MASTER

An exploration of the buying decision process of residential consumers
the application of a choice-based conjoint experiment to reveal housing preferences

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AN EXPLORATION OF THE BUYING DECISION PROCESS OF RESIDENTIAL CONSUMERS: THE APPLICATION OF A CHOICE-BASED CONJOINT EXPERIMENT TO REVEAL HOUSING PREFERENCES

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Preface

The report in front of you is the result of my graduation project. It contains the last step to finalize the study of Innovation Management at the Eindhoven University of Technology.

The final project was carried out at the Innovation, Technology, Entrepreneurship and Marketing (ITEM) department, but there was substantial support from the Urban Planning department (faculty of Architecture, Building, and Planning) during my graduation process. This was due to the fact that my project was executed externally for a construction company, Hendriks Coppelmans Ontwikkeling (HCO) in Eindhoven. HCO is the development department of a construction company, Hendriks Coppelmans Bouwgroep B.V. (HCB), which is located in Uden.

During this project, I was able to put my theoretical knowledge about innovation and marketing into practice. Until then, the construction industry was a relatively unknown world to me. Afterwards, I can say that I have broadened my horizon and increased my knowledge during this period. I have visited the "Woonduurverlenger" symposium at the Esus Group in Veldhoven, which combined the trend of ageing of the population with new and innovative living concepts. Furthermore, I had several meetings with a broker "Bernheze Makelaars" in Uden, were I could share my thoughts about important buying aspects of different residential consumers.

This report is the result of hard work, determination and persistence. However, it was not possible to finish my study without the help of others. Therefore, I would like to take the opportunity to thank some influential persons who have supported me during this project.

First, I would like all colleagues that worked with me at HCO. Angelique, Anita, Bart, Françoise, Hans, Marion, Oltjan, Ron and Wim. Thank you all for the constructive discussions and for providing me a warm and pleasant work environment. Special thanks goes to Loes Boley and Rene Beks, who have acted as my company supervisors. I would like to thank Rene for sharing very specific market knowledge and practical insights and Loes for all the feedback sessions that gave me a lot of valuable input.

In addition, I would like to express my gratitude to my university supervisors Joost Wouters, Ad de Jong and Aloys Borgers. Joost gave me guidance and support on the marketing issues, while Aloys and Ad provided me insights in the conjoint analysis technique and supplied the essential Limdep software.

Last but not least, I would like to thank my family and friends for showing their interest in my project. Especially, my parents and sister played a crucial role. Thanks for encouraging and supporting me unconditionally during my entire study. Your expressed confidence in my capabilities, made me reach this important milestone in my life!

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Abstract

This master thesis investigates housing preferences and decision making of residential consumers. The process of buying a new home is simulated with a choice-based conjoint experiment in which different potential customers have to express their preference for a hypothetical new home. These hypothetical new homes are described in terms of housing profiles. A housing profile consists of a bundle of attributes. Every attribute can have different levels, which are generated in a statistical efficient way. The information that is gained on the choice processes is used to estimate mathematical models that will reveal the utility of certain attributes. When utility differs between groups, this knowledge can lead to a market segmentation, i.e. different customers will value several housing attributes in a different way. As a result, Hendriks Coppelmans Ontwikkeling (HCO) will be able to target their customers in a more effective manner in the future.

Executive Summary

The purpose of this research is to get better insight in consumer behavior in the real estate market. The traditional way to approach residential consumers was via mass marketing. Nowadays, residential consumers have become more critical and have developed more individual needs and preferences. However, individual targeting will be very costly for developers of real estate. Therefore, a more efficient manner to target consumers is by identifying segments of consumers and approach them according to their housing preferences.

Even though market segmentation is one of the most established concepts in marketing, there are still some shortfalls in the body of research, which create a gap between theory and practice and lead to failure in the implementation of segmentation (Sausen et al., 2005).

In this master thesis the following research questions were addressed:

1. How can a valid segmentation of residential consumers be made for the housing market of Noord-Brabant?
2. Which segments of consumers can be discerned in the housing market of Noord-Brabant and how do they differ from each other in terms of housing preferences and decision making?

Firstly, a literature research was done on the market segmentation topic. The selection of appropriate segmentation bases and methods is crucial with respect to the number and type of segments that are identified in segmentation research, as well as to their usefulness to the firm.

Benefit segmentation which is categorized as product-specific / unobservable is a better way to segment the market than via a general / observable way such as demographics. Conjoint analysis is an appropriate method to conduct benefit segmentation.

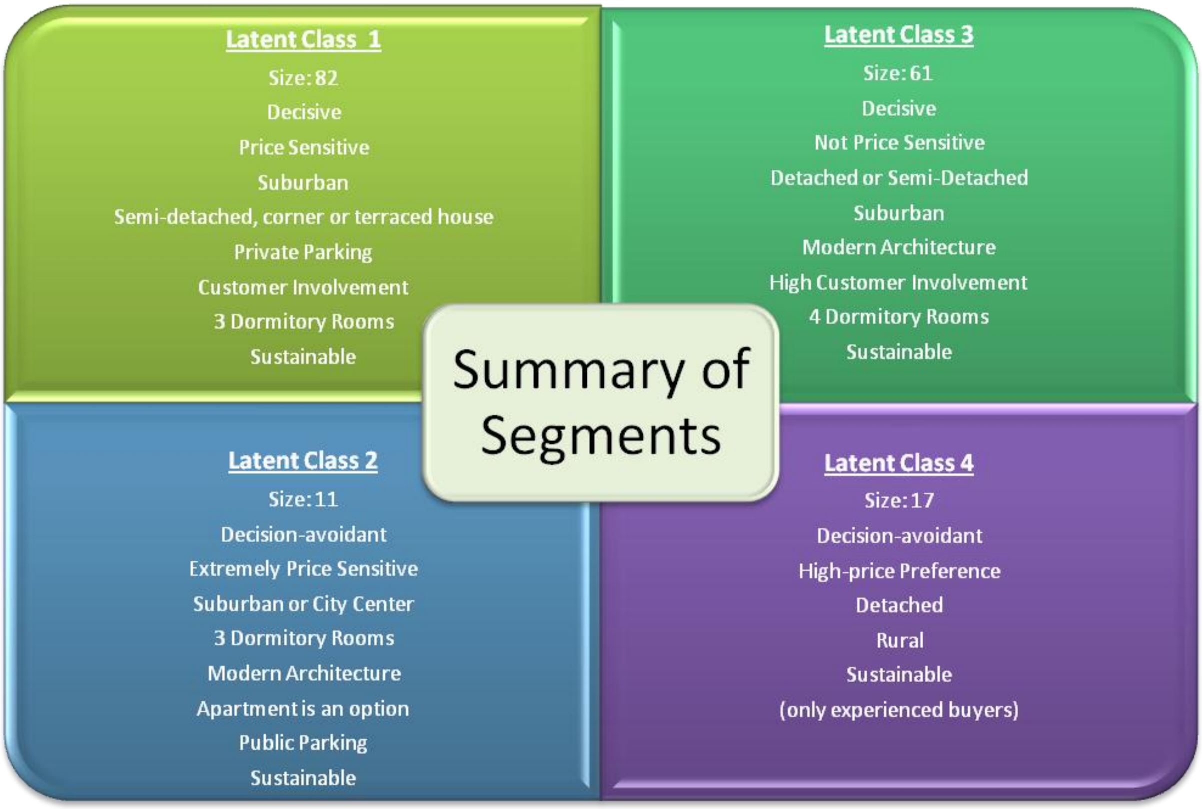
A classification of segmentation methods can be made by applying an *a priori* or *post-hoc* approach. The second way of classifying segmentation approaches is according to whether *descriptive* or *predictive* statistical methods are used. The area of post-hoc predictive methods seems to be the most favorable in terms of effectiveness. Mixture regression methods (including latent class models) currently provide the most powerful algorithms for market segmentation.

For the research design 9 prominent housing attributes were selected. Every attribute can have different levels, which are generated in a statistical efficient way. The information that is gained on the choice processes of the respondents is used to estimate mathematical models that will reveal the utility of certain attributes. When utility differs between groups, this knowledge can lead to a market segmentation, i.e. different customers will value several housing attributes in a different way.

A choice-based conjoint experiment revealed results at the aggregate level and group level. This was done by estimating multinomial logit models, a priori segmentation models and post-hoc latent class models.

A-priori segmentation gives small but interesting differences between subgroups. It provides more information than the standard MNL model. In this case, it seems more meaningful to separate on the basis of buying experience than gender. Nevertheless, post-hoc segmentation with latent classes gives the impression to be the most effective method to segment the housing market. Latent class models showed the highest internal validity indicated by a high Rho^2 value.

The post-hoc latent class models revealed four market segments, which are summarized below.



Heterogeneity is indicated by varying characteristics for each segment. Discrepancies in predominantly the attributes price, location and dwelling type, imply that different target strategies have to be worked out for each segment.

A limitation that can be mentioned is that the sample size was actually too small in order to come to a very sophisticated segmentation with relevant target groups for HCO. A number of 200 respondents per subgroup is necessary to accomplish this.

As a future research implication, it could be interesting to replicate this study in the Randstad area to investigate whether apartments are a more attractive dwelling type in this region. It is expected that the optimal location for a Randstad inhabitant will shift more from suburban to urban location, with a rural location as the least preferred alternative. Thus, other regional studies should be conducted in order to come to a comprehensive view of the total Dutch housing market.

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HENDRIKS COPPELMANS
BOUW EN ONTWIKKELING

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TU/e Technische Universiteit Eindhoven University of Technology

1 Introduction

This research is conducted for Hendriks Coppelmans Ontwikkeling (HCO) and aims to study housing preferences and decision-making of real estate consumers.

Most real estate studies are based on neoclassical economic theory that assumes people make rational economic decisions about renting and buying real estate as part of their attempt to maximize utility (Gibler and Nelson, 2003). Most real estate researchers and educators do not examine the human influences that real estate consumers have on real estate demand. Instead, most real estate educators continue to approach the market from a production orientation rather than a consumer marketing orientation. Analysts stratify real estate markets by property types that are defined by physical construction rather than consumer benefits. Property is valued based on physical attributes rather than consumer perception of the space, atmosphere and linkages. However, residential and other real estate customers such as retail tenants often consider nonfinancial, perceptual factors in selecting a site (Smith, Garbarino and Martini, 1992).

Rather than ignore the human element of decision-making, or put all aspects of nonfinancial decision factors in a black box called ''tastes and preferences,'' real estate students, teachers, researchers and practitioners can benefit from integrating the study of consumer behavior with the economic approach to real estate. Greater knowledge of real estate consumers and their behavior will lead to better understanding and prediction of consumers' actions in the real estate market.

The purpose of this research will be to get better insight in consumer behavior in the real estate market. The traditional way to approach residential consumers is via mass marketing. Nowadays, residential consumers have become more critical and have developed more individual needs and preferences. However, individual targeting will be very costly for developers of real estate. Therefore, a more efficient manner to target consumers is by identifying segments of consumers and approach them according to their housing preferences.

Even though market segmentation is one of the most established concepts in marketing, there are still some shortfalls in the body of research, which create a gap between theory and practice and lead to failure in the implementation of segmentation (Sausen et al., 2005).

This thesis will try to fill this gap for a specific business case by examining the literature on methods to create a valid segmentation of residential consumers in the housing market of Noord-Brabant. This will contribute to the scientific knowledge on market segmentation. Based on this knowledge, a survey will be designed and conducted. As a result, segments of consumers will be discerned and the differences in terms of their housing preferences and decision making will be shown. This kind of information is also very valuable for management decision making at HCO.

1.1 Guideline to the report

The remainder of this document is organized as follows. Chapter 2 deals with the problem context and the most important reasons to start this project. Eventually, this results in two research questions. Chapter 3 will handle the theory that is most relevant to the research questions, namely market segmentation theory. Chapter 4 deals with the methodology that is best suited to approach the research questions. The research design will be presented and the method of data collection and data analysis will be explained in chapter 5.

Subsequently, Chapter 6 will present the results. Chapter 7 deals with the discussion of the results followed by a conclusion which attempts to answer the research questions. Besides the managerial implications are revealed. The future research implications and limitations will be presented in the final chapter.

2 Research problem

In this chapter we will describe the context in which this research project is executed. First, we start with a short company description. After that, we will present recent developments in the Dutch housing market. Consecutively, the research questions will be presented.

2.1 Brief company description

The project is executed at Hendriks Coppelmans Ontwikkeling (HCO) in Eindhoven, which is part of Hendriks Coppelmans Bouwgroep B.V. (HCB) in Uden. HCB has its roots almost 90 years ago with the foundation of two traditional family businesses in 1922. Hendriks started with a building company in Oss. After the founder died his sons took over the business and made it expand throughout the years with new establishments in Uden (1969), Den Bosch (1976) and Cuijk (1976). The brothers decided to split up and go their own way in 1984. The establishments in Oss and Den Bosch became independent. In 1989 the business in Cuijk was transferred to Eindhoven. In 1997, Hendriks Bouwbedrijven acquired Coppelmans Bouwbedrijven and a new market-oriented and innovative company was born: Hendriks Coppelmans Bouwgroep B.V. The merger resulted both the clientele and the number of employees to double up.

Nowadays, it is a medium-sized business in the construction industry that consist of 150 employees and about 150 co-workers which serve contractors or suppliers. HCB is specialized in house construction. The primary working domain consists of the areas of Noord-Brabant, Limburg and the southern part of Gelderland in the Netherlands. The annual turnover of the company is approximately 45 million euro.

This turnover is almost equally divided over three main activities: development, realization (construction) and renovation (maintenance).

2.2 Problem context

2.2.1 Shift towards market orientation

Traditionally, the construction industry is widely perceived as slow to innovate and has trailed many manufacturing industries in implementing management and technology innovations (Veshosky, 1998). However, a new era seems to appear in this industry, in which innovation becomes highly important due to an increase in competition.

HCO has to deal with these changing conditions in the new housing estate market. During the last decade there has been a transformation from a supplier-oriented market to a more demand-oriented market. Due to scarcity of potential buyers and a decline of the price of houses, it becomes more difficult to sell new houses, since house owners refuse to sell their current house at a reduced price level.

Additionally, there is another trend among consumers. Potential buyers are developing more critical attitudes and become more demanding, e.g. in terms of value for money. Furthermore, they are aware of the consequences of the economic crisis and this strengthens their bargaining position.

During the first quarter of 2009 only half the amount of dwellings were sold compared to the first three months of 2008 in the Netherlands (Bouwkennis, 2009).

Table 2.1 shows some more recent figures that provide evidence for an unstable market. It can be concluded that especially buildings in the higher price segment are very sensitive for fluctuations (a 42,31% and 34,59% decrease for detached and semi-detached houses respectively). Table 2.1 also shows that the decline in sales for every dwelling type is higher in Noord-Brabant than the average sales decline in the Netherlands.

Table 2.1: Sales per dwelling type

	Noord-Brabant		Percentual change (%)	Netherlands		Percentual change (%)
Dwelling Type	**Sales 2008**	**Sales 2009**	**2009 vs. 2008**	**Sales 2008**	**Sales 2009**	**2009 vs. 2008**
Semi-detached	2.900	1.897	-34.59%	19.303	13.095	-32.16%
Apartment	4.587	3.088	-32.68%	54.117	39.555	-26.91%
Corner House	4.146	2.805	-32.34%	23.949	17.055	-28.79%
Terraced	10.206	6.925	-32.15%	59.689	41.551	-30.39%
Detached	3.396	1.959	-42.31%	19.968	12.651	-36.64%
Unknown*	788	513	-34.90%	5.366	3.625	-32.45%
Total	26.023	17.187	-33.95%	182.392	127.532	-30.08%

Source: CBS and Kadaster, January 2010
*** Objects that cannot be categorized in one of the available groups**

Table 2.2: Market price development

	Noord-Brabant		Percentual change (%)	Netherlands		Percentual change (%)
Dwelling Type	**Average Market Price 2008**	**Average Market Price 2009**	**2009 vs. 2008**	**Average Market Price 2008**	**Average Market Price 2009**	**2009 vs. 2008**
Semi-detached	€313.026	€290.032	-7.35%	€294.737	€270.606	-8.19%
Apartment	€191.793	€182.687	-4.75%	€195.121	€186.370	-4.48%
Corner House	€257.308	€247.611	-3.77%	€248.318	€233.981	-5.77%
Terraced	€239.911	€228.436	-4.78%	€235.042	€225.890	-3.89%
Detached	€488.430	€460.747	-5.67%	€424.608	€393.149	-7.41%
Unknown*	€343.107	€306.769	-10.59%	€308.941	€308.941	-7.46%
Total	€277.906	€258.962	-6.82%	€254.918	€238.258	-6.54%

Furthermore, table 2.2 indicates that the average market price of a house further decreases in 2009, but is higher than average in Noord-Brabant. Based on these facts, it is reasonable to assume that a potential customer will be more reluctant to buy a new home in the area of Noord-Brabant. This is a serious threat for the long-term financial growth for developers in the construction sector. It will be the question how developers, such as HCO, can deal with such a massive decline in order to stay competitive and keep performing in the future.

As a consequence, construction companies and developers have the tendency to become more customer-oriented. A shift towards market orientation seems desirable in this industry.

Without the skills and structural arrangements to collect market intelligence and disseminate them through the organization, the development firm will be unable to respond to customer needs and satisfy them (Kohli & Jaworski, 1990; Narver *et al.,* 2004). Kohli & Jaworski (1990) argue that adopting a market orientation is only useful when the benefits exceed the cost of required resources.

In case of HCO, it seems not only worthwhile to make a step in this direction, it almost looks like a necessity to follow this trend in order to survive in a more competitive industry.

Research indicates that offering more buyer options and giving buyer assistance are the most popular marketing methods used to stimulate sales (Bouwkennis, 2009). However, there is a major limitation. From a developers viewpoint it is unrealistic to give the customer the opportunity to make **all** the choices by himself. Next to practical obstacles concerning certain building standards and requirements that have to be fulfilled and limitations from municipalities related to zoning and visual quality plans, the most important problem will be to offer a new building at a reasonable price.

Besides, every customer is unique and has his own preferences. One customer may prefer little interference during the building process doing a lot of work by himself, while another requires a high level of involvement of the developer where every single detail will be elaborated. Therefore, the right balance has to be found at the continuum of commodity and customization for different types of customers.

2.2.2 Mismatch between supply and demand

It is essential for the progress and continuity in real estate production that supply of new buildings and living environment will fit demand of real estate consumers as good as possible.

There is a link between quantitative targets and the qualitative constellation of new building plans. If demand and supply fit insufficiently, this will bring a major risk. Project plans will not be realized in time or even not at all. Recently, several studies have shown that the match between supply and demand wishes of new estate consumers is not optimal.

This is understandable for the current house supply – future restructuring and transformation challenges are present here – but it also holds for new development projects.

When considering the mismatch in the area of Noord-Brabant, the Netherlands, which is one HCO's major working domains, nowadays a surplus exists in terms of apartments that are planned. Furthermore, there is a lack of owner-occupied property and a decline in private commission (custom build). It is important that such situations will be prevented for in the near future.

A factor that plays a crucial role for HCO is throughput time. Traditionally, the entire process, including **(1) research plan, (2) preliminary design, (3) final draft, (4) specification phase, (5) procedures and licenses, (6) site preparation, (7) sales preparation, (8) contracting phase and (9) building phase**, can take about 7 years. The innovative concept "Versneld Bouwen", which was introduced several years ago at HCO, is a good means to overcome throughput time difficulties.

Thus, when HCO selects a site for development, it should keep in mind that the current target customer with appropriate characteristics for this location, will be outdated in the future at the moment of realization.

All these aspects, such as a long throughput time and changing market conditions contribute to potential mismatches that are very undesirable. The construction phase can only start if 70% of the dwellings are sold. Otherwise, the risk involved for the construction company is too high. The best way to sell your dwellings under difficult market conditions is by exactly knowing your customer's needs and trying to satisfy them by using the right marketing channels. Therefore, it seems reasonable to further investigate housing preferences and other factors that will influence the buying decision of potential customers.

2.3 Problem statement

During the intake process several interviews with colleagues were conducted in order to structure the problem mess. Furthermore, desk research was done in order to get valuable company data and market information. In addition, a symposium (see www.woonduurverlenger.nl) was visited in order to get acquainted with some of the latest market trends in the construction industry.

Hendriks Coppelmans has the mission to contribute to the right of every person on proper housing. It aims to improve the standard of living by anticipating and listening carefully to every customer's needs. However, at this moment the level of fulfillment of this mission is still unsatisfactory. This can be considered as a real problem of strategic importance that has to be solved in the end. Excellent customer knowledge becomes vital for HCO in order to cope with changing market conditions. Sales is expected to further decline without this knowledge and this may have detrimental consequences for HCO's financial position.

Thus, obtaining insight in consumer buying behavior is a key issue to work on. Although, there are several studies concerning consumer buying behavior and decision-making in the last decades, we still can conclude that buying behavior in the field of housing and real estate is relatively unexplored. Therefore, it can be considered as a relevant problem from a scientific as well as a company perspective.

Hence, we can state that the combination of information of all these sources has led to the formation of the following problem statement:

Problem statement

There is insufficient customer knowledge at HCO with respect to the buying decision of new housing consumers to adequately serve the customer's needs

2.4 Research Questions

Based on the information that was gathered during the orientation process the following research questions were developed:

1. How can a valid segmentation of residential consumers be made for the housing market of Noord-Brabant?

2. Which segments of consumers can be discerned in the housing market of Noord-Brabant and how do they differ from each other in terms of housing preferences and decision making?

3 Market segmentation

3.1 Introduction

In the previous chapter the research problem was investigated. Its essence is the need for a comprehensive segmentation of customer groups on the housing market that allows for successful marketing and communication strategies. In this chapter the concept of market segmentation is defined and positioned (3.2), various segmentation methods are assessed (3.3) and a specific method for the assignment is proposed (3.4).

3.2 Definition and positioning

All marketing strategy is built on STP – Segmentation, Targeting, and Positioning. A company discovers different needs and groups in the marketplace, targets those needs and groups that it can satisfy in a superior way, and then positions its offerings so that the target market recognizes the company's distinctive offering and image. If a company does a poor job of positioning, the market will be confused as what to expect. If a company does an excellent job of positioning, then it can work out the rest of its marketing planning and differentiation from its positioning strategy.

We define positioning as follows: **Positioning** is the act of designing the company's offering and image to occupy a distinctive place in the mind of the target market. The end result of positioning is the successful creation of a customer-focused **value proposition**, a cogent reason why the target market should buy the product (Kotler et al., 2009).

Market segmentation is thus an essential element of marketing in industrialized countries (Wedel and Kamakura, 2000). Market segmentation strategies may be seen to be analogous to market strategies, namely, an integrated set of decisions by which a company expects to achieve its marketing goals (Day, 1990; Slater and Olsen, 2001). Goods can no longer be produced and sold without considering customer needs and recognizing the heterogeneity of those needs. Earlier last century, industrial development in various sectors of the economy induced strategies of mass production and marketing. Those strategies were manufacturing oriented, focusing on reduction of production costs rather than satisfaction of consumers. But as production processes became more flexible, and consumers affluence led to the diversification of demand, firms that identified the specific needs of groups of customers were able to develop the right offer for one or more submarkets and thus obtained a competitive advantage (Wedel and Kamakura, 2000).

As market-oriented thought evolved within firms, the concept of market segmentation emerged. Since its introduction by Smith (1956), market segmentation has become a central concept in both marketing theory and practice. Smith recognized the existence of heterogeneity in the demand of goods and services, based on the economic theory of imperfect competition (Robinson, 1938). He stated: "Market segmentation involves viewing a heterogeneous market as a number of smaller homogeneous markets, in response to differing preferences, attributable to the desires of consumers for more precise satisfaction of their varying wants. "

Five main objectives of market segmentation can be derived:

(1) *Exploitation of New Customer Potentials*

(2) *Development of Existing Customers Potential*

(3) *Increasing Customer Profitability*

(4) *Improving Targeting of Marketing Measures*

(5) *Identification/Exploitation of New Sub-Markets*

Even though market segmentation is one of the most established concepts in marketing, there are still some shortfalls in the body of research, which create a gap between theory and practice and lead to failure in the implementation of segmentation (Sausen et al., 2005).

The concept of strategic segmentation is specified as key in resolving these issues. It is shown that in any form of strategic segmentation, the following two questions need to be answered consistently: What is the objective of performing market segmentation? Which unit of analysis will be selected for the segmentation? Based on empirical findings, a taxonomy of four segmentation strategies is developed that addresses these shortfalls. The findings show that segmentation can be induced from the customer as well as from the market; but most importantly, there has to be consistency between the objective and the unit of analysis of a market segmentation. These findings provide both useful managerial implications as well as a framework for further research.

Recent changes in the market environment present new challenges and opportunities for market segmentation. For example, new developments in information technology provide marketers with much richer information on customers´ actual behavior, and with more direct access to individual customers via database marketing and geo-demographic segmentation. Consequently, marketers are now sharpening their focus on smaller segments with micro marketing and direct marketing approaches.

In business segmentation most attention appears to have focused on four main areas:

(1) The development of segmentation bases and models (e.g. Hummel, 1960; Haley, 1968; Wind and Cardozo, 1974; Bonoma and Shapiro, 1983; Moriarty and Reibstein, 1986; File and Prince, 1996);

(2) Research methodologies in terms of data requirements and collection methodologies (e.g. Webster, 1978; Silk and Kalwani, 1982; Flodhammar, 1988; Mitchell, 1994);

(3) The development and application of statistical analysis tools (e.g. Frank and Green, 1968; Green and Carmone, 1977; Rao and Winter, 1977; Acito and Jain, 1980; Klastorin, 1983; Green and Krieger, 1991; Fish *et al.*, 1995; Balakrishnan *et al.*, 1996; and

(4) The implementation of segmentation into strategy (e.g. Beik and Buzby, 1973; Mahajan and Jain, 1978; De Kluyver and Whitlark, 1986; Piercy and Morgan, 1995).

These are sub-areas which have been investigated largely in isolation from one another. This not only has resulted in a fragmented view of segmentation, which fails to recognize the long-term strategic nature of the concept, but also has severely limited progress over the last few decades (Goller et al., 2002).

The identification of market segments and their elements is highly dependent on the *bases* (variables or criteria) and *methods* used to define them. The selection of appropriate segmentation bases and methods is crucial with respect to the number and type of segments that are identified in segmentation research, as well as to their usefulness to the firm. The choice of different bases may lead to different segments being revealed; much the same holds also for the application of different segmentation methods. Furthermore, the choices of methods and bases are not independent. The segmentation method will need to be chosen on the basis of (1) the specific purposes of the segmentation study and (2) the properties of the segmentation bases selected (Wedel and Kamakura, 2000).

3.3 Segmentation approaches

3.3.1 General vs product specific

A segmentation basis is defined as a set of variables or characteristics used to assign potential customers to homogeneous groups. Following Frank, Massy and Wind (1972), we classify segmentation bases into *general* (independent of products, services or circumstances) and *product-specific* (related to both the customer and the product, service and/or particular circumstances) bases (Frank, Massy and Wind, 1972; see also Baker, 1988; Wilkie and Cohen, 1977). Furthermore, we classify bases into whether they are *observable* (i.e. measured directly) or *unobservable* (i.e. inferred). That typology holds for the bases used for segmentation of both consumer and industrial markets, although the intensity with which various bases are used differs across the two types of markets. Those distinctions lead to the classification of segmentation bases first proposed by Frank, Massy and Wind, 1972), shown in Figure 3.1.

Figure 3.1: Classification of Segmentation Bases

	General	Product-specific
Observable	Cultural, geographic, demographic and socio-economic variables	User status, usage frequency, store loyalty and patronage, situations
Unobservable	Psychographics, values, personality and life-style	Psychographics, benefits, perceptions, elasticities, attributes, preferences, intention

Especially, benefit segmentation seems to be an interesting technique to apply on the housing market. Haley (1968) argued that the benefits that people seek in products are the basic reasons for heterogeneity in their choice behavior, and benefits are thus the most relevant bases for segmentation. An effective method for assessing benefits in segmentation studies is conjoint analysis (Green and Srinivasan, 1978; Cattin and Wittink, 1982; Green and Krieger, 1991).

Table 3.1 consists of an evaluation of the four segmentation bases on six criteria (Wedel and Kamakura, 2000). Virtually all of the evidence on the effectiveness of alternative bases is derived from applications to consumer markets, and that a certain segmentation basis may be preferred depending on the specific requirements of the study at hand. In general, the most effective bases are found in the class of product-specific unobservable bases. The major advantage of benefit segmentation is that it scores very high on actionability and responsiveness compared to the general, observable segmentation base, which is most frequently used as the standard for segmentation.

Table 3.1: Evaluation of Segmentation Bases

Bases/ Criteria	Identif-iability	Substan-tiality	Acces-sibility	Stabi-lity	Action-ability	Respon-siveness
1. General, observable	++	++	++	++	-	-
2. Specific, observable						
Purchase	+	++	-	+	-	+
Usage	+	++	+	+	-	+
3. General, unobservable						
Personality	±	-	±	±	-	-
Life style	±	-	±	±	-	-
Psychographics		-	±	±	-	-
4. Specific, unobservable						
Psychographics	±	+	-	-	++	±
Perceptions	±	+	-	-	+	-
Benefits	+	+	-	+	++	++
Intentions	+	+	-	±	-	++

++ very good, + good, ± moderate, - poor, -- very poor

3.3.2 Statistical methods

Segmentation is essentially a grouping task, for which a large variety of methods are available and have been used. The methods employed in segmentation research can be classified in two ways. First, they can be classified into *a-priori* and *post-hoc* approaches (Green, 1977; Wind, 1978). A segmentation is called *a priori* when the type and number of segments are determined in advance by the researcher and *post hoc* when the type and number of segments are determined on the basis of the results of data analyses.

The second way of classifying segmentation approaches is according to whether *descriptive* or *predictive* statistical methods are used. *Descriptive* methods analyze the associations across a single set of segmentation bases, with no distinction between dependent or independent variables. *Predictive* methods analyze the association between two sets of variables, where one set consists of dependent variables to be explained/predicted by the set of independent variables. Figure 3.2 provides an overview of this classification.

Figure 3.2: Classification of Methods Used for Segmentation

	A Priori	**Post-hoc**
Descriptive	Contingency tables, Log-linear models	Clustering methods, Nonoverlapping, overlapping, Fuzzy techniques, ANN, Mixture models
Predictive	Cross-tabulation, Regression, Logit and Discriminant analysis	AID, CART, Clusterwise Regression, ANN, Mixture models

Table 3.2 gives an evaluation of the various methods on different criteria. The post-hoc predictive research area seems to be the most powerful in terms of strength.

Table 3.2: Evaluation of Segmentation Methods

Methods/ Criteria	Effectiveness for segmentation	Effectiveness for prediction	Statistical properties	Application known	Availability of programs
1. A-priori, descriptive					
- log linear models	±	--	+	++	++
- cross tabs	±	--	++	++	++
2. A-priori,predictive					
- regression	-	++	++	++	++
- discriminant analysis	-	++	++	++	++
3. Post-hoc, descriptive					
- non overlapping	++	--	-	++	++
- overlapping	++	--	-	-	-
- fuzzy	++	--	-	±	+
4. Post-hoc, predictive					
- AID	±	+	-	++	+
- 2-stage segmentation	+	+	-	+	±
- clusterwise regression	++	++	±	+	+
- mixture regression	++	++	+	+	+
- mixture MDS	++	++	+	±	-

++ very good, + good, ± moderate, - poor, -- very poor

The traditional method for predictive clustering is automatic interaction detection, AID. However, Doyle and Hutchinson (1976) provided empirical evidence that for market segmentation, clustering methods are preferable to AID, which fell into disrepute at the end of the 1970s.

Although the fuzzy clusterwise regression procedures are powerful approaches to segmentation in which classification and prediction are combined, the disadvantages is that users must subjectively specify fuzzy weight parameters that influence the degree of separation of the clusters and that statistical properties of the estimators are not established.

The disadvantages are largely alleviated by latent class (or mixture regression models). Mixture regression models simultaneously group subjects into unobserved segments and estimate a regression model within each segment relating a dependent variable to a set of independent variables (cf. Wedel and DeSarbo, 1994). Mixture, mixture regression and mixture MDS methods currently provide the most powerful algorithms for market segmentation.

Conjoint analysis constitutes an important area for post-hoc predictive segmentation research. That methodology is particularly useful for post-hoc predictive segmentation because its more recent developments allow for the grouping of consumers according to how they respond to product features in making choice decisions. Since the process of buying a house is a choice process that has a lot of similarities with this type of decision making, the conjoint analysis area seems a worthwhile domain to be explored further. Conjoint analysis will be further elaborated upon in the next chapter.

4 Conjoint Analysis

A new home consists of a combination of several characteristics. Altogether, these characteristics are perceived in a certain way by a potential customer. The perceived value of these housing attributes determines the attractiveness of a housing profile. In the end, this perceived value will determine whether a potential customer decides to buy a new house or not. In this chapter we will explain why conjoint analysis is the most appropriate method to reveal preferences of different consumers.

4.1 Why Conjoint Analysis

The topic of housing choice and housing preference continues to be heavily researched. It is an area of interest to scholars in numerous disciplines. Timmermans et al. (1994) gives an overview of cross-sectional modeling approaches of housing preference and housing choice. A distinction is made between **revealed preference** and **stated preference** models.

Revealed models are based on observational data of households' actual housing choices in real markets. In contrast, stated preference and choice models are based on people's reactions to hypothetical houses. There are some important major disadvantages related to revealed preference research (Oppewal and Timmermans, 1992).

The first problem is that relevant variables may strongly correlate in real markets, which leads to estimation and interpretation problems. These problems can only be avoided by applying data reduction techniques like principal components analysis. This is a general problem in doing survey research.

Another problem which is related to the abovementioned problem is a lack of experimental control and this may lead to ambiguous conclusions concerning the causes of observed choice behavior. There is always a possibility that a non-observed underlying variable was the actual reason for the observed behavior. It should be noted that the consequences of specification errors are more serious for discrete choice models than for simple regression analysis (Horowitz, 1981; 1985).

A third problem has to do with the specification of the choice set. In "revealed" applications it is not always clear which alternatives were available or traded-off by the consumer. Finally, it can be mentioned that the survey as a data collection method in revealed choice studies is in essence not very efficient, since only one actual choice per respondent is observed. Furthermore, it is not possible to observe and gather information about new (types of) alternatives in the market. As a consequence, only unreliable choice models will be developed for new market situations.

The most important practical reason to choose for a **stated preference research** is the absence of revealed data. For decades, HCO has developed new houses, but it was never monitored exactly who the buyer was and what his/her motives were to buy a specific house.

Therefore, it seems logical to look further at the class of stated preference models, which can be differentiated in **algebraic and non-algebraic models**. The algebraic models can be further split up into compositional and decompositional (conjoint) models.

It is found that revealed choice models are not well-suited for identifying underlying preferences structures, as too many factors driving housing choice are confounded. Compositional models are easy to administer. They do not require much expertise to estimate and apply. However, their reliability, validity and predictive accuracy is substantially lower than that of conjoint models. Conjoint models compare well in terms of rigor, theoretical foundations, advanced error theory, and flexibility for developing more sophisticated and advanced models. Decision plan nets (non-algebraic) have the advantage of flexibility, but a potential drawback is that their reliability is in question (Timmermans et al., 1994). Therefore, the conjoint model seems to be the most appropriate method to deal with Research Question 1 and 2. Figure 4.1 presents a hierarchical decision tree which leads to the methodology selection.

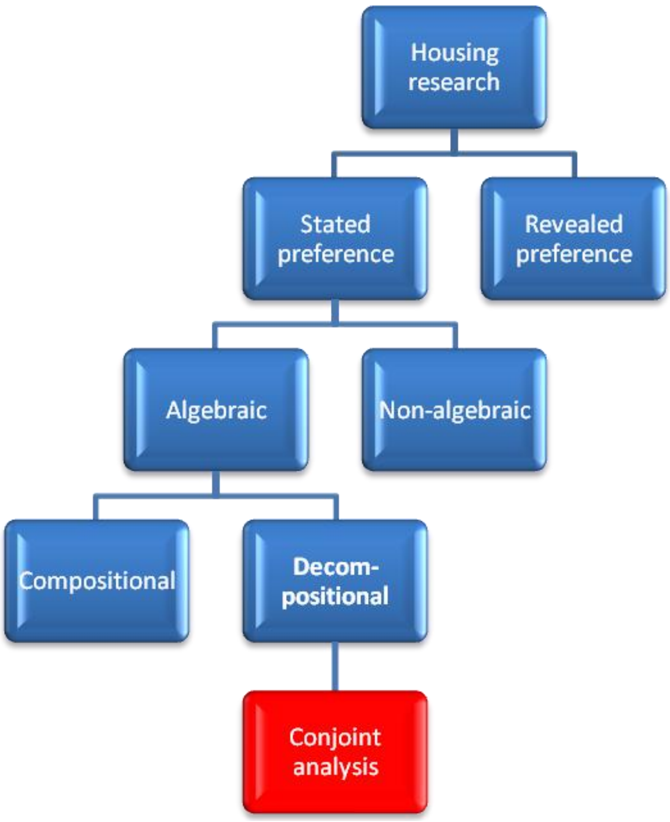

Figure 4.1: Methodology selection

4.2 Choice-based conjoint: Adding another touch of realism

In recent years, many researchers in the area of conjoint analysis have directed their efforts toward a new conjoint methodology that provides increased realism in the choice task.

With the overriding objective of understanding the respondent's decision-making process and predicting behavior in the marketplace, traditional conjoint analysis assumes that the judgment task, based on ranking or rating, captures the choices of respondent. Yet researchers argue that this approach is not the most realistic way of depicting a respondent's actual decision process, and others have pointed to the lack of formal theory linking these measured judgments to choice (Louviere and Woodworth, 1983).

What emerged is an alternative conjoint methodology, known as **choice-based conjoint**, with the inherent face validity of asking the respondent to choose a full-profile stimulus from a set of alternative stimuli known as a **choice set**. This method is much more representative of the actual process of selecting a product from a set of competing products.

Choice-Based Conjoint analysis started to become popular in the early 1990s, and lately has become the most widely used conjoint technique in the world (Orme, 2009). CBC interviews closely mimic the purchase process for products in competitive contexts. Instead of rating or ranking product concepts, respondents are shown a set of products on the screen and asked to indicate which one they would purchase.

Buying a new house can be better simulated with a **decision task** than giving every offered option a **rank or rating**. Furthermore, the traditional method becomes more complex when the number of ranking or rating tasks increases. For example, when 32 different profiles with new homes are displayed all at once to a respondent it becomes difficult to process all the information, keep it in mind, and determine the difference between e.g. rank 15 and 16. Choice-based tasks will overcome this difficulty by offering 16 separate questions in which a respondent has to choose only 1 out of 2 profiles. Another solution can be offering only 8 choice sets with 4 alternatives or even choice sets of varying size. However, we expect that a set with 2 alternatives will be difficult enough already to evaluate by a respondent.

Despite the benefits of choice data, they contain less information than ratings per unit of respondent effort. After evaluating a number of product concepts, the respondent tells us which one is preferred. We do not learn whether it was strongly or just barely preferred to the others; nor do we learn the relative preference among the rejected alternatives (Orme, 2009).

Moreover, choice-based conjoint provides an option of not choosing any of the presented stimuli by including a no-choice option in the choice set. Whereas traditional conjoint measures assumes respondents' preferences will always be allocated among the set of stimuli, the choice-based approach allows for market contraction if all the alternatives in a choice set are unattractive. Furthermore, the "no preference" option forms an escape, when the stimuli are equally attractive.

Especially, the latter approach adds to reality in real estate decision-making. HCO often has to deal with potential customers that will choose not to buy or delay their buying decision.

Next to choice-based conjoint, adaptive conjoint analysis (ACA) could have been a reasonable alternative for the somewhat old-fashioned traditional approach. ACA went on to become the most popular conjoint software tool and method in both Europe and in the US throughout the 1990s. ACA's main advantage was its ability to measure more attributes than was advisable with the traditional conjoint approach (e.g. Hair et al., 2006). With ACA, it was possible to study a dozen to two-dozen attributes, while still keeping the respondent engaged and providing good data. ACA accomplished this by having varying sections of the interview that adapted to respondents' previous answers. In each section, only one or a few attributes were presented at a time, so as not to overwhelm the respondent with too much information at once. The software led the respondent through a systematic investigation over all attributes, resulting in a full set of preference scores for the levels of interest (part-worth utilities) by the end of the interview (Orme, 2009).

In terms of limitations, the foremost was that ACA needed to be computer-administered. The interview adapts to respondents' previous answers, which cannot be done via paper-and-pencil. Like most traditional conjoint approaches, ACA is a main-effects model. This means that part-worth utilities for attributes are measured in an "all else equal" context, without the inclusion of attribute interactions. This can be limiting for some pricing studies where it is sometimes important to estimate price sensitivity for each brand in the study. ACA also exhibited another limitation with respect to pricing studies: when price was included as just one of many variables, its importance was likely to be understated, and the degree of understatement increased as the number of attributes studied increased. Many researchers continue to use ACA today, but they tend to avoid pricing applications and also take care to implement the latest best practices for ACA research.

However, we expect that price in this housing context can be a key attribute that plays a crucial role in the process of buying a new home. Therefore, it seems advisable to discard the ACA technique in favor of the CBC method.

Taken together, we can state that a **choice-based method** will be more suitable than a traditional conjoint approach or adaptive conjoint analysis to investigate housing preference and decision-making for HCO's real estate consumers.

5 Research Design

The first step in constructing the research design of the choice-based conjoint experiment is to determine the appropriate number of attributes and levels.

There are limits to the inclusion of the number of attributes and levels in the choice task. Too many attributes will increase the complexity of the task for the respondent and to maintain reliability of the results the number of choice-tasks in the experiment has to be increased. This also holds for the total number of respondents. There is a risk that a respondent will get bored when he/she has to repeat more or less the same task for a long time. Therefore, it is decided to restrict ourselves to a maximum of 10 attributes. However, if we reduce the number of attributes too much a very influential factor may be left out and this will distort the final results.

Full-profile choice-based conjoint (CBC) analysis is generally not appropriate for studies involving large numbers of attributes. Each task presents concepts that are described on all the attributes, and there is a limit to how much information respondents can process without becoming confused or overloaded. Green and Srinivasan (1990) suggest about six as the maximum number of attributes to handle with full-profile concepts in traditional conjoint analysis. The effective limit for choice-based conjoint analysis may be even lower because respondents must process several full-profile concepts simultaneously. They believe that choice tasks involving more than about six attributes are likely to confuse respondents, though this depends greatly on the level text length and the familiarity of respondents with the product category.

However, psychological research of Miller (1956) about the magic number seven indicates that a human being is capable to process information about 7 plus or minus 2 objects / things at the same time. Therefore, we have decided to enrich the research design with the inclusion of 9 attributes. Restricting ourselves to solely a limited number of the 6 most important housing attributes may significantly distort the results of our experiment and may give an improper view of reality. Several other CBC studies have been conducted with a relatively large number of attributes (e.g. Molin et al., 1996; Borgers & Vosters, 2011)

Eventually, NLOGIT 4.0 with a LIMDEP package was provided by the Urban Planning Group of the Architecture, Building, and Planning department of the TU/e. This econometric software enables the researcher to treat individual data, which is used to estimate parameters at the aggregate level (multinomial logit modeling) or group level (latent class modeling).

5.1 Generating the attributes and levels

In advance of the final large-scale quantitative choice-based conjoint experiment, a small-scale qualitative research was needed in order to determine which attributes are the most important in buying a new home. First, a long list of attributes was created by asking all HCO employees which aspects they found to be the most important when buying a house. They were encouraged to mention as much aspects as possible. Furthermore, they had to make a ranking of all the attributes. The attribute that was the most important to him/her had to be placed the highest in the list and the least important things had to be set at the tail of the list. In order to prevent a one-sided (employer's) view on housing attributes, the same task was given to some friends and family members (potential customer view). The results were collected and based on rank and frequency a short list was constructed. Also the website Funda.nl served as a source of inspiration.

Next to this practical viewpoint also literature research was done (e.g. Timmermans & Van Noortwijk, 1995; Molin et al., 1996; Molin et al., 2001; Jansen et al., 2009; Earnhart, 2002). Extant research on housing topics was reviewed and it was possible to count the housing attributes that were used the most in choice-based conjoint studies. The next paragraph further explains why certain attributes are included or omitted from the CBC experiment.

5.1.1 Attribute selection

The long list of housing attributes consists of the following aspects, which will be displayed below in random order. The aspects that played a role in selecting a new house are: Tenure, Price, Dwelling Type, Location, Architectural Style, Number of (dormitory) Rooms, Size of the living room, Surface Area, Land Area, Garden, Garden depth, Garden Surface, Garden orientation, Balcony, Parking Space, Garage, Facilities in the neighborhood (supermarket, sports, school, church, etc.), Green in the environment, Type of buildings in the environment (high rise, low rise), Durable materials, Sustainable house, Distance to Work, Type of Roof, Sloped Roof, Effective Cubic Meters, Expansion options, Financial ability to buy the house, Amount of light in the house (intensity of light inside the rooms) and Customer Involvement during the buying process. The following 9 attributes were selected for the CBC experiment:

A1: Price

A2: Dwelling Type

A3: Location

A4: Number of dormitory rooms

A5: Architectural style

A6; Parking

A7: Customer involvement

A8: Sustainable / energy efficient

A9: Distance to supermarket

The attribute **Price**, or a variant of it such as monthly costs, is referred to in almost every housing study that is based on conjoint analysis (see e.g. Timmermans & Van Noortwijk, 1995; Molin et al., 1996; Molin et al., 2001; Jansen et al., 2009; Earnhart, 2002). Brokers often consider this attribute to be the most important. Also, the **Number of Dormitory Rooms** is discussed in these articles**.** The most important reason to include the attribute Number of Dormitory Rooms is that it gives the respondent a good indication about the total living area and is easier to interpret than cubic or squared meters. Furthermore, the latter terms are difficult to translate into a small number of actionable levels.

Dwelling type is also frequently mentioned. Sometimes, it will be left out and is assumed to be fixed. In the study about the VINEX location Meerhoven in Eindhoven (Molin et al., 1996) the dwelling type was only semi-detached (two-under-a head).

In Timmermans & Van Noortwijk (1995) **Location** is varied over 4 levels, i.e. the city center, other urban location, suburban location and rural location. Jansen et al. (2009) use only two levels (urban and rural) for the attribute residential environment, which can be compared to location.

Molin et al. (2001) give additional attributes which are related to the construct Location. Travel distance to school or work, availability of public transport and type of buildings in the neighborhood are some examples. For the latter factor a distinction will be made between terraced houses and apartments and semi-detached and detached houses respectively. Previous research by Molin et al. (1996) named a comparable factor, low-rise versus high-rise was the differentiating criterion in this study. Generally, developers as HCO, consider location to be the most import attribute in the buying decision process of a new house. The process of land acquisition and site selection is one of the key competences of a good developer.

Another frequently cited attribute is the architecture of the dwelling. Earnhart (2002) discusses **Architectural style** and makes a distinction between Cape Cod, Colonial and Ranch style. However, we have to deal with the Dutch market and therefore these typical American styles are not usable here. It seems reasonable to use classical/traditional and modern style as the two levels for Architectural Style. A contemporary style can also be thought of, but according to an interview with a broker at Bernheze makelaars a choice between the two levels classic and modern will be difficult enough already.

Next to this, the presentation method of profiles will be an issue. A picture can tell a respondent more than a thousand words. Computer-based studies more and more replace the old-fashioned paper-and-pencil studies. Nevertheless, **visualization** of architectural style has certain risks. Respondents can interpret the attribute in another way than what it actually stands for.

Color aspects can play a significant role here. Someone may have a preference for modern architecture above classical, but makes a reverse choice due to a new aspect that is not explicitly mentioned in the choice task, e.g. red bricks. If the picture of the hypothetical house was displayed in exactly the same manner, but now with white bricks the respondent could have made a different choice. A way to solve this problem is by making **sketches**. Additionally, another problem may arise, namely that the respondent automatically will link architectural style with the dwelling type which is showed in the profile picture. A way to overcome possible interaction effects is by creating a **collage** with several dwelling types included in one profile picture. A study on the effects of presentation style (Orzechowski et al., 2005) suggests that less costly verbal descriptions of housing attribute levels likely suffice to elicit valid housing preferences. The estimated utilities for the attribute levels will not be significantly influenced by presentation style.

In the end, we have decided to solely construct profiles which contained abstract words. The attribute and level names were chosen very carefully with little room for speculation. The terms should be clear and unambiguous for every respondent.

Parking space is the sixth attribute which was added to the design. Two-levels were suggested: public and private parking. The degree of **Customer involvement** during the entire development and buying process was also incorporated in the design. HCO wants to know if there is a significant difference between high and low involvement for certain customers and what the relative importance is compared to the other attributes. It is a company-related attribute which can be leading in strategy determination.

The last two attributes that were chosen are **Sustainable/Energy efficient** building and **Distance to supermarket**. The first one of these seems to be interesting, since there is a trend in which people become more aware of the consequences of global warming. Furthermore, it is interesting to know what kinds of persons are willing to invest in durable and sustainable goods. Is there an environmental or financial motivation to do this?

The attribute Distance to supermarket is derived from the more general term distance to facilities. Distance to facilities is still a too broad and vague concept. It can vary from the availability of a school (mostly important for families with young kids) to sport facilities and cafes and restaurants (which can be attractive for single individuals). Since a supermarket is relevant for almost every potential customer, we decided to choose for this refinement.

It was decided to **exclude** the attribute **Garden**. Presence or absence of a garden, thus two levels (yes and no), would create too many infeasible profiles. In combination with the other attributes the design will contain a lot of prohibited pairs. Besides, it would be more logical to replace garden with balcony in case of an apartment. This interaction with dwelling type may cause naming and framing problems as well as interpretation problems when analyzing the results. Therefore, garden was omitted from this design.

5.1.2 Mixed-array design

One of the first researchers that paid attention to the field of experimental designs in conjoint analysis was Sidney Addelman (Addelman, 1962).

The most commonly used factorial plans involve factors which all occur with the same number of levels. Experiments which utilize these plans are known as symmetrical factorial experiments.

However, there are many experimental situations which involve factors that do not at all occur with the same number of levels. These experiments are known as asymmetrical factorial experiments.

Initially, we determined that **Price** and **Dwelling Type** should be varied over 6 different levels. **Price** could be set at levels between 150.000 and 400.000 euro (with an increase in steps of 50.000,) while the possible **Dwelling Type** levels were: Apartment, Patio, Terraced, Corner, Semi-Detached and Detached House. Especially for dwelling type it is advisable not to leave out one or more of the abovementioned levels. The complexity of the design will be reduced, but the segmentation will be less meaningful. However, if we attempt to give all the other attributes 6 levels we cannot even think of 6 architectural styles.

Therefore, we made an attempt to construct a mixed-array design with 3 and 2 levels for the other attributes [1]. The MA.36.2.2.3.5.6.2 from Zhang et al. (2001) was selected. It means that we have a mixed-array with 36 runs or different housing profiles, in which every profile will have 2 attributes with 6 levels, 5 attributes with 3 levels, and 2 attributes with 2 levels.

Unfortunately, this resulted in a too high number of **prohibited pairs**, e.g. a detached house of only 150.000 euro is not conform market expectations and an apartment of 400.000 euro seems very unattractive to be chosen.

As a consequence, we decided to construct two separate designs, a so-called low-price segment and a high-price segment. Depending on budget or income the respondent was assigned to the experiment that was best suited to his personal financial situation.

Two orthogonal mixed-arrays (MA.16.2.6.4.3) were used. The main difference between the designs can be seen in Price, Dwelling Type, Number of Dormitory Rooms and Parking Space. This is mainly done to reduce the number of prohibited/unrealistic pairs. In the low-price segment levels varied from 175.000 to 250.000 euro, while in the high-price segment a range of 250.000 to 400.000 euro was applied. The dwelling types apartment and semi-detached appeared in both designs, whereas a terraced and corner house versus patio and detached house where unique to the low and high price segment respectively. The two levels for number of dormitory rooms differed from 2 and 3 to 3 and 4. The distinctive criterion for parking space was public versus private parking in the low-price segment. Since, it is assumed that a detached house has at least one private parking place by definition, it is unrealistic to still vary between public and private. Half of the profiles will become unfeasible then. Therefore, we have chosen for a variation in the number (i.e. 1 or 2) of private parking places.

The exact content of the final designs that were created can be found in Table 5.1 and 5.2 (see Appendix A).

[1] http://www2.research.att.com/~njas/oadir/

A full factorial where all stimuli have to be evaluated, will give $2^6 \cdot 4^3 = 4096$ profiles. Obviously, this number of alternatives is too much for one respondent. The smallest fractional factorial design produces just 4 choice sets with 4 alternatives per choice set. However, we expect that choosing among 4 alternatives with 9 attributes will be a very complex task. The respondent will have enough difficulty already in making a choice for 1 out of 2 housing profiles. A design with 16 stimuli can be created to estimate the main-effects. This implies that we can build 8 choice sets, in which two housing profiles have to be traded-off against each other. In addition, a third option "No preference" will be added to the choice set.

Johnson & Orme (1996) suggest that there is a modest increase in reliability as we process through the interview, at least for the first 20 tasks. The gain from respondents learning how to answer choice tasks seems to outweigh the loss from fatigue and boredom, even for studies up to 20 tasks. Therefore, we have decided to double up the number of choice sets to 16, because it will reveal more reliable information for every respondent.

An MA.32.2.6.4.3 (see Appendix B) was generated simply by making a duplication of the 16 runs design and shifting all levels one upwards. Thus, level 0 becomes level 1, level 1 becomes level 2, level 2 becomes level 3, and level 3 becomes level 0 for the four-level attributes. Level 0 and 1 only had to be switched for the six remaining two-level attributes.

According to Huber and Zwerina (1996) four properties characterize efficient choice designs.

The new design with 32 runs still has the important properties of **orthogonality** and **level balance**.

Level balance is the requirement that the levels of an attribute occur with equal frequency.

Orthogonality is satisfied when the joint occurrence of any two levels of different attributes appear in profiles with frequencies equal to the product of their marginal frequencies (Addelman, 1962).

The third, **minimal overlap**, becomes relevant for choice designs, because each attribute level is only meaningful in comparison to others within a choice set. Minimal overlap means that the probability that an attribute level repeats itself in each choice set should be as small as possible. The last criterion is called **utility balance**. This means that alternatives in a choice set have more similar choice probabilities.

A questionnaire with profiles where no overlap occurs can be easily created. Combining profile 1 and 17, 2 and 18,…, 16 and 32 leads to choice sets where housing profiles do differ on all 9 aspects. However, there is a major drawback to this procedure (see Sawtooth's technical paper on CBC, 2008). The authors of Sawtooth software caution against questionnaires with no level overlap.

If a respondent has a critical "must-have" level, then there is only one product per choice task that could satisfy him/her. In that case, it would be difficult to learn much more about the person's preference beyond that one most critical level. Instead, they prefer **random task generation**. The "Balanced Overlap" design methodology may also be used.

Eventually, we came up with a sort of compromise in which six different questionnaire versions were constructed. Five versions were randomly generated[2]. If a pair had six or more attribute levels in common within a choice set, it was rejected and a new pair was drawn. Also, choice sets with duplicate profiles were not allowed. The sixth questionnaire version was unique in the sense that it satisfied the criterion of minimal overlap. Figure 5.1 shows the different questionnaire designs (see Appendix C).

5.2 Data Collection

5.2.1 Type of questionnaire

There are different ways to approach the respondent with a questionnaire. One of the most traditional methods that can be used is by doing paper-and-pencil studies. Another form in survey research is the computer assisted personal interview (CAPI). Portable computers are used here to record respondent's answers of face-to-face interviews directly into a computer rather than onto a paper questionnaire. Since we aim to target a large number of respondents, this way of collecting data is unfavorable, because it will be very time consuming. The best solution can be found in distributing an **online questionnaire**.

An online questionnaire has the advantage that it enlarges the accessibility of the research. The respondent can fill in the questionnaire anytime he wants and doesn't have to make extra efforts by bringing the filled-in document to a letterbox. It is likely that this will increase the response.

Furthermore, it saves time for the researcher, because it is not necessary to convert the input manually into a file. Also, from a cost perspective it is beneficial in the sense that is saves paper and envelopes. On the contrary, there can be also a disadvantage. We should be careful for bias in the sample. Some people that don't have Internet at home or dislike to work on a computer may refuse to participate in the research, while otherwise they would have been benevolent.

As a student there was little budget available to conduct the research. Several options for creating a free online questionnaire, such as Google Docs, ThesisTools, Surveymonkey, and Enquetemaken.be were considered. Eventually, the latter website was chosen, because it had the most advanced package. Variations in type of questions were possible and images could be added to improve the design. Furthermore, a processing bar was shown as an indication of how much time the total task would last. The missing value problem was eliminated by constructing mandatory questions. The respondent received a warning when he (accidentally) passed over a question and could not continue before finalizing all the obligatory questions. Another strength is interim evaluation. With this tool it is possible to prevent e.g. a skewed male-female ratio. Finally, the branching option (where unnecessary questions automatically will be skipped due to previous answers of the respondent) was a unique feature. The major weaknesses of www.enquetemaken.be were the errors that may occur during duplication of a full questionnaire. As a consequence, a lot of manual work had to be done and therefore we had to restrict ourselves to only six questionnaire variants. Appendix D shows an example of the questionnaire including choice sets with housing profiles.

[2] www.random.org

5.2.2 Sample

The target was to obtain a net sample size of 300 respondents. This seems to be large enough in order to make a meaningful segmentation.

However, the length of the questionnaire, which was about 20 minutes, was certainly a barrier for respondents to participate. Eventually, 171 respondents in total were willing to cooperate. A respondent must represent a potential buyer. It is thus not necessary to include only those persons with buying intention. It is desirable that respondents vary as much as possible in terms of age (however, a minimum age of 18 is required), sex, income and educational level. Otherwise a prior segmentation is already done, which may distort the general results.

The respondents should be all potential customers that live or work in the area of Noord-Brabant. It does not make sense to approach other areas with potential new housing consumers. The scope should be limited to the working domain that is relevant for HCO.

Respondents were attracted/recruited via three means:

- Accost people in the streets (Den Bosch and Eindhoven)
- Social media (spreading an e-mail via Hyves with the online questionnaire)
- Mailing (via Bernheze makelaars 531 visitors of the website brabantnieuwbouw.com were approached)

Only the response rate of the latter can be calculated. Since 33 persons were willing to help, the response rate is equal to 33/531*100 = 6,2%. This is quite reasonable for persons that actually don't have commitment at all with a student's research.

The total number of people which have received the questionnaire is unknown. It is expected to be somewhere between 1000 and 2000. Via the social network approach a request was done to the (potential) respondent to forward the e-mail to relatives and friends who (would like to) live in the area of Noord-Brabant. Despite calculation problems with the response rate, this "snowball" method has the advantage that it can be helpful in increasing the sample size.

5.2.3 Descriptive statistics

Table 5.3 is a summary of the answers on questions 17 to 27 of the questionnaire. It gives an indication about the diversity in the net sample size. Initially, we strived to get an equal number of males and females in our sample. Eventually, there was a slight deviation from this goal, but the 55-45% proportion seems acceptable. Also, the age of the respondents varied to a large extent. Only, the elderly people, so called seniors, seem to be a little bit underrepresented. A possible explanation for this can be a lack of experience with the Internet. There are a considerable number of beginning house buyers present in the sample. However, a positive aspect is the relatively low number of students in this group. This could have led to the introduction of some bias.

Tenure (80% buy and 20% rent) can be benchmarked with the WoON research (WoON, 2009). This research indicates that 58.9% buy and 41.1% rent a house. An overrepresentation of buyers in our sample can only be considered to be positive, since our research deals with preferences of potential home buyers.

Overall, we may assume that we have a representative sample that is balanced on most aspects and is more or less similar to reality.

Table 5.3: Sample Statistics

Variable	Percentage					
	Male	*Female*				
Gender	55	45				
	18-30	*30-40*	*40-55*	*55+*		
Age	33,7	17,8	29,2	19,3		
	Primary Education	*MAVO/ VMBO-t*	*HAVO/VWO*	*MBO*	*Higher vocational (HBO)*	*University*
Education	7,6	7,6	7,0	28,7	31,0	18,1
	Full-time	*Part-time*	*Retired*	*Student*	*Housewife*	*No job*
Work	53,8	27,5	7,0	5,8	2,9	2,9
	Single without children	*Single with child(ren)*	*Married or cohabiting without children*	*Married or cohabiting with child(ren)*	*Living with friends (students)*	*Living with parents*
Household composition	12,3	2,3	36,8	35,1	1,8	11,7
	< €2000	*€2000-2500*	*€2500-3000*	*€3000-3500*	*>€3500*	*Unknown*
Households' monthly net income	19,3	15,8	12,9	13,5	18,2	20,3
	Yes	*No*				
Dual income	59,6	40,4				
	Owner-Occupied	*Rent*				
Tenure	80,1	19,9				
	Detached	*Semi-detached*	*Corner house*	*Terraced*	*Apartment*	*Patio*
Current dwelling	21,1	26,3	11,1	24,6	16,4	0,6
	City center	*Outside the city center*	*Medium-sized place*	*Village*		
Current location	11,1	11,7	46,2	31,0		
	Yes	*No*				
Buying experience	67,8	32,2				
Total	N=171					

Source: Own work

5.3 Data Analysis

This paragraph will describe how the choice-based conjoint results will be gathered, i.e. the data analysis technique that will be used to determine the utilities. A difference between **a priori** and **post-hoc** models can be made. Furthermore, the level of analysis can vary from **aggregate** to **group** and therefore there are different models applied. Relative importance of every attribute will be calculated and also the level values will be displayed. Finally, we will see if there is a discrepancy between certain groups by applying a segmentation technique.

In a conjoint choice model each respondent has to choose one alternative from each of several choice sets. These choice sets are constructed by dividing the set of profiles over 16 choice sets for every respondent. In this chapter we assume that each choice set contains the same number of alternatives, viz. 3, without losing generality.

Next to two housing profiles, a base alternative “no preference” is used in each choice set to scale the utility over choice sets. Furthermore, it offered the respondent an escape. Regular choice alternatives are most often coded in the design matrix with effect-type or dummy coding. We have chosen for dummy coding. The “no preference” alternative has been coded as a series of zeros. This leads to the introduction of one additional parameter (Basecon) which needs to be estimated in the model.

In order to formulate models for conjoint choice experiments, we start from random utility maximization (McFadden, 1976). According to random utility theory (e.g. Train, 2003), each alternative i has a utility (U_i). This utility consists of a structural (V_i) and a random (ε_i) component.

(1) $U_i = V_i + \varepsilon_i$

The structural component is assumed to be an additive function of the characteristics of the alternative:

(2) $V_i = \sum_k \beta_k X_{ik}$

where X_{ik} represents characteristic k of alternative i and β_k is the parameter for characteristic k. Note that a housing profile is characterized by 9 attributes. However, three attributes have four levels and six attributes have two levels. This implies that for each four-level attribute only three parameters have to be estimated, where one level serves a reference level. The same holds for the six two-level attributes, where only one parameters needs to be estimated. Thus, in total $3\times(4-1)+6\times(2-1)+1=16$ parameters values will be calculated for the model. β_0 represents the Basecon parameter, which is used to determine the attractiveness of the “no preference” option.

5.3.1 Multinomial Logit Model

The most popular discrete choice model is the Multinomial Logit (MNL) model. The logit model is obtained by assuming that each ε_i in equation (1), is independently and identically distributed extreme value. The distribution is also called Gumbel and type I extreme value (and sometimes, mistakenly, Weibull) (Train, 2003). The density for each unobserved component of utility is:

$$(3)\quad f(\varepsilon_i) = \exp^{-\varepsilon_i} \times \exp^{-\exp^{-\varepsilon_i}}$$

and the cumulative distribution is

$$(4)\quad F(\varepsilon_i) = \exp^{-\exp^{-\varepsilon_i}}$$

Now, the multinomial logit model can be used to calculate the probability p_i that alternative i will be chosen. This model is defined as:

$$(5)\quad p_i = \frac{\exp(V_i)}{\sum_j \exp(V_j)}$$

The overall log likelihood value of the estimated model is equal to the sum, across all observations, of the logarithmic transformation of the predicted probability p_i for those profiles that were observed chosen by the subjects, according to the following equation:

$$(6)\quad LL(\beta) = \sum_{n=1}^{N} \sum_{i} y_{ni} \ln p_{ni}$$

where $y_{ni} = 1$ if person n chose i and zero otherwise.

The log likelihood is then compared to the log likelihood of the null model $LL(null)$. The null model is based on the uniform distribution of choice probabilities. Consequently, as there are three profiles in each choice set c, the log likelihood of each choice set is equal to:

$$LL(null)_c = \ln(1/3) = -1.0986$$

To obtain the overall value of this log likelihood, these values should be summed across all observations, which is equal to the number of respondents N times the number of choice sets per respondent c, which is equal to 16. Because the number of alternatives is constant for each choice set, the overall log likelihood depends on the number of observations. In case of three alternatives per choice set, the overall log likelihood for the null model can be written as:

$$LL(null) = -1.0986 \times N \times c$$

The external validity of the MNL model can be determined with the goodness-of-fit measure, Rho^2. Rho^2 indicates how well the estimated model predicts the choices made by subjects during the experiment.

Finally, we can calculate the Rho-square of the estimated model with:

$$(7) \quad Rho^2 = 1 - \frac{LL(\beta)}{LL(null)}$$

This measure ranges between 0.0 (no improvement compared with the null-model) to 1.0 (a perfect prediction of each observed choice). A higher Rho^2 value indicates a better performance. According to Hensher et al. (2005), a Rho^2 of 0.3 and higher presents a decent fit for a discrete choice model. However, according to Louviere et al. (2000) values between 0.2 and 0.4 can be considered to be indicative of extremely good model fits. Thus, if the Rho^2 is above 0.2, we can state that the model results are satisfying and have enough predictive power. The objective of the parameter estimation process is optimizing Rho^2.

5.3.2 Post-hoc Segmentation: The Latent Class Model

The MNL model suffers from the problem that it treats all subjects in the sample as homogeneous, and does not deal with heterogeneity. The MNL model cannot be estimated at the individual level, and thus subject-specific part-worths cannot be obtained (e.g., Elrod et al., 1992). The issue of subject heterogeneity has received a lot of attention in the marketing literature and has become a topic of much research (cf. Wedel et al., 1999). Basically, there are two ways to accommodate heterogeneity. In this section we deal with one, where one specifies a discrete distribution of the response coefficients β_j across the population, that is, one postulates that groups of respondents exist with different part-worths. This leads to latent class or finite mixture discrete choice models, which have been applied to conjoint choice experiments by Kamakura et al. (1994), and DeSarbo et al. (1995). Nowadays, probit models are totally superseded by mixed logit models.

Finite mixture models connect very well to marketing theories of market segmentation (Wedel and Kamakura, 1997) and have enjoyed considerable success. Managers seem comfortable with the idea of market segments, and the models appear to do a good job of identifying segments from conjoint choice data.

5.3.3 A priori segmentation: comparing two predefined subgroups

Another modeling option, which may be an enrichment of the standard MNL model, is to take into account the role of predefined background variables.

We have decided to conduct analyses on two interesting background variables:

- gender (male/female)
- buying experience(yes/no)

An a priori segmentation technique can reveal for each background variable whether there are differences in utilities between the two subgroups. We have chosen for gender and buying experience, since the subgroups are mutually exclusive.

The total number of parameters in the MNL model is duplicated and all receive a gamma prefix. Depending on the subgroup a correction factor will be applied, $(\beta + \gamma)$ or $(\beta - \gamma)$, to estimate the utility for each subgroup.

In the end, the post-hoc segmentation and a priori segmentation results can be compared with each other and it can be stated which method is proven to be the most effective.

6 Results

In this chapter the results of the questionnaire will be presented. The dataset that came out of the questionnaire is a very valuable source of information. The main focus of this housing research is on the **indirect results** (Q1-Q16). Thus, the most important findings can be derived from the choice-based conjoint experiment.

The sample statistics (Q17-Q27) were already mentioned in Table 5.3. It showed enough diversity in type of respondents to come up with an appropriate market segmentation.

The most important **direct results** of the additional questions (Q28-Q45) are summarized and can be found in appendix E. Nevertheless, the scope of our research is on the indirect results.

6.1 Aggregate level results

First, we started with an analysis at the aggregate level. Two multinomial logit (MNL) models were estimated, one for the respondents who received the low-price segment questionnaire and another for the respondents who were a-priori assigned to the high-price segment.

This will give a general impression of the average residential consumer in Noord-Brabant. However, we should be aware that the MNL model assumes homogeneity.

Irrespective of the fact if a respondent has the intention to buy a new home or not, he was assigned to a low or high price segment questionnaire. This was done based on his income or financial position. In total, 93 of the 171 respondents have chosen to fill in the low-price segment questionnaire. The other 78 respondents have completed the high-price segment questionnaire and is thus slightly lower.

Initially, we aimed for a total number of 300 respondents. Despite of not meeting the target, we can state that there will be enough information to estimate proper models. The estimated parameters and goodness of fit of the two multinomial logit models for the low-price segment and the high-price segment are presented in Table 6.1. Several parameters that were estimated in both models are significant at a 0.05 level, the level that is commonly used as the standard in scientific research. Nonetheless, the total number of respondents in our sample turned out to be somewhat lower than expected. As a consequence, we can make a relaxation to the $p < 0.10$ significance level for this research.

Table 6.1: Estimated parameters and goodness-of-fit of the two conjoint models (MNL)

Rho^2	0.26	Low-Price segment		Rho^2	0.18	High-price segment	
Attribute	Level	B	Sign	Attribute	Level	β	Sign
No Preference	Basecon	-0.73	0.0002**	No Preference	Basecon	0.53	0.0142**
Price	€175.000	0	-	Price	€250.000	0	-
	€200.000	-0.22	0.0561*		€300.000	0.05	0.7311
	€225.000	-0.20	0.0595*		€350.000	0.22	0.0716*
	€250.000	-0.48	0.0000**		€400.000	0.10	0.4385
Dwelling Type	Apartment	0	-	Dwelling Type	Apartment	0	-
	Terraced	0.35	0.0022**		Semi-detached	1.26	0.0000**
	Corner house	1.01	0.0000**		Patio	0.81	0.0000**
	Semi-detached	1.15	0.0000**		Detached	1.79	0.0000**
Location	Rural	0	-	Location	Rural	0	-
	Suburban	0.31	0.0088**		Suburban	0.24	0.0717*
	Outside city center	0.01	0.9443		Outside city center	-0.21	0.1078
	City center	-0.25	0.0153**		City center	-0.54	0.0000**
Dormitory rooms	2	0	-	Dormitory rooms	3	0	-
	3	0.41	0.0000**		4	0.20	0.0215**
Architecture	Classic	0	-	Architecture	Traditional	0	-
	Modern	0.05	0.4578		Modern	0.18	0.0340**
Parking	Public	0	-	Parking places	1	0	-
	Private	0.21	0.0048**		2	-0.03	0.6880
Customer involvement	Low	0	-	Customer involvement	Low	0	-
	High	0.23	0.0015**		High	0.26	0.0023**
Sustainable/Energy efficient	No	0	-	Sustainable/Energy efficient	No	0	-
	Yes	0.31	0.0000**		Yes	0.33	0.0001**
Distance to supermarket	Cycling	0	-	Distance to supermarket	Cycling	0	-
	Walking	0.14	0.0541*		Walking	-0.01	0.9145

** Significant at $p < 0.05$, *Significant at $p < 0.10$

6.1.1 The low-price segment MNL

First of all, we can observe that the internal validity of the aggregate low-price segment model is acceptable. The Rho^2 of the model is quite good.

$$Rho^2 = 1 - \frac{-1207.466}{-1634.735} = 0,261369 .$$

Firstly, we can observe that **basecon** has a strong negative beta-value of -0.73. This implies that the respondents, in general, were able to make a choice for one of the two housing profiles that were offered in the experiment. Thus, it is very unlikely that they have chosen for the alternative “No preference” in the choice set. This is an encouraging result.

When considering the attribute **price**, we can see three beta-values for the levels 200.000, 225.000 and 250.000 euro. The 175.000 level is omitted from the model and can be used as a reference or null level. The 250.000 euro level differs significantly from the 175.000 level and has a negative value of -0.48. Thus, respondents attach a negative utility to a higher price level. P200 and P225 are almost significant, p = 0.0561 and p = 0.0595 respectively. Both have a negative beta parameter, $\beta = -.022$ and $\beta = -0.20$, when compared to the reference level. Thus, potential customers perceive not a lot of difference between a 200.000 euro and 225.000 euro price level.

Dwelling type shows a stepwise increase in utility. Apartments are the least preferred. A terraced house is already considered to be significantly more valuable, followed by a corner house which is even more attractive. Finally, the semi-detached house has the highest positive beta-value (1.15).

A suburban **location** is the most desired place for people who want to live in the area of Noord-Brabant. A rural location and a place outside the city center are approximately equally attractive and as a consequence do not differ significantly from each other. However, a city center location is the least preferred and significantly varies from a rural location ($\beta = -0.25$).

Furthermore, it makes a lot of difference whether there are two or three **dormitory rooms**. As expected, a new home with three dormitory rooms is the most favorable ($\beta = 0.41$)

The same holds for private parking vs. public **parking** ($\beta = 0.21$), high vs. low **customer involvement** ($\beta = 0.23$) and a **sustainable/energy efficient** new home vs. not sustainable/energy-efficient ($\beta = 0.32$).

The distance of a new home to the nearest supermarket is also important. Obviously, a supermarket within walking distance has a higher utility than one at cycling distance. The beta-coefficient ($\beta = 0.14$) is somewhat lower and the significance level is slightly above 5% (0.0541).

The only insignificant attribute in the model is **architectural style**. A modern style vs. classic style did not reveal many differences ($\beta = 0.05$ with a significance level of 0.46).

6.1.2 The high-price segment MNL

In total, 78 of the 171 respondents have chosen to fill in the high-price segment questionnaire.

The Rho^2 of the model is just below 0.20, but acceptable. $Rho^2 = 1 - \frac{-1123.342}{-1371.068} = 0{,}180681$.

Firstly, we can observe that **basecon** is significant again. In contrast to the low-price MNL model, this high-segment MNL model contains a strong POSITIVE beta-value of 0.53 for basecon now!

This implies that the respondents, in general, have chosen relatively more often for the alternative “No preference” in the experiment.

When considering the attribute **price**, we can see three beta-values for the levels 300.000, 350.000 and 400.000 euro. The 250.000 level is omitted from the model and can be used as a reference or null level. None of the price levels does differ significantly from the 250.000 euro reference level.

We can conclude that respondents, in general, are less price sensitive in this segment and sometimes even can give a higher utility to higher prices for a new home. Although not significant, it can be noticed that all beta-coefficients are positive for the price levels of 300k, 350k and 400k euro.

Dwelling type shows the most extreme variations in utility. Apartments are still the least preferred dwelling types. A patio house is already considered to be significant more valuable $\beta = 0.81$, followed by a semi-detached house which is even more attractive $\beta = 1.26$. Finally, the detached house has the highest positive beta-value $\beta = 1.80$.

Just as in case with the low-segment MNL model, a suburban **location** remains the most desired place for people who want to live in the area of Noord-Brabant, $\beta = 0.24$ indicates a positive utility, but the value is not significantly different from a rural location. A place outside the city center is somewhat less preferred than a rural location. However, this is found to be just above the p = 0.10 level $\beta = -0.21$. Conversely, a city center location is the least preferred and significantly varies from a rural location ($\beta = -0.54$).

Furthermore, it can be mentioned that a new home with four **dormitory rooms** has a higher utility than a house with only three dormitory rooms, $\beta = 0.21$.

Surprisingly, also **architectural style** is significant. In contrast to the expectation, “modern” is chosen above “classic” architecture, $\beta = 0.18$.

Next to this, high vs. low **customer involvement** ($\beta = 0.26$) and a **sustainable/energy efficient** new home vs. not sustainable/energy-efficient ($\beta = 0.33$) are important attributes.

The two variables **parking** and **distance to supermarket** can be considered as insignificant. In the higher price segment, it is assumed that everyone possesses at least one private parking place. Therefore, in the experiment it was tested whether there is a major difference between one and two private parking places. The models indicates no significant results, $\beta = -0.03$.

The distance of a new home to the nearest supermarket is not important enough when considered simultaneously with the other attributes. Obviously, one expects that a supermarket within walking distance will have a higher utility than one at cycling distance. The beta-coefficient ($\beta = -0.01$) indicates that there is no influence at all in the high segment model for this attribute.

6.2 Group level results

6.2.1 Post-hoc segmentation: the latent class model

In addition, a refinement was made by estimating post-hoc latent class models. By applying these models it can seen if further unobserved sub segments do exist within the low-price or high-price segment that can be targeted separately.

6.2.1.1 Low-price segment LCM

The results of the latent class model in the low-price segment are summarized in Table 6.2.

McFadden's Pseudo R-squared is equal to: $1-\dfrac{LL(\beta_{LCM,Low})}{LL(null)}=1-\dfrac{-1085.488}{-1634.735}=0.3360$

This value is substantial higher than the Rho^2 calculated earlier for the low-price segment MNL model and thus indicates an improvement. The analysis revealed that two significant classes can be identified.

Table 6.2: Estimated parameters for sub segments in the low-price segment (based on LCM)

Rho^2	0.34	Latent Class 1		Latent Class 2	
Segment Size / Percentage	**N = 93**	**82**	**88%**	**11**	**12%**
Attribute	**Level**	**β**	**Sign**	**β**	**Sign**
No Preference	**Basecon**	-1.97	0.0000**	1.85	0.0001**
Price	**€175.000**	0	-	0	-
	€200.000	-0.21	0.1144	-0.58	0.0078**
	€225.000	-0.12	0.2935	1.07	0.0003**
	€250.000	-0.48	0.0001**	1.01	0.0002**
Dwelling Type	**Apartment**	0	-	0	-
	Terraced	0.34	0.0053**	0.50	0.1149
	Corner house	1.09	0.0000**	0.50	0.1303
	Semi-detached	1.25	0.0000**	0.84	0.0017**
Location	**Rural**	0	-	0	-
	Suburban	0.22	0.0897*	1.07	0.0018**
	Outside city center	0.04	0.7290	-0.32	0.4254
	City center	-0.39	0.0006**	0.99	0.0005**
Dormitory rooms	**2**	0	-	0	-
	3	0.46	0.0000**	0.61	0.0057**
Architecture	**Classic**	0	-	0	-
	Modern	0.02	0.8158	0.42	0.0412**
Parking	**Public**	0	-	0	-
	Private	0.26	0.0015**	-0.40	0.0868*
Customer involvement	**Low**	0	-	0	-
	High	0.21	0.0061**	0.41	0.1085
Sustainable/Energy efficient	**No**	0	-	0	-
	Yes	0.31	0.0001**	0.41	0.0270*
Distance to supermarket	**Cycling**	0	-	0	-
	Walking	0.11	0.1808	0.36	0.1215

** Significant at $p < 0.05$, *Significant at $p < 0.10$

6.2.1.2 High-price segment LCM

The results of the latent class model in the high-price segment are summarized in Table 6.3.

McFadden's Pseudo R-squared is equal to: $1-\frac{LL(\beta_{LCM,High})}{LL(null)}=1-\frac{-903.0816}{-1371.068}=0.3413$

This value is substantial higher than the Rho^2 calculated earlier for the low-price segment MNL model and thus indicates an improvement. The analysis revealed that two significant classes can be identified.

Table 6.3: Estimated parameters for sub segments in the high-price segment (based on LCM)

Rho^2	0.34	Latent Class 3		Latent Class 4	
Segment Size / Percentage	N = 78	61	78%	17	22%
Attribute	Level	β	Sign	β	Sign
No Preference	Basecon	-1.04	0.0007**	2.94	0.0000**
Price	€250.000	0	-	0	-
	€300.000	0.06	0.7275	0.13	0.6913
	€350.000	0.20	0.1457	0.56	0.0748*
	€400.000	0.03	0.8197	0.53	0.0964*
Dwelling Type	Apartment	0	-	0	-
	Semi-detached	1.40	0.0000**	1.42	0.0001**
	Patio	0.89	0.0000**	0.41	0.3289
	Detached	1.83	0.0000**	2.49	0.0000**
Location	Rural	0	-	0	-
	Suburban	0.43	0.0076**	-0.51	0.0561*
	Outside city center	-0.08	0.6332	-0.95	0.0021**
	City center	-0.50	0.0003**	-0.84	0.0000**
Dormitory rooms	3	0	-	0	-
	4	0.24	0.0190**	0.16	0.4428
Architectural Style	Classic	0	-	0	-
	Modern	0.22	0.0222**	0.21	0.3463
Private Parking Place	1	0	-	0	-
	2	-0.01	0.8926	-0.00	0.9949
Customer involvement	Low	0	-	0	-
	High	0.27	0.0044**	0.21	0.3701
Sustainable/Energy efficient	No	0	-	0	-
	Yes	0.35	0.0002**	0.51	0.0085**
Distance to supermarket	Cycling	0	-	0	-
	Walking	-0.01	0.9243	-0.10	0.6402

** Significant at $p < 0.05$, *Significant at $p < 0.10$

6.2.2 A Priori Segmentation: Gender and Buying Experience

6.2.2.1 Male versus Female

The output of the a priori gender MNL model indicates that we can barely observe differences in how men and women perceive housing attributes in the low-price segment. Males receive a +1 indication, while females belong to the -1 group. The model fit is a little bit better than the standard MNL model for the low-price segment ($Rho^2 = 0.2670$ vs. $Rho^2 = 0.2614$), but this can be also due to an increase of the number of parameters in the model. Only two significant findings at the $p<0.10$ level can be found.

In general, a male prefers a semi-detached dwelling type more than a female in the low-price segment. Furthermore, he has some more aversion to living in the city center than a female. This is highlighted in table 6.4 of Appendix F.

In the same manner we can read off in Table 6.5 that there are not many differences in choice behavior between men and women. Also here the model fit is slightly better ($Rho^2 = 0.1929$ vs. $Rho^2 = 0.1807$) than the standard MNL. in general, we can state that in the high-price segment women attach a higher utility to a detached dwelling type and a patio dwelling than men do.

6.2.2.2 Experienced versus inexperienced buyer

For this analysis all experienced buyers received a +1 indication, while the inexperienced buyers where coded with -1 in the model for estimating the gamma coefficients. For the low-price segment $Rho^2 = 0.2823$ and for the high-price segment $Rho^2 = 0.1959$.

Buying experience reveals five gamma parameters that do indicate some variation in utility between a starter and experienced buyer (see Table 6.6 of Appendix G). First , we can observe that the experienced buyer is more decision-avoidant than a starter on the housing market. Furthermore, he differs significantly in terms of preference for location. There's an clear shift to rural, indicated by lower utilities for suburban, outside and within city center locations. In general, a potential customer with buying experience is more reluctant to live in an urban environment in the low-price segment.

The same aversion against living in an urban environment can be noted for the high-price segment (see Table 6.7). Furthermore, a semi-detached house is significantly less attractive for the experienced buyer. Finally, it appears that a high price of 350.000 euro is more appreciated by experienced buyers, also the 400.000 euro price level seems to be more preferred. However, the significance level is just above $p = 0.10$.

7 Discussion and Conclusion

In this chapter we first start with a more thorough evaluation of the results. The discussion provides a comprehensive view of how the outcomes should be interpreted in a scientific way.

Finally, conclusions will be drawn in order to give an answer on the research questions.

7.1 Discussion

7.1.1. Interpretation of the MNL models

In the low-price segment we found a significant negative beta-value for the price level 250.000 euro in comparison to the 175.000 euro level. This is totally conform the expectation that someone prefers to buy a new home for the lowest price as possible. The utilities of the 200.000 and 225.000 euro level were approximately the same $\beta = -0.22$ and $\beta = -0.20$ and almost significant at $p < 0.05$ with . However, the expectation of monotonically decreasing utilities for increasing price levels is unfortunately not met. In the high price segment MNL model we do not find price sensitivity at all. A reasonable explanation for this phenomenon can be that respondents have a higher income or budget in this class. As a consequence, they have more money to spend. Probably, these potential new home buyers prefer the more expensive dwellings, because they look for **social economic status** or **image**.

For dwelling type we see a monotonically increasing pattern of utilities in the low-price segment. Apartment is the least attractive, while a semi-detached is the most frequently chosen option. In a ceteris paribus situation for the other attributes, this is certainly a plausible result, because the average market price of a semi-detached house (€290.032) is much higher than an apartment (€182.687), terraced house (€228.436) or corner house (€247.611) (see Table 2.2). The high-price segment MNL can be interpreted similarly. Starting from the viewpoint of an apartment utility increases for patio, semi-detached and detached dwellings respectively. Perhaps different results would have come out of this experiment when we had decided to add the adjective “luxury” to apartment in the high-segment design.

Also, the results of most preferred location seem to be very reasonable. Rural is less attractive since this is mostly associated with a lack of facilities. Also the other side of the spectrum, city center, is likely to be unattractive. Therefore, it seems logical that there is an optimum for the suburban living environment. This holds for the low-price as well as the high-price MNL model.

Architectural style is not significant in the low-price segment. We could have already anticipated on this result, because our sample contains many different people (see descriptive statistics) which easily could have a lot of variety in tastes and preferences for architecture. The significant positive beta for “modern” in the high-price segment is slightly surprising. A possible reason for this may be that customers with a higher income/budget want to have exclusive or extraordinary things, e.g. a special type of roof. It is interesting to investigate whether there is a relationship between modern architecture and gaining social status.

The NVB Huizenkopers in Profiel research shows that there is more sympathy for modern architecture in urban areas and for older home buyers. However, it is not very convincing due to a lack of scientific support for this statement (NVB Huizenkopers in Profiel, p. 90; 2010). According to other research, in general a traditional or classic style is more preferred in the Dutch market (e.g. WoON, 2009; Repelakker, 2009). Also the WBO research (2009) shows contradictory results (80% traditional, 20% modern architecture) with this CBC experiment.

Customer involvement and sustainable/energy efficiency seems to be two topic of strategic importance in the future. In both the low-price and high-price MNL model these attributes are significant.

Difference between the two models can be found for parking and distance to supermarket. Both attributes are only significant for the low-price MNL model. Private parking is preferred above public parking, but in the high-price segment were at least one private parking place is assumed, no significant difference can be found with having two parking places. An explanation for no difference between cycling and walking distance to the supermarket in the high-price segment, can possibly be derived from another attribute in the model. The most preferred location is more rural and less urban. Living in a more rural environment automatically implies being at a larger distance from facilities such as a supermarket.

7.1.2. Interpretation of the low-price LCM model

Next to the majority of the respondents, which belong to the "normal" class of 88% of the sample, a special class of about 12% of the sample predominantly diversifies itself by having a significant positive attitude towards choosing the "No preference" alternative.

According to Johnson and Orme (1996), there are at least two hypotheses for why respondents may choose "None", which in our case is more or less the same as the "No preference" alternative.

Economic Hypothesis: One hopes that respondents choose "No preference" to indicate that no offering is sufficiently attractive. If that is true, then "No Preference" responses may be useful in forecasting how category volumes would change with differences in attractiveness of products.

Decision Avoidance Hypothesis: Perhaps respondents choose "No preference" as a way of avoiding difficult choices. Previous analysis of other choice-based data had suggested that respondents may also choose "No preference" when the two most attractive concepts are nearly tied in utility. If that is true, then interview behavior would not reflect behavior likely to be found in real-world purchases, and "No preference" responses would be less useful in forecasting category volumes.

Another reason why respondents frequently have chosen the "No preference", might be just **laziness or boredom** of the specific respondent. The main goal of a respondent then is just skipping the questions in order to complete the questionnaire as soon as possible. If this is the case, the results become less valuable of course.

If we take a look at the other parameter values, it is remarkable that latent class 2 is more price sensitive (P200, P225 and P250 all significantly differ from P175). Furthermore, for dwelling type the terraced and corner house do not have a significant higher utility than an apartment. Thus, apartment seems to be more attractive for respondents in latent class 2 than in latent class 1. Besides, the city center location is significant again, though the parameter sign has reversed now. As a consequence, it can be interpreted that this specific group makes a shift to the right on the rural-urban spectrum when compared with the majority of the sample.

All these characteristics form a logical explanation why the private parking place parameter is not significant anymore for latent class 2. Instead the parameter is even negative (but insignificant). Someone who prefers to live in an apartment in the city center of an urban location is likely to accept a new home without a private parking place. Due to a lack of room for parking space, a (multi-storey) car park can be a frequently chosen solution for this group. Another interpretation might be that this group doesn't need to have a car at all, cannot afford to buy a car or travels by bike or public transport.

Last but not least, the architectural style "modern" is important in latent class 2. If we reflect on this result simultaneously with the other characteristics of the segment, we cannot be astonished. In general, the whole segment seems more cosmopolitan than latent class 1 and therefore a modern view on architecture is expectable.

Briefly, we can state that, while considering all model characteristics, latent class 1 is the most interesting customer group to target for HCO. Not much attention should be paid to latent class 2, since it consists of price sensitive and/or decision-avoidant potential customers.

7.1.3 Interpretation of the high-price segment LCM

The majority of the respondents in the high-price segment LCM will be categorized in latent class 3. Seventy-eight percent belongs to this "normal" group. Latent class 4 has a size of approximately 22% of the high-price segment sample. In comparison with latent class 2 in the low-price LCM, again we find decision avoidance behavior or economic reasons to favor the "no preference" option in latent class 4 ($\beta = 2.94$, $p = 0.0000$). It is remarkable that this decision avoidant group is almost twice as large as in the low-price LCM (22% vs. 12%).

There can be a relationship with the economic downturn which was present at the moment of filling in the questionnaire. Table 2.1 illustrates that sales primarily stagnates for expensive dwellings. Therefore, we may assume that customers in this high-price segment are more reluctant to buy a new home than in the low-price segment.

Hitherto, for both high-price segment models (i.e. MNL and LCM) no price sensitivity can be found in the parameter estimates for the attribute price. Nevertheless, we can observe two positive beta-values for 350.000 and 400.000 euro in class 4, which are nearly significant ($p < 0.10$). This wider range can be accepted here, since we deal with a small-scale study and a relatively small sample size. It appears that a higher housing price leads to a higher utility for latent class 4.

Furthermore, the patio dwelling type seems less attractive at the cost of a detached house, which is by far the most preferred alternative. In contrast with latent class 3 of the high-price segment, latent class 4 identifies respondents who are looking for more space and like to live in a rural environment.

A more profound glance at latent class 4 reveals that this group consists of only experienced buyers. Furthermore, they have a high income or budget to spend. However, we should be aware that it's likely that they refuse to sell their current house at a lower price in times of a crisis, which reduces the chance of buying an expensive new home. Thus, their preference for expensive dwellings is an opportunity for developers to keep in mind (because of a higher profit margin), but this group can better be targeted in times of prosperity and economic welfare.

Background characteristics of the four identified segments can be found in Appendix H.

7.3 Conclusion

This paragraph will present the conclusions of this research project. An answer will be given on two research questions, which will be recapitulated below.

1. How can a valid segmentation of residential consumers be made for the housing market of Noord-Brabant?

Firstly, a literature research was done on the market segmentation topic. The selection of appropriate segmentation bases and methods is crucial with respect to the number and type of segments that are identified in segmentation research, as well as to their usefulness to the firm.

A **segmentation base** typology can be made consisting of four quadrants: *general, product-specific, observable and unobservable*.

Benefit segmentation which can be categorized into the product-specific / unobservable base is considered to be the best option. It scores very well on six criteria, especially on actionability and responsiveness. An effective method for assessing benefits in segmentation studies is conjoint analysis (Green and Srinivasan, 1978; Cattin and Wittink, 1982; Green and Krieger, 1991).

A classification of **segmentation methods** can be made by applying an *a priori* or *post-hoc* approach. The second way of classifying segmentation approaches is according to whether *descriptive* or *predictive* statistical methods are used.

The area of post-hoc predictive methods seems to be the most favorable in terms of effectiveness.

Mixture regression methods (including latent class models) currently provide the most powerful algorithms for market segmentation.

In the research area of housing preference and housing choice a distinction is made between **revealed preference** and **stated preference** models. A major weakness of revealed models is a lack of experimental control. It is not always clear which choice alternatives were available for a respondent, and therefore interpretation problems can occur. Furthermore, it is not possible to observe and gather information about new (types of) alternatives in the market. Especially, the latter seems necessary for a company that wants to develop new and innovative housing concepts.

Therefore, the choice-based conjoint technique, which belongs to the stated preference models, seems to be the most suitable method that can be applied for segmenting the housing market. The post-hoc latent class model is expected to perform best in terms of rigor.

2. Which segments of consumers can be discerned in the housing market of Noord-Brabant and how do they differ from each other in terms of housing preferences and decision making?

A-priori segmentation gives small but interesting differences between subgroups. It provides more information than the standard MNL model. In this case, it seems more meaningful to separate on the basis of buying experience than gender. This is indicated by more significant gamma parameters and and higher model fit. Nevertheless, post-hoc segmentation with latent classes gives the impression to be the most effective method to segment the housing market.

The post-hoc latent class models revealed four market segments. A summary will be provided in Figure 7.1. Heterogeneity is indicated by varying characteristics for each segment. Discrepancies in predominantly the attributes price, location and dwelling type, imply that different target strategies have to be worked out for each segment. The only attribute-level that is significant and represented in all segments is a high sustainable and energy efficient dwelling.

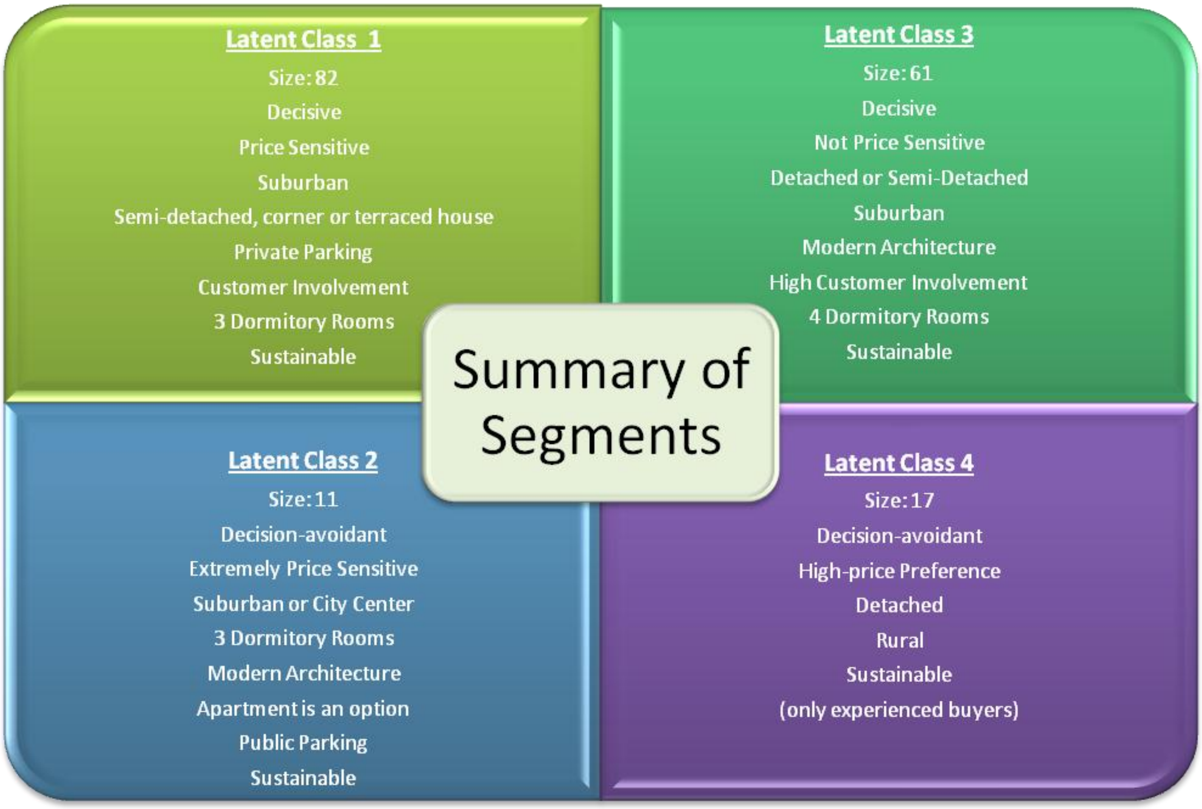

Figure 7.1: Summary of segments

7.4 Managerial implications and recommendations

- Latent class 1 and 3 are the largest segments and are interesting to target for HCO. Latent class 2 and 4 are considerably smaller and less attractive to target. Respondents in the latter two classes are decision-avoidant. Therefore it is expected that they also will be more reluctant to buy a new home in the real world.

- Another important advice to HCO is to avoid projects with apartments or patio dwellings during the economic crisis. The combination of a surplus of apartments in the area of Noord-Brabant together with the results of the CBC experiment, which indicate a low utility for apartments, imply a high risk that is involved with these types of projects. Patio dwellings should be build for a specific target group, mostly elderly people, but it's only worthwhile to invest in this dwelling type when there is sufficient market potential.

- Location appears to be the most important attribute of the nine attributes that were investigated during this research. Latent class 1 and 3 show high utilities for a suburban location. Latent class 2 is more urban oriented, while latent class 4 prefers a rural environment. Viewed from a customer perspective, HCO should be eager to develop projects in a suburban environment. Land purchase in a midsized place of about 30.000 inhabitants seems the most desirable strategic choice. However, we should keep in mind that this conclusion is derived apart from the fact that e.g. governmental, political or legislation issues may play an important role. For every project, we should not lose sight of these situational factors.

- Do not cut down the number of dormitory rooms from 3 to only 2 bedrooms in order to save costs or increase the project's profit. Potential customers may refuse to buy the dwelling. A lower buying price cannot compensate the effect of a lack of space. In the higher price segment 4 dormitory rooms are significantly preferred above 3 dormitory rooms. However, we expect that reducing the number of bedrooms in this segment may have a less dramatic effect on sales.

- It seems dangerous to build new homes without a private parking place in the low-price segment. Therefore, economizing on this aspect in a building project seems undesirable, since it leads to a significant utility reduction for the potential customer.

- The extent of customer involvement, which was until now not researched yet, is in both segments considered to be a significant parameter when evaluated in a bundle of housing attributes. According to the CBC results, it seems a responsible or sensible strategic choice for HCO to give customers more involvement in a building project. Though, from a practical viewpoint this may lead to capacity problems for the buyer assistant, because of an increasing workload.

- Energy efficiency and sustainability of new homes has gained more attention during the last decade, amongst others because of the effects of global warming. However, this aspect was not investigated before in a conjoint experiment about housing. In comparison with customer involvement, also this “new” housing attribute had a significant impact in the low price as well as the high price segment. This is an encouraging result and as a consequence there is a challenge for more future investigations on this topic. The suggestion to HCO will be to realize future projects, in which attention is paid to energy efficient and sustainable dwellings. Sustainability can be a unique selling point to certain customers. Successful projects in the past can serve as a means of exposure to potential new customers and may improve the image of the company.

8 Limitations and future research implications

The CBC experiment led to aggregate results and segment results. Both types of models performed well, whereas the latter models showed the highest validity in terms of a high McFadden R-squared. Though, there are some limitations that have to be mentioned.

8.1 Limitations

The first limitation is that the number of levels effect may distort the interpretability of the CBC results. Since, we have chosen for a mixed-array design, all attributes cannot be treated equally. A logical rule of thumb will be that the three 4-level attributes automatically will have a higher importance than the six 2-level attributes, i.e the range of beta-values will be wider by definition, because more levels are compared with each other. The result of this number of levels effect may lead to improper calculations with respect to percentages attached to certain market segments.

Secondly, the sample size was actually too small in order to come to a very sophisticated segmentation with relevant target groups for HCO. A number of 200 respondents per subgroup is necessary to accomplish this. However, this seems an unrealistic target that almost never can be achieved in a master thesis project due to the limited time and resources available. Furthermore, the presence of direct questions in addition to the CBC experiment has led to a substantial lengthier questionnaire. This also could have been a barrier for some respondents to fill in the total questionnaire.

Thirdly, a limitation might be that it is not clear whether the estimated utilities on aggregate and group level are stable over a longer period of time. The effect of an economic crisis can be measured in repetitive follow-up studies conducted in times of economic welfare.

A fourth limitation is the fact that it is difficult to generalize the results of the CBC experiment. The results can only be applied to the area of Noord-Brabant. Even in a small country like the Netherlands there can be substantial regional differences.

8.2 Future research implications

New choice-based conjoint experiments can be conducted in the future on project level by HCO or other developers. A presentation style with virtual reality instead of a verbal description can be used to give the potential customer a higher project involvement. Several choice options that can be added to the basic dwelling for a certain price have to be traded off. The choice behavior of respondents enables developers to determine what type of dwellings have to be built in an early stage of the project.

It would be interesting to replicate this study in the Randstad area to investigate whether apartments are a more attractive dwelling type in this region. It is expected that the optimal location for a Randstad inhabitant will shift more from suburban to urban location, with a rural location as the least preferred alternative. Thus, other regional studies should be conducted in order to come to a comprehensive view of the total Dutch housing market.

Surprisingly, modern architecture is significant in the high price segment (in the low-price segment there was no difference at all between traditional and modern architecture). A possible reason for this may be that customers with a higher income/budget want to have exclusive or extraordinary things, e.g. a flat roof. It is interesting to investigate whether there is a relationship between modern architecture and gaining social status.

The main focus of this master thesis aimed at the choice-based experiment. Nonetheless, also direct questions were asked and the most important results can be found in the appendix.

An extensive dataset offers opportunities to look more thoroughly at these aspects. Hypotheses can be stated and tested about several themes, such as risk behavior (e.g. is income or education related to amount of risk that someone is willing to take when buying a new home) or search behavior (e.g. to see whether a difference in communication behavior is needed for certain subgroups, which groups prefer IT communication above personal contact and vice versa).

Also the topic of energy efficiency/sustainability can be further explored. The CBC experiment revealed that it plays a significant role when buying a new home. Still, the underlying motives to invest in energy efficiency and sustainability remain unclear. We can research if there is a discrepancy between idealists and economists and how much money they are willing to spend on sustainable or durable measures. A developer needs to know when he has to communicate the “green” message versus the “economic” message to which target group.

The last theme of interest that can be elaborated is the relationship between customer involvement and freedom of choice (mass, group or individual approach). A comprehensive view on this topic may lead to better positioning of projects in the future.

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Appendix A: Attribute and Level Selection

Table 5.1: Low-price segment design

Attribute	Nr	Level
A1: Price	0	€ 175.000
	1	€ 200.000
	2	€ 225.000
	3	€ 250.000
A2: Dwelling type	0	Apartment
	1	Terraced
	2	Corner house
	3	Semi-detached
A3: Location	0	Small town / rural area
	1	Suburban location
	2	Outside the city center
	3	City center
A4: Number of dormitory rooms	0	Two
	1	Three
A5: Architectural style	0	Traditional
	1	Modern
A6: Parking	0	Public
	1	Private
A7: Customer involvement	0	Low
	1	High
A8: Sustainable/Energy efficient	0	No
	1	Yes
A9: Distance to supermarket	0	Within cycling distance
	1	Within walking distance

Table 5.2: High-price segment design

Attribute	Nr	Level
A1: Price	0	€ 250.000
	1	€ 300.000
	2	€ 350.000
	3	€ 400.000
A2: Dwelling type	0	Apartment
	1	Semi-detached
	2	Patio
	3	Detached
A3: Location	0	Small town / rural area
	1	Suburban location
	2	Outside the city center
	3	City center
A4: Number of dormitory rooms	0	Three
	1	Four
A5: Architectural style	0	Traditional
	1	Modern
A6: Parking	0	1 private parking place
	1	2 private parking places
A7: Customer involvement	0	Low
	1	High
A8: Sustainable/Energy efficient	0	No
	1	Yes
A9: Distance to supermarket	0	Within cycling distance
	1	Within walking distance

Appendix B: The MA.32.2.6.4.3 Design

Table 5.3: The MA.32.2.6.4.3 design

Profile	A1	A2	A3	A4	A5	A6	A7	A8	A9
1	0	0	0	0	0	0	0	0	0
2	0	2	2	1	1	0	1	0	1
3	2	0	2	0	1	1	1	1	0
4	2	2	0	1	0	1	0	1	1
5	0	3	3	0	0	1	1	1	1
6	0	1	1	1	1	1	0	1	0
7	2	3	1	0	1	0	0	0	1
8	2	1	3	1	0	0	1	0	0
9	3	0	3	1	1	0	0	1	1
10	3	2	1	0	0	0	1	1	0
11	1	0	1	1	0	1	1	0	1
12	1	2	3	0	1	1	0	0	0
13	3	3	0	1	1	1	1	0	0
14	3	1	2	0	0	1	0	0	1
15	1	3	2	1	0	0	0	1	0
16	1	1	0	0	1	0	1	1	1
17	1	1	1	1	1	1	1	1	1
18	1	3	3	0	0	1	0	1	0
19	3	1	3	1	0	0	0	0	1
20	3	3	1	0	1	0	1	0	0
21	1	0	0	1	1	0	0	0	0
22	1	2	2	0	0	0	1	0	1
23	3	0	2	1	0	1	1	1	0
24	3	2	0	0	1	1	0	1	1
25	0	1	0	0	0	1	1	0	0
26	0	3	2	1	1	1	0	0	1
27	2	1	2	0	1	0	0	1	0
28	2	3	0	1	0	0	1	1	1
29	0	0	1	0	0	0	0	1	1
30	0	2	3	1	1	0	1	1	0
31	2	0	3	0	1	1	1	0	1
32	2	2	1	1	0	1	0	0	0

Appendix C: Choice set creation (random and minimal overlap)

Choice set	Version1 random generation	Version 2 random generation	Version 3 random generation	Version 4 random generation	Version 5 random generation	Version 6 minimal overlap
1	27 vs 18	20 vs 19	10 vs 1	16 vs 3	5 vs 13	1 vs 17
2	28 vs 25	22 vs 21	2 vs 3	1 vs 6	12 vs 21	2 vs 18
3	2 vs 7	28 vs 30	24 vs 19	13 vs 4	7 vs 16	3 vs 19
4	6 vs 20	12 vs 25	21 vs 13	15 vs 19	8 vs 6	4 vs 20
5	3 vs 15	3 vs 6	23 vs 17	17 vs 22	29 vs 3	5 vs 21
6	19 vs 16	13 vs 27	7 vs 25	11 vs 32	17 vs 31	6 vs 22
7	22 vs 29	8 vs 26	5 vs 6	10 vs 21	30 vs 25	7 vs 23
8	12 vs 23	16 vs 14	12 vs 16	31 vs 29	15 vs 19	8 vs 24
9	30 vs 4	11 vs 18	29 vs 22	7 vs 14	9 vs 11	9 vs 25
10	32 vs 17	2 vs 32	26 vs 8	28 vs 2	2 vs 18	10 vs 26
11	24 vs 5	24 vs 9	14 vs 15	18 vs 23	26 vs 23	11 vs 27
12	9 vs 8	23 vs 5	4 vs 30	9 vs 24	10 vs 14	12 vs 28
13	11 vs 10	4 vs 15	11 vs 18	8 vs 12	1 vs 24	13 vs 29
14	31 vs 13	1 vs 17	32 vs 9	26 vs 27	22 vs 32	14 vs 30
15	14 vs 21	7 vs 10	20 vs 27	30 vs 20	20 vs 28	15 vs 31
16	26 vs 1	29 vs 31	31 vs 28	25 vs 5	4 vs 27	16 vs 32

Figure 5.1: Different questionnaire designs

Appendix D: Example of Questionnaire

Versie 2.5

WOONWENSEN ONDERZOEK

Voor mijn studie Technische Bedrijfskunde aan de TU Eindhoven ben ik momenteel bezig met een **afstudeeronderzoek** naar de **woonwensen van de nieuwbouwconsument**. Met dit onderzoek wil ik in kaart brengen welke factoren een belangrijke rol spelen bij de aankoop van een nieuwbouwwoning.

Het eerste deel van dit onderzoek is een **keuze-experiment**, waarbij ik u 16 keer vraag te kiezen uit twee verschillende woningen. De woningen worden omschreven door middel van 9 kenmerken.
Het tweede deel van de enquête bevat vragen over uzelf, zoals leeftijd en geslacht, en vragen over zaken die een rol spelen bij de aankoop van een nieuwbouwwoning.

De **invultijd** bedraagt ongeveer **20 minuten**. Bij voorbaat dank voor uw medewerking; elke ingevulde enquête levert een belangrijke bijdrage aan mijn afstudeerproject! Als dank zal ik onder de respondenten die hun **e-mailadres invullen 10 cadeaubonnen t.w.v. 25 euro verloten**.
Veel succes met de vragen!

Joris van Bergen

Deelname aan dit onderzoek is volledig anoniem.
Persoonlijke gegevens worden strikt vertrouwelijk behandeld.
Uw e-mailadres (niet verplicht) en antwoorden worden afzonderlijk van elkaar verwerkt.

Start de enquête

Versie 2.5

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DEEL I: KEUZE-EXPERIMENT
Tijdens dit experiment wordt u gevraagd om telkens te kiezen uit twee verschillende nieuwbouwwoningen. Beschouw het alsof het om een echte aankoopsituatie gaat. Houd bij uw keuze dus ook rekening met uw beschikbare budget/inkomen. Indien u echt geen voorkeur heeft, kies dan voor "geen voorkeur".

* 1 **Naar welke woning gaat uw voorkeur uit?** **Toelichting bij de kenmerken**

Kenmerken	Woonprofiel 1	Woonprofiel 2
Prijs	€ 250.000	€ 400.000
Woningtype	Vrijstaand	Vrijstaand
Locatie	Centrum van stad (>60.000 inwoners)	Kleine woonplaats (<15.000 inwoners)
Slaapkamers	3	4
Architectuur	Klassiek	Modern
Eigen parkeerplaatsen	2	2
Keuzevrijheid bij ontwerp	Veel	Veel
Energiezuinig/duurzaam	Wel	Niet
Supermarkt	Op loopafstand	Op fietsafstand

- Woonprofiel 1
- Woonprofiel 2
- Geen voorkeur

< Vorige | Volgende >

TOELICHTING

Keuzevrijheid bij het ontwerp

Veel:	Veel inspraak/keuzemogelijkheden, bijvoorbeeld over de architectuur van de woning, indeling (o.a. woonkamer voor/achter) en uitbreidingsmogelijkheden.
Weinig:	Weinig inspraak/keuzemogelijkheden, standaard keuzes, bijvoorbeeld over het type keuken en de plaats van stopcontacten.

Patiowoning

Een gelijkvloerse woning met minimaal één slaapkamer en badkamer op de begane grond eventueel met een bovenverdieping.

Versie 2.5

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* 16 **Naar welke woning gaat uw voorkeur uit?**

Kenmerken	Woonprofiel 31	Woonprofiel 32
Prijs	€ 350.000	€ 350.000
Woningtype	Patio	Twee-onder-één kap
Locatie	Kleine woonplaats (<15.000 inwoners)	Buiten centrum van stad (>60.000 inwoners)
Slaapkamers	4	3
Architectuur	Klassiek	Modern
Eigen parkeerplaatsen	2	1
Keuzevrijheid bij ontwerp	Weinig	Weinig
Energiezuinig/duurzaam	Wel	Wel
Supermarkt	Op loopafstand	Op fietsafstand

- Woonprofiel 31
- Woonprofiel 32
- Geen voorkeur

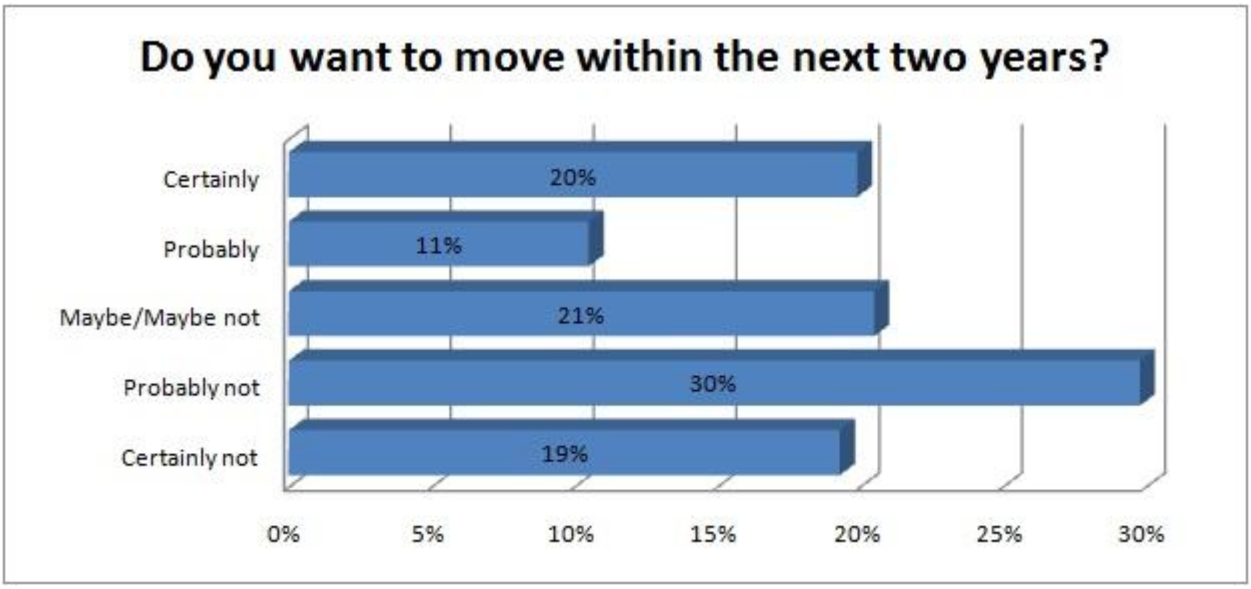
< Vorige | Volgende >

Gelieve op vraag 16 een antwoord in te vullen.
Keer terug naar de vragenlijst

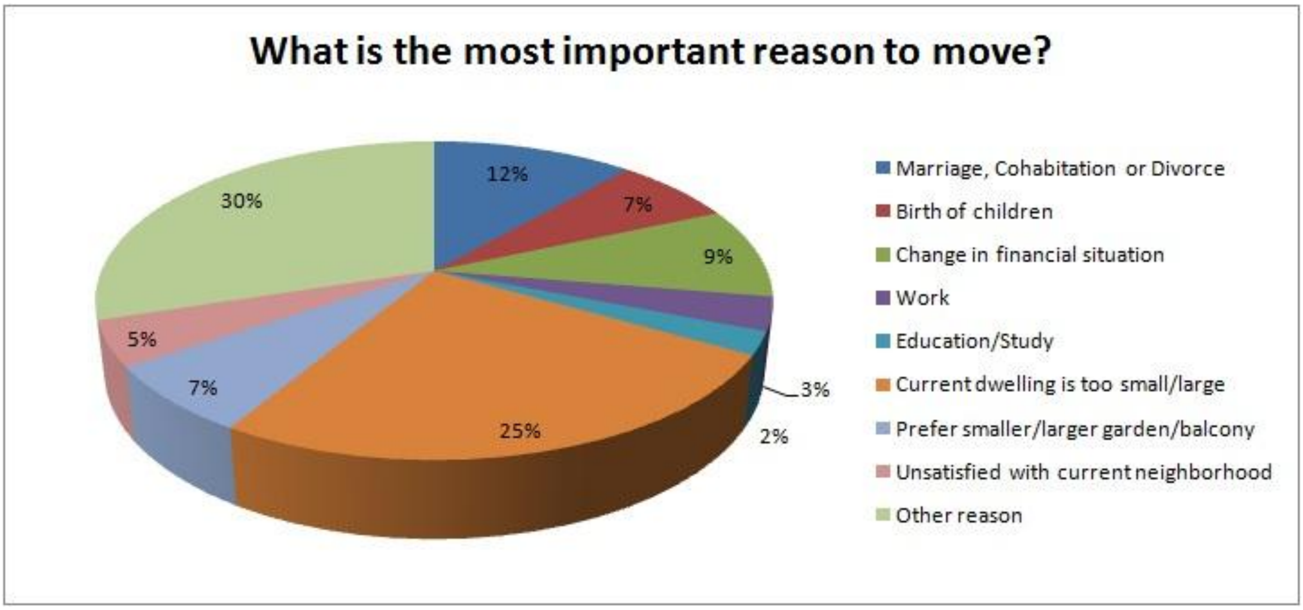
Gegarandeerde compleetheid van de enquêtes
Wanneer een respondent een antwoord overslaat en op "volgende" klikt, ontvangt hij hierover automatisch een melding. Hiermee worden *missing values* in het onderzoek voorkomen.

Appendix E: Direct results

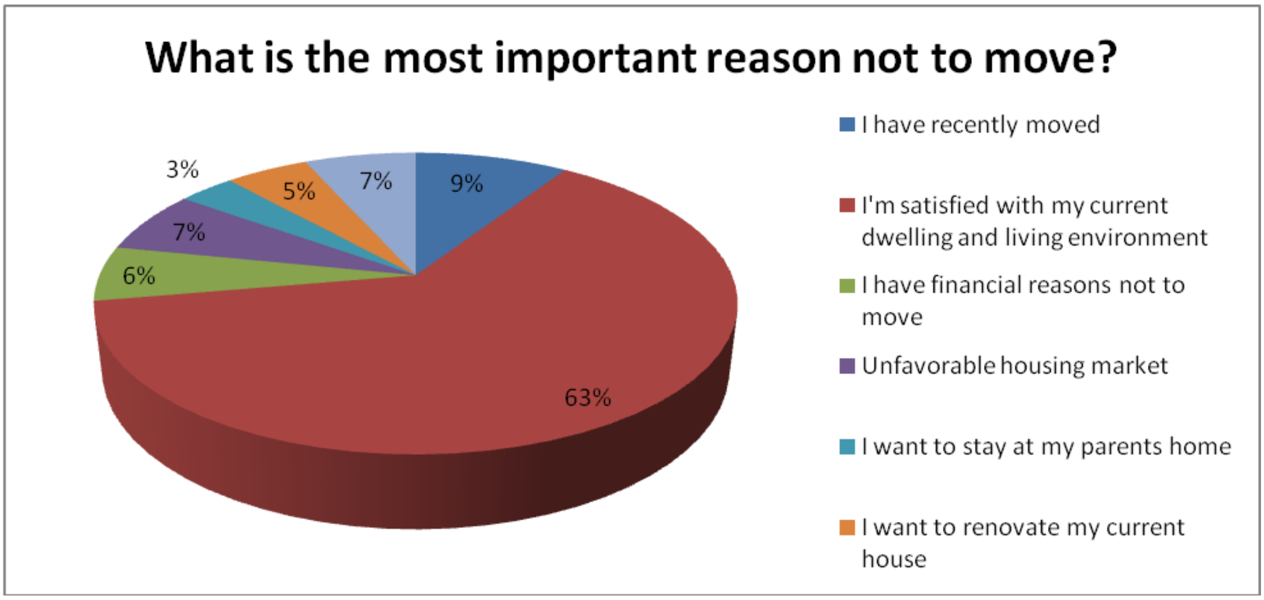
Question 28: N=171



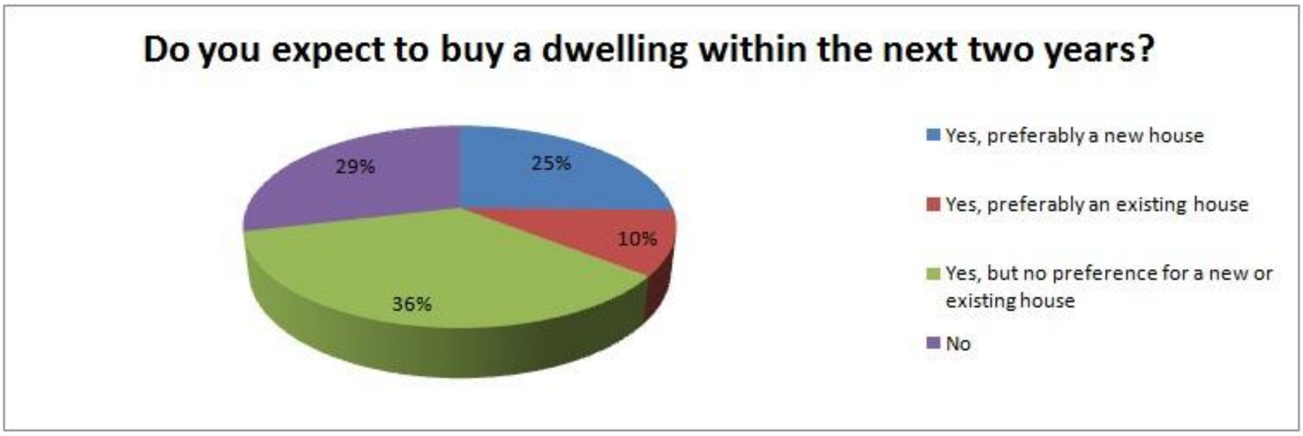
Question 29: N=87



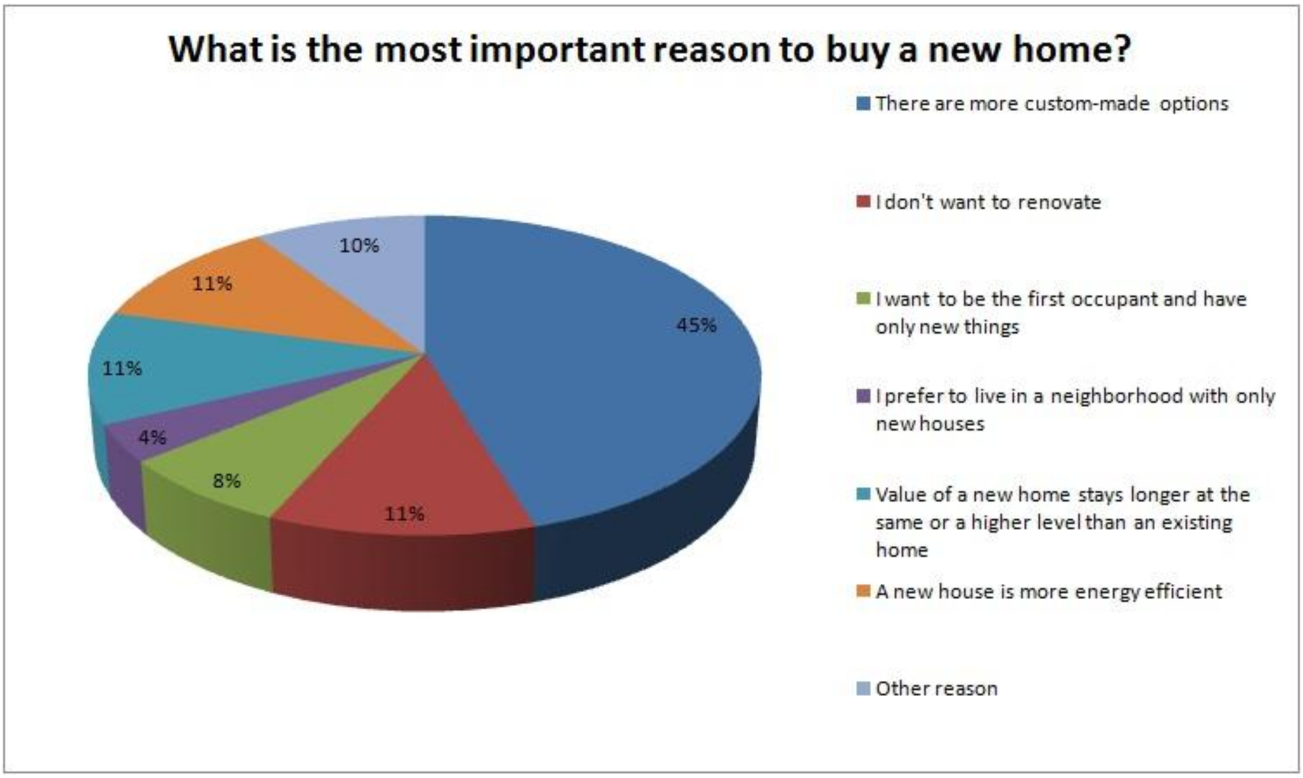
Question 30: N=119



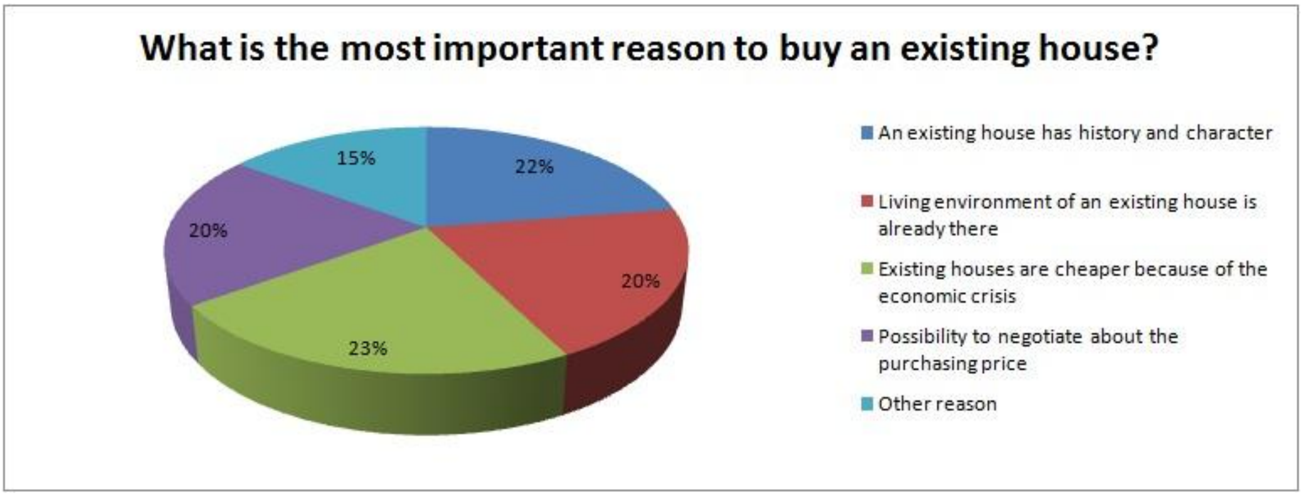
Question 31: N=87



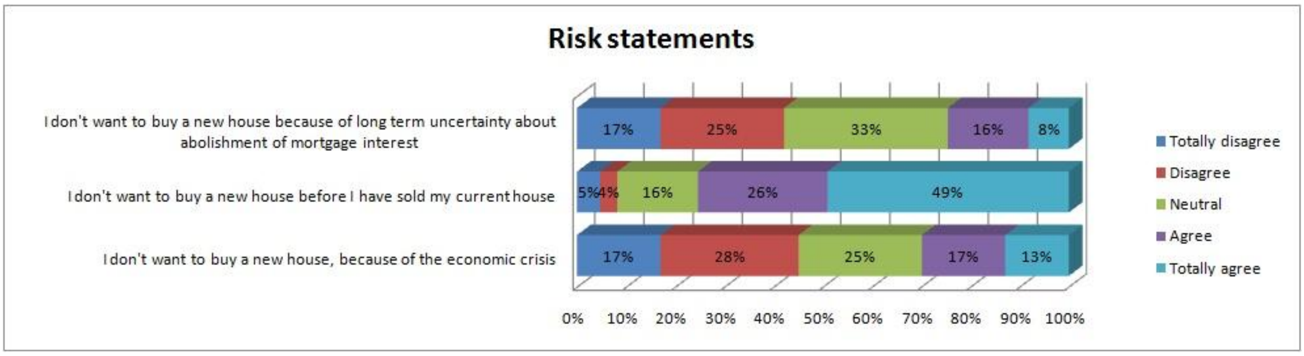
Question 32: N=53



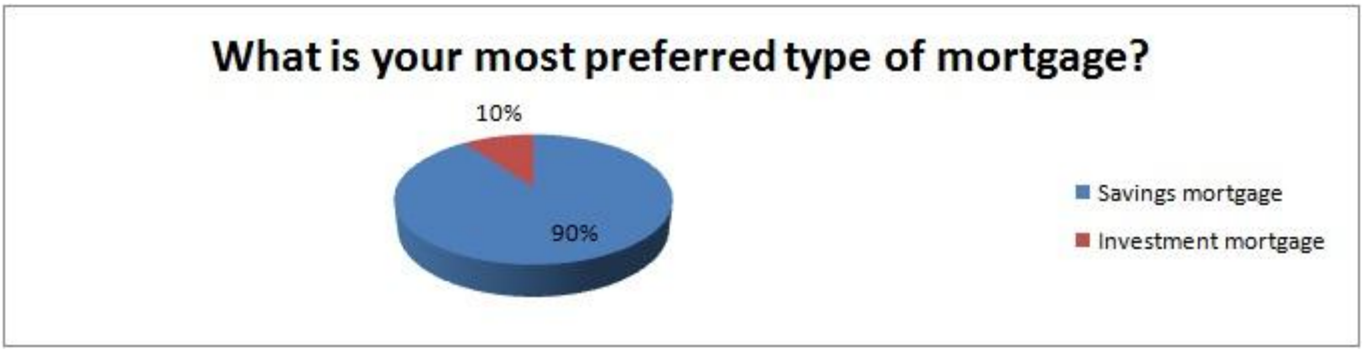
Question 33: N=40



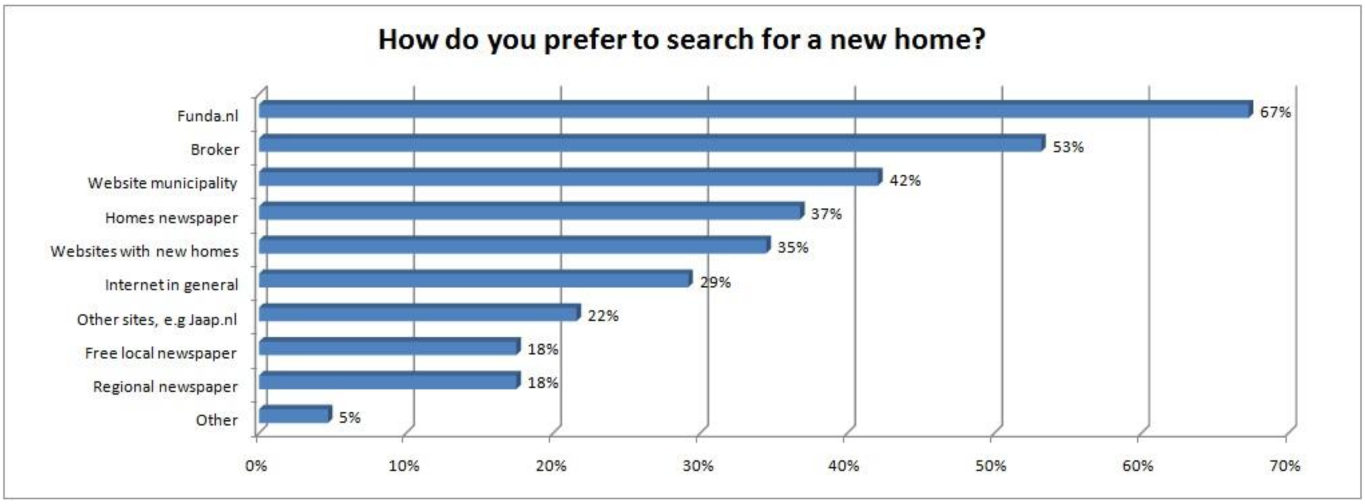
Question 34,35 and 36: N=171



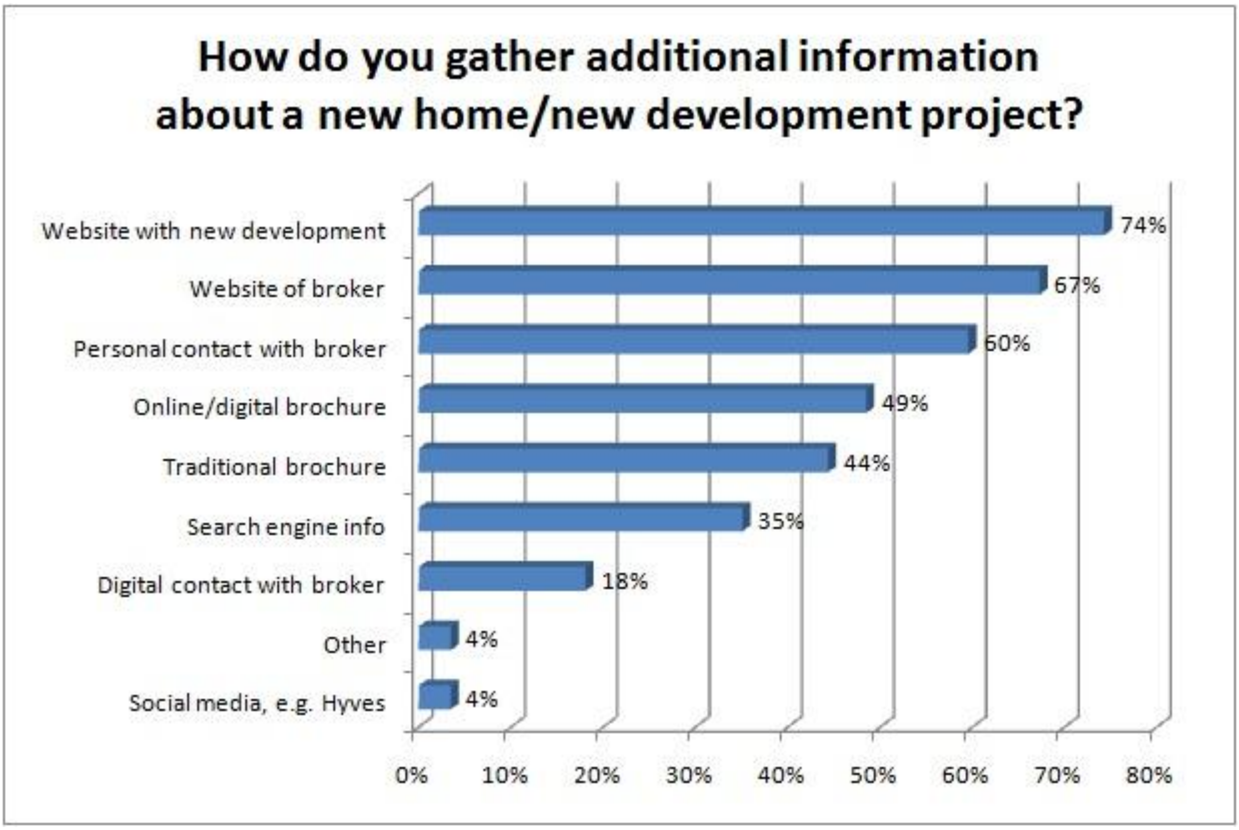
Question 37: N=171



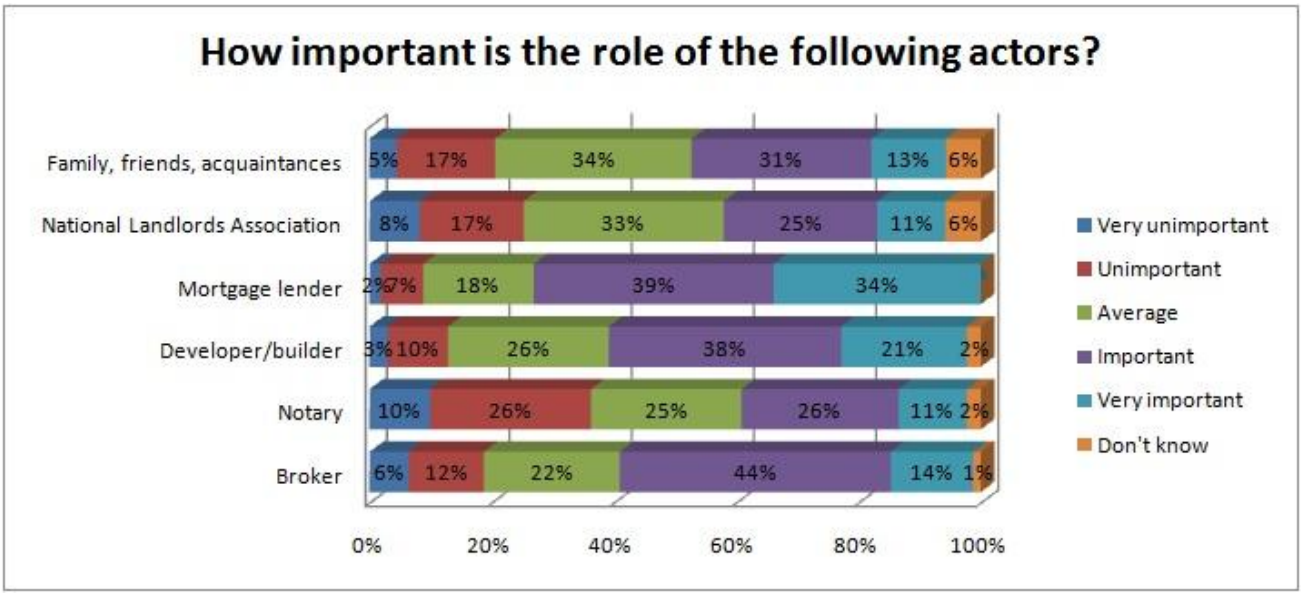
Question 38: N=171



Question 39: N=171



Question 40: N=171



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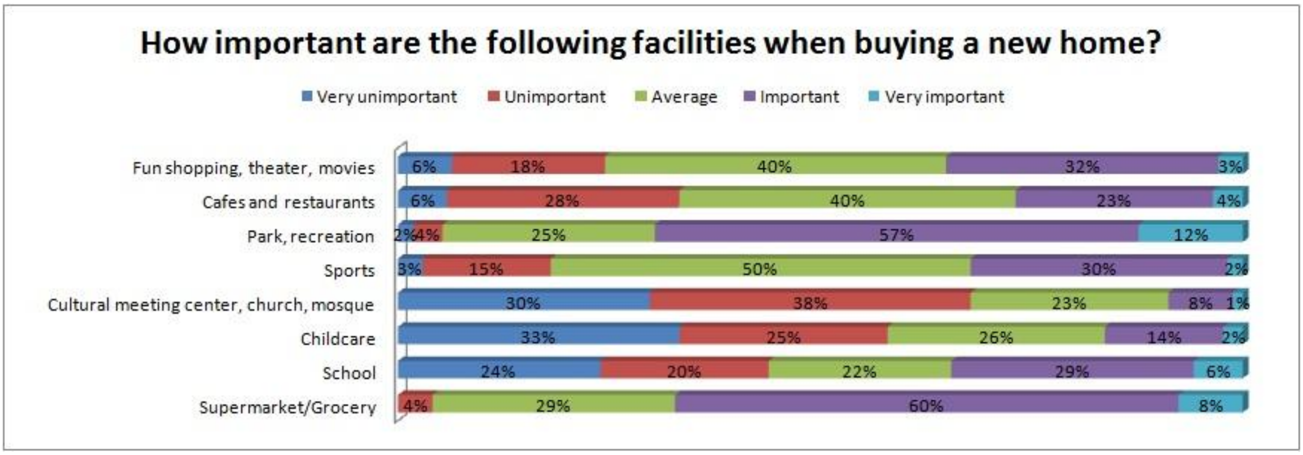
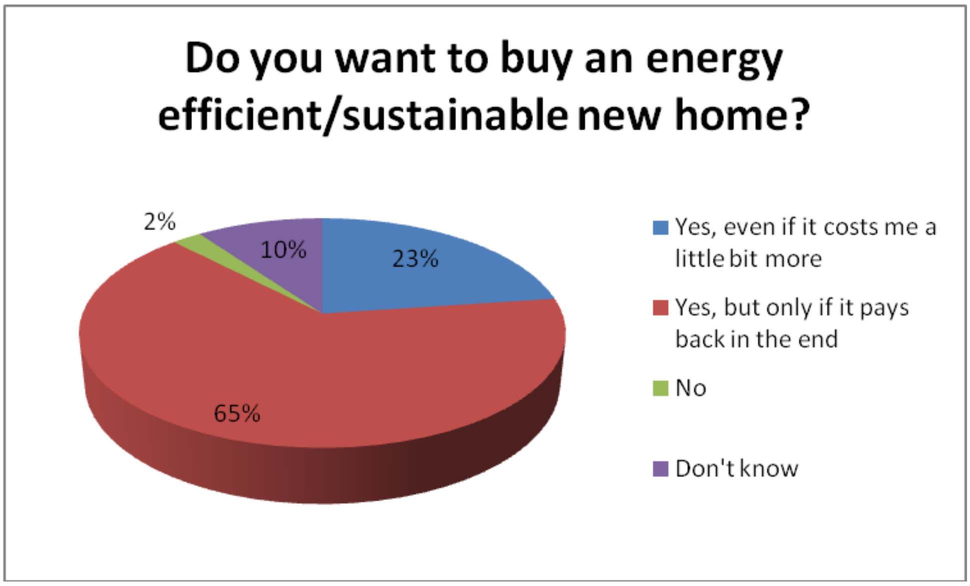
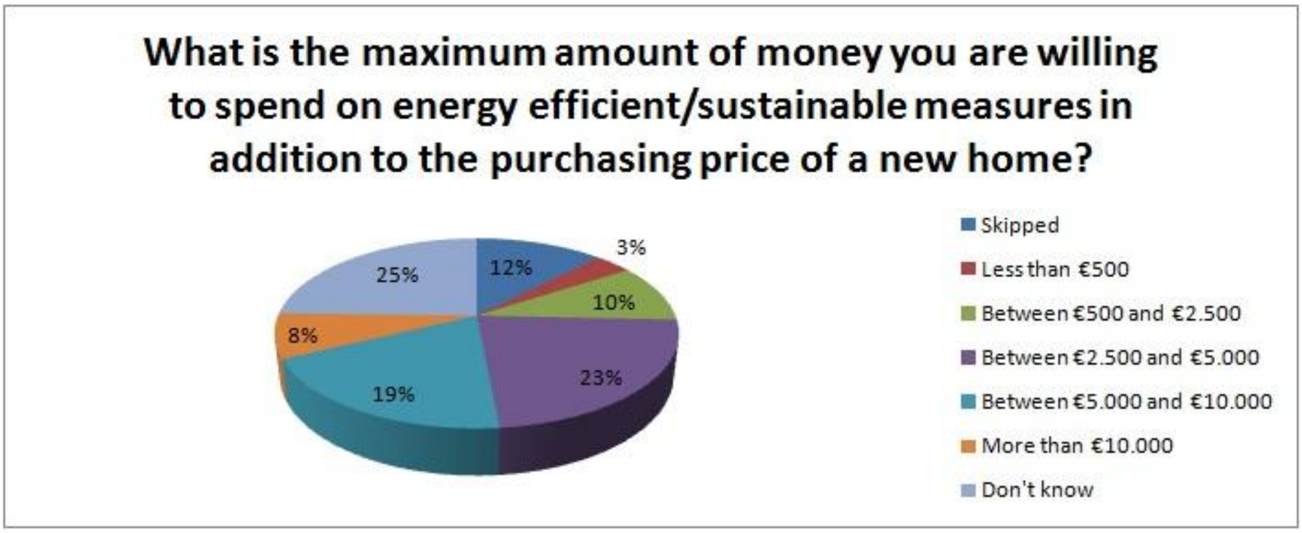
Question 41: N=171



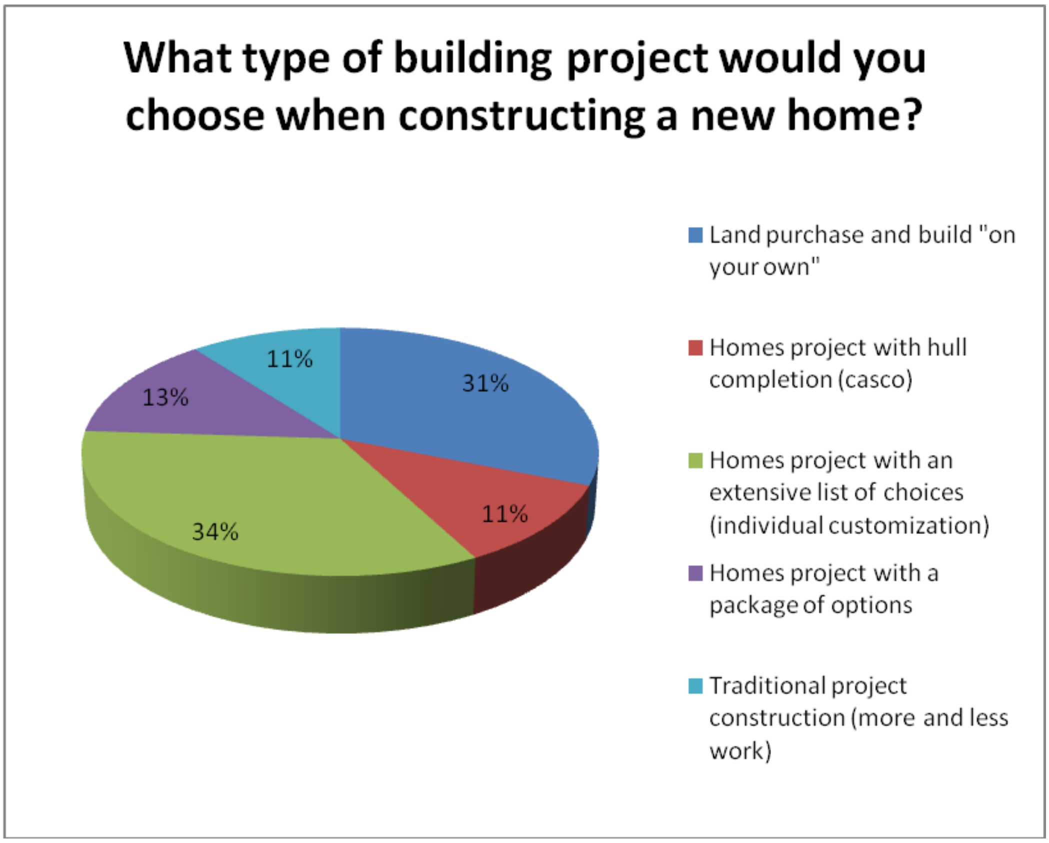
Question 42: N=171



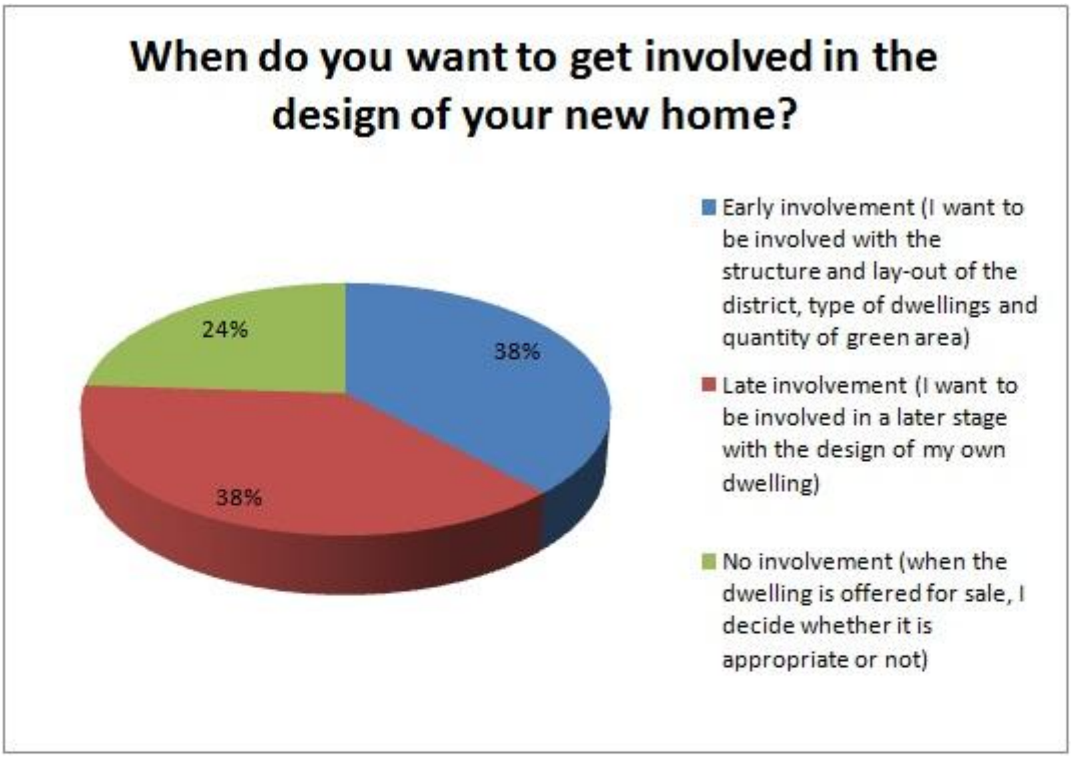
Question 43: N=171



Question 44: N=171



Question 45: N=171



Appendix F: Limdep output for Gender

Table 6.4: Low-price MNL for gender

RHO² = 1-(-1198.250/-1634.735) = 0.2670				
Male	+ Group	Female - Group		
Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]
BASECON	-.75400408	.19983521	-3.773	.0002
P200	-.20386815	.11936646	-1.708	.0877
P225	-.18222751	.10631427	-1.714	.0865
P250	-.47262149	.11534816	-4.097	.0000
TERRACED	.36894628	.11552036	3.194	.0014
CORNER	1.02557992	.11159870	9.190	.0000
SEMI	1.17583899	.11316416	10.391	.0000
SUBURBAN	.30908020	.12005794	2.574	.0100
OUTSIDE	.00501323	.11938861	.042	.9665
CITY	-.26930174	.10546207	-2.554	.0107
DORMS3	.40984080	.07949239	5.156	.0000
MODERN	.05526114	.07422707	.744	.4566
PRIVATE	.20971370	.07743849	2.708	.0068
CUST_INV	.22601482	.07382740	3.061	.0022
ENERGY	.31577476	.07533322	4.192	.0000
WALKING	.14267895	.07496591	1.903	.0570
YBASECON	-.08263709	.19983521	-.414	.6792
YP200	.11417957	.11936646	.957	.3388
YP225	.08782517	.10631427	.826	.4088
YP250	.03750539	.11534816	.325	.7451
YTERRACE	.12900576	.11552036	1.117	.2641
YCORNER	.14527330	.11159870	1.302	.1930
YSEMI	.21871778	.11316416	1.933	.0533*
YSUBURB	.09997570	.12005794	.833	.4050
YOUTSID	-.02876357	.11938861	-.241	.8096
YCITY	-.17581977	.10546207	-1.667	.0955*
YDORMS3	-.02517596	.07949239	-.317	.7515
YMODERN	.01448879	.07422707	.195	.8452
YPRIVATE	.00039270	.07743849	.005	.9960
YCUSTINV	-.01530766	.07382740	-.207	.8357
YNRG	-.00619460	.07533322	-.082	.9345
YWALK	.03490620	.07496591	.466	.6415

** Significant at $p < 0.05$, *Significant at $p < 0.10$

Table 6.5: High-price MNL for gender

RHO^2 = 1-(-1106.573/-1371.068) = 0.1929				
Male + Group		Female - Group		
Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]
BASECON	.39038741	.23623521	1.653	.0984
P300	-.02746380	.14657776	-.187	.8514
P350	.21656558	.13216905	1.639	.1013
P400	.02142031	.13984872	.153	.8783
SEMI	1.36696319	.14639338	9.338	.0000
PATIO	.89572435	.14044918	6.378	.0000
DETACHED	1.97977427	.14911329	13.277	.0000
SUBURBAN	.24197521	.14739682	1.642	.1007
OUTSIDE	-.26743622	.14695136	-1.820	.0688
CITY	-.60734187	.13376567	-4.540	.0000
DORMS4	.21482290	.09730414	2.208	.0273
MODERN	.17884463	.09306813	1.922	.0546
PP2	-.07098285	.09508407	-.747	.4553
CUST_INV	.22219505	.09275195	2.396	.0166
ENERGY	.32669109	.09140681	3.574	.0004
WALKING	.00179367	.09304239	.019	.9846
YBASECON	.31859422	.23623521	1.349	.1775
YP300	.12010434	.14657776	.819	.4126
YP350	-.03680412	.13216905	-.278	.7807
YP400	.13738500	.13984872	.982	.3259
YSEMI	-.23977046	.14639338	-1.638	.1015
YPATIO	-.24906507	.14044918	-1.773	.0762*
YDETACHE	-.44021568	.14911329	-2.952	.0032**
YSUBURB	-.03561227	.14739682	-.242	.8091
YOUTSIDE	.11798526	.14695136	.803	.4220
YCITY	.17141263	.13376567	1.281	.2000
YDORMS4	-.03705694	.09730414	-.381	.7033
YMODERN	.03232524	.09306813	.347	.7283
YPP2	.09205290	.09508407	.968	.3330
YCUSTINV	.11086040	.09275195	1.195	.2320
YNRG	.01042085	.09140681	.114	.9092
YWALK	-.03055875	.09304239	-.328	.7426

** Significant at p < 0.05 , *Significant at p < 0.10

Appendix G: Limdep output for Buying Experience

Table 6.6: Low-price MNL for Buying Experience

$RHO^2 = 1-(-1173.184/-1634.735) = 0.2823$				
Experienced	+ Group	Inexperienced	- Group	
Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]
BASECON	-.89196932	.20541653	-4.342	.0000
P200	-.23216066	.11936460	-1.945	.0518
P225	-.21737863	.10677419	-2.036	.0418
P250	-.49947774	.11603426	-4.305	.0000
TERRACED	.34101968	.11520884	2.960	.0031
CORNER	1.01767061	.11093963	9.173	.0000
SEMI	1.17570980	.11318391	10.388	.0000
SUBURBAN	.31487450	.12001534	2.624	.0087
OUSTIDE	.00455330	.11911530	.038	.9695
CITY	-.27627167	.10667669	-2.590	.0096
DORMS3	.40944608	.07924541	5.167	.0000
MODERN	.04920417	.07444056	.661	.5086
PRIVATE	.22574627	.07722191	2.923	.0035
CUST_INV	.24392598	.07411610	3.291	.0010
ENERGY	.31525478	.07542673	4.180	.0000
WALKING	.13734420	.07529583	1.824	.0681
YBASECON	.48221499	.20541653	2.347	.0189**
YP200	-.04796694	.11936460	-.402	.6878
YP225	-.11032064	.10677419	-1.033	.3015
YP250	.01154558	.11603426	.100	.9207
YTERRACE	.08657456	.11520884	.751	.4524
YCORNER	.07697004	.11093963	.694	.4878
YSEMI	.06411179	.11318391	.566	.5711
YSUBURB	-.23426064	.12001534	-1.952	.0509*
YOUTSIDE	-.23110613	.11911530	-1.940	.0524*
YCITY	-.50293205	.10667669	-4.715	.0000**
YDORMS3	-.01730328	.07924541	-.218	.8272
YMODERN	.12764661	.07444056	1.715	.0864*
YPRIVATE	.07479995	.07722191	.969	.3327
YCUSTINV	.05557212	.07411610	.750	.4534
YNRG	-.07819407	.07542673	-1.037	.2999
YWALK	-.08488975	.07529583	-1.127	.2596

** Significant at $p < 0.05$, *Significant at $p < 0.10$

Table 6.7: High-price MNL for buying experience

RHO^2 = 1-(-1102.445/-1371.068) = 0.1959				
Experienced + Group		Inexperienced - Group		
Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]
BASECON	1.29281903	.75721118	1.707	.0878
P300	-.15769524	.27425358	-.575	.5653
P350	-.09844329	.21965126	-.448	.6540
P400	-.20405321	.23853172	-.855	.3923
SEMI	2.06278560	.36074249	5.718	.0000
PATIO	1.16185303	.28088936	4.136	.0000
DETACHED	2.21975196	.29642130	7.489	.0000
SUBURBAN	1.03504968	.39416474	2.626	.0086
OUTSIDE	.33102600	.30488309	1.086	.2776
CITY	.00630930	.27724777	.023	.9818
DORMS4	.25683330	.17627939	1.457	.1451
MODERN	.38879989	.17559134	2.214	.0268
PP2	.23797133	.20623951	1.154	.2486
CUST_INV	.47405330	.17824182	2.660	.0078
ENERGY	.62406053	.19906189	3.135	.0017
WALKING	.25043179	.17876289	1.401	.1612
YBASECON	-.76598904	.75721118	-1.012	.3117
YP300	.28408167	.27425358	1.036	.3003
YP350	.40418364	.21965126	1.840	.0658*
YP400	.38961807	.23853172	1.633	.1024
YSEMI	-.89643661	.36074249	-2.485	.0130**
YPATIO	-.37421664	.28088936	-1.332	.1828
YDETACHE	-.44403607	.29642130	-1.498	.1341
YSUBURB	-.88008821	.39416474	-2.233	.0256**
YOUTSIDE	-.62112695	.30488309	-2.037	.0416**
YCITY	-.63648084	.27724777	-2.296	.0217**
YDORMS4	-.05975162	.17627939	-.339	.7346
YMODERN	-.23117969	.17559134	-1.317	.1880
YPP2	-.29772902	.20623951	-1.444	.1488
YCUSTINV	-.24392675	.17824182	-1.369	.1712
YNRG	-.31434443	.19906189	-1.579	.1143
YWALK	-.28435029	.17876289	-1.591	.1117

** Significant at p < 0.05 , *Significant at p < 0.10

Appendix H: Background characteristics of the latent segments

Table 7.1: Background characteristics of Latent class 1

Variable	Percentage					
	Male	*Female*				
Gender	47,6	52,4				
	18-30	*30-40*	*40-55*	*55+*		
Age	50,0	17,1	17,0	15,9		
	Primary Education	*MAVO/ VMBO-t*	*HAVO/VWO*	*MBO*	*Higher vocational (HBO)*	*University*
Education	8,5	11,0	7,3	34,1	20,7	18,3
	Full-time	*Part-time*	*Retired*	*Student*	*Housewife*	*No job*
Work	51,2	30,5	4,9	8,5	2,4	2,4
	Single without children	*Single with child(ren)*	*Married or cohabiting without children*	*Married or cohabiting with child(ren)*	*Living with friends (students)*	*Living with parents*
Household composition	17,1	2,4	29,3	26,8	3,7	20,7
	< €2000	*€2000-2500*	*€2500-3000*	*€3000-3500*	*>€3500*	*Unknown*
Households' monthly net income	32,9	17,1	9,8	13,4	2,4	23,4
	Yes	*No*				
Dual income	47,6	52,4				
	Owner-Occupied	*Rent*				
Tenure	69,5	30,5				
	Detached	*Semi-detached*	*Corner house*	*Terraced*	*Apartment*	*Patio*
Current dwelling	11,0	22,0	13,4	37,8	15,9	0,0
	City center	*Outside the city center*	*Medium-sized place*	*Village*		
Current location	13,4	11,0	54,9	20,7		
	Yes	*No*				
Buying experience	46,3	53,7				
Total	N=82					

Source: Own work

Table 7.2: Background characteristics of Latent class 2

Variable	Percentage					
	Male	*Female*				
Gender	36,4	63,6				
	18-30	*30-40*	*40-55*	*55+*		
Age	36,4	45,5	9,1	9,1		
	Primary Education	*MAVO/ VMBO-t*	*HAVO/VWO*	*MBO*	*Higher vocational (HBO)*	*University*
Education	9,1	0,0	9,1	36,4	36,4	9,1
	Full-time	*Part-time*	*Retired*	*Student*	*Housewife*	*No job*
Work	54,5	27,3	0,0	0,0	9,1	9,1
	Single without children	*Single with child(ren)*	*Married or cohabiting without children*	*Married or cohabiting with child(ren)*	*Living with friends (students)*	*Living with parents*
Household composition	27,3	9,1	54,5	0,0	0,0	9,1
	< €2000	*€2000-2500*	*€2500-3000*	*€3000-3500*	*>€3500*	*Unknown*
Households' monthly net income	36,4	0,0	0,0	18,2	9,1	27,3
	Yes	*No*				
Dual income	54,5	45,5				
	Owner-Occupied	*Rent*				
Tenure	81,8	18,2				
	Detached	*Semi-detached*	*Corner house*	*Terraced*	*Apartment*	*Patio*
Current dwelling	9,1	0,0	9,1	45,5	27,3	9,1
	City center	*Outside the city center*	*Medium-sized place*	*Village*		
Current location	18,2	18,2	45,5	18,2		
	Yes	*No*				
Buying experience	72,7	27,3				
Total	N=11					

Source: Own work

Table 7.3: Background characteristics of Latent class 3

Variable	Percentage					
	Male	*Female*				
Gender	62,3	37,7				
	18-30	*30-40*	*40-55*	*55+*		
Age	16,4	26,2	31,2	26,2		
	Primary Education	*MAVO/ VMBO-t*	*HAVO/VWO*	*MBO*	*Higher vocational (HBO)*	*University*
Education	4,9	3,3	8,2	19,7	42,6	21,3
	Full-time	*Part-time*	*Retired*	*Student*	*Housewife*	*No job*
Work	52,5	26,2	11,5	4,9	1,6	3,3
	Single without children	*Single with child(ren)*	*Married or cohabiting without children*	*Married or cohabiting with child(ren)*	*Living with friends (students)*	*Living with parents*
Household composition	6,6	1,6	37,7	50,8	0,0	3,3
	< €2000	*€2000-2500*	*€2500-3000*	*€3000-3500*	*>€3500*	*Unknown*
Households' monthly net income	1,6	16,4	21,3	11,5	36,1	13,1
	Yes	*No*				
Dual income	70,5	29,5				
	Owner-Occupied	*Rent*				
Tenure	88,5	11,5				
	Detached	*Semi-detached*	*Corner house*	*Terraced*	*Apartment*	*Patio*
Current dwelling	32,8	36,1	6,6	8,2	16,4	0,0
	City center	*Outside the city center*	*Medium-sized place*	*Village*		
Current location	8,2	14,8	36,1	41,0		
	Yes	*No*				
Buying experience	86,9	13,1				
Total	N=61					

Source: Own work

Table 7.4: Background characteristics of Latent class 4

Variable	Percentage					
	Male	*Female*				
Gender	76,5	23,5				
	18-30	*30-40*	*40-55*	*55+*		
Age	5,9	17,6	58,9	17,6		
	Primary Education	*MAVO/ VMBO-t*	*HAVO/VWO*	*MBO*	*Higher vocational (HBO)*	*University*
Education	11,8	11,8	0,0	29,4	35,3	11,8
	Full-time	*Part-time*	*Retired*	*Student*	*Housewife*	*No job*
Work	70,6	17,6	5,9	0,0	5,9	0,0
	Single without children	*Single with child(ren)*	*Married or cohabiting without children*	*Married or cohabiting with child(ren)*	*Living with friends (students)*	*Living with parents*
Household composition	0,0	0,0	58,8	41,2	0,0	0,0
	< €2000	*€2000-2500*	*€2500-3000*	*€3000-3500*	*>€3500*	*Unknown*
Households' monthly net income	5,9	17,6	5,9	17,6	29,4	23,5
	Yes	*No*				
Dual income	82,4	17,6				
	Owner-Occupied	*Rent*				
Tenure	100,0	0,0				
	Detached	*Semi-detached*	*Corner house*	*Terraced*	*Apartment*	*Patio*
Current dwelling	35,3	29,4	17,6	5,9	11,8	0,0
	City center	*Outside the city center*	*Medium-sized place*	*Village*		
Current location	5,9	0,0	41,2	52,9		
	Yes	*No*				
Buying experience	100,0	0,0				
Total	N=17					

Source: Own work

List of abbreviations

ACA	= Adaptive Conjoint Analysis
CBC	= Choice-based conjoint
HCB	= Hendriks Coppelmans Bouwgroep B.V.
HCO	= Hendriks Coppelmans Ontwikkeling
LCM	= Latent Class Model
MA	= Mixed-array
MNL	= Multinomial Logit
OA	= Orthogonal Array
WBO	= Woningbehoefteonderzoek
WoOn	= WoonOnderzoek Nederland

List of parameters

Basecon	= A base constant used to estimate the utility for the “no preference”-option
P175	= A price level of 175.000 euro
P200	= A price level of 200.000 euro
P225	= A price level of 225.000 euro
P250	= A price level of 250.000 euro
P300	= A price level of 300.000 euro
P350	= A price level of 350.000 euro
P400	= A price level of 400.000 euro
Apartm	= A dwelling type with level “Apartment”
Terraced	= A dwelling type with level “Terraced house”
Corner	= A dwelling type with level “Corner house”
Semi	= A dwelling type with level “Semi-detached”
Patio	= A dwelling type with level “Patio”
Detached	= A dwelling type with level “Detached”
Rural	= A location with level “rural” is a village with less than 15.000 inhabitants
Suburban	= A location with level “suburban” is a mid-sized place (30.000 inhabitants)
Outside	= A location with level “outside” is an urban place outside the city center (>60.000 inhabitants)
City	= A location with level “city” is an urban place in the city center (>60.000 inhabitants)
Dorms2	= A house with two dormitory rooms
Dorms3	= A house with three dormitory rooms
Dorms4	= A house with four dormitory rooms
Classic	= A classic or traditional architectural style
Modern	= A modern architectural style
Public	= Public parking
Private	= Private parking

PP1	= One private parking place
PP2	= Two private parking places
Cust_inv	= A high level of customer involvement
Energy	= A high level of energy efficient and sustainable measures
Walking	= The nearest supermarket is within walking distance