AN INSIGHT INTO HOMEOWNERS' CHOICE FOR HOLIDAY AND LONG-TERM RENTAL

Results of a Stated Choice Experiment in Amsterdam

by

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PREFACE

This master thesis is the result of my graduation research as the final part of my master's Construction Management and Engineering (CME) at the University of Technology in Eindhoven (TU/e). Studying at the TU/e was an interesting and challenging experience for me and carrying out this graduation project was one of the hardest yet valuable components.

I would first like to thank my thesis supervisor Tao and Gamze. Tao was always available for helping me patiently whenever I ran into a trouble spot or had a question about my research. He has taught me the methodology to carry out the research and to present the research works properly. Gamze provided me valuable inspirations for the subject and insightful comments on this thesis. It was a great privilege and honor to work and study under their supervision.

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Finally, I must express my very profound gratitude to my parents for their love and unconditional support throughout my years of study and to my boyfriend for his faith and continuous encouragement through the process of researching and writing this thesis. This accomplishment would not have been possible without them.

Amanda Feng

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SUMMARY

Private rental sector (PRS) plays an important role in the urban housing market, by providing a housing option to a group of home seekers including students, young professionals, and childless couples. Its importance is especially significant in some global cities where there has been a great shortage of rental housing in recent years. Traditionally, properties provided in the PRS are long-term (private) rentals which are usually rented out to tenants (usually residents) for at least three months. However, as the takeoff of the sharing economy, properties in the PRS are increasingly no longer used solely for residents' living. Holiday rental, short-term rental of residential homes to tourists arranged through online accommodation platforms, has mushroomed into a global phenomenon.

Accompanying its popularity, holiday rental is criticized to erode the supply of long-term rental housing by encouraging conversion to the holiday rental. Evidences show that numerous holiday rental properties are highly available year-round for tourists, which means they are locked out of the long-term private rental market. Policymakers and researchers around the world have been struggling with limiting holiday rentals and promoting long-term rentals. It will be interesting and meaningful to first understand the homeowners' choice behavior behind this phenomenon that some choose to supply the holiday rental market while others supply the market for long-term rentals.

Therefore, the objective of this research is to obtain more insights in the determinants influencing homeowners' decisions to supply holiday rental and long-term rental, resulting in the main research question: Which factors influence homeowners' choice for holiday and long-term rental? To answer this question, a stated choice experiment has been conducted where a total of 218 Amsterdam residents were consulted in a digital survey. The 218 respondents were presented with a total of nine choice sets arranged in three sets with the same context setting. Each choice set includes two rental alternatives ("holiday rental" & "long-term rental") and an option "none of these" in case they are not willing to rent anyway. The attributes included in the alternatives are identified based on an extensive literature review together with an expert interview and cover occupancy rate, daily income, days limit, tourist tax, long-term rental subsidy, managing method, neighbors' attitude and respective numbers in the neighborhood. The attached context consists of three parts, namely type, condition and location of the rental property. Apart from the experiment, the respondents were also asked a few socio-demographic questions. After the data was collected, data was first analyzed using a multinomial logit model, executed in the software program 'Nlogit'. This analysis facilitates the research with the influence of every attribute level on the housing

choice. The existence of heterogeneity is verified with the mixed logit model and the differences between classes of homeowners is further examined with a latent class model.

The results show that financial factors have the most influential effects on homeowners' rental choice. High occupancy rate and high daily income have a positive influence on the choice of holiday rental, while a high daily income of long-term rental also incentivizes homeowners to choose it. When an entire house is rented, the negative influence of low daily income is particularly strong on both choices. In terms of policy instruments, the days limit policy on holiday rental shows significant effects on homeowners' rental choice in the sense that the 30-day limit on holiday rental appears to be a major deterrent in the choice for holiday rental. The 180-day limit also deters this choice compared to the 33-day limit which basically means no limit. Moreover, the 30-day limit policy seems to be especially effective for highly educated homeowners. However, other policy instruments such as tourist tax and long-term rental subsidy seem not to have significant effects on homeowners' rental choice. Regarding social influence, neighbors' negative attitude also shows a significant negative effect on holiday rental choice. This effect is particularly strong when homeowners, especially young homeowners want to rent out an entire house. Moreover, managing method and popularity of holiday rental or long-term rental have no significant effect. Besides the influences of attributes, rental property's type and condition, as context variables, also have a significant effect on homeowners' rental choice while the property location does not. The holiday rental is preferred when a homeowner has a spare room in a good condition while long-term rental is preferred when a homeowner has a spare home (apartment or house) in a moderate or poor condition. The socio-demographic characteristics of homeowners are also relevant to their rental choice. Young, male homeowners prefer holiday rental while old-aged, female homeowners with low incomes prefer long-term rental.

This study provides a quantitative analysis being the first one that measures homeowners' choice preferences for holiday and long-term rental and provides governments with useful insights in the effects of policy instruments on holiday rental and long-term rental. Governments can, therefore, use the knowledge generated in this thesis as underpinning for their considerations of future policymaking. Finally, the research recommends investigating the effects of other relevant attributes that are not included within this research (e.g., cost, social interactions, and other policy instruments) and repeating the experiment in other cities having a larger sample of homeowners in future research. It also recommends examine the sensitivities of the findings, e.g. elasticity of certain attributes such as days limit, daily income, occupancy rate or to execute predictions based on scenario analysis.

ABSTRACT

With the emergence of sharing economy, an increasing number of homeowners choose to rent out their homes as holiday rental in place of supplying the market for long-term rentals. This paper aims at investigating the influence of factors on homeowners' choice to supply holiday rentals and long-term rentals. A multinomial logit model is applied to disclose homeowners' choice preferences of holiday and long-term rental attributes on average as well as the influence of particular context and socio-demographic variables on the rental choice and preferences. A mixed logit model is employed to test the existence of taste variations for attributes and a latent class model incorporating membership functions is employed to further examine differences between classes of homeowners. A stated choice experiment designed for identifying the rental choice behavior of homeowners provides the data for model estimation. The main findings indicate that financial factors including occupancy rate and daily income have a substantial impact on rental preference. Policy instruments like 30-day limit appear to be a major deterrent in the choice for holiday rental. Neighbors' attitude towards holiday rental also influences homeowners' rental choice. Furthermore, the results show that property types and conditions as context variables have a significant effect and there are differences in preferences among different socio-demographic groups.

Keywords: Rental choice behavior, Holiday rental, Long-term rental, Stated choice experiment, Discrete choice modeling

LIST OF ABBREVIATIONS

ASC	Alternative-specific constants
BIC	Bayesian Information Criterion
CME	Construction Management and Engineering
CT	Census tracts
DCM	Discrete choice modeling
EM	Expectation-Maximization
HR	Holiday rental
IID	Independently and identically distributed
LC	Latent class
LTR	Long-term rental
ML	Mixed logit
MLE	Maximum likelihood estimation
MNL	Multinomial Logit
OIS	Research Information and Statistics
PRS	Private rental sector
RUT	Random utility theory
SC	Stated choice
SD	Standard deviations
SHS	Standard Halton sequence

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CHAPTER 1: INTRODUCTION

Private rental sector (PRS) plays an important role in the urban housing market, by providing a housing option to the home seekers who are not willing or able to buy their own homes or has no opportunities to enter the social housing market due to disqualification or inefficiencies such as long waiting lists (de Boer, R. & Bitetti. R, 2014). Additionally, The PRS can promote flexibility in the housing system, making it easier to move with changing job opportunities or to adapt to changing family circumstances and to reduce the macroeconomic risks of home-ownership (André 2012). “The restructuring of welfare states in association with demographic and social change, labor force mobility and greater housing market diversity, has led to increased interest in the PRS as a place to live, an investment opportunity and a means of providing flexibility in housing systems” (Hulse ea. 2010).

Traditionally, properties provided in the PRS are long-term (private) rentals which are usually rented out to tenants (usually residents) for at least three months. In recent years, however, properties in the PRS are increasingly no longer used solely for residents’ living. Holiday rental has mushroomed into a global phenomenon. Holiday rental (HR), also called as “short-term rental” or “vacation rental”, are rental of residential homes to tourists for fewer than thirty days—often arranged through online accommodation platforms. In the meanwhile, there has been a large shortage of long-term rental (LTR) housing in recent years in many global cities such as Sydney, Helsinki, and Auckland (Hulse, Reynolds, Stone, & Yates, 2015; Otter, 2017; Wood & Ong, 2017).

1.1 Problem definition

The popularity of holiday rental, however, prompts concerns about PRS and the whole residential housing market. Critics claim platforms like Airbnb erode the supply of long-term rental housing by encouraging conversion to holiday rental (Hill 2015; Buchanan 2015), i.e. holiday rentals remove housing that would otherwise be rented in the PRS as long-term rentals. Numerous holiday rental properties are highly available year-round for tourists. Those holiday rentals probably don't have the owner present, could be illegal, and more importantly, are displacing residents - in other words, they are locked out of the long-term private rental market (Stone, 2018). Even if not all of them would be on the rental market otherwise, loss of any units in a city that already has a large waiting list for long-term rental housing is a problem (Childers, 2017).

Obviously, the holiday rental platforms cause some homeowners to choose to supply the holiday rental market in place of supplying the market for long-term rentals. Policymakers and researchers around the world have been struggling with limiting holiday rentals and promoting long-term rentals. However, homeowners' choice behavior behind this phenomenon has rarely been examined and barely understood. Therefore, the objective of this research is to identify and analyze the influence of factors on homeowners' choice to supply holiday rentals and long-term rentals.

1.2 Research questions

The main research question that will be answered within the thesis is:

Which factors influence homeowners' choice for holiday and long-term rental?

Sub questions that will contribute to the main question within the thesis are:

- *What are the main preferences of homeowners regarding holiday and long-term rental?*
- *What are the effects of rental property contexts on homeowners' choice for holiday and long-term rental?*
- *What are the differences in homeowners' preferences for holiday and long-term rental under different rental property contexts?*
- *What are the relationships between homeowners' socio-demographic characteristics and their choice for holiday and long-term rental?*
- *What are the differences in homeowners' preferences for holiday and long-term rental between different groups of homeowners varying in age, gender, education, income, work status, and landlord experience?*

1.3 Research design

To implement the research idea, we use Amsterdam, the capital city of the Netherlands as a case study. Because there is no existing data about the preference of Amsterdam's homeowners, we need to collect data and thus an experiment in the context of Amsterdam needs to be designed.

Figure 1 shows the overall structure of the research. As can be seen, the research starts with a literature study which provides an input for the following experimental design. This design of the stated choice experiment includes three parts in the order of (i) identifications of attributes, context variables, and their associated levels, (ii) experimental design generation as well as (iii) online survey construction. In the meantime, an expert interview is conducted to verify the attributes and levels. Once the online questionnaires are distributed and filled in by a reasonable number of respondents, the data will be collected, prepared and finally analyzed using discrete choice models to obtain a thorough understanding the choice preferences of homeowners.

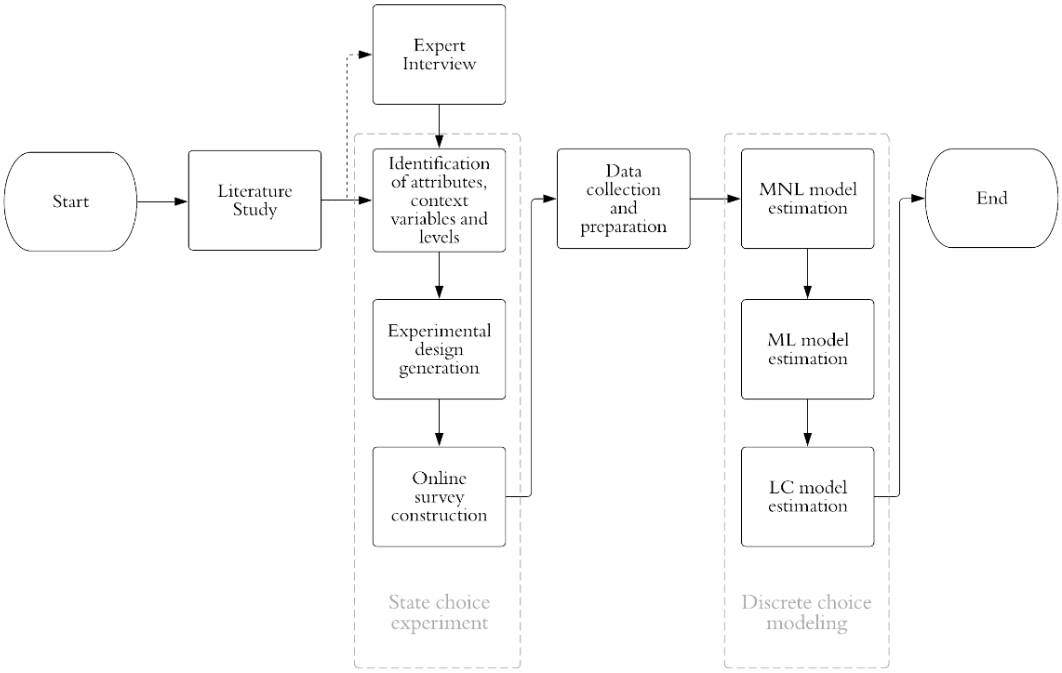

Figure 1 Research model

1.4 Significance of the study

Given the context of holiday and long-term rental choices, this study contributes to the state of art research in the housing market by further understanding the choice preferences of homeowners. It contributes to the academic understanding of homeowners' rental choice behavior by disclosing their preference for holiday rental and long-term rental. Previous studies mostly used qualitative research methods such as in-depth interviews, while this study will provide quantitative analysis. Additionally, socio-demographic characteristics of holiday rental hosts and long-term rental landlords have been identified in literature respectively; this research aims to provide more knowledge on this topic as well.

In addition, the research also has a clear practical relevance in terms of policy decision making. At the city level, this research can provide governments with useful insights into the effects of policy instruments on holiday rental by understanding the preferences of homeowners for holiday and long-term rental. Governments can, therefore, use the knowledge generated in this thesis as underpinning for their considerations of future policymaking. Although the experiment was taken in Amsterdam, other cities can also learn from this study.

1.5 Reading guide

This chapter provided a brief introduction to the subject and the main outlines of the thesis. Chapter 2 extensively discusses the relevant literature on the topic of holiday rental, long-term rental and choice behavior. Chapter 3 describes the methodology of the research. Chapter 4 presents and discusses the results of the study. Chapter 5 concludes this thesis by summarizing the main findings as well as their scientific and societal importance and provides recommendations for the future research.

CHAPTER 2: LITERATURE REVIEW

The main aims of this chapter are to have a better understanding of the topic of holiday and long-term rental, and more importantly, to capture the factors that may influence the homeowners' choice for holiday and long-term rental from the existing literature. Therefore, all relevant subjects for the thesis are presented. This chapter is organized from a global view to a local perspective. The literature review starts with an extensive discussion about holiday rental to learn its development and impacts. Then some stimulating policy options for the long-term private rental will be introduced. Following that, the case of Amsterdam will be presented to learn the experience of holiday and long-term rental in the local context. Then the focus will be on the discussions about the factors influencing homeowners' choice behavior. Finally, this chapter will end with a contextual framework of the research and an explanatory conclusion.

2.1 Holiday rental

Holiday rental has risen from obscurity to a global phenomenon in just a few years. It was the recent rise of online short-term accommodation platforms (e.g., Airbnb and HomeAway) that has enabled holiday rental to grow explosively (Wegmann & Jiao, 2017b).

These platforms are part of the rapidly growing and evolving 'sharing economy', generally defined as "an economic system that is based on people sharing possessions and services, either for free or for payment, usually using the internet to organize this" (Cambridge Dictionary). The sharing economy improves economic efficiency. In the case of holiday rental platforms, it allows individuals to make money from under-utilized properties and at the same time allows other individuals to have access to accommodation that they need without having to own the property (Borangiu et al., 2016).

The market leader, Airbnb, was founded in 2008 by three guys who could not afford the rent and put a mattress in their apartment to earn some extra money (Gallagher, 2018). This led to their idea of using the internet to match unused spaces and homes with those short-term accommodation seekers (Gallagher, 2018). After many failures, Airbnb has a considerable growth since 2010. The number of guests reached 17 million in the summer of 2015 (see Figure 2) (Smariga, 2015). In 2018, Airbnb was estimated to be worth over $38 billion and became one of the world's largest holiday rental accommodation brands (Trefis, 2018). Airbnb claimed they "provide access to 7 million unique places to stay in more than 100,000 cities and 191 countries and regions" (Airbnb, 2019).

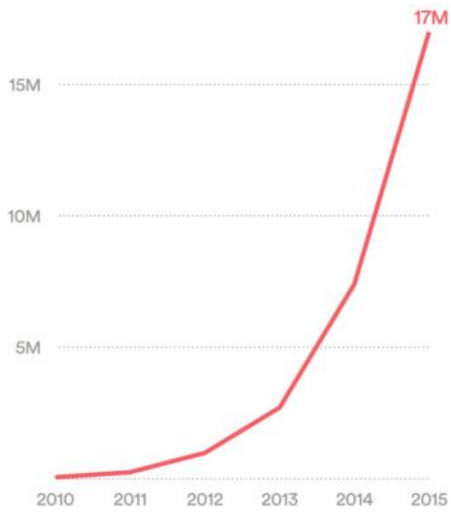

Figure 2 Number of Airbnb guests in the summer of 2015 (Source: Airbnb)

2.1.1 Property management agency for holiday rental

Accompanying the popularity of holiday rentals, numerous property management agencies emerged with the purpose of “providing a great variety of management services that span all the value-creation stages of a value chain” to holiday rental hosts (Sigala, 2018). Specifically, they assist hosts with: property decoration and design services, cleaning services, property security services, accounting and management consulting services (e.g. legal and tax services), etc. (Sigala, 2018). Sigala (2018) concluded that an increasing number of property management agencies enable and facilitate homeowners to ‘become’ professionists which means they can provide a hospitality experience similar to the hotel service. In this way, the holiday rental market is shaped and evolved into a commercialized ‘authentic’ hospitality experience (Sigala, 2018).

2.1.2 Impact of holiday rental on housing markets

The impact of holiday rental on local housing markets by reducing supply and raising rents and prices is an important issue and has received much attention. In Berlin, Schäfer and Braun (2016) find that over 5,500 Airbnb listings (0.3% of Berlin’s housing stock) are rented beyond the 90-day limit set by the government. The authors also find that rents have increased more significantly in areas with higher Airbnb density. In Boston, Horn and Merante (2017) state that every standard deviation increase in Airbnb stock is associated with a 0.4% increase in rents (and 3.1% in high-Airbnb-density areas), and a 5.9% decrease in long-term rental supply. The authors conclude that every 75.8 Airbnb listings equate with 4.5 fewer long-term rental properties. In Barcelona, Gant (2016) finds that in high-density areas, holiday rentals represent up to 17% of homes. Gant also interviewed locals about Airbnb’s impacts and finds nearly all of her 42 interviewees speak of displacement concerns. Gant summarizes that displacement occurs in various forms, including housing shortages, rent increases and frustrations with daily disruptions, which together produce a snowball effect of residents leaving and being replaced by tourism investors. Finally, in New York City, Wachsmuth and Weisler (2018) explain that because Airbnb creates a new opportunity to generate revenue through residential housing, it creates a “rent gap” in the sense that landlords’ actual earnings are smaller than their potential earnings. This leads to loss of rental housing via direct expulsions and indirect displacement as housing is made unaffordable.

2.1.3 The neighbors of holiday rental

In addition to influencing housing markets, holiday rentals are also criticized to have an impact on the daily life of locals especially neighbors. Gurran and Phibbs (2017) analyzes the written submissions by local planners and other interested parties to a government inquiry into holiday rental in Sydney, and find greater opposition coming from urban areas, characterized by concerns about issues like noise, traffic, parking, and waste management. In addition to the disruptions, Wegmann and Jiao (2017a) add that neighbors can experience a reduced sense of security as frequently changing ‘guests’ can have access to common areas in the case of entire apartments or rooms within a building are rented. The authors also point out that the quality of life impacts can be imposed by any type of holiday rental, whether the entire home or otherwise, and whether a given rental is rented occasionally or constantly. Horton (2015) also finds that holiday rentals allow hosts to impose a cost on their neighbors, particularly in apartment buildings where individuals live in close proximity and there are often heavily used common spaces. The author explains that ‘guests’ with no stake in maintaining good relations with neighbors will be more troublesome than the hosts. “A business built on beggar-thy-neighbor is very unattractive.” (Horton, 2015)

In order to learn how neighbors perceive the effect of holiday rentals and what they did in respond, a survey was conducted by OIS (2018) among 576 Amsterdam residents. The results show that half of the respondents have experienced a nuisance caused by holiday rentals in their area. Most of them do not take action and about a quarter ring the bell while only 9% report the nuisance to the municipality (OIS, 2018).

2.2 Long-term rental

After many years of decline (since the Second World War), long-term private rental has experienced a sizable growth over the past 10-15 years across many advanced economies (Pawson, Hulse, & Morris, 2017). In the aftermath of the 2008 financial and economic crisis, the recourses which governments can allocate to different housing policies (e.g. housing allowances) are limited, which makes PRS mode important. Policies aiming at promoting the

PRS are becoming a significant instrument to assure housing availability and affordability (Boer & Bitetti, 2014).

Boer and Bitetti (2014) propose some policy options to stimulate the long-term private rental: (i) housing allowance for tenants, (ii) tax relief measures aiming for neutrality, (iii) related investment costs deduction, (iv) supply subsidies, especially for low-income rental housing, (v) landlords should be entitled to discount depreciation from rental income, (vi) landlords should be entitled to increase the annual rent with part of the modernization costs when they renovate the rental property. Kath, Margaret, Wendy, and Judith (2015) also find that tax incentives could encourage the current profile of small-scale investors to invest in lower rent segments of PRS. Boer and Bitetti (2014), however, warn that it is hard to create an equal opportunity for succeeding in every country.

2.3 Long-term and holiday rental in Amsterdam

This section introduces the status of long-term private rental supply and holiday rental supply as well as the holiday rental regulations in the city of Amsterdam.

2.3.1 Long-term rental supply in Amsterdam

In Amsterdam, the latent demand for residential housing becomes manifest after the crisis in 2008 (Gemeente Amsterdam, 2019b). The housing prices are rising to a level that is not achieved anywhere else in the Netherlands (Gemeente Amsterdam, 2019b). An increasing housing shortage is being observed in the metropolitan municipalities, and the Amsterdam metropolitan region (MRA) is one of them, where the housing shortage is 6.6 % of the entire housing stock, i.e. one in every 15 homes that are needed is missing (Capital value, 2019). As a result, more residents of Amsterdam than ever will leave the city in search of locations with a more moderate price level (Gemeente Amsterdam, 2019b).

The total Amsterdam housing stock in 2018 consisted of almost 433 thousand homes, of which around 70% were rented properties (CBS, 2019). The majority of these long-term rental properties was the corporation home, but it was decreasing in size. Only a decade ago more than half of the Amsterdam housing stock consisted of corporation homes. That share was 43.1% in 2017 (see Figure 3) (OIS, 2019). The rest of the long-term rental properties were owned by private landlords. The share of PRS is gradually growing to a quarter of the total (OIS, 2019).

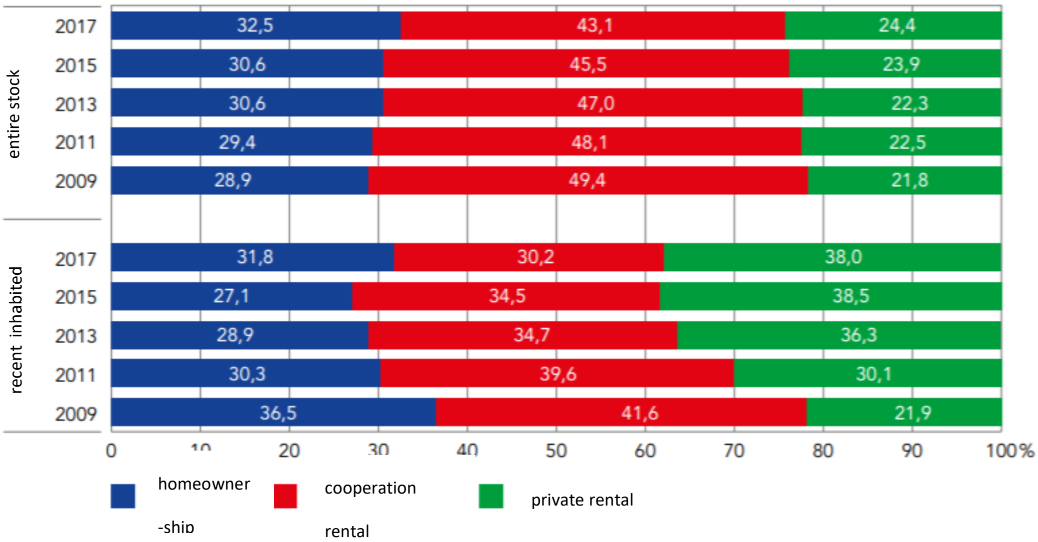

Figure 3 Amsterdam’s housing stock and recently inhabited housing by segment (Source: Gemeente Amsterdam)

The long-term private rentals can be further divided into two categories: social housing rentals and free sector. The rental category depends on the value of the main characteristics of the residence calculated via the housing valuation system (woningwaarderingsstelsel) (Gemeente Amsterdam, 2019c). Based on the results, rental homes that cost €720.42 or less in base rent per month (2019 threshold) are considered social housing rentals and therefore the rents are regulated; rental homes that cost more than the threshold are called free sector and landlord is free to set their own rental price (Gemeente Amsterdam, 2019c).

Because the property valuation (WOZ) value counts in the housing valuation system and these house values in Amsterdam have risen sharply, almost all Amsterdam rental properties can be liberalized in the event of a change. As a result, long-term private rental properties are increasingly being let in the free sector in all districts, as ca be seen from Figure 4. In 2007, 6% of the total housing stock was rented in the free sector by private landlords in a long-term, and in 2017, this number became 15%. Furthermore, a relatively large free sector rental market has emerged particularly in Center and South (18% and 20% respectively). In the contrast, the social rental of private landlords decreased from 18% to 13% of the housing stock; this mainly happened in the West and South.

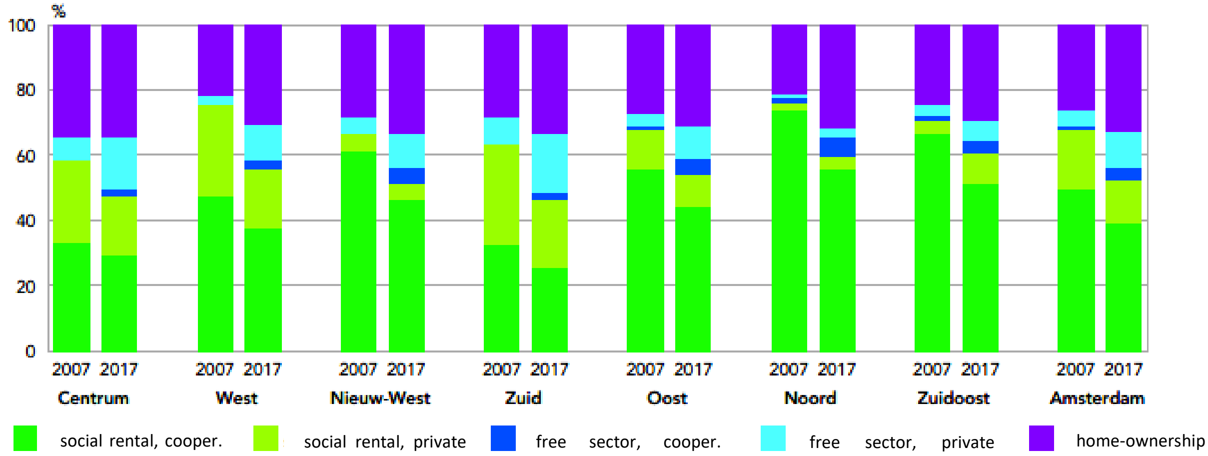

Figure 4 Amsterdam's housing stock by segment, 2007 and 2017 (percentages) (Source: Gemeente Amsterdam)

Regarding the rents, long-term private rental tenants in Amsterdam on overage paid €823 per month in Amsterdam in 2017 and the rents have risen by an average of €78 per month since 2015 (see also Figure 5) (Gemeente Amsterdam, 2019b). Moreover, the free market part of the long-term private rental is growing, and its rent is getting higher and higher compared to rents in the regulated segment. long-term private rental tenants in the free sector paid €1,160 per month in 2017, which is much higher than in the regulated segment (€489 per month) (Gemeente Amsterdam, 2019b).

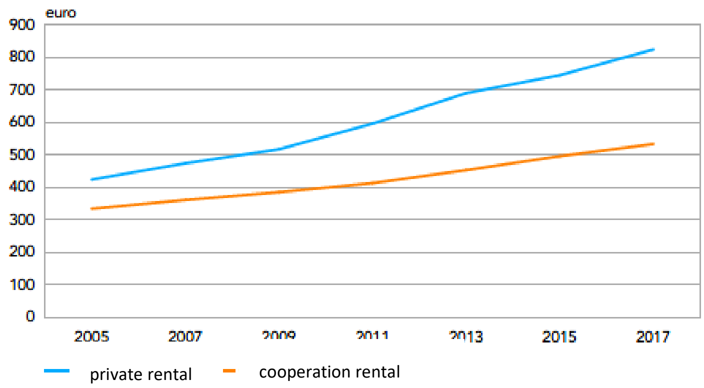

Figure 5 Average basic rent by rental sector in Amsterdam, 1997-2017 (Source: Gemeente Amsterdam)

2.3.2 Holiday rental supply in Amsterdam

The phenomenon of holiday rental has taken off for a number of years in Amsterdam. Figure 6 shows the number of listings on different platforms in December and it can be clearly seen that the listings on Airbnb are many times larger than that of other platforms, such as Booking, HomeAway and HouseTrip. Airbnb is the absolute market leader in Amsterdam.

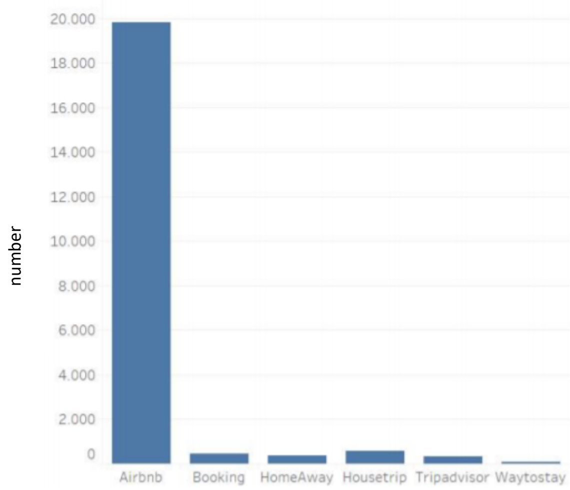

Figure 6 Listings in December 2018 on different accommodation platforms in Amsterdam (Source: Gemeente Amsterdam)

According to a report from the municipality of Amsterdam, there were approximately 21,040 active listings (rented at least once in a year) in Amsterdam on Airbnb in 2018, of which 79% are entire houses or apartments (Gemeente Amsterdam, 2019d). Figure 7 shows a continuous increase in the number of listings on Airbnb between 2016 and 2018. The total number of listings in 2016 is 17,113 and in 2017 this number is 19,063 (Gemeente Amsterdam, 2019d).

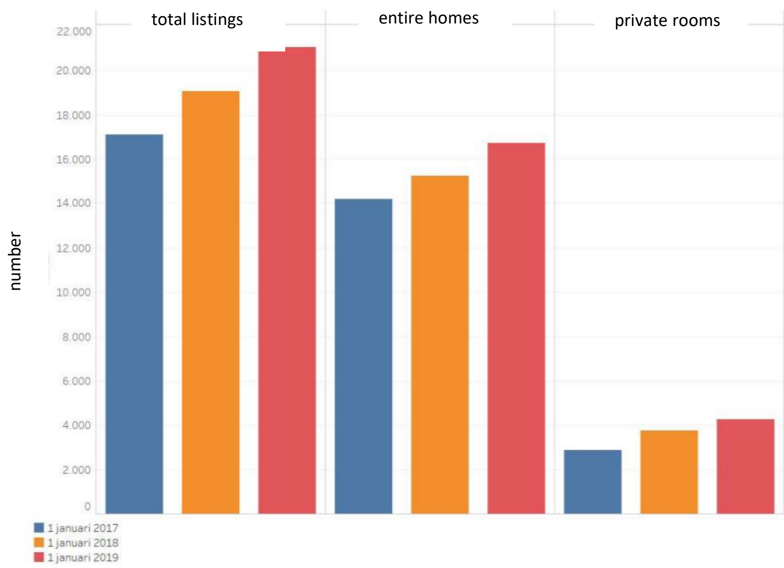

Figure 7 Number of Airbnb listings by property types 2016-2018 in Amsterdam (Source: Gemeente Amsterdam)

The number of listings per quarter in each district in 2018 is shown below (Figure 8). It can be seen that the supply per quarter is approximately the same in all districts. The majority of listings are located in the West, the Centrum, the Zuid and the Oost district, while the first one has the largest number of Airbnb listings. In contrast, there is relatively little supply in the Zuidoost district.

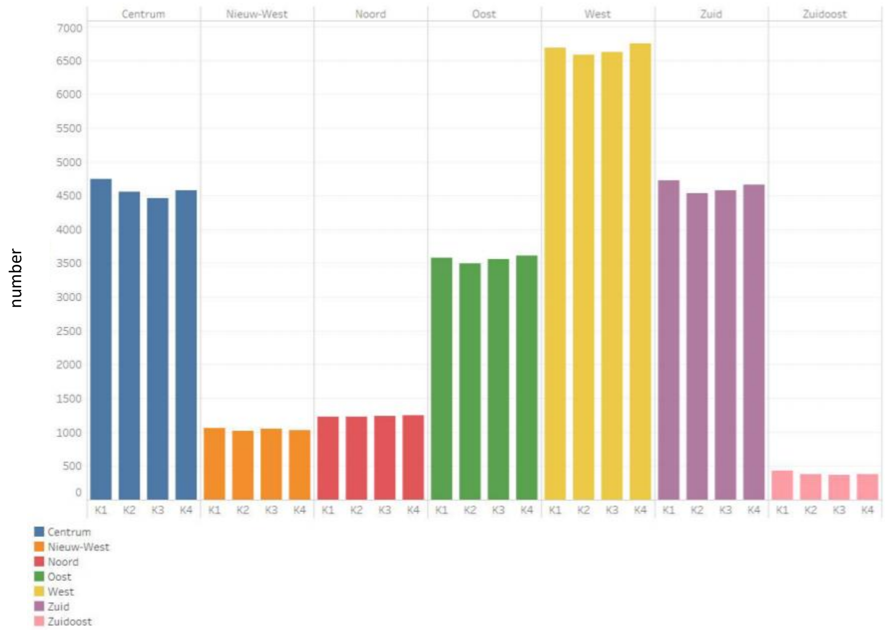

Figure 8 Airbnb listings per district per quarter in Amsterdam (Source: Gemeente Amsterdam)

Figure 9 shows the total holiday rental supply on Airbnb in relation to the total housing stock per district in Amsterdam. The housing stock figures include the number of owner-occupied homes, long-term corporation rentals, and private rentals. Airbnb figures include private rooms and shared rooms in addition to entire homes. The figures are therefore not fully comparable. Relatively speaking, the percentage of holiday rental supply in the district's total housing stock is the greatest in the Centrum and West districts. Approximately 1 in 8 homes is offered in Centrum, and in West that is about 1 in 9 homes. This may suggest the existence of holiday rental's impact on residential housing supply in the Centrum and West districts in Amsterdam.

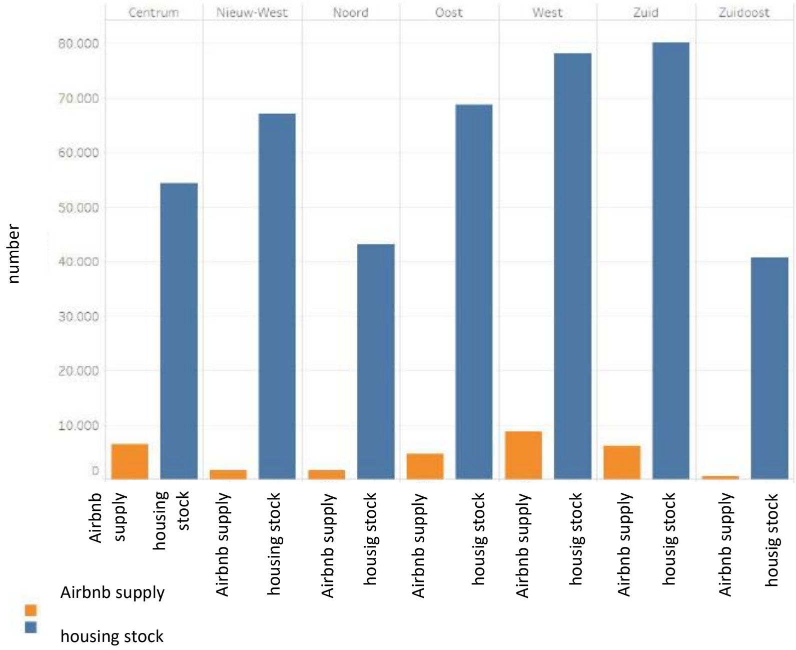

Figure 9 Airbnb's total supply in relation to the housing stock per district in Amsterdam (Source: Gemeente Amsterdam)

Furthermore, "the stricter rules that the municipality of Amsterdam has imposed on Airbnb hosts have little effect for the time being", according to the latest Airbnb report from property consultant Colliers International and data supplier AirDNA (Bakker, 2019). No less than 40% of the rented Airbnb homes in Amsterdam were rented out longer than the permitted 60 days in 2018, and 19% were even longer than 120 days (see Figure 10) (Bakker, 2019). As a result, these all-year-around highly available homes can no longer be bought or rented by long-term accommodation seekers. This displacement effect increases the shortage of homes and requires more to be built to meet demand (Bakker, 2019).

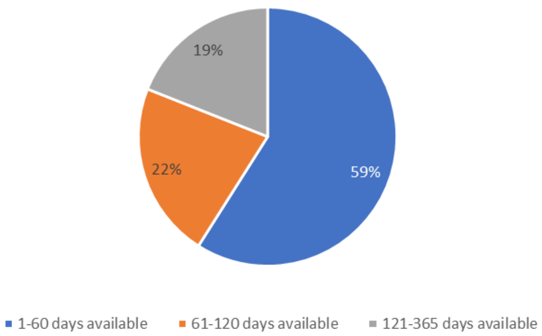

Figure 10 Available days on Airbnb and HomeAway in 2018 in Amsterdam (Data source: AirDNA)

Regarding the finance aspect of holiday rentals, the data company AirDNA employs two indicators to represent, namely the average daily rate and the occupancy rate. AirDNA collected data about holiday rentals listed on Airbnb and HomeAway; according to them, the average daily rate of was €165 in 2018 according to AirDNA (AirDNA, 2019). Interestingly, this figure is the highest amongst all European and U.K. cities, exceeding London. As for the occupancy rate, in 2018, this number on average was as high as 86% (AirDNA, 2019). This means in general holiday homes are easy to be rented in Amsterdam. It can be seen that in Amsterdam, holiday rental has a handsome financial return as the average daily rate and occupancy rate are both quite high.

2.3.3 Holiday rental regulations in Amsterdam

Concern over the impact of holiday rentals on housing has garnered significant attention from Amsterdam policymakers and has motivated the city to impose stricter regulations on holiday rentals. Two main measures are currently taken by the municipality of Amsterdam: First, they collect the tourist tax (7% of the listing price) directly from holiday rental hosts by asking them to declare the amount they earned each year (Gemeente Amsterdam, 2019e). Another regulation is that they limit the time for entire homes' renting. As of 1 January 2019, holiday rental hosts can only rent out their entire homes in Amsterdam for a maximum of 30 nights per calendar year (compared to the 60-day limit from 2016 to 2018), unless they have a specific permit that allows them to rent out for more nights (Gemeente Amsterdam, 2019a). Furthermore, the municipality of Amsterdam announced its intention to ban Airbnb rentals entirely in three parts of the city, including the red-light district (Boztas, 2018). Despite the efforts Municipality of Amsterdam has made, however, the amount of highly available entire homes/apartments on Airbnb is still huge as mentioned before. Therefore, the effect of current regulations needs to be examined and more customized policies are needed, in order to make Airbnb "less attractive" to homeowners.

2.4 Factors influencing homeowners' choice behavior

This section summarized the findings from the literature regarding influences on choice behavior. Five groups of factors have been identified, namely finance, socio-demographic characteristics, social influence, policy, and rental property's characteristics.

2.3.1 Finance

Finance is found to be a very important factor that influences homeowners' choice for holiday rental in many studies. Ikkala and Lampinen (2015) had 11 in-depth semi-structured interviews with Airbnb hosts in Helsinki, Finland, and observe that the possibility of earning money is an important factor in igniting participation in the holiday rental. Lampinen and Cheshire (2016) interviewed 12 Airbnb hosts in the San Francisco Bay Area, U.S., and find that earning money by hosting is mentioned frequently by hosts although it is very rarely the sole rationale for their participation. For many hosts, holiday rental is a convenient source of additional disposable income. Karlsson and Dolnicar (2016) directly asked 244 Airbnb hosts to tell their main reasons for becoming a holiday rental host via online survey and most answers (82%) fall into income category, where “for money” and “to afford luxury” are the most frequent motivations while only 16% uses the money to pay the bill. This finding seems reliable due to the comparatively large number of Airbnb hosts surveyed. Crommelin and Troy (2018)’s interviews with 50 Airbnb hosts in Sydney and Melbourne also finds that the main reason for hosting on Airbnb is to earn additional money from housing assets, in a way that is perceived to minimize risk. More importantly, the authors point out that the way better returns drive the hosts’ decision to choose holiday rental over long-term rental largely. Furthermore, the interviews reveal that some holiday rental hosts will likely return to long-term rental market over time due to a perception of declining profitability.

Slightly different from the holiday rental, finance is found to be the dominant determinant for homeowners to serve long-term rental market (Haffner, Hoekstra, Oxley, & van der Heijden, 2010; Lord, Lloyd, & Barnes, 2013; Ronald & Kadi, 2018; Scanlon & Whitehead, 2006). In the U.K., Lord et al. (2013) find that 63% of private landlords think investing in long-term rental property is the safest way to make money and nearly half (49%) think it is the best way to save for retirement. Similarly, Scanlon and Whitehead (2006) also comment that pension and investment purposes are the dominant reasons. In addition, 75% of long-term rental landlords stated that financial factors were behind their decision to continue being landlords. Ronald and Kadi (2018)’s survey results also suggest using the long-term rental property as a source for financing future welfare expenses is a key motivation for becoming a long-term rental landlord.

2.3.2 Socio-demographic characteristics of homeowners

Many studies have found that socio-demographic characteristics of homeowners are also related to their choice for holiday rental. Schor (2017) finds holiday rental hosts interviewed are highly educated, and many have well paying full-time jobs. Similarly, Crommelin and Troy (2018) comment that holiday rental hosts tend to be in the young and not to be in the lowest income brackets. Ke (2017) and Sarkar, Koohikamali, and Pick (2019) use another method in which they link a large number of Airbnb listings located in the U.S. and NYC neighborhoods respectively with census tracts (CT) data using OLS regressions. Interestingly, they both argue that holiday rental may be particularly attractive to low-income homeowners; this result is not consistent with what the previous studies have found. In addition, Ke (2017) finds income and education are the two most influential factors that are linked to the choice for holiday rental; areas, where there are a larger portion of residents with higher education degrees, have more holiday rental hosts. Sarkar et al. (2019) conclude that neighborhoods with a higher proportion of age 21+, white, males, employments with internet capabilities and digital skills are more likely to participate.

Those analyzing the role of financial factors typically assume that landlords are fully informed and rational. However, survey findings such as those reported in Kemp and Rhodes's (1997) study of Scottish landlords shed doubt on this assumption. Surveys also find key demographic characteristics of landlords that include the presence of children, retirement status, and divorce and separation to be correlated with rental decisions. Surveys in U.K. Scotland, Netherlands and Australia suggest that long-term rental landlords are more likely to be middle-aged (Crook, Ferrari, & Kemp, 2009; Lord et al., 2013; Ronald & Kadi, 2018; Wood & Ong, 2013), married (Crook et al., 2009; Lord et al., 2013; Plaut & Plaut, 2013), well-educated (Crook et al., 2009; Lord et al., 2013; Ronald & Kadi, 2018; Soaita, Searle, McKee, & Moore, 2017), raised up in an owner-occupied housing (Ronald & Kadi, 2018; Soaita et al., 2017) and high earner (Scanlon & Whitehead, 2006; Soaita et al., 2017). Interestingly, there seems to be no agreement with the work status. A survey in the Netherlands shows that employees (37%), self-employed (27%) and retired (20%) form the majority of long-term rental landlords in the Netherlands's private rental market (CBS, 2019). In Scanlon and Whitehead's (2006) survey in the U.K., about a third of landlords worked full-time and a similar proportion was retired. However, Wood and Ong's (2013) survey in Australia reveals that once retired, there is a sharp increase in the likelihood of exit from rental investments.

2.3.3 Social influence

Social influence has been found to be an important factor that can affect an individual's choice behavior in the study of travel behavior, residential location, and employment decisions (Páez, Scott, & Volz, 2008), which means individuals' choice behavior are likely to be influenced by others' behavior. In the context of homeowners' rental choice, there are two sources of social influence that may matter: neighbors' objection and many neighbors arranging holiday rental (or long-term rental).

As discussed before, holiday rentals can bring a negative impact on the daily life of neighbors. Therefore, those affected neighbors will have complaints more or less and that could harm the homeowner's relationship with them. To make things even worse, neighbors may even report the nuisance for instance to the government. Horton (2015) mentions that holiday rental hosts do not compensate or consider the interests of their neighbors. However, this needs to be examined. It is likely that homeowners think a good relationship with neighbors are important to them and (or) they probably do not want to take the risk of being reported.

The second type of social influence is an approximation of 'peer pressure' which is the direct influence on people by peers. When there is a large number of holiday rentals for instance in the neighborhood, homeowners are likely to get influenced and follow those holiday rental hosts' behavior.

2.3.4 Policy

Policy instruments are often included in the studies of choice behavior in various fields. For instance, results show that policies such as housing policy and income tax, etc. influence individuals' choice behavior in homeownership (Tazelaar, 2017). Moreover, the policy does not necessarily have to be the real policy as in reality; policy at the theoretical level or future policy options that are under consideration may have an effect on an individual's choice behavior and their influence also worth being examined. Arentze, Feng, Timmermans, and Robroeks (2012) introduced road bonus to respondents as a policy instrument that the national government might consider in the future, in order to test its impact and provide insights for the policymaker.

In the context of Amsterdam, there are mainly two policy instruments about holiday rental as mentioned before: days limit and tourist tax which are also applied in some other cities in the world. The purpose is to discourage homeowners from supplying the holiday rental market. However, the effects of these policy instruments on homeowners' rental choice are not clear yet. As for long-term rental, there is a potential chance that a subsidy could be introduced to courage homeowners choosing the long-term rental market to supply.

2.3.5 Rental property's characteristics

Although no existing literature has taken the rental property's characteristics into account, they may affect homeowners' rental choice behavior too since housing characteristics are distinguished in pieces of literature regarding housing choice and preferences. Specifically, the type, size, condition and location of the property are commonly identified as important variables influencing sample' choice behavior (Jabareen, 2005; Timmermans & van Noortwijk, 1995).

2.5 Conclusion

In summary, previous research shows that finance is a very important factor influencing homeowners' choice in holiday rental and a dominant factor influencing their choice in long-term rental. Socio-demographic characteristics are found to have effect as well. There is no literature directly showing that social influence, policy, and rental property's characteristics have an effect on homeowners' rental choice, but some supporting evidence suggests that it may be worthwhile to examine their influence too. Besides these five groups of factors found in the existing literature, managing methods may be considered as one potential influential factor too, since the emergence of property management agencies shows that homeowners have different preferences for managing methods. Therefore, in total six groups of factors were identified for this study. They are assumed to have effects on homeowners' rental choice for holiday and long-term rental. The conceptual framework is then generated for this study (see Figure), showing this process.

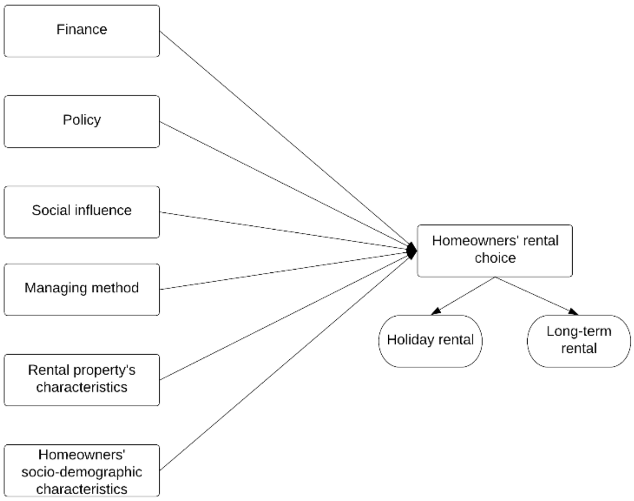

Figure 11 Conceptual framework

Specifically speaking, the finance factor can be represented by two attributes of holiday and long-term rental, including the daily income and the occupancy rate, which are the two indicators of profitability used by the data company AirDNA. For holiday rental, there are two main existing policy instruments namely tourist tax and days limit, and for long-term rental, there are some potential policy options and with the help of the expert interview, the most promising one(s) will be selected. As for rental property's characteristics, type, condition, and location will be considered in this study. A few homeowners' socio-demographic characteristics that may influence homeowners' rental choice have been identified in previous studies, namely gender, age, income, education, and work status. Besides these, whether the homeowner has experience of renting out properties to tourists or residents may also have an effect and therefore needs to be considered as well.

CHAPTER 3: METHODOLOGY

The main methods selected for this study are the stated choice (SC) experiment and discrete choice modeling (DCM). This chapter provides information concerning the two methods as well as justifications for the use of the methods. It also presents the description of the research process, which includes various stages, namely experimental design, expert interview, data collection, and data analysis.

3.1 Stated choice method

As mentioned in the introduction, the main question of this research is: which factors influence homeowners' choice for HR and LTR. Thus, measuring homeowners' choice behavior is required for this study to disclose the underlying factors and their preferences for those factors.

Generally, there are two broad types of methods to measure an individual's choice behavior (see Figure 12): (i) revealed choice/preference method and, (ii) stated choice/preference method. The first method is based on observations of an individual's behavior in real market situations, whereas the stated method is based on observations of responses in controlled hypothetical situations (Kemperman, 2000). There are two broad categories of stated response: (i) An individual is asked to choose one of the combinations of attributes which define services or products. (ii) An individual is asked to indicate his preferences among a set of combinations of attributes on one of two metric scales – a rank ordering or a rating scale (Hensher, 1994). Among the stated preference approaches, the compositional approach can be distinguished from the decompositional approach. In the compositional approach, respondents evaluate the attractiveness of the levels of each attribute on some rating scale as well as the relative importance of each attribute (Kemperman, 2000). In contrast, decompositional approaches require respondents to make trade-offs among attributes so importance weights of attributes are derived from responses (Kemperman, 2000).

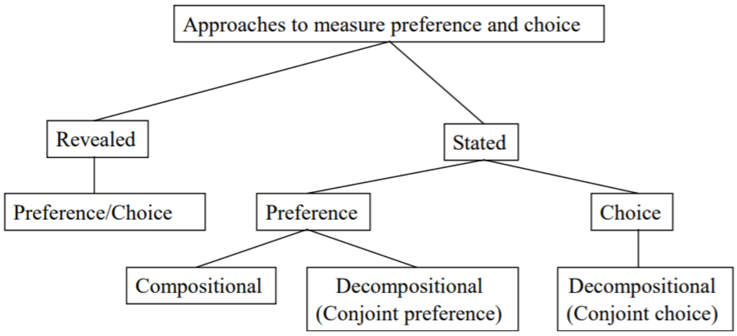

Figure 12 An overview of preference and choice measurement approaches (Source: Kemperman, 2000)

For privacy reasons, it is not possible to approach a sufficient number of landlords especially holiday rental hosts in Amsterdam. Therefore, it is very difficult to collect the observational data and thus revealed choice/preference modeling approach cannot be applied to this study. Decompositional approach is preferred over the compositional approach because the former is based upon a more realistic task that homeowners perform on the real market. Considering there are only two alternatives ("HR" and "LTR") without considering the "no preference" option and the stated choice approach is easier for respondents, the stated choice approach was selected for this study.

The stated choice method has been applied in many different fields such as marketing, transport, and environment valuation, etc. (Shen, 2005). It has also been applied to the field of real estate, although until now there is not much literature as in marketing and transport studies. Kemperman (2000) summarized manifold strengths of SC method as follows: (i) The internal validity is often high since the choice sets are constructed, controlled and randomly assigned to respondents by the researcher. (ii) The relative importance of attributes influencing people's choices can be measured quantitatively. (iii) More than one observation per respondent can be made. (iv) Variables that are not yet available in the market can be included and estimated in the model so the impact of planning or policy decisions on an individual's behavior can be assessed. However, there is a concern about the external validity of this method because individuals may make different choices in hypothetical choice situations and in real situations (Kemperman, 2000). In the study, over complex choice tasks should be avoided, and the design should be as realistic and reasonable as possible, so as to extract preferences that more closely reflect true behavior in real markets. Another great challenge which I may face in the process of research is how best to take into account the huge amount of variation in reasoning underlying the same choice outcome, and the rejection of the non-chosen alternatives (Hensher, Rose, & Greene, 2015).

3.2 Modeling approach

As mentioned in section 3.1, to analyze the stated choice data generated from the stated choice experiment, a statistical choice model is required. Discrete choice models can describe, explain, and predict choices between two or more discrete alternatives (Train, 2009). As mentioned in section 3.1, discrete choice models are developed based on random utility theory (RUT).

3.2.1 Random utility theory

Random utility theory assumes individuals use process rule or utility function to integrate information about the attributes of alternatives (J. J. Louviere & Timmermans, 1990). Not all but part of attributes and alternatives may be chosen by individuals to consider and evaluate because of the limitation in human information processing capabilities or differences in personal tastes. Individuals are assumed to form impressions about various important attributes of alternatives and make value (utility) judgments. These utilities are then integrated by individuals into an overall impression (utility) of an alternative. It is assumed that individuals try to choose the best option for their circumstances in a utility maximization process. The choice stated by individuals is the outcome which reveals their attribute utilities. Therefore, the functional form of an individual's or group's utility function can be diagnosed by designing an stated choice experiment and performing certain statistical analyses on the stated choice data (J. J. Louviere & Timmermans, 1990).

As mentioned, Individuals try to choose the alternatives they like best but may not choose what seems to the analyst to be the preferred alternative (Jordan J. Louviere, Hensher, & Swait, 2000). Such variations in choice can be explained by proposing a random element as a component of the individual's utility function as follows:

$$U_i = V_i + \varepsilon_i \tag{1}$$

where U_i is the unobservable, true utility of alternative i; V_i is the structural (observed) component of utility; and ε_i is the random (unobserved) component.

Typically, the observed component of utility function involves a simple linear combination of the captured explanatory variables and parameter estimates (J. J. Louviere & Timmermans, 1990), as shown in Equation (2):

$$V_i = \sum_k \beta_{ik} X_{ik} \tag{2}$$

where β_{ik} is the utility coefficient associated with the captured key explanatory variable X_{ik} (e.g., socio-demographic characteristics of the respondent, context variables, attributes of the alternative and interactions between these elements).

The unobserved component of utility captures the factors that affect utility but are not measured within V and not observable by the analyst. The presence of this random component permits the analyst to make probabilistic statements about individuals' choice behavior (Jordan J. Louviere et al., 2000). The probability that an individual will choose the alternative i from the choice set $\boldsymbol{J}$ can be expressed as:

$$P_i = P\big(U_i > U_j; \forall\, i \neq j \in J\big) = P(\varepsilon_j < \varepsilon_i + V_i - V_j; \forall\, i \neq j \in J) \qquad (3)$$

3.2.2 Discrete choice models

To transform the above random utility model into a choice model, certain assumptions about the distribution of the random component in the sampled population are required (Shen, 2005). Many different probabilistic choice models can be derived by making different assumptions about this distribution.

The most basic and commonly applied discrete choice model, the Multinomial Logit (MNL) model, assumes that the random variables are independently and identically distributed (IID) across alternatives and observations following EV1 distribution (Hensher et al., 2015). In other words, the unobserved effects are not correlated and their distributions are all the same (Train, 2009). In the MNL model, the probability that individual n will choose alternative i from the choice set of J alternatives can be expressed as:

$$P_{in} = \frac{\exp(V_{in})}{\sum_{j=1}^{J} \exp(V_{jn})}; j = 1, \ldots, i, \ldots, J \qquad (4)$$

The mixed logit (ML) model assumes that parameters vary from one individual to another. It is, therefore, a model that takes the heterogeneity of the population into account. It assumes that at least some of the parameters are random and they follow continuous distributions over the sampled population (J. J. Louviere & Timmermans, 1990). The mean and variance of the parameters are both estimated, and the significance of the variance indicates the existence of heterogeneous preferences (Feng, Arentze, & Timmermans, 2013). The ML model is summarized in Equation (5):

$$\mathrm{P}\left(choice_{ns} = \mathrm{i} \middle| X_{nsj}, Z_n, V_n\right) = \frac{\exp(V_{nsi})}{\sum_{j=1}^{J}\exp(V_{nsj})} \tag{5}$$

where

$V_{nsj} = \beta_n{}' X_{nsj}$

$\beta_n = \beta + \Delta Z_n + \Gamma V_n$

$X_{nsj} =$ the attributes of alternative j in choice situation s faced by individual n;

$Z_n =$ a set of characteristics of individual n that influence the mean of the taste parameters;

$V_n =$ a vector of random variables with zero means and known variances and zero covariances.

the latent class (LC) model assumes that there are certain numbers of latent (unobserved) classes among individuals (Feng et al., 2013). Unlike the ML model which specifies the random parameters to follow a continuous joint distribution, the LC model uses a discrete number of classes to describe the joint function of the parameters (Feng et al., 2013). Within each class, the choice preferences are assumed to be homogeneous (Feng et al., 2013). Within class c, the probability of an individual n choosing alternative i is:

$$\mathrm{P}(\mathrm{choice}_n = \mathrm{i}|class = c) = \frac{\exp(\alpha_{ic}+\beta'_c X_{ni})}{\sum_{j=1}^{J}\exp(\alpha_{jc}+\beta'_c X_{nj})}; \mathrm{j} = 1, \dots, \mathrm{i}, \dots, \mathrm{J} \tag{6}$$

where α_{ic} is the class-specific constant; β'_c is a vector of the utility parameters for class c; X_{nj} is a vector of independent variables that are varied by alternatives.

The classes are unknown at first and the probability of individual n being in class c, namely the class membership probability, can be represented by Equation (7):

$$W_{nc} = \frac{\exp(\theta_c Z_n)}{\sum_{c'=1}^{C}\exp(\theta_{c'} Z_n)}; c = 1, \dots, c', \dots, C \tag{7}$$

Where Z_n is a vector of class variables of respondent related characteristics; θ_c is the vector of parameters to be estimated for class c.

The unconditional probability of choosing alternative i is:

$$P_{ni} = \sum_{c'=1}^{C} P_{ni|c} W_{nc} \tag{8}$$

Three models have been selected to be applied to this research, namely the Multinomial Logit (MNL) model, the Mixed Logit (ML) and the Latent Class (LC) model. The MNL model was often used (and also in this study) to provide the foundation for the analysis of discrete choice modeling. Then the ML model and LC model were both used to identify the heterogeneity in homeowners' rental choice preference. The benefit of using ML model is that it can accommodate individual unobserved heterogeneity by allowing parameters to differ across observations, and thus, can provide more reliable parameter estimates (Cerwick, Gkritza, Shaheed, & Hans, 2014). However, this method has limitations such as a distribution relating how parameters vary across observations that need to be assumed and it requires a great deal of computation effort (Cerwick et al., 2014). These requirements can be relaxed in the LC model which, however, does not account for the possibility of variation within a class as it assumes homogeneous characteristics of the within-class observations (Cerwick et al., 2014). Due to the fact that each model has its benefits and limitations, these two advanced discrete choice models were both used in this study.

3.2.3 Estimation method

The ultimate purpose of estimating the choice model is generally to obtain unbiased estimates of the parameters β's, which contains marginal utilities of attributes (Adamowicz, Louviere, & Swait, 1998). The most common method when dealing with discrete data is called "maximum likelihood estimation" (MLE) (Hensher et al., 2015). Given a sample of k observations, the probability for the model to reproduce the whole sample is called the likelihood and is given by:

$$\mathrm{L}(\beta) = \prod_k \prod_i {P_{ik}}^{y_{ik}}(\beta) \tag{9}$$

where $P_{ik}(\beta)$ is the probability function corresponding to the discrete choice model under consideration. y_{ik} is an indicator variable; it is defined as 1 if observation k chose alternative i and 0 otherwise (Bierlaire, 2003).

Therefore, the log-likelihood function is:

$$\mathrm{LL}(\beta) = \sum_k \sum_i y_{ik} \ln P_{ik}(\beta) \tag{10}$$

The unknown parameters β's can be obtained by maximizing the log-likelihood function (Hensher et al., 2015).

However, one disadvantage of MLE is that it does not work particularly well for an incomplete data set. For the LC model, the belonging of individuals to the corresponding latent class is a piece of missing information. Therefore, MLE is usually used in MNL and ML model while it is not suitable for the LC model. The more complex Expectation-Maximization (EM) can treat the estimation of LC model parameters as an estimation problem in presence of missing data, which is an iterative way to approximate the maximum likelihood function (Mooijaart & van der Heijden, 1992).

3.3 Experimental design

The foundation of this study is the design of stated choice experiment (termed as "experimental design"). Figure 13 shows an overview of the experimental design process composed by Hensher et al. (2015). This process begins with specifying the problem, such that it would be clear what should be achieved in the end. Once the problem is specified, the list of alternatives, attributes and attribute levels within the experiment needs to be identified and refined. Then in stage three, the statistical properties of the design are considered, and the experimental design may be generated using a statistical package. The attributes selected in stage two need be allocated to specific columns of the design. This is followed by constructing choice sets that will be used in the questionnaire. The order of appearance of these choice sets shown to each respondent is randomized to avoid biases from order effects. The final stage is the construction of the survey which includes choice sets as well as other questions that may be necessary to answer the original research problem. A detailed description of how I went through these stages is provided below.

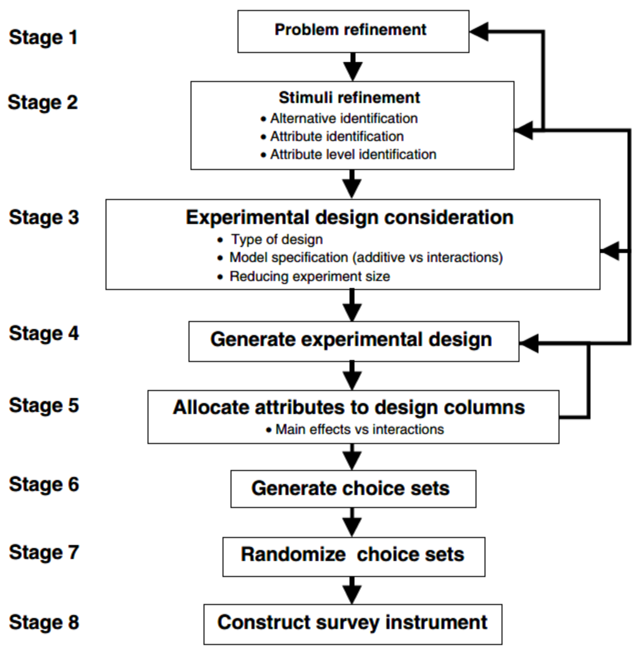

Figure 13 Experimental design process (Source: Hensher, 2015)

3.3.1 Stage 1 and 2: problem and stimuli refinement

The research problem is to capture the preference of landlords on the choice of rental method, between holiday rental and long-term rental. Therefore, holiday rental and long-term rental were alternatives in the experiment. Furthermore, homeowners may be unwilling to choose either of these two alternatives. Instead, they may want to sell the property or keep it there without doing anything to it. Therefore, a no-choice alternative labeled "none of these" were also included in the experiment.

Rental choice behavior is complex and according to literature, there are various factors that could influence landlords' rental choice. Based on a literature review and an expert interview, important attributes and their associated levels were identified, as Table 1 presents.

Table 1 Attributes and levels

Category	Attribute	Level		Explanation
		Holiday rental	Long-term rental	
Finance	Occupancy rate	35% 65% 95%	65% 95%	The total number of days in a year that the property will be occupied by tenants divided by the number of available days in a year.
	Daily income (euros)	100 200 300	30 60 90	The average daily income generated by renting out a specific property.
Managing method	Managing method	Yourself Agency	Yourself Agency	A rental property can be managed by either a landlord himself or by a property management agency.
Policy	Days limit (days)	30 180 330		The maximum number of days that is allowed by Amsterdam municipality for an entire home to be rented out in a year.
	Tax	1000 2000 3000		Additional tourist tax charged on holiday rental hosts per year by the municipality.
	Subsidy		1000 2000 3000	The financial aid per year given by the municipality to landlords to encourage long-term rental.
Social influence	Neighbors' attitude	Objection neutral		Neighbors may be unhappy with the negative influence caused by the tourist guests in the

			rental property and thus may report it to the municipality.
Number in the neighborhood	small large	Small large	The number of holiday rental/long-term rental properties in the neighborhood where the property is located. The larger the number is, the more popular this rental type is.

The attributes can be grouped into four categories: income, managing method, related policy, and social influence.

Finance

Financial reward is the most influential factor found in the literature review. The first and second attributes, occupancy rate and daily income, which are the indicators of income, are therefore included in the choice set.

For holiday rental, the occupancy rate means the number of booked days on the platform divided by the total number of days available over the year (Airdna, 2019). It varies in a wide range. Additionally, since holiday rentals by nature mostly attract tenants in the form of tourists, travelers (both business and leisure), visitors, and vacationists, their performance can be extremely seasonal. Therefore, the occupancy rate may also vary in different seasons. Three levels for this attribute were assumed: 35%, 65% and 95% which represent low, middle and high occupancy rate respectively. For long-term rental, the occupancy rate of a rental property is the number of days in a year that the property will be occupied by a tenant; the number is usually high and can be as high as 100% sometimes. For this attribute, two levels were assumed: 65% and 95%, as it is not likely to have a low occupancy rate in Amsterdam.

Daily income for holiday rental hosts means the price per night listed on Airbnb minus the part was taken by Airbnb. Three levels were set for this: €100, €200 and €300. When determining the levels, to make the number more realistic for respondents, data about all listing prices in Amsterdam on 8 April 2019 provided by Inside Airbnb (Inside Airbnb, 2019). were used as reference. For long-term rental landlords, daily income equals the monthly rent divided by 30 days. The rents were adjusted in this way so as to have a more direct comparison between holiday rental and long-term rental in terms of income. The average monthly rent in the free sector in Amsterdam in 2019 is €23.28 per 100 m^2 (Damen, 2019), so the average daily rent is €77.6 per 100 m^2. Considering both rooms and entire apartments/houses were considered in the experiment, the final levels were set as €30, €60 and €90.

Managing method

As mentioned in the literature review, there is a certain number of holiday rental hosts using the service provided by property management agencies which manage the advertisement, communicate with (potential) guests, take care of guests and all the work that comes with it. Two levels were assumed for the managing method attribute: managing by yourself and managing by the agency.

Related policy

Days limit is an important policy regarding holiday rental in Amsterdam. Currently, the maximum days that an entire home can be rented in a year is 30 days. Landlords who break the policy will get fined. However, there are still many landlords doing so because it is hard for the municipality to catch them. To examine the influence of different days limits, three levels were assumed: 30, 180 and 330 days.

Additional taxation in terms of tourist tax has been applied to Amsterdam holiday rental hosts. On the other hand, a long-term rental subsidy was introduced to respondents as a policy instrument that Amsterdam municipality may consider in the future to stimulate homeowners to choose (or change to) long-term rental. In absolute terms, the same tax and subsidy levels were used for holiday rental and long-term rental respectively. For the convenience of respondents, three levels were assumed: €1000, €2000 and €3000 per year.

Social influence

As mentioned in the literature review, holiday rental has caused negative influences on residents especially neighbors, and many Amsterdam residents expressed their unsatisfaction with their neighbors who rented their homes to tourists as holiday rentals and some would report the “trouble” to the municipality. Therefore, neighbors’ attitude may influence homeowners’ decisions about renting as holiday rental because they may want to avoid trouble and have a harmonious relationship with their neighbors. Two levels were distinguished for a neighbors’ attitude attribute: objection and neutral.

Another important form of social influence is that when a large number of homeowners in the neighborhood renting out their properties to tourists (or residents), homeowners may want to follow the peer. This attribute was defined in terms of the number of holiday rentals (or long-term rentals) in the neighborhood and two levels were assumed, namely small and large.

In addition to the attributes of alternatives, also several context variables were varied in the experiment. It is important to examine context effects since people may have specific preferences in different choice contexts (Feng et al., 2013). In other words, preferences or utility functions can only be valid if certain requirements are met because contexts (backgrounds) affect people's evaluation (Timmermans & van Noortwijk, 1995). Therefore, context variables are necessary and the relation between context and choices made needs to be specifically addressed in the processes of both experimental design and model development (Feng et al., 2013). Another reason for including them in the experiment was that they may increase a sense of reality and, thus, help respondents to make a vivid imagination of a presented choice situation (Arentze et al., 2012).

To examine a series of context effects, the regular stated choice experiment needs to be upgraded to a context-dependent stated choice experiment, where participants to make choices between choice alternatives assuming that a certain context applies (Molin & Timmermans, 2010). This requires the construction of two experiments: a regular experiment with choice alternatives and a context experiment that varies the context variables (Molin & Timmermans, 2010). These are then combined by nesting the choice alternatives under the context descriptions (Molin & Timmermans, 2010).

The context variables in this study include type, condition, and location of the rental property. Table 2 shows all the context variables and their levels. Property type is potentially a significant contextual factor, as homeowners with a spare room may find meeting and hosting new people very frequently particularly objectionable. Condition of property was defined qualitatively as 'poor', 'moderate' and "good'. Homeowners may be sensitive to the tear and wear caused to the property in a very good condition by renting it out to tenants for long periods. The location of the property was detailed as: inside Amsterdam center, inside the ring road A10 but outside Amsterdam center as well as inside the city of Amsterdam but outside the ring road A10.

Table 2 Context variables and levels

No.	Context variables	Level 1	Level 2	Level 3
1	Type of property	Room	Entire apartment	Entire house
2	Condition of property	Poor	Moderate	Good
3	Location of property	Inside Amsterdam center	Inside the ring road A10 but outside Amsterdam center	Inside the city of Amsterdam but outside the ring road A10

3.3.2 Stage 3, 4 and 5: experimental design generation

Having identified the alternatives, attributes and levels in the regular experiment and context variables and levels in context experiment, a decision must be made as to the design to be used for each experiment. A typical choice is between a full factorial design and a fractional factorial design. Full factional design is a design in which all possible combinations of the attribute alternatives are used. The number of all possible combinations equals L^M, where L is the number of attribute levels and M is the number of attributes. In the context experiment, there are three variables with 3 levels yielding 27 (i.e., $3^3 = 27$) possible combinations. Full factional design fits well in this experiment. However, in the regular experiment, there are 6 attributes with 3 levels and 6 attributes with 2 levels. This yields 93,312 (i.e., $3^6 \times 2^6 = 46656$) different treatment combinations. From a practical viewpoint, it is unreasonable to provide respondents with such a huge amount of choice sets. Therefore, the alternative fractional factorial design was chosen in which only a fraction of the treatment combinations was used.

The second issue is to choose which treatment combinations to use in the fractional factorial design. A random selection is likely to produce statistically inefficient or sub-optimal designs (Hensher et al., 2015). To selects the optimal treatment combinations to use, Hensher et al. (2015) presented the steps to generate an orthogonal design (see Figure 14). In this study, an orthogonal main effects only design was used in which all main effects (treated as linear) were modeled; interaction effects are assumed non-significant and therefore ignored. This assumption is mostly reasonable because the main effects explain the largest amount of variance in response data (Hensher et al., 2015). Through the orthogonal main effects only design, the main effects are independently estimable of all other effects. In this experiment, there are 2 labeled alternatives, 6 attributes with 3 levels and 6 attributes with 2 levels in total, and only linear effects are estimated. Each L-level attribute requires (L-1) degrees of freedom for main effects to be estimated and thus a minimum of 18 (i.e. $6 \times 2 + 6 \times 1 = 18$) degrees of freedom would be required for the design used to estimate the main effects. The design requires $\mathrm{S} \times (\mathrm{J} - 1) \geq 18$, where s is the number of the treatment combinations (i.e. choice situations) and J is the number of alternatives which is 2 in this case, hence $\mathrm{S} \geq 18$. In the end, the design size of treatment combinations was set as 72, which is greater than the required number and could produce an integer when divided by 6.

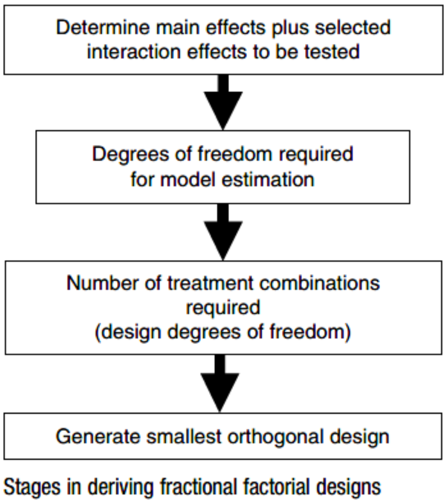

Figure 14 Stages in deriving fractional factorial designs (Source: Hensher, 2015)

Certain software containing computational algorithms are usually used to generate treatment combinations for factorial designs. In this study, R with AlgDesign package was employed. Firstly, a full factorial design for the context experiment was generated given variables' names and the number of levels of each variable. Then, a fractional factorial design with a design size of 72 treatment combinations was generated given attributes' names and the number of levels of each attribute as well as the number of trials (design size). Appendix A provided the code.

The generated results were copied and pasted on Excel to test the correlation of main effects. Noticing the results were presented with specific design codes, they were represented by orthogonal code. The result of the correlation check showed, as can be seen in Appendix A, there are no correlations between the attributes, implying the designs are orthogonal (Hensher et al., 2015).

Finally, the code in the generated designs was replaced by the real value of the levels. The 72 treatment combinations (see appendix B) and 27 combinations of contexts (see appendix B) were later used a pool of choice sets and as a pool of context profiles within the online survey system respectively.

3.3.3 Stage 6, 7 and 8: choice sets generation and online survey construction

The generation of the combined context - choice tasks followed the method used by (Molin & Timmermans, 2010). Each respondent has presented nine choice sets arranged in three sets with the same context setting. The combined choice sets and contexts were generated for a respondent as follows. First, a context situation was randomly drawn from the pool of context profiles. This was followed by a random draw from the pool of the choice sets. To limit the amount of new information presented to the respondent, the same context applied for the following two (randomly drawn) choice sets as well. This procedure was repeated twice to generate the next two sets that each contain three combined context - choice tasks. Hence, each respondent was presented in a total of three different contexts and nine different choice sets. An example of a choice task is shown in Figure 15. The levels of any given attributes or context variables were controlled to appear the same number of times as all other levels for that particular attribute or context variable and thus this was a balanced design.

Imagine you have **an entire spare house** in **good condition** located **inside the center of Amsterdam**. Which option would you choose in the future to rent your property out?

	Holiday rental	*Long-term rental*
Occupancy rate	65%	95%
Daily income	100 Euro/day	60 Euro/day
Rental days limitation	180 days	
Holiday rental tax	- 1000 Euro/year	
Long-term rental subsidy		+ 2000 Euro/year
Managing by	Yourself	Agency
Neighbors' attitude	Objection	
Respective numbers in the neighborhood	Small	Large
Your choice	○	○
	○ **None of these**	

Figure 15 An example of a choice task

The above could be realized together with other parts of the survey using the "Berg Survey System 2.2" which is the online questionnaire system of the Built Environment department of the Eindhoven University of Technology. The online survey started with an introductory page explaining the research and data policy. The next page was about socio-demographic characteristics of the respondents, which included questions about age, gender, education level, work status, household status, income, 6-digit postcodes and numbers of residential properties owned in Amsterdam. Then there came questions about respondents' opinions on holiday rental. They were also asked if they are or used to be a holiday rental host or long-term rental landlord. The final part was the SC experiment which consists of a page with an explanation of the attributes and an example choice set followed by the 9 choice tasks. The complete online survey in Dutch with screenshots of each page and the English version can be found in appendix C.

3.4 Expert interview

An expert interview is an interview type in which open questions are asked to a person that is an expert in his or her field of activity (Flick, 2006). According to Stake (1995), an expert interview is the main road to multiple realities and the selection of the right expert(s) is crucial. In this study, the main purpose of the expert interview is to validate the outcome of identification of the attributes and their associated levels, based upon the expertise of an Amsterdam's policymaker. To realize that, an expert interview with Wilbert Kalfsvel, an advisor in the team of a holiday rental in Amsterdam municipality was carried out.

The most important findings of the expert interview regarding the discussion of relevant attributes and levels are:

- In order to collect data of proper quality, not all influencing factors of landlords' rental choice behavior would be included in the experiment and the choice sets could not be too comprehensive.
- The occupancy rate is an important attribute and thus needs to be included within the choice sets. The actually booked days per property are not provided by Airbnb; in the meanwhile, long-term rentals in Amsterdam are easy to be rented out because of the large demand.
- Daily income is another important attribute that needs to be included within the choice sets. Long-term rental income should take the rents in the private free sector in Amsterdam as a reference because most of the houses in the social housing sector belong to housing associations and their rents are controlled by the government.
- There are a few holiday rental management companies in the Netherlands, namely The Friendly Host, Bnbmanager, Myhomebnb, Host je Huisje, Airbnb host Haarlem, etc. These start-ups grew larger and larger in recent years. Regarding long-term rental agency, Kamernet and Funda are the biggest players.
- The days limit in Amsterdam is that it is not allowed to rent out the entire apartments or houses as holiday rental in total more than 30 days per year. Despite the existence of the policy, however, there are still a large number of landlords ignoring or breaking this policy because Airbnb does not share the data with the municipality, and it is very difficult for the municipality to identify those illegal landlords.
- Supply subsidy designed for long-term rental landlords as a future policy could be included in the choice sets as well in order to give an indication if landlords are sensitive to this policy instrument. Its associated levels should be at least 1000 euros; if it's set too low then it's hard to have an impact on landlords' choice.
- A qualitative description about the number (size) is more understandable than a quantitative percentage description for respondents.

3.5 Data collection

Before the data collection phase, the minimum sample size requirement needs to be imposed to enable accurate predictions (Wiktor Adamowicz, Jordan Louviere, Joffre Swait, 1998). Orme (2006) proposed the rule-of-thumb method which suggests that the sample size required for the main effects depends on the number of choice tasks (t), the number of alternatives excluding the "none of these" alternative (a), and the highest number of levels for any of the attributes (c) according to the following formula:

$$\mathrm{N} > 500\ \frac{c}{\mathrm{t}\times\mathrm{a}} \tag{11}$$

However, the number 500 intended in Equation (11) is seen as a minimum threshold for researchers. It would be better to have 1000 or more representations per main effect level and thus the optimized formula is obtained:

$$\mathrm{N} > 1000\ \frac{c}{\mathrm{t}\times\mathrm{a}} \tag{12}$$

According to formula (12), the recommended minimum number of respondents for this SC experiment is 167 respondents; t=9, a=2, c=3. Meanwhile, Orme (2006) suggests a minimum sample size of 200 respondents based on his experience. Therefore, the minimum number of respondents needed is 200 for this experiment.

People who are living in the city of Amsterdam is the target group for this study. Online questionnaires are randomly sent via email to 1000 members of the city panel of Research Information and Statistics (OIS). OIS, which is part of the municipality of Amsterdam, collects data about Amsterdam and processes this data into useful information. All the panel members are Amsterdam residents living within the border of Amsterdam municipality (red border in Figure 16). The yellow circle in Figure 16 represents the A10 ring road, and the solid red shows the Amsterdam center. From 26 June to 19 July 2019, 532 respondents started the questionnaire and 349 of them completed it.

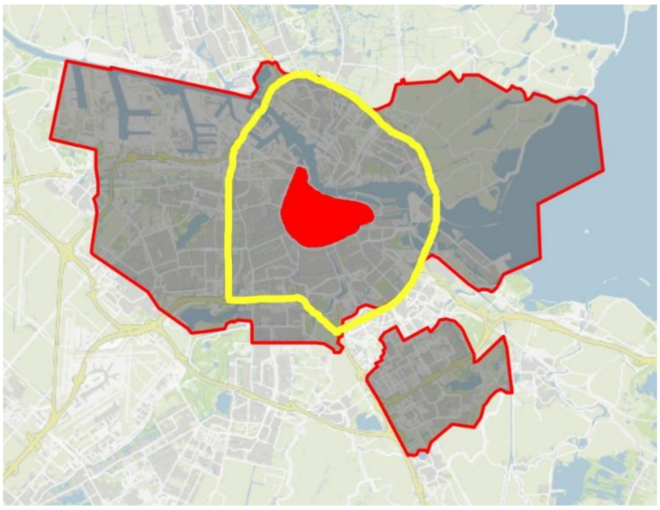

Figure 16 Overview of the survey area

To get reliable results, it is important to clean poor quality responses. Data were checked using two criteria: (i) If a respondent meets my target criteria. All respondents are above the age of 18, and all the postcodes provided are valid and belong to the city of Amsterdam, so no respondent is filtered out. (ii) If a respondent chooses the same answer repeatedly. Among 349 respondents, 131 respondents chose ‘none of these’ as the answer for all the 9 choice sets in the SC experiment, so these answers have been removed. In the end, 218 correct responses were obtained. This indicates the minimum sample size requirement of 200 respondents is fulfilled. Later five answers have been modified from “others, namely” to other options (See Appendix D for more details).

3.6 Data analysis method

The software package NLOGIT 5.0 was used to estimate the discrete choice models. It is the most popular software package for choice model estimation and has been trusted worldwide by analytics experts and institutions for over 25 years and could, therefore, be considered as a good tool for this research. First of all, the original panel data were formatted and entered into Nlogit. Then the data are analyzed through three discrete choice models, namely MNL (and MNL+) model, ML model and finally, LC model.

3.6.1 Data Set up for Nlogit

The original panel data consisted of two sets (two excel workbooks); one set with the choice data and another set with data about the socio-demographic characteristics (SECs) of the respondents. The SECs of a respondent is invariant across decisions. As such, socio-demographic data were entered into the choice data set keeping the levels of the socio-demographic data constant for an individual but vary across individuals.

Then the merged data set was coded using effect coding (see Appendix E). The attribute occupancy rate has not been effects coded because the two alternatives have a different number of levels of this attribute. In order to determine the effect coding of the attribute levels, the middle(or the last) level was considered to be the base level which could be seen as a comparison group, and the impact of an attribute level compared to the base level could be identified (Hensher et al., 2015). In this way, attribute variable is represented by n - 1 indicator variables (where n is the number of levels). For a variable with three levels, for example, these indicator variables are coded as follows. The first level is coded as (1, 0), the second level (base level) as (-1, -1) and the third level as (0, 1). Coded in this way the effects of the three levels are represented as $(\beta_1, \beta_2, \beta_3)$ where β_1 and β_3 are estimated values and β_2 can be calculated as $\beta_2 = -\beta_1 - \beta_3$. Thus, the parameters show effects of each level of the base variable relative to an average (utility) value. Context variables and socio-demographic variables were also effects coded using the same system. For the no-choice alternative ("neither of these two"), there are no observable attribute levels. Therefore, the levels of the non-observed attributes were coded as missing (0). The above procedure was done in Excel.

Nlogit, unlike some other statistical packages, required the use of several rows of data to represent a single subject. As such, each row was transformed into three rows with every single line represent data of one alternative. The choice variable indicated which alternative within a choice set was chosen. A "1" indicates that an alternative was selected, while "0" indicated that it was not. The accounting index "alti" variable and the "cset" variable were added for each row which informed Nlogit which alternative was assigned to a line of data and the number of choices (three) in the choice set respectively. This data transformation process was realized using Java. Finally, the data were properly formatted and imported into Nlogit.

3.6.2 MNL model estimation

To evaluate the variables which were finally included in the model, a MNL model was first estimated. According to Hensher et al. (2015), "for variables associated with descriptions of respondents and other contextual influences that are not attributed descriptions of alternatives also have a role in choice models". Therefore, the MNL model includes not only the main effects of attributes but also the context effects and socio-demographic characteristics to examine the significance of marginal effects. A number of variables with respect to individuals' social-demographics were available through the questionnaire administered jointly with the stated choice experiment. Several representative variables affecting homeowners' rental choice preferences were examined, which includes age, gender, education level, income level, work status, and landlord experience.

The commands (inputs) for the estimation of all the final models in this study can be seen in Appendix F. The utility functions specified for each of the two alternatives (holiday rental and long-term rental) were equivalent to the utility function shown in Equation (13).

$$V_i = \beta_{0i} + \beta_{1i} f(X_{1i}) + \beta_{2i} f(X_{2i}) + \beta_{3i} f(X_{3i}) + \cdots + \beta_{ki} f(X_{ki}) \tag{13}$$

Where

β_{1i} is the parameter associated with attribute (or context variable or socio-demographic variable) X_1 and alternative i

β_{0i} is the alternative-specific constant, which represents on average the unobserved sources of utility.

Considering the parameters might be very different across the alternatives, utility functions were specified to contain alternative-specific parameter (ASP) estimates. As for the no-choice alternative, its utility function was specified as 0 so that β_{ki} will be interpreted relative to the no-choice alternative.

The above MNL model assumed that there were no significant interaction effects present within the data. However, attributes and context variables (or socio-demographic variables) are not necessarily independent (Hensher et al., 2015). Therefore, an extended specification of the MNL model (referred to as MNL+) was later conducted to analyze interaction effects between the main attributes and context variables (or socio-demographic variables). Each estimated parameter shows the increase or decrease of the effect of the concerned attribute level caused by the concerned level of the context variable. Potentially, there are many interaction effects; parameters were estimated for each interaction but only those interaction effects that appeared to be significant were included in the final specification of the model.

3.6.3 ML model estimation

The Mixed Logit (ML) model is estimated to check for random taste variation within the sample and the existence of random taste variation was tested for each main effect variable after controlling all the context effects, socio-demographic effects and interaction effects. Three key issues were considered specifying the mixed logit model suggested by Hensher and Greene (2003).

First one is about the selection of random parameters. The random parameters provide information about the degree of preference heterogeneity through their estimated standard deviations (SDs). A common test to select random parameters is to assume that all parameters are random, estimate the model and then examine the estimated SDs of the random parameters (van Puyvelde, Caers, Du Bois, & Jegers, 2015). Based on the result of this test, a few parameters associated with the main attributes and alternative-specific constants were finally treated as random variables.

The second issue is to select the distribution of random parameters. A number of predefined functional distributions are possible among which the most popular options are normal, triangular, uniform and lognormal distributions. The lognormal distribution is favored when the mean estimate of a random parameter needs to be of a specific sign (nonnegative). However, a major disadvantage of this distribution is its long upper tail, which may result in extremely high SD estimates (Hensher et al., 2015). The problem with other three distributions is they may give the wrong sign to a random parameter when the estimated SD of such a parameter becomes higher than its mean (Hensher et al., 2015). A possible solution to this problem is to impose a constraint on the distribution by making the SD of each random parameter a function of the mean (Hensher et al., 2015). For example, in a constrained symmetrical triangular distribution, the domain range equaled twice the mean and every parameter estimate was constrained to be of the same sign. Phanikumar and Maitra (2006) summarized the advantages of this distribution as follow: (i) the bounded nature of the triangular distribution helps in early convergence of the model, (ii) it keeps the sign of the estimate the same for all respondents (i.e., there is no reversal of sign throughout the respondents) unlike normal or triangular distributions, and (iii) it provides simplicity in WTP estimations. Applications of constrained triangular distributions in mixed logit models have been found in several studies (Phanikumar & Maitra, 2006; Timsina, Jourdain, & Shivakoti, 2016; van Puyvelde et al., 2015) yet it is still fairly limited, which may be due to limitations in econometric software (van Puyvelde et al., 2015). Different distributions were tested in this study in order to find the best fit distribution(s).

The third issue is the selection of the number and type of draws for the simulations. recommend that several hundred random draws be employed in estimation while Bhat (2001) recommends 1,000 random draws. In addition, standard Halton sequence (SHS) was the most common form of intelligent draw used in model estimation to date. Therefore, 1000 Halton draws were selected for this study.

3.6.4 LC model estimation

The LC model consists of main attributes, context variables, and interactions with context variables which were included in the MNL+ model. To identify the membership for each segment, socio-demographic variables associated with individuals were incorporated into membership functions, among which the significant ones were finally treated as membership variables.

To identify the optimal number of classes, the Bayesian Information Criterion (BIC) is often suggested to be used as a good indicator (Nylund, Asparouhov, & Muthén, 2007). It can be expressed (Schwartz, 1978) as:

$$\mathrm{BIC} = -2\mathrm{LL} + \mathrm{p}\log(n) \tag{14}$$

where LL is the log-likelihood function at convergence; p is the number of parameters in the model; n is the sample size.

When estimating parameters with different number of classes, the model with the least BIC value is thought to be the best (Feng et al., 2013).

3.6.5 Model validation

In order to determine if the outputs of the models were acceptable, the models were checked in three aspects: parameter significance, face validity, and goodness-of-fit. In terms of parameter significance, at least some parameters should be significant. Regarding face validity, the signs of the parameters need to be as expected.

The goodness-of-fit of the model was analyzed to determine if a model performs well. The performance of the model is expressed in terms of the rho-squared, and the rho-squared of a model can be calculated using Equation (15):

$$\rho^2 = 1.0 - [LL(\beta)/LL(0)] \tag{15}$$

where

$LL(\beta)$ is the loglikelihood using estimated parameters

$LL(0)$ is the loglikelihood using base model (also called “null-model” and “constant-only” model). A base model using the market shares within the data is equivalent to a model estimated with ASCs only.

According to Jordan J. Louviere et al. (2000), a model can be considered usable if the rho-squared value is above 0,1. However, preferably the rho-squared should be between 0,2 and 0,4.

3.7 Conclusion

This chapter first discussed the methods to measure choice behavior and stated choice experiment was selected as a main method for this study due to the lack of revealed data. Then another method used in this study, the discrete choice modeling was introduced. Discrete choice models are developed based on random utility theory (RUT); MNL and ML models are estimated using the MLE method while the LC model applies the EM algorithm. Following the design stages suggested by Hensher et al. (2015), the SC experiment has been designed and the accompanying questionnaire has been constructed. The data collection process has also been described. Last but not least, the data analysis process in this study was described from data format setup, model estimations to data validation. Chapter 4 will present the results of data analysis given in this chapter.

CHAPTER 4: RESULTS AND DISCUSSION

In this chapter, first, a description of the sample's characteristics is provided. After that, the estimation results of MNL (and MNL+), ML and LC model are presented and finally, the meaning of the results and possible explanations will be discussed at the end.

4.1 Descriptive statistics

Information about the respondents were derived from the answers of socio-demographic questions deigned in the questionnaire. Table 3 shows descriptive statistics on some of the key variables related to socio-demographic characteristics. Those variables have been re-categorized into less levels, resulting in more observations per level for further analysis. The last column in Table 3 presents Dutch population statistics by the end of 2018 provided by CBS, a Dutch governmental institution that gathers statistical information about the Netherlands.

The residential addresses of respondents were plotted based on the four-digit postcodes they provided. As can be seen from Figure 17, the location of their homes was spread across the city. There was no respondent living in North West Amsterdam as it is an industrial district which includes a large part of the port of Amsterdam.

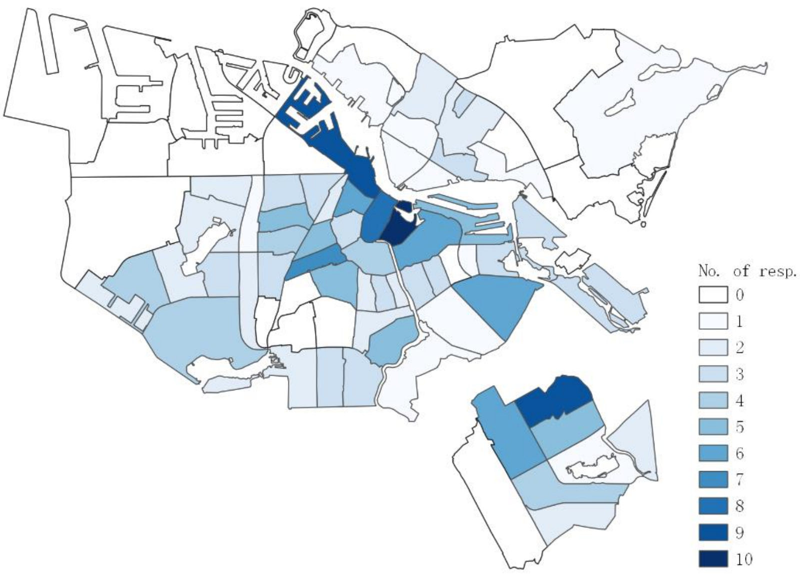

Figure 17 Distribution of survey respondents in the city of Amsterdam

Amongst 218 respondents, males (53.2%) were slightly more represented than females (46.8%) compared to Dutch population statistics. Moreover, participants were spread across all age ranges above 18 years old, with the largest group in the 64+ age range (18.8%). In order to do further estimations, age groups have been merged into three groups: young (18–39), middle-aged (40-59) and old-aged (≥60), so that the groups were more evenly spread (respectively 28.9%, 39.4%, and 31.7%). This age group distribution was similar to Dutch population statistics

The educational level showed high peaks at HBO and university levels which were regarded as high-education levels. 31.2% of the respondents chose HBO and 50.5% were at the university level. Compared to Dutch population statistics (30%), the sample had an overrepresentation of people with a high education level (81.7%), which might influence the estimation results. However, this was consistent with the landlords' profile in the previous studies which found landlords tended to be highly-educated. The lower education levels than the above two levels have been categorized into one level (low-/middle- education level) to make the groups more evenly spread.

Similarly, the net monthly household income of the sample also showed a peek at the high-income level (more than € 3125) with a share of 43.6%. This level was highly represented compared to Dutch population statics (18.3%), but it was consistent with the existing finding that landlords tended not to be in the low-income groups (Andreotti et al., 2017). For the same reason as education level variable, all the lower income levels have been recategorized into low-/middle- education level group to make the groups more evenly spread.

Almost half (49.5%) of the respondents had a full-time job which was slightly highly represented compared to Dutch population statistics (35.4%). Those who did not have any full-time job but suited other work status categories have been put into one group named "other", to make the groups more evenly spread.

Regarding the landlord experience, the majority (83.5%) of the sample had no experience while only 14 respondents were holiday rental hosts, 19 respondents were long-term rental landlords and 3 respondents had both experiences as a holiday rental host and a long-term rental landlord. This variable has been recategorized into two groups: "Is/was a landlord" and "No landlord experience".

Table 3 Results of descriptive statistics

Variable	Category	Fre.	%	Merged category	Fre.	%	NL %
Gender	Male	116	53.2	Male	116	53.2	49.7
	Female	102	46.8	Female	102	46.8	50.3

	Other	0	0.0				
Age	< 18	0	0.0	Young (18–39)	63	28.9	32.3
	18 - 24	8	3.7	Middle-aged (40-59)	86	39.4	35.7
	25 - 29	17	7.8	Old-aged (≥60)	69	31.7	32.0
	30 - 34	20	9.2				
	35 - 39	18	8.3				
	40 - 44	15	6.9				
	45 - 49	24	11.0				
	50 - 54	24	11.0				
	55 - 59	23	10.6				
	60 - 64	28	12.8				
	> 64	41	18.8				
Highest education level	Primary school	0	0.0	Low-/middle-education level	40	18.3	70.0
	Preparatory secondary vocational education	2	0.9	High-education level	178	81.7	30.0
	Junior general secondary education	6	2.8				
	Secondary vocational education	16	7.3				
	senior general secondary education and Pre-university education	16	7.3				
	Higher professional education	68	31.2				
	Higher academic education	110	50.5				
	Other	0	0.0				
Net monthly household income	No more than € 625	2	0.9	Low-/middle-income level	104	47.7	81.7
	€ 626 to € 1250	17	7.8	High-income level	95	43.6	18.3
	€ 1251 to € 1875	18	8.3	Unknown	19	8.7	
	€ 1876 to € 2500	27	12.4				
	€ 2501 to € 3125	40	18.3				
	More than € 3125	95	43.6				
	Prefer not to say	19	8.7				
Work status	No work	17	7.8	Full-time work	108	49.5	35.4
	Student	9	4.1	Other	110	50.5	64.6
	Part-time work	39	17.9				
	Full-time work	108	49.5				
	Retired	40	18.3				
	Other	5	2.3				
Landlord experience	Having HR landlord exp.	14	6.4	Is/was a landlord	36	16.5	NA
	Having LTR landlord exp.	19	8.7	No landlord experience	182	83.5	NA
	Having HR &LTR landlord exp.	3	1.4				
	No landlord experience	182	83.5				

Source: Author, CBS

4.2 Estimation results

As described in section 3.6, MNL (and MNL+), ML and LC models were estimated, and the results are given below.

4.2.1 Results of MNL and MNL+ model

Estimation results of the MNL model, shown in Table 4, include the main effects of attributes, context variables, and socio-demographic variables. Furthermore, Table 4 also shows the estimation results of an extended specification of the MNL model (referred to as MNL+) that was conducted to analyze the interaction effects of attributes with context variables and socio-demographic variables.

According to the results, rho squared values are 0.096 for the MNL model and 0.103 for the MNL+ model. This value is quite low for both models, which implies the models may not explain the data very well. Furthermore, a few parameters are significant and all parameters that are significant have signs as expected. Therefore, the MNL and MNL+ models are regarded to be acceptable.

Table 4 Estimation results of MNL and MNL+ model

	MNL				MNL+			
	HR		LTR		HR		LTR	
	Coeff.	P	Coeff.	P	Coeff.	P	Coeff.	P
Alternative-specific constants (ASCs)								
Holiday rental	-0.455**	0.026			-0.466**	0.023		
Long-term rental			0.676**	0.013			0.682**	0.013
Attributes								
occupancy rate	0.530**	0.028	0.135	0.669	0.533**	0.028	0.133	0.674
daily income €100	-0.424***	0.000			-0.435***	0.000		
daily income €300	0.268*	0.056			0.275*	0.053		
daily income €30			-0.299***	0.000			-0.294***	0.000
daily income €90			0.256***	0.001			0.253***	0.000
max 30 days	-0.421***	0.000			-0.246**	0.025		
max 330 days	0.357***	0.000			0.264**	0.015		
tax €1000	0.012	0.890			0.003	0.969		
tax €3000	-0.042	0.604			-0.046	0.572		
subsidy €1000			-0.038	0.564			-0.043	0.518
subsidy €3000			0.035	0.601			0.045	0.498
managed by an agency	0.029	0.621	-0.029	0.540	0.024	0.678	-0.024	0.614
neighbor: objection	-0.197***	0.008			-0.150**	0.016		

large no. in nbhd.	0.078	0.180	0.011	0.819	0.071	0.229	0.010	0.827
Context variables								
room	-0.347***	0.000	-0.463***	0.000	-0.327***	0.001	-0.467***	0.000
entire house	0.097	0.327	0.190**	0.018	0.055	0.590	0.194**	0.015
poor condition	-0.514**	0.000	-0.445***	0.000	-0.509***	0.000	-0.444***	0.000
good condition	0.179*	0.070	0.001	0.994	0.186*	0.061	0.000	0.999
in the center of AMS	0.025	0.801	0.003	0.974	0.039	0.692	-0.001	0.987
outside the ring of AMS	-0.138	0.162	-0.104	0.192	-0.159	0.112	-0.103	0.197
Socio-demographic variables								
age 18-39	1.029***	0.000	0.657***	0.000	1.026***	0.000	0.661***	0.000
age ≥ 60	-1.120***	0.000	-0.562***	0.000	-1.114***	0.000	-0.567***	0.000
low-/middle-income lvl.	-0.307***	0.007	-0.303***	0.001	-0.332***	0.004	-0.306***	0.001
high-income lvl.	0.139	0.237	0.207**	0.027	0.146	0.215	0.205**	0.029
male	0.199***	0.008	0.105*	0.077	0.197***	0.009	0.108*	0.069
High-education lvl.	0.082	0.367	0.124*	0.082	0.085	0.351	0.125*	0.080
full-time work	-0.026	0.745	0.006	0.930	-0.034	0.672	0.003	0.962
landlord	0.221**	0.022	0.123	0.140	0.225**	0.020	0.125	0.134
Interactions								
daily income €100 * room					-0.022	0.858		
daily income €300 * room					0.113	0.335		
daily income €100 * entire house					-0.222*	0.077		
daily income €300 * entire house					0.038	0.742		
daily income €30 * room							0.136	0.147
daily income €90 * room							-0.042	0.654
daily income €30 * entire house							-0.163*	0.075
daily income €90 * entire house							0.060	0.527
max 30 days * high education level					-0.278**	0.012		
max 330 days * high education level					0.154	0.151		
neighbor: objection * room					0.165**	0.048		
neighbor: objection * entire house					-0.140*	0.094		
neighbor: objection * age 18-39					-0.180**	0.033		
neighbor: objection * age ≥ 60					0.245**	0.012		
Sample size				218				218
LL0				-2043.20				-2043.20
LLβ				-1846.44				-1833.58
ρ^2				0.096				0.103

Note: ***， **and *are 1%, 5% and 10% significant, respectively.

The estimated alternative-specific constants (ASCs) are presented in Table 4. The main utility derived from the holiday rental is -0.455 and the main utility derived from the long-term rental is 0.676. This suggests respondents in average are more inclined to long-term rental in this experiment. By design, however, all attribute and context levels appeared an equal number of times for all observed choices, which is not representative of the number of times the attribute and context levels applied in reality. Hence, the estimated constants cannot fully indicate the shares of holiday rentals and long-term rentals in the real market.

Figure 18 shows the main effects of attributes graphically. An extensive explanation is given below:

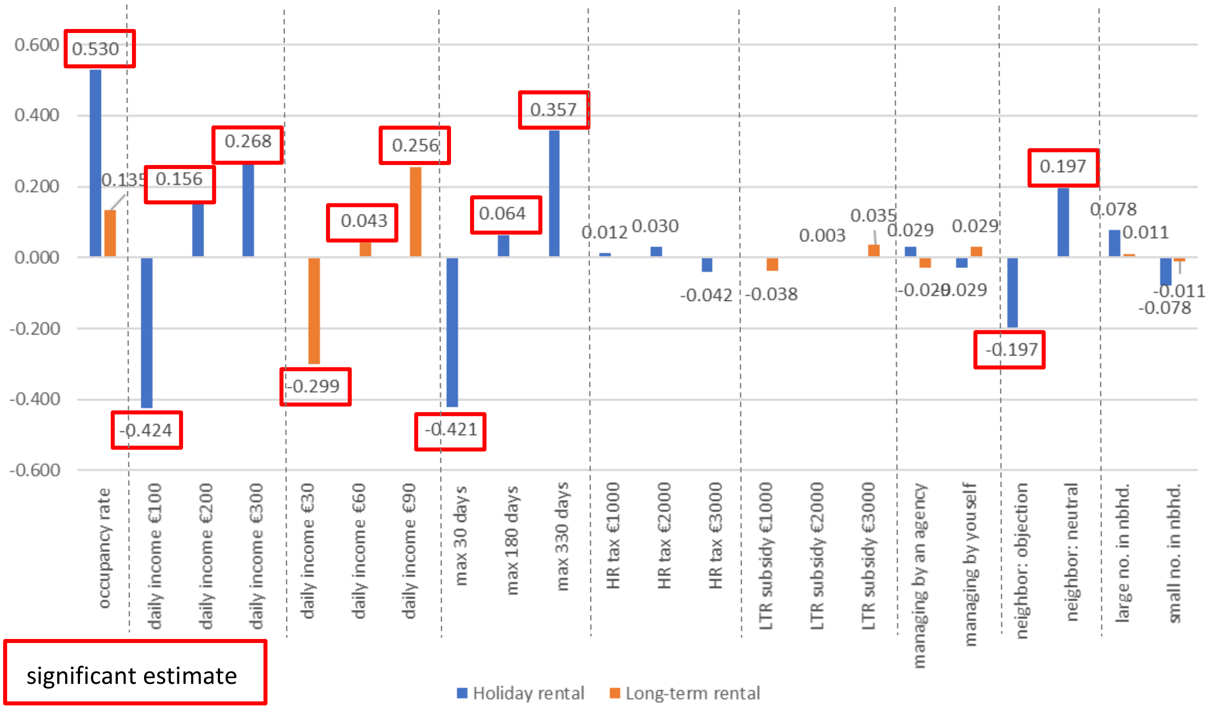

Figure 18 Utilities of main effect attributes

Occupancy rate

The occupancy rate appears to be the most influential attribute of all variables for the choice of holiday rental. The positive sign of the estimated coefficient means that if the occupancy rate increases so do the probability of holiday rental being chosen, suggesting that homeowners prefer more days being booked, which is reasonable. However, this attribute is not significant for the choice of long-term rental.

Daily income

As expected, the daily income attribute has a strong influence on both holiday rental and long-term rental. For holiday rental, homeowners have a preference for obtaining €300 per night over €200 per night as well as a strong dislike of only receiving €100 per night. For long-term rental, a daily income of €90 is much preferred than €60 while €30 is strongly disliked.

Tourist tax

Moreover, daily income has a much bigger effect on the choice of holiday rental than the additional tourist tax imposed on it. Taxation of €1000 or €2000 per year is preferred while homeowners are not willing to pay €3000 additional tax per year for holiday rental. However, as this attribute is not significant, no strong conclusion can be drawn from this.

Long-term rental subsidy

For the choice of long-term rental, daily income also has a much bigger effect than subsidy. €3000 bonus has a positive impact while both €1000 and €2000 are not appreciated. Similar to tourist tax, this attribute is not significant so the conclusion drawn from this cannot be regarded as strong either.

Days limit

The days limit is found to be another important attribute for holiday rental. Homeowners have a strong preference for max 330 days policy and a slight preference for max 180 days, while they have a strong dislike for max 30 days. Additionally, keeping everything else constant, a max 30 days policy (-0.421) has the same level of deterring effect as daily income €100 does (-0.424). This means the days limit on holiday rental is very likely to have a big influence on homeowners' rental choice, and thus this policy may be effective to a certain extent when introduced in the city.

Managing method

For the attribute managing method, homeowners prefer to have the holiday rental managed by the agency than by themselves, whereas they prefer to have the long-term rental managed by themselves than an agency. However, this attribute estimates are found not significant for both holiday rental and long-term rental which means this conclusion is less reliable.

Neighbors' attitude

Neighbors' attitude also shows a significant effect on holiday rental choice. A holiday rental to which neighbors have objection is not preferable. This suggests homeowners tend to avoid such situations where they may receive complaints from neighbors or even investigations if the issue is reported to the municipality.

Numbers in the neighborhood

A large number of holiday rentals or long-term rentals in the neighborhood are preferred over a small number for the choice of holiday rental and long-term rental respectively. Nevertheless, this attribute shows no significant effect on both alternatives which suggests homeowners' choice behavior is not likely to be influenced by other homeowners.

The estimated context effects are presented visually in Figure 19. An extensive explanation is given below.

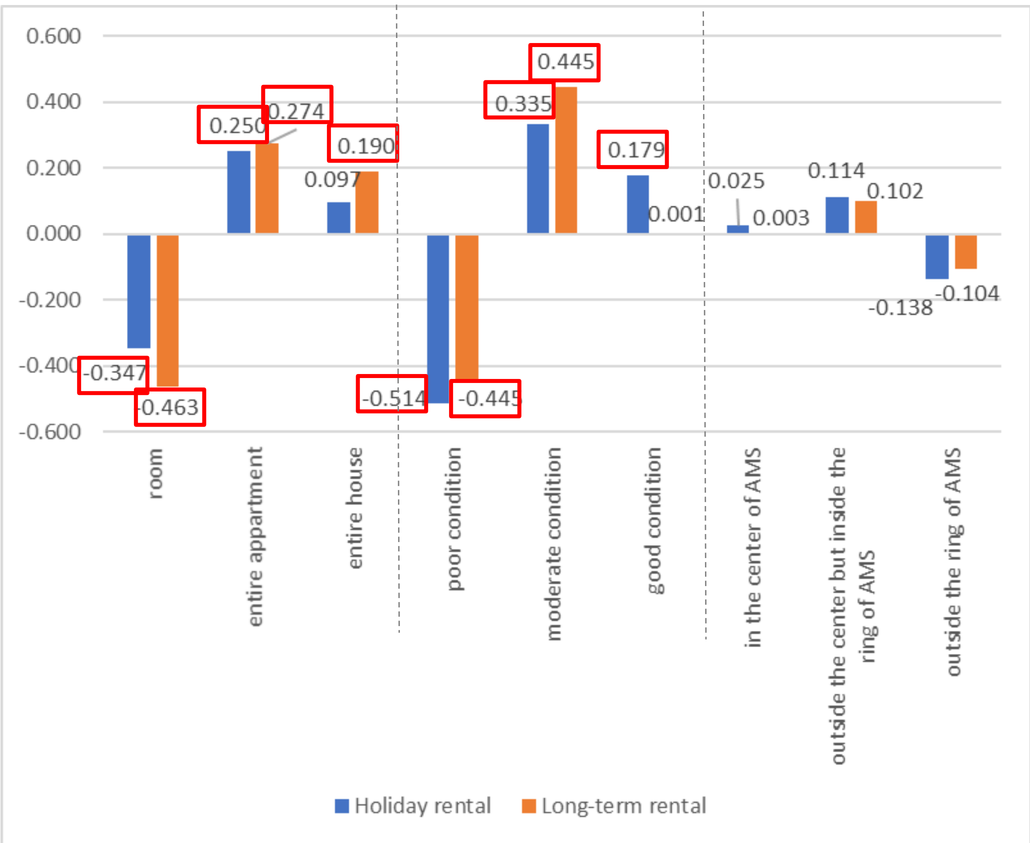

Figure 19 Effects of context variables

Property type

The parameters for property types are found to be significant for both holiday rental and long-term rental. The negative signs of the parameters for room show that room is strongly disliked for both alternatives. The reason may be that homeowners are not willing to live with neither various short-term guests nor long-term tenants. The result also shows the entire apartments are preferred over entire houses for both holiday rental and long-term rental. Furthermore, a holiday rental is preferred when homeowners has a spare room while long-term rental is preferred when homeowners have a spare home (apartment or house).

Property condition

The parameters for property conditions are also significant for both alternatives. The negative signs of the parameters for poor condition mean that poor condition is strongly disliked. It is likely that homeowners find a room/home in poor condition is not easy or suitable to rent out.

Rental property in a moderate-condition is preferred over a good condition, especially for long-term rental. This can be explained as for long-term rental, you have less control of your property and higher risks of more wear and tear on your property. Therefore, homeowners may be more willing to have a moderate-condition property to be rented in a long term rather than a good-condition one. Moreover, a holiday rental is preferred when the rental property is in good condition and long-term rental is preferred otherwise.

Property location

The context variable property location does not show significance to both alternatives. This suggests the influence of rental property's location on homeowners' choices on holiday rental or long-term rental can be ignored.

The estimated effects of homeowners' socio-demographic variables are presented visually in Figure 20. An extensive explanation is given below:

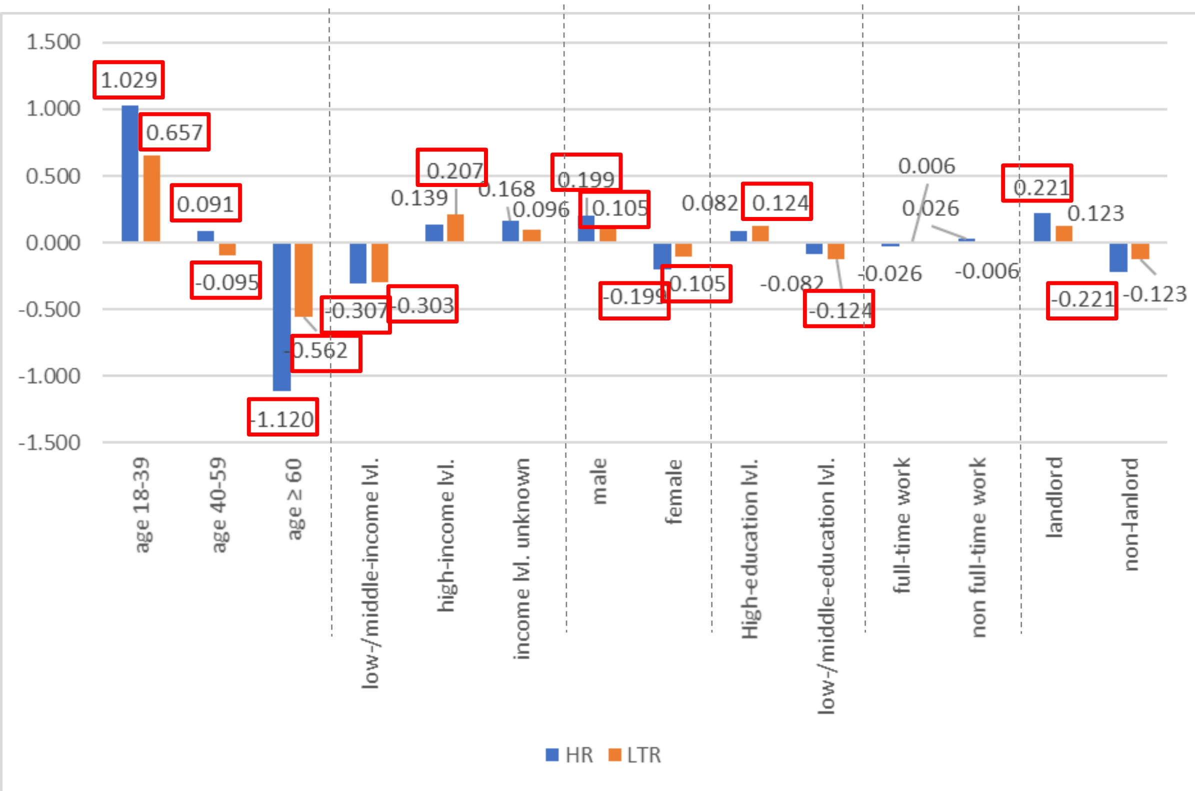

Figure 20 Effects of socio-demographic variables

Age

The parameters for age are significant for both holiday and long-term rental. Young homeowners are more likely to rent out their property than middle-aged and old-aged homeowners are least likely to rent. Furthermore, young and middle-aged homeowners prefer holiday rental while old-aged landlords prefer long-term rental. It is likely that the difficulty of using an online platform for holiday rental is more negatively important for old-aged homeowners.

Income

The parameters for low/middle-income levels are negatively significant for both rental choices, whereas the parameter for high-income level is positively significant for long-term rental. This suggests people with high-income levels are more likely to rent their properties out relative to those with low/middle-income level. This is consistent with existing findings that landlords tend to have a high-income level (Soaita et al., 2017).

Gender

The parameters for gender are found to be significant for both alternatives. The positive signs of coefficients for males and negative signs of coefficients for females show that males are more likely to rent their properties compared to females. Moreover, males prefer holiday rental than long-term rental while females prefer long-term rental. It may be because male homeowners prefer high returns and risks while stable rental income is more important for female homeowners.

Education

The parameters for education level are significant for alternative long-term rental. People with high-education levels are more likely to rent out their property for the long term in comparison with people with lower education. This is logical because as we discussed before, landlords tend to have high-level income and those high-income earners are more likely to be highly educated.

Work status

The parameters of work status are not significant for both alternatives. This suggests there is no significant relationship between homeowners' rental choices and their work status.

Landlord experience

The parameter for landlord experience variable is significant for alternative holiday rental. The result shows people who are or used to be a landlord (either holiday rental or long-term rental) are more likely to make their rooms/homes as a holiday rental in the future compared to people who do not have any landlord experience.

The parameter estimations of MNL+ (Table 4) indicate that significant interactions between certain attributes and context/ socio-demographic variables exist. The results are consistent with that of the basic MNL model with better goodness-of-fit and meaningful parameter signs.

Interaction between daily income and type of rental property

As can be seen from Figure 21, for both holiday and long-term rental, there exist significant interaction effects between the lowest level of daily income and the entire house. An entire house further increases a dislike for receiving €100 per night as a holiday rental and earning €30 per day as a long-term rental. This is logical because entire houses usually have a higher rent than rooms and thus an income of €100 per night and €30 per day are far from satisfaction for homeowners.

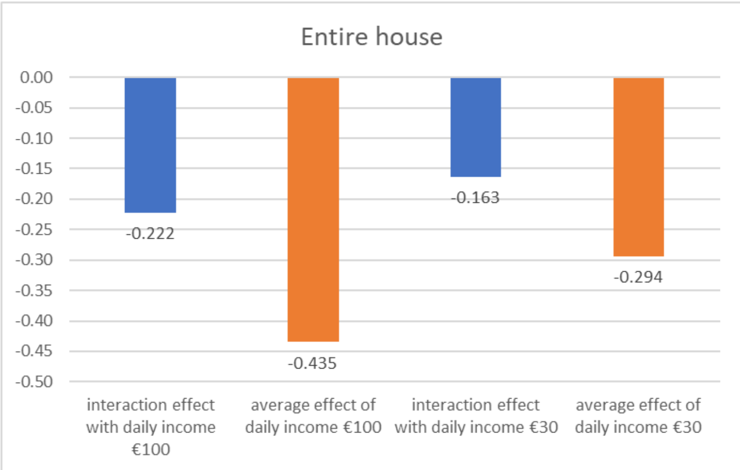

Figure 21 Interaction effect between daily income €100 (and €30) an entire house

Interaction between days limit and homeowner's education level

As shown in Figure 22, the socio-demographic effect is negatively significant for highly educated group when facing a 30-day limit on holiday rental. Furthermore, this interaction effect is larger than the average effect of max 30 days, which indicates that the dislike for this policy is particularly strong for highly educated group. A likely explanation is that homeowners with high education levels are cautious and tend to follow the 30 days rules, so this factor is very important to them.

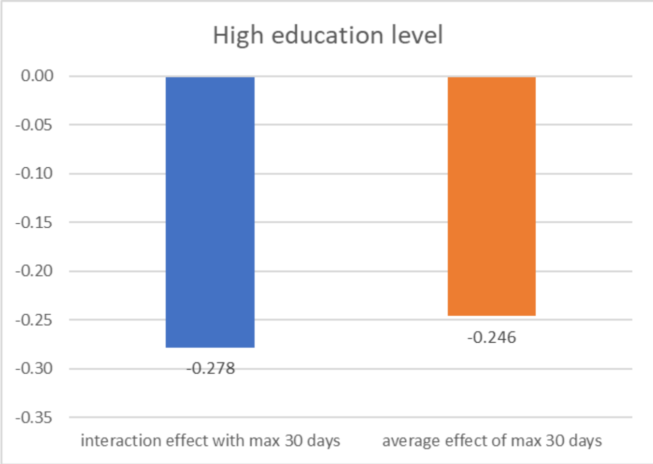

Figure 22 Interaction effect between max 30 days and high education level

Interaction between neighbors' attitude and room type (and homeowner's age)

Figure 23 shows that the type of property has an influence on the preference for neighbors' attitude. As could be expected, the dislike of neighbors having objection is somewhat smaller when a room is rented, and this dislike is stronger when an entire house is rented. In other words, homeowners avoid particularly in case of an entire house is rented as a holiday rental. This can be explained as when an entire house is rented to a group of tourists, neighbors are more likely to suffer the nuisance, etc. and thus have stronger objections. Interestingly, the preference for neighbors' attitudes also appears to interact with the socio-demographic variable age. Younger homeowners display a stronger dislike for neighbors having objection compared to the old-aged category. However, the explanation for this is not clear.

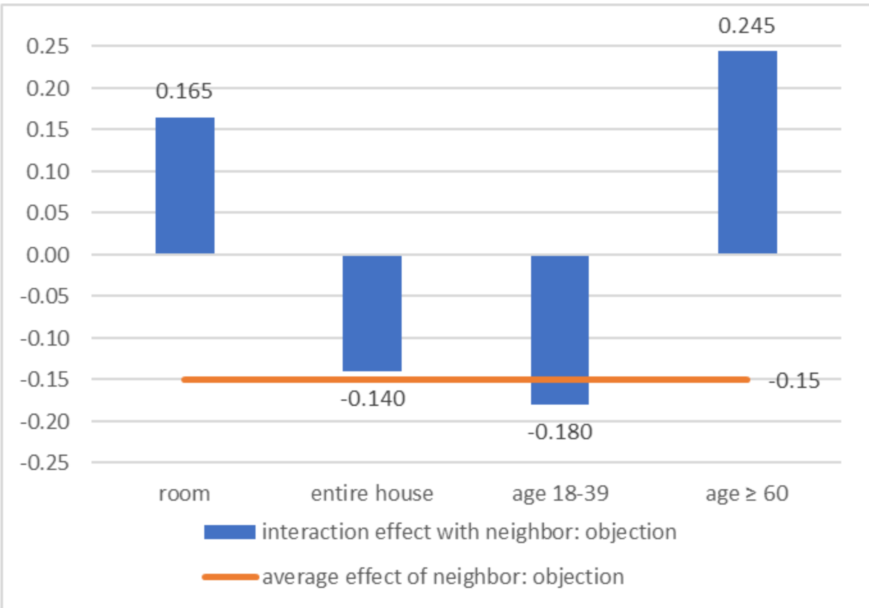

Figure 23 Interaction effect with neighbor: objection

4.2.2 Results of ML model

To select random parameters and to determine the distribution of random parameters, we first assumed that all attribute parameters are random and tested the model based on normal distribution and constrained distribution respectively. As can be seen from the estimation results shown in Appendix G, the parameter signs for several random variables including tax, subsidy, and the number of long-term rentals in the neighborhood in the model based on normal distribution was opposite to the ones in the model based on constrained distribution model and MNL+ model. Moreover, the estimated SDs of these random parameters were very high. The wrong given signs occurred might be because the estimated SDs of such random parameters became higher than their means, which was a problem with normal distribution and other two popular distributions. Therefore, the constrained triangular distribution was selected for random parameters in this study. Furthermore, those have significant SDs were selected as random parameters in the final ML model.

The estimation results of the final ML model in comparison with MNL+ model can be seen from Table 5. The coefficients of the ML model were consistently close to those for the MNL+ model. Furthermore, the rho squared value is 0.103 for the ML model which is almost the same as that for the MNL+ model (0.103).

Table 5 Estimation results of ML model in comparison with MNL+ model

	ML				MNL+			
	HR		LTR		HR		LTR	
	Coeff.	P	Coeff.	P	Coeff.	P	Coeff.	P
Alternative-specific constants (ASCs)								
Holiday rental	-0.477**	0.026			-0.466**	0.023		
Long-term rental			0.610**	0.021			0.682**	0.013
Attributes								
occupancy rate	0.504**	0.032	0.211	0.491	0.533**	0.028	0.133	0.674
daily income €100	-0.445***	0.000			-0.435***	0.000		
daily income €300	0.278**	0.050			0.275*	0.053		
daily income €30			-0.298***	0.000			-0.294***	0.000
daily income €90			0.256***	0.000			0.253***	0.000
max 30 days	-0.245**	0.029			-0.246**	0.025		
max 330 days	0.264**	0.017			0.264**	0.015		
tax €1000	-0.004	0.964			0.003	0.969		
tax €3000	0.048	0.571			-0.046	0.572		
subsidy €1000			-0.044	0.521			-0.043	0.518
subsidy €3000			0.046	0.499			0.045	0.498

managing by an agency	0.026	0.666	-0.026	0.597	0.024	0.678	-0.024	0.614
neighbor: objection	-0.155**	0.015			-0.150**	0.016		
large no. in nbhd.	0.072	0.231	0.011	0.826	0.071	0.229	0.010	0.827
Context variables								
room	-0.326***	0.001	-0.473***	0.000	-0.327***	0.001	-0.467***	0.000
entire house	0.053	0.609	0.196**	0.016	0.055	0.590	0.194**	0.015
poor condition	-0.514***	0.000	-0.447***	0.000	-0.509***	0.000	-0.444***	0.000
good condition	0.190*	0.059	-0.001	0.986	0.186*	0.061	0.000	0.999
in the center of AMS	0.041	0.683	-0.001	0.986	0.039	0.692	-0.001	0.987
outside the ring of AMS	-0.160	0.113	-0.104	0.201	-0.159	0.112	-0.103	0.197
Socio-demographic variables								
age 18-39	1.035***	0.000	0.663***	0.000	1.026***	0.000	0.661***	0.000
age ≥ 60	-1.126***	0.000	-0.569***	0.000	-1.114***	0.000	-0.567***	0.000
low-/middle-income lvl.	-0.332***	0.004	-0.306***	0.001	-0.332***	0.004	-0.306***	0.001
high-income lvl.	0.147	0.219	0.210**	0.027	0.146	0.215	0.205**	0.029
male	0.199***	0.009	0.108*	0.072	0.197***	0.009	0.108*	0.069
High-education lvl.	0.087	0.349	0.129*	0.074	0.085	0.351	0.125*	0.080
full-time work	-0.036	0.665	0.003	0.959	-0.034	0.672	0.003	0.962
landlord	0.225**	0.022	0.122	0.148	0.225**	0.020	0.125	0.134
Interactions								
daily income €100 * room	-0.021	0.869			-0.022	0.858		
daily income €300 * room	0.114	0.340			0.113	0.335		
daily income €100 * entire house	-0.228*	0.076			-0.222*	0.077		
daily income €300 * entire house	0.038	0.745			0.038	0.742		
daily income €30 * room			0.140	0.143			0.136	0.147
daily income €90 * room			-0.042	0.661			-0.042	0.654
daily income €30 * entire house			-0.168*	0.074			-0.163*	0.075
daily income €90 * entire house			0.062	0.525			0.060	0.527
max 30 days * high education level	-0.284**	0.012			-0.278**	0.012		
max 330 days * high education lvl.	0.160	0.144			0.154	0.151		
neighbor: objection * room	0.169**	0.049			0.165**	0.048		
neighbor: objection * entire house	-0.142*	0.095			-0.140*	0.094		
neighbor: objection * age 18-39	-0.184**	0.033			-0.180**	0.033		
neighbor: objection * age ≥ 60	0.251**	0.011			0.245**	0.012		
SDs of random parameters								
holiday rental constant	0.477**	0.026						
long-term rental constant	0.610**	0.021						
occupancy rate (HR)	0.504**	0.032						
daily income €100 (HR)	0.445***	0.000						
daily income €300 (HR)	0.298***	0.000						

daily income €30 (LTR)	0.256***	0.000		
daily income €90 (LTR)	0.167**	0.050		
max 30 days (HR)	0.245**	0.029		
max 330 days (HR)	0.264**	0.017		
neighbor: objection (HR)	0.155**	0.015		
Sample size			218	218
LL0			-2043.20	-2043.20
LLβ			-1834.18	-1833.58
ρ^2			0.103	0.103

Note: ***， **and *are 1%, 5% and 10% significant, respectively.

Table 5 shows the taste variation by means of the standard deviations of the random parameters for all the significant attributes and alternative-specific constants. The standard deviations of the random coefficients are statistically significant, providing evidence of preference heterogeneity in the homeowners for the attributes specified as random.

As can be seen, the standard deviations for holiday rental constant and long-term rental constant are relatively high (0.477 and 0.610), which means people have a high taste variation for these two alternatives; this makes sense as some people have a strong intrinsic preference for one alternative and others do not.

Respondent's preferences are found to be heterogeneous for a few attributes. For holiday rental's occupancy rate, the taste variation is the largest among all attributes (SD = 0.504). This might be possibly explained as some homeowners are satisfied with an occupancy rate of 65% and do not need the occupancy rate to be as high as 95% because this will also bring heavier workload. For daily income, the taste variation also exists both in holiday and long-term rental. This might be due to the variations in rental property types assumed. Homeowners may have different preferences for daily income when they were going to rent out different types of properties (room, apartment or house). The heterogeneity in respondent's preferences for days limit policy could be explained by the differences in education level as this attribute is found to interact with education level as mentioned in section 4.2.1. Moreover, the heterogeneity in respondent's preferences for neighbors' attitude may be explained by the differences in age groups or the type of properties, with which the interaction has also been found in section 3.2.1.

Overall, the estimates in the ML model reveal significant taste variations for the following attributes: occupancy rate, daily income, days limit, and neighbors' attitude. Further research on the nature of this heterogeneity was done in the following LC model.

4.2.3 Results of LC model

All the socio-demographic variables were first included in the membership function in a 2-class model and the estimation results indicated that only the variable of age is significant (see Appendix H1), and consequently, we included this variable into the final membership function.

To determine the best number of classes, we tested the model based on 2-classes and 3 classes respectively and then calculated the BIC values for both models using Equation (14) in section 3.6.4 calculated. As can be seen from Table 6, the results showed the 3-class model had lower BIC value compared to the 2-class model. The 3-class model, therefore, was identified as the best fit model. However, when looking in-depth into the outcome of the 3-class model, there seems to be no significant values for membership variables, which means no conclusions can be drawn from this model (see appendix H2). Therefore, the final latent class model was estimated based on 2 classes.

Table 6 BIC values for 2-class and 3-class LC model

	LL	**number of parameters (p)**	**sample size (n)**	**BIC**
2 classes	-1633.08	85	218	3464.93
3 classes	-1540.50	129	218	3382.66

The estimation results of the latent class model are reported in Table 7. The goodness-of-fit of LCM (ρ^2=0.201) outperforms those of MNL+ (ρ^2=0.103) and ML (ρ^2=0.103) models. The rho squared value is above 0.2 which suggests this 2-class model is sufficiently reliable.

Table 7 Estimation results of LC model

	LCM - Class 1				LCM – Class 2			
	HR		LTR		HR		LTR	
	Coeff.	P	Coeff.	P	Coeff.	P	Coeff.	P
Alternative-specific constants (ASCs)								
Holiday rental	-1.798***	0.000			1.057***	0.000		
Long-term rental			-0.468	0.262			2.410***	0.000
Attributes								
occupancy rate	1.547**	0.036	0.121	0.810	0.857***	0.005	0.149	0.749
daily income €100	-0.200	0.454			-0.566***	0.000		
daily income €300	0.167	0.513			0.220**	0.029		
daily income €30			-0.256**	0.017			-0.425***	0.000
daily income €90			0.313***	0.004			0.250**	0.011
max 30 days	-0.752***	0.001			-0.755***	0.000		

max 330 days	0.876***	0.004			0.582***	0.000		
HR tax €1000	0.040	0.864			-0.011	0.920		
HR tax €3000	0.152	0.504			-0.003	0.974		
LTR subsidy €1000			0.044	0.684			-0.152	0.113
LTR subsidy €3000			0.044	0.680			0.077	0.433
managing by an agency	-0.101	0.543	-0.079	0.293	0.035	0.646	0.055	0.430
neighbor: objection	0.332	0.151			-0.326***	0.000		
large no. in nbhd.	0.315*	0.051	0.162**	0.033	0.034	0.637	0.095	0.166
Context variables								
room	-0.503*	0.064	-0.640***	0.000	-0.206	0.317	-0.328	0.104
entire house	0.271	0.251	0.220**	0.050	0.008	0.971	0.205	0.313
poor condition	-1.206***	0.000	-0.837***	0.000	-0.189	0.397	-0.030	0.890
good condition	0.394	0.133	0.248**	0.038	-0.043	0.845	-0.319	0.144
in the center of AMS	0.141	0.526	-0.025	0.826	-0.001	0.996	-0.014	0.946
outside the ring of AMS	0.068	0.769	-0.085	0.482	0.087	0.717	0.106	0.646
Interactions								
daily income €100 * room	0.103	0.777			-0.033	0.831		
daily income €300 * room	-0.376	0.307			0.138	0.345		
daily income €100 * entire house	-0.573*	0.072			-0.165	0.279		
daily income €300 * entire house	0.346	0.246			-0.004	0.980		
daily income €30 * room			0.131	0.406			0.175	0.207
daily income €90 * room			-0.169	0.300			-0.044	0.747
daily income €30 * entire house			-0.010	0.948			-0.250*	0.063
daily income €90 * entire house			0.152	0.318			0.040	0.777
neighbor: objection * room	-0.044	0.858			0.177*	0.084		
neighbor: objection * entire house	0.135	0.538			-0.177*	0.092		
Membership variables								
Constant	-0.221	0.205						
age 18-39	-1.024***	0.001						
age ≥ 60	1.138***	0.000						
Class size				45.5%				54.5%
LL0								-2043.20
LLβ								- 1633.08
ρ^2								0.201

Note: ***， **and *are 1%, 5% and 10% significant, respectively.

In the 2-class LC model, the second class is treated as the reference, positive values of membership variables relate to class 1 while negative values relate to class 2. Estimates of age 18-39 in the membership function is β=-1.024 (p=0.001) and estimates of age ≥ 60 in the membership function is β=1.138 (p=0.000), as shown in Table 7, provides evidence that class

1 primarily consists of old-aged respondents and class 2 primarily consists of young respondents.

As expected, homeowners in each of the classes are most sensitive to the occupancy rate of holiday rental among all the influential factors; $\beta=1.547$ ($p=0.036$) for class 1 and $\beta=0.857$ ($p=0.005$) for class 2. The results are consistent with those of MNL models. In the case of the strength of impacts between two classes, the old-aged group has larger coefficient than the young group. This means that old-aged homeowners are more sensitive to the occupancy rate relative to young homeowners.

The attributes related to days limit policy are significant to respondents in each of the classes; β(max 30 days)=-0.752 ($p=0.001$), β(max 330 days)=0.876 ($p=0.004$) for class 1; and β(max 30 days)=-0.755 ($p=0.000$), β(max 330 days)=0.582 ($p=0.000$) for class 2. The results indicate that respondents always dislike the max 30 days policy and prefer a max 330 days policy. Moreover, young homeowners are slightly more sensitive to max 30 days policy while old-aged homeowners are more sensitive to max 330 days policy.

Regarding the differences in responding to daily income between young and old-aged homeowners, the young group is very sensitive to the daily income of holiday rental ($p1=0.000$, $p2=0.029$), while the old-aged group is insensitive to that ($p1=0.454$, $p2=0.513$). This means that young homeowners take the daily income of holiday rental more into account. On the other hand, homeowners in both classes are sensitive to the daily income of long-term rental; β(daily income €30)=-0.256 ($p=0.017$), β(daily income €90)=0.313 ($p=0.004$) for class 1 and; β(daily income €30)=-0.425($p=0.000$), β(daily income €90)=0.250 ($p=0.011$) for class 2. The coefficients suggest that young homeowners are more sensitive to daily income €30 while the old-aged is more sensitive to daily income €90.

In terms of social influence, young homeowners are sensitive to neighbors' attitude ($p=0.000$) while the young group is insensitive to it ($p=0.151$). This is consistent with what has been found about the interaction between neighbors' attitude and age. Young homeowners particularly try to avoid the case where neighbors have objections to their holiday rental. However, the old-aged group is sensitive to the popularity of both holiday rentals and long-term rentals in the neighborhood ($p1=0.051$, $p2=0.033$), while the young group is insensitive to it ($p1=0.637$, $p2=0.166$). This may be because old-aged homeowners are more likely to follow the peer.

Regarding the differences in context effects between the young and the old-aged. Young homeowners are not sensitive to any context variables while the old-aged group is very sensitive to the poor condition of holiday rental property (p=0.000) and long-term rental (p=0.000), as well as the room rented for holiday rental (p=0.000). The old-aged group is also lightly sensitive to the entire house (p=0.050) and good condition (p=0.038) for long-term rental.

As for the context effects on daily income and neighbors' attitude, the interactions with property type show different responses from the two classes. For holiday rental, the interaction effect between daily income €100 and the entire house is significant for the old-aged homeowners (p=0.072), but not for the young group (p=0.279). On the other hand, for long-term rental, the result shows the interaction effect between daily income €30 and the entire house is significant for young homeowners (p=0.063) rather than the old-aged group (p=0.948). Furthermore, the interaction effects between neighbors' attitude and property type are also significant for the young group (p1=0.084, p2=0.092), but not for the old-aged (p1=0.858, p2=0.538).

4.3 Discussion

Results of the MNL model show that respondents in average are more inclined to long-term rental in this experiment. This is consistent with reality: despite the popularity of holiday rental, there are more traditional long-term rentals on the private rental market.

The result also indicates that the occupancy rate of holiday rental has a significant effect while the occupancy rate of long-term rental does not. The reason may be that long-term rentals can be easily rented out the full year in Amsterdam since there the demand exceeds the supply, so it may be hard for respondents to imagine a relatively low occupation rate (65%). i.e., this attribute may be omitted by some of the respondents. Daily income has a positive influence on the rental choice. The highest level of daily income is most preferred while the lowest daily income is least preferred both for holiday and long-term rental. This makes sense because the higher the daily income is, the more money homeowners can earn keeping the rental days equal. The significance and importance of these two attributes associated with finance indicate that financial factor has a considerably influential impact on homeowners' choice for holiday and long-term rental, which supports our findings in the literature review.

Two policy instruments, tax, and subsidy do not show a significant effect, which is unexpected. A possible explanation is that even the highest level of tax and subsidy (€3000) is still quite low for homeowners compared to what they earn from rentals. Therefore, they are not sensitive to these two attributes. Results also show that 30-day limit has an influential negative effect on homeowners’ choice for holiday rental which is reasonable since the profit is then largely reduced. However, as mentioned in the literature review, no less than 40% of the rented holiday homes in Amsterdam were rented out longer than the permitted 60 days in 2018, which suggest the 60-day limit policy is not that effective. What needs to be kept in mind here is the respondent may give dishonest answers or behave differently when he or she meet this situation in reality and therefore causes the bias.

The managing method does not show a significant effect on homeowners’ rental choice. This may be because most respondents have no experience as landlords, so they find it hard to imagine how it is like to manage a rental property and what an agency could do for them. Therefore, this attribute was not taken into account by many respondents, though there is no evidence to prove the guess.

As for social influence, neighbors’ negative attitude has a significant negative effect on the choice of holiday rental while the popularity of holiday rental or long-term rental does not matter for homeowners. This suggests homeowners do take neighbors’ attitudes into account, but they do not have a tendency to follow others, i.e. they are not affected by peer pressure.

The context effects indicate that the type and condition of the rental property have a significant effect on homeowners’ rental choice while the property location does not. This insignificance can be explained as respondents can hardly imagine a place where he or she has never lived since he or she has limited knowledge of that place. Specifically, the results indicate that holiday rental is preferred when a homeowner has a spare room in a good condition while long-term rental is preferred when a homeowner has a spare home (apartment or house) in a moderate or poor condition. The interaction effects show that the negative effects of both low daily income and neighbors’ negative attitude would be enhanced when an entire house is rented, and neighbors’ negative attitude would be somewhat smaller when a room is rented. This may partly explain why long-term rental is preferred when a homeowner has a spare entire home.

Regarding the relationship between homeowners’ socio-demographic characteristics and their rental choice, young, male homeowners prefer holiday rental while old-aged, female homeowners with low incomes prefer long-term rental. This could be explained by the heterogeneity in the respondent’s choice preferences for the following attributes: occupancy rate, daily income, days limit, and neighbors’ attitude, as suggested by ML model result. LC model further specifies that taste variation is primarily among different age groups. Young homeowners are more sensitive to a daily income of holiday rental and neighbors’ attitude than old-aged homeowners who care more about occupancy rate of holiday rental, 330 -day limit policy and the popularity of holiday and long-term rentals in the neighborhood. Furthermore, interaction effect shows that highly educated homeowners are more sensitive to the 30-day limit policy than those with low or middle education. It is likely that highly educated people tend to obey the policy instead of risking breaking it.

CHAPTER 5: CONCLUSION

In this chapter, the major findings and both scientific and social contributions of this study are highlighted; after that areas for future research are identified.

5.1 Research findings

The study has sought to identify and analyze the influence of factors on homeowners' choice to supply holiday rental and long-term rental. The main research question and four sub-questions guided this study, and their answers are given below.

SQ1: What are the main preferences of homeowners regarding holiday and long-term rental?
The results indicate that homeowners have strong preferences for high occupancy rate regarding holiday rental, and for each booked night, they prefer earning €300 and want to avoid a return of €100. As for long-term rental, they have a strong preference for earning €90 and avoiding €30 per day. As strong as a dislike for earning €100 per night is a preference to avoid the 30-day limit on holiday rental. Instead, homeowners show a strong preference for the 330-day limit which basically means no days limit. Preferences have also been found for avoiding receiving objections from neighbors.

SQ2: What are the effects of the rental property context on homeowners' choice for holiday and long-term rental?
The type and the condition of rental property have a significant effect on homeowners' choice for holiday and long-term rental while the location does not show any significant effect. When the property is an entire apartment in a moderate condition, homeowners are more likely to rent it out than when it is a room in a poor condition. Furthermore, the holiday rental is preferred when homeowners have a spare room in a good condition while long-term rental is preferred when homeowners have a spare home (apartment or house) in a poor or moderate condition.

SQ3: What are the differences in homeowners' preferences for holiday and long-term rental under different rental property contexts?
When an entire house is rented, homeowners' preferences for avoiding earning €100 per night as holiday rental or €30 per day as long-term rental and receiving neighbors' objections are particularly strong. On the other hand, the dislike for receiving neighbors' objections towards holiday rental is somewhat smaller when a room is rented.

SQ4: What are the relationships between homeowners' socio-demographic characteristics and their choice for holiday and long-term rental?

In general, young, male homeowners with high incomes are more likely to rent out their properties. Highly educated homeowners are more likely to rent out their properties for the long term than those with low or middle level of education. Homeowners who are/were landlords are more likely to make their property available for holiday rental in the future than those without landlord experience. In terms of preference, young (strongly) and middle-aged (slightly), male homeowners prefer holiday rental while old-aged, female homeowners with low incomes prefer long-term rental. Furthermore, no significant relationship has been found between homeowners' rental choice and whether they work full-time.

SQ5: What are the differences in homeowners' preferences for holiday and long-term rental between different groups of homeowners varying in age, gender, education level, income level, work status, and landlord experience?

Taste variations for occupancy rate, daily income, days limit, and neighbors' attitude are found primarily among different groups of age. Young homeowners are more sensitive to a daily income of holiday rental and neighbors' attitude than old-aged homeowners who care more about occupancy rate of holiday rental, 330-day limit policy and the popularity of holiday and long-term rentals in the neighborhood. Additionally, highly educated homeowners are more sensitive to the 30-day limit policy than those with low or middle education levels.

MQ: Which factors influence the choice of homeowners for holiday and long-term rental?

Financial factors have the most influential effects on homeowners' rental choice. High occupancy rate and high daily income have a positive influence on the choice of holiday rental, while a high daily income of long-term rental also incentivizes homeowners to choose it. When an entire house is rented, the negative influence of low daily income is particularly strong on both choices.

In terms of policy instruments, the days limit policy on holiday rental shows significant effects on homeowners' rental choice in the sense that the 30-day limit on holiday rental appears to be a major deterrent in the choice for holiday rental. The 180-day limit also deters this choice compared to the 330-day limit which basically means no limit. Moreover, the 30-day limit policy seems to be especially effective for highly educated homeowners. However, other policy instruments such as tourist tax and long-term rental subsidy seem not to have significant effects on homeowners' rental choice.

Regarding social influence, neighbors' negative attitude also shows a significant negative effect on holiday rental choice. This effect is particularly strong when homeowners, especially young homeowners want to rent out an entire house. Moreover, managing method and popularity of holiday rental or long-term rental have no significant effect.

Type and condition of the rental property, as context variables, have a significant effect on homeowners' rental choice while the property location does not. Holiday rental is preferred when a homeowner has a spare room in a good condition while long-term rental is preferred when a homeowner has a spare home (apartment or house) in a moderate or poor condition. The socio-demographic characteristics of homeowners are also relevant to their rental choice. Young, male homeowners prefer holiday rental while old-aged, female homeowners with low incomes prefer long-term rental.

5.2 Scientific and social relevance

First of all, this research enhances the academic understanding of homeowners' rental choice behavior. Previous studies mostly used qualitative research methods such as in-depth interviews to understand a single rental method, while this study provided a quantitative analysis being the first one that measures homeowners' choice preferences for holiday and long-term rental. The study provides mode evidence that financial factor is the most influential factor for homeowners to rent out their properties as a holiday or long-term rental. The results also indicate that other factors such as the days limit and neighbors' attitude regarding holiday rental are determinants for homeowners' choice as well. The rental property's context effects have also been checked for the first time; the results show that rental property's type (room or house or apartment) and condition (poor or moderate or good) have a significant effect on homeowners' rental choice preferences. The study also identifies the taste variation for the rental choice preferences among different groups. Moreover, this study contributes to the knowledge on the supply side of private rental housing by discovering the socio-demographic characteristics of homeowners who prefer holiday rental and those who prefer long-term rental.

On the city level, this research provided governments with useful insights into the effects of policy instruments on holiday rental and long-term rental. The results indicate that 180-day and especially the 30-day limit policy could be effective to discourage homeowners to supply holiday rental market. The study also shows additional tax and subsidy do not have a significant effect on homeowners' rental choice. Governments can, therefore, use the knowledge generated in this thesis as underpinning for their considerations of future policymaking.

5.3 Recommendations for future research

Some recommendations are outlined for the stakeholders directly related to the topic to keep investigating in this field. Obviously, not all factors that influence homeowners' rental choice behavior could be taken into account in this study due to the complexity in the experiment design and the capacity to obtain a sufficient number of respondents. Thus, the first recommendation is to investigate the effects of other relevant attributes that are not included within this research, such as cost, social interactions, and other policy instruments. Another limitation of this study is that the number of respondents is limited and most of them have no experience of renting out their residential properties, so it is worthwhile to have a larger sample of landlords in future research. The third implication for further research is to repeat the experiment in other cities considering the different environments and cultures. Finally, it could be valuable to examine the sensitivities of the findings, e.g. elasticity of certain attributes such as days limit, daily income, occupancy rate or to execute predictions based on scenario analysis.

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APPENDIX A: EXPERIMENTAL-DESIGN-GENERATION CODE AND CORRELATION MATRIX

A1. Code for experiment design generation

```
con<-gen.factorial(c(3,3,3), varNames=c("type","cond","loca"), factors = "all")
att<-gen.factorial(c(3,3,3,3,3,3,2,2,2,2,2,2), varNames=c("prob1", "mday1", "dinc1", "tax1",
    "inc2", "subs2", "mana1", "neig1", "numb1", "prob2", "mana2", "numb2"), factors = "all")
attT<-optFederov(~.,att,nTrials=72)
attT[["design"]]
```

A2. Correlation matrix of the main effects

	prob1	*prob2*	*dinc1*	*dinc2*	*mana1*	*mana2*	*mday1*	*tax1*	*subs2*	*neig1*	*numb1*	*numb2*
prob1	1											
prob2	0	1										
dinc1	0	0	1									
dinc2	0	-0.03402	-0.02083	1								
mana1	0	-0.05556	0	0	1							
mana2	0.034021	0	0	0	0	1						
mday1	0	0.034021	0.041667	-0.08333	0	0	1					
tax1	0	0	0	0	0.034021	0	0	1				
subs2	0	0	0	0	0	-0.03402	0	0	1			
neig1	0	0	0	0.034021	-0.05556	0	0	0	0	1		
numb1	0	0	0	0	0	0	0.034021	0	0	0	1	
numb2	0.034021	0	0	0	0	0	0	-0.03402	0.034021	0	0.055556	1

APPENDIX B: GENERATED EXPERIMENTAL DESIGN

B1. Context experiment design

AID	TYPE	COND	LOCA
1	1	1	1
2	2	1	1
3	3	1	1
4	1	2	1
5	2	2	1
6	3	2	1
7	1	3	1
8	2	3	1
9	3	3	1
10	1	1	2
11	2	1	2
12	3	1	2
13	1	2	2
14	2	2	2
15	3	2	2
16	1	3	2
17	2	3	2
18	3	3	2
19	1	1	3
20	2	1	3
21	3	1	3
22	1	2	3
23	2	2	3
24	3	2	3
25	1	3	3
26	2	3	3
27	3	3	3

B2. Choice experiment design

AID	PROB1	PROB2	DINC1	DINC2	MANA1	MANA2	MDAY1	TAX1	SUBS2	NEIG1	NUMB1	NUMB2
1	2	1	3	1	2	1	3	1	1	1	1	1
2	1	1	3	3	1	1	3	1	3	2	1	1
3	2	1	3	1	2	1	2	2	1	2	1	1
4	2	1	2	2	2	1	2	1	2	1	2	1

5	1	1	1	2	2	1	2	2	3	2	2	1
6	3	2	2	2	1	1	2	2	3	1	1	1
7	1	2	2	3	2	1	1	2	2	1	1	1
8	1	2	2	2	1	1	3	3	1	1	2	1
9	2	2	1	1	2	1	1	3	2	1	2	1
10	3	2	1	3	2	1	1	3	3	2	2	1
11	3	1	1	1	1	1	3	2	2	1	1	1
12	1	1	2	2	1	1	1	1	2	2	1	1
13	2	1	3	3	1	1	2	3	3	1	2	1
14	3	1	2	1	2	1	3	2	3	1	2	1
15	1	1	1	3	1	1	3	2	3	2	2	1
16	2	1	1	3	2	1	2	1	1	2	2	1
17	3	2	3	2	1	1	2	3	2	2	1	1
18	3	2	2	3	2	1	1	2	1	2	2	1
19	2	1	2	2	2	2	2	1	2	1	1	1
20	3	1	2	3	1	2	3	1	2	2	1	1
21	3	1	3	1	1	2	2	1	3	2	2	1
22	3	2	1	1	1	2	1	2	1	1	1	1
23	1	2	1	2	1	2	3	3	3	1	1	1
24	3	2	2	3	2	2	2	2	2	2	1	1
25	1	2	3	1	1	2	3	3	2	1	2	1
26	2	2	1	3	1	2	1	3	1	2	2	1
27	2	1	1	2	1	2	1	2	1	1	1	1
28	3	1	3	2	2	2	1	3	3	2	1	1
29	2	1	3	2	1	2	1	2	2	1	2	1
30	1	1	3	3	2	2	1	2	1	1	2	1
31	1	2	2	1	2	2	3	1	1	1	1	1
32	1	2	1	1	1	2	2	1	1	2	1	1
33	1	2	1	1	2	2	2	3	1	2	1	1
34	2	2	3	3	2	2	3	3	2	2	1	1
35	2	2	3	1	1	2	1	1	2	1	2	1
36	2	2	2	2	2	2	3	3	3	2	2	1
37	3	1	1	1	1	1	2	3	3	1	1	2
38	3	1	3	2	2	1	1	1	1	1	1	2
39	2	1	1	3	1	1	3	3	2	2	1	2
40	1	1	2	2	2	1	3	3	1	1	2	2
41	1	1	2	1	1	1	2	3	1	2	2	2
42	2	2	3	2	1	1	3	2	1	2	1	2
43	3	2	3	1	2	1	1	3	1	1	2	2
44	2	2	2	1	1	1	1	1	3	2	2	2
45	1	1	2	3	2	1	1	3	3	1	1	2
46	3	1	1	1	2	1	1	1	3	2	1	2

47	3	2	1	2	2	1	3	2	2	1	1	2
48	2	2	2	3	1	1	2	2	1	2	1	2
49	1	2	3	2	1	1	1	1	3	2	1	2
50	1	2	3	1	2	1	2	3	2	2	1	2
51	2	2	1	3	1	1	3	1	1	1	2	2
52	3	2	3	3	1	1	2	1	2	1	2	2
53	1	2	1	2	1	1	1	1	3	1	2	2
54	1	2	3	1	2	1	3	2	2	2	2	2
55	1	1	3	3	1	2	1	2	1	2	1	2
56	2	1	1	2	2	2	1	3	2	2	1	2
57	1	1	1	3	2	2	2	1	2	1	2	2
58	1	1	2	1	1	2	1	2	2	2	2	2
59	2	1	3	1	2	2	3	2	3	2	2	2
60	2	2	1	1	2	2	2	2	3	1	1	2
61	1	2	3	3	2	2	2	1	3	1	1	2
62	3	2	3	3	2	2	3	2	3	1	2	2
63	3	2	1	3	1	2	1	1	2	2	2	2
64	3	2	2	2	2	2	3	1	1	2	2	2
65	3	1	2	3	1	2	2	3	1	1	1	2
66	2	1	2	3	2	2	1	3	3	1	1	2
67	3	1	3	2	1	2	2	3	1	1	2	2
68	1	1	1	2	2	2	2	2	2	1	2	2
69	3	1	2	1	1	2	3	3	2	2	2	2
70	3	1	1	2	2	2	3	1	1	2	2	2
71	2	2	2	1	1	2	3	1	3	1	1	2
72	2	2	2	2	1	2	2	2	3	2	2	2

APPENDIX C: QUESTIONNAIRE

C1. Questionnaire in English

Introduction

Dear Amsterdammer,

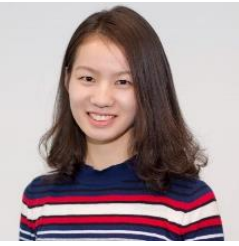
There is a large shortage of rental properties in Amsterdam. Many people believe that renting out properties to tourists aggravates this problem. The purpose of this questionnaire is to gain insight into holiday rentals in Amsterdam and to explore policy options.

This questionnaire is part of a graduation research project at Eindhoven University of Technology that focuses on the specific preferences of holiday and long-term landlords, and the way in which policymakers can respond. That is why we are interested in your opinion on holiday rental, your experience as a homeowner and your choices with regard to renting out your home in Amsterdam in the future.

Completing this survey will take approximately 10 minutes of your time. Participation is voluntary. Your answers are only seen by me and my supervisors and are not shared with others. Personal data is not used in publications and presentations and outcomes are never traceable to individuals. The data is stored encrypted on a secure network within the university. If the data is also used for future research, we will inform you about this.

Thank you for your participation and if you have any questions, feel free to contact me.

Kind regards,



Amanda Feng

Graduation intern at City of Amsterdam
MSc student at Eindhoven University of Technology
Construction Management & Engineering
E-mail: x.feng2@student.tue.nl

About You

1. What is your age?

- < 18
- 18 - 24
- 25 - 29
- 30 - 34
- 35 - 39
- 40 - 44
- 45 - 49
- 50 - 54
- 55 - 59
- 60 - 64
- > 64

2. What is your gender?

- Male
- Female
- Other, namely:

3. What is your highest education level?

- Primary school
- Preparatory secondary vocational education
- Junior general secondary education
- Secondary vocational education
- senior general secondary education and Pre-university education
- Higher professional education
- Higher academic education
- Other, namely:

4. What is your occupation?

- No work
- Student
- Working (part time, less or equal to 32 hours)
- Working (full time, more than 32 hours)
- Retired
- Other, namely:

5. What is the situation of your household?

- Single without (resident) children
- Single person with resident child (ren)
- Cohabiting / married without (resident) children
- Cohabiting / married with living child (ren)
- Living at home with others (no family)
- Other, namely:

6. What is your net monthly household income?

- No more than € 625
- € 626 to € 1250
- € 1251 to € 1875
- € 1876 to € 2500
- € 2501 to € 3125
- More than € 3125
- I prefer not to say

7. What is the 6-digit zip code (1234 AA) of your current living place?

- I prefer not to say

8. How many residential properties do you own in Amsterdam?

- None
- One
- More than one
- I prefer not to say

Your Opinion about Holiday Rental

Holiday rental is the temporary rental of a complete home or part of a home to tourists via online platforms such as Airbnb, HomeAway or Booking.com.
Long-term rental is the rental of a complete property or part of a property to non-tourists for periods of three months or longer.

9. When you go on vacation, how often do you rent a home/room via an online platform such as Airbnb, Booking, HomeAway?

- Always
- Very often
- Sometimes
- Rarely
- Never

10. What is your attitude towards your neighbor(s) renting out their properties to tourists?

- Very positive
- Positive
- Negative
- Very negative
- I do not know

11. In your opinion, to what extent does holiday rental contribute to the following developments within Amsterdam?

- Withdrawal of properties from rental market and increase in rent
- Withdrawal of properties from housing market and increase in housing price
- Crowdedness in the city
- Nuisance in the neighborhood
- Loss of cultural identity

(None, little, some, a lot, I do not know)

12. How satisfied are you with the current holiday rental regulation in Amsterdam?

(Very dissatisfied, dissatisfied, slightly dissatisfied, slightly satisfied, satisfied, very satisfied, I don’t know)

13. In your opinion, what is the maximum number of days per year that a complete home could be rented to tourists?

- 30 days
- 60 days
- 90 days
- 180 days
- 360 days (No limit)
- Other, namely:
- I do not know

14. Do you think holiday rental should be prohibited?

- Yes, in some parts of Amsterdam center
- Yes, within the whole Amsterdam center
- Yes, within the ring road A10
- Yes, in the whole city of Amsterdam
- No, it shouldn't be prohibited
- Other, namely:
- I do not know

15. What is your likelihood that you will become a landlord of a holiday home in the future (within 5 years)?

- Impossible
- Unlikely
- Fifty-fifty
- Likely
- Certain
- I do not know

16. To what extent are the motives below a reason for you to become a landlord of a holiday home?

- As main income
- To earn some additional income
- To meet new people and probably make friends with them

(Strongly disagree, disagree, slightly disagree, slightly agree, agree, strongly agree, I do not know)

17. Do you have experience of being a landlord in Amsterdam?

- Yes, I rented out all/part of my property (s) to tourists as holiday rental
- Yes, I rented out all/ part of my property (s) to non-tourists as long-term rental
- Yes, both holiday rental and long-term rental
- No

Stated Choice Experiment

In the stated choice experiment, you will be given a number of imaginary situations. These situations are composed for research purposes of the Eindhoven University of Technology and are not based on the policy of the municipality of Amsterdam. You make a choice for a rental method from the holiday rental, long-term rental and neither of these two. You receive a total of 9 of these choice questions, with each question varying with different contexts and attributes.

Below is an explanation of the attributes:

Occupancy rate: The total number of days in a year that the property will be occupied by tenants divided by the number of available days in a year.
Daily income: The average daily income generated by renting out a specific property.
Days limit: The maximum number of days that is allowed by Amsterdam municipality for an entire home to be rented out in a year.
Tourist tax: Additional tourist tax charged on holiday rental hosts per year by the municipality.
Long-term rental subsidy: The financial aid per year given by the municipality to landlords to encourage long-term rental.
Managing by: A rental property can be managed (including advertising, communicating, cleaning, maintaining, etc.) by either yourself or by a property management agency. The agency fee has already been deducted from the profit.
Neighbors' attitude: Neighbors may be unhappy with the negative influence caused by the tourist guests in the rental property and thus may report it to the municipality.
Respective numbers in the neighborhood**:** The number of holiday rental/long-term rental properties in the neighborhood where the property is located. The larger the number is, the more popular this rental type is.

Below you see one example of choice questions:

Imagine you have **an entire spare house** in **good condition** located **inside the center of Amsterdam**. Which option would you choose in the future to rent your property out?

	Holiday rental	*Long-term rental*
Occupancy rate	65%	95%
Daily income	100 Euro/day	60 Euro/day
Days limit	180 days	
Tourist tax	- 1000 Euro/year	
Long-term rental subsidy		+ 2000 Euro/year
Managing by	Yourself	Agency
Neighbors' attitude	Objection	
Respective numbers in the neighborhood	Small	Large
Your choice	○	○
	○ **None of these**	

(The answer has already been ticked in this example for illustration purposes.)

C2. Online Dutch questionnaire screen shot

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

Amsterdam vakantieverhuur vs lange-termijn verhuur

(Readonly)

Welkom bij het onderzoek Amsterdam vakantieverhuur vs lange-termijn verhuur!

Beste Amsterdammer,

In Amsterdam bestaat een groot tekort aan huurwoningen. Veel mensen zijn van oordeel dat de verhuur van woningen aan toeristen dit probleem vergroot. Deze vragenlijst heeft tot doel inzicht te krijgen in de vakantieverhuur in Amsterdam en beleidsopties te verkennen.

Deze vragenlijst is onderdeel van een afstudeeronderzoek aan de Technische Universiteit Eindhoven dat zich richt op de specifieke voorkeuren van vakantie- en lange-termijn verhuurders, en de manier waarop beleidsmakers hierop kunnen reageren. Daarom zijn we geïnteresseerd in uw mening over vakantieverhuur, uw ervaring als huiseigenaar en uw keuzes met betrekking tot het verhuren van uw woning in Amsterdam in de toekomst.

Het invullen van deze enquête neemt ongeveer 10 minuten van uw tijd in beslag. Deelname is vrijwillig en anoniem. Uw antwoorden zijn nooit herleidbaar naar individuele personen.

Hartelijk dank voor uw medewerking en mocht u vragen hebben, aarzel dan niet mij te benaderen.

Vriendelijke groeten,

Amanda Feng

Afstudeerstagiaire Gemeente Amsterdam
MSc student at Eindhoven University of Technology
E-mail: x.feng2@student.tue.nl

Start

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

Amsterdam vakantieverhuur vs lange-termijn verhuur

(Readonly)

Deel 1: Over U

Wat is uw leeftijd?

18 - 24 jaar

Wat is uw geslacht?

- ( ) Man
- (•) Vrouw
- ( ) Anders, namelijk:

Wat is uw hoogst genoten opleiding?

- ( ) Basisschool/lagere school
- ( ) Voorbereidend middelbaar beroepsonderwijs (v(m)bo, lts, lbo, huishoudschool)
- ( ) Middelbaar algemeen voortgezet onderwijs (mavo, (m)ulo)
- ( ) Middelbaar beroesponderwijs (mbo, mts)
- ( ) Hoger algemeen en voorbereidend wetenschappelijk onderwijs (havo, vwo, hbs)
- ( ) Hoger beroepsonderwijs (hbo, pabo, hts, heao)
- (•) Wetenschappelijk onderwijs (universiteit, gepromoveerd)
- ( ) Anders, namelijk:

Wat is uw werksituatie?

- ( ) Niet werkzaam
- (•) Student
- ( ) Werkend (parttime, minder of gelijk aan 32 uur)
- ( ) Werkend (fulltime, meer dan 32 uur)
- ( ) Gepensioneerd
- ( ) Anders, namelijk:

Wat is de samenstelling van uw huishouden?

- (•) Alleenstaand zonder (inwonende) kinderen
- ( ) Alleenstaand met inwonend(e) kind(eren)
- ( ) Samenwonend/getrouwd zonder (inwonende) kinderen
- ( ) Samenwonend/getrouwd met inwonend(e) kind(eren)
- ( ) Thuiswonend met anderen (geen familie)
- ( ) Anders, namelijk:

Wat is het netto maandelijks inkomen van uw huishouden?

- ( ) Niet meer dan €625
- (•) €626 tot €1250
- ( ) €1251 tot €1875
- ( ) €1876 tot €2500
- ( ) €2501 tot €3125
- ( ) Meer dan €3125
- ( ) Zeg ik liever niet

Wat is de 6-cijferige (1234 AA) postcode van uw huidige woonadres?

De cijfers van mijn postcode zijn:	1091
De letters van mijn postcode zijn:	MR

☐ Zeg ik liever niet

Hoeveel woningen bezit u in Amsterdam?

- ○ Geen
- ◉ Eén
- ○ Meer dan één
- ○ Zeg ik liever niet

Vorige | Volgende

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

Amsterdam vakantieverhuur vs lange-termijn verhuur

(Readonly)

Deel 2: Uw mening over vakantieverhuur

Vakantieverhuur is het tijdelijk verhuren van een volledige / gedeeltelijke woning aan toeristen via online platforms zoals Airbnb, HomeAway of Booking.com.
Lange-termijn verhuur is verhuren van een volledige woning of deel van een woning aan niet-toeristen voor periodes van drie maanden of langer.

Als u op vakantie gaat, hoe vaak huurt u dan een huis/kamer via een online platform zoals Airbnb, Booking, HomeAway?

Nooit	Bijna nooit	Soms	Meestal	Altijd
○	○	◉	○	○

Wat is uw houding tegenover buurtgenoten die woningen aan toeristen verhuren?

- ○ Zeer positief
- ○ Positief
- ◉ Negatief
- ○ Zeer negatief
- ○ Ik weet het niet

In welke mate draagt vakantieverhuur naar uw mening bij aan de volgende ontwikkelingen binnen Amsterdam?

	Niet	Nauwelijks	Enigszins	Veel	Ik weet het niet
Onttrekking van woningen aan de huurmarkt en huurverhoging	○	○	◉	○	○
Onttrekking van woningen aan de woningmarkt en stijging van de huizenprijs	○	○	◉	○	○
Drukte in de stad	○	○	◉	○	○
Overlast in de buurt	○	◉	○	○	○
Verzwakking van de sociale cohesie	○	◉	○	○	○

Hoe tevreden bent u met de huidige regelgeving voor vakantieverhuur in Amsterdam?

Zeer ontevreden	Ontevreden	Enigszins ontevreden	Enigszins tevreden	Tevreden	Zeer tevreden	Ik weet het niet
○	○	○	◉	○	○	○

Wat is naar uw mening het maximale aantal dagen per jaar dat een volledige woning aan toeristen zou mogen worden verhuurd?

60 dagen ▾

Vindt u dat vakantieverhuur verboden zou moeten worden?

Anders, namelijk: ▾

In buurten waar veel overlast plaatsvind

Hoe groot acht u de kans dat u in de toekomst (binnen 5 jaar) verhuurder van een vakantiewoning wordt?

Onmogelijk	Onwaarschijnlijk	Fifty-fifty	Waarschijnlijk	Zeker	Ik weet het niet
○	◉	○	○	○	○

In welke mate zijn de onderstaande motieven voor u een reden om verhuurder van een vakantiewoning te worden?

	Zeer mee oneens	Oneens	Enigszins oneens	Enigszins eens	Eens	Zeer mee eens	Ik weet het niet
Als hoofdinkomen	○	○	◉	○	○	○	○
Om extra inkomen te genereren	○	○	○	○	○	◉	○
Om nieuwe mensen te ontmoeten en de kans vrienden te maken	○	○	◉	○	○	○	○

Heeft u ervaring als verhuurder?

○ Ja, ik verhuur(de) mijn volledige / een deel van mijn woning(en) aan toeristen voor vakantieverhuur
○ Ja, ik verhuur(de) mijn volledige / een deel van mijn woning(en) aan niet-toeristen voor lange-termijn verhuur
◉ Ja, zowel vakantieverhuur als lange-termijn verhuur
○ Nee

Vorige | Volgende

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

Amsterdam vakantieverhuur vs lange-termijn verhuur

Page: Deel 5: Keuze experiment

Deel 5: Keuze experiment

In het keuze experiment hieronder worden u enkele denkbeeldige situaties voorgelegd. **Deze situaties zijn ontwikkeld voor onderzoeksdoeleinden van de Technische Universiteit Eindhoven en zijn niet gebaseerd op het beleid van de gemeente Amsterdam**. U kiest uit een verhuurmethode voor: vakantieverhuur, lange-termijn verhuur en geen van beide. U krijgt in totaal 9 keuzevragen voorgelegd die variëren in context en kenmerken.

Hieronder vindt u uitleg over de kenmerken en een voorbeeld van een vraag:

Stelt u zich voor dat u **een volledig huis over heeft** in **goede staat** gelegen **in het centrum van Amsterdam**. Welke optie zou u in de toekomst kiezen voor de verhuur van uw woning?

	Vakantieverhuur	**Lange-termijn verhuur**
Bezettingsgraad	65%	95%
Dagelijks inkomsten	100 Euro/dag	60 Euro/dag
Het maximale aantal dagen per jaar	180 dagen	-
Vakantieverhuurbelasting	1000 Euro/jaar	-
Subsidie	-	2000 Euro/jaar
Beheer door	Uzelf	Een bureau
Houding buren	Bezwaar	-
Aantal respectievelijk verhuurwoningen in de wijk	Klein	Groot
Uw keuze	☒	☐
	☐ **Geen van beide**	

(Het antwoord is ter illustratie reeds in dit voorbeeld aangekruist.)

Vorige | Volgende

Amsterdam vakantieverhuur vs lange-termijn verhuur

(Readonly)

Mocht u nog vragen/opmerkingen hebben (over de ingevulde gegevens, verbetering van de enquête, enz.) dan kunt u dat hieronder vermelden:

Hiermee bent u aan het einde gekomen van deze vragenlijst. Hartelijk dank voor uw deelname!

Om uw gegevens te Versturen dient u hieronder op de button te klikken.

Vorige

Versturen

APPENDIX D: MODIFICATIONS OF DATA

- 1 respondent filled in ‘Other, namely: VWO’ on the question about the highest Education level. However, ‘VWO’ was one of the answer possibilities, so this answer has been changed from ‘Other, namely:’ to ‘Hoger algemeen en voorbereidend wetenschappelijk onderwijs (havo, vwo, hbs)’

- 1 respondent filled in ‘Other, namely: enkele jaren universiteit, niet afgestudeerd’ on the question about the highest Education level. However, this suggested it was one of the answer possibilities, so this answer has been changed from ‘Other, namely:’ to ‘Hoger algemeen en voorbereidend wetenschappelijk onderwijs (havo, vwo, hbs)’

- 2 respondents filled in ‘Other, namely: arbeidsongeschikt’ on the question about the work status. However, ‘arbeidsongeschikt’ was one of the answer possibilities, so this answer has been changed from ‘Other, namely:’ to ‘Niet werkzaam’

- 1 respondent filled in ‘Other, namely: Alleenstaand met inwonende volwassen zoon’ on the question about the household composition. However, ‘Alleenstaand met inwonende volwassen zoon’ was one of the answer possibilities, so this answer has been changed from ‘Other, namely:’ to ‘Alleenstaand met inwonend(e) kind(eren)’

APPENDIX E: EFFECT CODING

Abbr.	Variables		No.	levels	Effect codes	
Attributes						
occu	Occupancy rate	HR	1	35%		
			2	65%		
			3	95%		
		LTR	1	65%		
			2	95%		
dinc	Daily income (€)	HR	1	100	1	0
			2	200	-1	-1
			3	300	0	1
		LTR	1	30	1	0
			2	60	-1	-1
			3	90	0	1
mday	Days limit	HR	1	30	1	0
			2	180	-1	-1
			3	330	0	1
tax	Tax (€)	HR	1	1000	1	0
			2	2000	-1	-1
			3	3000	0	1
subs	Subsidy (€)	LTR	1	1000	1	0
			2	2000	-1	-1
			3	3000	0	1
mana	Managing method		1	By an agency	1	
			2	By yourself	-1	
neig	Neighbors' attitude	HR	1	Objection	1	
			2	Neutral	-1	
numb	Numbers in the neighborhood		1	Large	1	
			2	Small	-1	
Context variables						
type	Type of property		1	Room	1	0
			2	Entire apartment	-1	-1
			3	Entire house	0	1
cond	Condition of property		1	Poor	1	0
			2	Moderate	-1	-1
			3	Good	0	1
loca	Location of property		1	In the center of Amsterdam	1	0
			2	Within A10 but outside the center of Amsterdam	-1	-1

		3	Within the city of Amsterdam but outside A10	0	1
Socio-demographic variables					
age	Age	1	18 - 39	1	0
		2	40 - 59	-1	-1
		3	≥ 60	0	1
inc	Income level	1	Low-/middle-income level	1	0
		2	High-income level	0	1
		3	Unknown	-1	-1
gen	Gender	1	Male	1	
		2	Female	-1	
edu	Highest education level	1	High-education level	1	
		2	Low-/middle education level	-1	
wor	Work status	1	Full-time work	1	
		2	other	-1	
exp	Landlord experience	1	Is/was a landlord	1	
		2	No landlord experience	-1	

APPENDIX F: MODEL INPUT

F1. Base model input

```
NLOGIT
;lhs = choice,cset,alti
;choices = hr,ltr,none
;rhs=one$
```

F2. MNL model input

```
NLOGIT
;lhs = choice,cset,alti
;choices = hr,ltr,none
;model:
u(hr) = hr + a1*prob + a2*dinc1 + a3*dinc2 + a4*mday1 +a5*mday2 + a6*tax1 + a7*tax2 +
a8*mana + a9*neig + a10*numb
+ c1*type1 + c2*type2 + c3*cond1 + c4*cond2 + c5*loca1 + c6*loca2
+ e1*age1 + e2*age2 + e3*inc1 + e4*inc2 + e5*gen + e6*edu + e7*wor + e8*exp /
u(ltr) = ltr + b1*prob + b2*dinc1 + b3*dinc2 + b4*subs1 + b5*subs2 + b6*mana + b7*numb
+ d1*type1 + d2*type2 + d3*cond1 + d4*cond2 + d5*loca1 + d6*loca2
+ f1*age1 + f2*age2 + f3*inc1 + f4*inc2 + f5*gen + f6*edu + f7*wor + f8*exp /
u(none)= 0 $
```

F3. MNL+ model input

```
Create; di1_ty1=dinc1*type1$
Create; di2_ty1=dinc2*type1$
Create; di1_ty2=dinc1*type2$
Create; di2_ty2=dinc2*type2$
Create; md1_ed=mday1 *edu$
Create; md2_ed=mday2 *edu$
Create; ne_ty1=neig*type1$
Create; ne_ty2=neig*type2$
Create; ne_ag1=neig*age1$
Create; ne_ag2=neig *age2$
NLOGIT
;lhs = choice,cset,alti
```

```
;choices = hr,ltr,none
;model:
u(hr) = hr + a1*prob + a2*dinc1 + a3*dinc2 + a4*mday1 +a5*mday2 + a6*tax1 + a7*tax2 +
a8*mana + a9*neig + a10*numb
+ c1*type1 + c2*type2 + c3*cond1 + c4*cond2 + c5*loca1 + c6*loca2
+ e1*age1 + e2*age2 + e3*inc1 + e4*inc2 + e5*gen + e6*edu + e7*wor + e8*exp
+ g1*di1_ty1 + g2*di2_ty1+ g3*di1_ty2 + g4*di2_ty2 + g5*md1_ed + g6*md2_ed + g7*ne_ty1
+ g8*ne_ty2 + g9*ne_ag1 + g10*ne_ag2 /
u(ltr) = ltr + b1*prob + b2*dinc1 + b3*dinc2 + b4*subs1 + b5*subs2 + b6*mana + b7*numb
+ d1*type1 + d2*type2 + d3*cond1 + d4*cond2 + d5*loca1 + d6*loca2
+ f1*age1 + f2*age2 + f3*inc1 + f4*inc2 + f5*gen + f6*edu + f7*wor + f8*exp
+ h1*di1_ty1 + h2*di2_ty1+ h3*di1_ty2 + h4*di2_ty2 /
u(none)= 0 $
```

F4. ML Model input

```
Create; di1_ty1=dinc1*type1$
Create; di2_ty1=dinc2*type1$
Create; di1_ty2=dinc1*type2$
Create; di2_ty2=dinc2*type2$
Create; md1_ed=mday1 *edu$
Create; md2_ed=mday2 *edu$
Create; ne_ty1=neig*type1$
Create; ne_ty2=neig*type2$
Create; ne_ag1=neig*age1$
Create; ne_ag2=neig *age2$
NLOGIT
;lhs = choice,cset,alti
;choices = hr,ltr,none
;rpl
;fcn = hr(t,1),ltr(t,1),a1(t,1),a2(t,1),a3(t,1),a4(t,1),a5(t,1),a9(t,1),b2(t,1),b3(t,1)
;pts= 1000
;halton
;model:
u(hr) = hr + a1*prob + a2*dinc1 + a3*dinc2 + a4*mday1 +a5*mday2 + a6*tax1 + a7*tax2 +
a8*mana + a9*neig + a10*numb
+ c1*type1 + c2*type2 + c3*cond1 + c4*cond2 + c5*loca1 + c6*loca2
```

+ e1*age1 + e2*age2 + e3*inc1 + e4*inc2 + e5*gen + e6*edu + e7*wor + e8*exp
+ g1*di1_ty1 + g2*di2_ty1+ g3*di1_ty2 + g4*di2_ty2 + g5*md1_ed + g6*md2_ed + g7*ne_ty1
+ g8*ne_ty2 + g9*ne_ag1 + g10*ne_ag2 /
u(ltr) = ltr + b1*prob + b2*dinc1 + b3*dinc2 + b4*subs1 + b5*subs2 + b6*mana + b7*numb
+ d1*type1 + d2*type2 + d3*cond1 + d4*cond2 + d5*loca1 + d6*loca2
+ f1*age1 + f2*age2 + f3*inc1 + f4*inc2 + f5*gen + f6*edu + f7*wor + f8*exp
+ h1*di1_ty1 + h2*di2_ty1+ h3*di1_ty2 + h4*di2_ty2 /
u(none)= 0 $

F5. LC model input

```
Create; di1_ty1=dinc1*type1$
Create; di2_ty1=dinc2*type1$
Create; di1_ty2=dinc1*type2$
Create; di2_ty2=dinc2*type2$
Create; ne_ty1=neig*type1$
Create; ne_ty2=neig*type2$
NLOGIT
;lhs = choice,cset,alti
;choices = hr,ltr,none
;pds=9
;pts=2
;lcm = age1,age2
;model:
u(hr) = hr + a1*prob + a2*dinc1 + a3*dinc2 + a4*mday1 +a5*mday2 + a6*tax1 + a7*tax2 +
a8*mana + a9*neig + a10*numb
+ c1*type1 + c2*type2 + c3*cond1 + c4*cond2 + c5*loca1 + c6*loca2
+ g1*di1_ty1 + g2*di2_ty1+ g3*di1_ty2 + g4*di2_ty2 + g5*ne_ty1 + g6*ne_ty2 /
u(ltr) = ltr + b1*prob + b2*dinc1 + b3*dinc2 + b4*subs1 + b5*subs2 + b6*mana + b7*numb
+ d1*type1 + d2*type2 + d3*cond1 + d4*cond2 + d5*loca1 + d6*loca2
+ h1*di1_ty1 + h2*di2_ty1+ h3*di1_ty2 + h4*di2_ty2 /
u(none)= 0 $
```

APPENDIX G: ML MODELS OUTPUT

G1. ML Model (normal distribution, random par. = all attributes and ASCs) output

```
Random Parameters Logit Model
Dependent variable              CHOICE
Log likelihood function     -1821.45388
Restricted log likelihood   -2155.47731
Chi squared [  80 d.f.]       668.04686
Significance level               .00000
McFadden Pseudo R-squared      .1549649
Estimation based on N =    1962, K =  80
Inf.Cr.AIC  =    3802.9 AIC/N =    1.938
Model estimated: Oct 18, 2019, 17:16:57
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
At start values -1833.5810  .0066******
Response data are given as ind. choices
Replications for simulated probs. = 100
Used Halton sequences in simulations.
Number of obs.=  1962, skipped    0 obs
```

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
	Random parameters in utility functions					
HR	-4.66302	5.82572	-.80	.4235	-16.08122	6.75519
LTR	.75896	.68321	1.11	.2666	-.58010	2.09803
A1	1.62827	1.35417	1.20	.2292	-1.02587	4.28240
A2	-1.78753	2.15889	-.83	.4077	-6.01887	2.44382
A3	.55718	.75359	.74	.4597	-.91982	2.03418
A4	-.88897	1.09411	-.81	.4165	-3.03339	1.25546
A5	.98346	1.19348	.82	.4099	-1.35572	3.32263
A6	-.77087	1.20862	.64	.5236	-1.59798	3.13972
A7	.04116	.40114	-.10	.9183	-.82738	.74505
A8	.12181	.34274	.36	.7223	-.54994	.79356
A9	-.63623	.79472	-.80	.4234	-2.19384	.92139
A10	.28236	.50466	.56	.5758	-.70676	1.27148
B1	.68460	.91296	.75	.4533	-1.10477	2.47397
B2	-.61757*	.35532	-1.74	.0822	-1.31399	.07885
B3	.48851*	.28898	1.69	.0909	-.07788	1.05491

B4	.02793	.20505	.14	.8917	-.37396	.42981
B5	-.04051	.23185	-.17	.8613	-.49493	.41390
B6	-.06773	.10917	-.62	.5350	-.28170	.14624
B7	-.00354	.10088	-.04	.9720	-.20126	.19417
	Nonrandom parameters in utility functions					
C1	-.67630	.66176	-1.02	.3068	-1.97332	.62073
C2	-.01958	.33693	-.06	.9537	-.67995	.64079
C3	-1.30970	1.06102	-1.23	.2171	-3.38926	.76987
C4	.88955	1.06553	.83	.4038	-1.19886	2.97796
C5	.24111	.42382	.57	.5694	-.58955	1.07178
C6	-.54470	.76174	-.72	.4746	-2.03769	.94829
E1	2.88718	2.82425	1.02	.3066	-2.64824	8.42261
E2	-3.32013	3.23493	-1.03	.3047	-9.66048	3.02022
E3	-.73007	.82030	-.89	.3735	-2.33784	.87769
E4	.12878	.39139	.33	.7421	-.63832	.89588
E5	.63163	.62294	1.01	.3106	-.58932	1.85257
E6	.16308	.33702	.48	.6285	-.49745	.82362
E7	-.01434	.29733	-.05	.9615	-.59709	.56842
E8	.61595	.81571	.76	.4502	-.98282	2.21472
G1	-.18424	.50569	-.36	.7156	-1.17537	.80690
G2	.38762	.61752	.63	.5302	-.82270	1.59794
G3	-.47840	.52961	-.90	.3664	-1.51641	.55961
G4	-.01758	.48087	-.04	.9708	-.96006	.92490
G5	-1.13559	1.37615	-.83	.4093	-3.83279	1.56162
G6	.72995	.94606	.77	.4404	-1.12431	2.58420
G7	.60195	.84588	.71	.4767	-1.05595	2.25985
G8	-.53447	.70941	-.75	.4512	-1.92489	.85595
G9	-.56259	.88610	-.63	.5255	-2.29931	1.17413
G10	1.07515	1.60747	.67	.5036	-2.07543	4.22574
D1	-.88353*	.51440	-1.72	.0859	-1.89172	.12467
D2	.46181	.32962	1.40	.1612	-.18422	1.10785
D3	-.82946*	.48224	-1.72	.0854	-1.77463	.11570
D4	.02568	.14903	.17	.8632	-.26641	.31777
D5	.04047	.16327	.25	.8042	-.27953	.36048
D6	-.20574	.23223	-.89	.3757	-.66090	.24943
F1	1.11995*	.67882	1.65	.0990	-.21051	2.45041
F2	-.89411*	.49994	-1.79	.0737	-1.87398	.08575
F3	-.51770	.34742	-1.49	.1362	-1.19863	.16322
F4	.37369	.25207	1.48	.1382	-.12036	.86775
F5	.13050	.11939	1.09	.2744	-.10350	.36450
F6	.21305	.17781	1.20	.2309	-.13546	.56156
F7	-.01646	.12422	-.13	.8946	-.25993	.22701

F8	.25399	.21976	1.16	.2478	-.17673	.68471
H1	.45492	.36890	1.23	.2175	-.26811	1.17795
H2	-.14981	.24110	-.62	.5344	-.62237	.32275
H3	-.32850	.25931	-1.27	.2052	-.83675	.17975
H4	.23835	.29045	.82	.4119	-.33092	.80761
	Distns. of RPs. Std.Devs or limits of triangular					
NsHR	.46095	.77976	.59	.5544	-1.06735	1.98925
NsLTR	.67726	1.66186	.41	.6836	-2.57994	3.93445
NsA1	2.79091	7.61916	.37	.7141	-12.14237	17.72420
NsA2	.07659	1.36982	.06	.9554	-2.60820	2.76139
NsA3	1.03305	1.93299	.53	.5930	-2.75553	4.82163
NsA4	.03924	.90698	.04	.9655	-1.73841	1.81689
NsA5	.05667	.75334	.08	.9400	-1.41984	1.53319
NsA6	3.08134	3.49711	.88	.3783	-3.77287	9.93556
NsA7	5.15562	6.54907	.79	.4311	-7.68032	17.99156
NsA8	3.73094	4.49481	.83	.4065	-5.07873	12.54060
NsA9	.76443	1.48722	.51	.6073	-2.15047	3.67933
NsA10	1.27800	1.27698	1.00	.3169	-1.22483	3.78083
NsB1	.06637	1.23791	.05	.9572	-2.35989	2.49263
NsB2	.73579	.59222	1.24	.2141	-.42494	1.89652
NsB3	.22114	.61866	.36	.7208	-.99142	1.43370
NsB4	3.01337	2.32636	1.30	.1952	-1.54621	7.57295
NsB5	.95854	.72615	1.32	.1868	-.46469	2.38177
NsB6	.79969	.72274	1.11	.2685	-.61685	2.21622
NsB7	.22976	.42356	.54	.5875	-.60041	1.05993

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

G2. ML (constrained triangular distribution, random par. = all attributes and ASCs) model output

Random Parameters Logit Model
Dependent variable CHOICE
Log likelihood function -1833.96668
Restricted log likelihood -2155.47731
Chi squared [61 d.f.] 643.02126
Significance level .00000
McFadden Pseudo R-squared .1491598
Estimation based on N = 1962, K = 61
Inf.Cr.AIC = 3789.9 AIC/N = 1.932

Model estimated: Oct 18, 2019, 17:28:45
Constants only must be computed directly
Use NLOGIT ;...;RHS=ONE$
At start values -1834.1644 .0001******
Response data are given as ind. choices
Replications for simulated probs. = 100
Used Halton sequences in simulations.
Number of obs.= 1962, skipped 0 obs

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
	Random parameters in utility functions					
HR	-.48008**	.21402	-2.24	.0249	-.89955	-.06061
LTR	.60530**	.25329	2.39	.0169	.10887	1.10173
A1	.50533**	.23559	2.14	.0320	.04358	.96708
A2	-.44360***	.09154	-4.85	.0000	-.62301	-.26419
A3	.16490*	.08517	1.94	.0529	-.00203	.33183
A4	-.24038**	.11224	-2.14	.0322	-.46036	-.02040
A5	.26268**	.11036	2.38	.0173	.04637	.47899
A6	.00563	.08644	-.07	.9480	-.17505	.16378
A7	-.04510	.08386	.54	.5907	-.11925	.20946
A8	.02680	.06033	.44	.6569	-.09146	.14505
A9	-.15299**	.06369	-2.40	.0163	-.27783	-.02815
A10	.07532	.06035	1.25	.2120	-.04296	.19361
B1	.21629	.29322	.74	.4607	-.35841	.79100
B2	-.30387***	.06811	-4.46	.0000	-.43735	-.17038
B3	.25826***	.06895	3.75	.0002	.12312	.39340
B4	-.04257	.06804	-.63	.5315	-.17592	.09078
B5	.04432	.06828	.65	.5163	-.08950	.17814
B6	-.02759	.04845	-.57	.5690	-.12254	.06736
B7	.01225	.04802	.26	.7986	-.08186	.10637
	Nonrandom parameters in utility functions					
C1	-.32552***	.10011	-3.25	.0011	-.52174	-.12929
C2	.05283	.10317	.51	.6086	-.14938	.25505
C3	-.51426***	.10146	-5.07	.0000	-.71311	-.31541
C4	.19024*	.10080	1.89	.0591	-.00732	.38781
C5	.04062	.09992	.41	.6843	-.15521	.23646
C6	-.15985	.10110	-1.58	.1139	-.35801	.03831
E1	1.03462***	.11809	8.76	.0000	.80316	1.26608
E2	-1.12523***	.12391	-9.08	.0000	-1.36809	-.88237
E3	-.33244***	.11608	-2.86	.0042	-.55995	-.10493

E4	.14708	.11948	1.23	.2183	-.08710	.38125
E5	.19901***	.07617	2.61	.0090	.04972	.34829
E6	.08798	.09260	.95	.3420	-.09350	.26947
E7	-.03652	.08274	-.44	.6589	-.19870	.12565
E8	.22442**	.09804	2.29	.0221	.03226	.41657
G1	-.02190	.12773	-.17	.8639	-.27224	.22844
G2	.11372	.11932	.95	.3405	-.12013	.34758
G3	-.22737*	.12859	-1.77	.0770	-.47941	.02467
G4	.03759	.11837	.32	.7508	-.19441	.26960
G5	-.28746**	.11226	-2.56	.0104	-.50749	-.06743
G6	.16090	.10961	1.47	.1421	-.05394	.37573
G7	.16772*	.08571	1.96	.0504	-.00026	.33570
G8	-.14173*	.08526	-1.66	.0965	-.30884	.02538
G9	-.18435**	.08632	-2.14	.0327	-.35353	-.01517
G10	.25142**	.09920	2.53	.0113	.05700	.44584
D1	-.47343***	.07956	-5.95	.0000	-.62936	-.31751
D2	.19602**	.08138	2.41	.0160	.03652	.35552
D3	-.44772***	.07993	-5.60	.0000	-.60438	-.29105
D4	-.00193	.08227	-.02	.9813	-.16318	.15932
D5	-.00131	.08025	-.02	.9870	-.15859	.15597
D6	-.10380	.08112	-1.28	.2007	-.26279	.05519
F1	.66257***	.09974	6.64	.0000	.46708	.85806
F2	-.56884***	.08975	-6.34	.0000	-.74474	-.39294
F3	-.30582***	.09040	-3.38	.0007	-.48300	-.12865
F4	.21007**	.09485	2.21	.0268	.02418	.39597
F5	.10833*	.06013	1.80	.0716	-.00952	.22618
F6	.12906*	.07223	1.79	.0740	-.01250	.27063
F7	.00351	.06642	.05	.9579	-.12668	.13369
F8	.12063	.08419	1.43	.1519	-.04439	.28564
H1	.14131	.09600	1.47	.1410	-.04685	.32947
H2	-.04188	.09661	-.43	.6647	-.23123	.14748
H3	-.16815*	.09407	-1.79	.0739	-.35254	.01623
H4	.06269	.09708	.65	.5184	-.12758	.25296
	Distns. of RPs. Std.Devs or limits of triangular					
TsHR	.48008**	.21402	2.24	.0249	.06061	.89955
TsLTR	.60530**	.25329	2.39	.0169	.10887	1.10173
TsA1	.50533**	.23559	2.14	.0320	.04358	.96708
TsA2	.44360***	.09154	4.85	.0000	.26419	.62301
TsA3	.16490*	.08517	1.94	.0529	-.00203	.33183
TsA4	.24038**	.11224	2.14	.0322	.02040	.46036
TsA5	.26268**	.11036	2.38	.0173	.04637	.47899

TsA6	.00563	.08644	.07	.9480	-.16378	.17505
TsA7	.04510	.08386	.54	.5907	-.11925	.20946
TsA8	.02680	.06033	.44	.6569	-.09146	.14505
TsA9	.15299**	.06369	2.40	.0163	.02815	.27783
TsA10	.07532	.06035	1.25	.2120	-.04296	.19361
TsB1	.21629	.29322	.74	.4607	-.35841	.79100
TsB2	.30387***	.06811	4.46	.0000	.17038	.43735
TsB3	.25826***	.06895	3.75	.0002	.12312	.39340
TsB4	.04257	.06804	.63	.5315	-.09078	.17592
TsB5	.04432	.06828	.65	.5163	-.08950	.17814
TsB6	.02759	.04845	.57	.5690	-.06736	.12254
TsB7	.01225	.04802	.26	.7986	-.08186	.10637

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

APPENDIX H: LC MODELS OUTPUT

H1. LC model (membership variables = all socio-demographic variables, class = 2) output

```
Latent Class Logit Model
Dependent variable              CHOICE
Log likelihood function     -1627.21709
Restricted log likelihood   -2155.47731
Chi squared [  91 d.f.]      1056.52044
Significance level               .00000
McFadden Pseudo R-squared      .2450781
Estimation based on N =    1962, K =  91
Inf.Cr.AIC  =    3436.4 AIC/N =     1.751
Model estimated: Oct 18, 2019, 14:18:58
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
At start values -1934.5754  .1589******
Response data are given as ind. choices
Number of latent classes =             2
Average Class Probabilities
     .455  .545
LCM model with panel has      218 groups
Fixed number of obsrvs./group=         9
BHHH estimator used for asymp. variance
Number of obs.=  1962, skipped     0 obs
--------+--------------------------------------------------------------------
        |                 Standard            Prob.       95% Confidence
  CHOICE|  Coefficient       Error       z   |z|>Z*          Interval
--------+--------------------------------------------------------------------
        |Utility parameters in latent class -->> 1
    HR|1|   -2.16888***      .77335    -2.80  .0050    -3.68462   -.65314
    A1|1|   -1.29072        1.14971    -1.12  .2616    -3.54411    .96267
    A2|1|    -.00670         .41719     -.02  .9872     -.82438    .81098
    A3|1|     .29539         .50215      .59  .5564     -.68881   1.27960
    A4|1|     .86179**       .41367     2.08  .0372      .05101   1.67257
    A5|1|    -.86150         .76034    -1.13  .2572    -2.35173    .62873
    A6|1|     .14649         .37906      .39  .6992     -.59646    .88944
    A7|1|     .14739         .38828      .38  .7042     -.61363    .90841
    A8|1|    -.10065         .28147     -.36  .7206     -.65232    .45101
```

A9|1|	.32468	.27801	1.17	.2429	-.22021	.86956
A10|1|	.33722	.35350	.95	.3401	-.35562	1.03006
C1|1|	-.65230	.40874	-1.60	.1105	-1.45342	.14882
C2|1|	.34270	.42851	.80	.4239	-.49717	1.18258
C3|1|	-1.32917***	.48314	-2.75	.0059	-2.27610	-.38224
C4|1|	.54130	.46451	1.17	.2439	-.36913	1.45173
C5|1|	.23073	.38366	.60	.5476	-.52124	.98270
C6|1|	.19241	.33443	.58	.5651	-.46307	.84789
G1|1|	-.16201	.51017	-.32	.7508	-1.16193	.83791
G2|1|	-.23638	.60676	-.39	.6968	-1.42561	.95284
G3|1|	-.57105	.54049	-1.06	.2907	-1.63039	.48828
G4|1|	.30645	.54272	.56	.5723	-.75726	1.37016
G5|1|	-.02201	.38504	-.06	.9544	-.77667	.73266
G6|1|	.09297	.41596	.22	.8231	-.72230	.90824
LTR|1|	-.44593	.59058	-.76	.4502	-1.60345	.71160
B1|1|	.10569	.74193	.14	.8867	-1.34847	1.55985
B2|1|	-.25875*	.14897	-1.74	.0824	-.55074	.03323
B3|1|	.30286*	.15609	1.94	.0523	-.00307	.60880
B4|1|	.04370	.15170	.29	.7733	-.25363	.34103
B5|1|	.03520	.17139	.21	.8373	-.30072	.37112
B6|1|	-.07965	.08452	-.94	.3460	-.24532	.08602
B7|1|	-.15382	.11727	-1.31	.1896	-.38367	.07603
D1|1|	-.62986***	.10076	-6.25	.0000	-.82734	-.43238
D2|1|	.20251**	.09705	2.09	.0369	.01230	.39272
D3|1|	-.81102***	.11204	-7.24	.0000	-1.03061	-.59143
D4|1|	.23402**	.10360	2.26	.0239	.03097	.43707
D5|1|	-.02604	.11001	-.24	.8129	-.24166	.18959
D6|1|	-.10310	.10878	-.95	.3432	-.31630	.11010
H1|1|	.14521	.23994	.61	.5450	-.32507	.61549
H2|1|	-.15026	.24694	-.61	.5429	-.63426	.33375
H3|1|	-.01500	.18936	-.08	.9369	-.38614	.35615
H4|1|	.12881	.21647	.60	.5518	-.29546	.55308
|Utility parameters in latent class -->> 2						
HR|2|	1.08657***	.27856	3.90	.0001	.54060	1.63254
A1|2|	.84597**	.37783	2.24	.0252	.10545	1.58650
A2|2|	-.51537***	.12275	-4.20	.0000	-.75595	-.27480
A3|2|	.20422	.12735	1.60	.1088	-.04539	.45383
A4|2|	-.75494***	.12536	-6.02	.0000	-1.00064	-.50925
A5|2|	.56119***	.12662	4.43	.0000	.31301	.80936
A6|2|	-.03152	.12759	-.25	.8049	-.28160	.21856
A7|2|	.00178	.14623	.01	.9903	-.28483	.28838
A8|2|	.02594	.09032	.29	.7740	-.15109	.20296

A9|2|	-.31321***	.08684	-3.61	.0003	-.48342	-.14300
A10|2|	.02357	.09385	.25	.8017	-.16037	.20752
C1|2|	-.16060	.24542	-.65	.5129	-.64162	.32042
C2|2|	-.06182	.19496	-.32	.7512	-.44394	.32030
C3|2|	-.26334	.21074	-1.25	.2115	-.67638	.14971
C4|2|	-.02501	.26945	-.09	.9260	-.55313	.50311
C5|2|	-.06830	.23216	-.29	.7686	-.52333	.38673
C6|2|	.15610	.24263	.64	.5200	-.31945	.63165
G1|2|	-.00876	.19335	-.05	.9639	-.38772	.37021
G2|2|	.11854	.17801	.67	.5054	-.23035	.46744
G3|2|	-.14648	.20430	-.72	.4734	-.54690	.25394
G4|2|	.02089	.21818	.10	.9237	-.40673	.44851
G5|2|	.17977	.13635	1.32	.1873	-.08747	.44701
G6|2|	-.16198	.13348	-1.21	.2249	-.42359	.09963
LTR|2|	2.35877***	.55313	4.26	.0000	1.27466	3.44289
B1|2|	-.08083	.65242	-.12	.9014	-1.35954	1.19789
B2|2|	-.41501***	.12265	-3.38	.0007	-.65539	-.17462
B3|2|	.26517***	.10236	2.59	.0096	.06455	.46580
B4|2|	-.14718	.11806	-1.25	.2125	-.37859	.08422
B5|2|	.08137	.13654	.60	.5512	-.18625	.34899
B6|2|	.05494	.09218	.60	.5512	-.12573	.23562
B7|2|	.09346	.09888	.95	.3445	-.10033	.28725
D1|2|	-.29704	.24056	-1.23	.2169	-.76853	.17444
D2|2|	.14407	.18246	.79	.4297	-.21354	.50169
D3|2|	-.11226	.20812	-.54	.5896	-.52016	.29565
D4|2|	-.27207	.23383	-1.16	.2446	-.73036	.18622
D5|2|	-.06654	.20783	-.32	.7488	-.47387	.34080
D6|2|	.19940	.23589	.85	.3979	-.26293	.66173
H1|2|	.14421	.15454	.93	.3507	-.15868	.44711
H2|2|	-.05229	.18494	-.28	.7774	-.41476	.31018
H3|2|	-.23164	.14772	-1.57	.1169	-.52116	.05788
H4|2|	.06200	.16165	.38	.7013	-.25482	.37883
| This is THETA(01) in class probability model.						
Constant|	-.35248	.40641	-.87	.3858	-1.14902	.44406
_AGE1|1|	-1.06000***	.35952	-2.95	.0032	-1.76466	-.35535
_AGE2|1|	1.12483***	.33830	3.32	.0009	.46179	1.78788
_INC1|1|	.30861	.31751	.97	.3311	-.31369	.93092
_INC2|1|	-.37946	.32400	-1.17	.2415	-1.01450	.25557
_GEN|1|	-.22454	.22111	-1.02	.3099	-.65790	.20882
_EDU|1|	-.11238	.27482	-.41	.6826	-.65101	.42626
_WOR|1|	.02258	.22920	.10	.9215	-.42664	.47181

```
    _EXP|1|    -.30269         .33469     -.90  .3658     -.95867    .35330
        |This is THETA(02) in class probability model.
Constant|         0.0     .....(Fixed Parameter).....
  _AGE1|2|        0.0     .....(Fixed Parameter).....
  _AGE2|2|        0.0     .....(Fixed Parameter).....
  _INC1|2|        0.0     .....(Fixed Parameter).....
  _INC2|2|        0.0     .....(Fixed Parameter).....
   _GEN|2|        0.0     .....(Fixed Parameter).....
   _EDU|2|        0.0     .....(Fixed Parameter).....
   _WOR|2|        0.0     .....(Fixed Parameter).....
   _EXP|2|        0.0     .....(Fixed Parameter).....
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
Fixed parameter ... is constrained to equal the value or
had a nonpositive st.error because of an earlier problem.
```

H2. LC model (membership variables = age, class = 3) output

```
Latent Class Logit Model
Dependent variable               CHOICE
Log likelihood function     -1540.50226
Restricted log likelihood   -2155.47731
Chi squared [ 129 d.f.]      1229.95010
Significance level               .00000
McFadden Pseudo R-squared      .2853081
Estimation based on N =    1962, K = 129
Inf.Cr.AIC  =    3339.0 AIC/N =    1.702
Model estimated: Oct 18, 2019, 14:12:22
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
At start values -1934.5949  .2037******
Response data are given as ind. choices
Number of latent classes =            3
Average Class Probabilities
     .186  .513  .301
LCM model with panel has      218 groups
Fixed number of obsrvs./group=        9
BHHH estimator used for asymp. variance
Number of obs.=  1962, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
  CHOICE|  Coefficient       Error        z    |z|>Z*         Interval
```

	Utility parameters in latent class -->> 1					
HR|1|	-17.9190	4252.476	.00	.9966	-8352.6181	8316.7801
A1|1|	-5.61355	944.7182	-.01	.9953	-1857.22718	1846.00008
A2|1|	-2.75932	1763.395	.00	.9988	-3458.95018	3453.43155
A3|1|	-1.59453	1149.338	.00	.9989	-2254.25548	2251.06642
A4|1|	-7.31595	156.6663	-.05	.9628	-314.37628	299.74438
A5|1|	-1.24877	335.2275	.00	.9970	-658.28252	655.78499
A6|1|	-.78252	298.2258	.00	.9979	-585.29434	583.72930
A7|1|	1.30468	148.8656	.01	.9930	-290.46654	293.07591
A8|1|	-3.55312	119.5783	-.03	.9763	-237.92238	230.81613
A9|1|	-4.52424	4157.877	.00	.9991	-8153.81272	8144.76424
A10|1|	1.91873	433.1314	.00	.9965	-847.00312	850.84058
C1|1|	1.87503	4124.798	.00	.9996	-8082.58059	8086.33066
C2|1|	.35440	3770.422	.00	.9999	-7389.53637	7390.24517
C3|1|	-2.08364	375.5239	-.01	.9956	-738.09691	733.92962
C4|1|	-1.07530	759.6058	.00	.9989	-1489.87523	1487.72462
C5|1|	-4.29175	78.03417	-.05	.9561	-157.23592	148.65241
C6|1|	-2.84407	54.60588	-.05	.9585	-109.86964	104.18149
G1|1|	-.42514	1923.532	.00	.9998	-3770.47850	3769.62823
G2|1|	6.65323	1132.069	.01	.9953	-2212.16034	2225.46680
G3|1|	-2.47079	1688.623	.00	.9988	-3312.11068	3307.16910
G4|1|	-3.70840	938.6118	.00	.9968	-1843.35379	1835.93698
G5|1|	3.85209	4119.431	.00	.9993	-8070.08525	8077.78943
G6|1|	-5.26736	4244.191	.00	.9990	-8323.72917	8313.19444
LTR|1|	3.16082	6.06570	.52	.6023	-8.72774	15.04938
B1|1|	-.31790	4.76026	-.07	.9468	-9.64785	9.01205
B2|1|	-1.82558	3.70299	-.49	.6220	-9.08332	5.43215
B3|1|	.79586	3.91630	.20	.8390	-6.87996	8.47167
B4|1|	-.68219	.70055	-.97	.3302	-2.05524	.69086
B5|1|	.04094	1.12171	.04	.9709	-2.15757	2.23945
B6|1|	-.10430	.80470	-.13	.8969	-1.68147	1.47288
B7|1|	-.46044	.76481	-.60	.5472	-1.95945	1.03857
D1|1|	-5.74554	9.48056	-.61	.5445	-24.32709	12.83601
D2|1|	4.65347	8.12848	.57	.5670	-11.27807	20.58500
D3|1|	-5.63987	11.37392	-.50	.6200	-27.93235	16.65261
D4|1|	3.07171	5.81062	.53	.5971	-8.31690	14.46032
D5|1|	-.10318	1.28725	-.08	.9361	-2.62615	2.41978
D6|1|	-.68600	.73888	-.93	.3532	-2.13417	.76218
H1|1|	1.61201	3.49448	.46	.6446	-5.23704	8.46106
H2|1|	-.33841	4.37260	-.08	.9383	-8.90854	8.23173

H3|1|	.82286	4.16458	.20	.8434	-7.33956	8.98528
H4|1|	-.57807	3.46238	-.17	.8674	-7.36420	6.20806
|Utility parameters in latent class -->> 2						
HR|2|	.93841***	.26336	3.56	.0004	.42224	1.45457
A1|2|	.85994**	.38015	2.26	.0237	.11486	1.60503
A2|2|	-.49248***	.11900	-4.14	.0000	-.72571	-.25924
A3|2|	.24421*	.13256	1.84	.0654	-.01560	.50401
A4|2|	-.75604***	.12930	-5.85	.0000	-1.00946	-.50262
A5|2|	.57396***	.13294	4.32	.0000	.31341	.83451
A6|2|	-.00649	.12863	-.05	.9597	-.25861	.24562
A7|2|	-.01165	.16028	-.07	.9420	-.32580	.30249
A8|2|	.03183	.09654	.33	.7416	-.15739	.22105
A9|2|	-.30504***	.09487	-3.22	.0013	-.49099	-.11909
A10|2|	.01579	.09846	.16	.8726	-.17719	.20877
C1|2|	-.35044	.21809	-1.61	.1081	-.77789	.07702
C2|2|	-.06082	.19187	-.32	.7513	-.43687	.31524
C3|2|	-.11176	.20713	-.54	.5895	-.51773	.29421
C4|2|	-.21616	.24865	-.87	.3847	-.70350	.27118
C5|2|	-.15428	.23669	-.65	.5145	-.61818	.30962
C6|2|	.19779	.21734	.91	.3628	-.22819	.62377
G1|2|	-.01094	.20813	-.05	.9581	-.41886	.39698
G2|2|	.05226	.17129	.31	.7603	-.28346	.38798
G3|2|	-.08755	.20546	-.43	.6700	-.49025	.31515
G4|2|	.06984	.22701	.31	.7583	-.37509	.51477
G5|2|	.19526	.14168	1.38	.1681	-.08242	.47294
G6|2|	-.15026	.14168	-1.06	.2889	-.42794	.12742
LTR|2|	2.05985***	.56973	3.62	.0003	.94320	3.17649
B1|2|	-.05952	.66390	-.09	.9286	-1.36075	1.24170
B2|2|	-.47778***	.12686	-3.77	.0002	-.72643	-.22913
B3|2|	.31507***	.10331	3.05	.0023	.11259	.51756
B4|2|	-.15776	.11892	-1.33	.1846	-.39085	.07532
B5|2|	.10648	.13992	.76	.4467	-.16776	.38071
B6|2|	.03274	.08876	.37	.7122	-.14122	.20670
B7|2|	.12408	.10045	1.24	.2167	-.07280	.32096
D1|2|	-.40618*	.21634	-1.88	.0604	-.83019	.01783
D2|2|	.03531	.19008	.19	.8526	-.33724	.40785
D3|2|	.11458	.20188	.57	.5703	-.28108	.51025
D4|2|	-.51322**	.22109	-2.32	.0203	-.94656	-.07988
D5|2|	-.19405	.21639	-.90	.3699	-.61817	.23007
D6|2|	.19325	.21699	.89	.3731	-.23203	.61854
H1|2|	.21533	.15591	1.38	.1672	-.09025	.52091
H2|2|	-.11088	.19261	-.58	.5648	-.48840	.26664

H3|2|	-.33560**	.15145	-2.22	.0267	-.63244	-.03877
H4|2|	.17524	.16187	1.08	.2790	-.14202	.49250
|Utility parameters in latent class -->> 3						
HR|3|	-1.99464*	1.11858	-1.78	.0746	-4.18701	.19774
A1|3|	-1.84083	1.80332	-1.02	.3073	-5.37528	1.69361
A2|3|	.12874	.53188	.24	.8087	-.91371	1.17120
A3|3|	.27402	.81970	.33	.7382	-1.33255	1.88060
A4|3|	1.15141*	.59667	1.93	.0536	-.01803	2.32085
A5|3|	-1.05293	1.09163	-.96	.3348	-3.19248	1.08662
A6|3|	.12697	.45313	.28	.7793	-.76115	1.01509
A7|3|	.08749	.73712	.12	.9055	-1.35724	1.53221
A8|3|	-.13968	.35408	-.39	.6932	-.83368	.55431
A9|3|	.44057	.45818	.96	.3363	-.45743	1.33858
A10|3|	.34738	.60243	.58	.5642	-.83336	1.52812
C1|3|	-.74162	.59805	-1.24	.2150	-1.91379	.43054
C2|3|	.32312	.57512	.56	.5742	-.80411	1.45034
C3|3|	-1.10199*	.63032	-1.75	.0804	-2.33739	.13342
C4|3|	.39379	.56651	.70	.4870	-.71654	1.50413
C5|3|	.32818	.42760	.77	.4428	-.50991	1.16626
C6|3|	.29109	.43249	.67	.5009	-.55657	1.13876
G1|3|	-.12885	.72800	-.18	.8595	-1.55571	1.29801
G2|3|	-.39825	1.04723	-.38	.7037	-2.45079	1.65429
G3|3|	-.56516	.72144	-.78	.4334	-1.97917	.84884
G4|3|	.48551	.90896	.53	.5932	-1.29602	2.26704
G5|3|	.17638	.57639	.31	.7596	-.95333	1.30609
G6|3|	.06447	.61764	.10	.9169	-1.14609	1.27502
LTR|3|	-1.20405	.87256	-1.38	.1676	-2.91424	.50615
B1|3|	.42344	1.10866	.38	.7025	-1.74949	2.59638
B2|3|	-.22005	.25231	-.87	.3831	-.71457	.27447
B3|3|	.26945	.27821	.97	.3328	-.27584	.81473
B4|3|	.20918	.27963	.75	.4544	-.33887	.75724
B5|3|	.06082	.25198	.24	.8093	-.43306	.55470
B6|3|	-.12292	.11750	-1.05	.2955	-.35321	.10738
B7|3|	-.22034	.17091	-1.29	.1973	-.55532	.11464
D1|3|	-.00713	.16057	-.04	.9646	-.32184	.30758
D2|3|	-.01207	.17164	-.07	.9439	-.34849	.32435
D3|3|	-.70284***	.15803	-4.45	.0000	-1.01257	-.39310
D4|3|	.19912	.18382	1.08	.2787	-.16117	.55940
D5|3|	.11755	.19141	.61	.5391	-.25761	.49272
D6|3|	-.11963	.16916	-.71	.4794	-.45117	.21190
H1|3|	.04047	.40383	.10	.9202	-.75103	.83197

```
    H2|3|    -.09788          .42422     -.23  .8175     -.92932    .73357
    H3|3|     .03756          .31226      .12  .9043     -.57445    .64958
    H4|3|     .01350          .37042      .04  .9709     -.71250    .73950
        |This is THETA(01) in class probability model.
Constant|    -.42112          .45024     -.94  .3496    -1.30358    .46135
 _AGE1|1|     .51479          .96354      .53  .5932    -1.37372   2.40329
 _AGE2|1|     .03087          .79498      .04  .9690    -1.52727   1.58901
        |This is THETA(02) in class probability model.
Constant|     .55617**        .23627     2.35  .0186      .09308   1.01926
 _AGE1|2|    1.07467**        .48897     2.20  .0280      .11631   2.03303
 _AGE2|2|   -1.21371***       .42619    -2.85  .0044    -2.04903   -.37839
        |This is THETA(03) in class probability model.
Constant|       0.0    .....(Fixed Parameter).....
 _AGE1|3|       0.0    .....(Fixed Parameter).....
 _AGE2|3|       0.0    .....(Fixed Parameter).....
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
Fixed parameter ... is constrained to equal the value or
had a nonpositive st.error because of an earlier problem.
```