,656	1,011	229	57	26	11	51	83,483
%	5.59	48.58	38.59	5.58	1.21	0.27	0.07	0.03	0.01	0.06	100.00
Total	64,993	296,860	182,152	20,864	4,295	944	256	117	44	309	570,834
%	11.39	52.00	31.91	3.66	0.75	0.17	0.04	0.02	0.01	0.05	100.00

Table 4: percentage of people per household composition that own *x* cars

	Number of cars per household									
household	0	1	2	3	4	5	6	7	8	9	Total
single person	34,340	42,695	1,471	216	38	18	7	6	5	35	78,831
%	43.56	54.16	1.87	0.27	0.05	0.02	0.01	0.01	0.01	0.04	100.00
2 adults no kids	14,343	111,963	46,107	2,445	389	109	47	15	10	82	175,510
%	8.17	63.79	26.27	1.39	0.22	0.06	0.03	0.01	0.01	0.05	100.00
single parent + 1 kid	2,432	5,364	517	25	7	2	4	0	0	3	8,354
%	29.11	64.21	6.19	0.30	0.08	0.02	0.05	0.00	0.00	0.04	100.00
single parent + 2 kid	1,915	5,372	254	30	2	3	1	0	0	6	7,583
%	25.25	70.84	3.35	0.40	0.03	0.04	0.01	0.00	0.00	0.08	100.00
single parents + 3+ki	958	2,000	224	19	11	3	5	2	0	0	3,222
%	29.73	62.07	6.95	0.59	0.34	0.09	0.16	0.06	0.00	0.00	100.00
2 adults + 1 kid	2,369	22,555	19,275	925	154	37	8	5	0	20	45,348
%	5.22	49.74	42.50	2.04	0.34	0.08	0.02	0.01	0.00	0.04	100.00
2 adults + 2 kids	2,354	47,965	49,882	1,917	298	61	19	16	6	57	102,575
%	2.29	46.76	48.63	1.87	0.29	0.06	0.02	0.02	0.01	0.06	100.00
2 adults + 3+kids	1,507	23,743	23,174	1,000	130	54	10	14	2	32	49,666
%	3.03	47.81	46.66	2.01	0.26	0.11	0.02	0.03	0.00	0.06	100.00
Total	60,218	261,657	140,904	6,577	1,029	287	101	58	23	235	471,089
%	12.78	55.54	29.91	1.40	0.22	0.06	0.02	0.01	0.00	0.05	100.00

Table 5: Descriptive statistics hhAge1, hhAge2, hhAge3 & Age

Variable	Obs	Mean	Std. Dev.	Min	Max
hhAge1	570,834	.2720546	.6275299	0	7
hhAge2	570,834	.3230449	.6637967	0	8
hhAge3	570,834	.3193258	.6680122	0	9
hhAge4	570,834	2.083898	.780475	0	9
Age	570,834	41.03021	23.19802	0	99
hhCars	570,834	1.315871	.7940834	0	9

Table 6: Descriptive statistics Gender

Geslacht OP	Freq.	Percent	Cum.
Man	277,794	48.66	48.66
Vrouw	293,040	51.34	100.00
Total	570,834	100.00	

Table 7: Descriptive statistics Year

Year of observation	Freq.	Percent	Cum.
2005	64,052	11.22	11.22
2006	53,545	9.38	20.60
2007	52,218	9.15	29.75
2008	40,125	7.03	36.78
2009	33,583	5.88	42.66
2010	44,151	7.73	50.40
2011	42,319	7.41	57.81
2012	43,284	7.58	65.39
2013	42,329	7.42	72.81
2014	42,581	7.46	80.27
2015	37,334	6.54	86.81
2016	37,207	6.52	93.32
2017	38,106	6.68	100.00
Total	570,834	100.00	

Table 8: Descriptive statistics Inc_proxy

inc_proxy	Freq.	Percent	Cum.
1	55,040	11.91	11.91
2	99,861	21.61	33.52
3	182,222	39.43	72.95
4	124,987	27.05	100.00
Total	462,110	100.00	

Table 9: Descriptive statistics Urban form

Urban level	Freq.	Percent	Cum.
very Urban	84,115	14.74	14.74
Urban	153,705	26.93	41.66
moderate Urban	114,118	19.99	61.65
Rural	135,413	23.72	85.38
very Rural	83,483	14.62	100.00
Total	570,834	100.00	

Table 10: Descriptive statistics Household composition

Household composition	Freq.	Percent	Cum.
single person	78,831	16.73	16.73
2 adults no kids	175,510	37.26	53.99
single parent + 1 kid	8,354	1.77	55.76
single parent + 2 kids	7,583	1.61	57.37
single parents + 3+kids	3,222	0.68	58.06
2 adults + 1 kid	45,348	9.63	67.68
2 adults + 2 kids	102,575	21.77	89.46
2 adults + 3+kids	49,666	10.54	100.00
Total	471,089	100.00	

Table 11: Missing values

Variable	Missing	Total	Percent Missing
hhpers	0	570,834	0.00
hhAge1	0	570,834	0.00
hhAge2	0	570,834	0.00
hhAge3	0	570,834	0.00
hhAge4	0	570,834	0.00
Urban	0	570,834	0.00
Gender	0	570,834	0.00
Age	0	570,834	0.00
hhCars	0	570,834	0.00
inc_proxy	108,724	570,834	19.05
household	99,745	570,834	17.47

Appendix B: Model assumption controls

In this appendix the supportive output for testing the model assumptions are displayed.

Table 12: Correlation matrix

	hhpers	hhAge1	hhAge2	hhAge3	hhAge4
hhpers	1.0000				
hhAge1	0.5233	1.0000			
hhAge2	0.6679	0.1064	1.0000		
hhAge3	0.5181	-0.1180	0.1249	1.0000	
hhAge4	0.4840	0.1645	0.1465	0.1048	1.0000
Age	-0.5902	-0.4278	-0.4146	-0.2662	-0.1454
hhCars	0.3577	0.1538	0.1781	0.1308	0.3804
U1	-0.0732	0.0021	-0.0383	-0.0388	-0.1067
U2	-0.0202	-0.0062	-0.0117	-0.0080	-0.0198
U3	0.0175	0.0043	0.0070	0.0070	0.0253
U4	0.0421	0.0007	0.0245	0.0205	0.0559
U5	0.0328	0.0000	0.0182	0.0187	0.0424
Inc1	-0.2139	-0.0893	-0.0898	-0.0584	-0.2867
Inc2	-0.1621	-0.0761	-0.0943	-0.0810	-0.1106
Inc3	0.1062	0.0760	0.0336	0.0060	0.1458
Inc4	0.2041	0.0571	0.1244	0.1188	0.1632
hh1	-0.5932	-0.2107	-0.2326	-0.1978	-0.8052
hh2	-0.3847	-0.3564	-0.3936	-0.3346	0.3975
hh3	-0.0615	-0.0052	0.0006	0.0369	-0.1953
hh4	0.0354	0.0162	0.0865	0.1200	-0.2041
hh5	0.0941	0.0480	0.1133	0.1242	-0.1138
hh6	0.0925	0.1192	-0.0596	0.0261	0.1544
hh7	0.5210	0.3216	0.3304	0.2533	0.2280
hh8	0.6349	0.3109	0.5241	0.3631	0.1459
g1	0.0384	0.0103	0.0089	0.0015	0.0858
g2	-0.0384	-0.0103	-0.0089	-0.0015	-0.0858
y1	-0.0603	-0.0299	-0.0497	-0.0368	0.0211
y2	-0.0468	-0.0152	-0.0434	-0.0330	0.0220
y3	-0.0514	-0.0273	-0.0442	-0.0310	0.0191
y4	-0.0554	-0.0297	-0.0444	-0.0343	0.0149
y5	-0.0496	-0.0315	-0.0380	-0.0280	0.0121
y6	0.0529	0.0294	0.0436	0.0209	0.0073
y7	0.0447	0.0258	0.0377	0.0195	-0.0008

y8	0.0332	0.0178	0.0272	0.0169	-0.0047
y9	0.0318	0.0178	0.0246	0.0183	-0.0066
y10	0.0273	0.0136	0.0190	0.0200	-0.0084
y11	0.0144	0.0101	0.0103	0.0133	-0.0181
y12	0.0119	-0.0018	0.0135	0.0174	-0.0194
y13	-0.0005	-0.0054	0.0050	0.0093	-0.0271

	Age	**hhCars**	**U1**	**U2**	**U3**
Age	1.0000				
hhCars	-0.2376	1.0000			
U1	-0.0453	-0.1769	1.0000		
U2	-0.0105	-0.0386	-0.2709	1.0000	
U3	0.0095	0.0362	-0.2170	-0.3044	1.0000
U4	0.0227	0.0924	-0.2398	-0.3363	-0.2695
U5	0.0234	0.0848	-0.1753	-0.2459	-0.1970
Inc1	0.0833	-0.2440	0.0625	-0.0014	-0.0235
Inc2	0.1850	-0.2079	0.0011	-0.0086	-0.0059
Inc3	-0.1023	0.0978	-0.0564	-0.0008	0.0092
Inc4	-0.1309	0.2827	0.0159	0.0106	0.0134
hh1	0.2655	-0.3958	0.1047	0.0175	-0.0261
hh2	0.4526	0.0371	-0.0518	-0.0122	0.0097
hh3	-0.0882	-0.0780	0.0328	0.0136	-0.0061
hh4	-0.1136	-0.0689	0.0157	0.0096	-0.0008
hh5	-0.0783	-0.0448	0.0118	0.0045	-0.0046
hh6	-0.1909	0.1050	0.0082	0.0136	0.0006
hh7	-0.3868	0.2238	-0.0391	-0.0042	0.0136
hh8	-0.2963	0.1332	-0.0324	-0.0222	0.0037
g1	-0.0168	0.0686	-0.0106	-0.0036	-0.0005
g2	0.0168	-0.0686	0.0106	0.0036	0.0005
y1	0.0748	-0.0329	-0.0217	-0.0028	0.0173
y2	0.0587	-0.0184	-0.0088	0.0112	0.0140
y3	0.0728	-0.0108	-0.0112	0.0122	0.0085
y4	0.0819	-0.0166	-0.0247	-0.0025	0.0039
y5	0.0818	-0.0098	-0.0209	-0.0070	0.0003
y6	-0.0656	0.0209	-0.0178	-0.0137	-0.0013
y7	-0.0613	0.0170	-0.0114	-0.0140	-0.0020
y8	-0.0479	0.0180	-0.0078	-0.0157	0.0085
y9	-0.0430	0.0134	-0.0115	-0.0137	0.0004
y10	-0.0323	0.0098	-0.0068	-0.0183	0.0033
y11	-0.0263	-0.0032	0.0401	0.0248	-0.0164
y12	-0.0176	-0.0015	0.0475	0.0216	-0.0148
y13	-0.0066	-0.0005	0.0462	0.0231	-0.0190

	U4	**U5**	**Inc1**	**Inc2**	**Inc3**
U4	1.0000				
U5	-0.2177	1.0000			
Inc1	-0.0216	-0.0115	1.0000		
Inc2	0.0030	0.0131	-0.2080	1.0000	
Inc3	0.0223	0.0237	-0.3068	-0.4573	1.0000
Inc4	-0.0120	-0.0315	-0.2088	-0.3113	-0.4591
hh1	-0.0544	-0.0383	0.3011	0.1013	-0.1469
hh2	0.0287	0.0250	-0.0982	0.0717	0.0338
hh3	-0.0213	-0.0197	0.0575	0.0368	-0.0304
hh4	-0.0127	-0.0129	0.0358	0.0531	-0.0321
hh5	-0.0062	-0.0056	0.0158	0.0372	-0.0238
hh6	-0.0109	-0.0137	-0.0603	-0.0517	0.0585
hh7	0.0187	0.0087	-0.1156	-0.1322	0.0732

hh8	0.0264	0.0269	-0.0652	-0.0727	0.0146
g1	0.0074	0.0076	-0.1018	-0.0824	0.0567
g2	-0.0074	-0.0076	0.1018	0.0824	-0.0567
y1	-0.0064	0.0147	-0.0096	0.0331	0.0073
y2	-0.0069	-0.0128	-0.0182	0.0194	0.0104
y3	-0.0040	-0.0088	-0.0220	0.0185	0.0080
y4	0.0051	0.0189	-0.0286	0.0265	0.0104
y5	0.0051	0.0248	-0.0271	0.0219	0.0018
y6	0.0057	0.0313	0.0117	-0.0076	0.0130
y7	0.0143	0.0152	0.0223	-0.0069	0.0084
y8	0.0014	0.0171	0.0199	-0.0065	0.0056
y9	0.0103	0.0169	0.0228	-0.0063	0.0068
y10	0.0108	0.0140	0.0152	-0.0007	-0.0023
y11	-0.0126	-0.0406	0.0210	-0.0055	-0.0154
y12	-0.0144	-0.0442	-0.0127	-0.0332	-0.0195
y13	-0.0102	-0.0451	-0.0179	-0.0357	-0.0323

	Inc4	hh1	hh2	hh3	hh4
Inc4	1.0000				
hh1	-0.1637	1.0000			
hh2	-0.0349	-0.3884	1.0000		
hh3	-0.0460	-0.0621	-0.1051	1.0000	
hh4	-0.0436	-0.0586	-0.0992	-0.0159	1.0000
hh5	-0.0218	-0.0357	-0.0605	-0.0097	-0.0091
hh6	0.0307	-0.1533	-0.2593	-0.0415	-0.0391
hh7	0.1366	-0.2372	-0.4012	-0.0642	-0.0606
hh8	0.1060	-0.1510	-0.2554	-0.0409	-0.0386
g1	0.0953	-0.0695	0.0504	-0.0406	-0.0326
g2	-0.0953	0.0695	-0.0504	0.0406	0.0326
y1	-0.0340	0.0220	0.0454	-0.0080	-0.0152
y2	-0.0173	0.0151	0.0350	-0.0058	-0.0145
y3	-0.0107	0.0146	0.0418	-0.0035	-0.0168
y4	-0.0164	0.0181	0.0443	-0.0060	-0.0148
y5	-0.0030	0.0165	0.0432	-0.0098	-0.0115
y6	-0.0165	-0.0253	-0.0293	-0.0025	0.0024
y7	-0.0199	-0.0195	-0.0315	0.0044	0.0074
y8	-0.0153	-0.0154	-0.0217	0.0033	0.0083
y9	-0.0191	-0.0120	-0.0218	0.0025	0.0067
y10	-0.0084	-0.0116	-0.0185	0.0042	0.0090
y11	0.0071	0.0007	-0.0205	0.0073	0.0095
y12	0.0653	0.0038	-0.0180	0.0014	0.0069
y13	0.0865	0.0099	-0.0114	0.0070	0.0112

	hh5	hh6	hh7	hh8	g1
hh5	1.0000				
hh6	-0.0239	1.0000			
hh7	-0.0369	-0.1583	1.0000		
hh8	-0.0235	-0.1008	-0.1560	1.0000	
g1	-0.0123	0.0060	0.0153	0.0162	1.0000
g2	0.0123	-0.0060	-0.0153	-0.0162	-1.0000
y1	-0.0082	-0.0068	-0.0367	-0.0376	0.0143
y2	-0.0060	0.0014	-0.0281	-0.0323	0.0096
y3	-0.0121	-0.0029	-0.0309	-0.0334	0.0130

y4	-0.0085	-0.0057	-0.0354	-0.0343	0.0085
y5	-0.0078	-0.0113	-0.0330	-0.0278	0.0064

y6	**0.0031**	**0.0071**	**0.0310**	**0.0334**	**-0.0034**
y7	0.0041	0.0089	0.0291	0.0247	-0.0077
y8	0.0053	0.0052	0.0193	0.0196	-0.0062
y9	0.0044	0.0029	0.0168	0.0223	-0.0036
y10	0.0061	0.0010	0.0164	0.0163	-0.0070
y11	0.0005	0.0013	0.0126	0.0079	-0.0039
y12	0.0071	-0.0016	0.0100	0.0080	-0.0047
y13	0.0047	-0.0056	-0.0009	0.0038	-0.0074

	g2	**y1**	**y2**	**y3**	**y4**
g2	1.0000				
y1	-0.0143	1.0000			
y2	-0.0096	-0.0765	1.0000		
y3	-0.0130	-0.0740	-0.0673	1.0000	
y4	-0.0085	-0.0672	-0.0611	-0.0591	1.0000
y5	-0.0064	-0.0605	-0.0550	-0.0532	-0.0483
y6	0.0034	-0.0943	-0.0858	-0.0829	-0.0753
y7	0.0077	-0.0917	-0.0834	-0.0807	-0.0733
y8	0.0062	-0.0934	-0.0850	-0.0822	-0.0746
y9	0.0036	-0.0920	-0.0837	-0.0809	-0.0735
y10	0.0070	-0.0921	-0.0838	-0.0810	-0.0736
y11	0.0039	-0.0858	-0.0780	-0.0754	-0.0685
y12	0.0047	-0.0847	-0.0771	-0.0745	-0.0677
y13	0.0074	-0.0861	-0.0783	-0.0757	-0.0688

	y5	**y6**	**y7**	**y8**	**y9**
y5	1.0000				
y6	-0.0678	1.0000			
y7	-0.0660	-0.1028	1.0000		
y8	-0.0672	-0.1047	-0.1018	1.0000	
y9	-0.0662	-0.1031	-0.1003	-0.1022	1.0000
y10	-0.0663	-0.1032	-0.1004	-0.1023	-0.1008
y11	-0.0617	-0.0961	-0.0935	-0.0952	-0.0938
y12	-0.0610	-0.0950	-0.0924	-0.0941	-0.0927
y13	-0.0619	-0.0965	-0.0939	-0.0956	-0.0942

Table 13: Household compositions consisting of at least 3 adults

		Age kid(s)	Youngest 0-5 years, oldest 18-24 years	Youngest 0-5 years, oldest 25 of ouder	Youngest 6-11 years, oldest 18-24 years	Youngest 6-11 years, oldest 25 or older	Youngest 12-17 years, oldest 18-24 years	Youngest 12-17 years, oldest 25 or older	Youngest 18-24 years	Youngest 25 or older, oldest 25 or older	Total	Total households with at least three adults
		Period	**2010**	**2010**	**2010**	**2010**	**2010**	**2010**	**2010**	**2010**		**727166**
non married couple with kids	**1 child**	**amount**							14025	4494	**18519**	
non married couple with kids	**2 kids**	**amount**	494	22	1314	66	6923	238	4344	344	**13745**	
non married couple with kids	**3 or more kids**	**amount**	1105	45	1816	108	2205	196	446	32	**5953**	
married couple with kids	**1 child**	**amount**							163298	117580	**280878**	
married couple with kids	**2 kids**	**amount**	924	91	6344	370	101200	2594	100673	11039	**223235**	
married couple with kids	**3 or more kids**	**amount**	7078	262	24194	1333	55006	4662	15798	750	**109083**	
single parent household	**2 kids**	**amount**	515	35	3057	175	22858	970	22137	6911	**56658**	
single parent household	**3 or more kids**	**amount**	1631	57	4767	283	8007	930	2808	612	**19095**	

Table 14: Heteroskedasticity test Model 1

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of hhCars
chi2(1) = 1283.34
Prob > chi2 = 0.0000

Table 15: Heteroskedasticity test Model 2

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of hhCars
chi2(1) = 1285.50
Prob > chi2 = 0.0000

Table 16: Heteroskedasticity test Model 3

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of hhCars
chi2(1) = 1528.87
Prob > chi2 = 0.0000

Appendix C: Regression results

In this appendix the regression results alongside with some supporting graphs are displayed.

Table 17: Regression model 1: income interaction

VARIABLES	(1) hhCars
hhAge1	-0.0601***
	(0.00805)
hhAge2	-0.0494***
	(0.00801)
hhAge3	-0.0574***
	(0.00821)
Age	-0.00315***
	(6.14e-05)
Urban form	
Urban	0.191***
	(0.00318)
Moderate Urban	0.266***
	(0.00340)
Rural	0.332***
	(0.00334)
Very Rural	0.374***
	(0.00376)
Female	-0.00738***
	(0.00205)
Household composition	
2 Adults	0.475***
	(0.00285)
Single parent + 1 kid	0.125***
	(0.0109)
Single parent + 2 kids	0.169***
	(0.0178)
Single parent + 3(+) kids	0.192***
	(0.0261)
2 adults + 1 kid	0.625***
	(0.00911)
2 adults + 2 kids	0.703***
	(0.0163)
2 adults + 3(+) kids	0.727***
	(0.0262)
Year	
2006	0.0431***
	(0.0147)
2007	0.0795***

	(0.0154)
2008	0.0644***
	(0.0174)
2009	0.128***
	(0.0194)
2010	-0.0107
	(0.0134)
2011	-0.00269
	(0.0131)
2012	0.0180
	(0.0136)
2013	-0.0284**
	(0.0132)
2014	-0.0314**
	(0.0130)
2015	-0.0254*
	(0.0136)
2016	-0.0543***
	(0.0146)
2017	-0.0668***
	(0.0147)
Inc_proxy	
2	0.0209*
	(0.0110)
3.	0.249***
	(0.0106)
4	0.443***
	(0.0119)
Inc_proxy # Year	
2.inc_proxy#2006.year	-0.0167
	(0.0173)
2.inc_proxy#2007.year	-0.0447**
	(0.0178)
2.inc_proxy#2008.year	-0.0458**
	(0.0197)
2.inc_proxy#2009.year	-0.123***
	(0.0218)
2.inc_proxy#2010.year	0.0688***
	(0.0161)
2.inc_proxy#2011.year	0.0582***
	(0.0158)
2.inc_proxy#2012.year	0.0462***
	(0.0162)
2.inc_proxy#2013.year	0.0863***
	(0.0161)
2.inc_proxy#2014.year	0.0795***
	(0.0157)
2.inc_proxy#2015.year	0.0774***
	(0.0165)
2.inc_proxy#2016.year	0.0828***
	(0.0176)
2.inc_proxy#2017.year	0.102***
	(0.0176)
3.inc_proxy#2006.year	-0.0320*
	(0.0164)
3.inc_proxy#2007.year	-0.0490***
	(0.0171)
3.inc_proxy#2008.year	-0.0550***
	(0.0191)
3.inc_proxy#2009.year	-0.0988***
	(0.0212)
3.inc_proxy#2010.year	0.0316**
	(0.0154)
3.inc_proxy#2011.year	0.0314**

	(0.0150)
3.inc_proxy#2012.year	0.0188
	(0.0155)
3.inc_proxy#2013.year	0.0714***
	(0.0152)
3.inc_proxy#2014.year	0.0584***
	(0.0150)
3.inc_proxy#2015.year	0.0642***
	(0.0156)
3.inc_proxy#2016.year	0.0579***
	(0.0166)
3.inc_proxy#2017.year	0.0702***
	(0.0167)
4.inc_proxy#2006.year	-0.0106
	(0.0183)
4.inc_proxy#2007.year	-0.0219
	(0.0187)
4.inc_proxy#2008.year	-0.0297
	(0.0208)
4.inc_proxy#2009.year	-0.0770***
	(0.0228)
4.inc_proxy#2010.year	0.108***
	(0.0170)
4.inc_proxy#2011.year	0.110***
	(0.0169)
4.inc_proxy#2012.year	0.0934***
	(0.0173)
4.inc_proxy#2013.year	0.136***
	(0.0169)
4.inc_proxy#2014.year	0.145***
	(0.0167)
4.inc_proxy#2015.year	0.125***
	(0.0172)
4.inc_proxy#2016.year	0.123***
	(0.0177)
4.inc_proxy#2017.year	0.142***
	(0.0178)
Constant	0.464***
	(0.0106)
Observations	382,800
R-squared	0.295

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: regression model 2: interaction urban form

VARIABLES	(2) hhCars
hhAge1	-0.0611***
	(0.00805)
hhAge2	-0.0497***
	(0.00800)
hhAge3	-0.0569***
	(0.00821)
Age	-0.00318***
	(6.13e-05)
Inc_proxy	
2	0.0651***
	(0.00362)
3	0.274***
	(0.00357)
4	0.525***
	(0.00396)
Female	-0.00401**
	(0.00202)
Household composition	
2 Adults	0.485***
	(0.00274)
Single parent + 1 kid	0.128***
	(0.0109)
Single parent + 2 kids	0.174***
	(0.0178)
Single parent + 3(+) kids	0.201***
	(0.0261)
2 adults + 1 kid	0.634***
	(0.00907)
2 adults + 2 kids	0.715***
	(0.0163)
2 adults + 3(+) kids	0.739***
	(0.0261)
Urban form	
Urban	0.171***
	(0.0108)
Moderate Urban	0.246***
	(0.0111)
Rural	0.302***
	(0.0113)
Very Rural	0.349***
	(0.0119)
Year	
2006	-0.00429
	(0.0129)
2007	0.0344***
	(0.0133)
2008	0.00384
	(0.0146)
2009	0.0280*
	(0.0156)
2010	0.0185
	(0.0128)

2011	0.0389***
	(0.0127)
2012	0.0415***
	(0.0129)
2013	0.0130
	(0.0127)
2014	0.0102
	(0.0125)
2015	0.0157
	(0.0118)
2016	-0.00521
	(0.0120)
2017	-0.0123
	(0.0119)
Urban form # Year	
Urban#2006.year	0.0294*
	(0.0157)
Urban#2007.year	0.0163
	(0.0161)
Urban#2008.year	0.0113
	(0.0175)
Urban#2009.year	-0.00402
	(0.0188)
Urban#2010.year	0.0334**
	(0.0157)
Urban#2011.year	0.0155
	(0.0156)
Urban#2012.year	0.00678
	(0.0156)
Urban#2013.year	0.0267*
	(0.0155)
Urban#2014.year	0.0249
	(0.0155)
Urban#2015.year	0.0247*
	(0.0146)
Urban#2016.year	0.0250*
	(0.0148)
Urban#2017.year	0.0312**
	(0.0149)
Moderate Urban#2006.year	0.0347**
	(0.0163)
Moderate Urban#2007.year	0.0112
	(0.0167)
Moderate Urban#2008.year	0.0254
	(0.0184)
Moderate Urban#2009.year	-0.0138
	(0.0195)
Moderate Urban#2010.year	0.0243
	(0.0162)
Moderate Urban#2011.year	0.0146
	(0.0163)
Moderate Urban#2012.year	0.00226
	(0.0160)
Moderate Urban#2013.year	0.0337**
	(0.0163)
Moderate Urban#2014.year	0.0318**
	(0.0158)
Moderate Urban#2015.year	0.0366**
	(0.0161)
Moderate Urban#2016.year	0.0131
	(0.0161)
Moderate Urban#2017.year	0.0307*
	(0.0164)
Rural#2006.year	0.0174
	(0.0164)
Rural #2007.year	-0.00402

	(0.0167)
Rural #2008.year	0.0357**
	(0.0181)
Rural #2009.year	0.0340*
	(0.0193)
Rural #2010.year	0.0306*
	(0.0160)
Rural #2011.year	0.00833
	(0.0159)
Rural #2012.year	0.0305*
	(0.0162)
Rural #2013.year	0.0606***
	(0.0162)
Rural #2014.year	0.0448***
	(0.0158)
Rural #2015.year	0.0484***
	(0.0157)
Rural #2016.year	0.0298*
	(0.0159)
Rural #2017.year	0.0450***
	(0.0159)
Very Rural#2006.year	0.0446**
	(0.0182)
Very Rural #2007.year	-0.00622
	(0.0182)
Very Rural #2008.year	-0.000602
	(0.0190)
Very Rural #2009.year	0.00120
	(0.0204)
Very Rural #2010.year	0.00955
	(0.0170)
Very Rural #2011.year	-0.00857
	(0.0171)
Very Rural #2012.year	0.0311*
	(0.0177)
Very Rural #2013.year	0.0518***
	(0.0174)
Very Rural #2014.year	0.0547***
	(0.0171)
Very Rural #2015.year	0.0390**
	(0.0181)
Very Rural #2016.year	0.0383*
	(0.0197)
Very Rural #2017.year	0.0578***
	(0.0188)
Constant	0.438***
	(0.0101)
Observations	382,800
R-squared	0.294

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: regression model 3: interaction household composition

VARIABLES	(3) hhCars
hhAge1	-0.0616***
	(0.00772)
hhAge2	-0.0478***
	(0.00767)
hhAge3	-0.0550***
	(0.00786)
Age	-0.00352***
	(6.29e-05)
Inc_proxy	
2	0.0957***
	(0.00376)
3	0.309***
	(0.00378)
4	0.561***
	(0.00417)
Female	0.000176
	(0.00203)
Urban form	
Urban	0.192***
	(0.00317)
Moderate Urban	0.267***
	(0.00340)
Rural	0.333***
	(0.00333)
Very rural	0.375***
	(0.00376)
Household Composition	
2 Adults	0.566***
	(0.00767)
Single parent + 1 kid	0.234***
	(0.0283)
Single parent + 2 kids	0.285***
	(0.0356)
Single parent + 3(+) kids	0.496***
	(0.0662)
2 adults + 1 kid	0.734***
	(0.0150)
2 adults + 2 kids	0.842***
	(0.0184)
2 adults + 3(+) kids	0.869***
	(0.0288)
Year	
2006	0.00849
	(0.00875)
2007	0.0366***
	(0.00897)
2008	0.00334
	(0.00944)
2009	0.0116

	(0.00993)
2010	0.180***
	(0.01000)
2011	0.185***
	(0.00986)
2012	0.194***
	(0.00991)
2013	0.194***
	(0.0102)
2014	0.175***
	(0.00932)
2015	0.184***
	(0.00980)
2016	0.154***
	(0.00989)
2017	0.139***
	(0.00964)
Household composition # Year	
2 Adults#2006	0.00920
	(0.0113)
2 Adults #2007	-0.00816
	(0.0114)
2 Adults #2008	0.00586
	(0.0120)
2 Adults #2009	0.0134
	(0.0127)
2 Adults #2010	-0.140***
	(0.0124)
2 Adults #2011	-0.149***
	(0.0124)
2 Adults #2012	-0.145***
	(0.0123)
2 Adults #2013	-0.152***
	(0.0127)
2 Adults #2014	-0.129***
	(0.0119)
2 Adults #2015	-0.141***
	(0.0125)
2 Adults #2016	-0.146***
	(0.0126)
2 Adults #2017	-0.103***
	(0.0125)
Single parent + 1 kid#2006	0.0672*
	(0.0393)
Single parent + 1 kid #2007	-0.0674*
	(0.0399)
Single parent + 1 kid #2008	-0.00239
	(0.0473)
Single parent + 1 kid #2009	0.0780
	(0.0512)
Single parent + 1 kid #2010	-0.171***
	(0.0395)
Single parent + 1 kid #2011	-0.182***
	(0.0371)
Single parent + 1 kid #2012	-0.171***
	(0.0346)
Single parent + 1 kid #2013	-0.164***
	(0.0350)
Single parent + 1 kid #2014	-0.150***
	(0.0367)
Single parent + 1 kid #2015	-0.177***
	(0.0371)
Single parent + 1 kid #2016	-0.204***
	(0.0360)
Single parent + 1 kid #2017	-0.210***

	(0.0345)
Single parent + 2 kids#2006	0.0114
	(0.0498)
Single parent + 2 kids #2007	-0.0190
	(0.0455)
Single parent + 2 kids #2008.	0.0420
	(0.0505)
Single parent + 2 kids #2009	0.0585
	(0.0571)
Single parent + 2 kids #2010	-0.152***
	(0.0410)
Single parent + 2 kids #2011	-0.157***
	(0.0415)
Single parent + 2 kids #2012	-0.181***
	(0.0377)
Single parent + 2 kids #2013	-0.224***
	(0.0422)
Single parent + 2 kids #2014	-0.155***
	(0.0412)
Single parent + 2 kids #2015	-0.158***
	(0.0438)
Single parent + 2 kids #2016	-0.240***
	(0.0397)
Single parent + 2 kids #2017	-0.236***
	(0.0387)
Single parent + 3(+) kids#2006	0.0107
	(0.0871)
Single parent + 3(+) kids #2007	0.183
	(0.220)
Single parent + 3(+) kids #2008	0.0765
	(0.0996)
Single parent + 3(+) kids #2009	0.226**
	(0.103)
Single parent + 3(+) kids #2010	-0.423***
	(0.0690)
Single parent + 3(+) kids #2011	-0.318***
	(0.0804)
Single parent + 3(+) kids #2012	-0.415***
	(0.0702)
Single parent + 3(+) kids #2013	-0.421***
	(0.0753)
Single parent + 3(+) kids #2014	-0.434***
	(0.0695)
Single parent + 3(+) kids #2015	-0.452***
	(0.0744)
Single parent + 3(+) kids #2016	-0.452***
	(0.0746)
Single parent + 3(+) kids #2017	-0.476***
	(0.0702)
2 adults + 1 kid#2006	0.0162
	(0.0191)
2 adults + 1 kid #2007	0.0270
	(0.0194)
2 adults + 1 kid #2008	0.0450**
	(0.0208)
2 adults + 1 kid #2009	0.0658***
	(0.0241)
2 adults + 1 kid #2010	-0.170***
	(0.0187)
2 adults + 1 kid #2011	-0.170***
	(0.0190)
2 adults + 1 kid #2012	-0.189***
	(0.0189)
2 adults + 1 kid #2013	-0.196***
	(0.0195)
2 adults + 1 kid #2014	-0.203***
	(0.0186)

2 adults + 1 kid #2015	-0.198***
	(0.0188)
2 adults + 1 kid #2016	-0.188***
	(0.0196)
2 adults + 1 kid #2017	-0.189***
	(0.0202)
2 adults + 2 kids#2006	0.00984
	(0.0152)
2 adults + 2 kids #2007	0.0208
	(0.0157)
2 adults + 2 kids #2008	0.0467***
	(0.0166)
2 adults + 2 kids #2009	0.0390**
	(0.0182)
2 adults + 2 kids #2010	-0.229***
	(0.0150)
2 adults + 2 kids #2011	-0.225***
	(0.0147)
2 adults + 2 kids #2012	-0.215***
	(0.0152)
2 adults + 2 kids #2013	-0.222***
	(0.0151)
2 adults + 2 kids #2014	-0.218***
	(0.0146)
2 adults + 2 kids #2015	-0.224***
	(0.0151)
2 adults + 2 kids #2016	-0.227***
	(0.0155)
2 adults + 2 kids #2017	-0.215***
	(0.0153)
2 adults + 3(+) kids #2006	0.0476**
	(0.0231)
2 adults + 3(+) kids #2007	0.0358
	(0.0234)
2 adults + 3(+) kids #2008	0.0778***
	(0.0250)
2 adults + 3(+) kids #2009	0.0469*
	(0.0263)
2 adults + 3(+) kids #2010	-0.236***
	(0.0201)
2 adults + 3(+) kids #2011	-0.215***
	(0.0205)
2 adults + 3(+) kids #2012	-0.231***
	(0.0205)
2 adults + 3(+) kids #2013	-0.238***
	(0.0206)
2 adults + 3(+) kids #2014	-0.224***
	(0.0202)
2 adults + 3(+) kids #2015	-0.229***
	(0.0205)
2 adults + 3(+) kids #2016	-0.204***
	(0.0210)
2 adults + 3(+) kids #2017	-0.225***
	(0.0213)
Constant	0.325***
	(0.00809)
Observations	382,800
R-squared	0.297

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Dynamic effect 2 adults

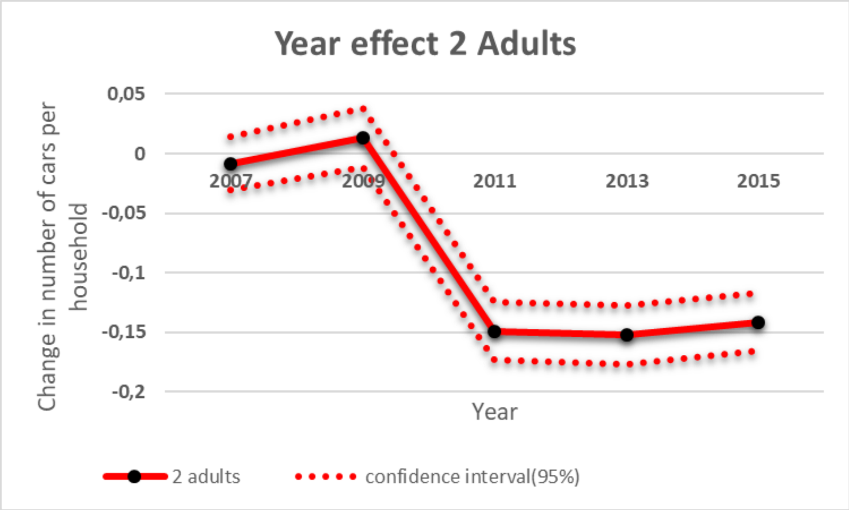


Figure 2: Dynamic effect single parent + 1 kid

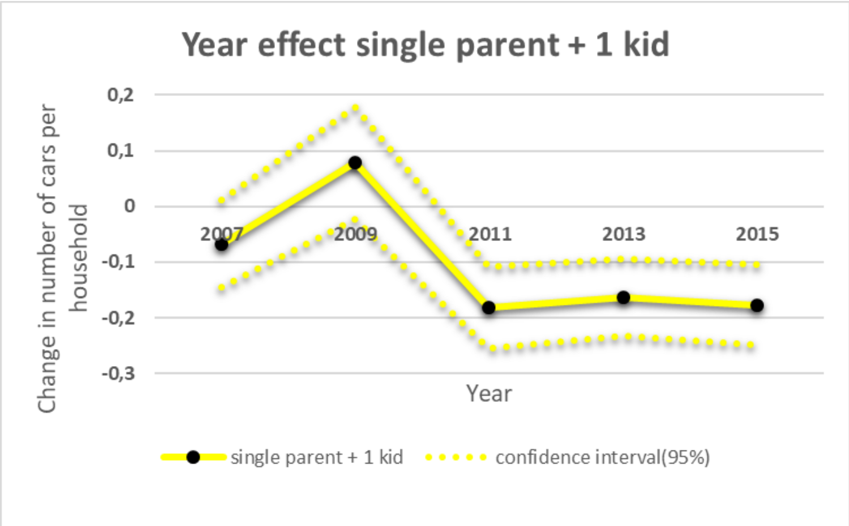


Figure 3: Dynamic effect single parent + 2 kids

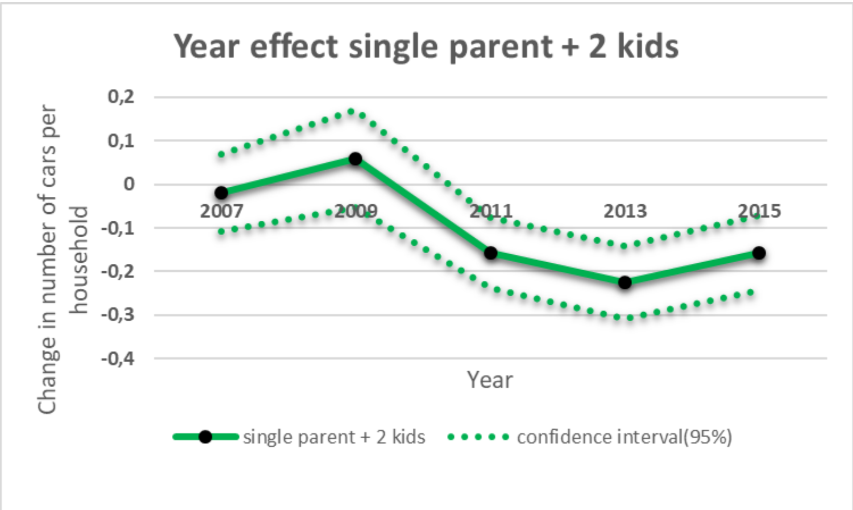


Figure 4: Dynamic effect single parent + 3(+) kids

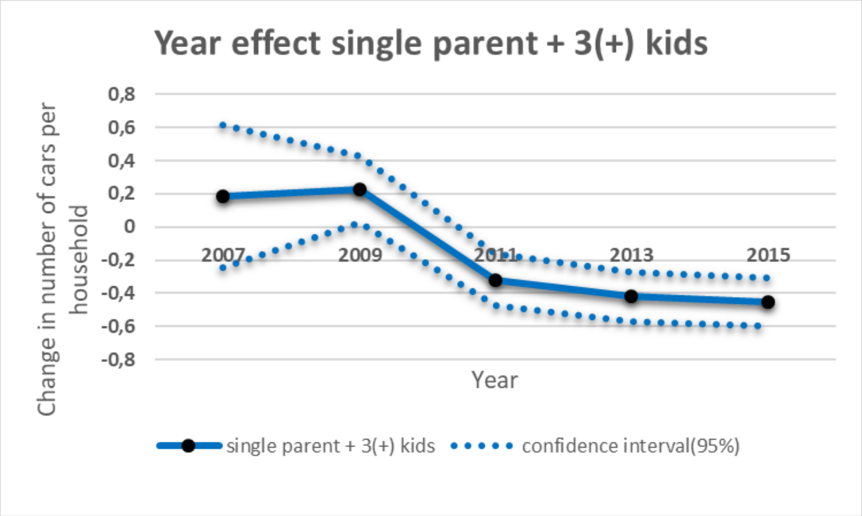


Figure 5: Dynamic effect 2 adults + 1 kid

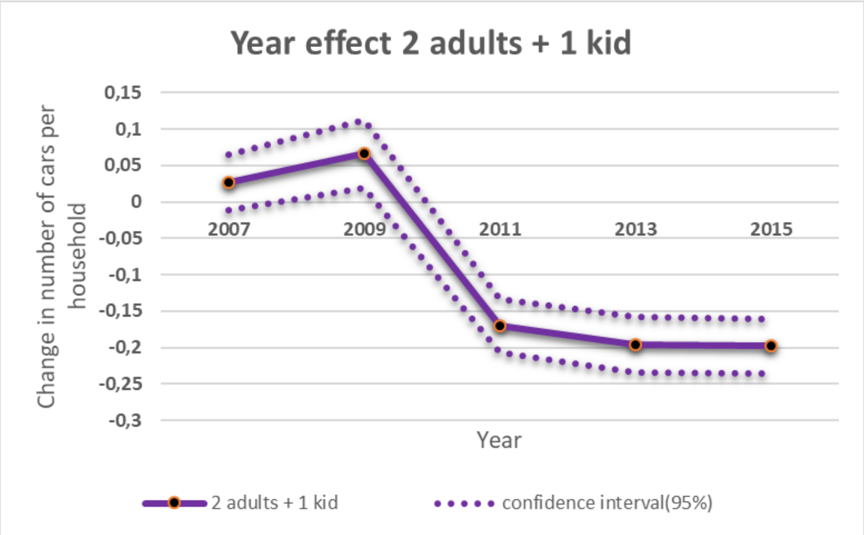


Figure 6: Dynamic effect 2 adults + 2 kids

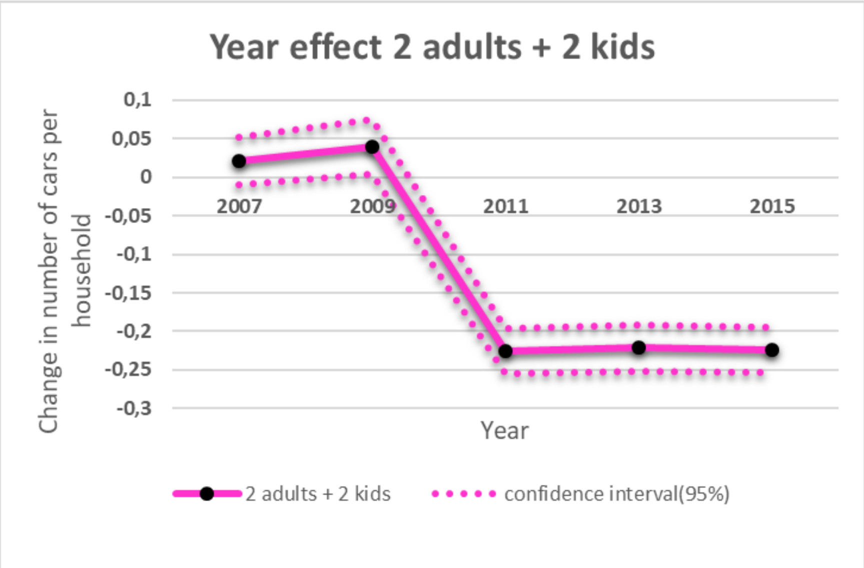
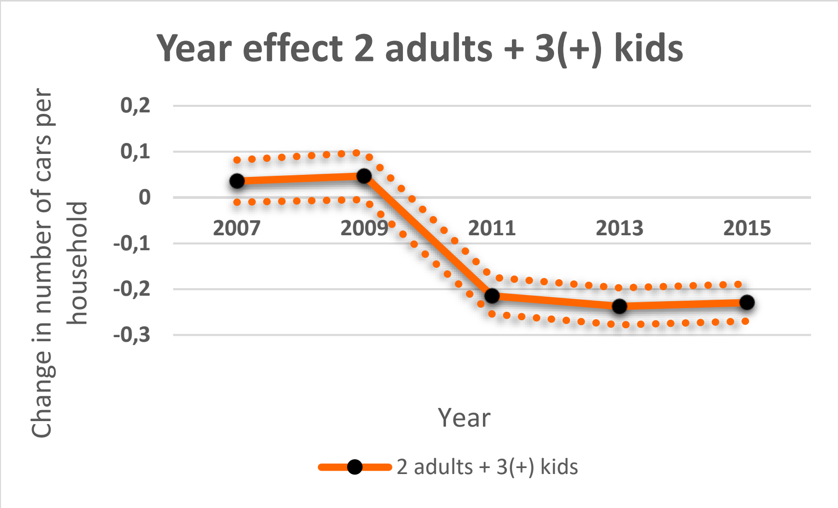


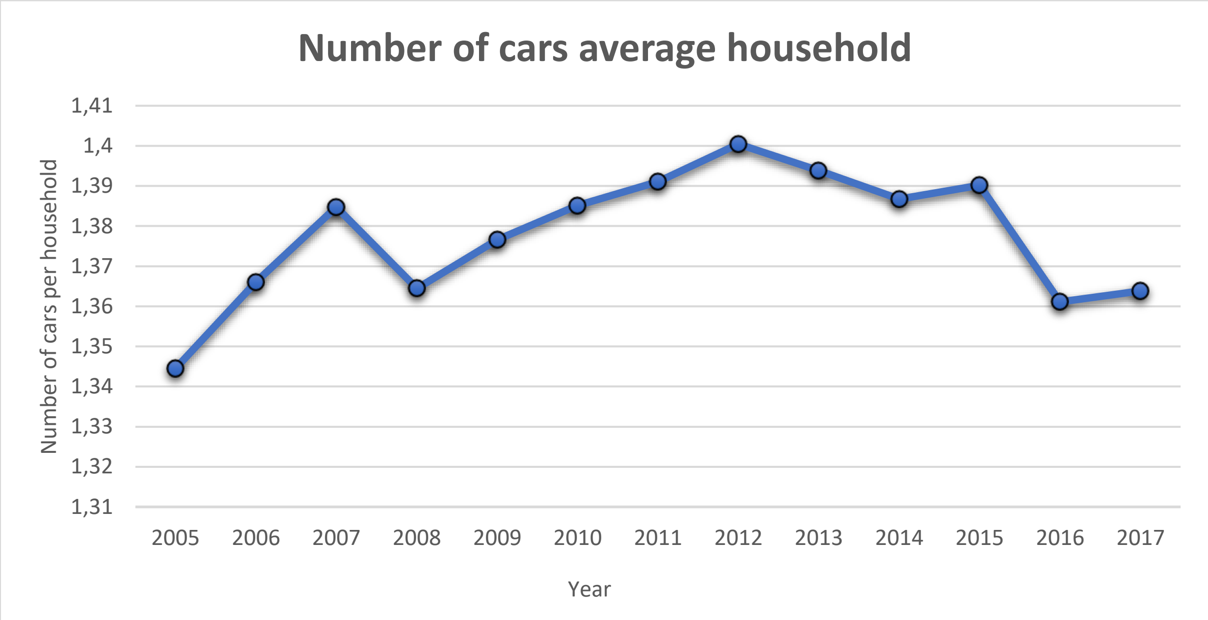
Figure 7: Dynamic effect 2 adults + 3(+) kids



Appendix D: Household car ownership average Dutch household

In this appendix, an example is displayed of the base model. This research tried to determine the dynamic effects of car ownership determinants. However, in this appendix the predicting powers of the base model are showed. Using the model without the interaction effects, a prediction is made for the average household in the Netherlands. The average Dutch household is defined as: a family of two parents with two children living in an urban environment, the household income lays in income group 3 and the children are considered two young children in the age category 0-6 years old, so *hhAge1*. All the chosen values are high frequently presence in the dataset, as can be checked in tables 5 through 10 in Appendix A. For *Age*, 41 years old is chosen, because this is the average age of respondents (table 5, Appendix A). First the regression output is displayed in table 20 below. The regression is made with White standard errors, as the Breusch Pagan test showed the model suffers heteroskedasticity (table 21). The regression output shows all the variables are significant on the 1% level, except for *gender*. For this reason, *gender* is not included in the calculation for the household level of an average Dutch household. Using the definition of a typical Dutch household and the model of table 20, a graph is made with average number of cars per household (Figure 8).

Figure 8: average household car ownership typical Dutch household



The figure shows the typical Dutch familie owns on average between 1.34 and 1.4 cars between 2005 and 2017. So, it did not change much throughout these years. The value shows, that the majority of these households own 1 or more cars. This is in line with the expectation, as higher income (group 3) and the household composition drive up household car ownership.

Table 20: Regression output base model

VARIABLES	(1) hhCars
hhAge1	-0.0610***
	(0.00805)
hhAge2	-0.0496***
	(0.00800)
hhAge3	-0.0567***
	(0.00821)
2.Urban	0.192***
	(0.00318)
3.Urban	0.267***
	(0.00340)
4.Urban	0.333***
	(0.00334)
5.Urban	0.375***
	(0.00376)
2.Gender	-0.00386*
	(0.00202)
Age	-0.00318***
	(6.13e-05)
2006.year	0.0216***
	(0.00475)
2007.year	0.0402***
	(0.00480)
2008.year	0.0200***
	(0.00507)
2009.year	0.0320***
	(0.00543)
2010.year	0.0406***
	(0.00463)
2011.year	0.0465***
	(0.00464)
2012.year	0.0559***
	(0.00465)
2013.year	0.0493***
	(0.00473)
2014.year	0.0422***
	(0.00462)
2015.year	0.0456***
	(0.00476)
2016.year	0.0166***
	(0.00486)
2017.year	0.0193***
	(0.00489)
2.inc_proxy	0.0655***
	(0.00362)
3.inc_proxy	0.275***

	(0.00356)
4.inc_proxy	0.526***
	(0.00395)
2.household	0.485***
	(0.00274)
3.household	0.128***
	(0.0109)
4.household	0.173***
	(0.0178)
5.household	0.199***
	(0.0261)
6.household	0.634***
	(0.00908)
7.household	0.714***
	(0.0163)
8.household	0.739***
	(0.0262)
Constant	0.417***
	(0.00612)
Observations	382,800
R-squared	0.294

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21: Heteroskedasticity test

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance
Variables: fitted values of hhCars
chi2(1) = 1265.69
Prob > chi2 = 0.0000