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Dynamic modelling of household car ownership

Including the effect of life events and built environment factors

Dynamic modelling of household car ownership: including the effect of life events and built environment factors

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Preface

Writing this thesis was the capstone of my time at the faculty of Technology, Policy, and Management. In this period, I experienced several transitions related to housing, daily occupation, and travel means. For example, I relocated twice, I started to work as an intern at Significance in The Hague, and recently I purchased a public transport season ticket due to the upcoming transition from being a student to a working life. This shows how 'life events', like changing work and residential relocation, are related to daily travel decisions, which is one of the contributions of this research.

Looking back to the process of writing and finishing my thesis, I am filled with gratitude and excitement, even though it did not always proceed as I hoped. First of all, I am thankful for having been part of Significance during my graduation process, since I learned a lot being here, both on a professional as well as on a personal level. Next to that, the support of Rijkswaterstaat was of great value, since it enabled me to do this research.

In particular, I want to thank Marco Kouwenhoven, who, as my first supervisor, contributed greatly to this work by both challenging me, and helping me to focus on the main goal of this research. Next to that, I would like to thank the other members of my graduation committee as well: Caspar Chorus for being involved and interested, even when I was still orienting on my topic, and for giving valuable feedback during our meetings; Amineh Ghorbani for her stimulating contribution during the first phases; and Martijn Warnier for joining the committee in the last phase and helping me to finalize my thesis. The insights of Gerard de Jong in the final phase were valuable as well.

Finally, I am thankful for family, friends and roommates, who supported and stimulated me, but at times were a valuable source of distraction as well. Above all, I thank God for being my strength and, especially in more stressful times, for providing a 'peace that surpasses all understanding'.

Maarten van de Kamp
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Content

Abstract

All over the world, governments are facing sustainability challenges. This is not an easy assignment, especially in dense and growing cities: pollution, CO2-emissions and congestion are common problems, among others induced by the use of cars. Car ownership is an important intermediate factor affecting car use, so knowing the underlying causes for changing car ownership levels is crucial to influence travel behaviour and to contribute to a more sustainable future.

Car ownership research is traditionally mainly focussed on the effect of socio-demographic characteristics, like age, income and having a driving license. However, these factors are not able to explain the trend of decreased car ownership for young people that is visible in developed countries. Recent research showed that life events related to work, family and residential location, and built environment factors are other promising explanatory factors of changing car ownership.

However, the Dutch car ownership models – which are used to inform policymakers – do not incorporate life events and built environment factors adequately due to a lack of data. Having more of these promising explanatory variables included in them would improve their representation of car transaction choices and thereby contribute to effective policies. Recently, a retrospective dataset including life events and built environment factors became available, which made it possible to include their effects in a car ownership model. Next to that, it was found that, instead of simulating car ownership statically (independent from the previous number of cars), it is theoretically better to model it a dynamic way (taking into account car ownership of last year). However, such dynamic models are still a rarity in the literature.

To address these identified gaps, this thesis examines to what extent the forecasts of household car ownership in the Netherlands are affected by the inclusion of life events and built environment factors in a dynamic model. To this end, the dynamic model is enriched in two steps: first in terms of structure (static versus dynamic), and secondly regarding substance (without or with the effect of life events and the built environment). Both the dynamic and the static model use the same datasets for model estimation and application, so in this way the outcomes of these models are comparable to each other.

To develop the dynamic model, which includes the effects of life events and the built environment, a microsimulation approach is used. In this way, car ownership choices of the previous years could be taken into account to inform current transaction decisions. This comes closer to the way how these decisions are actually made: starting from their initial number of cars, households decide whether or not they want to acquire, dispose, or replace a car. The impact of various factors on these transaction decisions are quantified with transaction choice models, while the static model uses holding choice models (which regard the choice for an absolute number of cars instead of a change therein). The dynamic model is therefore theoretically better able to model car ownership than the static model.

The use of a transaction choice model, instead of a holding model, resulted in a substantial log-likelihood increase and improved its model fit significantly ($p<0.001$). Subsequently including the effects of life events and built environment factors significantly improved its explanatory power too, using a 99.9% significance level as well. Using a transaction model and accounting for the effect of these additional variables thus greatly improve the capacity to explain car ownership choices.

The empirical findings of this research confirmed much recent work, but also provided new insight into the nature of car ownership decisions. First of all, these findings provide a deeper insight into the effects of a variety of life events on car transaction behaviour, for example by identifying multiple lead-

lag effects, but by highlighting life events with a spatial component as well (relocation and job transitions).

Relocating increases the chance of all types of car transactions (acquisition, replacement and disposal). Furthermore, it has a delayed positive effect on car disposals, while an anticipated relocation results in more acquisitions. The latter was not found by other authors before. Job transitions mainly result in more car acquisitions, but also in more replacements. The latter is true as well for an anticipated work change, which confirms recent findings. Contrary to other research, a positive effect of retirement on car disposals and replacements in the same year was found. Next to that, changes in household composition were found to affect car transactions, but not as substantially as other authors found. Finally, as expected, obtaining a licence has major positive effects on car acquisitions, which is also true for obtaining a licence in the years before and after car acquisition.

The main built environment factor with an effect on car transactions is the availability of free parking near the residential location: car acquisitions and replacements are more likely, while the chance of disposal is reduced when there is free parking. This is in line with the limited number of studies on the impact of residential parking. However, other categories of built environment factors – like public transport availability, the proximity of amenities, and the traditional 5Ds of compact development – showed no or less clear effects on car ownership.

Before it was examined how the effects of life events and built environment factors could subsequently be applied, the validity of a dynamic model without these factors was examined. This was done by comparing it with the static model. Both models demonstrated plausible aggregate outcomes on a longer term, in line with the outcome of the current model, although some deviant trends were observed. However, this could be explained by limitations imposed by using a smaller sample of the application data (with different socio-demographic characteristics). On a shorter term, the forecasts of the dynamic model were even better in line with the historic car ownership trend than that of the static model. This confirms previous findings that dynamic car ownership models are more suitable for short-run and medium-run forecasts than static models.

Including the effects of life events and built environment factors in the dynamic model resulted in a lower car ownership trend (up to 1.4% lower). Also its ability is shown to inform transportation and urban planning policies, by examining the effect of increased paid parking, both on a national level as on the level of Rotterdam. Altogether, a dynamic model is both theoretically and practically a competent opponent of a static model, because of its ability to generate better car ownership forecasts by including additional variables, and to inform transportation and urban planning policies.

Despite the conclusion that this dynamic model is a promising and powerful tool to model household car ownership in the Netherlands, it is not without limitations. It is recommended for further research to address them by using an application dataset that reflects characteristics of the population and the built environment in a more accurate way (and can be taken into account completely), by extending the model with additional modules (e.g. vehicle type choice), and by using a more extensive estimation dataset.

Despite the steps that need be taken to go from a dynamic model with potential to one that can be directly used to inform decision-making, the findings of this research already have some policy implications. First of all, restrictive parking regimes in the dynamic model resulted in car ownership reductions up to 1.5% in 2030. This aligns well to the empirical outcomes that the absence of free nearby parking is related to more acquisitions and less disposal. Therefore, reducing the availability of free parking with permits and/or paid parking, and stimulating centralised parking (to increase the distance to parking spots) are policy measures with the potential to reduce car ownership.

These parking measures align well to the opportunities opened up by residential relocations and occupational transitions. This research confirms that especially these life events can be seen as window of opportunity to change travel behaviour (Ministry of Infrastructure and Environment, 2016; Müggenburg, Busch-Geertsema, & Lanzendorf, 2015). The habit-breaking effect of these life events on travel behaviour can be utilized by targeting publicity campaigns at those who change residential or job location. To change people’s travel behaviour, it is crucial that alternatives are present and (made more) attractive, which can be done with intensified commuting arrangements to encourage the use of public transport or bike (especially for new employees). By doing that, travel habits can be broken, negative externalities related to car ownership and use can be reduced, and further steps can be taken towards a more sustainable and accessible future.

1. Introduction

Governments all over the world are facing sustainability challenges. To provide for liveability and accessibility, especially in dense and growing cities, is not an easy assignment: pollution, CO2-emissions and congestion are common problems, among others induced by the use of cars. Therefore, one of the policy aims in the Netherlands is to make mobility increasingly more sustainable, which includes stimulating the use of electric cars, public transport and bike (Ministry of Infrastructure and Water Management, 2017). Added to that, especially in major Dutch inner cities, more room is made for shared and 'active' transportation (cycling and walking), and parking is increasingly moved to the edges of the city and garages to discourage car use (Municipality Amsterdam, 2013; Municipality Rotterdam, 2016a, 2016b; Municipality The Hague, 2011; Municipality Utrecht, 2016).

Car *ownership* is an important intermediate factor affecting car *use*. This relates for example to the time and distance travelled as well as the negative externalities related to that (Van Acker, Mokhtarian, & Witlox, 2014), so one way to reduce car use is to reduce car ownership. Therefore, knowing the underlying causes for changing car ownership levels is crucial to influence travel behaviour and to work towards a more sustainable future.

Traditionally, car ownership is mainly explained by looking at socio-demographic characteristics, like age, income and having a driving license. However, there is uncertainty about how car ownership will develop in the future, which transcends these factors. First of all, it is unknown what the impact is of upcoming transport services (i.e. shared mobility, mobility as a service, and autonomous vehicles) and ongoing climate policies (e.g. banning cars from inner cities, or taxes for polluting cars) on car ownership and use (Fatmi & Habib, 2018; Van Paassen, 2018).

The second question that brings uncertainty is whether socio-demographic characteristics are able to fully explain changing car ownership, for example in case of the trend that is visible in developed countries (Van Wee, 2015). Here, especially for young people, the growth of car ownership and use seems to decrease, flatten out, or is even reversed (Goodwin & Van Dender, 2013), also in the Netherlands (CBS, 2017a). Although some point at a changing attitude towards the car, several papers argue that, in the Dutch context, situational factors are a more realistic explanation for this trend (KiM, 2014; Oakil, Manting, & Nijland, 2016; Ruijs, Kouwenhoven, & Kroes, 2013; Van der Waard, Jorritsma, & Immers, 2013): young adults increasingly study and live in urban areas, resulting in decreased car ownership and use until they are settled down. Part of the uncertainty related to the future of car ownership can be reduced by examining the effects of these situational factors.

According to PBL Netherlands Environmental Assessment Agency (PBL, 2016), there is no absolute necessity in urban areas for having a car due to the combination of a solid public transport network and the proximity of many amenities (e.g. supermarkets). Added to that, as seen before, parking is increasingly subjected to restrictive municipal policies: for example, in dense cities where space is more valuable and scarce, this could reduce the number of cars owned by households and thereby affect travel behaviour in general. Built environment (BE) factors are therefore important aspects when looking to changes in car ownership, especially when noticing that the importance of economic factors for car ownership, like price and income, seems to be reduced, although they are still considerable (Goodwin & Van Dender, 2013; Maltha, Kroesen, Van Wee, & Van Daalen, 2017).

Other situational factors affecting car ownership are demographic transitions, which are often visible in the occurrence of 'life events' (Chatterjee & Scheiner, 2015). These are for example related to changes in household composition (e.g. getting a child), residential choices (like moving to another town), and job transitions.

Life events and built environment factors are thus promising explanatory factors of changing car ownership. However, the current Dutch car ownership models – which are currently used to inform decision-making of the Ministry of Infrastructure and Water Management – do not yet incorporate these components adequately: life events are not incorporated at all and only a limited number of BE factors is included (MuConsult, 2017; Significance, 2017). Having more of these promising explanatory variables included would improve the representation of car ownership choices and thereby contribute to effective policies. This is especially relevant considering the ongoing urbanisation and stimulation of compact development by the Dutch government (Ministry of the Interior and Kingdom Relations, 2018). Incorrect forecasts of car ownership levels might lead to redundant additional infrastructure being built, unexpected congestion and nuisance to occur, or spatial planning lacking thoughtful consideration. For example, the number of parking spots needed in new neighbourhoods might be overestimated. Including the effects of life events and built environment factors – like parking aspects, public transport accessibility, and the availability and proximity of amenities – could improve car ownership modelling and forecasting, and thereby inform decision-making processes in a better way.

A major reason for the fact that life events and built environment factors are not incorporated well in the Dutch car ownership models is a lack of data. With the new retrospective dataset of Van de Kamp (2019), however, it is possible to include these factors.

The current models, though, are not able to incorporate the effects of life events and built environment factors well. Therefore, this thesis amongst others examines the development of a new car ownership model for households in the Netherlands, that includes the effects of these factors.

The development of the new car ownership model is informed by a literature review on the effects of life events and built environment factors on car ownership, and by a review on the nature of different car ownership models and the question whether the effects of life events and built environment factors are captured (see section 1.1). Furthermore, the research goals and question (section 1.2), and research approach (1.3) are part of this chapter.

1.1 Literature review

The literature study carried out in order to inform the development of a new model of household car ownership in the Netherlands has two components. First, scientific work related to car ownership is examined, resulting in an overview of the current knowledge of factors affecting car ownership decisions (paragraph 1.1.1). Secondly, it is analysed whether this knowledge is or can be implemented in a variety of car ownership models for the public sector (1.1.2). These reviews result in a knowledge gap for the Dutch context.

1.1.1 Explaining household car ownership

In order to find relevant scientific literature regarding car ownership in general and, more specifically, regarding the relation with life events and built environment factors, the first literature review was conducted. After an exploration with search engines and Google Scholar, the use of Scopus resulted in 45 papers.[1] Five of them were directly selected for this thesis, based on the criteria that all relevant variables and types of data collection should be captured. This relatively small number of relevant initial papers retrieved using the search string probably relates to the variety of descriptions used in the literature, especially regarding the built environment, and the limited work on car ownership compared to for example car use. Based on the same criteria, also additional literature was selected

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[1] The search strings used were: TITLE ((car OR vehicle OR auto*) AND (ownership OR availability) AND review) and TITLE((car ownership OR vehicle ownership OR (mobility tool*) ownership) AND ((residential *location) OR (urban form) OR accessibility OR neighb* OR (Built Environment) OR parking OR spatial) OR (life* OR (mobility biogr*))).

that was found by examining citations and references in the initial papers, which together are visible in Table 1.

Table 1. Research on car ownership and the effects of the life event of residential relocation and built environment (BE) measures (based on work of Rau & Manton, 2016; Schoenduwe, Mueller, Peters, & Lanzendorf, 2015; Van de Kamp, 2019)

Research characteristics			**Dep. Var.**		**Life Ev.**	**Built Envir.**	
Author (Year)	*Data collection type (years covered, country)*	*Sample size*	*Car own*	*Car use*	*Resid. reloc.*	*5D[b]*	*Parking*
Van Acker et al. (2014)	Cross-sect. (-, BEL[a])	1,878	x		x		
Christiansen et al. (2017)	Cross-sect. (-, NOR)	2,000	x				x
Ettema & Nieuwenhuis (2017)	Cross-sect. (-, NL[a])	355		x	(x)	(x)	
Yin, Shao, & Wang (2018)	Cross-sect. (-, CHI[a])	12,977	x	x		x	(x)
Woldeamanuel et al. (2009)	Panel (3, Ger)	3,175	x		x	(x)	x
Rashidi & Mohammadian (2011)	Panel (3, USA[a])	615	x		x	(x)	
Clark et al. (2016)	Panel (1, UK)	19,334	x	x	x	(x)	
Van de Coevering et al. (2016)	Panel (7, NL[a])	1,322		x	x	(x)	
Cao et al. (2007)	Retrosp. (2, USA[a])	547		x	x	(x)	(x)
Yamamoto (2008)	Retrosp. (3, JAP[a])	2,183	x		x	(x)	
Verhoeven (2010)	Retrosp. (>10, NL[a])	710	x	x	x		
Scheiner & Holz-Rau (2013)	Retrosp. (14, GER[a])	791		x	x	x	x
Beige & Axhausen (2017)	Retrosp. (20, SWI[a])	1,140	x	x	x		
Calastri et al. (2018)	Retrosp. (>10, GB[a])	1,747	x	x	x		(x)
Pontes de Aquino (2018)	Retrosp. (20, NL[a])	350		x	x	x	
Van de Kamp (2019)	Retrosp. (20, NL)	718	x		x	x	x

[a] Research carried out on a regional level, not national
[b]The five Ds of the built environment are density, diversity, design, destination accessibility and distance to transit
(x): included in a limited or simple way

A first categorisation was based on type of *data collection*. Often, car ownership research is cross sectional, which means that data of one point in time is available. However, conclusions about causality cannot easily be made in this way (Van de Coevering, Maat, & Van Wee, 2015). Other research uses a longitudinal perspective, for example with the use of panel data of multiple years. Another longitudinal approach is using retrospective questioning, where people are asked to look back and recall for example past events or situations. Next to data collection, distinctions are also made based on the dependent variable ("dep. var."): not all research examines car *ownership*, but solely researched effects on car *use*. Lastly, whether or not relevant categories of independent variables (life events and built environment factors) are included in the literature is displayed in Table 1. It is chosen to only include the life event of residential relocation, since most of the time the effects of multiple life events on car ownership or use are examined at once. Built environment factors are split into five traditional factors (5D) and parking, since the effect of the latter on car ownership is often taken into account together with other factors (Stevens, 2017).

The remainder of this section discusses the results of this literature review, respectively by examining research regarding the effect of *life events* on car ownership, and research on the effect of the (changing) *built environment* on that.

Car ownership and life events

Traditionally, car ownership is mainly explained by looking at socio-demographic characteristics, which can have both positive (+) as negative (-) effects. Examples of that are income (+), education level (+), being male (+), age (+ & -), and the number of driving licenses (+) in a household (Chatterjee & Scheiner, 2015; De Jong, Fox, Daly, Pieters, & Smit, 2004). However, car ownership is increasingly seen as a longer term decision shaping daily travel behaviour (Scheiner, 2018; Van Acker et al., 2014), just like other social, economic or spatial factors (like work and housing). Research with this long-term perspective can be described with different names like 'mobility biographies' (Scheiner & Holz-Rau, 2013), 'life course' (Beige & Axhausen, 2008) or 'life trajectory' (Verhoeven, 2010) approach.

In this approach, life events have a central position, which can break habitual travel behaviour. Often a change in social role or status plays a role here, for example by becoming a parent: having a child might strengthen the need for a new car and/or a new house. Changes in household composition, education, employment, and residential location – which are often interrelated – were found to affect travel behaviour in the review of Chatterjee & Scheiner (2015).

According to Zhang, Yu, & Chikaraishi (2014), *residential relocation* is more important for changes in car ownership than other life events. Most authors find it is mainly related to higher car ownership levels (Beige & Axhausen, 2012, 2017; Chatterjee & Scheiner, 2015; Gu, Feng, Yang, & Timmermans, 2020; Oakil, Ettema, Arentze, & Timmermans, 2014; Van de Kamp, 2019; Zhang et al., 2014), although positive effects on car disposal have been found as well (Cao, Naess, & Wolday, 2019; Clark, Chatterjee, et al., 2016).

Higher car ownership levels are often related to work related life events: previous research found positive effects of (anticipated) job transitions (Chatterjee & Scheiner, 2015; Gu et al., 2020; Van de Kamp, 2019), an increasing distance to work (Beige & Axhausen, 2012; Van de Kamp, 2019). However, Oakil, Ettema, et al. (2014b) found a positive effect of employment changes and a similar (but delayed) effect of retirement on car *disposals*. Chatterjee & Scheiner (2015) mention three papers that did not find any effect of retirement though.

Changes in household composition are found to affect car transactions as well, for example due to childbirth or other increases in household size, while lower car ownership was found to be related to a child leaving, and losing a partner (Chatterjee & Scheiner, 2015; Klein & Smart, 2019; Müggenburg et al., 2015; Oakil, Ettema, et al., 2014). However, not all of these effects are always found: Müggenburg, Busch-Geertsema, & Lanzendorf (2015) mention for example some authors that did not find an effect of childbirth on car transactions.

Finally, Clark, Chatterjee, et al. (2016) found that obtaining a driving licence positively affects car acquisitions. All in all, this and other life events are important variables to examine when researching car ownership.

Car ownership and the built environment

One of the life events with an impact on car ownership we discussed is residential relocation. This can be explained with two mechanisms: besides having a 'habit-breaking' effect, a residential relocation is accompanied by a changing residential environment, which affects car ownership as well. However, these mechanisms are often examined separately.

Some of the papers in Table 1 consider the impact of just a residential relocation (the first mechanism) and do not take into account related changes in built environment factors. Others only included a simplified measure: Yamamoto (2008) for example looked at the type of areas people lived in and moved to (e.g. urbanized), but had no additional built environment factors.

On the other hand, the impact of several built environment factors on car ownership has been studied extensively in the past decades (second mechanism). However, this was often without a specific focus on residential relocation. The reviews of Ewing & Cervero (2010) & Stevens (2017) give a good overview of such research. These studies indicate that compact development, a specific form of urban planning, is related to reduced driving. This has been specified with several categories of factors, the 5Ds: *Density*, *Diversity* (of land use), *Design* (of street network), *Destination accessibility* (e.g. jobs and amenities), and *Distance to transit* (e.g. train station). An overview of them, including description and mechanism, is provided in Table 2.

Most of the (often cross-sectional) 5D-studies do not look at built environment in case of residential relocation, like research of Yin et al. (2018). Some exceptions to that are listed in Table 1 (see Pontes de Aquino, 2018; Scheiner & Holz-Rau, 2013; Van de Kamp, 2019). However, two of those do not analyse car ownership, but solely focus on car use. Only Van de Kamp (2019) examines the effects of a changing built environment on car ownership in case of residential relocation, with limited results due to a low explanatory power. Others look at built environment factors in case of residential relocation as well, but use simplified built environment factors, which is indicated in the table with '(x)'. Clark, Chatterjee, et al. (2016), for example, used a quite comprehensive approach related to car ownership, residential relocation and some built environment factors as well. However, they mainly looked at public transport factors. Among others they found that poorer access to public transport predicts higher car ownership levels.

The impact of *residential parking* on car ownership is often lacking here (Ewing & Cervero, 2010; Stevens, 2017), despite its relevance for car ownership in denser cities and recent findings that it is a significant factor affecting car ownership (Albalate & Gragera, 2020; Christiansen et al., 2017; De Groote, Van Ommeren, & Koster, 2016; Guo, 2013; Ostermeijer, Koster, & Van Ommeren, 2019; Van de Coevering, 2008). Relevant parking aspects that are found to reduce car ownership are for example a lower number of places, a higher distance to them, and a higher parking tariff (and/or the need for a permit). The effect of parking aspects, together with other built environment factors, is therefore important to take into account when examining car ownership (Van Wee, 2015).

Table 2. Overview of the 5Ds of the built environment affecting travel behaviour (TB), based on Stevens (2017, p. 8).

5Ds	**Example**	**Mechanism affecting TB**
Density	Population, households, or jobs per unit area	Placing destinations closer together
Diversity	Mixture of different land uses in a given area	Different amenities close to homes
Design	Network characteristics (like intersections)	Walking and biking more attractive
Destination access.	Distance to destinations (like downtown)	Destinations close to homes
Distance to transit	Distance to the nearest transit stop	Transit more attractive

As Elldér (2018) acknowledges, changing travel behaviour is related to the built environment factors captured in these 5Ds. However, he points out that a "general lack of conceptual models and insufficient theoretical grounding is sometimes noted in the built-environment/travel literature" (p. 1). According to him, it would make more sense that (a part of) travel is influence by the presence of amenities, instead of for example density: amenities (like grocery stores, parks, hospitals, schools, and restaurants) facilitate daily activities that induce travel. Therefore, amenities at closer distance are used more to minimize the cost of time or money, although not always: quality plays a role as well (Naess, Peters, Stefansdottir, & Strand, 2018). Still, focussing on the effect of the proximity and number of amenities on car ownership would theoretically be better than using factors like density.

The view of Elldér (2018) aligns well with other perspectives on the way the built environment facilitates travel behaviour: Naess (2015) says it does so "by determining the *distances* between locations where different activities may take place, and by facilitating various *modes* of travelling" (p. 285, emphasis added), while Van de Kamp (2019) focuses on how it reduces driving "by decreasing distance to local destinations and by decreasing car attractiveness compared to other modes" (p. 12).

Therefore, a focus on built environment factors explicitly related to these mechanisms might explain car ownership changes in a better way than by looking solely at the 5Ds.

Identifying *causal* effects of the built environment on car ownership can be complicated, since other factors might affect this relation: households could not only choose a residential location based on locational preferences, but on their travel attitudes as well. This is called residential self-selection (Cao, Mokhtarian, & Handy, 2009; Van de Coevering et al., 2016). However, the effects of residential self-selection are not easily found and research findings are not in agreement. Although several studies control for third variables like travel attitudes (e.g. Ettema & Nieuwenhuis, 2017), identifying causality is not necessarily guaranteed this way. In case of cross-sectional research, with data on one point in time, only *associations* can be identified (Van de Coevering et al., 2015). This does not mean that these factors are unimportant though: people living in a place that does not match their travel preferences are enabled to do so when new neighborhoods are developed close to for example a train station.

All in all, life events and built environment factors are important variables to include in a car ownership model. Parking aspects and specific factors related to distance to local destinations and the attractiveness of different transportation modes should be part of that (e.g. proximity to public transport), since these are likely to affect car ownership as well.

1.1.2 Modelling car ownership

Considering the results of the first literature review, a variety of car ownership models for the public sector can be analysed on whether and how this knowledge is or could be implemented. Internal documents, search engines and Google Scholar were used for exploration, which resulted in the first models mentioned in see Table 3 (Fox, Patruni, Daly, & Lu, 2011; MuConsult, 2017; Significance, 2017). Subsequently, the use of Scopus resulted in 69 papers[2]. After reading the abstract, four of them were directly used for this part of the review (De Jong, 1996; Fatmi & Habib, 2018; Fridstrøm, Østli, & Johansen, 2016; Hennessy & Tol, 2011; Kitamura, 2009). By checking citations in, and references to, these papers, additional literature was found. Next to models that are suitable for forecasting, no other car ownership models are included in the selection of car ownership models (see Table 3).

The remainder of this section reflects on the literature, first by classifying car ownership models based on the exploration phase of this review, and secondly by analysing whether current car ownership models that are suitable for forecasting include, or are able to include, built environment factors and life events.

Types of car ownership models

Car ownership models can take on a variety of forms, so categorizing them is greatly recommendable. In the past, several authors have done that, including De Jong, Fox, Daly, Pieters, & Smit (2004) and more recently Anowar, Eluru, & Miranda-Moreno (2014). Based on these reviews, a first distinction can be made between *disaggregate* and *aggregate* car ownership models. The first refers to models where the unit of observation is the individual decision-maker (i.e. person or household), whereas the latter examines car ownership on a higher level (e.g. zones, countries). Some aggregate car ownership models use a system dynamics (SD) approach. However, according to Gómez Vilchez & Jochem (2019), they are typically not able to include individual characteristics of people, which includes life event and BE factors. An example of this is research of Jensen, Cherchi, Mabit, & Ortúzar (2017). For this reason, SD models are excluded from this review.

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[2] The search string used was: TITLE (car OR vehicle OR auto*) AND TITLE-ABS-KEY ((ownership OR transact*) AND model* AND (forecast* OR simulat*) AND polic*).

In contrast, disaggregate models focus on the level where actual car ownership decisions are taken, namely the household level. De Jong et al. (2004) look at both aggregate and disaggregate models, due to their focus on models that were used in the public sector at that time. Anowar et al. (2014) limit themselves to disaggregate models, because in such models a higher level of precision can lead to more relevant findings for policymakers. However, these models are often not available on a national scale.

Among disaggregate models, De Jong & Kitamura (2009) and Potoglou & Kanaroglou (2008) distinguish between *holding* and *transaction* models, respectively examining absolute levels of car ownership and changes in the number of household cars (transactions). Transaction models include both duration- and transaction frequency models. The first model the holding duration of a car at the time of acquisition, while the latter model the frequency of car transaction types (e.g. disposal or replacement). In this thesis, only transaction frequency models are meant when discussing transaction models.

Furthermore, car ownership models can be classified based on the way time is included, as Anowar et al. (2014) do. They make the distinction between *static* and *dynamic* models. In contrast with static models – that only take a 'snapsnot' of household car ownership at a particular point in time – dynamic models are able to capture the development of car ownership decisions over time. Holding models are often not truly dynamic, according to De Jong & Kitamura (2009), while transaction models are dynamic by nature. They conclude it is most logical to model household car ownership as a dynamic behavioural process, developing over time, because the number of vehicles owned by a household results from several time-dependent transaction decisions instead of from repeated decisions about the optimal size of the vehicle fleet. Using such a static equilibrium assumption, would "lead to an unrealistically high number of transactions" (De Jong et al., 2004, p. 24). Also other authors state that travel forecasting models should be dynamic in their representation of choice behaviour (Ben-Akiva, Bottom, Gao, Koutsopoulos, & Wen, 2007; Clark, Lyons, & Chatterjee, 2016). Although dynamic models are theoretically better able to model car ownership than static models, Anowar et al. (2014) conclude that they are still a rarity in the literature (pp. 15, 17).

Car ownership models in practice

Several car ownership models that are suitable for forecasting are found, see Table 3, both on a national (Fox et al., 2011; Fridstrøm et al., 2016; Hennessy & Tol, 2011; Hugosson, Algers, Habibi, & Sundbergh, 2014; MuConsult, 2017; Significance, 2017) and a regional level (Duivestein, 2013; Eluru et al., 2008; Fatmi, 2017). Several of the national models that are used for forecasting (upper part of the table) are aggregate models, probably because of the relatively high data requirements related to implement a disaggregate model with such scope. The regional models (lower part of Table 3) are all disaggregate models.

Remarkable as well is the finding that the national models that are actually used for forecasting are often static: only the Swedish national model (Hugosson et al., 2014) and the Dutch Carbontax (Revnext, 2019) are dynamic. However, these (aggregate) models are rather limited in terms of the included independent variables. In the Swedish model, only socio-economic variables and petrol costs are part of the model for vehicle entry probabilities. Here, the percentage of cars to be disposed is based on make and age. Carbontax includes substantially more variables, but these are mainly related to the costs of owning a car type (e.g. costs of batteries for electric vehicles).

Table 3. Selection of car ownership (simulation) models suitable for forecasting.

Model and/or region (authors)	Aggr. level	Type H/T[3]	Type D/S[4]	**Independent variables included** *Househ. Dem.*	*Indiv. Attr.*	*Empl. Attr.*	*Lifecycle Attr.*	*BE*	*PT Attr.*	*Park-ing*	*Ame-nities*	*Car costs*	*Unobs. Effects*
BIG, NO (Fridstrøm et al., 2016)[5]	Aggr.	-	S									x	
HERMES, IRL (Hennessy & Tol, 2011)[5]	Aggr.	-	S	x	x								
SW (Hugosson et al., 2014)[5]	Aggr.	-	D	x								x	
Carbontax, NL (Revnext, 2019)[5]	Aggr.	-	D									x	
NATCOP, GB (Fox et al., 2011)[5]	Disag.	H	S	x	x	x		(x)				x	
Dynamo, NL (MuConsult, 2017)[5]	Disag.	H	S	x	x	x		(x)				x	
Carmod, NL (Significance, 2017)[5,6]	Disag.	H	S	x	x	x		(x)		(x)			
NL (Kitamura, 2009)	Disag.	H	D	x	x		x	(x)	x				x
Amsterdam NL (Pieters, 2018)[5]	Disag.	H	S	x	x			x		x			
CEMSELTS, Texas USA (Eluru et al., 2008)[6]	Disag.	T	D	x	x	x							
ILUTE, Toronto CAN (Duivestein, 2013)[5,6]	Disag.	T[7]	D	x	x	x		(x)					
iTLE, Halifax CAN (Fatmi & Habib, 2018)[5,6]	Disag.	T	D	x	x	x	x	x			x		

(x): included in a limited or simple way

[3] Holding (H) or transaction (T) model
[4] Dynamic (D) or static (S) model
[5] Actually used for forecasting
[6] The model mentioned is either a bigger transport model - including a car ownership submodule (e.g iTLE) - or is part of a bigger transport model (e.g. Carmod)
[7] Characteristics of the initial population are specified with a holding model

The Norwegian and Irish models – BIG (Fridstrøm et al., 2016) and HERMES (Hennessy & Tol, 2011) – are similar to the Swedish model in the sense that they are aggregate models and that explanatory variables are rather simple. Only demographic factors or individual vehicle characteristics are used here, like make, retail price, tax percentage and kilometre fuel cost.

Dynamo, a Dutch car ownership model (version 3.1), is a national model as well (MuConsult, 2017). Based on external factors (like economic trends and financial policies), first the size of the total Dutch car fleet is calculated for a specified year, thereby balancing supply and demand. Subsequently, the number of cars per household *type* – which are combinations of household size, number of workers, age, and income – is determined. Here, a distinction is made between 150 car types (broadly defined as combination of age, fuel type, weight, and type of ownership). This assignment per household type also takes into account the average urbanisation level, car type availability, household car kilometres, number of lease cars, and vehicle tax levels, together with some interaction terms.

Although Dynamo includes some elements that have been labelled as dynamic – like an equilibrium-price for second hand cars that is partially based on the market-price in previous years, survival probabilities of lease cars and demolition rates for older cars – the model as a whole is classified as static because the absolute levels of household car ownership are still independent from that of previous years.

Since Dynamo does not provide a spatial distribution of household car ownership, another model is used in the Netherlands to do so, as part of the National Model System LMS used for mobility and traffic forecasts (Significance, 2017). This car ownership sub model, called Carmod, is dependent on the total number of cars per household type that Dynamo provides. Next to that, it uses zone-specific data (for each of the 1406 Dutch zones used in the LMS) and the distribution of household types per zone and its spatial aggregation level is therefore lower than Dynamo. Amongst others, Carmod gives the level of household car ownership for each zone as output. This is calculated with estimates from multinomial logit models.

Carmod takes a variety of variables into account. Next to the number of licenses, also income, household size, population density, workplace density, age, number of workers, parking tariff, sex, urbanisation level and the share of agricultural jobs are included in one or more of the logit models.

The last national model used for forecasting, the British NATCOP (Fox et al., 2011), is comparable to Carmod: differences are for example related to the inclusion of car costs (running and purchasing cost). The national model of Kitamura (2009) is an early example of a disaggregate dynamic model, although it is not in use for forecasting.

Three of the regional car ownership models included in Table 3 – ILUTE, iTLE and CEMSELTS – are quite similar: all of them are disaggregate dynamic models, use multinomial logit (MNL) models[8] that distinguish between transactions and type choice, and include a wide range of individual and household variables in them. However, differences are visible in model structure and the inclusion of BE characteristics and life events. The iTLE model of Fatmi (2017) is the most comprehensive in this respect, by including accessibility and neighbourhood measures (including dwelling types and distances to work, central business district and shopping centres). Next to that, its structure is more elaborate than the ILUTE (Duivestein, 2013) and CEMSELTS (Eluru et al., 2008) model: next to splitting the choice between 'Do nothing' and a transaction (acquisition, trade and disposal) it adds choice models for whether or not to own a vehicle in the lifetime and for first-time vehicle purchase. The

[8] The iTLE model has a slightly different MNL-use than the other two models by applying Latent Segmentation, which uses multiple MNL models to capture heterogeneous choice behaviour of different population segments.

recent prototype for Amsterdam (Pieters, 2018) is a regional model that also includes parking, although it uses a different approach than the other models.

Based on this review of it is concluded that findings regarding the effect on car ownership of BE factors and life events have not yet been widely incorporated into car ownership models for the public sector. Only the regional iTLE model of Halifax (Canada) seems to accomplish that quite well. The current Dutch model Dynamo, although it is quite comprehensive compared to other models, is rather limited in this respect: built environment factors – like parking, public transport accessibility and proximity of amenities – and life events like changes in work and household composition are not yet included. Undoubtedly, this has to do with model structure. iTLE simulates the population as individuals and is therefore able to account for spatial heterogeneity of car transaction behaviour, while Dynamo is a model with very little spatiality and is not able to do that. Although a spatial distribution is provided by Carmod, its representation of car ownership decisions is restricted by its dependence on the outcomes of Dynamo, the limited inclusion of BE factors, and the absence of life events.

Another conclusion of this review is that there are not many dynamic car ownership models used for forecasting, despite that these are theoretically better in representing household car ownership. Only the regional model for Toronto does so (Duivestein, 2013). Other models, that are not (yet) used for forecasting, still show the potential of using a transaction model, both on a regional level (CEMSELTS, iTLE) as on a national level (Kitamura, 2009).

Data requirements

Since we examined various types of car ownership models and sometimes different phrases are used in the literature to describe them, it is good to first discuss the terms used in this thesis before assessing the data requirements related to them. Although we only examined car ownership models that are used for forecasting purposes, not all car ownership models do that. Especially with disaggregate models, sometimes only the effects on car ownership are quantified (e.g. higher income relates to higher car ownership), but not further applied (e.g. using calculated probabilities of distinct household types on car ownership or transactions). Only when implementing empirical results in a dynamic model, the term simulation can only be used. In a static application model this is not the case, because there is no interdependency between different years (Miller, 2019). Therefore, we reserve the terms 'static model' and 'dynamic model' for *applied* car ownership models. The phrases 'car ownership model' or 'modelling car ownership' refer to applied models as well, while 'holding' and 'transaction' models describe the *estimated empirical* models used to inform them.

Developing a car ownership model requires data, both for estimation and application. In general, for disaggregate models, estimation data is taken from *revealed preference* research, containing data of actual choice behaviour: in this case car ownership decisions. Such estimation data can have multiple sources (as seen in Table 1). Often, it stems from cross sectional research, which means that data of one point in time is available. Other research uses a longitudinal perspective, for example with the use of panel data of multiple years. Another longitudinal approach is using retrospective questioning, where people are asked to look back and recall for example past events or situations. With these estimation data, the impact of various factors on car ownership decisions is quantified with parameters.

The estimated parameters can be used to model car ownership in a region or country (see Figure 1). To do that, characteristics of the relevant population are used to assess its car ownership behaviour. Often, this application data is an aggregation of the total population. This is for example the case for

Dynamo, that takes future characteristics of the Dutch population from the scenario study Welfare, Prosperity and the Human Environment (WLO). Other models use microsimulation (e.g. iTLE), where individual members of the population are modelled.

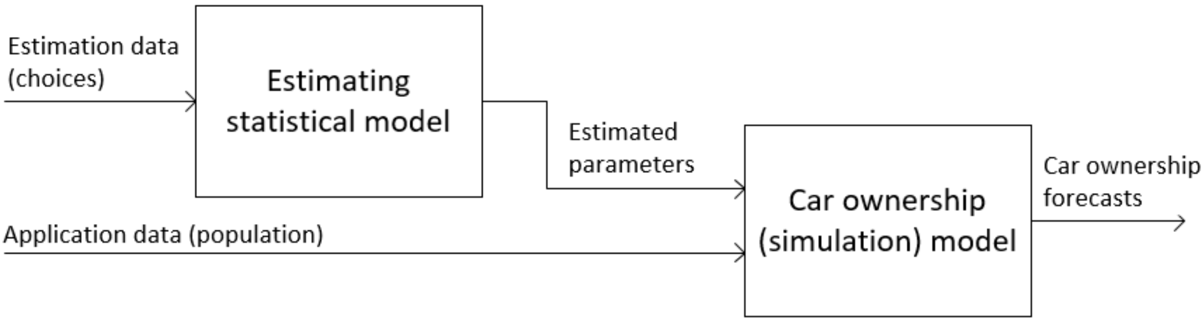

Figure 1. The processes of model estimation and application.

Including the effects of both life events and built environment factors that we found in the literature in a car ownership model comes with additional requirements compared to a model that only takes socio-demographic characteristics into account. Table 4 shows what these requirements are, thereby distinguishing between static and dynamic models.

Both static and dynamic models have the same data requirements to include *built environment factors* in it: assuming that these factors are present in the estimation dataset, it is only needed that application data of the relevant population has a certain level of spatial disaggregation in order to distinguish between different regions and their spatial characteristics.

To model the effect of *life events* on car ownership, first of all the estimation dataset needs to include them. Although this can be done with a cross-sectional survey, it is preferred to use longitudinal estimation data since it is easier to identify lead and lagged effects (i.e. effects of life events in the year before or after). Next to that, longitudinal data enables capturing a time effect: over time. This input requirement is the same for both static and dynamic application models. However, take the effect of life events into account in a dynamic model, one needs to have population data of multiple subsequent years. Without car ownership decisions being affected by these decisions in the previous year, it would be a static application model. Next to that, using individual households instead of aggregate household types would be recommended in case of dynamic models, since this enables a more reliable connection between the choice behaviour in subsequent years, especially regarding delayed and anticipated effects of life events on car ownership.

Table 4. Data requirements for including life events and built environment (BE) factors in static and dynamic models.

Applied	**Including BE factors requires**		**Including life events requires**	
model	*Estimation data*	*Application data*	*Estimation data*	*Application data*
Static	-	Spatiality	Longitudinal	-
Dynamic	-	Spatiality	Longitudinal	Subsequent years, individuals

Until recently, very few longitudinal estimation datasets were available that include the effects of life events and built environment factors (see Table 1). The first suitable dataset comes from the Dutch Mobility Panel, which runs since 2013 (KiM Netherlands Institute for Transport Policy Analysis, 2018). Currently, only the datasets of the first four years are available; next to that, data on amenities is not incorporated. The second Dutch dataset is that of Verhoeven (2010), with retrospective data on life events. However, most of these factors have not been measured at the household level and the sample size is relatively small. Van de Kamp (2019) uses a larger retrospective dataset, including information about life events and built environment factors since 2000. According to Miller (2019), such retrospective information concerning housing and employment can be beneficial for dynamic transportation models to obtain a better understanding of the impact neighbourhood and transportation systems have on households' (car transaction) decisions.

Application data with a spatial aggregation level that can capture built environment effects is not widely available. This is especially true for the development of dynamic models, which comes with the additional need for application data of subsequent years, preferably microdata of individual households. Two recent sources were identified that meet these conditions: both the population synthesizer of Goudappel Coffeng (Brederode, 2018) and the population simulator of Significance (2019) can provide such microdata.

1.2 Research goals and question

As shown in the previous section, recent findings about factors affecting car ownership are generally not included in car ownership models, despite the associations found. Especially specific built environment factors – like parking, public transport accessibility, and the proximity of amenities – and life events (e.g. childbirth, or residential relocation) are not well represented in contemporary car ownership models, including the current models that are used to inform Dutch transportation policies. Therefore, the first aim of this thesis is to examine the effect of including these factors in a simulation model of household car ownership in the Netherlands.

Secondly, since De Jong & Kitamura (2009) conclude that the most realistic way to model household car ownership is with dynamic models, the second goal is to assess the added value of a dynamic model compared to a static model (similar to the current models).

Since the required estimation and application data are available to achieve both goals (see Table 4), this thesis aims to answer the following research question:

> *To what extent are the forecasts of household car ownership in the Netherlands affected by the inclusion of life events and built environment factors in a dynamic model?*

By answering this research question, transportation and urban planning policies can be informed as well, not only because of potentially better car ownership forecasts, but also since dynamic models allow for more detailed policy evaluations (De Jong & Kitamura, 2009), for example regarding parking measures.

1.3 Research approach

Ideally, to examine how the inclusion of life events and built environment factors in the dynamic model affects the forecasts of household car ownership in the Netherlands, a direct comparison of this new model with the current disaggregate Dutch models (Dynamo and Carmod) would be preferred. However, since the available estimation dataset differs from that of Dynamo and Carmod, a direct comparison between these models would not be valid. Therefore, also a static model similar to Dynamo and Carmod is constructed, which is used as reference point to assess the added value of the dynamic model. Both the dynamic model and the static model use the same estimation and application data, so in this way their outcomes can be compared to each other.

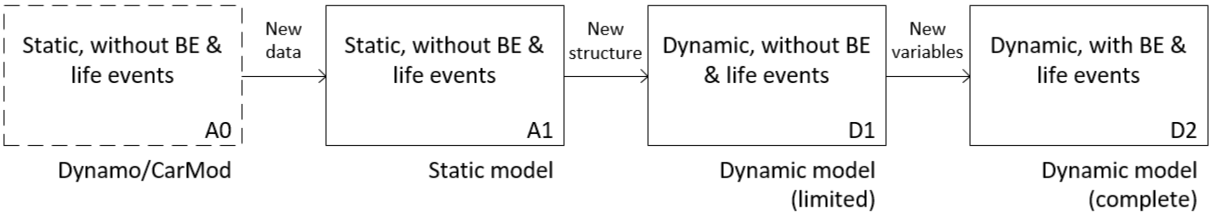

Figure 2. Overview of the characteristics of the different models discussed in this thesis. Dotted line is for current models.

Since the dynamic model is enriched in terms of structure (static versus dynamic) as well as substance (without or with the effect of life events and the built environment), it is assessed in two steps (see Figure 1 and Table 5). The first step evaluates whether its dynamic structure is able to improve the forecasts of household car ownership compared to the static model.

After that, the effect of including life events and built environment factors is assessed by comparing a limited version of the dynamic model (without these factors) with a model including them. With these stepwise improvements, a good assessment of this complete dynamic model is made. Although it is possible to account for the effect of built environment factors and even for that of life events in a static model, it is chosen not to do that here due to the complexity of doing so. More importantly, it does not provide much additional insight into the effect of built environment factors and life events on car ownership, since it is possible to assess this with the dynamic model, together with the effect of going from a static to a dynamic (by including former car ownership).

Table 5. Stepwise enrichment towards a car ownership model including built environment (BE) factors and life events.

	Estimation	Variables included in choice and application model			
Application model	**choice model type**	*Socio-demographics*	*Former car ownership*	*Additional BE factors*	*Life events*
A1. Static	Holding	✓	✗	✗	✗
D1. Dynamic (limited)	Transaction	✓	✓	✗	✗
D2. Dynamic (complete)	Transaction	✓	✓	✓	✓

To conclude about the extent to which the forecasts of household car ownership in the Netherlands are affected by the inclusion of life events and built environment factors in a dynamic model, the following research objectives are set:

A. *Conceptualising (differences between) the static and dynamic models of household car ownership in the Netherlands*
B. *Assessing the effect of stepwise improving the incorporated choice models towards the inclusion of life events and built environment factors*
C. *Developing the static and dynamic model – including life events and built environment factors – and validating them by assessing their car ownership forecasts*

1.3.1 Estimation – Discrete choice modelling

To enable a comparison between the static and dynamic models, they use the same retrospective estimation dataset to assess the impact of the variety of factors on household car ownership choices. Discrete choice modelling is used to quantify these effects, although other statistical models were evaluated as well.

The nature of the dynamic model requires that the choice for a certain number of cars is determined relative to that of the previous year (i.e. seeing it as a transaction). Considering the discrete nature of these transaction choices, continuous statistical modelling approaches are not suited to be used in the dynamic model. Other approaches are discrete choice modelling and logistic regression modelling. With the latter, it is possible to analyse data in which the dependent variable is at an nominal or ordinal scale, while the measurement level of the independent variables is not restricted (Pedhazur, 1997).

However, doing an ordered logistic regression, would not respect the nature of car transaction changes: no difference would then be assumed between the choice to 'do nothing' and the choice to replace a car. In this way, car transaction choices cannot be captured in a satisfying way. Next to that, it would probably have violated the 'proportional odds assumption' that is part of an ordered logistic regression. This assumption states that the relationship between '-1' (car disposal) and '0' (no change in number of cars) is the same as the relationship between '0' and '+1' (acquisition). The result is that only one set of coefficients for both comparisons is given, which limits distinguishing between them. Using the same original dataset, analyses of Van de Kamp (2019) indeed revealed that the proportional odds assumption would not hold, so an ordered logistic regression would not fit the goal of this research. Using multiple binary logistic regression models could deal with this limitation, but this has the disadvantage that multiple models would be needed instead of one.

Therefore, multinomial logit (MNL) models are estimated to capture household car ownership transactions. Choice modelling is often based in Random Utility Maximization (RUM) theory (McFadden, 2000): people will choose for an alternative with the highest expected utility, which depends on the various attributes of alternatives (for example price and quality). Another advantage of using choice modelling is that it is relatively easy to interpret its outcomes, and to incorporate them into the dynamic model.

In the static model, discrete choice modelling is used to capture car ownership behaviour as well, in order to compare the outcomes of the different choice models. Note that the nature of the choice models in the static model differs from that in the dynamic model: respectively, holding choice models (capturing the choice for an absolute number of cars) and transaction choice models are used (capturing the choice for a change in number of cars).

1.3.2 Application – Microsimulation

The outcomes of the discrete choice models are applied differently in the static and dynamic model. In the static application model, the estimates of the holding choice models are implemented. Due to the high spatial aggregation level and the independence from the results of previous years, it was possible to develop this model using a spreadsheet.

In contrast, the dynamic model is developed using a microsimulation approach and incorporates transaction choice model. Microsimulation is specifically used for simulation involving disaggregate systems and is characterised by a dynamic and stochastic evolution of the system's state (Miller, 2019). This matches well with the aim of this thesis: examining the impact of including life events and built environment factors in a dynamic car ownership model. The static and/or aggregate approaches discussed in section 1.1.2 are not capable of capturing dynamic transaction behaviour, so using microsimulation is a fitting approach.

A microsimulation approach comes close to Agent-Based Modelling (ABM), as Gilbert (2007) and Miller (2019) state. Central to ABM are explicitly modelled agents, who are aware of their environment and are capable to respond to it according to some behavioural rules to achieve a certain goal (Miller, 2019; Nikolic & Kasmire, 2013). The main difference between them is that ABM explicitly focusses on interaction between agents, while these interactions are not included in a microsimulation approach. The focus on individual agents is similar though: each agent has a state that defines it (e.g. the number of cars owned by a family or their residential location) and its actions are governed by decision rules (like a probability to buy a car in case of residential relocation). In this case, the decision rules of the agents in the dynamic application model are informed by the empirical results of the transaction choice models.

The dynamic car ownership model can be viewed as a socio-technical system, which is composed of "a social network of actors and a physical network of technical artefacts" (Dijkema, Lukszo, & Weijnen, 2013, p. 1). This is exemplary for research within the CoSEM programme. This thesis fits well within this definition, since the focus of it is on modelling and simulating the effects of socio-demographic characteristics, life events of individuals and/or their household members, and the (physical) built environment on car transaction choices. Added to that, also effects of other actors are taken into account, for example that of local municipalities implementing stricter parking regimes, which are aimed at safeguarding public goals like sustainability and accessibility.

1.3.3 Structure

The remainder of this thesis is structured based on the four research objectives. Each of these objectives is discussed in a separate chapter, starting with a conceptualisation of the static and dynamic models in chapter 2, revealing structural similarities and differences (objective A). Subsequently, chapter 3 discusses the effect of the stepwise improvement of the choice models on their ability to explain car ownership choices, which is done by including life events and built environment factors in them (objective B). After that, chapter 4 elaborates on the application of these different choice models in the static and dynamic model, including extensive validation (objective C). Finally, in the concluding chapter, the results of this research are discussed, recommendations for further steps are given, and some implications for policymakers are provided.

2. Conceptualisation of Car Ownership Models

This chapter provides a conceptualisation of the static and dynamic models of household car ownership (research objective A), in order to assess their structural similarities and differences. Section 2.1 starts with the static model, while the dynamic model is discussed in section 2.2. Finally, a short conclusion is given in section 2.3. The literature review of section 1.1 supported the identification of relevant variables and the structural relations between various parts of the models, which is also used as input for the choice model estimation (chapter 3).

The two developed models, in contrast with Dynamo and Carmod, use the same datasets for model estimation and application, which in the end makes a comparison between their outcomes possible (see Figure 3). For estimation, the retrospective dataset of Van de Kamp (2019) is used, which amongst others contains information related to (changes in) car ownership, residential location, employment and family. Application of these models is done with input of a population simulator (Significance, 2019). This simulator captures part of the life-course of the Dutch population since 2014, including (changes in) the residential environment, work location, and household composition.

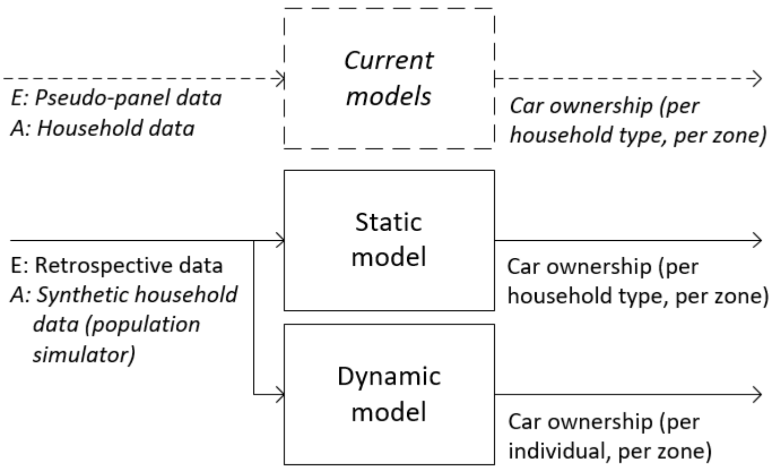

Figure 3. Input (estimation [E] and application [A] data) and output of various car ownership models. Data and models in italics are external.

2.1 Static Model

The static model can be used to assess future car ownership and has a similar structure compared to Dynamo and Carmod, although it is simplified in some places (see Figure 4). Some variables are left out in the static model due to data availability. No modules balancing demand and supply of second-hand cars or for vehicle type choice are included in the static model. Although incorporating the latter, a type choice model, was intended because data for it was available, it was left out because in the end it did not fit within the scope of this research project. The core modules in the static model – distributing households among household types, determining the number cars per household type, and providing a spatial distribution – are similar to that in Dynamo and Carmod.

It is chosen to use 2014 as base year for the static model. This makes it possible to validate the model with observed car ownership trends. Calibrating the models is done in a similar way as in Dynamo and Carmod, regarding the total number of cars as well as their spatial distribution.

2.1.1 Processes

To examine future car ownership, the static model starts with calculating the number of households per household type (process S1), based on output of the population simulator for the specified year.

Instead of first determining the share of business cars, like in the current models, determining the number of households per type is immediately followed by calculating the total **number of cars** (S2). This is based on the estimated parameters of the nested holding model (see section 3.3). Compared to Dynamo, a smaller number of variables is used to determine household car ownership per household type: car characteristics are not included, and some variables are measured in a different way (like age and number of workers).

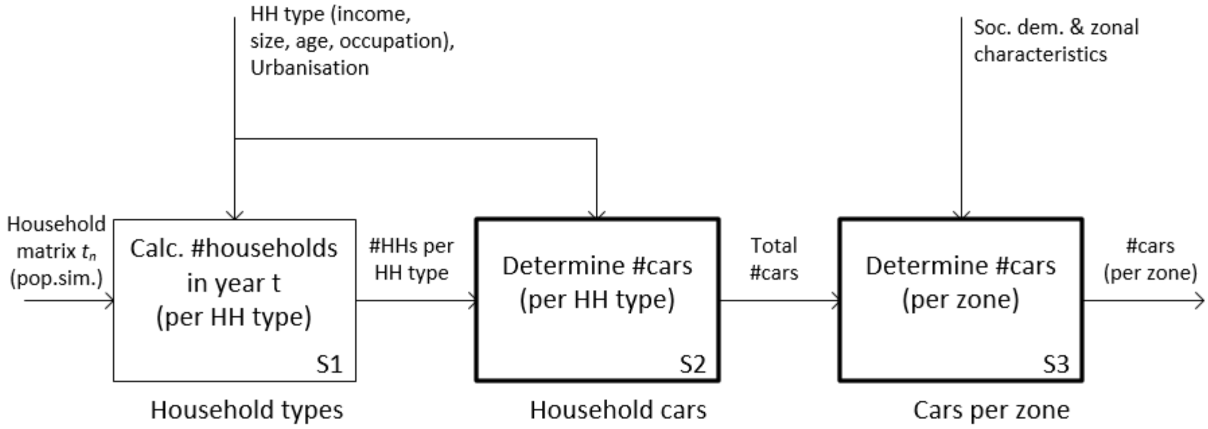

Figure 4. Conceptual model of the static model. Processes based on holding choice models have an accentuated shape.

A zonal distribution of household car ownership is provided in a similar way as Carmod does, based on the outcomes of the zonal holding model (S3). The main difference is that a choice between three alternatives is modelled (having 0, 1, or 2 or more cars), while Carmod has four categories. Next to that, similar variables are used to determine household car ownership, although some adjustments were made because of data availability. Since occupational data is not available on the household level, individual work status is used in combination with household size to indicate the number of workers. Furthermore, the age group of the respondent is used, instead of the age of the head of the household, and the absolute household income instead of the restincome after owning one or multiple cars.

2.2 Dynamic model

The main differences between the static model and the dynamic model are that the latter does not use household types, but simulates individual households and their members, and that the output of a certain year affects the choices made in the next. Its structure is relatively simple (see Figure 5): after updating the characteristics of the population, a car transaction is chosen, and car age is assigned in case a car is bought.

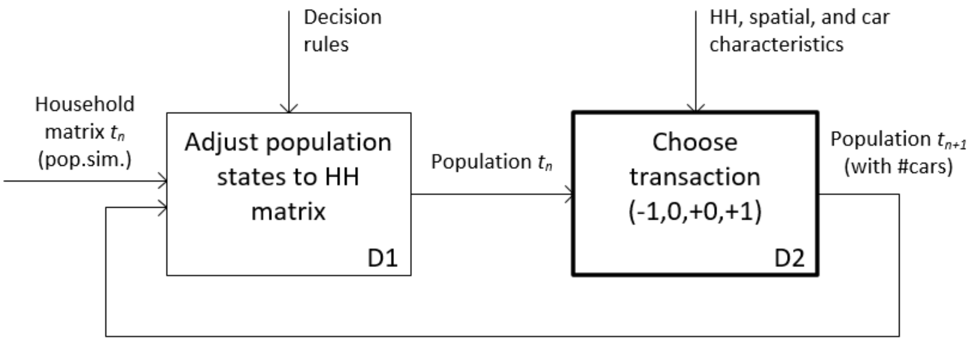

Figure 5. Conceptualisation dynamic model. The process based on a transaction choice model has an accentuated shape.

Just like in the static model, 2014 is used as base year for simulating car transactions of households in order to historically validate the model. However, since initial car ownership and life events are part of the dynamic model – describing a change in variables in two subsequent years – the first year transaction that is simulated is that in 2015, with the situation in 2014 as starting point.

2.2.1 Processes

The first step in the dynamic model is adjusting the states of each individual (and his/her associated household) in the synthetic Dutch population, based on the output of the population simulator (D1). For each year in the simulation, individual and household characteristics are provided, which includes household size, residential location, occupation, age, income, education level and driving licence possession. Since each household and each individual has a unique identifier, life events are captured as well. For each household also their residential location is modelled, which enables simulating the effect of spatial factors on car transactions. To do so, 1406 zones are used, each with its own unique characteristics (like the availability of free nearby parking).

Based on the updated states of the household population, the car transaction procedure (D2) determines the chance of choosing each transaction type and stochastically picks one of them. For each household, the choice between four alternatives is modelled: disposal (-1), no transaction (0), replacement (+0), and acquisition (+1). Since car ownership decisions are taken on the household level, these car transaction choices are modelled on the household level as well, although individual characteristics are still taken into account.

This car transaction behaviour is dependent on variables that are similar to those included in the static model, but next to that on additional variables as well (a variety of life events and built environment factors). Two versions of the dynamic model are developed: one with these additional variables and one without them. In Table 6 – which shows an overview of the variables used in the different models – categories with the additional variables have been marked with an asterix. The impact of each factor on these probabilities is dependent on the outcome of the transaction choice models (see section 3.4). In the end, the population has a new car ownership state and the process of updating and transacting is walked through again for the following year.

Table 6. Overview of variable categories used in Dynamo and Carmod, the static model, and the dynamic model for household car ownership.

Category	Dynamo/Carmod	Static model	Dynamic model
Car ownership	0, 1, 2+ cars	0, 1, 2+ cars	-1, 0, +0, +1
Car charac-teristics.	Car costs Car use Car availability	-	Car age Initial number of cars
Household char.	Socio-demographics Licence possession	Socio-demographics Licence possession	Socio-demographics Licence possession
Built Environment	Urbanisation Pop./employment density Zonal parking tariff	Urbanisation Pop./employment density Zonal parking tariff	Urbanisation Population density Zonal parking tariff Free parking availability* Public transport accessibility* Distance to supermarket*
Life events	-	-	Life events related to family, work, home, licence possession*

**Only in the complete dynamic model*

2.3 Conclusion

In this chapter we examined the structural characteristics of the models developed for this thesis. First of all, we saw that the static model is a simplified representation of the current models, though without losing its distinctive features that are relevant for this research. These characteristics relate both structure and content: since it is a static model, there is no interdependence between household car ownership levels in subsequent years. Besides that, no effect of life events and built environment factors on car ownership is modelled.

The dynamic model is different in both aspects: by incorporating a car transaction choice model (i.e. a change compared to the previous year) it is theoretically better able to capture car ownership decisions. Secondly, by incorporating life events and built environment factors, it is likely that the capacity of this model to capture these decisions is higher. In the next chapter, this ability is examined.

3. Choice Models for Car Ownership Decisions – Estimation

Having seen the structural differences between the static and dynamic models, we can now assess the effect of stepwise improving the choice models incorporated in them, towards one that includes life events and built environment factors (objective B). These effects on car ownership are quantified using discrete choice modelling, based on a retrospective dataset. This chapter therefore starts with a description of this estimation dataset in section 3.1, followed by an overview of the model estimation process (section 3.2).

Subsequently, section 3.3 discusses the outcomes of the holding choice models that capture how household car ownership is affected in the static model. Afterwards, the effects of the two improvements that are central in this thesis are assessed in section 3.4: first, this regards the step from a holding to a transaction choice model (needed in the dynamic model), while the second step is the inclusion of life events and built environment factors.

3.1 Retrospective estimation data

As seen before, the static model and the dynamic model use the same estimation dataset, which is based on a retrospective survey. This retrospective data was collected on behalf of Significance and financially supported by Rijkswaterstaat (part of the Dutch Ministry of Infrastructure and Water Management), while fieldwork was done by Accent MR. Participants in the survey were found through an online panel between January and June 2019. They answered questions related to car ownership, residential location, household composition, occupation and various other individual or household characteristics from the period 2000 to 2019. Except for employment, questions about all these topics were asked at the household level, considering that decisions related to residential location and car ownership are not individual concerns. To select participants, criteria regarding urbanisation and age were used. Together with some difficulties in the process of data collection, this made that the initial dataset contained a higher share of participants in extremely urbanised areas and a higher share of respondents of 50 years and older. In the end, this initial dataset includes information of 1,487 respondents, distinguished by urbanisation (Table 7) and age (Table 8). A more detailed description of the survey design and data collection is given by Van de Kamp (2019).

Table 7. Distribution urbanisation (CBS, 2019d).

Urbanisation level	Population	Sample
Selection G4 (extr. urbanised)	14%	11%
Other extremely urbanised	13%	26%
Strongly urbanised	23%	22%
Moderately urbanised	16%	14%
Hardly urbanised	17%	14%
Not urbanised	17%	13%

Table 8. Distribution age (CBS, 2019a).

Age	Population	Sample
18 to 35 years	24%	14%
35 to 50 years	25%	23%
50 to 65 years	27%	31%
65+ year	24%	32%

Since it was an individual questionnaire, some variables in the estimation dataset are only available at the individual level. Since a car transaction is a household decision, having for example occupational information on the household level would provide a better picture of household car ownership. Next to occupation, also age is measured at an individual level. This could for example cause a bias in case of children living with their parents. However, since only people of 18 years and older were questioned, the impact of this bias is assumed to be small. Lastly, not all information on licence possession is available for everyone in the household. Although the moment of obtaining a licence for other household members is known, it cannot be guaranteed that those people were part of the household at that time, which reduces certainty about the number of licenses, especially for longer times ago.

The retrospective dataset of Van de Kamp (2019) was coupled to secondary data sources from CBS (2019d, 2019b), Significance (2017) and KiM (2017), to enrich the model estimation process with additional zonal information. Among others this relates to accessibility, urbanisation levels, and the proximity of local destinations for each of the 1406 zones, which are mainly used to estimate parameters for the transaction model.

The initial dataset contained 1,487 cases: one for every respondent. This has been transformed into an estimation dataset with 24,920 cases, where for every respondent each year from 2001 to 2018 is taken into account separately. Each case is therefore a snapshot of a variety of individual, household and spatial characteristics in that year. A great advantage of this data compared to other data is that it contains information on changes in these characteristics compared to the previous year as well (life events).

Table 9. Sample description: car transactions since 2000.

Observation years (average)	16.8	
Number of cases	24,920	*100%*
Additional cars	646	*2.6%*
Replaced cars	2,211	*8.9%*
Disposed cars	175	*0.7%*
No change	17,005	*68.2%*
Missing	4,883	*19.6%*

From almost 20% of these cases car transaction information is lacking (see Table 9), since respondents did not always provide a complete and consistent overview of their car ownership state since the year 2000 (or the year they turned 18). Especially in the first ten years cases are missing (Figure 6): years closer to the present decreasingly contain missing cases. Furthermore it can be concluded that these missing cases do not heavily affect the distribution of specific car transaction types (Figure 7): although the share of acquisitions and replacements slightly increases over the 18 years in the estimation dataset, it is not considered to affect the suitability of these data for this research.

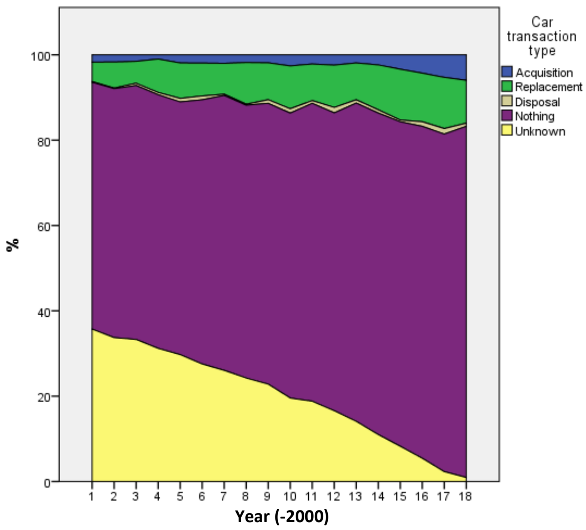

Figure 6. Car transactions per year (incl. missing values).

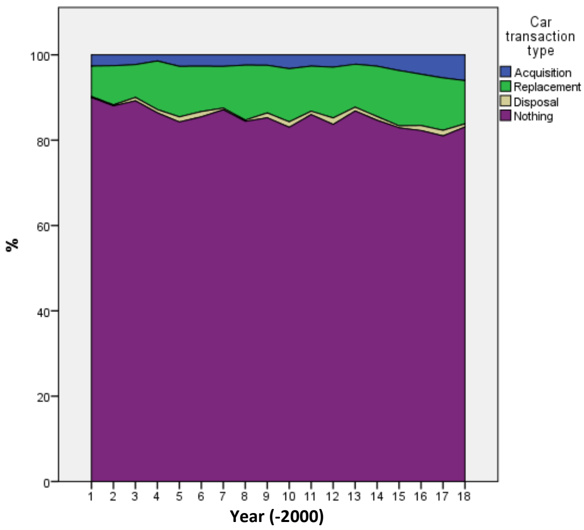

Figure 7. Car transactions per year (excl. missing values).

Another check of the estimation dataset is done using the original dataset. Here, it was indicated for each car whether it was a replacement or an additional car, so this could be compared to the car transaction numbers in the estimation dataset. A difference was found between them: less acquisitions were found in the estimation dataset. However, part of this difference could be explained by the fact that this dataset contains a lower share of younger people, which more often acquire a car than older people. The remaining difference can be explained by choices that were made to structure this data (e.g. disposing and acquiring a car in the same year was always considered to be a replacement) and response bias (e.g. stating that a car is an additional car, while it in fact replaced another according to the data). All in all, it is expected that using these estimation data can result in valuable insight regarding the effects on household car ownership.

3.1.1 Data exploration

When exploring these estimation data, some interesting differences were found between car transaction behaviour of different groups. As expected, socio demographic factors that are part of the choice models for both the static model and dynamic model are important in this respect (see Table 10 and 11): younger people acquire an additional car relatively often compared to older people. The older one gets, the lower the share of car acquisitions. After 65 years, the share of having no car transaction in a car seems to be higher than before. Furthermore, a higher net disposable household income per year goes together with a higher share of car replacements and acquisitions. Age and income are therefore examples of promising socio-demographic variables that could explain car transaction behaviour.

Table 10. Age distribution around car transactions.

	Car transaction type			
Age	*Disp.*	*Noth.*	*Repl.*	*Acq.*
18 to 35	0.9%	84.7%	8.4%	6.1%
36 to 50	1.0%	84.7%	10.8%	3.5%
51 to 65	0.9%	84.3%	12.5%	2.3%
66 and older	0.5%	87.1%	10.8%	1.5%

Table 11. Car transactions distinguished per income group.

	Car transaction type			
HH income	*Disp.*	*Noth.*	*Repl.*	*Acq.*
Missing	0.7%	88.1%	8.9%	2.3%
Below 20k	1.1%	88.9%	7.6%	2.5%
20-30k	0.8%	85.1%	11.5%	2.6%
30-40k	0.7%	84.2%	11.5%	3.6%
Above 40k	1.0%	82.1%	12.6%	4.3%

Table 12. Car transactions distinguished per urbanisation level.

	Car transaction type			
Urbanisation	*Disp.*	*Noth.*	*Repl.*	*Acq.*
Missing	0.8%	89.7%	6.0%	3.5%
Extr. urban.	0.9%	87.0%	9.0%	3.0%
Strongly urb.	0.7%	84.4%	11.8%	3.1%
Moderately	1.0%	82.1%	13.2%	3.6%
Hardly urb.	0.8%	82.4%	13.9%	2.9%
Not urban.	1.0%	82.7%	12.6%	3.7%

When examining the relation between car transactions and urbanisation – which is one of the few spatial factors included in the holding model, indicating the population density (CBS, 2020) – no clear pattern is visible. Although the share of replacements seems to be lower in more urbanised areas at the expense people not involved a car transaction, the number of disposals and acquisitions seems to be relatively stable across areas with different urbanisation (Table 12).

In contrast, the availability of free nearby parking, one of the additional built environment factors, is a promising explanatory variable of car transactions (see Table 13): the presence of free parking seems to be connected to more car acquisitions, especially in case of initially having no cars, more replacements and less disposals.

Table 13. Car transactions distinguished per parking regime and number of cars.

		Car transaction type			
#cars	**FreePark?**	*Disp.*	*Noth.*	*Repl.*	*Acq.*
0	No	-	94.4%	-	5.6%
0	Yes	-	89.4%	-	10.6%
1	No	1.1%	85.7%	11.4%	1.8%
1	Yes	0.5%	83.1%	14.3%	2.2%
2	No	10.3%	82.7%	6.4%	0.6%
2	Yes	4.9%	81.6%	11.8%	1.6%

One of the life events examined in this thesis is residential relocation, which could very well be related to car transactions as well (see Table 14). In years of relocation, more transactions are done, related to acquisitions and replacements as well as to disposals.

A more detailed description of the estimation dataset can be found in Appendix A. All in all, it is indicated that sociodemographic factors, built environment factors and life events are promising explanatory factors for changing car ownership.

Table 14. Car transactions around relocations.

	Car transaction type			
Relocation	*Disp.*	*Noth.*	*Repl.*	*Acq.*
No	159	16,359	2,072	587
	0.8%	*85.3%*	*10.8%*	*3.1%*
Yes	16	646	139	59
	1.9%	*75.1%*	*16.2%*	*6.9%*

3.2 Model estimation process

To quantify the effects of various explanatory factors on car ownership, multinomial logit (MNL) choice models are constructed in statistical software Biogeme (Bierlaire, 2018). Utility functions are specified for each choice alternative, which in the end can be applied to calculate the probabilities of choosing them: a higher utility (relative to the utility of other alternatives) results in a higher probability of being chosen.

The impact of each factor on the total utility of an alternative is estimated using the retrospective estimation dataset, which contains for each year both the absolute number of cars (for the holding model) and the change therein (for the transaction model). Besides an alternative specific constant (ASC), which is used to capture intrinsic preferences for each alternative, several other variables have an impact on the total utilities. The weights for these factors (utility parameters) are represented by betas (β).

A simplified example of a set of utility functions can be seen in equations 1 and 2, where the utilities of the choice alternatives 'acquisition' and 'do nothing' are respectively shown as V_{Acq} and V_{Noth}. In principle, one choice alternative is treated as reference category, since the values of the estimated parameters have no meaning beside their relative size compared to other parameters. Therefore, in this case, the utility for someone with a driving licence to acquire a car is relative to a fixed utility for this person to do nothing. The probability of choosing to acquire a car can subsequently be calculated using equation 3:

V_{Acq} = ASC_Acq + Licence * β_License (eq. 1)
V_{Noth} = 0 (eq. 2)
P_{Acq} = $\exp(V_{Acq}) / (\exp(V_{Acq}) + \exp(V_{Noth}))$ (eq. 3)

Estimation of the parameters (betas) in the utility functions is based on the Maximum Likelihood-principle, which is about looking for the set of parameter values that makes the choices in the estimation dataset the most likely. This is done by evaluating the log-likelihood (LL) function. The final (and highest) LL of a choice model can be compared to other models with the Likelihood ratio test in cases where one model is an extension of another. Whether or not the extended model is better than the other model is dependent on the LL increase, and a threshold. This threshold is based on the number of variables that is added in the extended model (i.e. degrees of freedom), and the preferred significance level (where 95% is conventional). If the increase of LL is higher than the threshold, it can be concluded that the extended model has a statistically significant better model fit.

3.2.1 General approach and assumptions

Since the holding choice models were developed with similar variables as used in Dynamo and Carmod, their utility functions were more or less prespecified, which was not the case for the transaction model. The goal of the latter was to find the relevant effects of additional built environment factors and life events, so it could not be decided up front which variables would be in it. Therefore, one by one additional variables were included in the model in order to find the model that is significantly better than other models. Whether the inclusion of a variable resulted in a better model fit is evaluating with the Likelihood Ratio Statistic (LRS).

In some cases where a model with an additional variable was not better than a model without this variable, there was reason to keep it in the model, since the outcome of the estimation is the best ‘guess’ for this parameter value. Here, a trade-off had to be made between practical applicability (of the models of chapter 4) and theoretical certainty (that the estimated value is actually different from zero in the population). Since the estimation dataset is already not completely representative, choosing for practical applicability (and thus possibly including insignificant parameters) does not hinder the goal of this research, namely comparing a dynamic model with a static model.

For model estimation often multiple dummy variables were included in the utility functions, which makes it easier to capture non-linear effects. Income, for example, is taken into account with dummies for each of the four income classes.

Since the estimation dataset contains information of car transaction choices over multiple years, there are also multiple cases per respondent, which could be correlated. Therefore, to account for this dependency, the ‘sandwich estimator’ is used, resulting in more robust outcomes. However, using this method does not affect the estimated utility parameters, but only increases their standard error (Daly & Hess, 2010). Using the ‘jack-knife’ method would account for a bias in the estimated coefficients as well as in the accuracy of these estimates. However, for practical reasons it is chosen to use the sandwich estimator. This is done for all choice models discussed in this chapter.

Although preferences for specific car transactions might have changed over time, it assumed that household car ownership decisions are stable over time. This has been validated by splitting the data and running one of the models again (see appendix B), which showed that the vast majority of the estimated parameters using the second half of the data falls within the confidence interval of the model that uses the first half of data. Therefore, only one set of utility parameters is estimated per model. The resulting parameters are incorporated in the decision rules of the various car ownership models (see chapter 4), in order to calculate total utilities for each alternative and provide probabilities for choosing them.

3.2.2 Included variables

With these starting points choice models were estimated for the two versions of the dynamic model (with and without life events and built environment factors) and the static model. For all of these models, Table 15 below shows which variables are included in them, and which variables were added but not found to improve the model significantly (striked through).

In the holding models in general the same variables are included as in the holding models used in Dynamo and Carmod, except some variables for which no data was available (i.e. car characteristics) or that were not captured on a household level, but only individually (occupation, age). Next to that, it is not chosen to optimize the model fit of the holding models by including new variables (like education level or Gross Domestic Product), although that might have improved the comparison with the limited transaction model. Instead, it is chosen to work with variables resembling that of Dynamo and Carmod, mainly due to pragmatic reasons. Furthermore, finding other variables that significantly affect household car ownership in the holding models would not be expected, since the estimation dataset of Dynamo and Carmod is substantially larger and thus better able to detect such effects. Therefore, a valid comparison between the holding and transaction models can still be made in this way.

Table 15. Overview of all variables used in the choice models for Dynamo and Carmod, the static model, and the dynamic model for household car ownership.

Category	**Variable**	**Holding models (Dynamo/Carmod)**	**Holding models (for static model)**	**Transaction models (for dynamic model)**
Household	*Occupation*	Number of workers; Head is student (Carmod); Number of workers (Carmod)	Occupation type (Respondent); Occupation type x HH size (Zonal)	Occupation type (Respondent)
	Age	Age group oldest person; Age trend; Age HH head (Carmod)	Age group (Respondent); Age group (Zonal)	Age group (Respondent)
	Income	Income class; Rest income (Carmod)	Income class; Income class (Zonal)	Income class
	Driving licenses	Number in HH (Carmod); People without licence (Carmod); FemLic (Carmod)	Number in HH (Zonal); People without licence (Zonal); Yes/no x Gender (Zonal)	Number in HH; Yes/no (respondent); ~~People without license~~; Yes/no x Gender
	Other	Household size	Household size	Household size; Education level; GDP; ~~Gender~~
Spatial variables	*Urbanisation*	Urbanisation (ln); Interactions with soc.dem.; Urbanisation level (Carmod) Pop. density within 1km (Carmod)	Urbanisation (ln); Interactions with soc.dem.; Urbanisation dummies (Zonal) Pop. density within 1km (Zonal)	Urbanisation (ln); ~~Urbanisation dummies~~ Pop. density within 1km
	Jobs, amenities	Employment density (1 & 5km); %Agricultural/total jobs (Carmod)	Employment density (1 & 5km); %Agricultural/total jobs (Zonal)	~~Employment density (1 & 5km);~~ ~~%Agricultural/total jobs~~ Distance to closest big supermarket* ~~Distance to other amenities*~~
	Parking	Tariff per hour (Carmod)	Tariff per hour (Zonal)	Tariff per hour; Free Parking (dummy)*; ~~Parking limitations (Selection G4)~~*
	Public transport accessibility	-	-	~~(Changing) Proximity train station*;~~ ~~(Changing)~~ PT accessibility (BBI)*

Table 15 (continued).

Category	Variable	Holding models (Dynamo/Carmod)	Holding models (for static model)	Transaction models (for dynamic model)
Life events	*Work change*	-	-	Another/new job* ~~Another/new job previous year~~* Another/new job subsequent year* Retirement* ~~Retirement previous year~~* ~~Retirement subsequent year~~*
	Relocation	-	-	Relocation* Relocation previous year* Relocation subsequent year*
	HH change	-	-	Change in #children* Change in #children previous year* ~~Change in #children subsequent year~~* Change in partner* ~~Change in partner previous year~~* ~~Change in partner subsequent year~~*
	Licence change	-	-	Additional license* Additional licence previous year* Additional licence subsequent year*
Car charac-teristics	*HH kilometres (HHkm)*	HHkm per year; Interaction HHkm, Age	-	-
	Car types	Max. utility available types	-	-
	Businesscars	%Business cars per HH type	-	-
	Car costs	Average purchase price Car taxes	-	-
	Car age	-	-	Car age
	Number of cars	-	-	Initial number of cars

**Only in the complete dynamic model; striked through is tested but not included in the end*

3.3 Holding choice models for the static model

Just like in Dynamo and Carmod, not all of the promising factors that can explain car ownership decisions are part of the holding models for the static model. A nested holding model is used here in order to enable the distribution of cars per household type (like Dynamo), while a zonal holding model is estimated in order to spatially distribute the total number of cars (like Carmod).

Similar to Dynamo, a nested holding model is used (see Figure 8), which is used in process S2 (see Figure 4): first, utility parameters were estimated for having one or multiple cars compared to having no cars; subsequently, parameters for the choice between having one car and having two or more cars were estimated. Their utility functions are shown in equations 4 and 5. For all these variables, having no car is the reference. For the second choice the alternative used as reference is having one car, so utility parameters are estimated for have two or more cars. In nested holding model mainly socio-demographic characteristics like age, income and household size are included; life events and spatial factors are not part of them, except urbanisation.

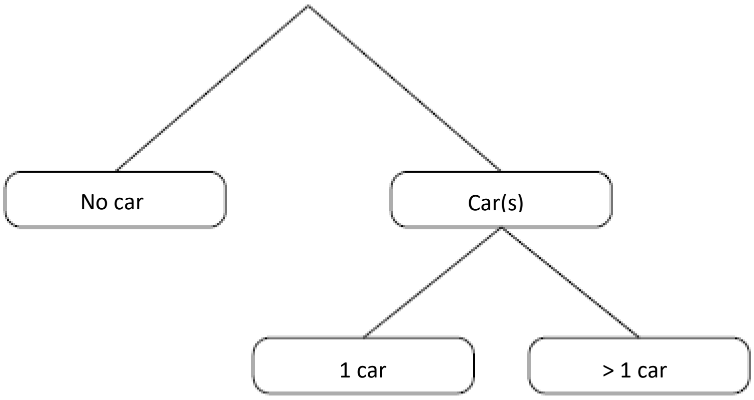

Figure 8. Nested structure used in the holding model (MuConsult, 2017).

$$
\begin{aligned}
\{Eq.4\}\ U\ (1+ car) \\
= {} & ASC\_1pl + \beta\_Occ\_FT\_car * Work\_FT + \beta\_Occ\_PT\_car * Work\_PT \\
& + \beta\_Occ\_Stud\_car * Stud + \beta\_Occ\_Ret\_car * Retired * (1 - Retired\_Miss) \\
& + \beta\_Occ\_No\_car * NoOccup \\
& + \beta\_Age35\_car * Age1 + \beta\_Age35\_50\_car * Age2 + \beta\_Age50\_65\_car * Age3 \\
& + \beta\_Age65\_car * Age4 \\
& + \beta\_HHsize1\_car * HHsize1 + \beta\_HHsize2\_car * HHsize2 \\
& + \beta\_HHsize3\_car * HHsize3 + \beta\_HHsize\_Miss\_car * HHsize\_Miss \\
& + \beta\_Inc12\_car * Inc12 + \beta\_Inc3\_car * Inc3 + \beta\_Inc4\_car * Inc4 \\
& + \beta\_Inc56\_car * Inc56 + \beta\_Inc\_Miss\_car * Inc\_Miss \\
& + \beta\_Ln\_urb\_car * Ln\_urb * (1 - Ln\_urb\_Miss) \\
& + \beta\_Ln\_urb\_Oc\_PT\_car * Ln\_urb * (1 - Ln\_urb\_Miss) * Work\_PT \\
& + \beta\_Ln\_urb\_Oc\_Ret\_car * Ln\_urb * (1 - Ln\_urb\_Miss) * Retired * (1 \\
& - Retired\_Miss) \\
& + \beta\_Ln\_urb\_Age35\_50\_car * Ln\_urb * (1 - Ln\_urb\_Miss) * Age2 \\
& + \beta\_Ln\_urb\_Age50\_65\_car * Ln\_urb * (1 - Ln\_urb\_Miss) * Age3 \\
& + \beta\_Ln\_urb\_Age65\_car * Ln\_urb * (1 - Ln\_urb\_Miss) * Age4 \\
& + \beta\_Ln\_urb\_Inc3\_car * Ln\_urb * (1 - Ln\_urb\_Miss) * Inc3 \\
& + \beta\_Ln\_urb\_Inc4\_car * Ln\_urb * (1 - Ln\_urb\_Miss) * Inc4 \\
& + \beta\_Ln\_urb\_Inc56\_car * Ln\_urb * (1 - Ln\_urb\_Miss) * Inc56 \\
& + \beta\_Ln\_urb\_2p\_car * Ln\_urb * (1 - Ln\_urb\_Miss) * HHsize2 \\
& + \beta\_Ln\_urb\_3p\_car * Ln\_urb * (1 - Ln\_urb\_Miss) * HHsize3
\end{aligned}
$$

$\{Eq. 5\}\ U\ (2+\ cars)$
$$= ASC\_2cars + \beta\_Age35\_2cars * Age1 + \beta\_Age35\_50\_2cars * Age2 + \beta\_Age50\_65\_2cars * Age3 + \beta\_Age65\_2cars * Age4 + \beta\_HHsize1\_2cars * HHsize1 + \beta\_HHsize2\_2cars * HHsize2 + \beta\_HHsize3\_2cars * HHsize3 + \beta\_HHsize\_Miss\_2cars * HHsize\_Miss + \beta\_Inc12\_2cars * Inc12 + \beta\_Inc3\_2cars * Inc3 + \beta\_Inc4\_2cars * Inc4 + \beta\_Inc56\_2cars * Inc56 + \beta\_Inc\_Miss\_2cars * Inc\_Miss + \beta\_Ln\_urb\_2cars * Ln\_urb * (1 - Ln\_urb\_Miss)$$

The zonal holding model has a different structure compared to the nested holding model: instead of using one reference alternative for all variables, for some variables a different reference alternative is in place in the zonal model. Therefore, three utility functions are used (equations 6-8). Just like the nested model, mainly socio-demographic characteristics are included here, although some zonal characteristics are part of it as well. The parameter estimates stemming from it are used in process S3 of the static model (Figure 4).

Since occupation status was not available on the household level in the estimation dataset, estimation of a model with these parameters would be limited because the occupational status of other household members is not included here. Therefore, interaction variables of occupation and household size are included instead. In this way, part of the heterogeneity caused by this limitation is captured.

$\{Eq. 6\}\ U\ (0\ cars)$
$$= ASC\_0cars + \beta\_Age35pl\_0cars * Age35pl + \beta\_Age50pl\_0cars * Age50pl + \beta\_Age65pl\_0cars * Age65pl + \beta\_FemLic\_0cars * FemLic + \beta\_Occ\_Stud\_0cars * Stud + \beta\_VStUrb\_0cars * Very\_strong\_urbanised + \beta\_Rural\_0cars * Rural + \beta\_Agri\_0cars * Agri * (1 - Agri\_Miss) + \beta\_ParkTar\_0cars * ParkTar * (1 - ParkTar\_Miss)$$

$\{Eq. 7\}\ U\ (1\ car)$
$$= ASC\_1car + \beta\_FemLic\_1car * FemLic + \beta\_NoLic\_1car * NoLic * (1 - NoLic\_Miss) + \beta\_Lic2\_1car * License2 + \beta\_Lic3pl\_1car * License3 + \beta\_Inc12\_1car * Inc12 + \beta\_Inc3\_1car * Inc3 + \beta\_Inc4\_1car * Inc4 + \beta\_Inc56\_1car * Inc56 + \beta\_Inc\_Miss\_1car * Inc\_Miss + \beta\_Occ\_Stud\_1plcars * Stud + \beta\_Occ\_FT\_HH1\_1car * HHsize1 * Work\_FT + \beta\_Occ\_PT\_HH1\_1car * HHsize1 * Work\_PT + \beta\_Occ\_No\_HH1\_1car * HHsize1 * NoOccup + \beta\_Occ\_Ret\_HH1\_1car * HHsize1 * Retired * (1 - Retired\_Miss) + \beta\_Occ\_FT\_HH2\_1car * (HHsize2 + HHsize3) * Work\_FT + \beta\_Occ\_PT\_HH2\_1car * (HHsize2 + HHsize3) * Work\_PT + \beta\_Occ\_No\_HH2\_1car * (HHsize2 + HHsize3) * NoOccup + \beta\_Occ\_Ret\_HH2\_1car * (HHsize2 + HHsize3) * Retired * (1 - Retired\_Miss) + \beta\_EmployDens5\_1car * EmployDens5 * (1 - EmployDens5\_Miss) + \beta\_EmployDens1\_1car * EmployDens1 * (1 - EmployDens1\_Miss) + \beta\_PopuDens1\_1car * PopuDens1 * (1 - PopuDens1\_Miss) + \beta\_ParkTar\_1car * ParkTar * (1 - ParkTar\_Miss) + \beta\_Rural\_1car * Rural$$

$$\{Eq.8\}\ U\ (2+\ cars) \\ = ASC\_2cars + \beta\_NoLic\_2cars * NoLic * (1 - NoLic\_Miss) \\ + \beta\_Lic2\_2cars * License2 + \beta\_Lic3pl\_2cars * License3 \\ + \beta\_Inc12\_2cars * Inc12 + \beta\_Inc3\_2cars * Inc3 + \beta\_Inc4\_2cars * Inc4 \\ + \beta\_Inc56\_2cars * Inc56 + \beta\_Inc\_Miss\_2cars * Inc\_Miss \\ + \beta\_Occ\_Stud\_1plcars * Stud \\ + \beta\_Occ\_FT\_HH1\_2cars * HHsize1 * Work\_FT \\ + \beta\_Occ\_PT\_HH1\_2cars * HHsize1 * Work\_PT \\ + \beta\_Occ\_No\_HH1\_2cars * HHsize1 * NoOccup \\ + (\beta\_Occ\_Ret\_HH1\_2cars * HHsize1 * Retired + \beta\_Occ\_Ret\_HH2\_2cars \\ * (HHsize2 + HHsize3) * Retired) * (1 - Retired\_Miss) \\ + \beta\_Occ\_FT\_HH2\_2cars * (HHsize2 + HHsize3) * Work\_FT \\ + \beta\_Occ\_PT\_HH2\_2cars * (HHsize2 + HHsize3) * Work\_PT \\ + \beta\_Occ\_No\_HH2\_2cars * (HHsize2 + HHsize3) * NoOccup \\ + \beta\_EmployDens5\_2cars * EmployDens5 * (1 - EmployDens5\_Miss) \\ + \beta\_EmployDens1\_2cars * EmployDens1 * (1 - EmployDens1\_Miss) \\ + \beta\_PopuDens1\_2cars * PopuDens1 * (1 - PopuDens1\_Miss)$$

After specifying these equations in Biogeme, the nested holding model and the zonal holding model were run. The resulting parameter outcomes are shown in Tables 16 to 18. Although a direct comparison between the parameter estimates used in the current models and those used in the static model developed in the context of this thesis would not be a valid, comparing them to each other can still build some trust in the ability of the estimation dataset to capture car ownership choices. Therefore, the estimates used in the current models are displayed as well.

3.3.1 Estimates nested holding model and Dynamo

In general, the parameter estimates used in the static model resemble those used in the current models. We can start with the outcomes of the first choice model for the static model (Table 16), where the utility for having one or multiple cars compared to not having cars is estimated. We can see that in general they align well with the estimates of Dynamo (MuConsult, 2017). This applies to household income (higher income means higher utility for having a car), household size (lowest utility for one-person households), age (older people have a higher utility), occupational status (not working means a lower utility) and the natural logarithm of urbanisation (higher value is higher utility). Also, some differences between the two sets of parameters are visible. Bigger household have a somewhat higher utility for having a car compared to two-person households in the choice model for Dynamo, while that of the holding choice model shows a lower value. However, the latter is not found to be statistically significant, so a higher sample size would be needed to disentangle the effect of household size even more.

Furthermore, the parameter estimates of the interaction variables of the natural logarithm of urbanisation with various socio-demographic factors show differences in size and strength compared to that of Dynamo. However, many of the estimates of the holding model are not statistically significant, while the ones with significant values correspond better to Dynamo's estimates (e.g. Ln_urb x Income). So, despite these differences, the outcomes of the first choice model align quite well with the outcomes of the current model.

For the second choice model, which is used to provide the utility for having two or more cars relative to that of having one car, the estimated parameters for income, household size and age are similar to that of Dynamo (see Table 17). Although the size of the parameters is not always comparable (e.g. regarding age), examining their sign shows no differences.

Table 16. Estimation results of the first holding model (used in the static model).

	Holding model 1				**Dynamo 1**	
Variable	*Utility for having car(s) for …*	*Value*	*Rob. SD*		*Variable*	*Value*
ASC	Constant utility for having car(s)	1.65	0.262		ASC	N/A
Income 1 & 2	... HHs in income class 1 or 2 (below 20k)	-1.21	0.248		Income 1 (below 20k)	0
Income class 3	... HHs in income class 3 (between 20 and 30k) *[ref.]*	0	0		Income 2 (20-45k)	0.999
Income class 4	... HHs in income class 4 (between 30 and 40k)	-0.159	0.238	*	Income 3 (45-60k)	1.446
Income class 5 & 6	... HHs in income class 5 & 6 (more than 40k)	-0.120	0.255	*	Income 4 (more than 60k)	1.611
HH size = 1	... HHs with one person	-1.11	0.211		HH size 1	0
HH size = 2	... HHs with two people *[reference]*	0	0		HH size 2	0.695
HH size ≥ 3	... HHs with three or more people	-0.321	0.213	*	HH size 3/more	0.783
< 35 years	... age of respondent below 35 *[reference]*	0	0		Age_35min	0
35-50 years	... age of respondent of 35 to 50	0.444	0.157		Age_35-64	0.434
50-65 years	... age of respondent of 50 to 65	0.763	0.203		Age_65-79	0.812
≥ 65 years	... age of respondent of 65 and higher	1.45	0.387		Age_80pl	-0.128
Fulltime	... respondent with fulltime job *[reference]*	0	0		0 workers	-0.702
Parttime	... respondent with parttime job	0.234	0.333	*	1 worker	0
No occupation	… respondents without occupation	-0.966	0.148		>1 worker	-0.248
Student	... respondent that is student	-0.895	0.341			
Retired	… respondent that is retired	0.360	0.378	*		
Ln(Urb)	... each urbanisation level (natural logarithm)	1.42	0.359		Ln Urb	1.134
Ln(Urb) x 2p	... interaction urbanisation and HHs of 2 people	-0.562	0.322	*	Ln Urb x 2p	0.456
Ln(Urb) x 3p	... interaction urbanisation and HHs of 3 or more	-0.225	0.348	*	Ln Urb x 3p	0.423
Ln(Urb) x Age35-50	... interaction urbanisation and age group 2	-0.192	0.264	*	Ln Urb x 35-64	-0.082
Ln(Urb) x Age50-65	... interaction urbanisation and age group 3	0.201	0.325	*	Ln Urb x 65-79	-0.525
Ln(Urb) x Age65+	... interaction urbanisation and age group 4	0.179	0.452	*	Ln Urb x 80pl	-0.720
Ln(Urb) x Inc3	... interaction urbanisation and income class 3	-0.005	0.339	*	Ln Urb x inc2	0.128
Ln(Urb) x Inc4	... interaction urbanisation and income class 4	0.207	0.351	*	Ln Urb x inc3	0.333
Ln(Urb) x Inc5	... interaction urbanisation and income class 5	0.949	0.432		Ln Urb x inc4	0.716
Ln(Urb) x Parttime	... interaction urbanisation and parttime worker	-1.10	0.368		Ln Urb x 0 workers	-0.287
Ln(Urb) x Retired	... interaction urbanisation and retired	-0.790	0.474	*	Ln Urb x 2+ workers	-0.010

**P>0.05*

Table 17. Estimation results of the second holding model (used in the static model).

	Holding model 2				**Dynamo 2**	
Variable	*Utility for having two or more cars for …*	*Value*	*Rob. SD*		*Variable*	*Value*
ASC	Constant utility for having two or more cars	-2.70	0.222		ASC	N/A
Income 1 & 2	... HHs in income class 1 or 2 (below 20k)	0.105	0.277	*	Income 1	0
Income class 3	... HHs in income class 3 (between 20 & 30k) *[ref.]*	0	0		Income 2	-0.136
Income class 4	... HHs in income class 4 (between 30 & 40k)	0.566	0.178		Income 3	0.300
Income class 5	... HHs in income class 5 (more than 40k)	0.786	0.190		Income 4	0.482
HH size = 1	... HHs with one person	-0.993	0.263		HH size 1	0
HH size = 2	... HHs with two people *[reference]*	0	0		HH size 2	2.649
HH size ≥ 3	... HHs with three or more people	0.487	0.167		HH size 3/more	3.046
< 35 years	... age of respondent below 35 *[reference]*	0	0		Age_35min	0
35-50 years	... age of respondent of 35 to 50	-0.402	0.167		Age_35-64	-0.219
51-65 years	... age of respondent of 50 to 65	-0.510	0.182		Age_65-79	-2.130
≥ 65 years	... age of respondent of 65 and higher	-0.425	0.232	*	Age_80pl	-1.723
Ln(Urb)	... each urbanisation level (natural logarithm)	0.648	0.126		Ln Urb	0.670
					Index fixed car costs	-2.464
					HH kms	0.091
					Ln Trend 35-	0.117
					Ln Trend 35-64	0.150
					Ln Trend 65-79	0.073
					Ln Trend 80+	-0.025
					Share leasecars	1.213
					HHkms x Age1	-0.066
					HHkms x Age2	-0.055
					HHkms x Age3	-0.050
					Ln Taxes	-0.369

**P>0.05*

Table 18. Estimation results of the zonal holding model (used in the static model).

Variable	**Utility having car(s) for …**	**Estimates per alternative** *0 cars*	*1 car*	*2+ cars*	**Carmod##** *0 cars*	*1 car*	*2 cars*	*2+ cars*
ASC	Constant utility for having one/multiple cars		0.931	-2.27		0.8465	-4.207	-7.007
Income 1 & 2###	...hh in income class 1 or 2 (below 20k)		-.938	-.791		i*0.6947	i*1.574	i*1.920
Income class 3	...hh in income class 3 (between 20 and 30k) *[ref.]*		0	0		i*0.6947	i*1.574	i*1.920
Income class 4	...hh in income class 4 (between 30 and 40k)		0	.496		i*0.6947	i*1.574	i*1.920
Income class 5	...hh in income class 5 (more than 40k)		.204*	.905		i*0.6947	i*1.574	i*1.920
License2	...hh with two driving licenses		0.166*	1.89		1.496	4.403	3.032
License3	...hh with three driving licenses		0	2.77		1.458	4.786	5.572
NoLic	...number of hh members without driving license		-0.834	-0.506		0.1152	0.1480	
Lic x Female	...female respondent with licence	-0.761	-0.327		0.7498	0.4423		
< 35 years	...age of respondent below 35 *[reference]*	0			0			
≥ 35 years	...age of respondent of 35 and higher	-0.493			-0.1900#			
≥ 50 years	...age of respondent of 50 and higher	-0.389			-0.2217#			
≥ 65 years	...age of respondent of 65 and higher	-0.658			-0.7953			
Student	...respondent that is student		0	0	1.294			
Working x HH1	...respondent with fulltime/parttime job *[reference]*		0	0				
Retired x HH1	… respondent that is retired *[reference]*		0	0				
No occup. x HH1	… respondent without occupation		-0.949	-1.94				
Fulltime x HH2	...respondent with fulltime job in bigger household		1.16	0.292*				
Parttime x HH2	...respondent with parttime job in bigger household		1.01	0.261*				
Retired x HH2	… respondent that is retired in bigger household		1.01	0				
No occup. x HH2	… respondent without occupation in bigger HH		0.298*	-0.704				
Pop. Density /100	...increasing population density (1km range)/100		0	-0.653*		-0.598	-1.095	-1.639
Rural	...rural areas (urbanisation level = 1)	-.737*	-.282*		-0.5809	-0.2328		
Very strong urban.	...very strongly urbanised areas (urbanisation = 5)	.583			0.2012			
Empl. density 1km	...increasing employment density (1km range) /100		0	.836*		-0.310	-0.684	-1.32
Empl. density 5km	...increasing employment density (5km range) /100		1.55*	2.12*		-1.37	-2.05	-2.33
Agricult. share	...increasing share of agricultural jobs in a zone	-.0436*			-2.965			
Parking tariff /100	...increasing parking tariff in a zone	.360*	.143*		0.2648	0.1109		

*#Carmod uses age group 55+ instead of 50+; ##Parameter estimates from Carmod that cannot easily be compared have been omitted (e.g. number of workers); *P>0.05*
###In Carmod, income is accounted for by means of a continuous measure, so the parameter estimates have to be multiplied with a scaled income factor (i)

3.3.2 Estimates zonal holding model and Carmod

The zonal holding model is compared to that of Carmod (Significance, 2017). The utility parameters regarding income, licence possession, and age do not display surprising effects (see Table 18): the utility for having multiple cars is higher for people with a higher income, more licenses in the household, and the utility for having no car is lower for older people.

The utility parameters related to occupation could not easily be compared to that of Carmod, due to a different model specification because of data availability. Only the effect of being a student could be examined directly for both models. The positive utility observed in the estimation for Carmod was not found in zonal holding model. Assuming that the estimations of Carmod are valid and there actually is a lower utility for students to own a car (which is reasonable), an explanation for its absence can be found in the estimation dataset. This might be due to the nature of these data (since it contains only people from 18 years or older, so younger students are missing), or its size (Carmod uses a bigger sample and is therefore better able to detect this effect).

Other comparisons regarding occupational factor can be made in a more indirectly way. As shown in Table 18, bigger households, despite occupational status of the respondent, have a higher utility to own a car. When the respondent in the estimation dataset does not work this is true as well, although this goes together with a lower utility compared to a worker. In Carmod, the utility for owning one or multiple cars is higher when there are more workers in the household (which also means a bigger household). Based on each of the choice models separately, it can be concluded that both household size and occupation affect the number of cars. The utility parameters for all socio-demographic factors show therefore no unexpected outcomes.

Lastly, the group of zonal characteristics is examined. As we can observe in Table 18, the model estimation resulted in various insignificant estimates, including those for population density, a low urbanisation (rural) and the parking tariff. This can explain that the signs of the utility parameters for employment density and the share of agricultural jobs in a zone are different from that in Carmod, since these are insignificant as well. Only the positive parameter estimate for owning no cars in very strongly urbanised areas is statistically significant, which is also the case in Carmod.

All in all, it is concluded that the retrospective estimation data leads to parameter estimates that are similar to those used in the current models, which increases confidence in their ability to capture car ownership choices. However, only after applying these outcomes in the static model a valid assessment of them can be made, so this will be covered in the next chapter. First, an assessment of improving this model is made though, which is done by including the effects of life events and built environment factors in a transaction model.

3.4 Towards a transaction choice model with life events and BE factors

To include life events and built environment factors in a dynamic model, the use of a transaction choice model is needed. Therefore, instead of the choice between owning 0, 1, or 2 or more cars, the choice between no transaction (0), car acquisition (+1), replacement (+0), and disposal (-1) is modelled.

Two transaction models were estimated: first of all, a limited one with similar variables as in the holding models, for validation reasons (see section 3.4.1). Secondly, a complete model with variety of life events and built environment factors was estimated, which is discussed in section 3.4.2.

First of all, the complete transaction model was developed. Since it was built from scratch, the process of setting it up was more elaborate compared to that of the holding models. The main approach was including parameters one by one, and afterwards assessing whether they significantly increased model fit. This was done per category of variables, starting with those that were also included in the holding models. Subsequently other groups of variables were included and assessed: first some car related aspects (e.g. number of cars, car age), followed by accessibility (e.g. parking availability, public transport, and amenities) and life events (e.g. relocation and getting a child).

The limited version was created with the same parameters included as the complete model, although built environment factors and life events were excluded. It was not chosen to add or change variables in order to improve model fit, since the results would probably not outweigh the effort for doing that. Only the spatial characteristics that are part of Carmod were added again here, which include employment and population density, and the parking tariff indicator. However, only the latter was found to improve the model significantly (but only for replacements). The resulting utility functions[9] for the complete and limited transaction choice model can be found in Appendix C.

Due to the reduced number of variables, re-estimating the limited model might result in less reliable coefficients compared to the complete version: the effects of omitted variables might be transferred to a third related variable (for which the effect as a result is under- or overestimated). However, re-estimation results in a better model fit compared to a similar model that uses the estimated parameters of the complete model. So, despite this third-variable effect, a re-estimated limited model is better able to predict car transaction choices than a model with the same parameter values as in the complete version. Therefore, it is chosen to re-estimate the limited version.

3.4.1 Using a transaction model

Next to assessing the sign and size of the estimated parameters, the added value of using a transaction model can be evaluated by using the Ben-Akiva & Swait test (1986). This test gives an upper bound for the probability that a model is the best representation of the actual data-generating process, despite having a lower log-likelihood than another (non-nested) model.

The transaction model used to assess its added value compared to a holding model, is different from the one discussed in the rest of this paper. The choice is modelled in a similar way as in the holding model (having 0, 1, or 2 or more cars), while the distinguishing nature of a transaction model is maintained. This is done by making the choice for the number of cars conditional on the initial car ownership state: for households with no cars, only the choice between no transaction and acquisition was modelled; for one-car households the choice between no cars (disposal), one car (replacement of no transaction), and two cars (acquisition); and for households with two or more cars the choice between two or more cars (acquisition, replacement or no transaction) and one car (disposal). The latter, though, is only possible for households initially owning two cars.

Table 19. Model fit assessment transaction model compared to holding models.

Model	**Null-LL**	**Final LL**	**#observations**	**#parameters**	**P**
1. Nested holding model	-21,627	-12,424	19,686	37	-
2. Zonal holding model	-21,627	-11,883	19,686	37	<0.001
3. Transaction model (adj.)	-21,627	-5,518	19,686	20	<0.001

Using the adjusted transaction model instead of a holding model results in a significantly better model fit ($p<0.001$), as seen in Table 19. We can observe a great effect on the log-likelihood compared to both the national (see section 3.3.1) and the zonal holding model (section 3.3.2). The zonal model outperforms the nested (national) model as well ($p<0.001$).

[9] For variables in both transaction models, not doing a car transaction is the reference category, so utility parameters are estimated for disposing, replacing and acquiring a car. In case a car replacement went together with a car disposal or acquisition in the same year, only the latter is taken into account, while acquiring two cars in the same years counts as one.

Table 20. Estimation results of the transaction choice models used in the dynamic model.

		Limited						Complete					
Variable	**Utility car transaction for …**	*Acq*	*SE*	*Repl*	*SE*	*Disp*	*SE*	*Acq*	*SE*	*Repl*	*SE*	*Disp*	*SE*
ASC	Constant utility for car transaction	-6.94	(0.388)	-4.18	(0.266)	-5.09	(0.196)	-7.28	(0.383)	-4.79	(0.280)	-4.78	(0.267)
Inc12	…income class 1 or 2 (below 20k)	-	-	-0.314	(0.106)	0.681	(0.229)	-	-	-0.299	(0.105)	0.655	(0.226)
Inc4	…income class 4 (30 to 40k)	0.360	(0.112)	-	-	-	-	0.312	(0.109)	-	-	-	-
Inc56	…income class 5 or 6 (40k+)	0.457	(0.112)	0.198	(0.0715)	-	-	0.422	(0.107)	0.195	(0.0712)	-	-
Age35_50	…max. HH age of 35 to 50	-	-	0.408	(0.0915)	-	-	-	-	0.349	(0.0901)	-	-
Age51_65	…max. HH age of 50 to 65	-	-	0.582	(0.0964)	-	-	-	-	0.514	(0.0945)	-	-
Age65	…max. HH age of 65 and higher	-	-	0.433	(0.108)	-0.616	(0.264)	-	-	0.399	(0.108)	-0.508	(0.265) *
Occ_FT/PT	…fulltime or parttime job [ref]	-	-	-	-	-	-	-	-	-	-	-	-
Occ_HH1_No	…no occupation in 1p HH	-0.591	(0.217)	-0.668	(0.138)	-	-	-0.520	(0.206)	-0.611	(0.142)	-	-
Occ_HH2_No	…no occupation in 2p HH	-	-	-0.246	(0.0704)	-	-	-	-	-0.196	(0.0717)	-	-
Occ_Ret	…retired people	-0.517	(0.175)	-	-	-	-	-0.412	(0.176)	-	-	-	-
Educ_Higher	…higher education	0.202	(0.101)	-	-	-	-	0.164	(0.0972) *	-	-	-	-
Educ_Lower	…lower education	-0.375	(0.121)	-	-	-	-	-0.320	(0.121)	-	-	-	-
GDP	…change in GDP (%)	0.107	(0.0273)	-	-	-0.0824	(0.0417)	0.103	(0.0273)	-	-	-0.0958	(0.0418)
Cars0	…initially having no car	2.13	(0.119)	-	-	-	-	2.10	(0.118)	-	-	-	-
Cars2	…initially having two/more cars	-0.882	(0.253)	-	-	2.38	(0.189)	-0.953	(0.249)	-	-	2.50	(0.192)
Car_age1_2	…max. car age of 1 to 2 years	-	-	-1.13	(0.163)	-0.812	(0.409)	-	-	-1.13	(0.162)	-0.796	(0.416) *
Car_age6_10	…max. car age of 6 to 10 years	-	-	-0.151	(0.0715)	-	-	-	-	-0.165	(0.0716)	-	-
Car_age11pl	…max. car age of 11/more years	0.475	(0.127)	-	-	0.424	(0.190)	0.452	(0.130)	-	-	0.467	(0.190)
Lic	…having a license	1.87	(0.371)	1.94	(0.243)	-	-	1.75	(0.361)	1.89	(0.244)	-	-
FemLic	…women having a license	0.312	(0.0917)	-	-	-	-	0.269	(0.0890)	-	-	-	-
Lic2	…HHs with two licenses	0.685	(0.116)	-	-	-	-	0.732	(0.112)	-	-	-	-
Lic3pl	…HHs with three/more licenses	1.57	(0.209)	-	-	-	-	1.39	(0.192)	-	-	-	-

**P>0.05*

Table 20 (continued).

		Limited						Complete					
Variable	**Utility car transaction for …**	*Acq*	*SE*	*Repl*	*SE*	*Disp*	*SE*	*Acq*	*SE*	*Repl*	*SE*	*Disp*	*SE*
Ln_urb	…natural logarithm urbanisation	0.309	(0.0811)	-	-	-	-	0.242	(0.0853)	-	-	-	-
PopuDens /100	…increasing popul. density/100	-	-	-0.170	(0.122)	-	-	-	-	-0.267	(0.0879)	-	-
ParkTar/100	…zonal parking tariff/100	-	-	-0.150	(0.0531)	-	-	-	-	-	-	-	-
FreePark	…free nearby parking available	-	-	-	-	-	-	0.358	(0.127)	0.625	(0.0948)	-0.581	(0.223)
BBI_100_110	…PT accessibility of 100 to 110	-	-	-	-	-	-	-	-	0.0944	(0.0549) *	-	-
BBI_110pl	…PT accessibility higher than 110	-	-	-	-	-	-	-	-	-	-	-0.436	(0.268) *
Dsuperm_750pl	…higher distance to supermarket	-	-	-	-	-	-	0.208	(0.107) *	-	-	-	-
ToWork	…a job transition	-	-	-	-	-	-	0.753	(0.152)	0.422	(0.106)	-	-
ToWork_pl1y	…a job transition (next year)	-	-	-	-	-	-	-	-	0.391	(0.108)	-	-
ToRetired	…transition to retirement	-	-	-	-	-	-	-	-	0.514	(0.147)	1.35	(0.329)
Reloc	…relocation (dummy)	-	-	-	-	-	-	0.643	(0.163)	0.516	(0.104)	0.786	(0.298)
Reloc_min1y	…relocation (last year)	-	-	-	-	-	-	-	-	-	-	0.729	(0.289)
Reloc_pl1y	…relocation (next year)	-	-	-	-	-	-	0.530	(0.168)	-	-	-	-
CHILDmin	…decrease in #children (dummy)	-	-	-	-	-	-	-	-	0.365	(0.140)	-	-
PARTNmin	…loss of a partner	-	-	-	-	-	-	-	-	-	-	2.33	(0.421)
LicPlus	…increase in driving licenses	-	-	-	-	-	-	1.11	(0.169)	-	-	-	-
LicPlus_min1y	…increase in licenses (last year)	-	-	-	-	-	-	0.569	(0.197)	-	-	-	-
LicPlus_pl1y	…increase in licenses (next year)	-	-	-	-	-	-	0.526	(0.240)	-	-	-	-

**P>0.05*

Although the transaction model displayed in Table 19 has a significantly better model fit than the holding model, it did not allow for a distinction between a choice to do nothing and replacing a car. Therefore, the model estimates discussed below are stemming from a different transaction model (see appendix C for the utility functions).

Assessing the sign and size of the estimated parameters of the limited transaction model (left half of Table 20) shows that more or less the same patterns are obtained as in the holding models. We can make a couple of observations. First, as expected, socio-demographic factors are important explanatory variables of changing car ownership. A higher utility for car acquisition is visible for households or people with higher incomes, a higher education level, and a growing economy (GDP), while not having a job and living on your own, having a lower education, and being retired have a negative utility for car acquisition. At the same time, being 65 years or older is related to a lower disposal utility, although this parameter is significant only using a 10% significance level. Lower income households, in contrast, are more prone to dispose a car.

Furthermore, parameters more directly related to car transactions (e.g. initial car ownership) are important as well. Not having a car increases the utility to acquire one, while already having two or more cars decreases this utility and makes it more likely to dispose one. A maximum car age of 1 or 2 years also decreases the car disposal utility, and also that for replacements. An outcome that might not directly be expected, is that having a car that is more than 11 years old, the utility for both car acquisition as that for car disposal increases. The latter is explained easily, because older cars are more likely to show defects, but the first is not that obvious. However, it might very well be possible that households in this case decide to buy another car and not (yet) sell their obsolete car.

The parameters related to licence possession show the expected utilities. The more licenses present in a household, the higher the utility for buying a car, also when the respondent has a license. For women with a license, this effect is even stronger.

When examining the limited built environment parameters, we can see that both 'traditional' parameters (urbanisation and population density) affect car transactions, although the latter only affects the utility to replace a car. Living in less urbanised areas increases the utility of household car acquisition.

3.4.2 Including life events and built environment factors

The estimated parameters of complete transaction model (including life events and additional built environment factors) are shown in Table 20 as well (right half). Based on the log-likelihood of both transaction models and the difference in number of parameters (degrees of freedom, df), the LRS (Likelihood Ratio Statistic) was computed. Chi square (χ^2) values were used to assess model fit: the complete model is superior to the limited one since the LRS is substantially higher than the critical chi square value at a 0.1% significance level (see Table 21). Therefore, it is concluded that life events and built environment factors significantly improve the ability to explain car transaction choices for the dynamic model.

Table 21. Model fit complete and limited model: with and without life events (LE) and built environment (BE) factors.

Model	Null-LL	Final LL	#parameters	df	LRS	Crit. χ^2	P
Limited: without BE & LE	-27,805	-9,896	37				
Intermediate: only with BE	-27,805	-9,840	43	6	211	22.458	<0.001
Complete: with BE & LE	-27,805	-9,723	58	15	233	37.697	<0.001

From the additional built environment factors especially the presence of free nearby parking is an important explanatory variable, since it affects the utility for all three the transactions. Car disposals are less likely when there is free parking, and car replacements and acquisitions are more likely. The effects for public transport accessibility and distance to supermarkets are less promising, since the related parameters values are not significant using a 5% significance level. Furthermore, the effect of a higher public transport accessibility (BBI) is even a bit counterintuitive. One might say that a better public transport would lead to more car disposals, but here the opposite is visible.

The effect of life events on car transaction seem to be even more substantial than the spatial effects. Acquisitions are more likely in case there is a job transition in the same year, an increase in licenses in the previous, current or next year, and a residential relocation in the current or coming year. Just like free parking, a relocation affects all three transaction types: moving to another home goes more often together with a car transaction, just as we saw before in chapter 3. Another remarkable finding is that an anticipated relocation increases the chance of car acquisition, while relocating also has a lagged effect on car disposal the year afterwards. Anticipated and delayed effects are also found for the positive effect of gaining a licence on car acquisitions. Losing a partner also increases the utility for car disposal, while a decrease in number of children makes replacement more likely. A possible explanation for this is that a smaller household needs a smaller car, which is confirmed by type choice estimations (see Appendix C.1).

3.5 Conclusion – stepwise improvement choice models

In this chapter we have seen that the holding models result in plausible estimates compared to those used in Dynamo and Carmod, but that a transaction model, with similar variables, outperforms them significantly ($p<0.001$). Subsequently, including both life events and built environment factors to the transaction model significantly improved the explanatory power of the model, using a 99,9% significance level.

Especially the free parking indicator (built environment factor), an increase in the number of licenses (life event) and residential relocation (life event) are found to be important factors that influence car transactions. Next to that, lead-lag effects are found for these two life events, but also for a job transition: effects on car transaction behaviour are not always visible in the year a life event occurs, but sometimes sooner or later than that.

Naturally, these findings have implications for car ownership simulations, since these effects need to be captured adequately. The next chapter elaborates on how this is done in the dynamic model, but also how the static model is operationalised without these effects.

4. Development of Car Ownership Models

The empirical results of chapter 3 were incorporated in both the static model and the dynamic model. In this chapter we elaborate on how these models work, including extensive validation, and assess how including the effects of life events and built environment factors in the dynamic model affects forecasts of household car ownership (objective C). After a description of the application dataset in section 4.1, both the static model (section 4.2) and the dynamic model (section 4.3) are discussed, while section 4.4 gives a short intermediate conclusion.

4.1 Application dataset

Both models make use of the same synthetic population of the Netherlands, stemming from a population simulator (Significance, 2019). For each year between 2014 to 2030, this simulator provides an overview of the characteristics of each person and of each household in the Netherlands, including socio-demographic factors and spatial characteristics (see Table 22 and 23). Because each household and each person has a unique identifier, it is possible to capture their development over the years, which enables identifying life events.

Table 22. Input of the car ownership models: household variables.

Relevant household variables	Description
Household ID	Unique household identifier
Residential location	Number of one of the 1406 LMS zones
Household income	Absolute household income
Relocation (except base year)	Dummy indicating residential relocation

Table 23. Input of the car ownership models: person variables.

Relevant person variables	Description
Household ID	Unique household identifier
Person ID	Unique person identifier
Age	Absolute age
Gender	Gender: male or female
Social participation	Occupation
License	Dummy: licence possession or not
Education level	Highest completed eduction
Role in household	Dummy: head of the household or not
Location work/education	Number of one of the 1406 LMS zones

In the static model only an aggregation of the application dataset is used to calculate household car ownership levels for each of the 48 household types. The dynamic development of household characteristics is therefore not taken into account in this model.

In contrast, the dynamic model keeps the dynamic perspective of the application dataset and models household car transaction behaviour for every individual household over the years. Therefore, this model is able to account for the effect of life events and the built environment on car transaction behaviour in a better way. Since the application dataset contains the residential location of each household, the models are able to link each household to a zone and its spatial characteristics, including parking and public transport accessibility, urbanisation levels, and the proximity of local destinations (see Table 24). These data are the same that were used in the estimation dataset and came from CBS (2019d, 2019b), Significance (2017) and KiM (2017). In total 1,406 zones are used, which are the same that are part of the National Model System LMS for mobility and traffic forecasts. The next sections describe both the static model and the dynamic model in more detail.

Table 24. Input of the car ownership models: zonal variables.

Zonal variables	Description
BBI	Indicator public transport accessibility (per LMS zone)
Urbanisation	Level from highly urbanised (1) to not urbanised (5)
Distance to supermarket	Absolute distance to closest supermarket
Population density 1km	Population density within 1km of center LMS zone
Empl. density 1km	Employment density within 1km of center LMS zone
Empl. density 5km	Employment density within 5km of center LMS zone
Agricultural share	Share of agricultural jobs (per LMS zone)
Parking tariff	Parking Tariff (cents per hour) per LMS zone

4.2 Static model implementation

With the static model, household car ownership for a specific year is calculated, using the steps of Figure 4: after obtaining the number of households (step 1), the total number of cars per household type is calculated (2). Subsequently, a regional distribution of cars is provided (3). Model implementation is mainly done in Microsoft Excel (2016), with some input stemming from SPSS (IBM Corp, 2017).

In step 1, the number of households of a specific type is calculated. To do that, first the output of the population simulator for the end of a chosen year is converted in SPSS to a suitable format for Excel. This is done by aggregating this population data into *48 household types*, which are combinations of four (household) income classes, three household size groups, and four age groups. Since the estimation dataset only contained individual occupational information, a further distinction into *person types* is used, in order to capture the effect that the occupation of individual household members has on car ownership. Since five occupation types are used, this resulted in 240 person types, so each household type consists of five person types. Finally, for each of these types the number of people and households is summed.

With the number of people per person type, first individual probabilities for choosing a specific level of car ownership are determined per person type in step 2. To do that, the estimated parameters of Table 16 and 17 are used, which include the effects of income, household size, age, occupation and various interaction effects with the natural logarithm of urbanisation. For each individual, the utility components of the latter are calculated for the three car ownership choices (S2a in Figure 9). The corresponding probabilities (S2b) are subsequently averaged per person type (S2c). These average probabilities (which are only based on the urbanisation parameters) are converted back to a utility component related to urbanisation (S2d). This is done to be able to add the utility components related to income, household size, age and occupation to it (S2e). Per person type, this results in a total utility per choice alternative, which is converted to a probability per choice alternative (S2f).

After that, an aggregation of these individual probabilities is used to calculate the chances of choosing a specific car ownership level per household type (S2g). In case that there are for example five households of household type 1, with ten adult people belonging to those households: two of them with person type A and the other eight with person type B. Since one fifth of the people is type A, one fifth of the households uses the probabilities corresponding with this type (1 household). The other four households use the probabilities corresponding with person type B. This is done for each household type, resulting in a distribution of households with zero, one, or two or more cars per type. The total number of cars is obtained by summing the number of households with one car with 2.29 times the number of households with two cars (S2h). This multiplication factor stems from Carmod (Significance, 2017).

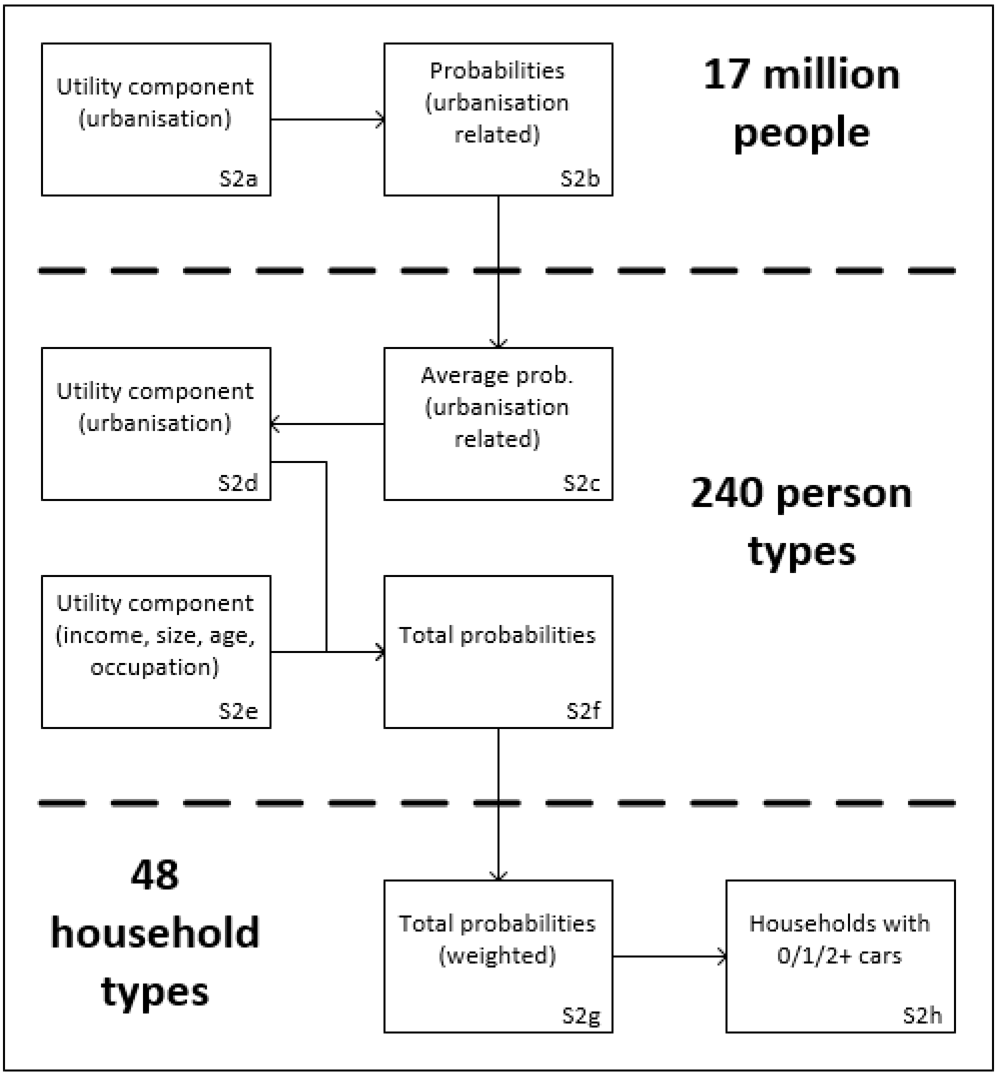

Figure 9. Step 2 in the static model.

Finally, in step 3, the output of step 2 – the total number of cars – is distributed spatially (see Figure 10). This is done in a similar way as in step 2, by first aggregating the population data into multiple household types. Next to that, a distribution between 1406 zones is made, by which it is possible to capture spatial heterogeneity of car ownership behaviour of similar households in different zones. The effect of zonal characteristics is captured in this way. However, contrary to step 2, within households no further distinction is made between person types.

A small correction is in place in the static model to align the outcome of the third step with that of the second step. The reason for that is that the total number of cars in step 3 often differs from that of step 2. Since the national outcome (step 2) is probably more reliable than the regional outcome (step 3), the number of cars stemming from step 3 is corrected. This is done by a correction of the estimated ASCs (shown in appendix D, Table 34), which assures that the number of cars in both submodules are aligned.

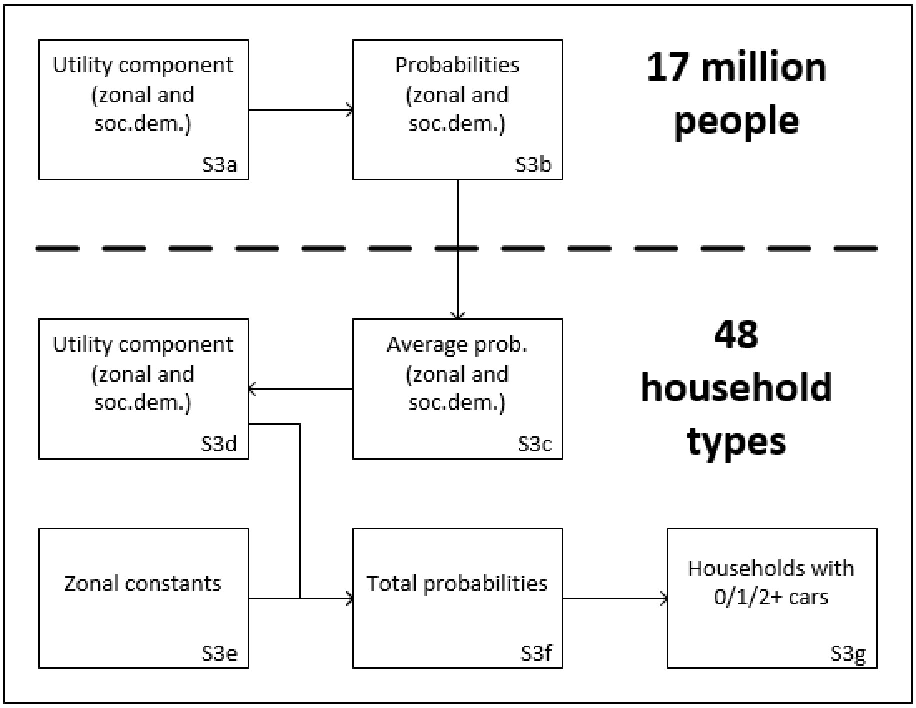

Figure 10. Step 3 in the static model.

Before the static model was used, it first had to be calibrated. For the national car ownership module (step 2), calibration took place by adjusting the estimated ASCs to align the car ownership outcomes in the base year to reality. These ASCs capture the intrinsic preference for a certain level of car ownership, but since the estimation data is not a representative reflection of the Dutch population, these constants need to be adjusted. This helps to bridge the gap to the application dataset, which reflects the Dutch population substantially better. For the zonal car ownership module (step 3), calibration took place on a zonal level. Appendix D describes the calibration process in more detail, while its outcomes are shown in Table 25.

Table 25. Calibration conditions and outcomes static model base year (2014).

	#HH0	#HH1	#HH2	TOT-HH	TOT-cars	Cars/1000HH
CBS	-	-	-	7,665,198	7,979,083	1,040.95
	-	-	-			
Carmod	1,854,441	4,136,674	1,674,445	7,665,560	7,979,083	1,040.90
	(24.2%)	(54%)	(21.8%)			
Static model	1,854,443	4,136,672	1,674,444	7,665,559	7,979,079	1,040.90
	(24.2%)	(54%)	(21.8%)			

4.2.1 Validation

After calibration the static model was ready to be used for car ownership modelling in later years. Since 2014 is used as base year, its outcomes can be compared to actual outcomes up to 2018 (from Carmod and CBS) in order to historically validate it. For Carmod, only the outcomes for 2014 and 2018 were available, so for the intermediate years the number of cars is interpolated based on the number of households (see Figure 11). This explains why it is not a strictly linear effect. Despite some differences with the observation from CBS and the Carmod forecasts up to 2018, the general car ownership trend of the static model seems to be quite reasonable with an average absolute difference of 0.73% with the forecasts of Carmod.

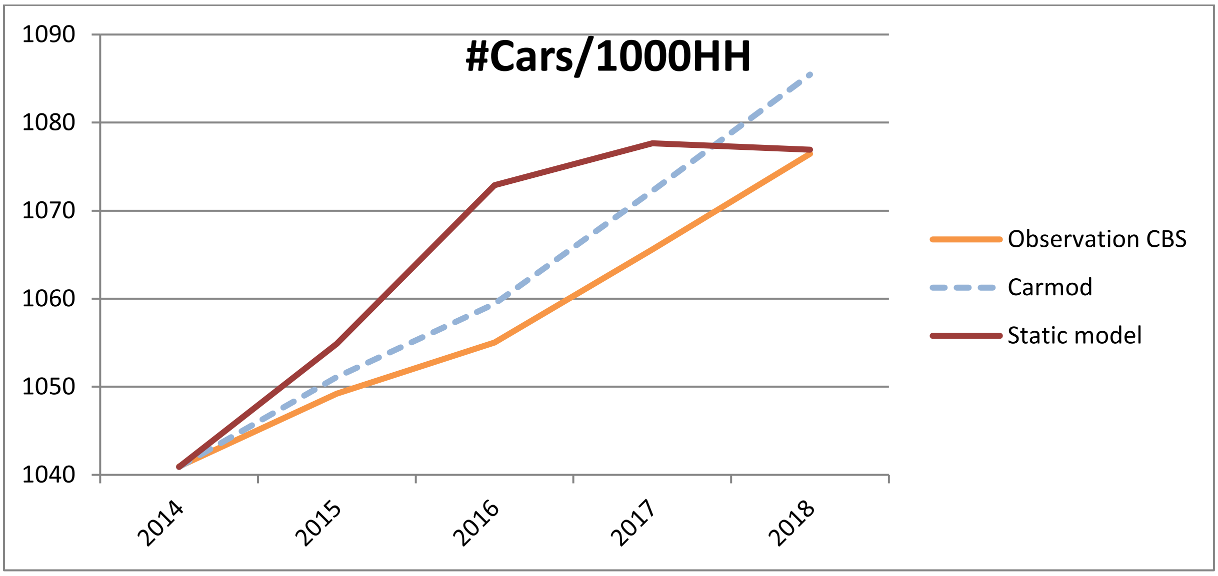

Figure 11. Static model compared to historic data with respect to the number of cars per household.

When examining the *total* number of cars instead of the average per 1000 households (see Table 26), more substantial differences can be found though. The static model in 2018 is for example more than 3% higher than the statistics of Carmod and CBS for that year. However, this is explained by the fact that the number of households in the static model, stemming from the population simulator, are much higher than Carmod and CBS state as well.

All in all, based on a comparison with historical data, it can be concluded that this model is able to predict household car ownership decisions quite well, since the average car ownership levels per 1000 households are close to statistics of CBS and outcomes of Carmod. However, since the development over time of the total number of households in the application dataset differs from the actual trend up to 2020, it cannot directly be used to assess total car ownership. Only indirectly this can be obtained by correcting it for the difference in number of households. Overall, the static model can sufficiently provide insight into household car ownership decisions.

Table 26. Outcomes static model up to 2018.

		2014	**2015**	**2016**	**2017**	**2018**
#cars	*CBS*	7,979,083	8,100,864	8,222,974	8,373,244	8,530,584
	Carmod	7,979,083	(8,101,039)	(8,223,325)	(8,373,811)	8,531,378
	Static model	7,979,079	8,233,464	8,505,188	8,685,096	8,838,247
#HH	*CBS*	7,665,198	7,720,787	7,794,075	7,857,914	7,924,691
	Carmod	7,665,560	(7,707,153)	(7,761,988)	(7,809,754)	7,859,718
	Static model	7,665,559	7,805,056	7,927,426	8,059,290	8,206,875
#cars/ 1000HH	*CBS*	1,041	1,049	1,055	1,066	1,076
	Carmod	1,041	(1,051)	(1,059)	(1,072)	1,085
	Static model	1,041	1,055	1,073	1,078	1,077

Besides a historic validation, a comparison with the outcomes of Carmod in 2030 is made. Carmod makes use of two scenarios for the future development of the Dutch population, stemming from scenario study Welfare, Prosperity and the Human Environment (PBL, 2015). Since the synthetic population in the static model uses an average income increase, the outcomes of the two Carmod scenarios have been averaged in Figure 12 as well. For the years between 2018 and 2030 this data is interpolated.

The level of household car ownership in 2030 according to the static model comes very close to that of Carmod. This confirms the validity of the static model to predict household car ownership, since it is only calibrated on data of 2014. This is especially remarkable considering the use of different estimation and application data as well as the fact that different choice models are used. In line with that, the static model is able to capture changing levels car ownership, which implies that the effects of demographic developments in the application dataset are captured by it as well.

Sensitivity analyses showed that an increase of the average household income of 10% results in approximately 4% more cars, which means that the income elasticity in the static model is around 0.40. This is in line the projected income elasticities for the Netherlands in 2015 that Dargay & Gately (1999) give (0.25 for cars, and 0.43 for all road vehicles), and the long-run income elasticities that Dargay (2002) provides for different models of car ownership in the UK (between 0.34 and 0.51).

Altogether, there is no reason to doubt the ability of the static model to function as a reference point to assess the added value of the dynamic model.

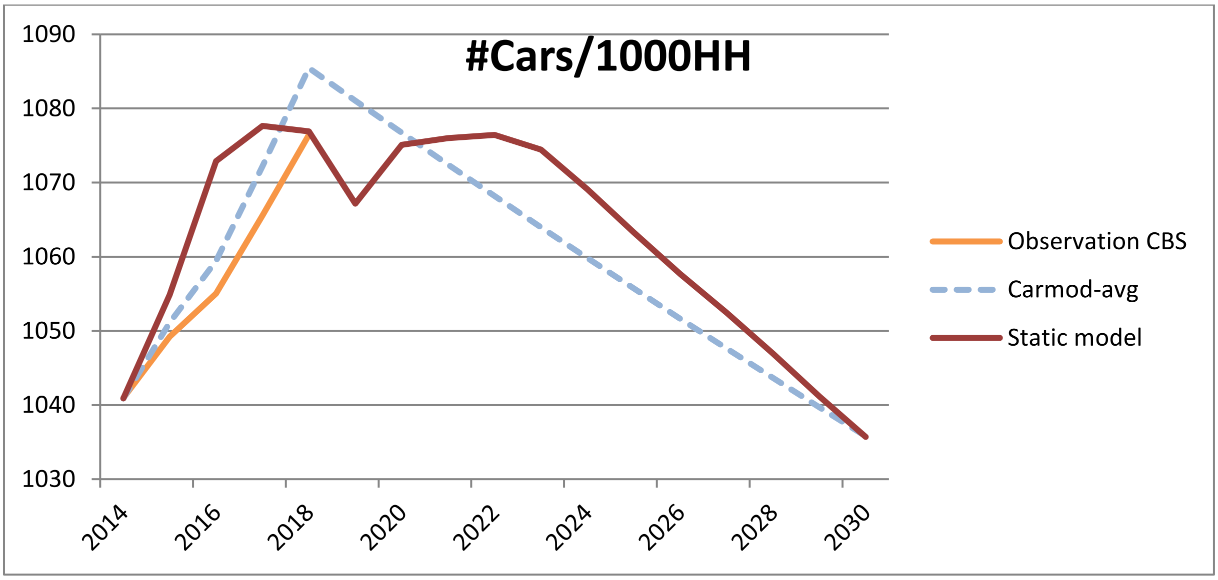

Figure 12. Static model compared to Carmod forecasts with respect to the number of cars per household.

4.3 Dynamic model implementation

Now we have seen that the static model results in valid outcomes with respect to the number of cars per household, we can assess the validity of the dynamic model in a similar way. This is done by comparing a version of the dynamic model with similar variables (the 'limited dynamic model') with the static model. Afterwards, the model with additional built environment factors and life events is assessed (the 'complete dynamic model'). First, however, it is described how the dynamic model operates.

In the dynamic model two core processes are used to simulate car transaction behaviour, which has been developed in NetLogo (Wilensky, 1999): a logo-based language, implemented in Java. First, the initial state of the model is set up, which includes zonal characteristics and the state of individuals and households (coming from the population simulator). The initial car ownership state of the population in the model is determined using the parameters of the static model.

After initialization, the actual car transaction process is started. Each year, this starts with updating the state of the population, for which the output of the population simulator is used. Based on the new characteristics of the population, a transaction type is chosen for each household by first calculating for each person the utility for each alternative. To do this, the estimated utility parameters of the transaction choice models are used, as shown in Table 18. Dependent on which version of the model it is, also changes in individual and household characteristics (life events) and additional spatial factors are taken into account. Both models also include the yearly change in GDP, based on the scenario study Welfare, Prosperity and the Human Environment (PBL, 2015).

Based on these utilities (D2a in Figure 13) the probability for each car transaction alternative is calculated (D2b). Subsequently, by averaging the probabilities of each *individual* adult member of the household, the probabilities for the *household* to choose each transaction are determined (D2c), since car ownership decisions are made at the household level. Lastly, with a random draw, a transaction type is chosen (D2d).

In case of replacement or acquisition, car age is assigned. When one of multiple cars is disposed or replaced, the oldest car is chosen. Finally, the household states are updated with the new car ownership conditions, together with some aggregate statistics related to the number of cars and the number of transactions per type.

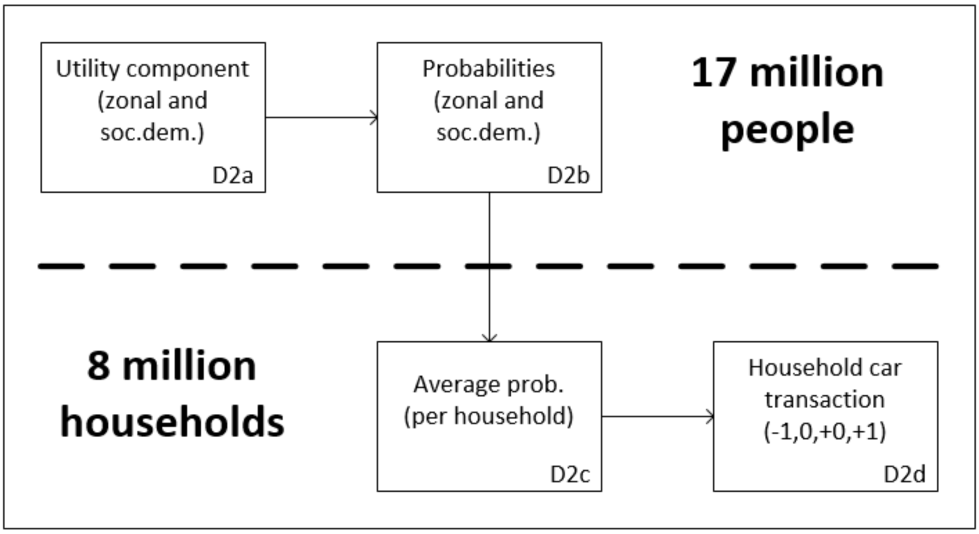

Figure 13. Process D2 in the dynamic model.

In process D2, all estimated utility parameters for household, individual and zonal characteristics in this model can be directly linked to one of the input variables (see Tables 22 to 24). The only exception is for the parameter for the availability of nearby free parking, for which the relation of the (self-indicated) presence of free nearby parking with the zonal parking tariff is used (see Appendix E.1). Together with life events and individual, household and spatial factors, this parking factor affects the car transaction behaviour of households in the Netherlands for a specific year.

For the same reasons as in the static model, the dynamic model was first calibrated as well, which was done by aligning the car transactions in the model with the number of transactions in 2015. In contrast with the static model, these transaction statistics are not immediately available. Therefore, an approximation of them is used, which is based on actual data. With the calibration targets, the dynamic model is calibrated twice, for both the limited and the complete model. This is done by running the model for one year (from 2014 to 2015) with varying combinations of ASCs for car acquisition, replacement and disposal. The combinations where the calibration targets were met, were used as starting conditions for the remaining model runs. In appendix E.2 the calibration process for the dynamic model is discussed more extensively.

4.3.1 Selection

Due to restrictions imposed by calculation speed it was not possible to run the dynamic model with the input millions of households, despite substantially improving the efficiency of the code: capturing the relevant individual and household characteristics of all these people resulted in an enormous demand of memory, taking weeks to do a single run. Using a different environment to develop the model would have been better.

Instead of using all of the application data, a smaller sample from the population simulator is used in the dynamic model (approximately one promille of the whole sample). However, this might hinder the validation of this model, since there is not a one-on-one connection anymore between the input of this model and that of the static model. To address this issue, a version of the static model was created using the same selection data.

Creating a selection for 2014 was done by randomly choosing one promille of all people in the full sample, and subsequently choosing all people that belong to their households. For later years, the same people are selected again, including new people belonging to their households. Not all new households have been included in the selection though. Each year only a percentage of them is included to assure that the population growth in the selection is similar to that in the full sample.

4.3.2 Validation of the limited dynamic model

The validity of the limited dynamic model is assessed by comparing its aggregate outcomes with that of the static model. Since the dynamic model uses a smaller input sample, a version of the static model with the same input is instantiated (the 'selection').

The development of the number of cars per household in dynamic and static models is shown in Figure 14. For the dynamic model, the mean of 500 model runs is displayed. Except for a deviant value for 2015 in the static model (selection), both models display a similar trend up to 2023. Comparing them with the observed outcome of CBS, the limited dynamic model is closer to it than the static model (+0.7% versus +1.2% in 2018). This strengthens the trust in the capacity of the dynamic model to generate realistic car ownership outcomes.

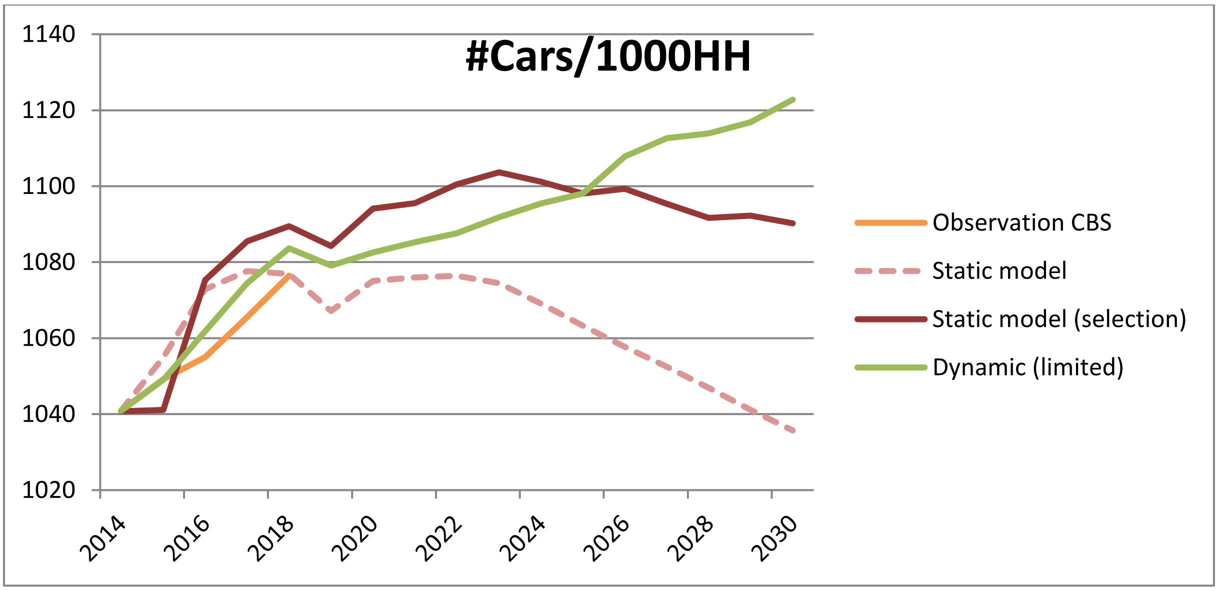

Figure 14. Dynamic model compared to the static model regarding the number of cars per household.

From 2023 onwards, the limited dynamic model displays a different trend than the static one using the selection. Instead of decreasing, car ownership levels increase even more after 2023 in the dynamic model. Up to 2022, on average, the dynamic model has a lower share of cars per 1000 households of 0.7%.The effect of using the limited input sample should not be underestimated, though. As seen with the static model, the number of cars using a selection of the sample is substantially higher than when the full sample is used.

That using the smaller sample leads to an overestimation of the number of cars can be explained by examining the characteristics of the sample (see appendix E.3). The share of lower income households is substantially lower in the selection. In the static model and the dynamic model they have a lower utility for having of buying more cars, so a higher number of cars is not surprising here. Other explanations can be found in a lower share of retired people, less people with a lower education, less one-person households and less people with no occupation, which are all related to lower probabilities for having or getting less cars (see Tables 16 to 18). Using the full sample would therefore result in much lower averages for household car ownership.

4.3.3 Including life events and built environment factors

The complete dynamic model, including life events and built environment factors, is different from the limited version, although more or less the same trends are visible in Figure 15. In 2030, the car ownership outcomes in the complete model are 1.4% lower than in the limited version, although it is growing over the years. The difference is fully explained by life events and built environment factors. It can therefore be concluded that the inclusion of life events and built environment factors in the dynamic model reduces its aggregate outcomes considerably.

Sensitivity analyses showed that an increase of income and GDP of 10% results in approximately 3.6% more cars in both the complete and the limited dynamic model (i.e. an elasticity of 0.36). Just like in the static model, the income elasticity in the dynamic model is in line with findings of Dargay & Gately (1999) and Dargay (2002).

All in all, the dynamic model results in plausible aggregate outcomes. The long-term trend can be explained by the deviant population characteristics stemming from the use of the smaller sample, while on a shorter term a good approximation of the observed number of cars per 1000 households is obtained (only +0.7% in 2018).

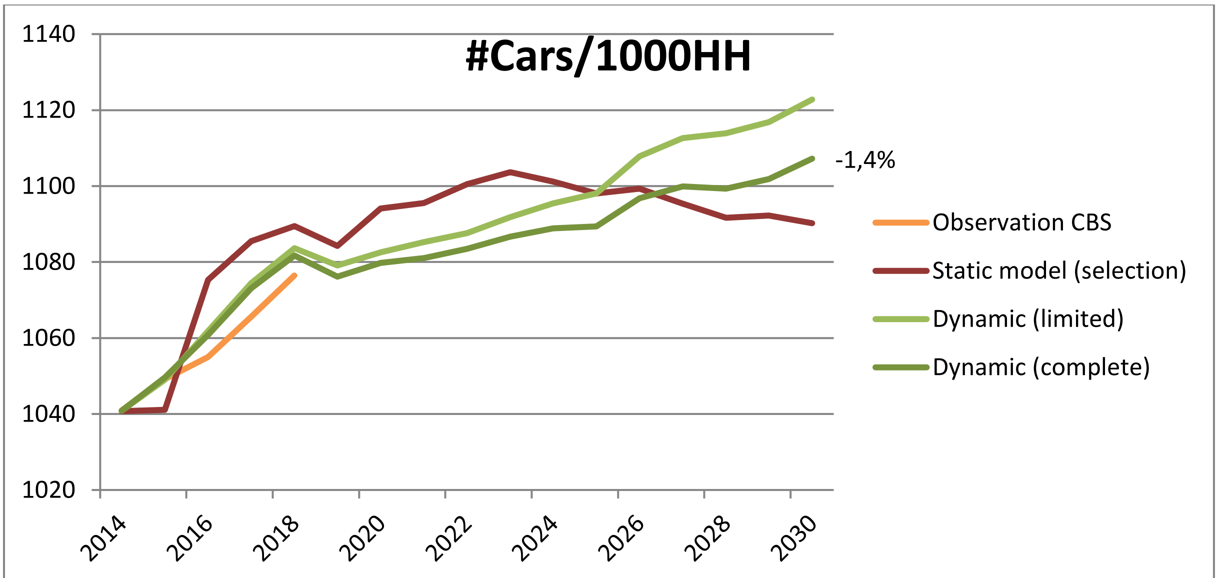

Figure 15. Complete dynamic model compared to the limited version regarding the average number of cars.

4.4 Dynamic model use – restricted parking

Considering the current policies to reduce car ownership and use by implementing restricting parking regimes, we examine the impact of such policies here, starting in 2018. For each of the 1406 zones in the dynamic model, a chance was assigned to each household to have free parking available near the residential location. By changing these probabilities, the impact of two scenarios on car ownership levels is assessed: first one with a stricter parking regime for all zones, and secondly, a more extreme scenario was tested with no free parking available anywhere. Table 27 shows the number of zones facing a specific chance of free parking in each scenario. A stricter regime does not mean a changing parking fee in places that already have paid parking, but only a limited availability of free parking.

Table 27. Chance on free parking in two restrictive parking scenarios.

	Number of Zones				
Chance of free parking	*100%*	*79%*	*67%*	*0%*	*Total*
Complete model – base	988	224	116	78	1406
Scenario 1: all stricter	0	988	224	194	1406
Scenario 2: all paid	0	0	0	1406	1406

With a stricter parking regime in all zones (scenario 1), car ownership decreases by 0.3%, while this is 1.6% in the 'all paid' scenario (see Figure 16). With more than nine million households in 2030, this would result in a reduction of respectively more than 25 thousand and more than 150 thousand cars in these scenarios.

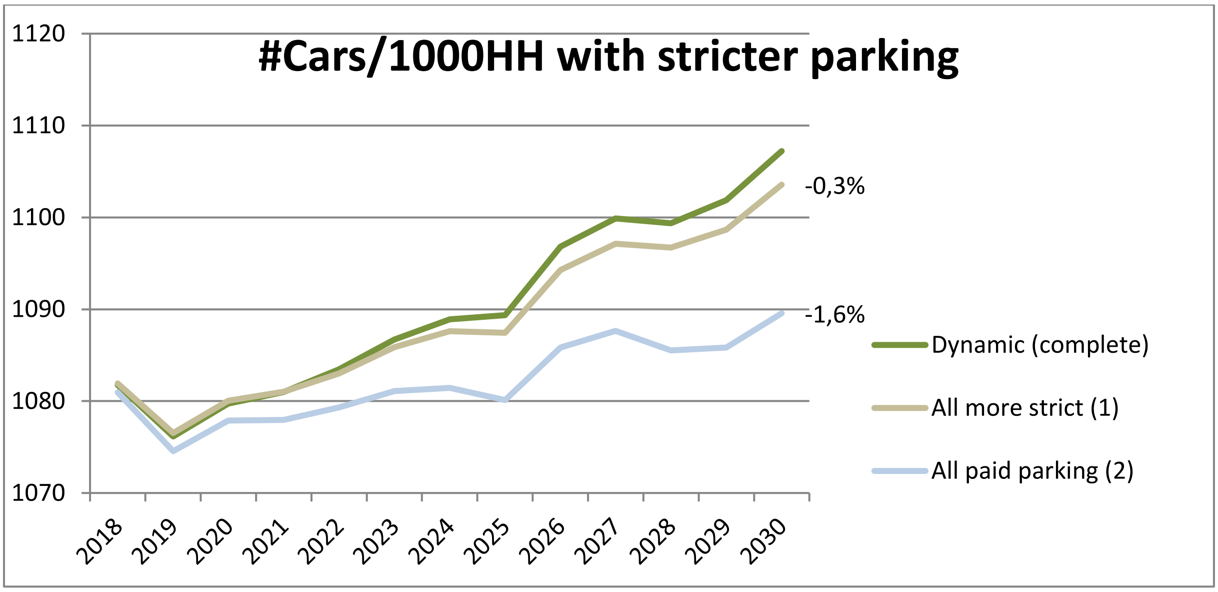

Figure 16. The effect of restrictive parking scenarios on the average number of cars.

Since a parking regime with only paid parking is not everywhere in the Netherlands a realistic option, the case of Rotterdam is examined. From the four biggest Dutch cities, Rotterdam is the one with lowest share of paid parking in our microsimulation model: in only 5 out of 21 zones there is only paid parking. By contrast, in Amsterdam this is the case in 28 out of 29 zones.

Similar to the national outcomes, having only paid parking results in a car ownership level in Rotterdam that is 1.5% lower in 2030 (while in The Hague this is only 0.2%). Already in 2020, after two years, this is a 0.8% reduction. With 500 to 600 thousand inhabitants in these zones in Rotterdam, this means a decrease of 3,500 to 4,200 cars.

4.5 Conclusion

We saw in this chapter that both the static and dynamic car ownership model result in plausible aggregate outcomes on the long run, supported by comparisons with the predicted development of cars, and by sensitivity analyses for changes in income. On a shorter term the dynamic model came even closer to the observed statistics than the static model (+0.7% versus +1.2%).

Including life events and built environment factors to the dynamic model results in decreased car ownership (-1.4% for 2030). In scenarios with stricter parking regimes, this is reduced even more. All in all, the ability of the dynamic model to simulate car ownership and assess policy scenario's is confirmed.

5. Conclusions and recommendations

Based on the results of the previous chapters we can answer the question this thesis started with: To what extent are the forecasts of household car ownership in the Netherlands affected by the inclusion of life events and built environment factors in a dynamic model?

In order to answer this question a static and a dynamic model have been developed: both use the same population data to simulate household car ownership, and the same data to estimate of the underlying choice models. This allows a fair assessment of the differences between these two models.

We started with examining the structure of the static model, which is similar to the current Dutch model that is part of the national transport model system of Rijkswaterstaat: mainly the effects of socio-demographic factors on household car ownership were included here, so the effect of life events and additional built environment factors is not accounted for. Furthermore, due to its static nature, there is no interdependence between household car ownership levels in subsequent years.

In contrast, the dynamic model – which includes the effects of life events and the built environment on household car ownership – uses a microsimulation approach. Here, car ownership decisions of previous years affect the current transaction decision, which comes closer to the way how the actual decisions are made: starting from their current number of cars, households decide whether or not they want to acquire, dispose, or replace a car. This is done by using a transaction choice model instead of a holding model. Theoretically, this dynamic model would therefore be better able to model car ownership than a static model.

The use of a transaction choice model, instead of a holding model, significantly improved its model fit ($p<0.001$), with a substantial log-likelihood increase. Including the effects of life events and built environment factors significantly improved its explanatory power as well, using a 99.9% significance level. Thus, using a transaction model to account for the effect of these additional variables greatly affects the capacity to explain (changes in) car ownership. A further discussion of the empirical results is given in the next section.

Before it was examined how life events and built environment factors could subsequently be included in the dynamic model, the validity of a model without these factors was examined. Both the limited dynamic model and the static model demonstrated plausible aggregate outcomes on the long run that were in line with the outcome of the current model, although some deviant trends were observed for both models. However, this could be explained by the limitations imposed by using a smaller sample of the application data (with different socio-demographic characteristics). On a shorter term, the forecasts of the dynamic model were even better in line with the historic car ownership trend than that of the static model. This confirms findings of De Jong et al. (2004) that “static car ownership models (…) are less suitable for short-run and medium-run predictions” (p. 27) compared to dynamic models.

Compared to the limited model, the inclusion of life events and built environment factors in the dynamic model reduces its outcomes regarding average household car ownership (up to 1.4% lower). A stricter parking regime resulted in even lower car ownership, both on a national level as in the case of Rotterdam. Overall, a dynamic model is both theoretically and practically a competent opponent of a static model, since it enables better car ownership forecasts by including additional variables, and it is able to inform transportation and urban planning policies.

5.1 Research contribution

Before being used in the dynamic model, the effects of life events and built environment factors on car ownership were quantified using transaction choice models. Altogether, this confirmed much recent work, but also provided new insight into the nature of car ownership decisions.

5.1.1 Life events

Especially life events with a spatial component were found to affect car transactions: both residential relocations and job transitions are important factors to consider. Relocating increases the chance of all types of car transactions (acquisition, replacement and disposal), while an anticipated relocation results in more acquisitions. The latter was not found by other authors before. The conclusion of Clark, Chatterjee, et al. (2016) that car ownership increases that coincide with residential relocations are predominantly driven by other factors, can therefore be questioned. A delayed positive effect of relocation on car disposals was found as well. Altogether, these findings confirm previous research on the impact of residential relocation on car ownership and transactions (Beige & Axhausen, 2012, 2017; Gu et al., 2020; Oakil, Ettema, et al., 2014; Van de Kamp, 2019; Zhang et al., 2014), including much research in the review of Chatterjee & Scheiner (2015).

Work related life events affect car transaction choices as well. Job transitions (i.e. new employer and/or different status) mainly result in more car acquisitions, but also in more replacements. The latter is true as well for an anticipated work change. This confirms the findings of Van de Kamp (2019) that anticipated work change around residential relocation increases car ownership. Also Gu et al. (2020) and four papers in the review of Chatterjee & Scheiner (2015) found a positive effect of a change in employer on the number of cars. Although not explicitly examined here, part of these effects can be due to a changing distance to work (Beige & Axhausen, 2012; Van de Kamp, 2019).

However, Oakil, Ettema, et al. (2014b) found a positive effect of employment changes on car *disposals*, just like a delayed positive effect of retirement on that. Both findings cannot be confirmed in our research, although we found that retirement substantially increases the chance of car disposal in the *same* year (instead of a delayed effect), and next to that the chance of replacement as well. This does not align with the findings of Chatterjee & Scheiner (2015), who mention three papers that did not find any effect of retirement.

Changes in household composition were found to affect car transactions, but not as substantially as other authors found. As an example, no effect of childbirth was found, despite previous findings (Chatterjee & Scheiner, 2015; Klein & Smart, 2019; Oakil, Ettema, et al., 2014). However, also Müggenburg, Busch-Geertsema, & Lanzendorf (2015) mention some authors that did not find an effect of childbirth on car transactions. In contrast, the positive effect of a child leaving on car disposal could not be confirmed, although we saw an increased chance of replacing a car, with a higher chance for smaller cars.

The loss of a partner has a strong positive effect on car disposals, confirming previous findings (Chatterjee & Scheiner, 2015; Müggenburg et al., 2015; Oakil, Ettema, et al., 2014). However, effects of an increase in household size could not be confirmed.

The last important life event discussed here is obtaining a license, with a major positive effect on car acquisitions. This was also found by Clark, Chatterjee, et al. (2016). In this research, though, we also found a positive effect for obtaining a licence in the years before and after car acquisition, which was not previously found.

All in all, this research provides a deeper insight into the effects of a variety of life events on car transaction behaviour, for example by identifying multiple lead-lag effects, but by highlighting life events with a spatial component as well. The effect of occupational transitions has been investigated less by mobility researchers according to Müggenburg et al. (2015), but here the importance of taking these into account is confirmed as well. The suggestion of Oakil, Arentze, Ettema, Hooimeijer, & Timmermans (2014) that very limited interdependencies exist among car ownership change, residential relocation and employment change, can therefore be rejected.

5.1.2 Built environment

The main built environment factor with an effect on car transactions is the availability of free parking near the residential location: car acquisitions and replacements are more likely, while the chance of disposal is reduced when there is free parking. This is in line with the limited number of studies on the impact of residential parking, which found that is a significant factor affecting car ownership and use (Albalate & Gragera, 2020; Christiansen et al., 2017; Guo, 2013; Ostermeijer et al., 2019; Van de Coevering, 2008).

Other promising categories of built environment factors – like public transport availability, and the proximity of amenities – showed less clear effects on car ownership. The conclusion of Clark, Chatterjee, et al. (2016) that poorer access to public transport leads to lower car ownership levels can therefore not be confirmed.

On the other hand, decreasing population density was found to increase the chance of car acquisition and replacement, confirming part of the effect of the traditional 5Ds (Ewing & Cervero, 2010; Stevens, 2017). However, no effect for employment density and share of agricultural jobs was found, so the search for better mechanisms that explain changes in car ownership and use is still ongoing, in line with what Elldér (2018) and Naess (2015) argue for. It might be the case that these built environment factors only affect car use instead of car ownership, since that is the focus of the majority of research on the effect of built environment factors.

5.2 Recommendations

We have seen that a dynamic model is a promising and powerful tool to model household car ownership in the Netherlands. In this way, the not only the impact of life events and built environment factors on car ownership can be captured, but also other inherent advantages of dynamic modelling can be utilized. For future revisions of the Dutch car ownership models, using a dynamic model structure instead of a static one can therefore be of added value to inform policymakers. In order to get there, we will examine eight recommendations to improve this research and to address the limitations of it.

5.2.1 Data quality and availability

Several challenges this research had to deal with, were data related. A major limitation was caused by the use of a smaller population sample, instead of the whole synthetic Dutch population up to 2030. Using the full sample would have been too time-intensive to simulate and therefore not be feasible in the context of this thesis. On a shorter term, with simulations up to 2019, the use of the smaller sample was not too problematic, but the smaller sample of 2030 showed several deficiencies compared to the full sample at that time, which was translated into the car ownership trend. Although a comparison with the static model could still be made, using the full sample would have resulted in a better indication of the development of household car ownership in the dynamic model.

The synthetic population itself was not without imperfections as well. The growth in the number of households up to 2018 did not resemble official statistics. The average number of cars per household came close to the statistics though, so the overestimation of households did not affect the overall functioning of the model heavily. Added to that, this deficiency did not hinder a comparison between the static model and the dynamic model, since both models used the same data. However, when this model would be used to inform decision-making, using the application data in its current state is not yet appropriate. The second recommendation is therefore to make the effort to improve it.

A third data-related issue has to do with the estimation dataset, that did not capture all relevant variables on a household level. For example, this related to occupation or licence possession, which limited the possibility of recognizing their effects on car ownership to a better extent. Still, we found multiple significant effect for parameters related to these variables. In case of future data collection, finding a way to measure these variables on the household level as well, could result in even more insight into car transaction choices.

Fourthly, improving the indicators for zonal characteristics, like parking, is essential to account for the effects of built environment factors. In contrast to the indicator used in this research, the parking tariff indicator that is used in the current model was not found to explain car transaction behaviour. Also, the indicators for population and employment density did not do that, so there is a need for better data on spatial characteristics that affect car transaction choices. One way this could be achieved is by adding more spatial detail. In the case of parking, there was heterogeneity within each of the 1406 zones regarding the extent to which free nearby parking was available. A lower spatial aggregation level would help to disentangle the effect of for example parking availability on car ownership.

The fifth recommendation relates to another data-challenge we came across, namely the availability of car transaction data that is used to calibrate the dynamic model. Here, an assumption is made regarding the ratio of car acquisitions and replacements, based on transaction information in the estimation dataset. This affects the outcome of the calibration process and therefore that of the model itself as well. However, the impact of using different assumptions is not examined in detail, although an exploration of it did not result in very divergent results. Still, better grounded calibration targets are recommended when using this model for evidence-based decision-making.

5.2.2 Research scope

The sixth recommendation is to extend the scope of the model. Type choice models, for example, were not part of the implemented dynamic model, although choice models were already estimated for that. This could have given additional insight into car transaction decisions, since replacing a small four-person car by a large seven-person bus is a different choice than a replacement the other way around. Also considering the rise of electrically driven cars, being able to make these distinctions in the dynamic model would have much added value. Next to that, using a different model structure might help to disentangle the effects on car transactions by using interaction variables with the initial number of cars. For example, the effect of household income on acquiring a first car is probably different than that on buying a second or third car.

Also, extended spatial analyses could have given insight into the development of zonal car ownership and could have helped to deepen the understanding of the main drivers of car transaction decisions. Recommendation seven is therefore to make use of the developed model to further examine spatial effects on car transaction.

Finally, in an ideal situation, this dynamic car ownership model would be part of a larger model of travel behaviour, since car ownership and -use are closely related to each other. The framework of Ben-Akiva et al. (2007) for disaggregate dynamic travel forecasting models can be helpful for that. With an extended model, one can model daily travel behaviour choices, extended supply and demand mechanisms, and interaction between agents (Miller, 2019), both within households ('Who can use the car?'), between households (e.g. carpooling), and between users of the same infrastructure (e.g. congestion effects). Using an agent-based modelling approach, by explicitly adding these interactions, can be beneficial for transportation models compared to this dynamic microsimulation model. However, the possibility to dynamically model car transactions and include the effects of life events and built environment factors is already a major advantage of the use of this dynamic model compared to a static model, although further research is needed to develop and test it even more.

5.2.3 Further steps

Considering the proven advantages of a dynamic model to improve car ownership modelling, further research in this direction can bridge the gap between 'a model with potential' and 'a model that is actually used'. Therefore, it needs first of all to address the limitations discussed before, by using an application dataset that reflects characteristics of the population in a more accurate way (and can be taken into account completely), by extending the model with additional modules (e.g. vehicle type choice), and by using a more extensive estimation dataset.

The latter can be especially challenging considering the uncertain future development of travel behaviour we discussed earlier, which includes car transaction choices as well. With no doubt it can be said that these will change in the coming decades, so it is crucial for research to keep paying attention to the factors that affect these choices. In the Netherlands, the Dutch Mobility Panel is probably a good means for that in the coming years, since it covers a wide range of relevant factors, including life events and spatial factors (KiM Netherlands Institute for Transport Policy Analysis, 2018).

5.3 Policy implications

Despite the steps that need be taken to go from a dynamic car ownership model with potential to one that can be directly used to inform decision-making, the findings of this research already have some implications for transportation and urban planning policies.

First of all, the analysis of restrictive parking regimes in the dynamic model showed that car ownership can be reduced up to 1.5% in 2030. This aligns well to the empirical outcomes that the absence of free nearby parking reduces the probability of car acquisitions and makes car disposal more likely. Two potential policy measures are implied: reducing the availability of free parking with permits and/or paid parking, and increasing the distance to parking spots, for example with centralised parking. This is something that for example the municipality Amsterdam (2020) is already doing: street parking is increasingly reduced, the use of (underground) parking garages is stimulated, and the number of parking places near new residential and business areas is decreased.

The latter aligns well to the opportunities opened up by residential relocations and occupational transitions. This research confirms that especially these life events can be seen as window of opportunity to change travel behaviour (Ministry of Infrastructure and Environment, 2016; Müggenburg et al., 2015). Municipal publicity campaigns targeted at those who change residential or job location can be launched to utilize the habit-breaking effects of these life event, thereby encouraging a deliberate evaluation of their daily and long-term travel choices. To change people's travel behaviour, it is crucial that alternatives are present and (made more) attractive.

Making car alternatives more attractive can for example be done with intensified commuting arrangements, by encouraging the use of public transport or bike (especially for new employees). In the Netherlands, this is currently visible in the stimulation of e-bikes, a travel allowance for kilometres by bike, and intensified pilots regarding Mobility as a Service (Ministry of Infrastructure and Water Management, 2018). Of course, such measures depend on the local context as well: in rural areas other mechanisms are at work than in Amsterdam, which asks for policies that are aligned to that particular situation and to the opportunities this brings with them.

All in all, a window of opportunity is opened to break travel habits and reduce the negative externalities related to owning and using cars. By doing that, further steps towards a sustainable and accessible future can be taken.

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Appendix A. Estimation data description

Descriptive statistics of variables in the estimation dataset are given in Table 28, while Table 29 shows their measurement level.

Table 28. Descriptive statistics estimation dataset.

Description	Valid	Perc.	Missing	Perc.
Age group	24920	100.0%	0	0.0%
Car age group of the oldest non-new car	13998	56.2%	10922	43.8%
Car price (average per weight class)	24920	100.0%	0	0.0%
Car transaction type	20037	80.4%	4883	19.6%
Car type of bought car (combination of fuel and weight)	2582	10.4%	22338	89.6%
Change in distance to train station compared to previous year	14769	59.3%	10151	40.7%
Change in number of children	24181	97.0%	739	3.0%
Change in number of children (next year)	24364	97.8%	556	2.2%
Change in number of children (previous year)	22760	91.3%	2160	8.7%
Change in number of driving licenses	24920	100.0%	0	0.0%
Change in number of driving licenses in next year	24920	100.0%	0	0.0%
Change in number of driving licenses in previous year	24712	99.2%	208	0.8%
Change in number of partners	24294	97.5%	626	2.5%
Change in number of partners (next year)	24477	98.2%	443	1.8%
Change in number of partners (previous year)	22859	91.7%	2061	8.3%
Change in number of people in the household	24284	97.4%	636	2.6%
Change in public transport accessibility compared to previous year	21857	87.7%	3063	12.3%
Distance to closest big supermarket	15152	60.8%	9768	39.2%
Distance to closest big supermarket (previous year)	16348	65.6%	8572	34.4%
Distance to closest department store	17021	68.3%	7899	31.7%
Distance to closest department store (previous year)	16348	65.6%	8572	34.4%
Distance to closest other groceries	17021	68.3%	7899	31.7%
Distance to closest other groceries (previous year)	16348	65.6%	8572	34.4%
Distance to closest train station	15152	60.8%	9768	39.2%
Distance to closest train station (previous year)	14831	59.5%	10089	40.5%
Distance to closest transfer train station	17021	68.3%	7899	31.7%
Distance to closest transfer train station (previous year)	16348	65.6%	8572	34.4%
Dummy for availability of electric cars	24920	100.0%	0	0.0%
Dummy for being retired	24704	99.1%	216	0.9%
Dummy for being student	24920	100.0%	0	0.0%
Dummy for close nearby parking	23030	92.4%	1890	7.6%
Dummy for close nearby parking (previous year)	24712	99.2%	208	0.8%
Dummy for having 2 licenses in the household	24920	100.0%	0	0.0%
Dummy for having 3 or more licenses in the household	24920	100.0%	0	0.0%
Dummy for having a license	24920	100.0%	0	0.0%
Dummy for having a license and being female	24920	100.0%	0	0.0%
Dummy for having no occupation	24920	100.0%	0	0.0%
Dummy for relocation	24920	100.0%	0	0.0%
Dummy for relocation (next year)	24920	100.0%	0	0.0%
Dummy for relocation (previous year)	24712	99.2%	208	0.8%

Table 28 (continued).

Description	Valid	Perc.	Missing	Perc.
Dummy for transition from one work (location) to another	24920	100.0%	0	0.0%
Dummy for job transition (next year)	24920	100.0%	0	0.0%
Dummy for job transition (previous year)	24712	99.2%	208	0.8%
Dummy for transition from student to working	24920	100.0%	0	0.0%
Dummy for transition from student to working (next year)	24920	100.0%	0	0.0%
Dummy for transition from student to working (previous year)	23433	94.0%	1487	6.0%
Dummy for transition to retirement	24920	100.0%	0	0.0%
Dummy for transition to retirement (next year)	24920	100.0%	0	0.0%
Dummy for transition to retirement (previous year)	23627	94.8%	1293	5.2%
Dummy for working fulltime	24920	100.0%	0	0.0%
Dummy for working parttime	24920	100.0%	0	0.0%
Education	24920	100.0%	0	0.0%
Employment density in 1km range of center LMS zone	22350	89.7%	2570	10.3%
Employment density in 5km range of center LMS zone	22350	89.7%	2570	10.3%
Gender	24920	100.0%	0	0.0%
Household size	24746	99.3%	174	0.7%
Natural logarithm of car price (average per weight class)	24813	99.6%	107	0.4%
Natural logarithm of Urbanisation	22357	89.7%	2563	10.3%
Number of big supermarkets within 1 kilometre	17021	68.3%	7899	31.7%
Number of big supermarkets within 1 kilometre (previous year)	16348	65.6%	8572	34.4%
Number of cars owned at the beginning of the year	20038	80.4%	4882	19.6%
Number of cars owned at the end of the year	20105	80.7%	4815	19.3%
Number of children	24369	97.8%	551	2.2%
Number of department stores within 5 kilometres	17021	68.3%	7899	31.7%
Number of department stores within 5 kilometres (previous year)	16348	65.6%	8572	34.4%
Number of licenses in the household	24920	100.0%	0	0.0%
Number of other groceries within 1 kilometre	17021	68.3%	7899	31.7%
Number of people without license in the household	22190	89.0%	2730	11.0%
Parking Tariff in LMS zone of residential location	22350	89.7%	2570	10.3%
Partner dummy	24482	98.2%	438	1.8%
Percentual change in Gross Domestic Product (GDP)	24920	100.0%	0	0.0%
Population density in 1km range of center LMS zone	22350	89.7%	2570	10.3%
Population density in 5km range of center LMS zone	22350	89.7%	2570	10.3%
Public transport accessibility of residential location (BBI)	22350	89.7%	2570	10.3%
Public transport accessibility of residential location (BBI, prev. year)	21863	87.7%	3057	12.3%
Share of agricultural jobs in LMS zone	22350	89.7%	2570	10.3%
Urbanisation	22357	89.7%	2563	10.3%
Urbanisation previous year	21870	87.8%	3050	12.2%
Yearly disposable (net) household income	23990	96.3%	930	3.7%

Table 29. Variables included in the estimation dataset, including description and source (if not from the survey). Distances in kilometres.

Category	Variable	Variable label	Value range
Dependent	Cars_0_1_or_more	Number of cars (categorized)	[0,1,2+]
	Car_trans	Changing number of cars	[-1, 0, +0 or +1]
Household & individual charac-teristics	Age	Age group in year of car change	[below 35,35-50,50-65,65 and above]
	Gender	Gender	[1=Female, 0=Male]
	Education	Education level	[Higher, second., lower, primary or none]
	Inc	Household income (CBS, 2019c)	[6 categories: groups of 10.000]
	GDP	Change in GDP compared to the previous year (%)	[Continuous]
	Work_FT	Dummy: working fulltime	[1=Yes, 0=No]
	Work_PT	Dummy: working parttime	[1=Yes, 0=No]
	NoOccup	Dummy: working less than 1 day?	[1=Yes, 0=No]
	Stud	Dummy: being student	[1=Yes, 0=No]
	Retired	Dummy: being retired	[1=Yes, 0=No]
	HH_size	Household size	[1,2,3+]
	Partn	Dummy: partner in year of car change	[1=Yes, 0=No]
	Childr	Number of children in year of car change	[0, 1, 2 or more]
	Lic	Dummy: Possession of driving licence	[1=Yes, 0=No]
	FemLic	Interaction dummy: possession of driving licence x female	[1=Yes, 0=No]
	Licenses	Number of licenses in the household	[0,1,2,3+]
	NoLic	Number of people without licence in the household	[0,1,2,3+]
	License2	Dummy: two licenses in the household	[1=Yes, 0=No]
	License3	Dummy: two licenses in the household	[1=Yes, 0=No]
Car charac-teristics	Car_age	Car age (years)	[0,1-2,3-5,6-10,11+]
	Cars_Befo	Number of cars owned before relocation	[0, 1, 2 or more]

Table 29 (continued).

Category	Variable	Variable label	Value range
Spatial variables	Urb5	Urbanisation level (CBS, 2019d)	[1-5]
	Free_Park	Dummy: free parking availability	[Free nearby/not free nearby]
	BBI(_min1y)	Public Transport accessibility (BBI) (KiM, 2017)	[0-90,90-95,95-100,100-105,105+]
	BBI_ch	Difference in Public Transport accessibility (BBI)	[Decrease/increase of 0, 0-5, 5-15, 15+]
	Dtrain	Distance to closest train station (CBS, 2019b)	[0-1,1-1.5,1.5-2,2-3,3-5,5+]
	Dtrain_ch	Difference in distance to closest train station	[Decrease/increase of 0, 0-1, 1-3, 3+]
	ParkTar	Parking Tariff per hour (Significance, 2017)	[Continuous]
	PopuDens1	Population density in zones within 1km (Significance, 2017)	[Continuous]
	PopuDens5	Population density in zones within 5km	[Continuous]
	EmployDens1	Employment density in zones within 1km	[Continuous]
	EmployDens5	Employment density in zones within 5km	[Continuous]
	Agri_share	Share of agricultural jobs (Significance, 2017)	[Continuous]
	Dist_Big_superm	Distance to closest big supermarket (CBS, 2019b)	[0-0.5,0.5-0.75,0.75-1,1+]
	Dist_Other_groceries	Distance to closest other groceries (CBS, 2019b)	[0-0.5,0.5-0.75,0.75-1,1+]
	Dist_Dep_store	Distance to closest department store (CBS, 2019b)	[0-1,1-1.5,1.5-2,2-3,3+]
	Am_Big_superm	Number of big supermarkets within 1 km (CBS, 2019b)	[0,0-1,1-1.5,1.5-2,2-3.5,3.5+]
	Am_Other_groceries	Number of other groceries within 1 km (CBS, 2019b)	[0,0-2.5, 2.5-5,5-7.5,7.5-15,15+]
	Am_Dep_store	Number of department stores within 5 km (CBS, 2019b)	[0,0-1,1-2,2-3,3-5,5+]
	FromStud(_min/pl1y)	Dummy: working after study (and in previous/next year)	[1=Yes, 0=No]
	WorkToWork(_min/pl1y)	Dummy: change between jobs (and in previous/next year)	[1=Yes, 0=No]
Life events	ToRetired	Dummy: retirement (and in previous/next year)	[1=Yes, 0=No]
	Reloc(_min/pl1y)	Relocation (and in previous/next year)	[1=Yes, 0=No]
	Partn_Ch(_min/pl1y)	Gaining/losing a partner (and in previous/next year)	[+,0,-]
	Childr_Ch(_min/pl1y)	Difference in number of children (idem)	[+,0,-]
	Others_Ch	Difference in number of other people (idem)	[+,0,-]
	Lic_Ch(_min/pl1y)	Acquiring driving licence (and year before/after)	[1=Yes, 0=No]

Appendix B. Car ownership decisions over time

The assumption that household car ownership decisions in different years are stable has been validated by splitting the data and running the first choice model for the static model again. The vast majority (30 out of 33) of the estimated parameters using the second half of the data falls within the confidence interval of the model that uses the first half of data (see Table 31). The expected number of parameters outside one of the confidence intervals is in this case 1.65 (5% multiplied by 33), so with only three parameters outside there is no reason to correct parameters for time effect.

Table 30. Confidence interval (95%) of the estimated parameter values of the first choice model of the nested holding model, using half of the data, compared with the parameter estimates of the others half of the data (green indicates a value within the confidence interval).

Holding model 1	**HalfA**		**95% conf. Int.**		**HalfB**
Parameter	*Value*	*Robust SE*	*Lower*	*Upper*	*Value*
ASC_car	1.530	0.336	0.87	2.19	2.200
ASC_nocar	0	0	0	0	0
B_Age35_50_car	0.616	0.204	0.22	1.02	0.152
B_Age35_car	0	0	0	0	0
B_Age50_65_car	0.836	0.264	0.32	1.35	0.458
B_Age65_car	2.370	1.09	0.23	4.51	1.020
B_HHsize1_car	-1.260	0.268	-1.79	-0.73	-1.250
B_HHsize2_car	0	0	0	0	0
B_HHsize3_car	-0.529	0.274	-1.07	0.01	-0.191
B_Inc12_car	-1.170	0.280	-1.72	-0.62	-1.320
B_Inc3_car	0		0	0	0
B_Inc4_car	-0.153	0.308	-0.76	0.45	-0.292
B_Inc56_car	-0.0203	0.291	-0.59	0.55	-0.208
B_Inc_Miss_car	-0.282	0.429	-1.12	0.56	-0.789
B_Ln_urb_2p_car	-1.040	0.350	-1.73	-0.35	-0.365
B_Ln_urb_3p_car	-0.537	0.356	-1.23	0.16	-0.280
B_Ln_urb_Age35_50_car	-0.351	0.296	-0.93	0.23	0.262
B_Ln_urb_Age50_65_car	0.0757	0.363	-0.64	0.79	0.565
B_Ln_urb_Age65_car	-0.667	0.918	-2.47	1.13	0.467
B_Ln_urb_Inc3_car	0.103	0.361	-0.60	0.81	-0.0319
B_Ln_urb_Inc4_car	0.222	0.420	-0.60	1.05	0.178
B_Ln_urb_Inc56_car	0.873	0.475	-0.06	1.80	0.930
B_Ln_urb_Oc_No_car	0.0783	0.315	-0.54	0.70	-0.247
B_Ln_urb_Oc_PT_car	-1.110	0.487	-2.06	-0.16	-1.170
B_Ln_urb_Oc_Ret_car	-1.350	0.657	-2.64	-0.06	-0.845
B_Ln_urb_Oc_Stud_car	0.173	0.682	-1.16	1.51	0.593
B_Ln_urb_car	1.680	0.410	0.88	2.48	1.260
B_Occ_FT_car	0	0	0	0	0
B_Occ_No_car	-1.080	0.216	-1.50	-0.66	-0.847
B_Occ_PT_car	0.264	0.451	-0.62	1.15	0.106
B_Occ_Ret_car	0.996	0.541	-0.06	2.06	0.169
B_Occ_Stud_car	-1.780	0.575	-2.91	-0.65	-0.798

Appendix C. Utility functions transaction choice model

The utility functions that are specified for the transaction choice models are found here. Equation 9 shows them for car acquisitions in the complete model. For car replacements and disposals, the same functions are used, although not for all parameters an estimate was provided: only for the ones found in Table 20. For the limited model, this is true as well, but here all parameters of life events and the built environment factors are fixed to zero.

$$
\begin{aligned}
\{Eq.9\}\ U\ (\mathit{Acquisition}) \\
&= \mathit{ASC\_acq} + \beta\mathit{\_Occ\_FT\_acq} * \mathit{Work\_FT} + \beta\mathit{\_Occ\_PT\_acq} * \mathit{Work\_PT} \\
&+ \beta\mathit{\_Occ\_Ret\_acq} * \mathit{Retired} * (1 - \mathit{Retired\_Miss}) + \beta\mathit{\_Occ\_No\_HH1\_acq} \\
&* \mathit{NoOccup} * \mathit{HHsize1} + \beta\mathit{\_Occ\_No\_HH2\_acq} * \mathit{NoOccup} \\
&* \mathit{HHsize2} \\
&+ \beta\mathit{\_Age35\_acq} * \mathit{Age1} + \beta\mathit{\_Age35\_50\_acq} * \mathit{Age2} + \beta\mathit{\_Age50\_65\_acq} * \mathit{Age3} \\
&+ \beta\mathit{\_Age65\_acq} * \mathit{Age4} \\
&+ \beta\mathit{\_Educ\_Higher\_acq} * \mathit{Educ\_Higher} + \beta\mathit{\_Educ\_Lower\_acq} \\
&* \mathit{Educ\_Lower} \\
&+ \beta\mathit{\_Inc12\_acq} * \mathit{Inc12} + \beta\mathit{\_Inc3\_acq} * \mathit{Inc3} + \beta\mathit{\_Inc4\_acq} * \mathit{Inc4} \\
&+ \beta\mathit{\_Inc56\_acq} * \mathit{Inc56} + \beta\mathit{\_Inc\_Miss\_car} * \mathit{Inc\_Miss} \\
&+ \beta\mathit{\_GDP\_acq} * \mathit{GDP\_change} \\
&+ \beta\mathit{\_Cars0\_acq} * \mathit{Cars0} + \beta\mathit{\_Cars2\_acq} * \mathit{Cars2} \\
&+ \beta\mathit{\_Car\_age\_1\_2\_acq} * \mathit{Car\_age\_1\_2} + \beta\mathit{\_Car\_age\_3\_5\_acq} * \mathit{Car\_age\_3\_5} \\
&+ \beta\mathit{\_Car\_age\_6\_10\_acq} * \mathit{Car\_age\_6\_10} + \beta\mathit{\_Car\_age\_11pl\_acq} \\
&* \mathit{Car\_age\_11pl} + \beta\mathit{\_Car\_age\_Miss\_acq} * \mathit{Car\_age\_Miss} \\
&+ \beta\mathit{\_FemLic\_acq} * \mathit{FemLic} + \beta\mathit{\_Lic\_acq} * \mathit{Lic} + \beta\mathit{\_Lic0\_1\_acq} * \mathit{License0\_1} \\
&+ \beta\mathit{\_Lic2\_acq} * \mathit{License2} + \beta\mathit{\_Lic3pl\_acq} * \mathit{License3} \\
&+ \beta\mathit{\_Ln\_urb\_acq} * \mathit{Ln\_urb} * (1 - \mathit{Ln\_urb\_Miss}) \\
&+ \beta\mathit{\_PopuDens1\_acq} * \mathit{PopuDens1} * 1 - \mathit{PopuDens1\_Miss} + \beta\mathit{\_ParkTar\_acq} \\
&* \mathit{ParkTar} * (1 - \mathit{ParkTar\_Miss}) \\
&+ \beta\mathit{\_Free\_park\_acq} * \mathit{Free\_Park} + \beta\mathit{\_BBI\_90min\_acq} * \mathit{BBI1} \\
&+ \beta\mathit{\_BBI\_90\_100\_acq} * \mathit{BBI2} + \beta\mathit{\_BBI\_100\_110\_acq} * \mathit{BBI3} \\
&+ \beta\mathit{\_BBI\_110pl\_acq} * \mathit{BBI4} + \beta\mathit{\_BBI\_Miss\_acq} * \mathit{BBI\_Miss} \\
&+ \beta\mathit{\_Dsuperm\_500min\_acq} * \mathit{Dsuperm1} + \beta\mathit{\_Dsuperm\_500\_750\_acq} \\
&* \mathit{Dsuperm2} + \beta\mathit{\_Dsuperm\_750pl\_acq} * \mathit{Dsuperm3} + \beta\mathit{\_Dsuperm\_Miss\_acq} \\
&* \mathit{Dsuperm\_Miss} \\
&+ \beta\mathit{\_ToWork\_acq} * \mathit{ToWork} + \beta\mathit{\_ToWork\_pl1y\_acq} * \mathit{ToWork} \\
&+ \beta\mathit{\_ToRetired\_acq} * \mathit{ToRetired} + \beta\mathit{\_Reloc\_acq} * \mathit{Reloc} \\
&+ \beta\mathit{\_Reloc\_min1y\_acq} * \mathit{Reloc\_min1y} + \beta\mathit{\_Reloc\_pl1y\_acq} * \mathit{Reloc\_pl1y} \\
&+ \beta\mathit{\_PartnMin\_acq} * \mathit{PartnMin} + \beta\mathit{\_ChildMin\_acq} * \mathit{ChildMin} \\
&+ \beta\mathit{\_LicensePlus\_acq} * \mathit{LicensePlus} + \beta\mathit{\_LicensePlus\_min1y\_acq} \\
&* \mathit{LicensePlus\_min1y} + \beta\mathit{\_LicensePlus\_pl1y\_acq} * \mathit{LicensePlus\_pl1y}
\end{aligned}
$$

C.1 Type choice estimates

A vehicle type choice model was estimated to deepen the understanding of car acquisition and replacement behaviour. As shown in Table 31, larger households are less prone to buy a car of less than 950 kilograms, and more inclined to buy a car of more than 1150 kilograms. With a higher car price, the utility for such cars is decreased for lower income households (below 20,000 euro per year), while a larger supply means a lower utility. This rather counterintuitive sign can probably be explained by the effect of price, since a larger supply is related to lower prices (and thus higher utilities for lower incomes).

Table 31. Estimation results of a vehicle type choice model.

		Fuel/powertrain				**Weight (kg)**									
Variable	**Utility car characteristic for …**	*Diesel*	*(Rob. SE)*	*Elec*	*(Rob. SE)*	*950-*	*(Rob. SE)*		*950-1150*	*(Rob. SE)*	*1150-1350*	*(Rob. SE)*		*1350pl*	*(Rob. SE)*
ASC	Constant for car characteristics	-1.79	(0.0816)	-2.93	(0.143)	-	-		0.781	(0.171)	0.632	(0.179)		-	-
HH2	…two-person household	-	-	-	-	-0.859	(0.357)		-	-	-	-			
HH3	…three-person household	-	-	-	-	-1.86	(0 .608)		-	-	-	-		-	-
HH2+	…more-person household	-	-	-	-	-	-		-	-	0.276	(0.144)	*	0.416	(0.183)
HH_miss	…missing household size	-	-	-	-	2.36	(1.22)	*	-	-	1.77	(0.806)		2.40	(0.941)
LN(price) x Inc3	…income class 3 (20 to 30k) x price	0.526	(0.0575)	0.526	(0.0575)	0.526	(0.0575)		0.526	(0.0575)	0.526	(0.0575)		0.526	(0.0575)
LN(price) x Inc4	…income class 4 (30 to 40k) x price	0.616	(0.0587)	0.616	(0.0587)	0.616	(0.0587)		0.616	(0.0587)	0.616	(0.0587)		0.616	(0.0587)
LN(price) x Inc56	…income class 5 or 6 (40k+) x price	0.584	(0.0575)	0.584	(0.0575)	0.584	(0.0575)		0.584	(0.0575)	0.584	(0.0575)		0.584	(0.0575)
LN(price) x Inc_Miss	…income class missing x price	0.472	(0.0930)	0.472	(0.0930)	0.472	(0.0930)		0.472	(0.0930)	0.472	(0.0930)		0.472	(0.0930)
LN(supply)	…larger supply of car type	-0.141	(0.0149)	-0.141	(0.0149)	-0.141	(0.0149)		-0.141	(0.0149)	-0.141	(0.0149)		-0.141	(0.0149)

**p>0.05*

Appendix D. Static model calibration

In the static model, both the national car ownership module and the zonal distribution module are calibrated, and respectively discussed in section D.1 and D.2.

D.1 Calibration national car ownership module (step 2)

Before the static model was used, it first had to be calibrated. Calibration took place by adjusting the estimated ASCs per zone and is explained below. These ASCs capture the intrinsic preference for a certain level of car ownership, but since the estimation data is not a representative reflection of the Dutch population, these constants need to be adjusted. This helps to bridge the gap to the application dataset, which reflects the Dutch population substantially better. Therefore, the outcomes of the model for the base year (2014) were aligned with statistics of Carmod (Significance, 2017), which are based on actual outcomes of 2014: Table 32 shows that the number of cars in Carmod is equal to data of CBS (2019e), although the number of households is slightly different.

To calibrate the model, the steps describes in the previous section were followed for the end of base year 2014, with the total number of cars per zone as output. Subsequently, for each zone, the constants (ASC's) for choosing one or multiple cars are corrected in such a way that the zonal distribution of cars corresponds to the base year distribution that Carmod uses (Significance, 2017). This is done by incorporating a zonal constant into the utility functions for owning one and two or more cars. For practical reasons, it is not chosen to optimize the zonal constants for each of the 1406 zones, but to categorise them at the COROP-level (40 zones). By doing this, the model outcomes of the base year were aligned to reality.

Table 32. Calibration conditions and outcomes static model base year (2014).

	#HH0	#HH1	#HH2	TOT-HH	TOT-cars	Cars/1000HH
CBS	- -	- -	- -	7,665,198	7,979,083	1,040.95
Carmod	1,854,441 (24.2%)	4,136,674 (54%)	1,674,445 (21.8%)	7,665,560	7,979,083	1,040.90
Target	1,854,443 (24.2%)	4,136,672 (54%)	1,674,444 (21.8%)	7,665,559	7,979,079	1,040.90
Static model	1,854,443 (24.2%)	4,136,672 (54%)	1,674,444 (21.8%)	7,665,559	7,979,079	1,040.90

The outcomes of the static model for 2014 are practically the same as that of Carmod (see Table 24). The minor differences in number of households with 0 cars, 1 car, or 2 or more cars (respectively #HH0, #HH1 and #HH2) are caused by the targets for the static model. Since there is a little difference in total number of households *per zone* between Carmod and the population simulator, the target distribution of households is corrected for that for each zone. However, in Carmod not each zone has the same multiplication factor for households with two or more cars, so a similar distribution of households in two zones can result in a different number of cars. Since the static model uses one single multiplication factor for all zones, the corrected zonal household distributions results in slightly different zonal car targets compared to Carmod. This explains that the total car target is somewhat lower than in Carmod. However, these differences are still negligible, so after calibration this model was ready to be used for car ownership modelling in later years.

D.2 Calibration zonal distribution module (step 3)

Calibration the static model for the base year was done by incorporating a zonal constant into the utility functions for owning one and two or more cars, which are shown in Table 33.

Table 33. Zonal constants used in calibration static model.

	Full sample		**Selection**	
COROP-Zone	*ASC 1 car*	*ASC 2/more cars*	*ASC 1 car*	*ASC 2/more cars*
1 (Oost-Groningen)	0.2176	1.2146	0.2176	1.2146
2 (Delfzijl en omgeving)	-0.46656	0.65204	-0.46656	0.65204
3 (Overig Groningen)	-0.740647	0.29383	-0.740647	0.29383
4 (Noord-Friesland)	-0.423585	0.6664	-0.423585	0.6664
5 (Zuidwest-Friesland)	-0.2944	0.87392	-0.2944	0.87392
6 (Zuidoost-Friesland)	-0.04483	1.08764	-0.04483	1.08764
7 (Noord-Drenthe)	0.1058	1.27657	0.1058	1.27657
8 (Zuidoost-Drenthe)	0.1098	1.17239	0.1098	1.17239
9 (Zuidwest-Drenthe)	0.07498	1.22681	0.07498	1.22681
10 (Noord-Overijssel)	-0.20399	1.04685	-0.20399	1.04685
11 (Zuidwest-Overijssel)	-0.54505	0.73559	-0.54505	0.73559
12 (Twente)	-0.00776	1.173315	-0.00776	1.173315
13 (Veluwe)	-0.024666	1.232021	-0.024666	1.232021
14 (Achterhoek)	0.025315	1.214165	0.025315	1.214165
15 (Arnhem/Nijmegen)	-0.324277	0.827978	-0.324277	0.827978
16 (Zuidwest-Gelderland)	0.330265	1.62817	0.330265	1.62817
17 (Utrecht)	-0.36352	0.956315	-0.36352	0.956315
18 (Kop van Noord-Holland)	-0.365585	0.93766	-0.365585	0.93766
19 (Alkmaar en omgeving)	-0.27443	1.0485	-0.27443	1.0485
20 (IJmond)	-0.19198	1.11431	-0.19198	1.11431
21 (Agglomeratie Haarlem)	-0.21384	1.05754	-0.21384	1.05754
22 (Zaanstreek)	-0.35738	0.89687	-0.35738	0.89687
23 (Groot-Amsterdam)	-0.825605	0.389129	-0.825605	0.389129
24 (Het Gooi en Vechtstreek)	0.10745	1.38457	0.10745	1.38457
25 (Leiden en Bollenstreek)	-0.622025	0.7487	-0.622025	0.7487
26 (Agglomeratie 's-Gravenhage)	-0.286514	0.775876	-0.286514	0.775876
27 (Delft en Westland)	-0.78937	0.534167	-0.78937	0.534167
28 (Oost-Zuid-Holland)	-0.36648	1.07716	-0.36648	1.07716
29 (Groot-Rijnmond)	-0.348295	0.81031	-0.348295	0.81031
30 (Zuidoost-Zuid-Holland)	-0.31099	1.0077	-0.31099	1.0077
31 (Zeeuwsch-Vlaanderen)	0.21392	1.2537	0.21392	1.2537
32 (Overig Zeeland)	-0.10226	1.07544	-0.10226	1.07544
33 (West-Noord-Brabant)	0.035035	1.25584	0.035035	1.25584
34 (Midden-Noord-Brabant)	-0.059568	1.12021	-0.059568	1.12021
35 (Noordoost-Noord-Brabant)	0.272648	1.53562	0.272648	1.53562
36 (Zuidoost-Noord-Brabant)	0.1701	1.32733	0.1701	1.32733
37 (Noord-Limburg)	0.1426	1.37482	0.1426	1.37482
38 (Midden-Limburg)	0.178649	1.37636	0.178649	1.37636
39 (Zuid-Limburg)	-0.096827	0.967313	-0.096827	0.967313
40 (Flevoland)	-0.528516	0.823636	-0.528516	0.823636

For later years, a correction on the utility for having no cars for all zones is done to distribute the total number of cars over the zones. Table 34 for each year shows the corrections that have been used.

Table 34. Yearly ASC corrections for zonal car ownership distribution in the static model.

Year	**ASC 0 cars (full)**	**ASC 0 cars (selection)**
2015	0.003364	0.596
2016	-0.03536	-0.0165
2017	-0.0360355	-0.027
2018	-0.024391	-0.018
2019	0.0178505	-0.004
2020	-0.0155775	-0.051
2021	-0.01819	-0.051
2022	-0.019604	-0.067
2023	-0.012523	-0.0735
2024	0.0076865	-0.054
2025	0.028246	-0.0225
2026	0.0477245	-0.0225
2027	0.065791	-0.006
2028	0.0832775	0.006
2029	0.1016735	0.004
2030	0.116737	0.016

Appendix E. Dynamic model implementation

To implement the dynamic model, among others some assumptions had to be made regarding parking (E.1), a calibration process was done (E.2) and a smaller sample from the population simulator is used in the dynamic model, which resulted in some differences in the characteristics of the population compared to that in the full sample.

E.1 Including parking effects

The only exception is for the parameter for the availability of nearby free parking, for which the relation of the (self-indicated) presence of free nearby parking with the zonal parking tariff is used (see Appendix E). Using the *Parking Tariff* per zone was not an option, since only the *Free Parking* indicator was found to be a significantly factor affecting car transaction behaviour. Still, in order to use the *Free Parking* indicator, the relation of it with the *Parking Tariff* per zone is used. Table 25 shows how the (self-indicated) presence of free nearby parking relates to the zonal parking tariff, using the year 2018 in the estimation dataset.

Table 35. Free parking in combination with zonal parking tariff (2018).

Free Par-king	**Zonal Parking Tariff (cents per hour)**												
	0	*1-50*	*51-100*	*101-150*	*151-200*	*201-250*	*251-300*	*301-350*	*351-400*	*401-450*	*451+*	*Un-known*	*Total*
No	42	13	25	25	61	18	22	27	3	3	11	7	257
	5%	7%	22%	31%	60%	38%	85%	90%	100%	50%	69%	78%	17%
Yes	827	170	91	55	41	29	4	3	0	3	5	2	1230
	95%	93%	78%	69%	40%	62%	15%	10%	0%	50%	31%	22%	83%

As Table 25 shows, there is not a one-on-one relationship between the two parking indicators: some people that did not indicate to have free nearby parking available were living in a zone *without* a parking tariff, while other could park nearby their house for free in a zone *with* a parking tariff. For this reason, simply assigning *FreeParking* to households in a zone with a *ParkingTariff* of 0 and not doing that for households in zones with a tariff of one and higher would not work. Therefore, a share of the households in a zone with a parking tariff can be assigned free parking in the dynamic model. The exact distribution of it can be seen in Table 26, which is based on an extended version of Table 25 that also considered urbanisation. In this way both the total share of free parking in the estimation dataset was maintained, but is at the same time the share of free parking in zones per urbanisation level optimized. This would not have been the case when the shares of Table 25 would have been used.

Table 36. Probabilities of assigning free parking to households in zones with a specific parking tariff.

Assign FreePark	**Zone with Parking Tariff** *0*	*1-100*	*100-200*	*200+*	**Total share**
No	0%	21%	33%	100%	17%
Yes	100%	79%	67%	0%	83%

The percentages of Table 36 have been assigned to the corresponding zones in the dynamic model, based on the zonal Parking Tariff. At the start of the simulation and when a household is relocating, a random draw decides whether a household is facing a parking regime or whether it has free nearby parking available, using the probabilities given here.

E.2 Calibration dynamic model

For the same reasons as in the static model, the dynamic model was first calibrated as well, which was done by aligning the car transactions in the model with the number of transactions in 2015. In contrast with the static model, these transaction statistics are not immediately available. Therefore, an approximation of them is used, which is based on actual data.

Using the number of households and the cars per household ratio from CBS (2019e), the target for the number of cars in 2015 is obtained for the dynamic model (see Table 29). Also, the net increase in number of cars in 2015 can be derived from that, since the numbers for 2014 are known. In terms of car transactions, this increase is the difference between total acquisitions and disposals.

Table 37. Calibration conditions for the dynamic model.

Conditions 2015	**HHs**	**Cars/HH**	**Cars**	**Cars last year**	**Net increase**
CBS (2019e)	7,720,787	1.0492	8,100,864	7,979,083	121,781
Dynamic model	7,805,056	1.0492	*8,189,281*	7,979,079	*210,202*
Dynamic selection	7,928	1.0492	8,*318*	8,073	*245*

Other data from CBS (2017b) give the total number of bought cars in 2015, distinguished between new and second-hand. This can be considered as the sum of the number of replaced and acquired cars, as seen in the third column of Table 30.

Before calibration could be started, it was needed to make an assumption, since no additional statistics were available. Two alternative assumptions could be made. The first option was to add the constraint that in the calibration process the sum of all changes to the ASCs had to be minimized in order to get an outcome that is closest to estimated constants. However, these constants apply to the estimation dataset, which contains relatively more people in the older age groups. Since car transaction behaviour is different per age group, the ASCs are presumably biased. This could result in an overestimation of the number of car replacements, since older people more often replace a car than that they acquire one, compared to younger people (see Table 9). Therefore, minimizing the change in the constants does not guarantee that the calibration process results in the most realistic share of each car transaction for the synthetic Dutch population.

Table 38. Final calibration conditions for the dynamic model.

				Final calibration targets			
Conditions 2015	**HHs**	**Acq + repl**	**Repl /Acq**	*#Acq*	*#Repl*	*#Noth*	*#Disp*
Dynamic model	7,805,056	*2,324,449*	2.801	*611,607*	*1,712,842*	*5,079,202*	*401,405*
Dynamic selection	7,865	*2,342*	2.801	*616*	*1,726*	*5,134*	*389*

The second option was to fixate the ratio of car replacements and acquisitions. However, immediately using the ratio coming from the estimation dataset would not be valid for the same reason as described above: the number over replacements would probably higher than in reality. Therefore, a weighing for age was applied, using the share of each age group in the total population since 2000. This resulted in a quite lower ratio of car replacements and acquisitions (of 2.801), which is more realistic considering the age distribution in the application dataset. Naturally, having more data on car transactions available to calibrate the dynamic model would improve it even more, but this can still be seen as a solid method.

Using the conditions described above, the model is calibrated twice: first for the limited version and secondly for the complete version, including additional spatial factors and life events. This is done by running the model for one year (from 2014 to 2015) with varying combinations of ASCs for car acquisition, replacement and disposal and checking which combination reached the calibration targets. It was needed to repeat each run multiple times (most of the time 120 times), because of the stochastic elements in it. In this way the average outcome would be reliable. The constants where the calibration targets are met, are used as starting conditions for the dynamic model runs (see Table 39).

Table 39. Calibration constants dynamic model.

Constant	Limited	Complete
ASC_acquisition	-5.9109	-6.4044
ASC_replacement	-2.395	-3.1229
ASC_disposal	-3.738	-3.5694

E.3 Population characteristics in selection sample

That using the smaller sample leads to an overestimation of the number of cars can be explained by examining the characteristics of the sample (see Table 40). The share of lower income households is substantially lower in the selection. Other explanations can be found in a lower share of retired people, less people with a lower education, less one-person households and less people with no occupation, which are all related to lower probabilities for having or getting less cars (see Tables 16 to 18).

Table 40. Comparison between a selection of sociodemographic variables in the full sample and in the selection.

			2014			**2030**	
Variable	**Value**	*Full*	*Selection*	*Diff.*	*Full*	*Selection*	*Diff.*
Age	*0-18*	21.5%	21.4%	*-0.1%*	17.6%	18.8%	*1.2%*
	18-30	14.4%	14.4%	*0.0%*	13.8%	16.6%	*2.8%*
	30-50	26.7%	26.4%	*-0.3%*	23.6%	28.8%	*5.2%*
	50-65	20.1%	20.3%	*0.2%*	19.9%	16.2%	*-3.7%*
	65+	17.3%	17.4%	*0.1%*	25.0%	19.7%	*-5.3%*
Occupation	*Below 6 years*	5.9%	6.1%	*0.2%*	5.2%	6.9%	*1.7%*
	Student/to school	16.8%	16.5%	*-0.3%*	14.4%	14.5%	*0.1%*
	Parttime	11.8%	11.7%	*-0.1%*	28.3%	30.4%	*2.1%*
	Fulltime	30.9%	31.1%	*0.2%*	30.6%	30.9%	*0.3%*
	Retired	17.6%	17.9%	*0.3%*	19.9%	15.6%	*-4.3%*
	Other	16.9%	16.7%	*-0.2%*	1.5%	1.7%	*0.2%*
License	*No license*	35.0%	34.8%	*-0.2%*	26.7%	27.6%	*0.9%*
	License	65.0%	65.2%	*0.2%*	73.3%	72.4%	*-0.9%*
Education	*No education*	13.4%	13.3%	*-0.1%*	11.7%	13.7%	*1.4%*
	Primary or lower	17.2%	17.1%	*-0.1%*	15.1%	13.8%	*-1.3%*
	Lower vocational	23.6%	23.4%	*-0.2%*	18.0%	16.2%	*-1.8%*
	Secondairy vocational	26.5%	26.4%	*-0.1%*	29.0%	29.1%	*0.1%*
	Higher education	19.4%	19.8%	*0.4%*	26.2%	27.2%	*1.0%*
Income	*Below 20k*	42.7%	43.0%	*0.3%*	39.8%	35.3%	*-4.5%*
	20-30k	15.8%	16.0%	*0.2%*	19.2%	20.3%	*1.1%*
	30-40k	9.3%	8.7%	*-0.6%*	13.5%	14.2%	*0.7%*
	More than 50k	32.2%	32.3%	*0.1%*	27.6%	30.2%	*2.6%*
Household size	*1*	34.9%	34.8%	*-0.1%*	47.1%	43.9%	*-3.2%*
	2	35.8%	36.0%	*0.2%*	31.6%	33.0%	*1.4%*
	3 or more	29.2%	29.2%	*0.0%*	21.3%	23.2%	*1.9%*