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der Christian-Albrechts-Universität zu Kiel

Consumers' Preferences and Willingness-To-Pay for Functional Dairy Products in
Germany

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Meiner Familie in Liebe gewidmet

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“Hinfallen, aufstehen,
Krönchen richten, weitergehen.”



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Summary

In most industrialized countries, functional foods have become more and more popular with consumers because of a growing awareness of the relation between health, nutrition, and diet. In general, functional food is defined as any food or food component providing health benefit beyond basic nutrition. Functional products are marketed with health claims that indicate the relationship existing between the consumption of a food item and the consumer's health. Considering the fact that functional foods are increasingly gaining significance in consumers' food choices in industrialized countries, several studies have investigated consumers' choice behavior in terms of functional foods. Surprisingly, very few studies have examined consumers' acceptance of and preferences for functional foods in Germany, although Germany represents one of the most important countries within the functional food market in Europe. Between 1995 and 2006, German sales of functional foods grew rapidly from 0.4 billion € in 1995 to 4.5 billion € in 2006. In particular, dairy products play an important role with regard to functional food innovations in Germany. Due to this development, it is of major interest for the food industry to investigate consumers' preferences and willingness-to-pay for functional dairy products in Germany.

This study examines consumers' preferences and willingness-to-pay for functional dairy product attributes in Germany using cross-sectional choice experiment data. Random parameter logit and latent class models are employed to model preference behavior and to account for preference heterogeneity among consumers. This choice experiment study further tests whether willingness-to-pay estimates obtained from a random parameter logit model are subject to starting point bias. That is, it is tested whether respondents anchor their willingness-to-pay for functional dairy products on the price amounts proposed to them in the initial payment question, or rather initial choice set. Very little work has been undertaken to examine the possible existence of starting point bias in choice experiments. This study uses a two-split sample approach to test for the presence of starting point bias in choice experiments. Specifically, sample A is shown a high-priced first choice set, whereas sample B is exposed to a lower set of prices in the first choice set. Data were collected by means of a questionnaire mailed to a randomly selected sample from an address list of 2683 German households from November 2010 to January 2011. This resulted in a total of 655 and 654 useable questionnaires for samples A and B, respectively, corresponding to a response rate of 49%.

This study further investigates consumers' real functional food choices in Germany by using a scanner database of yoghurt and dairy drink sales. Based on a sample of 39141 households, a bivariate probit model is employed to analyze factors that influence an individual's choice to purchase functional yoghurts and dairy drinks and to account for a possible correlation between the yoghurt and dairy drink decisions. The scanner data are further analyzed by using an almost ideal demand system model to estimate the real demand for functional and non-functional dairy products.

The empirical results of the random parameter logit model reveal significant preference heterogeneity among consumers with regard to price. Omega-3 fatty acids and a health claim of support for healthy blood vessels and healthy metabolism are found to be the most preferred attributes, whereas a health claim of just support for healthy blood vessels is ranked below these attributes. Furthermore, respondents reveal the highest positive willingness-to-pay for omega-3 fatty acids. This is probably because consumers are familiar with omega-3 fatty acids and their health related effects. Respondents also reveal preference for non-functional ice cream which can be explained by the fact that ice cream represents a hedonic product. The results further indicate that neither females nor males anchor their willingness-to-pay for functional dairy product attributes on the price amounts proposed to them in the initial choice set, implying that choice experiments are not significantly affected by starting point bias. More specifically, the study results show that choice experiments provide unbiased willingness-to-pay estimates for market goods since they are not susceptible to starting point bias. It is, however, significant to note that the method used to test for the presence of starting point bias strongly influences the results.

The results of the latent class model reveal class-specific heterogeneous preferences which can be explained by both the consumers' attitudes towards functional foods and healthy diet and socioeconomic characteristics. Specifically, three distinct classes of consumers are identified each revealing different preferences for the same functional dairy product attributes. Given that heterogeneous preferences are mainly driven by the consumers' attitude towards functional foods, the classes mostly comprise functional food skeptics, functional food advocates, and functional food neutrals. Dairy products fortified with omega-3 fatty acids and being non-functional are highly valued attributes in the class comprising functional food skeptics. Functional food advocates place high value on dairy products enriched with omega-3 fatty acids and bearing a health claim of support for healthy blood vessels and healthy

metabolism. However, members of this class reveal a negative preference for non-functional dairy products. Omega-3 fatty acids, oligosaccharides, and a health claim displaying an ingredient dependent property are found to be the most preferred attributes for the functional food neutrals. The findings generally suggest that attitudinal variables are crucial in explaining class membership, and as such emphasize the importance of incorporating all sources of heterogeneity such as socioeconomic data and attitudinal data.

The results obtained from the bivariate probit model indicate that the two choice decisions whether to purchase functional dairy drinks or not and whether to purchase functional yoghurts or not are not statistically independent. The results also reveal that the probabilities of purchasing functional dairy drinks and functional yoghurts are influenced by several socioeconomic characteristics. High income increases the probability of buying functional dairy products. Older people have a higher probability to purchase functional yoghurts and a lower probability to choose functional dairy drinks. Furthermore, male single-person households are less likely to buy functional dairy drinks and functional yoghurts. The probability of choosing functional dairy drinks is higher for people who live in big cities. The findings generally imply that food manufacturers should be aware of the relevant target group in order to develop successful functional products.

The empirical results of the almost ideal demand system model reveal that age and household size influence the consumption of functional and non-functional dairy products. The demand for yoghurts and dairy drinks (both functional and non-functional) is income inelastic, suggesting that these products are necessities. Own-price elasticities for functional yoghurts and functional dairy drinks are close to zero, implying that the demand for these functional dairy products tends to be price-independent. This is probably because functional dairy products provide health benefits and people suffering from ill health buy functional dairy products, regardless of market price behavior, since they feel the need to consume them. Furthermore, functional and non-functional dairy products (yoghurts and dairy drinks) are not likely to be seen as substitutes.

Zusammenfassung

Aufgrund der Tatsache, dass immer mehr Leute die Relation zwischen Gesundheit und Ernährung verstehen, haben funktionelle Lebensmittel bei den Konsumenten in den meisten Industrieländern zunehmend an Bedeutung gewonnen. Unter funktionellen Lebensmitteln (Functional Food) werden jegliche Lebensmittel oder Lebensmittelbestandteile verstanden, die über ihre Ernährungsfunktion hinaus einen gesundheitlichen Zusatznutzen versprechen. Die gesundheitsfördernde Wirkung des funktionellen Lebensmittels wird mittels Werbeaussagen (Health Claim = gesundheitsbezogene Angabe) kommuniziert. Aufgrund der Tatsache, dass funktionelle Lebensmittel eine immer wichtiger werdende Rolle bei der Lebensmittelwahl der Konsumenten in den Industrieländern zu spielen scheinen, haben zahlreiche Studien das Wahlverhalten der Konsumenten in Bezug auf funktionelle Lebensmittel untersucht. Erstaunlicherweise haben bisher nur sehr wenige Studien die Akzeptanz und Präferenzen der Konsumenten für funktionelle Lebensmittel in Deutschland untersucht, obwohl Deutschland innerhalb Europas zu einem der wichtigsten Absatzmärkte für funktionelle Lebensmittel zählt. Der Absatz funktioneller Lebensmittel in Deutschland ist von 0,4 Milliarden € im Jahr 1995 auf 4,5 Milliarden € im Jahr 2006 rapide gestiegen. Milchprodukte stellen das wichtigste Produktsegment bei funktionellen Lebensmitteln in Deutschland dar. Aufgrund dieser Entwicklungen ist es für die Lebensmittelindustrie von großem Belang, die Konsumentenpräferenzen und Zahlungsbereitschaften für funktionelle Milchprodukte in Deutschland zu ermitteln.

Diese Arbeit untersucht mit Hilfe von Querschnittsdaten eines Choice Experiments die Präferenzen und Zahlungsbereitschaften der Konsumenten für bestimmte Eigenschaften von funktionellen Milchprodukten in Deutschland. Dabei werden Random Parameter Logit und Latent Class Modelle angewandt, um die Präferenzen abzubilden und um mögliche Unterschiede in den Präferenzen zwischen den Konsumenten zu berücksichtigen. Des Weiteren untersucht diese Arbeit, inwiefern Zahlungsbereitschaften, die mit Hilfe des Random Parameter Logit Modells berechnet werden, anfällig gegenüber Starting Point Bias sind. Genauer gesagt wird überprüft, ob Probanden ihre angegebenen Zahlungsbereitschaften für die funktionellen Milchprodukte an die Preise anpassen, die in der ersten Frage bzw. im ersten Choice Set des Fragebogens zu sehen sind. Nur sehr wenige Studien haben bisher die mögliche Existenz von Starting Point Bias innerhalb von Choice Experimenten untersucht. Die vorliegende Arbeit unterteilt die Stichprobe in zwei Gruppen, um das Choice Experiment

auf Starting Point Bias zu prüfen. Dabei wird Gruppe A ein erstes Choice Set gezeigt, in dem hohe Preise zu sehen sind, während Gruppe B ein erstes Choice Set erhält, das niedrige Preise aufweist. Die Querschnittsdaten wurden mittels einer deutschlandweiten Briefbefragung erhoben. Dabei wurden 2683 zufällig von einer Adressliste ausgewählte Probanden zwischen November 2010 und Januar 2011 angeschrieben. Eine Rücklaufquote von 49% konnte erzielt werden, d.h. 655 Fragebögen von Gruppe A und 654 von Gruppe B kamen zurück.

Ferner untersucht diese Arbeit die realen funktionellen Kaufentscheidungen der Konsumenten in Deutschland. Hierfür wird ein Scanner Datensatz verwendet, der Informationen über alle gekauften Joghurts und Milchgetränke von 39141 Haushalten enthält. Mit Hilfe eines bivariaten Probit Modells werden die Faktoren analysiert, die die Kaufentscheidung beeinflussen, ob eine Person funktionellen Joghurt und funktionelle Milchgetränke wählt. Gleichzeitig wird berücksichtigt, ob es eine mögliche Korrelation zwischen den Joghurt- und Milchgetränk-Kaufentscheidungen gibt. Die Scanner Daten werden außerdem mit Hilfe eines Almost Ideal Demand System Modells analysiert, um die reale Nachfrage nach funktionellen und nicht funktionellen Milchprodukten zu schätzen.

Die empirischen Ergebnisse des Random Parameter Logit Modells zeigen eine signifikante Heterogenität der Präferenzen zwischen den Konsumenten in Bezug auf den Preis. Omega-3-Fettsäuren und der Health Claim "Unterstützt gesunde Blutgefäße und einen gesunden Stoffwechsel." sind die am meist präferierten Eigenschaften, wohingegen der Health Claim "Unterstützt gesunde Blutgefäße." bedeutungsmäßig hinter diesen Eigenschaften eingereiht wird. Ferner haben Probanden die höchste Zahlungsbereitschaft für Omega-3-Fettsäuren. Ein möglicher Grund hierfür ist, dass Konsumenten mit Omega-3-Fettsäuren und den gesundheitsfördernden Wirkungen dieser vertraut sind. Des Weiteren präferieren die Probanden nicht funktionelles Speiseeis, was wohl dadurch erklärt werden kann, dass Speiseeis ein Genussgut ist. Darüber hinaus deuten die Ergebnisse an, dass weder Frauen noch Männer ihre Zahlungsbereitschaften für die Eigenschaften der funktionellen Milchprodukte an die Preise des ersten Choice Sets anpassen. Dies bedeutet, dass Choice Experimente gegenüber Starting Point Bias unbeeinflusst bleiben. Genauer gesagt verdeutlichen die Ergebnisse also, dass Choice Experimente beste Schätzwerte in Bezug auf die Zahlungsbereitschaften für Marktgüter liefern, da sie nicht anfällig gegenüber Starting Point Bias sind. Jedoch muss gesagt werden, dass die Methode zur Prüfung auf Starting Point Bias stark die Ergebnisse beeinflusst.

Die Ergebnisse des Latent Class Modells offenbaren gruppenspezifische, heterogene Präferenzen, die durch zwei verschiedene Aspekte erklärt werden können. Zum einen scheint die Einstellung der Konsumenten zum Thema funktionelle Lebensmittel und zum Thema gesunde Ernährung eine Rolle zu spielen, zum anderen sind sozioökonomische Charakteristika entscheidend. Es können drei verschiedene Konsumentengruppen identifiziert werden, die unterschiedliche Präferenzen für die gleichen Eigenschaften von funktionellen Milchprodukten zeigen. Aufgrund der Tatsache, dass die heterogenen Präferenzen insbesondere durch die Einstellung der Konsumenten gegenüber funktionellen Lebensmitteln erklärt werden können, werden die drei Gruppen wie folgt benannt: Functional Food Skeptiker, Functional Food Befürworter und Functional Food Neutrale. Milchprodukte, die mit Omega-3-Fettsäuren angereichert und nicht funktionell sind, werden von den Functional Food Skeptikern präferiert. Functional Food Befürworter legen hingegen großen Wert auf Milchprodukte, die mit Omega-3-Fettsäuren angereichert sind und die mit dem Health Claim "Unterstützt gesunde Blutgefäße und einen gesunden Stoffwechsel." werben. Ferner haben Mitglieder dieser Gruppe eine negative Präferenz für nicht funktionelle Milchprodukte. Omega-3-Fettsäuren, Oligosaccharide und ein inhaltsstoffspezifischer Health Claim sind die Eigenschaften, die von den Anhängern der dritten Gruppe (Functional Food Neutrale) am meisten präferiert werden. Alles in allem verdeutlichen die Ergebnisse, dass einstellungsbezogene Variablen entscheidend für die Erklärung der Klassenzugehörigkeit sind. Somit wird klar, wie wichtig es ist, alle Ursachen heterogener Präferenzen zu berücksichtigen, d.h. sowohl sozioökonomische Charakteristika als auch einstellungsbezogene Faktoren.

Die Ergebnisse des bivariaten Probit Modells zeigen, dass die beiden Kaufentscheidungen, ob eine Person funktionelle Milchgetränke kauft oder nicht und ob sie funktionellen Joghurt kauft oder nicht, statistisch nicht voneinander unabhängig sind. Des Weiteren offenbaren die Ergebnisse, dass zahlreiche sozioökonomische Charakteristika die beiden Wahrscheinlichkeiten, funktionelle Milchgetränke und funktionellen Joghurt zu kaufen, beeinflussen. Ein hohes Einkommen erhöht die Wahrscheinlichkeit, funktionelle Milchprodukte zu kaufen. Ältere Leute offenbaren eine höhere Wahrscheinlichkeit, funktionellen Joghurt zu kaufen und eine geringere Wahrscheinlichkeit, funktionelle Milchgetränke zu wählen. Ferner kaufen männliche Ein-Personen-Haushalte eher nicht funktionelle Milchgetränke und funktionellen Joghurt. Menschen, die in Großstädten leben, haben eine höhere Wahrscheinlichkeit, funktionelle Milchgetränke zu kaufen. Die Ergebnisse

geben zu erkennen, dass Lebensmittelhersteller sich darüber im Klaren sein sollten, was die relevante Zielgruppe ist, um erfolgreiche, funktionelle Produkte zu entwickeln.

Die empirischen Ergebnisse des Almost Ideal Demand System Modells offenbaren, dass das Alter und die Haushaltsgröße den Konsum funktioneller und nicht funktioneller Milchprodukte beeinflussen. Die Nachfrage nach Joghurts und Milchgetränken (sowohl funktionell als auch nicht funktionell) ist einkommensunelastisch. Somit handelt es sich bei diesen Produkten um notwendige Güter. Die Eigenpreiselastizitäten von funktionellen Joghurts und funktionellen Milchgetränken sind fast Null. Dies bedeutet, dass die Nachfrage nach diesen funktionellen Milchprodukten dazu neigt, vom Preis unabhängig zu sein. Dies liegt womöglich daran, dass funktionelle Milchprodukte eine gesundheitsfördernde Wirkung versprechen und Konsumenten, die an gesundheitlichen Problemen leiden, funktionelle Milchprodukte unabhängig von deren Markt-Preis-Verhalten kaufen, da die Konsumenten es für notwendig halten, diese Produkte zu konsumieren. Ferner werden funktionelle und nicht funktionelle Milchprodukte (Joghurts und Milchgetränke) nicht als Substitute betrachtet.

List of Acronyms

AIC	Akaike Information Criterion
AIDS	Almost Ideal Demand System
BIC	Bayesian Information Criterion
CC	Complete Combinatorial
CLA	Conjugated Linoleic Acid
CVM	Contingent Valuation Method
DPH	Discovered Preference Hypothesis
EFSA	European Food Safety Authority
EU	European Union
FoCus	Food Chain Plus
FOSHU	Food for Specified Health Use
GfK	Gesellschaft für Konsumforschung
GEV	Generalized Extreme-Value Models
HC	Health Claim
IIA	Independence of Irrelevant Alternatives
IID	Independent and Identically Distributed
KMO	Kaiser-Meyer-Olkin measure of sampling adequacy
LA/AIDS	Linear Approximate Almost Ideal Demand System
LL	Log Likelihood
MNL	Multinomial Logit Model
PASSCLAIM	Process for the Assessment of Scientific Support for Claims on Foods
QUAIDS	Quadratic Almost Ideal Demand System
RPL	Random Parameter Logit
SLL	Simulated log likelihood function
SPB	Starting Point Bias
U.S.	United States of America
WTA	Willingness-To-Accept
WTP	Willingness-To-Pay

1. General Introduction

1.1 Problem Setting and Motivation

In most industrialized countries, the markets for functional foods have been growing rapidly over the last two decades (Chema et al. 2006). Functional foods are foods fortified with ingredients capable of generating health benefits. Estimates show that the market share of functional foods in Europe is expected to increase from less than 1% in 2000 to about 5% in 2013 (Menrad 2003). Between 2004 and 2007, the sales of fortified and functional products in Western Europe have experienced a rate of growth exceeding 10% (The Economist 2009), reaching a value of 0.8 billion U.S. \$ in 2006 (Datamonitor 2007). U.S. sales of functional foods grew from 11.3 billion \$ in 1995 to 18.5 billion \$ in 2001. This accounts for 3.7% of the total food sales (Markosyan et al. 2009). This trend is mostly due to the fact that consumers have increasingly recognized the link between health and diet, and as such are taking special interest in functional foods. Furthermore, developments in the functional foods market are being driven by changes in demographic patterns combined with advances in food technology and nutritional sciences.

As it is widely known now, the term functional food originated in Japan in the 1980s, when it was employed by the food industry to describe any food or food component providing health benefit beyond basic nutrition. It is rather a loose definition, and as such estimates of the size of the market vary hugely (Hilliam 1998). However, the United Kingdom, Germany, France, and Italy represent the most important countries within the functional food market in Europe (Bech-Larsen and Scholderer 2007). There is a growing range of functional foods on the European market. Within this market, functional dairy products have shown an impressive growth, bringing the market volume in Germany from around 5 million U.S. \$ in 1995 to 419 million U.S. \$ in 2000, of which 301 million U.S. \$ account for pro-, pre-biotic, and other functional yoghurts and around 118 million U.S. \$ for functional drinks (Menrad 2003).

Figure 1 presents the development of functional foods in Germany between 1995 and 2009. The German market for functional foods increased rapidly from 1995 to 2006. German sales of functional foods grew from 0.4 billion € in 1995 to 4.5 billion € in 2006, reaching a value of 4.52 billion € in 2009.¹

¹ Exchange rate: 1 U.S. \$ = 0.74€.

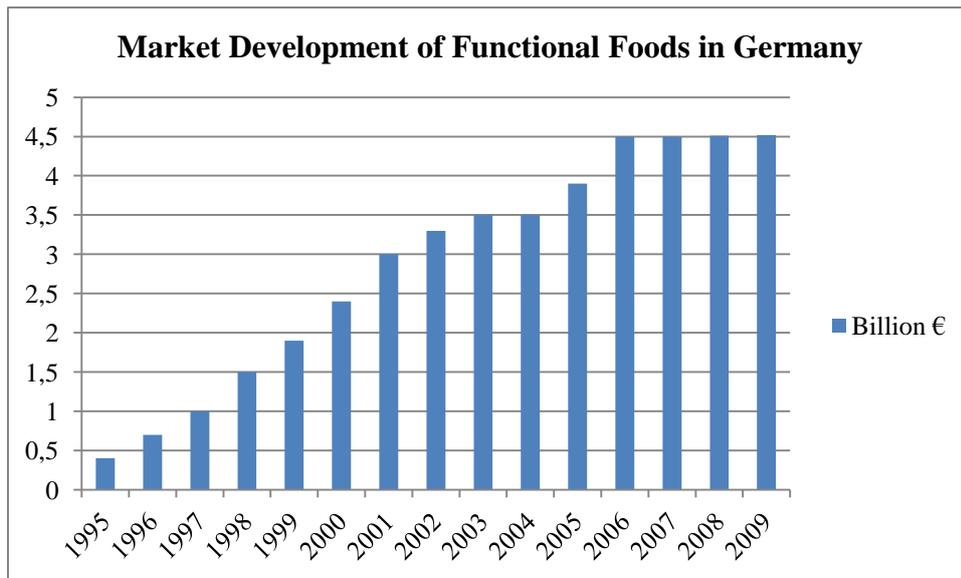


Figure 1 Market development of functional foods in Germany
 Source: IBH Retail Consultants (in Lebensmittel Zeitung (2011))

As indicated previously, functional dairy products have shown an enormous growth in Germany. However, there is also a general increase in the demand for dairy products. Table 1 presents the development of different dairy products in Germany between 2004 and 2011. The per capita consumption of yoghurt increased from 16.3kg in 2004 to 18.1kg in 2011 while the consumption of dairy drinks grew from 29.4kg in 2004 to 30.3kg in 2011. The consumption of cheese grew by 7% between 2005 and 2011.

Table 1 Development of different dairy products in Germany (per capita consumption in kg)

	2004	2005	2006	2007	2008	2009	2010	2011
Milk	53.3	53.0	53.3	53.7	54.9	54.1	53.5	53.6
Yoghurt	16.3	16.7	16.7	17.7	17.6	17.4	17.8	18.1
Dairy drink	29.4	29.8	29.7	30.6	29.6	29.5	29.8	30.3
Cheese	-	21.5	-	-	22.2	22.3	22.9	23.0

Source: Bundesministerium für Ernährung, Landwirtschaft und Verbraucherschutz (2012).

Given the increasing significance of functional foods in dietary choices of consumers in industrialized countries, a number of studies have examined consumers' acceptance of and preferences for functional foods (e.g., Chema et al. 2006; Labrecque et al. 2006; Peng et al. 2006). Although functional foods are increasingly gaining significance in Germany, there are only a few studies that have recently considered German consumers (e.g., Vassallo et al. 2009). This study aims to fill this gap in the literature by employing choice experiments to

measure consumers' preferences and willingness-to-pay for functional dairy product attributes in Germany. The study further aims to examine the actual choice behavior towards functional and non-functional dairy products by using actual market data.²

Most studies on functional food overlook the possibility of preference heterogeneity among consumers (e.g., Asselin 2005; Burton and Pearse 2002). For example, Peng et al. (2006) investigate the acceptance of conjugated linoleic acid (CLA)-enriched dairy products among Canadian consumers and key factors influencing the acceptance using an ordered probit model. Asselin (2005) employs a conditional logit model to value functional food attributes in omega-3 and vitamin enhanced eggs in Canada. Burton and Pearse (2002) examine consumers' preferences for functional food in Western Australia by using a conditional logit model. A limitation of these studies is the utilization of models that assume homogeneous preferences, and as such they do not explicitly account for heterogeneity of preferences among consumers. Preferences for attributes are, however, characterized by heterogeneity, which should be taken into consideration in order to estimate unbiased models (Kline and Wichelns 1998). In particular, there is evidence that consumers differ by the extent to which they purchase functional food (Bitzios et al. 2011). This study therefore employs random parameter logit and latent class models to account for preference heterogeneity.

The study also investigates whether choice experiments are able to reveal consumers' true willingness-to-pay for functional dairy products. That is, it is tested whether choice experiments are subject to starting point bias. Starting point bias occurs when respondents are insecure about their true preferences for the good being valued. Consequently, they regard the presented price as an approximate value of the good's real value and anchor their willingness-to-pay on the presented price. Several studies have investigated the influence of starting point bias in dichotomous choice contingent valuation method and found that this kind of contingent valuation is prone to starting point bias (e.g., Aprahamian et al. 2007; Boyle and Bishop 1988; Chien et al. 2005; Veronesi et al. 2011).

Dichotomous choice contingent valuation method can be seen as a special case of choice experiments with only one choice set (Ladenburg and Olsen 2008). A major reason why the choice experiment approach was developed is because it was expected to be less prone to

² This study takes place within Food Chain Plus (FoCus) project. FoCus is an interdisciplinary project at the Christian-Albrechts-University of Kiel which analyzes the food supply chain among the entire process chain by focusing on functional dairy products.

starting point bias, given the multiple cost options per choice set, and the multiple choice sets in one survey. However, recent work by Ladenburg and Olsen (2008) on preferences and willingness-to-pay for protecting Danish nature and motorway development using a choice experiment revealed the presence of starting point bias. Another study by Carlsson and Martinsson (2008) which focused on individuals' marginal willingness-to-pay to reduce power outages did not find any starting point bias in a choice experiment. Both studies employed a *t*-test to test for starting point bias which is a limitation since the *t*-test imposes normality, and as such can lead to biased estimates of the significance of the difference of two (willingness-to-pay) distributions (Poe et al. 1994). This study therefore employs both a *t*-test and the complete combinatorial method proposed by Poe et al. (2005). To the extent that very little work has been undertaken to examine the possible existence of starting point bias in choice experiments, this study makes a contribution to the empirical literature by investigating starting point bias in willingness-to-pay for market goods.

Furthermore, the study examines consumers' real choice decisions on functional food by using real market data. Most functional food studies use survey data and employ stated preference approaches (e.g., Bitzios et al. 2011; Chang et al. 2012). However, revealed preference data also have several advantages since they represent real life choices. This study contributes to the functional food literature by using a scanner database of yoghurt and dairy drink sales in order to reveal consumers' real preferences for and choice decisions on functional dairy products.

1.2 Background

The term functional food is used to describe foods fortified with specific ingredients (e.g., vitamins, minerals, omega-3 fatty acids, oligosaccharides, bioactive peptides, polyphenols, probiotic cultures) imparting certain health benefits. The concept of functional food has become more and more popular with consumers because of a growing awareness of the linkages between health, nutrition, and diet (Malla et al. 2007). Functional foods are products marketed with health claims that indicate the relationship existing between the consumption of food items and the consumer's health. Examples of functional foods are yoghurt-type drinks strengthening the immune system or blood cholesterol lowering spreads.

The problem with functional foods is that there is no legal definition of functional foods in Europe which has been regarded as an obstacle for their acceptance among consumers (Lähteenmäki et al. 2007). The term functional food originated in Japan in 1985, where the

food industry used the term to describe products enriched with specific ingredients providing greater health benefits than traditional products (Bogue and Ryan 2000). Japan has its own legislation for Food for Specified Health Use (FOSHU) and regards functional foods as products eaten as part of an ordinary diet (Lähteenmäki et al. 2007). In Europe, according to a widely used definition “a food can be regarded as functional if it is satisfactorily demonstrated to affect beneficially one or more target functions in the body, beyond adequate nutritional effects, in a way that is relevant to either an improved state of health and well-being and/or reduction of risk of disease” (Diplock et al. 1999). As noted by Diplock et al. (1999), functional foods must remain foods and not pills or capsules. Furthermore, they must demonstrate their effects in amounts that can normally be expected to be consumed in the diet. Criteria for satisfactory scientific demonstration have been proposed by an EU supported PASSCLAIM project (Process for the Assessment of Scientific Support for Claims on Foods). Its objective is to define criteria for assessing the scientific support for claims made in relation to foods (Aggett et al. 2005). A number of European countries have self-administered systems for approving health related claims in products. Although there is no commonly accepted official definition of functional foods, these approval systems broadly agree in two major aspects: functional foods have special scientifically substantiated health related claims and they should be eaten as part of a daily diet (Lähteenmäki et al. 2007). According to this strict demand for scientific evidence, only a few products can be regarded as true functional foods. However, an increasing diversity of food products is marketed with health related arguments, even though these products base their claims on assumptions that have not been verified. From the consumers’ point of view it is quite difficult to distinguish between the products qualifying as true functional foods and those that do not (Lähteenmäki et al. 2007).

Largely due to the Japanese government’s support of research into the field of functional foods, Japan is the largest market in the world for functional products (Euromonitor 2006). However, the regulatory situation of functional food in Europe represents a specific challenge. From a legal point of view, functional foods are positioned in a transitional zone between pharmaceuticals and foods. These areas are traditionally regulated by separate institutions and are subject to different regulations, which is why a gray area emerges with a high level of uncertainty (Menrad 2003). In December 2006 a regulation on the use of nutrition and health claims for foods was adopted by the European parliament and council (EC 1924/2006). This regulation contains harmonized rules for the use of health or nutritional claims on foodstuffs based on nutrient profiles to avoid the use of unjustified and potentially misleading claims.

The Health Claim Regulation will ensure that any claim made on a food label in the EU is clear and substantiated by scientific evidence, and as such it will enable consumers to make informed choices. The intention is to provide a community list of approved functional health claims (Heinonen 2009). The European Food Safety Authority (EFSA) is responsible for verifying the scientific substantiation of the submitted claims, some of which are currently in use, some of which are suggested by companies who want to submit claims for authorization in the EU (EFSA 2012).

1.3 Objectives of the Study

The main objective of this study is to measure consumers' preferences and willingness-to-pay (WTP) for functional dairy product attributes in Germany. The study also seeks to examine consumers' actual choice behavior towards functional dairy products. Specifically, the study aims at

- (i) determining the socioeconomic and psychographic reasons for choosing functional dairy products in Germany,
- (ii) identifying the preferred functional dairy product attributes,
- (iii) estimating the WTP for the attributes,
- (iv) examining the existence of preference heterogeneity,
- (v) investigating whether WTP estimates are subject to starting point bias (SPB), that is whether respondents state their true WTP,
- (vi) analyzing the factors that influence an individual's real willingness to purchase functional dairy products, and
- (vii) estimating the demand for functional and non-functional dairy products.

Objectives (ii), (iii), and (iv) are addressed using a random parameter logit and a latent class model. The latent class model is further employed to deal with objective (i), while the random parameter logit model is further used to study objective (v). Objective (vi) is tackled using a scanner database of yoghurt and dairy drink sales and a bivariate probit model, while the scanner data are further analyzed by employing an almost ideal demand system model in order to deal with objective (vii). The following research questions are addressed:

- (i) Which functional dairy product attributes are preferred by consumers and what factors have an impact on their preferences?
- (ii) Are there heterogeneous preferences for functional dairy product attributes and what are the determinants?
- (iii) Is SPB present in choice experiments?

- (iv) What factors determine consumers' real willingness to purchase functional yoghurts and functional dairy drinks?
- (v) How can the demand for functional and non-functional dairy products be characterized?

1.4 The Valid

In most industrialized countries, changes in demographic patterns – especially the increasing proportion of women in the labor force over the last 30 years – combined with advances in food technology and nutritional sciences have profoundly modified the demand for food. Furthermore, consumers have increasingly recognized the link between health and diet and are more and more taking responsibility for their own health. Given that functional foods are foods providing health benefits beyond basic nutrition, consumers have become increasingly interested in these products. In Europe, Germany represents one of the most important countries within the functional food market and functional dairy products constitute one of the most important groups of functional foods in Germany. Due to this development, it is of major interest to examine empirically consumers' preferences for functional dairy products in Germany. In order to get a clear understanding of the consumers' preferences for and choice decisions on functional dairy products, both stated and revealed preference data are used.

In addition, this study seeks to test whether choice experiments reveal consumers' true willingness-to-pay (WTP) for functional dairy products. In particular, it is tested whether women's and men's WTP values for market goods are affected by starting point bias (SPB) in a choice experiment. Both a *t*-test and the complete combinatorial method proposed by Poe et al. (2005) are employed in order to compare WTP estimates between two samples, and as such to test for the presence of SPB in choice experiments. The motivation for also employing the complete combinatorial test is that it is a non-parametric test imposing no normality assumptions like the standard *t*-test which has been used in past studies.

1.5 Outline of the Dissertation

The dissertation proceeds as follows: Chapter two presents a review of the literature on both consumers' preferences and starting point bias (SPB). The chapter gives an overview of the methods used to analyze consumers' preferences for market goods. The methods employed to measure attribute preferences and calculate willingness-to-pay (WTP) are also discussed and a critique of the methods and the econometric models used is presented. The issue of SPB is then addressed and studies dealing with this issue are presented. Chapter three describes the

theoretical framework for choice experiments as well as the econometric models employed in this study to analyze choice behavior. In particular, this chapter focuses on the econometric model specifications that account for preference heterogeneity. The chapter also presents the conceptual framework employed in this study to address starting point bias in choice experiments. Chapter four describes the methods that have been used in the choice experiment study, including the survey design. Chapter five presents the empirical results of the econometric models employed to examine consumers' choice behavior. Chapter six discusses the consumers' actual choice decisions on functional dairy products. In the final chapter, the results are summarized and ideas for future research are given.

2. Consumers' Preferences: A Literature Review

2.1 Introduction

This chapter presents a review of extant literature on both consumers' preferences in the area of food economics and starting point bias (SPB). An overview of methods used to assess consumers' preferences is given, including a presentation and discussion of the limitations of the different methods. The chapter then reviews studies that have examined the consumers' preferences for food and functional food and that have used such methods. The econometric models that have been employed to model the consumers' choice behavior are also discussed. Finally, studies on starting point bias are presented.

2.2 Preference Elicitation: Overview of Methods

This section presents the methods commonly used to measure consumers' preferences in the area of food economics. The concepts of revealed preference and stated preference are presented and discussed, followed by a description and discussion of different stated preference methods including conjoint analysis, contingent valuation, and choice experiments.

2.2.1 Choice Data

Choice data are data collected on choices made and are used to elicit the consumers' preferences. Two types of choice data have arisen as the primary sources of choice response. These are known as revealed preference and stated preference data. Both approaches link the utility, which the consumer derives from the choice, to the observed (revealed) or stated choice, and as such overcome the limitation of utility theory assuming that individual utilities are not observable. Revealed preference data represent data collected on choices made in an actual market (Hensher et al. 2005). Therefore, revealed preference data represent events that have been observed to have actually occurred. Data is collected on real attribute levels and alternatives chosen and not chosen. A number of possibilities exist as to how such data may be collected. For instance, the analyst observes a market and notes the alternatives as chosen and non chosen. Alternatively, some other means may be available to record choices within a market (e.g., shopping center scanner panels).

Stated preference data refer to situations in which a choice is made by considering hypothetical situations, e.g. survey questions. The hypothetical nature of stated preference data offers the analyst a significant benefit over revealed preference data. For instance, stated preference data are especially useful when considering the choice among existing and new alternatives since the latter cannot be observed in revealed preference data. This implies that

the attributes and the attribute levels of a product are not fixed in terms of what is currently on offer, and as such the stated preference approach provides a useful framework for modeling the value of new innovations or estimating potential demand for new products with new attributes before their introduction into the market. The analyst also has to rely on stated preference theory and methods in terms of goods not traded in real economic markets, e.g. environmental goods, since no revealed preference data exist to model the behavior of interest (Louviere et al. 2000). Figure 2 shows the technological frontier of revealed and stated preference data. This figure illustrates clearly that revealed preference data represent information up to the extent of the technological frontier as it currently exists (X_1 and X_2 are attributes). Stated preference data, however, allow the analyst to explore issues outside of the technological frontier.

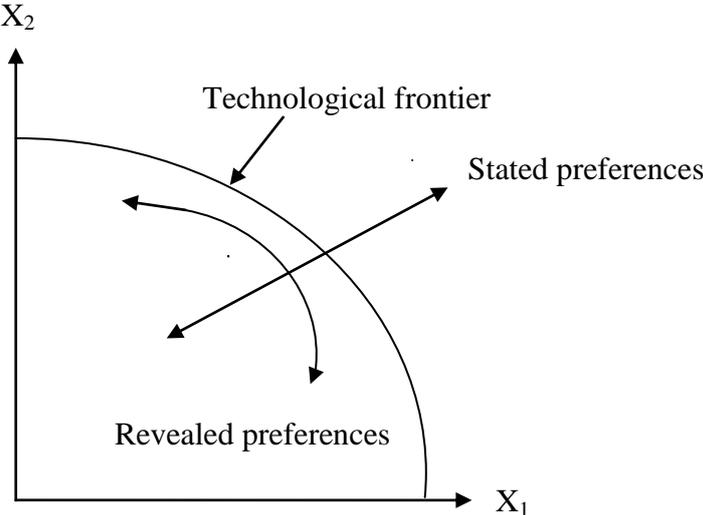


Figure 2 The technological frontier of revealed and stated preference data
Adapted from Figure 2.1, Louviere et al. (2000)

Although there are several advantages of stated preference data, it is important to note that the two data sources generally are complementary, so that the weaknesses of one can be compensated by the strengths of the other. Recognition of this complementarity underlies the growing interest in combining revealed preference and stated preference choice data. The main advantage of revealed preference data is that they represent real life choices, and as such account for personal constraints. Stated preference data, however, have to rely on what consumers say they will do, since they are hypothetical in nature. Therefore, they need to be properly designed to make the hypothetical scenarios as realistic as possible, taking into consideration personal constraints.

Extensive discussions have been ongoing regarding the possibility of eliciting preferences with stated preference methods and the extent of hypothetical bias. Hypothetical bias is the bias introduced by asking a hypothetical question and not confronting the respondent with a real situation (Carlsson 2011). Numerous potential sources of bias exist. For instance, there is increasing concern that valuations obtained in both hypothetical and non-hypothetical settings may be significantly influenced by social desirability bias, i.e. people have a propensity to misrepresent their true preferences out of concern for how they are viewed by others (Lusk and Norwood 2009). Another problem of stated preference surveys is the embedding effect, i.e. the same good is assigned a lower value if willingness-to-pay (WTP) for it is inferred from WTP for a more inclusive good rather than if the particular good is evaluated on its own (Kahneman and Knetsch 1992). Attribute non-attendance is also a problem analysts face when employing stated preference methods. This implies that respondents focus solely on a subset of attributes, ignoring all other differences between the alternatives (Hensher 2006). Several stated preference studies applying dichotomous choice contingent valuation methods have found that WTP estimates are influenced by starting point bias (SPB) (e.g., Aprahamian et al. 2007; Boyle and Bishop 1988; Veronesi et al. 2011). SPB occurs when individuals are unsure about their true preferences for the good being valued. As a result, they regard the presented price as an approximate value of the good's real value and anchor their WTP in this value. The present study tests whether WTP estimates obtained from a choice experiment are susceptible to SPB.

Stated preference methods have been employed extensively in the area of food economics in order to assess the value of goods and characteristics of goods. Examples of study areas are preferences for genetically modified food products (e.g., Lusk et al. 2003; Rigby and Burton 2005), animal welfare (e.g., Carlsson et al. 2007a), functional food (e.g., Chema et al. 2006; West et al. 2002), and food safety (e.g., Hamilton et al. 2003). As noted by Carlsson (2011), there are three main reasons for using a stated preference method instead of revealed preference methods in the area of food economics: there are public good aspects (e.g., people care about other people's consumption), the difficulty of disentangling preferences for different characteristics of goods using market data, and not all levels of the characteristics exist on the market today. In order to investigate hypothetical functional dairy products that do not exist on the German market yet, this study employs a stated preference method. The following section presents three different stated preference approaches.

Given that revealed preference data also have several advantages (e.g., they account for market and personal constraints), this study also uses actual market data in order to examine consumers' actual choice decisions on functional dairy products. Chapter six presents the results obtained from analyzing a scanner database of yoghurt and dairy drink sales.

2.2.2 Stated Preference Methods

Stated preference methods assess the values of goods and attributes of goods by using individuals' stated behavior in a hypothetical setting. A common objective in the use of stated preference methods is the derivation of measures designed to determine the amount of money people are willing to forfeit in order to obtain some benefit from the undertaking of some specific task (Hensher et al. 2005). Such measures are referred to as willingness-to-pay (WTP) measures and are used to assess the economic values of goods and their attributes. More specifically, economic values are commonly expressed in monetary terms but are interpreted by economists as difference in preference or utility levels (Freeman 2003). Economic values are, therefore, based on what people want, i.e. their preferences. It is important to note that an elicitation question in a stated preference survey can also be phrased in terms of willingness-to-accept (WTA). WTA aims at asking respondents what level of compensation they would be willing to accept for a loss. The choice between the WTP or WTA approach is a question of property rights: does the agent have to purchase the good in question (i.e. he/she wants to enjoy it) or does he/she have the right to sell it (Mitchell and Carson 1989)?

Stated preference method includes several different approaches such as conjoint analysis, contingent valuation, and choice experiments. In conjoint analysis, a person ranks several alternatives described by a number of attributes (Backhaus et al. 2006). It is generally agreed that 1964 marks the start of conjoint analysis (Green and Srinivasan 1978). The conjoint analysis literature is most extensive in academic and applied marketing, where it is widely employed to solve practical marketing research problems (e.g., Cattin and Wittink 1982; Green and Rao 1971). However, conjoint analysis is also used in many environmental valuation applications, since it provides richer preference information than methods based on selecting only the favorite alternative. That is, fewer respondents are required. There are recent advances in applied conjoint analysis suggesting that obtaining a ranking from a reiterated set of best-worst choices offers significant advantages in terms of cognitive effort (e.g., Scarpa et al. 2011). The main disadvantage of conjoint analysis is, however, that it may

place a significant level of cognitive burden on respondents, since respondents are asked to rank several alternatives.

The most established stated preference method is the contingent valuation method (CVM) (Carlsson 2011). In CVM studies, respondents are asked whether or not they would be willing to pay a certain amount of money for realizing a change in the level of a good, where most often the good is a public or quasi-public good (Mitchell and Carson 1989). As noted by Mitchell and Carson (1989), there are four different kinds of contingent valuation elicitation method – the open-ended question, the bidding game, the payment card, and the take-it-or-leave-it methods. The open-ended format aims at asking the respondents what maximum price they are willing to pay for the described good. Given that respondents often find it difficult to pick a value out of the air, the open-ended format tends to produce an unacceptably large number of nonresponses or protest zero responses to the WTP questions (Desvousges et al. 1983).³ The bidding game imitates an auction, and as such is modeled on the real-life situation. The payment card is an alternative to the bidding game. It maintains the properties of the direct question approach while increasing the response rates for the WTP questions by providing respondents with a visual aid which contains a large array of potential WTP amounts, ranging from zero to some large amount. Another important CVM is the take-it-or-leave-it approach (closed-ended/dichotomous choice questioning) which uses a large number of predetermined prices chosen to bracket expected maximum WTP amounts. This approach uses closed-ended questions, i.e. it first specifies a sum and then asks people to choose whether or not to pay the sum (Kealy and Turner 1993). Dichotomous choice CVM can be seen as a special case of choice experiment with only one choice set (Ladenburg and Olsen 2008). A further contingent valuation elicitation method is the take-it-or-leave-it with follow-up approach offering the potential for considerable gains in efficiency.⁴ In this approach, the respondents are asked a question requiring a yes or no answer about whether they would pay a specified price. If the answer is yes, another WTP question is asked using a higher price randomly chosen from a prespecified list. If the respondents say no, the follow-up question offers a randomly chosen lower price. Both take-it-or-leave-it approaches (take-it-or-leave-it approach, take-it-or-leave-it with follow-up approach) simplify the respondents' valuation choice, and as such are widely used in CVM studies. As indicated previously, contingent

³ In protest zero responses, respondents give a zero WTP amount even though the good does have some value for them.

⁴ A synonym for the take-it-or-leave-it with follow-up approach is double-bounded dichotomous choice contingent valuation approach.

valuation questions can be phrased in two ways: the willingness-to-pay (WTP) approach seeks to discern what the individual would pay to avoid a negative outcome (or to achieve a positive outcome), while the willingness-to-accept (WTA) approach seeks to discern how large a payment the individual would need to receive in order to accept the negative outcome (or not to receive a positive outcome). Basic economic theory suggests that with no income effects both approaches should give (approximately) the same answer. More specifically, in the case of quasi-linear utility the income effect is zero, and as such WTA and WTP are the same (Varian 2010). However, analysts have recognized that large and persistent disparities commonly arise in answers to contingent valuation surveys, that is, there are large differences between WTP and WTA (Hausman 2012). Further possible problems of CVM have been discussed in the literature for several years such as the existence of hypothetical response bias (e.g., starting point bias).

The third stated preference method is the choice experiment method, or stated choice method. The idea of designed choice experiments arose out of limitations encountered in using conjoint analysis to model transport and telecommunications choices in Australia (Louviere 2001). In particular, there was a need to estimate true demand by separating choosers from non-choosers. Furthermore, researchers recognized the need for tasks that more closely mimic real (travel) choice environments, that have more external validity, and that are easier for respondents to complete (Louviere 1988). As noted by Louviere (1988), individuals in real environments probably do not rank or rate (travel) alternatives (like in conjoint analysis); they choose one of them, or they choose not to choose any alternative. In a choice experiment, respondents are given a hypothetical setting and asked to choose their preferred alternative among several alternatives in a choice scenario. Usually respondents are asked to perform a sequence of such choice scenarios. Each alternative is described by several attributes, and the levels of the attributes vary between choice scenarios. Choosing the preferred alternative among several alternatives overcomes the limitation of ranking or rating alternatives, and as such choice experiments offer the analyst a significant benefit over conjoint analysis. The choice experiment method is a generalization of dichotomous choice CVM and it is the stated preference method that is most extensively employed in food economics (Carlsson 2011). This study employs a choice experiment, and as such the choice experiment method is discussed in more detail in section 4.2.

2.3 Preference Studies

This section reviews studies that have investigated consumers' preferences in the area of food economics. Both studies on food and functional food are presented. Furthermore, the methods employed to assess consumers' preferences are described as well as the econometric models that have been used.

2.3.1 Studies on Food

Studies on food have traditionally used models commonly based on forms of the Almost Ideal Demand System (AIDS) framework (Deaton and Muellbauer 1980) in order to analyze food demand, and as such the quantity purchased or the expenditure share (e.g., Asche et al. 1998; Tiffin and Tiffin 1999). These models became very popular models for food demand analysis in the 1980s and 1990s. In order to allow for more flexibility, Banks et al. (1996 and 1997) derived a Quadratic Almost Ideal Demand System (QUAIDS) specification in which expenditure shares are quadratic in the logarithm of income. Several authors have used the QUAIDS in analyzing the demand for food in different countries (e.g., Abdulai 2002; Moro and Sckokai 2000). However, emphasis in recent years has changed to assessing food demand using discrete choice models in order to investigate factors influencing choices. These models are quite beneficial since aggregation assumptions as well as assumptions regarding representative consumers or homogeneity of preferences can be relaxed. Furthermore, it is possible to incorporate consumer responses to prices and non-price characteristics in a single framework (Adamowicz and Swait 2011).

Many studies on food demand employing discrete choice analysis have focused on novel attributes or food characteristics in order to measure the welfare effects or willingness-to-pay (WTP) for these attributes. Carlsson et al. (2007b) examine consumer benefits of labels and bans on genetically modified foods employing a choice experiment. They use a random parameter logit model in order to account for preference heterogeneity among Swedish consumers. Burton et al. (2001) also investigate genetically modified food and analyze the consumers' attitudes towards this kind of food in the United Kingdom using a conditional logit specification within a choice modeling framework. In a follow-up study, Rigby and Burton (2005) employ a mixed logit model in order to reconsider the findings of their choice experiment and to account for preference heterogeneity among consumers. Preferences for organic food products have also been extensively investigated using discrete choice analysis. For instance, Gracia and de Magistris (2008) analyze Italian consumer's choice for organic foods within a random utility discrete choice model and specify a bivariate probit model.

Verhoef (2005) also examines organic products by employing a discrete choice model to explain the choice and purchase frequency of organic meat in the Netherlands and by specifying a probit and ordered probit model. Several discrete choice studies further examined preferences over methods of production and animal welfare. For instance, Carlsson et al. (2007a) use a choice experiment in order to investigate consumer preferences and WTP for farm animal welfare in Sweden. They allow for heterogeneity in preferences by employing a random parameter logit model.

As indicated previously, several studies on food have traditionally estimated demand systems by employing revealed preference data. It is, however, important to note that a number of food studies using revealed preference data have also applied hedonic price models in order to examine the factors that influence food prices, and as such investigate consumer preferences for different food attributes (e.g., He et al. 2008; Stanley and Tschirhart 1991). Hedonic price analysis is based on the assumption that the value of a product (e.g., yoghurt) is a function of its attributes (e.g., brand, flavor). The approach is based on Lancaster's consumer theory which is discussed in detail in section 3.1.1. Each of these attributes contributes to the total economic value of the product which under competitive market conditions is the market value of the product. That is, $p_i = f(a_{1i}, a_{2i}, \dots, a_{ni})$, where p_i is the market price of the i th product and $a_{1i}, a_{2i}, \dots, a_{ni}$ are the attributes $1, \dots, n$ for the i th product. This presentation allows the calculation of the marginal value or market price of each attribute, $\delta p_i / \delta a_{ni}$. Given that hedonic price analysis is based on revealed preference data, it is limited to valuation of existing attributes, and as such it is not possible to evaluate new products which are not on the markets yet.

During the last two decades, studies on food have also employed experimental valuations in order to examine consumers' WTP for different products (e.g., Huffman et al. 2007; Lusk and Fox 2003). In experimental valuation studies, participants make either consequential bids or choices with real products and real money (Alfnes and Rickertsen 2011). Experimental valuations are beneficial since analysts can investigate new products or products with new features (like stated preference methods). For instance, Lusk and Fox (2003) compare results from laboratory and field valuation experiments and utilize the Becker-DeGroot-Marschak valuation mechanism (Becker et al. 1964) in order to conduct an auction for cookies and analyze bids. Huffman et al. (2007) use a random n th-price auction and examine the role of consumers' prior beliefs about genetic modification on their WTP for foods that might be

genetically modified. It should be noted that experimental valuations are certainly beneficial in several ways but the problem with this kind of valuation is that much money is needed for implementation.

2.3.2 Studies on Functional Food

In the area of food economics, a number of studies have examined the acceptance of functional food. Labrecque et al. (2006) analyze the acceptance of functional food and compare French, American, and French Canadian consumers. They conduct factor analyses in order to reduce statement variables and further perform linear regressions. Their results suggest only minor differences among French, American, and French Canadian students' attitudes towards functional foods. Their findings also reveal that health-related and product-related benefits, credibility of information, and high knowledge have a positive effect on attitudes. Consumer acceptance of conjugated linoleic acid (CLA)-enriched dairy products among Canadian consumers has been investigated by Peng et al. (2006). They employ an ordered probit estimation and find no significant influence of education and gender on the consumer acceptance. However, their results suggest that middle-aged consumers and consumers with teenagers in the household are more likely to buy CLA-enriched dairy products. Based on a sample of 215 Belgian consumers, Verbeke (2005) examines the acceptance of functional foods by using a probit model specification. His findings indicate that belief in the health benefits of functional foods is the main positive determinant of acceptance. He further concludes that belief in the health benefits, knowledge of functional foods, and the presence of an ill family member outweigh socio-demographics as potential determinants of acceptance.

In order to investigate preferences for functional food, a number of studies have used conjoint analysis. For instance, Ares and Gámbaro (2007) examine the effect of different carriers (honey, yoghurt, vegetable cream soup, dulce de leche, marmalade) and enrichments (soluble fiber, calcium, antioxidant extracts, iron) on the perceived healthiness and willingness to try functional foods by employing a conjoint analysis in Uruguay. Their results suggest that carrier products have the largest effect on consumers' perception of healthiness and willingness to try. They also find that the highest positive relative utilities are achieved when the enrichment is a functional ingredient inherent in the product. Hailu et al. (2009) apply a conjoint analysis to elicit Canadian consumer preferences over attributes of functional foods and nutraceuticals using probiotics as the functional ingredient of interest. They observe that the type of product used to deliver the functional benefit (yoghurt, ice cream, pill) as well as

the source of health claims (e.g., verified by government or made by manufacturer of product) matters. However, noting that conjoint analysis may be disadvantageous since respondents have to rank alternatives is significant. This may place a significant level of cognitive burden on respondents.

Other studies have employed contingent valuation in order to assess consumers' willingness-to-pay (WTP) for different functional food attributes. Markosyan et al. (2009) measure consumers' WTP for antioxidant-enriched apples using contingent valuation questions in the United States. Based on the results of their take-it-or-leave-it with follow-up approach (dichotomous choice CVM with follow-up), they find that information regarding the potential health benefits of antioxidants has a positive significant effect on consumers' WTP. Their findings also indicate that respondents are willing to pay a small price premium for antioxidant-enriched apples (i.e., 7-10%). Maynard and Franklin (2003) also employ CVM in order to assess whether consumers are willing to pay premiums for cancer-fighting dairy products (high-CLA dairy products). Their results reveal that households with children and health-conscious consumers are most willing to pay premiums for cancer-fighting dairy products. Though CVM can shed some light on WTP for functional food attributes, it may be problematic since it is widely known to be susceptible to a number of hypothetical response bias (e.g., starting point bias) (Hausman 2012).

Preferences for functional food attributes have also been investigated using choice experiments. Asselin (2005) employs choice experiments and uses a conditional logit model, in his empirical estimation of choice data to value functional food attributes in omega-3 and vitamin enhanced eggs in Canada. His results reveal that respondents' health consciousness and health behavior scores significantly and positively affect their WTP for the functional attributes found in omega-3 eggs. Burton and Pearse (2002) also use a choice experiment to estimate consumer preferences for various beer attributes in Western Australia. They employ a conditional logit model and find that consumers are willing to pay a premium for a product with positive health benefits. A limitation of both studies is that they employ conditional logit models, and as such assume preference homogeneity among consumers. Although consumers have accepted many different functional products there is evidence that consumers differ by the extent to which they purchase food products with explicit functional properties (Bitzios et al. 2011). Given that new technologies are used to produce functional foods, some consumers even reject these kinds of food. This may be attributed to the fact that they perceive the use of

new technologies in food as risky. Other consumers prefer to consume “natural” foods and describe functional foods as “unnatural” and “potentially unsafe” (Markosyan et al. 2009). These findings give some support to the idea of heterogeneity in preferences for functional foods within the population, which should be accounted for in models in order to obtain unbiased estimates. As noted by Kline and Wichelns (1998), it is important to account for preference heterogeneity, since preferences often vary among individuals according to their socioeconomic characteristics, environment, and tastes.

During the past years choice experiment studies aimed at investigating attribute preferences for functional food have increasingly employed random parameter logit models to empirically model preference behavior. Chang et al. (2012) employ choice experiments and random parameter logit models to estimate U.S. consumers’ marginal WTP for soy attributes including taste, contents of soy protein, and health claim. Their findings indicate that individuals have widely varying preferences for soy-based food products. Their results further suggest that, while taste is the dominating attribute that drives consumers’ WTP for soy food products, consumers do respond to the information provided in the health claim. Bond et al. (2008) also use a choice experiment on red leaf lettuce attribute bundles in the United States. They estimate several random parameter logit models in order to analyze marginal utilities of various attributes related to general health claims, specific nutrition and health claims, certification logos, and certified organic claims. They find that consumers distinguish between labeling claims, and that attribute bundling effects are present. In their choice experiment study on functional wines in Spain, Barreiro-Hurlé et al. (2008) employ a random parameter logit model in order to account for heterogeneous preferences. Their results suggest that the functional attribute positively and significantly influences the probability of selecting a red wine and that the WTP for this attribute is as important as for ageing in wine. Furthermore, they conclude that consumer choices and valuation of functional wine are affected by consumer characteristics. The random parameter logit model is a major improvement in discrete choice analysis that overcomes the limitations of the conventional logit model by accounting for heterogeneous preferences and allowing the taste parameters to vary randomly over individuals. It is, however, not the appropriate model to explain the sources of heterogeneity. This caveat can be somehow overcome by introducing interaction variables of the attributes and socioeconomic characteristics. However, this may be a limitation since multicollinearity is a problem that often arises from too many interactions. The random parameter logit model is able to account for two types of variation in preferences. One is

unobserved variation captured through the random tastes whereas another is the variation due to varying socioeconomic characteristics.

Very few studies on functional food have recently considered preference heterogeneity that may result from endogenous preference segmentation which may be captured by using latent class models. It is, however, reasonable to assume that preferences are not unique to the individual, but rather a group of individuals (e.g., Hu et al. 2004), and as such it is important to account for heterogeneous class-specific preferences. Bitzios et al. (2011) use choice experiments and employ a latent class model to examine how the inclusion of a functional ingredient (to increase the quantity and effectiveness of fiber) influences consumer attitudes towards bread in the United Kingdom. Their results reveal that bread type is a major factor in determining choice, and that the inclusion of a functional ingredient yields relatively small measures of value. Furthermore, they find differences in WTP between respondent segments and that segment membership is explained by the underlying eating behavior of the respondent. Grunert et al. (2009) investigate health claim perception in five Nordic countries (Denmark, Finland, Iceland, Norway, Sweden) by employing a latent class approach. Their findings indicate that respondents can be grouped into two roughly equally sized classes differing in the type of claim preferred. More specifically, one class prefers long claims that give the full story consisting of active ingredient, physiological function, and health benefit, whereas respondents of the other class prefer short claims consisting of the health benefit only. Their results also suggest that a familiar ingredient is preferred to an unfamiliar one. The present study employs a choice experiment to examine consumers' preferences and WTP for functional dairy product attributes in Germany. Random parameter logit and latent class models are applied to assess the existence of preference heterogeneity and endogenous preference segmentation. Based on available literature, no previous attempt has been made to examine heterogeneous preferences for functional dairy products among consumers in Germany.

2.4 Studies on Starting Point Bias in Stated Preference Approaches

Stated preference approaches use individuals' stated behavior in a hypothetical situation in order to measure the value of goods. Due to the hypothetical nature of these approaches, the question arises whether individuals actually would do what they state they would do if it were for real. Debates have been ongoing about the extent of hypothetical bias within stated preference methods. As indicated previously, hypothetical bias is the bias introduced by asking a hypothetical question and not confronting the respondent with a real situation

(Carlsson 2011). Several sources of hypothetical bias and studies analyzing these sources exist. This section focuses on studies that have dealt with the effect of using different bid ranges for the price attribute.

A number of papers in the economics and psychological literature find that respondents, when uncertain about their preferences or assessment of the good being valued, anchor their valuation to the available information (e.g., Ariely et al. 2003; Wilson et al. 1996). More specifically, respondents may anchor the value they place on a good on the price amounts proposed to them in the initial payment question. This may happen when the uncertain respondent interprets the price amount as an approximate value of the good's real value and anchors his willingness-to-pay (WTP) in this value. That is, different starting points, or different price levels in the first payment question⁵, yield different estimates, or different WTP estimates, which are biased toward the initial values. This effect is known as the starting point bias (SPB) (Tversky and Kahneman 1974) or, more generally, the anchoring bias. One possible cause for this hypothetical bias is that respondents derive some utility from saying they are willing to pay for a good in order to conform to a social norm. That is, respondents perceive the survey bid values or price levels as providing information, such as what society or the experts believe these values should be.

2.4.1 Starting Point Bias in Contingent Valuation Studies

Studies applying the dichotomous choice contingent valuation method (CVM) ask respondents whether or not they would be willing to pay a specific price to obtain a change in the level of a good. Dichotomous choice CVM surveys are known to be subject to SPB. A number of economic studies have examined the influence of SPB in this kind of stated preference method (e.g., Aprahamian et al. 2007; Boyle and Bishop 1988; Boyle et al. 1985; Chien et al. 2005; Herriges and Shogren 1996; Veronesi et al. 2011).

In order to evaluate alternative riparian management practices in northcentral Iowa, Herriges and Shogren (1996) consider a dichotomous choice CVM with follow-up questioning (take-it-or-leave-it with follow-up approach) in which the respondents combine their true WTP with the first bid amount to form a revised WTP. They show that when anchoring occurs, both the estimated median WTP and the estimated dispersion of WTP in the population can be significantly biased. Chien et al. (2005) also investigate non-market goods and address SPB in a dichotomous choice CVM with follow-up questioning approach. They evaluate the health

⁵ In a choice experiment the first payment question is the first choice set.

benefits of air quality improvement in three major metropolitan areas in Taiwan and find a strong anchoring effect. A more recent study conducted by Veronesi et al. (2011) examines the role of the bid design and the underlying distribution of WTP on the impact of SPB. They also employ a dichotomous choice CVM with follow-up questioning approach and use Monte Carlo simulations. Based on their findings, they caution researchers that the consequences of SPB are complex and depend on the underlying distribution of WTP and on the bid design. Aprahamian et al. (2007) examine the possibility of heterogeneous anchoring (or SPB) when a first dichotomous choice question is used with an open-ended follow-up. That is, they assume that anchoring does not homogeneously affect respondents and that individuals do not anchor in the same way. The findings of their survey on air quality improvements in France indicate that 25% of respondents either do not anchor or only insignificantly anchor, 25% anchor almost perfectly, and the remainder is distributed between these two extremes. Based on available literature, all CVM studies dealing with starting point bias examined non-market goods. This may be attributed to the fact that CVM is widely used in the area of environmental economics.

2.4.2 Starting Point Bias in Choice Experiment Studies

The findings from the studies employing CVM reveal that SPB significantly influences the derived WTP, and hence stated WTP estimates may vary as a function of the respondents' true preferences and the presented prices. Both choice experiments and dichotomous choice CVMs are consistent with random utility theory, and hence dichotomous choice CVM can be seen as a special case of a choice experiment with only one choice set (Ladenburg and Olsen 2008). An important reason why choice experiments were developed is because they were expected to overcome the problem of SPB, given the multiple cost options per choice set, and the multiple choice sets in one survey. However, recent work by Ladenburg and Olsen (2008) found that choice experiments are equally prone to SPB as in the case of dichotomous choice CVMs. Until now, very little work has been undertaken to investigate the possible existence of SPB in choice experiments (Carlsson and Martinsson 2008; Ladenburg and Olsen 2008).

In their study on preferences and WTP for protecting Danish nature and motorway development, Ladenburg and Olsen (2008) examine the extent to which preferences and WTP estimates are affected by SPB in choice experiments, using a multinomial probit model. This is a pioneering work being the first to account for gender-specific SPB using choice experiments. In a two-split sample approach, they employ different sets of price levels in an Instructional Choice Set (ICS) presented prior to the actual choice sets. They find that female

respondents' preferences and WTP values are influenced by this bias, whereas male respondents' are not. Their results further reveal that the impact of SPB decays, as respondents evaluate more and more choice sets, implying that respondents go through a learning process, a finding that is consistent with the Discovered Preference Hypothesis (DPH).⁶ Carlsson and Martinsson (2008) also examine the presence of SPB in a choice experiment, focusing on individuals' marginal WTP to reduce power outages in Sweden and using a binary heteroskedastic logit model. They hypothesize that including a choice set with low prices and large attribute improvements as the first choice set in a sequence would make respondents state lower marginal WTP in the following choice sets. Using a split sample survey, their results do not indicate the presence of SPB since the first choice set has no significant impact on the estimated marginal WTP. A limitation of both studies is the utilization of a *t*-test to test for SPB since the *t*-test imposes normality assumptions. The present study employs a choice experiment to examine consumers' preferences and WTP for functional dairy products. Using a two-split sample approach, this study further tests whether WTP estimates are susceptible to SPB. SPB are examined in a pooled sample, as well as in samples disaggregated according to gender, in order to investigate gender-specific SPB. To the extent that very few studies have considered the issue of SPB in choice experiments, this study makes a contribution to the empirical literature by examining SPB in WTP for market goods. Furthermore, this study employs both a *t*-test and the complete combinatorial method proposed by Poe et al. (2005) in order to test for SPB in choice experiments.

2.5 Chapter Conclusions

The literature review shows huge gaps in studies on functional food to examine consumers' preferences and willingness-to-pay (WTP) for new functional dairy product attributes in Germany. The review of extant literature also indicates that less effort has been made to investigate the presence of starting point bias (SPB) in choice experiments in order to reveal consumers' true WTP estimates.

⁶ The DPH proposed by Plott (1996) states that when individuals are faced with new decisions in unfamiliar environments, initial decisions tend to suffer from large randomness and exhibit little conformity with standard economic theory of preferences, e.g. rationality. However, if individuals make repeated decisions and gain familiarity with the decision environment, decisions will gradually exhibit less randomness and greater rationality, i.e. preference anomalies will decay (As noted by Braga and Starmer (2005), preference anomalies are errors in stated preferences that can be expected to disappear as individuals become more experienced in relevant decision environments). At the theoretical level, DPH provides a possible defense for standard economic theory, whereby behavior initially deviates from standard economic theory, but tends to converge to the basic tenets with increasing experience. This implies that by training individuals, their preferences become more stable and rational, and as such less random. Ladenburg and Olsen (2003) consider SPB as an anomaly in behavior relative to standard economic theory of preferences, and as such interpret decaying anomalies, or rather decaying SPB, in terms of the DPH.

Revealed preference approaches using hedonic price analysis provide a useful framework for valuing attributes since they are based on utility theory. However, these approaches are limited to valuation of existing attributes not being able to analyze new products with new attributes. Stated preference approaches, however, are able to examine novel attributes of products which are not on the market yet, and as such are quite beneficial in the area of food economics. In particular, choice experiments represent a promising way for valuing attributes since they have several advantages over other stated preference approaches. The economic literature reviewed reveal that consumers are willing to pay a premium for functional foods. However, most stated preference studies on functional food have not taken into account preference heterogeneity among consumers even though there is evidence that consumers differ by the extent to which they purchase functional food. This is one gap that this research study intends to fill. Based on available literature, there is no study investigating preferences and WTP for functional dairy products in Germany. Random parameter logit and latent class models used for analysis represent major improvements in discrete choice analysis since they are able to account for preference heterogeneity, and as such provide opportunities to better model the consumers' choice behavior.

The literature review further reveals that many stated preference studies, especially in the area of environmental economics, have found an influence of SPB on the respondents' preferences and WTP values. However, most of these stated preference studies are based on contingent valuation and not on choice experiments. This is the second gap that this study aims to fill. In particular, this study investigates whether respondents' WTP values for a market good are affected by SPB.

Revealed preference data are based on real life choices, and as such also offer a number of advantages to the analyst. In order to get a clear understanding of the consumers' observed (real) choice decisions on functional dairy products, this study further aims to examine factors that may influence consumers' willingness to purchase functional dairy products by using a bivariate probit model. Furthermore, an almost ideal demand system model is employed to estimate the real demand for functional and non-functional dairy products.

3. Theoretical Framework for Choice Experiments and the Econometric Model

3.1 Theoretical Framework

Discrete choice experiments analyze decision makers' choices among alternatives. The decision makers can be people, households, firms or any other decision-making unit, and the alternatives might represent competing products, courses of action, or any other options over which choices must be made (Train 2003). This chapter presents the theoretical underpinnings of discrete choice experiments as well as the econometric models used to analyze choice experiment data. The conceptual framework employed to examine starting point bias (SPB) in choice experiments is also described and presented.

3.1.1 Lancaster's Consumer Theory

The theoretical underpinnings of choice experiments are based on consumer theory developed by Lancaster (1966) and discrete choice random utility theory explained in section 3.1.2. The basis for most microeconomic models of consumer behavior is the maximization of a utility function subject to a budget constraint. Lancaster's idea is that it is the attributes or characteristics of the goods rather than the goods per se that determine the utility they provide. Changes in those attributes can cause a discrete switch from one good to another that will provide the most beneficial combination of attributes, and hence the highest utility.

Lancaster's consumer theory implies that goods are used either singly or in combination to produce the characteristics that are the source of an individual's utility. This is the essential point of departure from the traditional consumer theory which assumes that goods are the direct objects of utility. Lancaster's approach may be defined more precisely as follows: an individual maximizes an ordinal utility function for attributes, $U(a)$ where a is a vector of attributes $1, \dots, s$, possessed by a single good or combination of goods subject to the budget constraint $px \leq Y$, where p is a vector of prices for each of these goods, x are the goods, and Y is income. A transformation between goods x and attributes a is represented by an equation system $a = Bx$, where B is an $s \times n$ matrix which transforms the n goods into s attributes of the alternatives and is invariant for all individuals. A range of mappings can exist such that a number of attributes can be produced by one good or a number of goods can produce one attribute. The model may therefore be written as:

$$\begin{array}{ll} \text{Maximize} & U(a) \\ \text{subject to} & px \leq Y \\ \text{with} & a = Bx \end{array} \tag{1}$$

$$a, x \geq 0.$$

The utility function $U(a)$ is defined on attributes-space while the budget constraint $px \leq Y$ is defined on goods-space. The equation system $a = Bx$ represents a transformation between attributes- and goods-space. In this model, the utility function can only be related to the budget constraint after both have been defined on the same space. There are non-negativity constraints $a, x \geq 0$ assumed to hold initially. However, in some applications they may not always form part of the model. Lancaster's approach assumes that goods are infinitely divisible, frequently purchased, and of low unit value. However, many goods are not perfectly divisible, especially goods relevant to discrete choice applications, which often investigate goods that are infrequently purchased (Louviere et al. 2000).

Rosen (1974) develops a goods attributes model for indivisible (or discrete) goods in which he assumes that an individual buys only one alternative of the good per year and that alternatives are available for a continuous range of attributes. Assuming this enables him to eliminate Lancaster's transformation from goods to attributes, and to state a model directly in terms of prices and quantities of attributes. If Hicks' (1946) composite good theorem holds, the prices of all other goods can be held constant except those under study. Thus, one intrinsic group of goods is assumed to yield attributes a_1, a_2, \dots, a_n . Defining all other goods consumed as k , Rosen's model can be specified as:

$$\begin{aligned} & \text{Maximize} && U(a_1, a_2, \dots, a_n, k) \\ & \text{subject to} && p(a_1, a_2, \dots, a_n) + k = Y, \end{aligned} \tag{2}$$

where the price of k is arbitrarily set equal to one, Y is the consumer's income, and $p(a_1, a_2, \dots, a_n)$ represents the price of one good yielding attributes a_1, a_2, \dots, a_n which are actually purchased. In this case the budget constraint defined in terms of the attributes can be non-linear. That is, if goods are not divisible, $p(a_1, a_2, \dots, a_n)$ does not need to be linear. Both Lancaster's and Rosen's models provide important theoretical frameworks for choice experiments. However, they have some limitations since they are extensions of traditional consumer theory. For instance, both models link utility directly to the attributes, without accounting for latent constructs such as attitudes and beliefs. Furthermore, these models would not hold if individual choice behavior is stochastic, since these models are basically static and deterministic.

3.1.2 Discrete Choice Theory

Discrete choice theory provides a simple and direct approach to examine consumers' choice decisions. In discrete choice theory, a discrete representation of the set of alternatives is assumed, and as such the consumption of one or more goods can be zero, implying that the maximization problem may have a "corner" solution, a point where the usual first-order conditions for an optimum do not hold (Ben-Akiva and Lerman 2000). Train (2003) indicates that the set of alternatives, called the choice set, exhibits the three following characteristics. First, the alternatives must be mutually exclusive from the individual's perspective, i.e. the individual chooses only one alternative from the choice set. Second, the choice set must be exhaustive in that all alternatives are included. Finally, the number of alternatives must be finite. The characteristics of mutual exclusivity and exhaustiveness are not restrictive, since appropriate definitions of alternatives can almost always assure that the alternatives are mutually exclusive and the choice set is exhaustive. The third characteristic, however, namely, that the number of alternatives is finite, is actually restrictive and represents the defining characteristic of discrete choice models. This characteristic distinguishes the realm of application for discrete choice models from that for regression models, since with regression models the dependent variable is continuous, implying that there is an infinite number of possible outcomes. A continuous space of alternatives assumed in microeconomic consumer theory allows the use of calculus to derive demand functions. Given that discrete choice models deal with a set of discrete choices, it is impossible to use the maximization technique of calculus to derive demand functions. Thus, instead of deriving demand functions, utility functions are applied directly in discrete choice theory. As in consumer theory, the concept of rational behavior is retained, and as such the individual is assumed to have consistent and transitive preferences over the alternatives. In general, rational behavior implies a consistent and calculated decision process in which the individual follows his or her own objectives (Ben-Akiva and Lerman 2000). More specifically, an individual acting rationally is assumed to compare alternatives and to choose that one which gives the greatest level of satisfaction or utility.

The underlying framework of choice experiments is derived by linking the Lancaster-Rosen standard approach described in the previous section to discrete choice theory. As indicated previously, a universal set of alternatives, called C , is assumed to exist. The constraints, e.g. the budget constraint faced by an individual n , determine his or her choice set $C_n \subseteq C$. A real-valued utility index U associated with every alternative can be defined,

$$U_{in}, i \in C_n \quad (3)$$

such that alternative $i \in C_n$ is chosen if and only if

$$U_{in} > U_{jn}, \quad \text{all } j \neq i, j \in C_n. \quad (4)$$

Using the Lancaster-Rosen approach, the utility function is defined in terms of the attributes:

$$U_{in} = U(a_{in}), \quad (5)$$

where a_{in} is a vector of the attribute values for alternative i as viewed by individual n . The choice set C_n is determined by several constraints, e.g. budget and time. The function $U ()$, which maps the attribute values to a utility scale is an ordinal utility function. Although the utility function can take several forms, an additive utility function is often assumed for simplicity. In empirical applications, a vector of socioeconomic characteristics S is usually introduced into the utility functions capturing the variability of tastes across individuals:

$$U_{in} = U(a_{in}, S_n), \quad (6)$$

where S_n is a vector of socioeconomic characteristics of individual n (Ben-Akiva and Lerman 2000).

3.1.3 Random Utility Theory

As indicated previously, traditional consumer theory assumes deterministic behavior. Random utility theory, however, postulates that individual choice behavior is intrinsically probabilistic, and as such random. This concept of random utility was put forward by Thurstone (1927) in psychology, introduced into economics by Marschak (1960) and further developed by McFadden (1974). The idea behind random utility in economic theory is that while consumers may have perfect information in terms of their utility functions, the analyst lacks precise knowledge about the consumers' decision processes, and as such uncertainty must be taken into account. In choice experiments, individuals have been observed not to choose the same alternative in repetitions of the same choice situations and violations of the transitive preferences assumption have also been detected. Given that it is not possible to specify the causes of these inconsistent and non-transitive preferences because they are usually unknown or known but not measurable, deterministic choice theory cannot be used. A probabilistic

choice mechanism was introduced to explain these behavioral inconsistencies. Furthermore, the probabilistic mechanism is also used to capture the effects of unobserved taste variations among individuals and unobserved attributes of the alternatives, and as such overcomes another weakness of traditional consumer theory (Ben-Akiva and Lerman 2000). Luce and Suppes (1965) distinguish between two approaches to the introduction of probabilistic choice theory. The constant utility approach hypothesizes that the utilities of alternatives are constant and that the choice probabilities for an individual are functions parameterized by those utilities. The alternative approach is the concept of random utility being more consistent with consumer theory and relevant to the present choice experiment. In this concept utilities are treated by the analyst as random due to observational deficiencies (that is, uncertainty occurs) resulting from unobserved attributes, unobserved taste variations, measurement errors, and use of proxy variables. Like traditional consumer theory, random utility theory assumes that an individual derives utility by choosing an alternative from a set of alternatives. A utility maximizing behavior is assumed, that is, an individual is always assumed to choose the alternative with the highest utility. The utilities are not known to the analyst with certainty (that is, they are latent), and as such treated as random variables. The actual choice of an individual, however, can be observed by the analyst and is a manifestation of the underlying utilities. From this perspective the behavioral choice rule available to the analyst is as follows: the probability of an individual n choosing alternative i from a finite set of alternatives in choice set C_n is equal to the probability that the utility of alternative i is greater than (or equal to) the utility associated with alternative j after evaluating each and every alternative in the choice set. This can be written as follows:

$$P(i \setminus C_n) = Pr [(U_{ni} \geq U_{nj}) \forall j \in C_n; i \neq j]. \quad (7)$$

Given that the utility function U_n can be decomposed into deterministic (V_n) and stochastic (ε_n) components, this is equivalent to:

$$P(i \setminus C_n) = Pr [(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}) \forall j \in C_n; i \neq j]. \quad (8)$$

The deterministic component contains information that is measurable by the analyst through a set of observed attributes and socioeconomic characteristics of the individual while the stochastic component consists of information that is not directly measurable, and as such not observable.

It is useful to rearrange equation (8) to reflect this:

$$P(i \setminus C_n) = Pr [(\varepsilon_{nj} - \varepsilon_{ni} \leq V_{ni} - V_{nj}) \forall j \in C_n; i \neq j]. \quad (9)$$

For the analyst ε is a random variable. Randomness arises because the analyst cannot peep into the head of each individual and fully observe the set of influencing factors and the complete decision calculus; which in turn, implies that the analyst can only explain choice up to a probability of event selection (Louviere et al. 2000). This means that the analyst has to establish a way of handling the information in ε associated with each individual, that is, distributional assumptions on ε have to be made (Hensher et al. 2005). Different discrete choice models are obtained from different assumptions about the distribution of ε and the model outputs represent the probabilities of individuals choosing each alternative.

To make discrete choice models operationally tractable, simplified assumptions are often made. Such assumptions include utility maximizing behavior, deterministic choice sets, easily measurable characteristics of individuals and simple error structures (ε) such as an extreme value type 1 (Gumbel) distribution. The multinomial logit model (MNL) (also referred to as the conditional logit model) represents the most basic choice model and is widely used due to its simple estimation resulting from its strong assumptions and its closed form solution (Hensher et al. 2005). This model assumes that the random components, ε , are independent and identically distributed (IID) extreme value type 1, that is, an extreme value type 1 distribution is assumed. The IID condition represents an important restriction and implies that the variances of the random components of the utilities are identical and all covariances are set to zero since the alternatives are independent.⁷ The underlying IID condition of the MNL has an equivalent behavioral association with a property known as the independence of irrelevant alternatives (IIA). The IIA property states that the ratio of the choice probabilities of any pair of alternatives is independent of the presence or absence of any other alternative in a choice set (Hensher et al. 2005).⁸ Although this may be reasonable under some

⁷ The specification of equal variances arises since the random components are constrained to have the same scale parameter λ . The scale parameter λ is an inverse function of the standard deviation of the unobserved effects associated with an alternative, and as such positive (Louviere et al. 2000). The scale parameter is equal to:

$\lambda = \sqrt{\frac{\pi^2}{6\sigma^2}}$. In the MNL, all variances are arbitrarily set equal to one, and as such the scale parameters for each alternative are equal to 1.283 (Hensher et al. 2005).

⁸ A well-known example illustrating the problem of the IIA property is the red bus/blue bus example (Ben-Akiva and Lerman 2000). Commuters initially face a decision between two modes of transportation: car and red bus. Suppose that an individual chooses between these two alternatives with equal probability, 0.5, so that the odds

circumstances, it is unreasonable in others. An important implication of IIA is that all pairs of alternatives are equally similar or dissimilar. Hensher et al. (2005) indicate that for the set of unobserved attributes, this amounts to assuming that all the information in the random components is identical in quantity and relationship between pairs of alternatives, and as such across all alternatives (hence the IID condition).⁹ The main disadvantage of the IIA assumption is that the MNL will perform poorly if there are some alternatives that are similar and highly correlated. A third drawback of the MNL is that it assumes homogeneous preferences for attributes across all consumers and the taste parameters of each individual are known and completely explained by their means only.

Many different discrete choice models have been developed largely to avoid the IIA assumption. Generalized extreme-value models (GEV) are based on a generalization of the extreme value distribution and relax the IIA assumption by allowing for correlations in unobserved factors over alternatives. If all correlations are zero, the GEV distribution becomes the product of independent extreme value distributions and the GEV model collapses to the standard logit model (Train 2003). The nested logit model has been applied by many researchers and is the most widely used member of the GEV family since its functional form is simple compared to other types of GEV models. This model places the alternatives into several groups called nests, with unobserved factors having the same correlation for all alternatives within a nest and no correlation for alternatives in different nests, that is, IIA holds within each nest but not across nests. As with the MNL, the nested logit model is relatively straightforward to estimate and offers the added benefit of being of a closed form solution. However, one limitation of the nested logit model is that it just partially relaxes the IIA (and IID) assumption and another restriction is that it does not allow for overlaps between nests (that is, each alternative is a member of only one nest). Several kinds of GEV models have been specified in order to overcome these limitations, e.g. cross-nested logit models containing multiple overlapping nests or the heteroskedastic extreme value model which has a different variance for each alternative. As indicated previously, GEV models are able to relax

ratio is equal to one. Now suppose a third mode (blue bus) is added. Assuming bus commuters do not care about the color of the bus, individuals are expected to choose between bus and car still with equal probability, i.e. the probability of choosing the car is still 0.5, while the probabilities of each of the two busses is 0.25. However, IIA implies that this is not the case: for the odds ratio between car and red bus to be preserved, the new choice probabilities must be 0.33 (car), 0.33 (red bus), and 0.33 (blue bus).

⁹ Hausman and McFadden (1984) propose a specification test for the MNL to test the IIA property. The test, known as the Hausman test of the IIA property, is conducted in two stages: first an unrestricted model complete with all alternatives is estimated before the analyst estimates a model synonymous with the alternative hypothesis using a restricted number of alternatives.

the IIA assumption. However, they cannot represent random taste variation and are not applicable to panel data when unobserved factors are correlated over time for each decision maker (Train 2003).

Probit models represent the other major group of discrete choice models also relaxing the IIA assumption. In addition, they can handle random taste variation and can be used with panel data. Given that the probit probabilities cannot be solved analytically, probit models are difficult to estimate, and as such they are less applied by researchers than GEV models. Probits assume that the unobserved factors are distributed jointly normal: $\varepsilon'_n = \langle \varepsilon_{n1}, \dots, \varepsilon_{nJ} \rangle \sim N(0, \Omega)$. With full covariance matrix Ω , any pattern of correlation and heteroskedasticity can be accommodated. The only restriction of probit models is that they assume normal distributions for all random components of utility. In some situations, however, unobserved factors, that is, the random components of utility may not be normally distributed, leading to perverse forecasts. For instance, price coefficients are known to be negative for everyone. Given that the normal distribution has density on both sides of zero, probit models, however, necessarily imply that some decision makers have a positive price coefficient (Train 2003). The use of a lognormal distribution is more appropriate in this situation, since it has density only on one side of zero. However, this distribution cannot be accommodated within a probit model.

The mixed logit model (also referred to as the random parameter logit, mixed multinomial logit, or hybrid logit model) allows the unobserved factors to follow any distribution, and as such is not restricted to normal distributions. More specifically, within a mixed logit model the unobserved factors are decomposable into two parts: one part that contains all the correlation and heteroskedasticity, and as such can follow any distribution, and another part that is IID extreme value. The mixed logit model is a highly flexible model that can approximate any discrete choice model derived from random utility maximization (McFadden and Train 2000). In addition, it obviates the three limitations of the MNL, that is, it allows for random taste variation, it does not exhibit restrictive forecasting substitution patterns (that is, no IIA assumption), and it permits correlation in unobserved factors over time. The mixed logit model has been known for many years but has only become fully applicable since the development of convenient numerical simulation methods for estimation (Train 2003). As noted by Amaya-Amaya et al. (2008), the number of studies employing variations of the mixed logit model is dramatically increasing in different applied fields such as marketing,

transportation or environmental economics. However, it is important to note that the application of the mixed logit model results in several challenges that the analyst must face, such as what distribution should be used and what coefficients should be specified as random. The mixed logit model (random parameter logit model) is discussed in more detail in section 3.3.1.

3.1.4 Preference Heterogeneity in Economic Choice Theory

Econometric choice models are accounting increasingly for preference heterogeneity among consumers. Following Desarbo et al. (1997), heterogeneity is a result of the individual differences consumers exhibit in terms of the choice decisions they make and the processes involved in making such decisions. More specifically, different consumers will place a different value or importance on the different attributes defining the alternatives in the choice set. Individual preferences and choices may differ due to differences in characteristics, experiences, contexts, and many more. Greene (2008) emphasizes the importance of accounting for preference heterogeneity in explaining choice behavior. Failure to account for preference heterogeneity when it is existent leads to biased parameter estimates, and as such misleading predictions of attribute valuations and welfare measures are the consequence.

Preference heterogeneity may be incorporated in choice models by introducing observed individual characteristics of the consumer into the deterministic component of the utility function presented in equation (8). This kind of heterogeneity is observable by the analyst and classified as observed heterogeneity. However, it is very likely that preference heterogeneity will remain even after accounting for differences in observed individual characteristics. Given that this remaining preference heterogeneity is not observable by the analyst, it is called unobserved heterogeneity (Bhat 2000). Several models have been developed in order to capture this unobserved heterogeneity. The mixed logit model described by McFadden and Train (2000) and Train (2003) captures unobserved heterogeneity by allowing the taste parameters to vary randomly across consumers. The latent class model represents another model used to capture unobserved heterogeneity. This model assumes that there are two or more classes of people with homogeneous tastes. Within each latent (that is, not observable by the analyst) class, preferences are assumed to be homogeneous; however, preferences and hence utility functions can vary between classes (e.g., Amaya-Amaya et al. 2008).

Sources of unobserved heterogeneity are for example psychographic data such as an individual's general perceptions or attitudes. Following McFadden (2001), consumers are

heterogeneous in unobserved characteristics such as their taste templates and the mechanisms they use to form perceptions. Perceptions refer to the individual's beliefs regarding the product attributes (McFadden 1986). Attitudes reflect the consumer's needs, values, and tastes. It is certainly not possible to observe an individual's general perceptions or attitudes. However, it is possible to observe indicators of an individual's general perceptions and attitudes (Swait 1994). Very little work has been undertaken to incorporate indicators of psychographic data in discrete choice modeling since these indicators are difficult to capture (e.g., Swait 1994).

3.2 Conceptual Framework of a Choice Model for Functional Dairy Products

The conceptual framework is based on the Lancaster-Rosen approach and discrete choice random utility theory. The framework focuses on identifying the underlying influences on an individual's choice behavior for functional dairy product attributes. A choice decision can be viewed as a decision-making process. Measurable inputs to the decision process are for example product attributes, socioeconomic characteristics or market constraints, while the direct measurable output of the process is market behavior, or rather choice behavior, e.g. product purchases. Figure 3 presents a simple path diagram of the underlying structural model representing the choice process for functional dairy product attributes. In the figure, rectangular objects are variables observable by the analyst whereas elliptical objects represent structural latent variables. It is assumed that socioeconomic characteristics as well as indicators of a consumer's general attitudes and perceptions are observable and influence preferences (Swait 1994). Preferences are also determined by the consumer's perceptions of product attributes, since functional dairy products can be viewed as discrete choice goods with several varying attributes. Preferences finally lead to the outcome of interest, the observed choice behavior. There will always be a number of constraints (e.g., budget constraint) influencing choice behavior, and as such denying the full achievement of the most preferred functional dairy product.

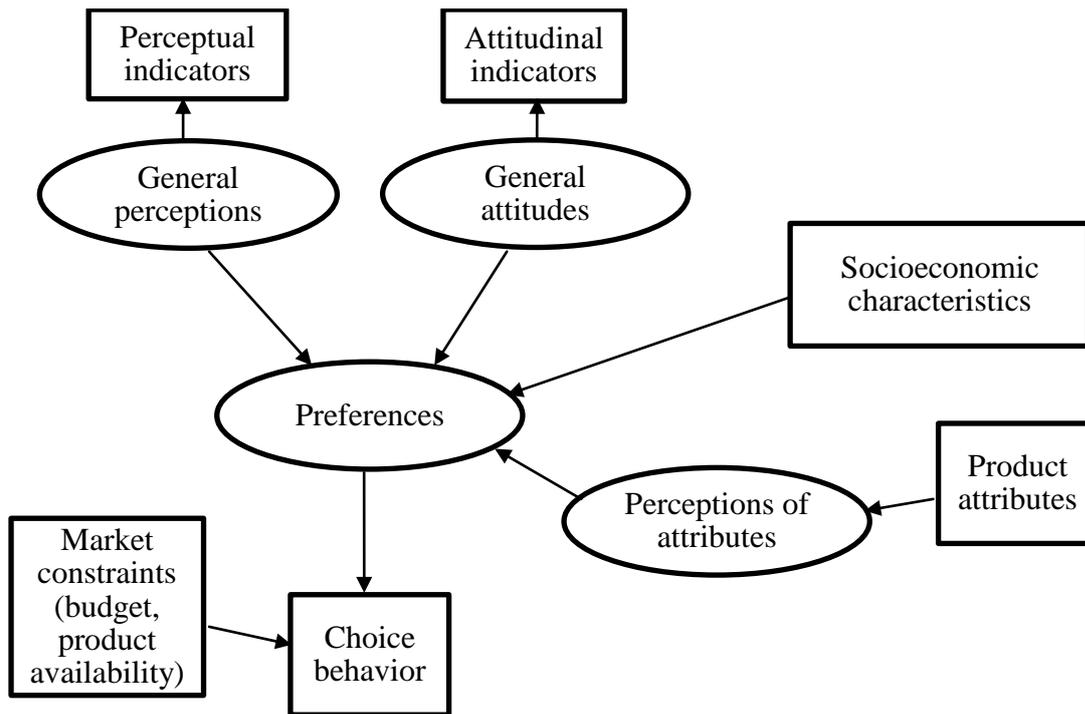


Figure 3 Choice process for functional dairy product attributes
Partially adapted from Figure 1, Swait (1994)

Following the Lancaster-Rosen approach, a consumer has preferences for different combinations of functional dairy product attributes, since these attributes generate utility (or disutility). More specifically, the attributes are the sources of utility. The consumer is assumed to form a utility function for the functional dairy products and assign a utility value for each dairy product by valuing and trading off the attributes that are important in his or her choice decision. A utility maximizing behavior is assumed, that is, the consumer will choose the dairy product with the highest positive utility value.

Given that the socioeconomic characteristics as well as the perceptual and attitudinal indicators (i.e. the psychographic indicators/variables) influence preferences and choice behavior, they are also included even though the sources of utility are strictly linked to the attributes of the dairy products. These socioeconomic and psychographic variables are not sources of utility of a dairy product per se, but can affect the role of unobserved attributes and can be considered as influences on the parameter estimates of observed attributes. Introducing interactions between attributes and socioeconomic or psychographic variables is one possibility to reveal the presence or absence of preference heterogeneity among consumers. Consumers' purchase intentions for functional dairy products are determined by their belief in the relationship between diet and health, their attitude towards functional foods and

socioeconomic characteristics. For instance, preference for a functional dairy product can be influenced by age. More specifically, older consumers are more likely to suffer from cardiovascular diseases than younger consumers, and as such they may prefer a health claim that is aimed at healthy blood vessels. Given that it is not possible to measure consumers' general perceptions and attitudes (it is just possible to measure perceptual and attitudinal indicators) and considering the fact that they tend to vary overtime and across individuals, they represent sources of unobserved preference or taste heterogeneity, and as such explain part of the random component of the utility function.

The economic model for functional dairy product attributes which is based on figure 3 accounts for unobserved heterogeneity and is presented in this section. In this model, $C_n = \{1, 2, \dots, J\}$ denotes a set of available functional dairy products, indexed from 1 to J . Each choice set C_n is assumed to have a finite set of J mutually exclusive and exhaustive functional dairy products to choose from in each choice situation. Functional dairy products are described by their observed attributes and attribute levels, where one of the attributes is the purchase price. An example of a functional dairy product (i.e. a possible treatment combination) could be a functional yoghurt fortified with omega-3 fatty acids and bearing a health claim of support for healthy blood vessels and healthy metabolism whose purchase price is 1.49€/500g.¹⁰ The J functional dairy products are determined depending on the type of design used to generate the treatment combinations and the number of attributes and attribute levels in the choice experiment. For each choice situation (i.e. for each choice set), a sampled consumer is assumed to have full knowledge of the factors influencing his/her choice decision when asked to choose the most preferred functional dairy product from the competing J products subject to the budget constraint. Following discrete choice and random utility theory, the consumer's resource allocation, q describing the quantities and attributes of the goods consumed can be written as:

$$q = (k_j(a_j), \varepsilon, x), \tag{10}$$

where k_j denotes the functional dairy products (discrete alternatives), a_j is a vector of observed attributes for the functional dairy products that are chosen and experienced, ε is a vector of unobserved attributes of a discrete alternative and x is a vector of quantities of other goods with its price equal to one. Consumers have a vector of observed characteristics s and a vector

¹⁰ Treatment combinations are combinations of attributes, each with unique attribute levels.

of unobserved characteristics ζ ; with (s, ζ) determining preferences over resource allocations. Given that consumers are heterogeneous in unobserved characteristics, it is assumed that the unobserved characteristics vary continuously with the observed characteristics of a consumer, that is, unobserved characteristics are a continuous random field indexed by the observed characteristics (McFadden 2001; McFadden and Train 2000). More specifically, $\zeta = \zeta(s)$ is a continuous random field with a regular canonical representation. This implies that the conditional distribution of the unobserved characteristics ζ will depend continuously on the observed characteristics s . However, the distribution of ζ cannot depend on q , since consumer theory postulates that tastes are established prior to assignment of resource allocations. The unobserved characteristics ζ of the consumer can be specified as:

$$\zeta(s) = f_0(v(s), s), \quad (11)$$

where $v(s)$ is a uniformly distributed continuous random field. This implies that consumers with similar observed characteristics will have similar distributions of unobserved characteristics. Consumer theory further postulates that the description of the resource allocation q does not depend on consumer characteristics. Therefore, consumer characteristics do not enter the objective description of the resource allocation q , although they will enter the consumer's evaluation of q . This implies that the distribution of ε cannot depend on (s, v) , although it may depend on a_j . It is assumed that ε is specified as a continuous random field with a regular canonical representation. This can be written as:

$$\varepsilon(a_j) = f(\mu(a_j), a_j), \quad (12)$$

where $\mu(a_j)$ is a uniformly distributed continuous random field. Then discrete alternatives with similar observed attributes will have similar distributions of unobserved attributes. Substituting the transformations f_0 and f into the definition of utility for discrete functional dairy products (choice alternatives), a random utility model that is continuous in its arguments can be written as:

$$U = U(k_j(a_j), x, s, \mu(a_j), v(s)), \quad (13)$$

where $\mu(a_j)$ and $v(s)$ are independently uniformly distributed continuous random fields. Given that consumers make choices subject to constraints (e.g., budget constraint), the consumer's utility maximization problem may therefore be written as:

$$\begin{aligned}
 & \text{Maximize } U(k_1(a_1), \dots, k_j(a_j), x, s, \mu(a_j), v(s)) && \text{subject to} \\
 & (a) \sum_{j=1}^J p_j k_j(a_j) + x \leq Y \\
 & (b) k_j(a_j), x \geq 0 \\
 & (c) k_i k_j = 0 \quad \text{all } i \neq j,
 \end{aligned} \tag{14}$$

where $U(\cdot)$ is the strictly quasiconcave utility function. Constraint (a) refers to the budget constraint where p_j is the price of the j th functional dairy product and Y is income. Constraint (b) specifies the non-negativity constraint ensuring that the consumer chooses a non-negative quantity of $k_j(a_j)$ and x . Following Hanemann (1984), an additional constraint (c) is incorporated restricting the choice alternatives in each choice set to be mutually exclusive. The traditional Marshallian demand function represents the solution to this problem. It is assumed that the consumer evaluates the attributes and attribute levels of the functional dairy products (alternatives) in each choice set, generates a utility function for the alternatives, and finally assigns a utility value for each alternative by valuing and trading off the attributes that are important in his/her choice decision. A utility maximizing behavior is assumed, that is, the consumer chooses the alternative with the highest utility. In addition, it is reasonable to assume that

$$k_j = 0 \rightarrow \frac{\delta U}{\delta a_j} = 0, \quad j = 1, \dots, J, \tag{15}$$

implying that the attributes of a functional dairy product j do not matter unless that product is actually consumed (Hanemann 1984). This property of “weak complementarity” is convenient, but not essential. From (14), the conditional indirect utility function can now be written as:

$$U'(p, a, Y, s, \mu, v) = \max \left[U \left(k_j(a_j), Y - p_j k_j(a_j), s, \mu(a_j), v(s) \right) \right] \quad j = 1, \dots, J. \tag{16}$$

U' is quasiconvex and decreasing in p_j and increasing in Y , and it satisfies Roy's Identity:

$$k_j(p_j, a, Y, s, \mu, v) = -\frac{\delta U' / \delta p_j}{\delta U' / \delta Y}. \quad (17)$$

Through Roy's Identity one can obtain the Marshallian demand function which describes the consumer's optimal functional dairy product choices given the prices, income, and the consumer's characteristics. Given that the preferences are incompletely observed from the point of view of the econometric investigator (that is, there is randomness in the utility function), a probability distribution is assigned over the discrete choice set resulting from trade-offs between the levels of utility each alternative is providing. The behavioral choice rule for a consumer's utility maximizing choice decision is then as follows: the probability of a consumer choosing functional dairy product j is equal to the probability that the utility of alternative j is greater than (or equal to) the utility associated with alternative i after evaluating each and every alternative in the choice set of $j = 1, \dots, J$ alternatives. This can be written as:

$$P(j) = Pr \left[U_j(k_j(a_j), Y - p_j k_j(a_j), s, \mu(a_j), v(s)) \geq U_i(k_i(a_i), Y - p_i k_i(a_i), s, \mu(a_i), v(s)) \right] \\ j = 1, \dots, J \quad \text{all } i \neq j, \quad (18)$$

where s are the observed characteristics of a consumer, $\mu(a)$ and $v(s)$ are independently uniformly distributed continuous random fields. Equation (18) forms the basis of econometric choice modeling presented in the next section in order to estimate utility parameters and to derive economic values of functional dairy product attributes. Different econometric models can be specified, depending on the assumptions about the specific functional form for the observed attributes a and distributions for $\mu(a)$ and $v(s)$ (the random elements).

As noted by McFadden and Train (2000), a well-specified random utility model exhibits zero probability of ties in a choice set, so that a realization $v = v(s)$ and $\mu_j = \mu(a_j)$ for $j = 1, \dots, J$ of the random elements in the model almost certainly determines a unique choice. When the utility function is continuously differentiable, a sufficient condition for this is that the Jacobian has rank at least $J - 1$, and that the support of (v, μ_1, \dots, μ_J) contains the space spanned by the Jacobian:

$$\begin{bmatrix} \delta U(k_1(a_1), x, s, \mu_1, v) / \delta v & \delta U(k_1(a_1), x, s, \mu_1, v) / \delta \mu_1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ \delta U(k_J(a_J), x, s, \mu_J, v) / \delta v & 0 & \dots & \delta U(k_J(a_J), x, s, \mu_J, v) / \delta \mu_J \end{bmatrix} \quad (19)$$

Including taste factors (determined by ν) of the required dimension that interact with a full-rank array of alternative attributes, or a full set of alternative-specific effects (determined by the μ_j), or some combination is a possible way to ensure no ties. McFadden and Train (2000) have established a convenient mixed logit model by advising the analyst to perturb the indirect utility function. In this model, independent extreme value type I disturbances are added to the indirect utility function scaled so that the probability that the original and perturbed indirect utility functions order alternatives differently is very low. The indirect utility is further approximated uniformly by a Bernstein-Weierstrauss polynomial in the observed arguments and the uniformly distributed vector of unobserved characteristics. This is done so that the probability of the approximation changing the preference order is very small. In order to obtain the mixed logit model, the analyst has to condition on the uniform random vector that enters the utility function and then integrate this vector out:

$$P_C(i) = \int_0^1 \dots \int_0^1 \frac{e^{z_i \alpha}}{\sum_{j \in C} e^{z_j \alpha}} \cdot G(d\alpha; \theta) . \quad (20)$$

In this formula, C is the choice set, z_j are vectors of polynomial functions of observed characteristics of the consumer and observed attributes of alternative j , α are polynomial transformations of the uniformly distributed continuous random fields $\mu(a)$ and $\nu(s)$, drawn from a cumulative distribution function $G(d\alpha; \theta)$, and θ is a vector of parameters of the mixing distribution G . The random parameters α may be interpreted as arising from taste heterogeneity in a population of multinomial logit consumers. The mixing distribution G may come from a continuous parametric family, such as log normal or multivariate normal, or it may have a finite set of points resulting in a model called latent class model. Both the mixed logit model and the latent class model offer alternative ways to capture unobserved preference heterogeneity and other potential sources of variability in unobserved sources of utility. The mixed logit model provides a flexible and computationally practical approach to discrete response analysis and it can approximate any random utility model (McFadden and Train 2000). As indicated previously, it obviates the three limitations of the multinomial logit by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time. Given that choice experiments often involve repeated choice decisions per respondent and considering the fact that due to these repeated decisions the likelihood of correlations in unobserved utility increases, these properties are quite important.

3.3 Econometric Choice Models

This section describes the random parameter logit model (mixed logit model) and the latent class model that have been employed to analyze the choices made by the consumers from the choice experiment survey and to estimate economic values (that is, the willingness-to-pay) of the functional dairy product attributes. As indicated previously, the random parameter logit model as well as the latent class model account for preference heterogeneity, or rather taste heterogeneity, and as such both models represent two advanced specifications of discrete choice modeling. A presentation and description of the conceptual framework used to examine starting point bias in choice experiments is also given.

3.3.1 Random Parameter Logit Model Specification

The random parameter logit model is based on the usual framework of consumer theory developed by Lancaster (1966) and McFadden's random utility theory (1974). A consumer is assumed to compare alternatives and to choose that one which gives the greatest level of satisfaction or utility. Hence, the probability of choosing an alternative, or rather a functional dairy product, increases as the utility associated with it increases. A consumer n faces a choice among J functional dairy products in each of t choice situations. The consumer n is assumed to consider the full set of offered functional dairy products in choice situation t and to select the product with the highest utility. The utilities are latent or unknown to the analyst. However, the analyst is able to observe the attributes of the functional dairy products, the characteristics of the consumer and the choices made. The utility associated with each functional dairy product j , as evaluated by each consumer n in choice situation t , is represented in a discrete choice model by a utility expression of the general form in (21):

$$U_{jtn} = \beta_n X_{jtn} + \varepsilon_{jtn}, \quad (21)$$

where X_{jtn} is a vector of observed variables that includes attributes of the functional dairy products and may also include characteristics of the consumer. Taste coefficient vector β_n is unobserved for each n and varies in the population with density $f(\beta_n | \theta)$ where θ are the true parameters of this distribution. The unobserved random term ε_{jtn} is independent and identically distributed (IID) extreme value type 1. An important issue arises with the random parameter logit model. There are two sets of parameters. First, there are the parameters β_n , which enter the logit formula. These parameters vary in the population with density $f(\beta_n | \theta)$. The second set are the population parameters θ that describe this density (e.g., mean and covariance of the β 's). More specifically, the population parameters θ describe the distribution

of individual parameters. The goal is to estimate θ . This specification is the same as for standard logit (also called conditional logit or multinomial logit) except that β varies over consumers rather than being fixed (Train 2003).¹¹

Conditional on β_n , the probability that consumer n chooses alternative i in choice situation t is standard logit, since the remaining random term ε is IID extreme value type 1. The probability takes a closed form between zero and one:

$$L_{nit}(\beta_n) = \frac{e^{\beta_n x_{nit}}}{\sum_j e^{\beta_n x_{njt}}}. \quad (22)$$

Given that the analyst does not know β_n and therefore cannot condition on β , the unconditional choice probability is employed. The unconditional probability is the integral of the conditional probability in (22) over all possible values of β_n , which depends on the parameters of the distribution of β_n :

$$P_{nit}(\theta) = \int L_{nit}(\beta_n) f(\beta_n | \theta) d\beta_n. \quad (23)$$

It is necessary to specify a distribution for the taste coefficients β and estimate the parameters of that distribution. The analyst is free to specify a distribution that satisfies his expectations about behavior. Several different distributional assumptions are possible, e.g. normal, lognormal, uniform, triangular or Rayleigh distributions. For instance, the lognormal distribution is beneficial when the coefficient is known to have the same sign for every individual, such as a price coefficient that is known to be negative for everyone for normal goods (Train 2003).

In this study, each respondent makes repeated choice decisions for different functional dairy products since each respondent evaluates several choice sets. Following Revelt and Train (1998), it is assumed that tastes vary across respondents, but not across repeated choice situations by an individual. Therefore, the probability of each sampled individual's sequence of observed choice decisions is needed. Let $i(n, t)$ denote the alternative that individual n chooses in choice situation t . Conditional on β_n , the probability of individual n 's observed sequence of choice decisions is the product of standard logits:

¹¹ There is a slight difference between the conditional logit model and the multinomial logit model as shown in Greene (2007).

$$S_n(\beta_n) = \prod_t \frac{e^{\beta_n X_{nit}}}{\sum_j e^{\beta_n X_{njt}}}. \quad (24)$$

The unconditional probability for the sequence of choice decisions is the integral of this product over all possible values of β_n , which depends on the parameters of the distribution of β_n :

$$P_n(\theta) = \int S_n(\beta_n) f(\beta_n | \theta) d\beta_n. \quad (25)$$

The only difference between a random parameter logit model with repeated choice decisions and one with only one choice decision per respondent is that the integrand involves a product of logit formulas, one for each choice situation, rather than just one logit formula. Given that the choice probability P_n is a mixture of logits with f as the mixing distribution, models of this form are also called mixed logit models. The probabilities do not exhibit the independence of irrelevant alternatives (IIA) property and different substitution patterns may be obtained by appropriate specifications of the mixing distribution f . This is handled through the random parameters, specifying each β_n associated with an attribute as having both a mean and a standard deviation (that is, it is treated as a random parameter instead of a fixed parameter) (Hensher et al. 2005).¹² The standard deviation of the taste coefficient vector β_n accommodates the presence of unobservable preference heterogeneity in the sampled population, that is, a statistically significant parameter estimate for the standard deviation suggests the existence of heterogeneity.

Given that the integral in equation (25) does not have a closed form, it cannot be calculated analytically, and as such exact maximum likelihood estimation is not possible. Instead, the probability is approximated through simulation and the simulated log likelihood function is maximized. More specifically, $P_n(\theta)$ is approximated by a summation over randomly chosen values of β_n . For a given value of the parameters θ , a value of β_n is drawn from its distribution, $f(\beta_n | \theta)$. Using this draw of β_n , the product of standard logits, $S_n(\beta_n)$, presented in equation (24) is calculated. This process is repeated for many draws, and the mean of the resulting $S_n(\beta_n)$'s is taken as the approximate choice probability:

¹² A fixed parameter treats the standard deviations as zero such that all the information in the distribution is captured within the mean.

$$SP_n(\theta) = \left(\frac{1}{R}\right) \sum_{r=1}^R S_n(\beta_n^r | \theta), \quad (26)$$

where R is the number of draws (replications) of β_n , $\beta_n^r | \theta$ is the r th draw from $f(\beta_n | \theta)$, and $SP_n(\theta)$ is the simulated probability of individual n 's sequence of choice decisions. As noted by Revelt and Train (1998), $SP_n(\theta)$ is an unbiased estimator of $P_n(\theta)$ whose variance decreases as R increases. Furthermore, $SP_n(\theta)$ is smooth, thus facilitating the numerical search for the maximum of the simulated log likelihood function. Finally, they note that $SP_n(\theta)$ is strictly positive for any R , so that the log of the simulated probability is always defined.

The simulated log likelihood function (SLL) is given as:

$$SLL(\theta) = \sum_n \ln(SP_n(\theta)). \quad (27)$$

The estimated parameters are those that maximize the simulated log likelihood function (Revelt and Train 1998).

Depending on the number of draws taken from the distribution, computation of the maximum likelihood choice probabilities by simulation can be time-intensive. In this study, Halton draws are used, since these draws are spread uniformly over the unit interval, and as such yield much more accurate approximations in Monte Carlo integration relative to standard pseudo-random draws (Hensher et al. 2005). Using Halton draws also provides dramatic gains in limiting the time taken for model convergence while producing no discernible degradation in model results. Bhat (2001) reports that when using Halton draws, comparable model results to models estimated using random draws may be obtained with only one-tenth the total number of draws.

As indicated previously, a random parameter associated with an attribute treats the standard deviations as non-zero, and as such is specified as having both a mean and a standard deviation. In general, the taste coefficient vector β_n (that is, the vector of random coefficients) can be expressed as:

$$\beta_n = b + \eta_n, \quad (28)$$

where b is the population mean and η_n is the stochastic deviation representing the individual's tastes relative to the average tastes in the population. The utility function presented in

equation (21) has to account for the two population moments of the taste coefficient vector β_n . Therefore, the utility that individual n obtains from each set of j functional dairy products in choice situation t can be written as:

$$U_{jtn} = bX_{jtn} + \eta_n X_{jtn} + \varepsilon_{jtn}. \quad (29)$$

The presence of a standard deviation η of a taste parameter accommodates the presence of preference heterogeneity in the sampled population. This is referred to as unobserved heterogeneity.

Within consumer research, few studies have used the random parameter logit modeling approach. For example, Rigby and Burton (2005) employ the random parameter logit model to examine consumers' preferences for genetically modified food in the United Kingdom while Lusk et al. (2003) use this model to compare consumer valuations of beef ribeye steaks in four different countries. Thunström (2010) investigates preference heterogeneity across households in terms of breakfast cereals also using a random parameter logit model. Although the random parameter logit model accounts for unobserved preference heterogeneity by allowing the taste parameters to vary randomly over individuals, it is not well-suited to explain the sources of heterogeneity (Boxall and Adamowicz 2002). These sources relate to the characteristics of individual consumers, such as socioeconomic variables or indicators of an individual's general perceptions and attitudes (i.e. psychographic variables). Including interactions of the attributes and socioeconomic (or psychographic) variables is a possibility to account for socioeconomic (or psychographic) variables within the random parameter logit model context. However, this represents a limitation since multicollinearity is a problem that often arises from too many interactions. Furthermore, there must be *a priori* knowledge of the elements of heterogeneity. A promising way for tackling these problems is the use of the latent class model (Boxall and Adamowicz 2002). The latent class model captures unobserved preference heterogeneity by generating classes of consumers. More specifically, the latent class model simultaneously groups consumers into relatively homogeneous classes and explains the choice behavior of class members (Swait 1994). Within each class, preferences are assumed to be homogeneous; however, preferences, and as such utility functions can vary between classes.

3.3.2 Latent Class Model Specification

The latent class model also accounts for preference heterogeneity. However, unlike the random parameter logit model which specifies the random parameters to follow a continuous joint distribution, the latent class model assumes that a discrete number of classes is sufficient to account for preference heterogeneity. More specifically, the mixing distribution $f(\beta_n | \theta)$ is discrete, with β_n taking a finite set of distinct values (Train 2003). Therefore, heterogeneity is captured by the latent classes in the population, each of which is associated with a different parameter vector in the corresponding utility. Individuals are intrinsically sorted into a number of classes based on their tastes. Members of each class have similar tastes. However, the classes are latent, i.e. they are not observable by the analyst. Within the class, the individual choices from one choice situation to the next are assumed to be independent and choice probabilities are generated by the conditional logit model (Greene 2007). The probability π that consumer n chooses dairy product i from a choice situation t of J alternatives, given that he belongs to latent class c is

$$\pi(nit \setminus c) = \prod_{t=1}^T \frac{e^{\beta_c X_{nit}}}{\sum_{j=1}^J e^{\beta_c X_{njt}}}, \quad (30)$$

where X_{nit} is a vector of observable attributes associated with dairy product i , and β_c is a class-specific coefficient vector used to capture heterogeneity in preferences across classes; t denotes the number of choice situations for consumer n . The β_c enables one to capture taste heterogeneity in preferences across classes. Unlike the random parameter logit model which allows the parameters to vary across each consumer, the latent class model assumes that the parameters vary across classes of consumers.

In order to construct an unobservable or latent membership likelihood function M^* , it is assumed that a finite number of classes exists in which each consumer can be classified with some probability π_{nc} . Classification variables influencing class membership are related to indicators of an individual's general perceptions and attitudes as well as socioeconomic characteristics. Following Boxall and Adamowicz (2002), this can be described by the following set of equations:

$$\begin{aligned} M_{nc}^* &= \tau_{pc} I_n^* + \tau_c S_n + \xi_{nc} \\ I_n^* &= \alpha_P I_n + \xi_{nP}, \end{aligned} \quad (31)$$

where M_{nc}^* is the membership likelihood function for consumer n and class c ; I_n^* is a vector of general latent perceptions and attitudes (latent psychographic constructs) of consumer n ; S_n is a vector of observed socioeconomic characteristics of consumer n ; I_n is a vector of observed indicators of the latent psychographic constructs held by consumer n ; τ and α_p are parameter vectors to be estimated; and the ξ vectors represent error terms. Relating this function to the classical latent variables approach where observed variables are related to the latent variable, M^* can be expressed at the individual level as:

$$M_{nc}^* = \Gamma_c Z_n + \xi_{nc}, \quad c = 1, \dots, C, \quad (32)$$

where the vector Z_n contains both the indicators of the latent psychographic constructs (I_n) and the socioeconomic characteristics (S_n) of consumer n ; Γ_c is a vector of parameters. Since the membership likelihood functions are random, a distribution of the error terms needs to be specified. Following Swait (1994), the error terms are assumed to be independently distributed across individuals and classes with an extreme value type 1 distribution. Accounting for these assumptions allows the probability of class membership to be characterized by the conditional logit form:

$$\pi(c) = \frac{e^{\Gamma_c Z_n}}{\sum_{c=1}^C e^{\Gamma_c Z_n}} \quad \Gamma_c = 0. \quad (33)$$

The c th parameter vector is normalized to zero to secure identification of the model (Greene 2008).

Since the classes are unknown, the conditional probability in equation (30) cannot be used, instead an unconditional probability is employed. The unconditional probability that consumer n chooses dairy product i in choice situation t is obtained by combining the conditional probability with the class membership probability in equations (30) and (33) to yield (34):

$$\pi(i) = \sum_{c=1}^C \left[\frac{e^{\Gamma_c Z_n}}{\sum_{c=1}^C e^{\Gamma_c Z_n}} \prod_{t=1}^T \frac{e^{\beta_c X_{nit}}}{\sum_{j=1}^J e^{\beta_c X_{njt}}} \right]. \quad (34)$$

This model allows choice attribute data and individual consumer characteristics to simultaneously explain choice behavior. The parameters Γ_c and β_c in equation (34) are estimated jointly using maximum likelihood estimation. As noted by Boxall and Adamowicz

(2002), the class membership function presented in equation (33) is not a behavioral relation, but a statistical classification process. As a result, it is possible to ignore the correlation between the error in the utility functions and the classification function.

It is worth noting that the latent class model does not impose the independence of irrelevant alternatives (IIA) on the observed probabilities (Shonkwiler and Shaw 1997). Furthermore, it is important to note that the latent class model represents a model located within a range of approaches. On one end of the range there is the single segment case which assumes perfect homogeneity of preferences (conditional logit model), and at the other end there is the case in which each individual is considered a segment and has its own set of parameters (random parameter logit/probit model) (Boxall and Adamowicz 2002).

In estimating latent class models the number of classes (or segments) C cannot be defined. Therefore, C must be imposed by the analyst and multiple statistical criteria must be employed to select the optimal number of classes in a set of estimations where the number of classes imposed varies in each estimation. The rationale behind these criteria is that while one expects improvement in the log likelihood values as additional classes are added to the model, the model fits must be penalized for the increase in the number of parameters that are added due to additional classes. The optimal number of classes is reached when additional classes provide little extra information. Within the literature several statistical criteria are employed as a guide to determine the number of latent classes. Following Bhat (1997), Boxall and Adamowicz (2002), and Swait (1994), the minimum Akaike Information Criterion (AIC), the minimum Bayesian Information Criterion (BIC) and ρ^2 have been used in this study to determine the optimal number of classes C . The model associated with the minimum BIC and AIC statistics and the maximum ρ^2 value is selected as the best model to fit the data.

Latent class models are increasingly used within consumer research to study discrete choice among multiple alternatives. For example, Glenk et al. (2012) use latent class models to investigate preferences of Scotch malt whisky consumers regarding the use of pesticides in agriculture and the provenance of food ingredients. Ortega et al. (2011) employ a latent class model (and a random parameter logit model) to assess urban Chinese consumer preferences for select food safety information attributes while Lim et al. (2012) use these models to examine the extent of consumers' willingness to trade-off between U.S. labeled steak and imported Canadian and Australian steak.

3.3.3 Estimation of Willingness-To-Pay for the Attributes

The choice modeling results can be employed to estimate willingness-to-pay (WTP) values for the different attributes. Recall that the total utility associated with a functional dairy product j as evaluated by each consumer n can be written as:

$$U_{jn} = \gamma_n P_{jn} + \beta_n X_{jn} + \varepsilon_{jn}, \quad (35)$$

where P_{jn} denotes the price of alternative j and X_{jn} is a vector of the other observed attributes of alternative j . γ_n is the monetary coefficient on price, β_n represents the coefficient vectors for the other attributes and ε_{jn} is the random term. WTP measures are generally calculated as the rate of change in the attribute divided by the rate of change of the price coefficient (marginal rate of substitution) represented as:

$$WTP = - \left(\frac{\delta U / \delta X_{jn}}{\delta U / \delta P_{jn}} \right) = - \frac{\beta_n}{\gamma_n}. \quad (36)$$

Ninety-five percent confidence intervals for the WTP estimates can be calculated using a parametric bootstrapping technique proposed by Krinsky and Robb (1986). More specifically, a distribution of 2000 observations for each WTP estimate can be simulated by drawing from a multivariate normal distribution parameterized with the coefficient and variance terms obtained from the models. This technique generates analogous results to estimating a standard error using the delta method, however, it relaxes the assumption that WTP is symmetrically distributed (Hole 2007). As noted by Poe et al. (2005), methods that rely on symmetry in confidence bounds such as the delta method are generally inappropriate. In this study, the calculation of WTP as shown in equation (36) is used for the class-specific WTP values in terms of the latent class model. The 95% confidence intervals for the WTP estimates of the latent class model are approximated using the Krinsky and Robb method.

The derivation of WTP measures in a random parameter logit model is a little bit different. Given that one or the other of the coefficients is estimated as a random parameter in this model, the WTP calculations must take this into account. More specifically, a random parameter consists of the mean parameter estimate as well as the derived standard deviation, and as such the WTP calculation has to incorporate both of them.¹³ Furthermore, Hensher and Greene (2003) suggest that to derive behaviorally meaningful WTP values, the distributions

¹³ Section 5.3.2 provides a detailed description of the WTP calculation in terms of the random parameter logit model applied in this study.

from which random parameters are drawn should be constrained. Although little is reported in literature as to the best constraint to use, Hensher et al. (2005) indicate that constraining the standard deviation parameter estimate to equal the mean of the random parameter estimate is quite beneficial in terms of a triangular distribution. WTP measures may be constructed using unconditional parameter estimates (population moments). As such, in using these unconditional estimates, the specific location on the distribution for any given individual is unknown. As noted by Hensher et al. (2005), unconditional parameter estimates are preferred if the analyst wishes to predict outside of the sample and not just within the sample.¹⁴ In order to obtain WTP measures using the unconditional parameter estimates, the population must be simulated. In this study, WTP measures of the random parameter logit model are derived using unconditional mean-constrained random parameter estimates.

3.3.4 Starting Point Bias in Choice Experiments

This section describes the conceptual framework employed in this study to address starting point bias (SPB) in the random parameter logit model. In contrast to dichotomous choice contingent valuation methods (CVMs), the prices attached to the alternatives in choice experiments are shown simultaneously within each choice set and not just as a single alternative with a single price. If SPB is present in a choice experiment, the prices used in the first choice set might influence the perception of the prices in the following choice sets (Ladenburg and Olsen 2008). More specifically, respondents when uncertain about their assessment of the product being valued, anchor the value they place on this product on the price levels proposed to them in the initial choice set. This may happen when the uncertain respondent interprets the price level as an approximation of the product's true value.

In this study, we use a two-split sample approach to test for the presence of SPB. Specifically, sample A was shown a high-priced first choice set, whereas sample B was exposed to a lower set of prices in the first choice set.¹⁵ Ideally, and in accordance with standard assumptions, the respondents' preferences and thus WTP should not be influenced by the set of prices in the first choice set. Thus, samples A and B ought to show similar preferences and WTP estimates.

The conceptual framework employed in this study to address SPB is a slightly modified version of the framework developed in Ladenburg and Olsen (2008) for SPB in choice

¹⁴ The use of conditional parameter estimates means that any output generated is limited to within the sample drawn as part of the study. Prediction outside of the sample is not possible unless one has a very robust set of mapping variables to assign a hold out sample observation to an observation used in model estimation (Hensher et al. 2005).

¹⁵ More detailed information about the two-split sample approach is given in section 4.3.2.

experiments.¹⁶ It is assumed that a utility maximizing individual n is faced with a choice ω related to a single action, $\omega \in (0, 1)$. The choice of action is then assumed to affect the individual's utility through two separate channels, which include a wealth component, W_n , and a health component, or perceived health benefits, M_n . Given these assumptions, the utility function $U(\cdot)$ for an individual n faced with the choice between purchasing or not purchasing functional dairy products, can be represented as:

$$U_n(\omega, g(f, p), c) = M_n(\omega, g(f, p), c) + W_n(\omega, g(f, p)), \quad (37)$$

where g is the stake of the game, which in a choice experiment is a joint function of the attributes (functional dairy product attributes f and price p) of the alternative related to action ω , and c denotes the cost of perceived health benefits. In a choice experiment, the wealth component, W_n , refers to the utility associated with the specific levels of the attributes represented by the alternative chosen in action ω . This component is expected to increase as the price decreases. That is, $\delta W_n / \delta p < 0$. The utility associated with the health component, M_n , relates to the perceived health benefits associated with the action ω and depends on ω , g and c .¹⁷ This implies that individuals derive some utility from opting for healthy functional dairy products. Levitt and List (2007) assume that g is the financial externality an action imposes on others. Applied in the present setting, selecting a high price dairy product could potentially impose a proportional financial externality on other individuals. Given that this assumption is not reasonable in terms of the present setting, we can assume that $\delta M_n / \delta p = 0$. Individuals may accept high cost because the product is perceived to have true health benefits. Hence, the cost positively affects M_n so that $\delta M_n / \delta c > 0$.

Given this model, SPB might influence the health component of utility, $M_n(\omega, g(f, p), c)$. The prices shown in the first choice set might be perceived as signals of higher hidden health benefits. Hence, the prices may signal high quality and as such influence the individual to make correct choices (Cameron and Quiggin 1994), resulting in individuals' WTP values being influenced by the prices of the first choice set through the cost of health factor. If the price levels in the first choice set are perceived as signals of the true health value, WTP estimates are expected to differ between the two samples. More specifically, compared to

¹⁶ They use a modified version of the model applied by Levitt and List (2007) in a laboratory experiment.

¹⁷ Levitt and List (2007) include an additional term s in M , denoting the influence on moral behavior from feeling scrutinized when being observed by an interviewer. Given that our data was collected via a mail survey not involving any direct social interaction, we assume the influence of scrutiny to be negligible, and hence s is left out in equation (37). This assumption is in accordance with Ladenburg and Olsen (2008) using an internet panel survey.

sample A, it is expected that the lower-priced first choice set sample B has a lower health utility component, and hence shows a lower WTP than sample A.

This then leads to the formulation of the null hypothesis that WTP estimates are identical in samples A and B, and as such are independent of the price levels displayed in the first choice set. If the null hypothesis is rejected, the presence of SPB in the data set would be established. Both a *t*-test and the complete combinatorial method proposed by Poe et al. (2005) are employed to test the null hypothesis of identical WTP measures in the two samples and to ensure reliable results. For independent samples, if sufficient memory is available, the complete combinatorial approach provides an exact measure of the difference of two distributions, and seems to be the preferred option (Poe et al. 2005).¹⁸ This non-parametric test calculates every possible difference between the two WTP distributions and does not impose normality assumptions such as the standard *t*-test. More specifically, the complete combinatorial test compares all possible combinations of the WTP estimates and does not assume that WTP is symmetrically distributed, as is the case for the *t*-test. Mørkbak et al. (2011) also apply both a *t*-test and the complete combinatorial test in order to compare different WTP estimates between two samples, and as such to examine whether an embedding effect exists in their choice experiment on food safety characteristics. We examine SPB in the pooled sample, as well as samples disaggregated according to gender, in order to investigate gender-specific SPB. This could also be done by interacting the gender variable with choice attributes.

¹⁸ I am grateful to Gregory L. Poe (Cornell University) for sending me the NLOGIT/Limdep program file originally written by Christian Vossler (University of Tennessee-Knoxville) in order to use the complete combinatorial method.

4. Methodology

4.1 Introduction

This chapter presents the methods used in the choice experiment study. The choice experiment method is discussed, including a description of the functional dairy product attributes and the choice experiment design used to create sets of discrete choice alternatives. The survey design is then described, followed by a discussion of principal component analysis used to reduce psychographic variables (perceptual and attitudinal indicators). Finally, variables employed and data are presented.

4.2 Choice Experiments

A choice experiment is an attribute-based stated preference method assessing the value of goods and characteristics of goods by using individuals' stated behavior in a hypothetical setting. Individuals are asked to choose their preferred alternative from a set of competing alternatives (referred to as choice set). Most commonly, each individual faces several choice sets within a single survey. Each alternative is described by a number of attributes, one of which is a monetary attribute, and the levels of the attributes vary between alternatives and choice sets. Attributes and their levels are identified and combined according to an experimental design to create choice sets. Analysts can then measure how individuals' choices change as the attributes and monetary amounts vary. Different models can then be used for choice data analysis in order to measure the utility for the different attributes and their levels. Given that stated preference data refer to situations in which a choice is made by considering hypothetical situations, these data are especially useful when analyzing new alternatives not traded on real markets (yet). Studies on consumers' preferences have employed different stated preference methods such as conjoint analysis, contingent valuation method (CVM), and choice experiments (Darby et al. 2008; Lusk 2003; Rigby and Burton 2005). Choice experiments differ from conjoint analysis in that individuals are asked to choose from a set of alternatives described by several attributes instead of ranking them. The choice-based task is similar to what consumers actually do in real markets, and as such choice experiments are quite more realistic than conjoint analysis. Choosing a preferred product from a group of products is a simple task that can easily be understood. A choice experiment is a generalization of CVM in the sense that rather than asking respondents to choose between a base case and a specific alternative, choice experiments ask respondents to choose between cases that are described by attributes (Adamowicz et al. 1998). However, CVM is commonly known to suffer from hypothetical bias. Therefore, choice experiments appear to be advantageous to both conjoint analysis and CVM.

4.2.1 Identification of Dairy Products and Relevant Attributes

The term functional food is used to describe foods enriched with specific ingredients generating certain health benefits. Therefore, functional foods are products marketed with health claims that indicate the relationship existing between the consumption of food items and the individual's health. The present study focuses on functional dairy products since they constitute one of the most important groups of functional foods in Germany. Specifically, yoghurt, cream cheese, and ice cream were chosen for investigation. Yoghurt was selected since it is the most successful carrier for functional ingredients and it is perceived as intrinsically healthy (Annunziata and Vecchio 2011). Cream cheese was accounted for because it remained of marginal importance in terms of being a preferable carrier for functional ingredients. This may be attributed to its unhealthy image (Euromonitor 2004). Given that ice cream represents a hedonic product, it was chosen in order to examine consumers' acceptance. As noted by van Kleef et al. (2002), consumers consider hedonic products like ice cream as significantly more suitable carriers for several functional ingredients than food technologists.

The complete set of attributes employed in the choice experiments and their respective levels are presented in table 2. In line with Lancaster's attribute theory of value, two attributes, namely functional ingredient and health claim, were included in the design of the choice experiment. These two attributes are quite important in terms of functional foods, since they are normally displayed on the product package, and as such tend to influence consumers' purchasing decisions. An additional monetary attribute, purchase price, was selected to capture WTP for the attributes. Each attribute was described by four different levels. The different purchase price levels considered were based on the existing market prices for functional dairy products and their conventional counterparts. Omega-3 fatty acids, oligosaccharides, bioactive peptides, and polyphenols were selected as the relevant ingredient levels, since this study takes place within Food Chain Plus (FoCus) and FoCus examines all of them along the entire process chain.¹⁹ In particular, FoCus analyzes their effects on blood vessels, and as such the health claim levels were identified accordingly.²⁰ The first health claim (HC 1) is a general, short health claim, whereas the second health claim (HC 2) represents a general, long health claim. Both health claim three (HC 3) and health claim four

¹⁹ Omega-3 fatty acids are polyunsaturated fatty acids commonly found in fish. Oligosaccharides are classified as dietary fibers found in milk or produced synthetically. Bioactive peptides are protein fragments found in milk. Polyphenols are defined as secondary plant compounds and occur in fruits and vegetables.

²⁰ As indicated previously, FoCus is a project at the Christian-Albrechts-University of Kiel which analyzes the food supply chain among the entire process chain by focusing on functional dairy products.

(HC 4) depend on the ingredient, while HC 3 is a short claim and HC 4 is a long claim (actually, HC 4 is a combination of HC 1 and HC 3).

Table 2 Attributes and attribute levels used in the choice experiment

Attributes	Attribute levels		
Price ^a	Yoghurt	Cream cheese	Ice cream
	1. 1.29€/500g (basic ^b)	1. 1.49€/200g (basic ^b)	1. 3.19€/1000ml (basic ^b)
	2. 1.49€/500g	2. 1.69€/200g	2. 3.49€/1000ml
	3. 1.79€/500g	3. 2.09€/200g	3. 3.99€/1000ml
Functional ingredient	4. 2.09€/500g	4. 2.49€/200g	4. 4.49€/1000ml
	1. Omega-3 fatty acids (Omega)		
	2. Oligosaccharides (Olig)		
	3. Bioactive peptides (Bio)		
Health claim	4. Polyphenols (Poly)		
	1. Supports healthy blood vessels. (HC 1)		
	2. Supports healthy blood vessels and healthy metabolism. (HC 2)		
	3. One property depending on the ingredient ^c (HC 3)		
	4. Two properties depending on the ingredient ^d (HC 4)		

^aExchange rate: 1 U.S. \$ = 0.74€.

^bThe basic price represents the price of the conventional non-functional food alternative included in each choice set.

^ca) Omega-3 fatty acids: Supports healthy blood triglyceride levels. b) Oligosaccharides: Supports healthy digestion. c) Bioactive peptides: Supports healthy blood pressure. d) Polyphenols: Protects body's cells against free radicals.

^da) Omega-3 fatty acids: Supports healthy blood vessels and healthy blood triglyceride levels. b) Oligosaccharides: Supports healthy blood vessels and healthy digestion. c) Bioactive peptides: Supports healthy blood vessels and healthy blood pressure. d) Polyphenols: Supports healthy blood vessels and protects body's cells against free radicals.

4.2.2 Choice Experiment Design

Once the attributes and corresponding levels have been selected, attribute levels have to be combined according to an experimental design to create alternatives and choice sets to be presented to each respondent. Experimental designs are fundamental parts of choice experiments. Several authors (e.g., Kuhfeld et al. 2004; Louviere et al. 2000) have highlighted the importance of experimental designs in developing reliable choice experiments. As noted by Louviere et al. (2000), the key statistical properties relevant to the design of choice experiments are identification and precision, which must be considered together with non-statistical properties such as realism and complexity. The aim of choice experiment designs is to maximize orthogonality and balance (Lusk and Norwood 2005). Perfect orthogonality necessitates that across the design all attributes are statistically independent of one another, implying zero correlations between the attributes. Balance requires that each level of each attribute occurs with equal frequency.

A full factorial design achieves perfect orthogonality and balance. It is defined as a design containing every possible combination of attribute and attribute level (Hensher et al. 2005). Each level of each attribute is combined with every level of all other attributes. For a full factorial design, all main effects, all two-way interactions, and all higher-order interactions are estimable and uncorrelated. As noted by Hensher et al. (2005), a main effect is defined as the direct independent effect of each attribute on a dependent variable. It is the difference in the means of each level of an attribute and the grand mean. An interaction effect, however, is the effect on a dependent variable obtained by combining two or more attributes which would not have been observed had each of the attributes been estimated separately. The point of concern in a full factorial design is that, such designs are practical only for small problems involving either small numbers of attributes or levels or both. The vast majority of stated preference problems are too large to allow one to use full factorials (Louviere et al. 2000). A number of different strategies have been employed to reduce the number of choice sets given to respondents, such as reducing the number of levels used within the design, using fractional factorial designs, blocking the design or using a fractional factorial design combined with a blocking strategy.

Fractional factorial designs are generated by selecting subsets of choice sets from the full factorial design (Lusk and Norwood 2005). In order to choose which choice sets to use, the analyst may randomly select a number of choice sets from the full factorial without replacement. However, random selection produces statistically inefficient or sub-optimal designs. An alternative strategy to select optimal combinations is to select the smallest orthogonal main effects design from the full factorial, which is determined by the total degrees of freedom required to estimate all implied main effects (Louviere et al. 2000). The total degrees of freedom are determined by summing the separate degrees of freedom in each main effect. Each main effect has exactly $L - 1$ degrees of freedom, where L is the number of levels of the attributes.²¹ In a main effects only design, a sub-set of the full factorial design is selected in such a way that all main effects are identifiable and completely orthogonal with each other (Lusk and Norwood 2005). Using a main effects only design significantly reduces the number of choice sets needed in an analysis. However, all fractional designs involve some

²¹ This is just true for non-linear effects (dummy or effects coded variables) which are mainly estimated. As noted by Hensher et al. (2005), assuming the estimation of a main effects only model, the degrees of freedom required of a design depend upon the types of effects to be estimated (linear or non-linear effects) and whether the design is labeled or unlabeled (experiments that use generic titles for the alternatives are called unlabeled experiments). For a detailed description see Hensher et al. (2005).

loss of statistical information, since only a fraction of the total number of possible combinations is employed.

The blocking design strategy is another method used to reduce the number of choice sets shown to any particular respondent. Blocking involves the analyst introducing another orthogonal column to the design, the attribute levels of which are used to segment the design (Hensher et al. 2005). For instance, considering a choice experiment with four different attributes, each described by two levels, the full factorial design yields a total of 16 treatment combinations. An additional four level orthogonal blocking variable may be introduced, thus producing four blocks of treatment combinations of size four. Each block is then given to a different respondent, implying that four different decision makers are required to complete the full design. If a two-level column is used, then two respondents will each receive eight treatment combinations. The main disadvantage in blocking design strategies is the increase in sample size required to complete the full factorial design.

Several researchers have suggested that from a statistical perspective, experimental designs underlying stated preference methods should impart the maximum amount of information about the parameters of the attributes relevant to each specific choice task, something that cannot be guaranteed with an orthogonal fractional factorial design (Hensher et al. 2005). This has resulted in the generation of designs known as optimal or statistically efficient designs. Several authors have addressed the generation of statistically efficient designs (e.g., Huber and Zwerina 1996, Kuhfeld et al. 2004). The difference between optimal designs and orthogonal fractional factorial designs is that optimal designs are statistically efficient while orthogonal fractional factorial designs have no correlations. More specifically, optimal designs optimize the amount of information obtained from a design. However, they are not perfectly orthogonal, since the attributes are very likely to be correlated. Attributes of an orthogonal fractional factorial design are statistically independent (i.e. uncorrelated).²² However, this kind of design may not be the most statistically efficient design available.

As noted by Hensher et al. (2005), the literature on optimal designs has tended towards designs which maximize the determinant of the variance-covariance matrix of the model to be estimated. Such designs are commonly known as D-optimal designs. In order to determine the

²² As noted by Rose and Bliemer (2004), orthogonality is likely lost in the data sets and during estimation process since parameters are estimated from the data sets received from the choice experiment and not from the design itself.

D-optimal design, it is common to use the inversely related measure to calculate the level of D-efficiency. More specifically, it is usual to minimize the determinant of the inverse of the variance-covariance matrix which is known as D-error, and as such minimizing the D-error corresponds to minimizing the elements of the variance-covariance matrix. A-efficiency and G-efficiency are two further possibilities used to measure the goodness of experimental designs. Kuhfeld et al. (2004) provide a detailed description of efficient experimental design generation and discuss A-, D-, and G-efficiency.

In this study, an orthogonal main effects design combined with a blocking strategy is created using SPSS software version 18 (PASW Statistics 2009).²³ A full factorial design which includes all possible combinations of the attributes would yield 64 (three attributes with four levels each, that is, 4^3) possible generic choice sets for yoghurt, cream cheese and ice cream, respectively.²⁴ Therefore, the whole design would consist of 192 (64×3) possible choice sets. Presenting decision makers with 192 choice sets may place a significant level of cognitive burden on respondents, which is likely to result in response unreliability. Therefore, an orthogonal main effects design has been generated from the full factorial design for each dairy product to create feasible choice sets. The main effects design is determined by the total degrees of freedom needed to estimate all implied main effects. An assumption has been made that all interaction effects of the attributes are not significantly different from zero. This assumption is justifiable given the findings of Dawes and Corrigan (1974) that the majority of variance within linear models can be explained by main effects only. Their findings imply that 70-90% of variance in linear models may be explained by main effects and the remaining 10-30% by interaction effects. In this study, the design has resulted in 32 choice sets for yoghurt, cream cheese and ice cream, respectively. Choice sets that just differed in one attribute level and that would have predefined consumers' choice (e.g., two identical products with different prices) have been excluded. This has resulted in 28 choice sets for yoghurt, cream cheese and ice cream, respectively.²⁵ An additional four level blocking variable has been introduced, and as such each respondent receives seven of the 28 choice sets per product (that is, each respondent evaluates a total of 21 choice sets). An effects coding structure for the attributes

²³ As noted by Hensher et al. (2005), several statistical packages (e.g., SPSS, Minitab, and SAS) are capable of generating experimental designs that may be of use.

²⁴ Generic choice sets imply that they do not refer to any particular brand.

²⁵ As indicated previously, the smallest orthogonal main effects design from the full factorial is determined by the total degrees of freedom required to estimate all implied main effects. Given that the present study accounts for three different attributes each described by four different levels, a minimum of ten degrees of freedom is required (nine plus one additional degree of freedom). That is, 28 choice sets are enough to estimate the parameters in our model.

and levels has been used in order to avoid confoundment with the grand mean of the utility function and to measure non-linear effects in the attribute levels (Hensher et al. 2005). Effects coding uses values for codes, which when summed over any given attribute, equal zero. By dummy coding the data, the base level of an attribute is perfectly confounded with the grand mean (that is, with the zero-utility associated with the conventional non-functional food alternative, which is the base level for the representative component of the utility function). Therefore, effects coding is the preferred coding structure as opposed to dummy coding. Table 3 presents a description of the effects coding structure for the attributes used in estimating the choice experiment models.

Table 3 Effects coding structure for the attributes

Variables	Units
Price	Price in €
Omega-3 fatty acids (Omega)	1 = omega-3 fatty acids, 0 = oligosaccharides, 0 = bioactive peptides, -1 = polyphenols
Oligosaccharides (Olig)	0 = omega-3 fatty acids, 1 = oligosaccharides, 0 = bioactive peptides, -1 = polyphenols
Bioactive peptides (Bio)	0 = omega-3 fatty acids, 0 = oligosaccharides, 1 = bioactive peptides, -1 = polyphenols
HC 1 ^a	1 = HC 1, 0 = HC 2, 0 = HC 3, -1 = HC 4 ^d
HC 2 ^b	0 = HC 1, 1 = HC 2, 0 = HC 3, -1 = HC 4
HC 3 ^c	0 = HC 1, 0 = HC 2, 1 = HC 3, -1 = HC 4

^aSupports healthy blood vessels.

^bSupports healthy blood vessels and healthy metabolism.

^cOne property depending on the ingredient.

^dTwo properties depending on the ingredient.

A conventional (non-functional) alternative has also been included in each choice set to act as a baseline alternative and to ensure that respondents are not forced to choose functional dairy products, which they may not desire at all. Each choice set consists of three alternatives: a conventional non-functional food alternative offered to the basic price and two functional food alternatives. Table 4 presents the choice sets for all three dairy products for block one. As indicated previously, there are four generated blocks. Choice sets generated for the other blocks are presented in appendix 1.

Table 4 Choice sets for all three dairy products (block one)

Choice set	Alt	Price (yoghurt/cream cheese/ice cream)	Omega	Olig	Bio	HC 1	HC 2	HC 3	Block
1	1	1.29€/1.49€/3.19€	0	0	1	0	0	1	1
1	2	1.79€/2.09€/3.99€	1	0	0	0	0	1	1
1	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	1
2	1	1.49€/1.69€/3.49€	-1	-1	-1	0	0	1	1
2	2	1.49€/1.69€/3.49€	0	1	0	1	0	0	1
2	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	1
3	1	1.79€/2.09€/3.99€	1	0	0	-1	-1	-1	1
3	2	2.09€/2.49€/4.49€	-1	-1	-1	0	1	0	1
3	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	1
4	1	2.09€/2.49€/4.49€	-1	-1	-1	0	1	0	1
4	2	1.79€/2.09€/3.99€	0	0	1	0	1	0	1
4	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	1
5	1	1.49€/1.69€/3.49€	0	1	0	1	0	0	1
5	2	2.09€/2.49€/4.49€	0	1	0	0	0	1	1
5	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	1
6	1	2.09€/2.49€/4.49€	0	1	0	-1	-1	-1	1
6	2	1.29€/1.49€/3.19€	0	0	1	-1	-1	-1	1
6	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	1
7	1	1.79€/2.09€/3.99€	0	0	1	0	1	0	1
7	2	1.49€/1.69€/3.49€	-1	-1	-1	-1	-1	-1	1
7	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	1

In order to construct the choice sets for the survey, the numerical codes have been replaced with the descriptive attribute level labels.

4.3 Survey Design

The data used in the analysis are from a survey conducted nationwide in Germany from November 2010 to January 2011. A pretest of the questionnaire was undertaken with 55 randomly selected individuals in order to ensure that respondents understand questions correctly. Addresses of the respondents were obtained from an agency (Schober Group) offering addresses for surveys and ensuring a representative sample of the German population in terms of gender, region, and age. Households of this agency agreed that they are willing to participate in surveys. Given that the present study examines functional foods which are products capable of generating health benefits and considering the fact that older people are more concerned with health than younger people (Roininen et al. 1999), respondents were surveyed by mail since it is easier for older people to participate in a paper-and-pencil survey than in an online survey. In order to increase the response rate, the following methods were applied. First, each respondent was offered to donate one Euro to one of a number of well-known charity organizations in return for participation (needless to say, that we transferred the Euro to the organization). Second, respondents could send the completed questionnaire

back by using a stamp-free envelope. Third, the anonymity of the respondents and the confidentiality of the answers were ensured.

4.3.1 Sample Size Determination

The sample was restricted to consumers aged 18 and above living in Germany. The calculation of the sample size followed the layout and description by Hensher et al. (2005) for choice data. For simple random samples, the minimum acceptable sample size, n , depends on the desired level of accuracy of the estimated probabilities, \hat{p} . If p is the true choice proportion of the relevant population, α is the level of allowable deviation as a percentage between \hat{p} and p , and β is the confidence level of the estimation such that $Pr(|\hat{p} - p| \leq \alpha p) \geq \beta$ for a given n , where $\beta = 1 - \alpha$. The minimum sample size is defined as:

$$n \geq \frac{q}{pa^2} \left[\Phi^{-1} \left(1 - \frac{\alpha}{2} \right) \right]^2, \quad (38)$$

where q is defined as $1 - p$ and $\Phi^{-1} \left(1 - \frac{\alpha}{2} \right)$ is the inverse cumulative distribution function of a standard normal (i.e. $N \sim (0,1)$) taken at $\left(1 - \frac{\alpha}{2} \right)$. The minimum sample size calculated using equation (38) represents the sample size required if each respondent is shown a single choice set. Therefore, it is not the minimum population sample size needed for the study, but rather the minimum number of total choices that are necessary to replicate the true population proportion within the acceptable error. In most stated preference studies, each decision maker is given multiple choice sets in the choice task, so that each individual does r choice sets. The minimum number of respondents required for a given choice study, is equal to the minimum number of choices divided by the number of choice sets r each decision maker is shown as part of the choice study.

In this study, a true population proportion p , of consumers who buy functional dairy products is approximated to be 12% based on ACNielsen (2006). A 10% level of allowable deviation of the drawn sample proportion from the true population proportion is assumed (Louviere et al. 2000). Substituting this into equation (38), yields 2817 number of choices. Given that each respondent evaluates seven choice sets, a minimum sample size of 402 individuals is yielded as shown in table 5. Assuming a response rate of 15%, a total of 2683 questionnaires were mailed to households in Germany in order to achieve the minimum sample size, and as such

obtain reliable and valid results. Based on available literature, a response rate of 15-20% can be assumed in mail surveys (paper-and-pencil surveys).

Table 5 Sample size determination

p	a	$q = (1 - p)$	r	Z^2	$\frac{q}{pa^2} \left[\Phi^{-1} \left(1 - \frac{\alpha}{2} \right) \right]^2$	$\frac{q}{rpa^2} \left[\Phi^{-1} \left(1 - \frac{\alpha}{2} \right) \right]^2$
0.12	0.1	0.88	7	3.8416 ^a	2817	402

Adapted from Hensher et al. (2005).

^a $\alpha = 0.05$ and $1 - \frac{\alpha}{2} = 0.975$ and $Z = 1.96$.

In this study, the total number of respondents was 1309 corresponding to a response rate of 49%. Achieving such a high response rate may be attributed to the fact that households participating are used to surveys.

4.3.2 Survey Instrument

As indicated previously, questionnaires were mailed to households. In the questionnaire, after welcoming the respondent and explaining the purpose of the research in the cover letter accompanying the questionnaire, information was provided about the term functional food. Next, respondents were asked to score several functional food and healthy diet related statements on a 7-point Likert scale with categories ranging from “completely disagree” to “completely agree”.²⁶ After providing information about the attributes used in the choice experiment, the choice sets for yoghurt, cream cheese, and ice cream were presented and respondents were asked to indicate which product they would purchase in each choice set. As noted earlier, each respondent evaluated a total of 21 choice sets, that is, seven choice sets per product. Finally, the questionnaire gathered information about socioeconomic aspects, as well as health behavior and lifestyle issues such as cigarette consumption and level of physical activity. The questionnaire is presented in appendix 2. The data setup followed the layout and description by Hensher et al. (2005) for choice data using NLOGIT software version 4.0 (Econometric Software, Inc. 2007).

As indicated in section 3.3.4, a two-split sample approach was employed in the choice experiment to investigate the presence of starting point bias (SPB) in the random parameter logit model. Specifically, two different versions of the questionnaire were given to samples A and B, that is, half of the 2683 questionnaires were mailed to sample A and the other half to sample B. The two versions only varied with respect to the first choice set of each dairy product: respondents answering version one (sample A) started with a first choice set

²⁶ More information about the statements is given in section 4.4.2.

displaying high price levels for the alternatives, whereas respondents answering version two (sample B) began with a first choice set displaying low price levels for the alternatives.²⁷ Both choice sets were selected from the orthogonal main effects design.²⁸ As indicated earlier, a response rate of 49% was achieved, yielding a total of 655 and 654 useable questionnaires for samples A and B, respectively.

4.4 Principal Component Analysis

4.4.1 Background

Principal component analyses are used to reduce psychographic variables (perceptual and attitudinal indicators shown in figure 3) entering the membership likelihood function in terms of latent class estimation. Principal component analysis is a statistical technique used for data reduction, and as such is employed to find optimal ways of combining variables into a small number of subsets (Field 2005).

The reliability of principal component analysis is dependent on sample size. Much has been written about the necessary sample size for principal component analysis. Backhaus et al. (2006) recommend having three times as many participants as variables. Tabachnick and Fidell (2001) suggest that a researcher has at least 300 cases for principal component analysis and Comrey and Lee (1992) class 300 cases as a good sample size, 100 as poor and 1000 as excellent. Even though principal component analysis does not rely on any distributional assumptions it is advisable to test if the variables used for the analysis are normally distributed (Backhaus et al. 2006). The reliability of principal component analysis is subsequently tested using the following test criteria:

- Bartlett's test of sphericity
- Kaiser-Meyer-Olkin measure of sampling adequacy

The Bartlett's test of sphericity tests the null hypothesis that the original correlation matrix is an identity matrix. For principal component analysis to work there need to be some relationships between variables and if the correlation matrix resembles an identity matrix then all correlation coefficients will be zero, or, more precisely, this means that variables only

²⁷ Given that an orthogonal main effects design combined with a blocking strategy was generated in order to reduce the number of choice sets, the prices displayed in the first choice set differ between the four generated blocks. For example in sample A block two the first choice set for yoghurt (cream cheese/ice cream) displayed prices of 2.09€ (2.49€/4.49€) and 1.79€ (2.09€/3.99€) for alternatives 1 and 2, respectively. Sample B block two, however, employed a lower set of prices for yoghurt (cream cheese/ice cream) at 1.29€ (1.49€/3.19€) and 1.29€ (1.49€/3.19€) for alternatives 1 and 2, respectively.

²⁸ Our two-split sample approach differs from the one used by Ladenburg and Olsen (2008), insofar as they employed different sets of price levels in an Instructional Choice Set (ICS) presented prior to the actual choice sets. In order to make our choice experiment as realistic as possible, we explicitly did not introduce respondents to an ICS, and as such did not remind them to be in a hypothetical environment.

correlate with themselves. As a result, principal component analysis will not provide a stable component solution.

The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) can be calculated for individual and multiple variables and represents the ratio of the squared correlation between variables to the squared partial correlation between variables. The KMO statistic varies between zero and one. A value of zero indicates that the sum of partial correlations is large relative to the sum of correlations, showing diffusion in the pattern of correlations. As a result, principal component analysis does not yield distinct and reliable components. A value close to one indicates that patterns of correlations are relatively compact and so principal component analysis is likely to be appropriate (Field 2005). A value of 0.5 is a suggested minimum (Kaiser 1974).

The determination of the number of components (component extraction) plays a major role in principal component analysis, and there are several criteria to decide which components should be retained. The following two techniques are quite common to determine whether a component is statistically important and should be extracted:

- Kaiser's criterion
- Scree plot

Kaiser's criterion recommends retaining all components with eigenvalues greater than one. Eigenvalues represent the amount of variation explained by a component, and as such are the variances of the principal components. Kaiser's criterion is based on the idea that components with an eigenvalue of less than one account for less variance than did the original variable which had a variance of one. The scree plot provides another reliable criterion for component selection (Stevens 1992). This plot graphs each eigenvalue against the component with which it is associated. By graphing the eigenvalues, the relative importance of each component becomes apparent. Usually there will be a few components with quite high eigenvalues, and many components with relatively low eigenvalues, and so this graph has a very characteristic shape: there is a sharp descent in the curve followed by a tailing off. The cut-off point should be at the point of inflexion of this curve and determines which and how many components should be retained (Cattell 1966).

Once components have been extracted, it is possible to calculate to what degree variables load onto these components (i.e. calculate the loadings of the variable on each component). Component loadings are the correlations between the variables and the components, and as such normally range from minus one to one. In general, most variables have high loadings on

the most important component, and small loadings on all other components. A technique called component rotation is used in order to discriminate between components and to facilitate the interpretation of components. If a component is a classification axis along which variables can be plotted (the axis line ranges from minus one to one, which are the outer limits of a correlation coefficient), then component rotation effectively rotates these component axes such that variables are loaded maximally to only one component (Field 2005). More specifically, rotation maximizes the loading of each variable on one of the extracted components whilst minimizing the loading on all other components. There are two types of rotation:

- Orthogonal rotation
- Oblique rotation

Before rotation, all components are independent and orthogonal rotation ensures that the components remain uncorrelated. Oblique rotation, however, allows the components to be correlated, and as such is said to be more realistic (Hair et al. 1998).

As indicated previously, components can be described in terms of the variables measured and the relative importance of them for that component. Having discovered which components exist, it is also possible to estimate an individual's score on a component, based on their scores for the constituent variables. Therefore, any further analysis can be carried out on the component scores rather than the original data (Field 2005). Component scores are linear composites, formed by standardizing each variable to zero mean and unit variance, and then weighting with score coefficients and summing for each component.

Finally, after principal component analysis, the reliability of the scale used for the questionnaire is tested in order to ensure accuracy of measurement, and as such consistency of the questionnaire. More specifically, with regard to the retained components the internal consistency is measured, that is, how closely related a set of statements is as a group. The most common measure of scale reliability is Cronbach's alpha (Cronbach 1951). Cronbach's alpha determines the internal consistency or average correlation of variables to gauge its reliability. Cronbach's alpha (α) is:

$$\alpha = \frac{k}{k-1} \left(1 - \frac{\sum_{i=1}^k S_i^2}{S_t^2} \right), \quad (39)$$

where k is the number of variables (statements), S_i^2 is the variance of variable (statement) i , and S_t^2 is the variance of the scale. Cronbach's alpha ranges in value from zero to one. A value of 0.6 is a suggested minimum; values substantially lower indicate an unreliable scale, and as such principal component analysis would not provide a stable component solution (Hair et al. 1998).

4.4.2 Generated Components

This section presents the generated components obtained from principal component analysis. Two analyses have been carried out to locate underlying dimensions (or rather the components) of consumers' attitudes towards functional foods and a healthy diet. These underlying dimensions enter the membership likelihood function in terms of latent class estimation. Components describing the attitudes towards functional foods are presented first. The results of principal component analysis used to assess consumers' attitudes towards a healthy diet are then reported. The principal component analyses have been carried out using SPSS software version 18 (PASW Statistics 2009).

Functional food related statements developed by Urala and Lähteenmäki (2007) have been included in the questionnaire in order to examine consumers' attitudes towards functional products using principal component analysis. One extra statement has been added dealing with the willingness-to-pay (WTP) for functional products ("I happily pay a higher price for foods with health claims.") (Landström et al. 2007). A total of 27 functional food related statements have been scored on a 7-point Likert scale with categories ranging from "completely disagree" to "completely agree".

As indicated previously, the reliability of principal component analysis is also dependent on sample size. Since a sample size of 1309 respondents has been achieved, the recommendations made by Backhaus et al. (2006), Tabachnick and Fidell (2001), and Comrey and Lee (1992) in terms of the necessary sample size for principal component analysis are taken into account. The ratings of negatively worded statements have been reversed before conducting principal component analysis in order to ensure a positive Cronbach's alpha and to facilitate component interpretation in terms of latent class estimation. Furthermore, the distributions of the statement variables have been studied using the Kolmogorov-Smirnov test in order to examine if they are significantly different from a normal distribution. Every test has been significant implying that the distributions of the statement variables are significantly different from a normal distribution. However, since the Kolmogorov-Smirnov test is a quite

strict test, histograms have been plotted for each statement variable in order to investigate if the distributions of the statement variables are close to normality. Resulting histograms have revealed that the distributions are quite normal looking, and since principal component analysis does not rely on any distributional assumptions this finding is considered to be adequate.

The reliability of principal component analysis has been tested using the test criteria presented in the previous section. Table 6 summarizes these test statistics and provides a short interpretation of results.

Table 6 Test criteria – principal component analysis in terms of functional food statements

Test value	Value (p-value/KMO-value)	Interpretation
Bartlett's test of sphericity	0.000 (p-value)	Null hypothesis is rejected; variables are correlated in the population.
Kaiser-Meyer-Olkin measure of sampling adequacy:		
Overall KMO statistic (multiple variables)	0.951 (KMO-value)	Kaiser evaluates this value as marvelous.
Lowest KMO statistic (for one individual variable)	0.826 (KMO-value)	Kaiser evaluates this value as meritorious.
Highest KMO statistic (for one individual variable)	0.982 (KMO-value)	Kaiser evaluates this value as marvelous.

All test criteria indicate a high reliability of the following principal component analysis. The Bartlett's test of sphericity is highly significant, and as such provides evidence of correlations between statement variables. The KMO values easily fulfill Kaiser's requirement of 0.5. As noted by Kaiser (1974), values between 0.8 and 0.9 are meritorious and values above 0.9 are marvelous. For these data, values either fall into the range of being meritorious or marvelous.

Since components are supposed to be correlated on theoretical grounds, it is reasonable to choose an oblique rotation. Given that the data set is very large – there are more than 1000 observations – promax rotation has been used (Hendrickson and White 1964). Promax represents an oblique rotation method commonly used for very large data sets (Brosius 2006; Field 2005).

In order to determine the number of components, Kaiser's criterion and the scree plot have been used. Both criteria have suggested that four components are statistically important, and

as such should be retained. These four components account for 59.4% of variance and can be interpreted as follows:

- Reward from using functional foods
- Necessity for functional foods
- Confidence in functional foods
- Safety of functional foods

Components are labeled with the same names as those used by Urala and Lähteenmäki (2007).

The first component is termed *reward from using functional foods*. Table 7 presents the statements that load highly onto this component as well as component loadings. As recommended by Kline (1994), only component loadings with an absolute value greater than 0.3 are interpreted. This is a reasonable criterion when the sample size is at least 100 (Kline 1994).

Table 7 Component 1 – reward from using functional foods

	Component loadings ^a			
	1	2	3	4
Functional foods help to improve my mood.	0.936	-0.106	-0.128	0.024
My performance improves when I eat functional foods.	0.920	-0.062	-0.058	-0.067
I actively seek out information about functional foods.	0.863	-0.170	-0.170	0.067
Functional foods can repair the damage caused by an unhealthy diet.	0.797	-0.145	-0.033	0.088
The idea that I can take care of my health by eating functional foods gives me pleasure.	0.790	0.021	0.050	-0.009
I am prepared to compromise on the taste of a food if the product is functional.	0.764	-0.136	-0.042	0.025
Functional foods make it easier to follow a healthy lifestyle.	0.724	0.084	0.109	-0.063
I can prevent disease by eating functional foods regularly.	0.685	0.075	0.185	-0.086
Functional foods promote my well-being.	0.682	0.100	0.154	-0.078
I happily pay a higher price for foods with health claims.	0.516	0.091	0.155	0.028

^aCorrelations between the variables and the components.

The statements that load highly onto component 1 all seem to relate to the rewarding aspect derived from the consumption of functional foods. The main focus of this component is that health, mood, and general well-being can be promoted by consuming functional foods. A high score on this component indicates that a respondent perceives the consumption of functional foods to be more pleasing and rewarding than a respondent whose score is low.²⁹

²⁹ An individual's score on a component has been calculated based on its scores for the constituent variables (statements). Latent class analyses are carried out on the component scores rather than the original data.

The second component describes the attitude towards the perceived need for functional foods. Therefore, this component is labeled *necessity for functional foods*. Statements that load highly onto this component and component loadings are displayed in table 8.

Table 8 Component 2 – necessity for functional foods

	Component loadings ^a			
	1	2	3	4
R I only want to eat foods that do not have any medicine-like effects.	-0.366	0.845	0.078	-0.160
R Health effects are not appropriate in delicacies.	-0.198	0.838	-0.027	-0.092
R Functional foods are consumed mostly by people who have no need for them.	-0.021	0.673	-0.082	0.125
R The growing number of functional foods on the market is a bad trend for the future.	-0.005	0.654	0.046	0.129
R It is pointless to add health effects to otherwise unhealthy foods.	0.024	0.639	-0.183	0.164
R Functional foods are a total sham.	0.163	0.611	0.073	0.014
R Functional foods are completely unnecessary.	0.330	0.577	-0.031	0.003
R For a healthy person it is worthless to use functional foods.	0.309	0.574	-0.115	0.101
R Exaggerated information is given about health effects.	0.147	0.441	-0.191	0.141

R = negative statement.

^aCorrelations between the variables and the components.

All statements loading highly onto this component have been negatively worded. In order to facilitate component interpretation, the ratings of these negatively worded statements have been reversed. This component measures how necessary or unnecessary functional foods are especially for society in general. Respondents who have a high score on this component believe that functional foods are completely necessary whereas respondents who have a low score regard functional foods as unnecessary.

The statements that load highly onto the third component all seem to relate to the consumers' confidence in functional foods. Therefore, this component is termed *confidence in functional foods*. Table 9 presents the statements that load highly onto this component and their associated component loadings.

Table 9 Component 3 – confidence in functional foods

	Component loadings ^a			
	1	2	3	4
The safety of functional foods has been very thoroughly studied.	-0.144	-0.123	0.974	0.020
Using functional foods is completely safe.	-0.017	-0.231	0.772	0.383
Functional foods are science-based top products.	0.173	0.015	0.737	-0.066
I believe that functional foods fulfill their promises.	0.235	0.148	0.618	-0.071
It is great that modern technology allows the development of functional foods.	0.332	0.207	0.350	-0.115

^aCorrelations between the variables and the components.

The main focus of this component is the credibility of functional foods and the belief in the scientific basis of promised health effects. A high score on this component means that a respondent trusts the information about functional foods. A low score indicates a respondent's distrust of functional foods.

The fourth component is labeled *safety of functional foods*. Statements that load highly onto this component as well as component loadings are displayed in table 10.

Table 10 Component 4 – safety of functional foods

	Component loadings ^a			
	1	2	3	4
R If used in excess, functional foods can be harmful to health.	0.047	-0.002	-0.039	0.858
R In some cases functional foods may be harmful for healthy people.	-0.045	0.050	0.076	0.839
R The new properties of functional foods carry unforeseen risks.	-0.061	0.214	0.212	0.563

R = negative statement.

^aCorrelations between the variables and the components.

Given that all statements loading highly onto this component have been negatively worded, ratings of these statements have been reversed in order to facilitate component interpretation. This component focuses on the possible nutritional risks and harmful aspects associated with the consumption of functional foods. Respondents who have a high score on this component believe that functional foods are completely safe. In contrast, low scores indicate that respondents regard functional foods as harmful.

The amount of variance explained by each component and Cronbach's alpha are displayed in table 11.

Table 11 Cronbach's alpha and percentage of variance explained (functional food statements)

	Component 1	Component 2	Component 3	Component 4
Cronbach's alpha	0.923	0.851	0.848	0.783
% of variance explained	40.1	9.3	5.5	4.4

As noted by Hair et al. (1998), a value of 0.6 is a suggested minimum in terms of Cronbach's alpha. As shown in the table, Cronbach's alpha of component 1 is 0.923, and as such indicates high reliability. The three remaining components also easily fulfill Hair's requirement of a value of 0.6, that is, all scales are reliable, and as such principal component analysis does provide a stable component solution.

In terms of the amount of variance explained by each component results reveal that component 1 accounts for 40.1% of total variance, and as such this component explains a relatively large amount of variance. The remaining components account for smaller amounts of variance, revealing values of 9.3%, 5.5%, and 4.4% for components 2, 3, and 4, respectively.

Table 12 presents the correlation matrix containing the correlation coefficients between components.

Table 12 Correlation matrix (functional food statements)

	Component 1	Component 2	Component 3	Component 4
Component 1	1.000	0.612	0.653	0.212
Component 2		1.000	0.559	0.374
Component 3			1.000	0.254
Component 4				1.000

The correlation coefficients indicate considerable correlations between the extracted components. Therefore, no independence between components can be assumed, and as such it has been reasonable to use an oblique rotation. Correlation coefficients reveal that there are positive, considerable correlations between components 1, 2, and 3. There is also some correlation between component 4 and the other components.

Results of this analysis are similar to other studies that examine the consumers' attitudes towards functional products using factor or principal component analysis. Urala and Lähteenmäki (2004) identify seven factors (*perceived reward from using functional foods, confidence in functional foods, necessity for functional foods, functional foods as medicine, absence of nutritional risks in functional foods, functional foods as part of a healthy diet, health effects of functional foods vs. their taste*) describing the consumers' attitudes towards

functional foods. However, they include 53 functional food related statements in the questionnaire compared to 27 statements used in this analysis.

In order to develop a shorter version of attitude measurement Urala and Lähteenmäki (2007) conduct another survey using only 26 functional food related statements. In accordance with the results previously presented, they detect four factors: *perceived reward from using functional foods*, *necessity for functional foods*, *confidence in functional foods*, and *safety of functional foods*. According to them, the strongest predictor in willingness to use functional foods is perceived, personal reward.

Landström et al. (2007) identify five factors (*personal reward from using functional foods*, *benefits of functional foods*, *safety of functional foods*, *confidence in functional foods*, *supporting functional foods*) even though they use, among other things, the same 26 functional food related statements developed by Urala and Lähteenmäki (2007). They only add two statements resulting in 28 functional food related statements.

Annunziata and Vecchio (2011) have recently examined the consumers' attitudes towards functional foods using 24 functional food related statements. They identify three underlying components, namely *healthiness of functional foods*, *confidence in functional foods*, and *satisfaction of functional foods*. According to them, confidence in functional foods seems to be the most crucial factor in consumers' willingness to use these foods. In accordance with Frewer et al. (2003), they argue, that from the consumers' point of view, the perceived risks of functional foods can be a strong barrier to the consumption of such products.

In order to examine whether broader components of acceptance of functional foods can be discerned, Niva and Mäkelä (2007) employ a principal component analysis using 17 functional food related statements. Their results reveal that acceptance can be decomposed into four components: *experiences in using functional foods*, *belief in product quality and safety*, *societal concerns relating to the development*, and *research and regulation*. In the context of functional foods, they argue, trust, or rather confidence, plays an important role and consists of two parts: trust in food safety and trust in the scientific communities studying the connections between food ingredients and their effects on the human body.

A second principal component analysis has been carried out reducing the healthy diet related statements. In order to examine consumers' attitudes towards a healthy diet via principal component analysis, questions concerning foods and diet have been included in the questionnaire. A total of 15 healthy diet related statements have been incorporated, scored on a 7-point Likert scale with categories ranging from "completely disagree" to "completely

agree”. The statements are partly based on the health attitude questionnaire developed by Roininen et al. (1999). One extra statement has been added concerning the product package (“I always read the description displayed on the product package.”) (Mecking et al. 2009).

Given that a sample size of 1309 has been achieved, the recommendations made by Backhaus et al. (2006), Tabachnick and Fidell (2001), and Comrey and Lee (1992) in terms of the necessary sample size for principal component analysis are taken into consideration. Before conducting principal component analysis the ratings of negatively worded statements have been reversed in order to ensure a positive Cronbach’s alpha and to facilitate component interpretation in terms of latent class estimation. The Kolmogorov-Smirnov tests have been significant implying that the distributions of the statement variables are significantly different from a normal distribution. However, subsequent histograms have revealed that the distributions are quite normal looking, and since principal component analysis does not rely on any distributional assumptions this finding is considered to be adequate.

Table 13 presents the test statistics used to examine the reliability of principal component analysis. Furthermore, a short interpretation of results is given.

Table 13 Test criteria – principal component analysis in terms of healthy diet statements

Test value	Value (p-value/KMO-value)	Interpretation
Bartlett’s test of sphericity	0.000 (p-value)	Null hypothesis is rejected; variables are correlated in the population.
Kaiser-Meyer-Olkin measure of sampling adequacy:		
Overall KMO statistic (multiple variables)	0.882 (KMO-value)	Kaiser evaluates this value as meritorious.
Lowest KMO statistic (for one individual variable)	0.728 (KMO-value)	Kaiser evaluates this value as middling.
Highest KMO statistic (for one individual variable)	0.938 (KMO-value)	Kaiser evaluates this value as marvelous.

Given that all test criteria confirm a high reliability, principal component analysis is appropriate for these data. The Bartlett’s test of sphericity is highly significant providing evidence of correlations between statement variables. The KMO values easily fulfill Kaiser’s requirement of 0.5. Values either fall into the range of being meritorious, middling or marvelous.

In order to account for correlations between components and for the large data set, promax rotation has been used. The determination of the number of components has been based on Kaiser’s criterion and the scree plot. Both criteria have suggested that four components are statistically important, and as such should be extracted. These components account for 56.8% of variance and can be interpreted as follows:

- General health interest
- Natural product interest
- Hysteria
- Specific health interest

Components 1 and 2 are labeled with the same names as those used by Roininen et al. (1999). The first component is termed *general health interest*. Statements that load highly onto this component as well as component loadings are displayed in table 14. As recommended by Kline (1994), only component loadings with an absolute value greater than 0.3 are interpreted.

Table 14 Component 1 – general health interest

	Component loadings ^a			
	1	2	3	4
It is important for me that my daily diet contains a lot of vitamins and minerals.	0.877	-0.132	0.059	-0.091
I always follow a healthy and balanced diet.	0.839	-0.226	0.169	-0.064
I am very particular about the healthiness of food I eat.	0.769	0.068	0.099	-0.102
It is important for me that my diet is low in fat.	0.633	-0.306	0.064	0.230
R The healthiness of food has little impact on my food choices.	0.476	0.381	-0.409	0.040
R I eat what I like and I do not worry much about the healthiness of food.	0.456	0.283	-0.198	0.283

R = negative statement.

^aCorrelations between the variables and the components.

In order to facilitate component interpretation, the ratings of two negatively worded statements have been reversed. The main focus of this component is an interest in eating healthily in general. Respondents who have a high score on this component are interested in a healthy diet. Low scores indicate that respondents do not care about eating well.

The statements that load highly onto the second component all seem to relate to the consumers’ interest in eating foods that do not contain additives and are organically grown. Therefore, this component is labeled *natural product interest*. Table 15 presents the statements that load highly onto this component and their associated component loadings.

Table 15 Component 2 – natural product interest

	Component loadings ^a			
	1	2	3	4
R In my opinion, organically grown foods are no better for my health than those grown conventionally.	-0.166	0.837	-0.100	-0.037
R In my opinion, artificially flavoured foods are not harmful for my health.	-0.251	0.639	0.222	0.052
I would like to eat only organically grown vegetables.	0.037	0.601	0.334	-0.131
R I do not care about additives in my daily diet.	0.141	0.344	0.298	0.269

R = negative statement.

^aCorrelations between the variables and the components.

Given that three statements loading highly onto this component have been negatively worded, ratings of these statements have been reversed in order to facilitate component interpretation. A high score on this component indicates that a respondent is interested in eating foods that are natural and without additives. A low score indicates that a respondent does not care if foods contain artificial ingredients or are with additives.

The third component is termed *hysteria*. Statements that load highly onto this component and component loadings are presented in table 16.

Table 16 Component 3 – hysteria

	Component loadings ^a			
	1	2	3	4
I do not eat processed foods, because I do not know what they contain.	-0.026	-0.073	0.739	0.200
I try to eat foods that do not contain additives.	0.262	0.197	0.626	-0.103
I always read the description displayed on the product package.	0.321	0.171	0.385	-0.033

^aCorrelations between the variables and the components.

This component focuses on the consumers' interest in eating foods that are unprocessed. Furthermore, it measures if a consumer is interested in the description of a product. It is somewhat similar to component 2 since it also deals with the aspect of food additives. However, respondents who have a high score on component 3 are a bit hysterical with regard to food products as they want to know everything about the product and they avoid eating processed foods. A low score indicates that a respondent is not hysterical in terms of food products.

The fourth component consists of statements dealing with specific healthy diet related aspects. Therefore, this component is labeled *specific health interest*. Table 17 presents the statements that load highly onto this component and their associated component loadings.

Table 17 Component 4 – specific health interest

	Component loadings ^a			
	1	2	3	4
R I do not avoid foods, even if they may raise my cholesterol.	-0.040	-0.046	0.033	0.839
R The healthiness of snacks makes no difference to me.	-0.053	0.008	0.142	0.755

R = negative statement.

^aCorrelations between the variables and the components.

Only two statements load highly onto this component. In order to facilitate component interpretation, the ratings of both negatively worded statements have been reversed. A high score on this component indicates that a respondent is interested in specific healthy diet related aspects like avoiding foods that raise cholesterol in blood. Low scores imply that respondents do not care about specific healthy diet related aspects.

Table 18 presents the amount of variance explained by each component and Cronbach's alpha.

Table 18 Cronbach's alpha and percentage of variance explained (healthy diet statements)

	Component 1	Component 2	Component 3	Component 4
Cronbach's alpha	0.783	0.615	0.629	0.627
% of variance explained	32.6	9.5	7.8	7.0

As noted by Hair et al. (1998), a value of 0.6 is a suggested minimum in terms of Cronbach's alpha, and as such components 1, 2, 3, and 4 fulfill this requirement. More specifically, scales of components 1, 2, 3, and 4 are reliable.

In terms of the amount of variance explained by each component results reveal that component 1 accounts for 32.6% of total variance, and as such this component explains a relatively large amount of variance. Components 2, 3, and 4 account for smaller amounts of variance as shown in table 18.

The correlation matrix containing the correlation coefficients between components is displayed in table 19.

Table 19 Correlation matrix (healthy diet statements)

	Component 1	Component 2	Component 3	Component 4
Component 1	1.000	0.479	0.316	0.466
Component 2		1.000	0.206	0.281
Component 3			1.000	0.160
Component 4				1.000

The correlation coefficients reveal moderate correlations between the extracted components. Therefore, no independence between components can be assumed, and as such it has been reasonable to use an oblique rotation. In particular, component 1 is positively interrelated with the other components, as indicated by the positive correlation coefficients.

Before comparing results of this analysis with other studies examining the consumers' attitudes towards a healthy diet using factor or principal component analysis, it is important to note that statements used in this analysis are just partly based on the health attitude questionnaire developed by Roininen et al. (1999).

Roininen et al. (1999) identify, among other things, a factor labeled *general health interest*. In the current principal component analysis this factor divides into two separate components, namely *general health interest* and *specific health interest*. Furthermore, Roininen et al. (1999) detect a factor labeled *natural product interest*. Similar to the factor *general health interest*, this factor also divides into two separate components in the current principal component analysis, namely *natural product interest* and *hysteria*.

In order to develop a measure that addresses the motives related to food choice, Steptoe et al. (1995) employ a factor analysis using 36 food choice related statements. They identify nine factors. In accordance with current results one of these factors is labeled *health* and consists of six statements related to an interest in eating healthily. Furthermore, another factor is termed *natural content* including three statements associated with the use of additives and natural ingredients, which is in line with the results of the current analysis. As noted by Steptoe et al. (1995), *health* is, among other things, the most important factor with regard to food choice.

Similar conclusions are drawn from a survey conducted by Ares and Gámbaro (2007). They use a modified version of the food choice questionnaire developed by Steptoe et al. (1995), only identifying seven factors. However, they also highlight the importance of *health* with regard to food choice which is in accordance with Steptoe et al. (1995). Furthermore, this finding is also reported by Lennernäs et al. (1997). According to them, *trying to eat healthy* represents one of the most important factors with regard to food choice.

In order to develop a scale to measure wellness, or rather a healthy lifestyle, Kraft and Goodell (1993) employ a principal component analysis using 19 statements and extracting four components. One of these components labeled as *health environment sensitivity* focuses on the person's worries concerning chemicals, nitrites or preservatives in food, which is in

line with the results of the current analysis. Another component termed *nutrition and stress management* deals with an interest in eating well (and stress reduction), which is in accordance with current results.

Niva and Mäkelä (2007) develop several statements related to a healthy diet, naturally produced foods and technology in food production in order to examine their relationship with the acceptance of functional foods. They identify two factors, namely *importance of healthy eating* and *acceptability of technology*. The factor *importance of healthy eating* includes five statements associated with an interest in eating healthily and an interest in avoiding processed and unnaturally produced foods. This factor seems to be consistent with some components of the current principal component analysis.

The eight functional food and healthy diet related components enter the membership likelihood function in terms of latent class estimation. These components represent the psychographic variables (perceptual and attitudinal indicators) shown in figure 3. In general, a high score on the functional food related components indicates a positive attitude towards functional food. Conversely, a low score indicates a negative attitude towards functional food. Respondents having a high score on the healthy diet related components are interested in a healthy diet. Low scores indicate that respondents do not care about healthy eating. As indicated previously, latent class analyses are carried out on the component scores rather than the original data.

4.5 Empirical Model Specification

In this study, the random parameter logit model and the latent class model presented in the previous chapter are employed to examine consumers' preferences and willingness-to-pay (WTP) for functional dairy products. In particular, the random parameter logit model is used to investigate the existence of preference heterogeneity and to test whether gender-specific WTP estimates are subject to starting point bias (SPB). The latent class model is employed to examine the sources of heterogeneity in preferences across classes of consumers and to estimate class-specific WTP measures for the attributes. Specifically, all sources of heterogeneity are incorporated in the latent class estimation, that is, socioeconomic and psychographic variables represented by the eight components are included.

Estimation of both models requires a specification of the form of the utility function. In this study, a linear in parameters utility function is assumed. In the random parameter logit model, the parameters that enter the utility function as random parameters need to be identified as well as the distribution from which they are drawn. Following Hensher et al. (2005), a

likelihood ratio test and a zero-based, asymptotic t -test for standard deviations have been used to identify random parameters. The vector X_{jm} in equation (21) includes the attribute levels of all functional dairy alternatives from the choice experiment. Estimated coefficients β may be interpreted in terms of the relationship between the explanatory variables and the probability of choice. In the random parameter logit model, both mean coefficients and standard deviations are estimated. The standard deviations reveal the amount of spread that exists around the mean of the random parameter, and as such provide estimates of individual specific parameter estimates. Since each respondent makes seven choices per dairy product, it is possible to examine how the levels of several attributes influence individual utility. Given that new functional products are analyzed and considering the fact that people have different opinions about these products, it is difficult to draw hypotheses in terms of the expected direction of influence on the utility function.

The attribute levels presented previously enter the deterministic component of the utility function for the random parameter logit and the latent class models. The analyst is able to observe the choice made by the respondent, which is assumed to be the utility maximizing alternative. Choice is a binary dependent variable taking the value of one for the chosen alternative and zero for the non-chosen alternative. Attribute levels with a positive coefficient increase an individual's utility, levels with a negative coefficient have a negative impact on the utility function. The price attribute is expected to have a negative sign due to the positive marginal utility for income generally exhibited by most individuals. Rational economic behavior assumes that utility increases when the price of the associated alternative decreases.

A number of socioeconomic and psychographic variables (perceptual and attitudinal indicators) influence consumers' preferences and choice behavior as presented in the choice process framework in figure 3. These variables enter the membership likelihood function of the latent class model in equation (33). Furthermore, socioeconomic variables interact with the X 's in the utility function in equation (21). Important variables that might influence consumers' preferences for functional dairy products are gender, age, household composition, education or income. Attitudes towards functional foods and a healthy diet may also play an important role and determine consumers' preferences. For instance, a respondent that perceives the consumption of functional foods as rewarding will be likely to choose functional products and not the non-functional alternative.

4.6 Data Description

The socioeconomic variables some of which have been employed for the econometric modeling are presented in table 20. Given that psychographic variables (perceptual and attitudinal indicators) represented by the components have a mean of zero and a standard deviation of one, they are not presented in the table.³⁰

Fifty five percent of respondents are women implying that there are more female respondents than male ones. The actual proportion of females in Germany is about 51% (Statistisches Bundesamt 2011). However, this is not unusual in food related surveys as females tend to be the main food shoppers. The average household size is 2.6. This is slightly above the average household size in Germany which was 2.0 in 2011 (Statistische Ämter des Bundes und der Länder 2011). The average age of respondents is 45 which compares well with the national average age of 44 in 2011 (Statistisches Bundesamt 2011). Twenty three percent of the sample households have children under the age of 12. In terms of education, 53% of respondents have an intermediate education, while 26% (18%) of respondents have an advanced (basic) level of education. Further descriptive statistics indicate that 54% of respondents have a per capita income of less than 929€ a month. Forty eight percent have a per capita income between 929 and 3418€. No one has a per capita income greater than 3418€ a month. East Germany represents a dummy indicating whether the respondent lives in the east of Germany or not. Twenty one percent of the sample population lives in the eastern part of Germany. The actual proportion of people living in the east of Germany is about 16% (Statistische Ämter des Bundes und der Länder 2011).

³⁰ As indicated in section 4.4.1, component scores are linear composites, formed by standardizing each variable to zero mean and unit variance, and then weighting with score coefficients and summing for each component.

Table 20 Summary statistics and variable definitions

Variable	Definition	Mean	Std. dev.
Gender	Dummy (1 = female, 0 otherwise)	0.55	0.50
Hhsize	Household size	2.60	1.21
Age	Age in years	45.08	15.50
Children < 12	Dummy (1 = if respondent has children under the age of 12, 0 otherwise)	0.23	0.42
Education			
Basic ^a	Dummy (1 = if respondent has a basic education, 0 otherwise)	0.18	0.39
Intermediate ^b	Dummy (1 = if respondent has an intermediate education, 0 otherwise)	0.53	0.50
Advanced ^c	Dummy (1 = if respondent has an advanced education, 0 otherwise)	0.26	0.44
Income levels ^d			
Low ^e	Dummy (1 = yes, 0 otherwise)	0.54	0.50
Medium ^f	Dummy (1 = yes, 0 otherwise)	0.48	0.50
High ^g	Dummy (1 = yes, 0 otherwise)	0.00	0.07
East Germany ^h	Dummy (1 = if respondent lives in the east of Germany, 0 otherwise)	0.21	0.41

Source: Survey data.

^aIncluding: not graduated yet, no school degree, GCSE.

^bIncluding: A-levels, professional training, master craftsman status.

^cIncluding: university degree, Ph.D..

^dEU definition: individuals are poor if they have an income of less than 60% of the average income of the population (less than 929€ a month in Germany in 2008); individuals are rich if they have an income of at least 200% of the average income of the population (at least 3418€ a month in Germany in 2008).

^ePer capita income is less than 929€ a month.

^fPer capita income is between 929 and 3418€ a month.

^gPer capita income is greater than 3418€ a month.

^hConsisting of the states Brandenburg, Mecklenburg-West Pomerania, Saxony, Saxony-Anhalt, and Thuringia.

Quite interesting is the finding that over half of the respondents consume functional food as indicated in figure 4. The figure shows that 53% of the sample population states that they consume functional foods while 35% of respondents report that they do not consume functional products. Twelve percent of the sample households indicate that they do not know if they consume functional foods.

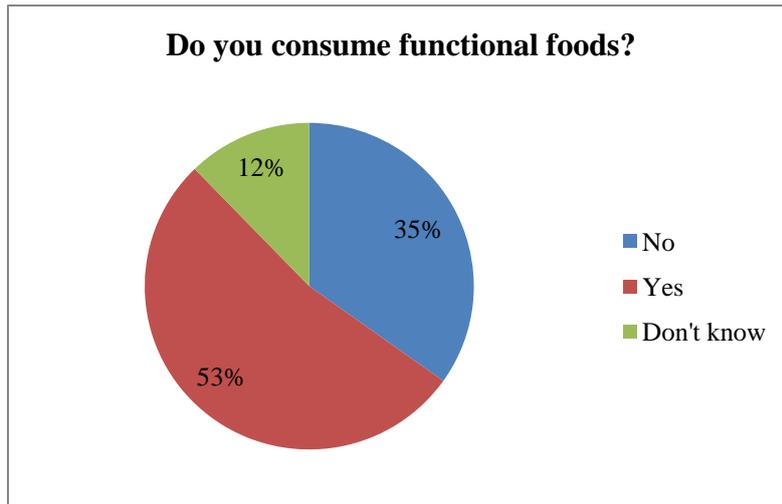


Figure 4 Consumption of functional foods
Source: Survey data

As indicated previously, the whole sample was split into two groups, or rather two samples A and B. This was done in order to investigate the presence of starting point bias (SPB) in the random parameter logit model. Information on some socioeconomic characteristics of both samples is presented in table 21.

Table 21 Descriptive statistics for samples A and B

	Sample A		Sample B		Significance in <i>t</i> -test
	Mean	Std. dev.	Mean	Std. dev.	
Gender (1 = female, 0 otherwise)	0.57	0.50	0.54	0.50	NS
Age (years)	45.77	15.79	44.36	15.18	NS
Education					
Basic ^a (1 = yes, 0 otherwise)	0.19	0.39	0.18	0.38	NS
Intermediate ^b (1 = yes, 0 otherwise)	0.53	0.50	0.53	0.50	NS
Advanced ^c (1 = yes, 0 otherwise)	0.25	0.44	0.27	0.44	NS
Income levels					
Low ^d (1 = yes, 0 otherwise)	0.55	0.50	0.53	0.50	NS
Medium ^e (1 = yes, 0 otherwise)	0.47	0.50	0.49	0.50	NS
High ^f (1 = yes, 0 otherwise)	0.00	0.06	0.01	0.08	NS

Source: Survey data.

NS denotes no significant difference.

^aIncluding: not graduated yet, no school degree, GCSE.

^bIncluding: A-levels, professional training, master craftsman status.

^cIncluding: university degree, Ph.D..

^dPer capita income is less than 929€ a month.

^ePer capita income is between 929 and 3418€ a month.

^fPer capita income is greater than 3418€ a month.

In sample A, women account for 57% of the total whereas their share is only 54% in sample B. The average age of respondents is 46 and 44 years for samples A and B, respectively. Nineteen percent (eighteen percent) of respondents in sample A (B) have a basic education, while 53% of respondents have an intermediate level of education in both samples. The share of respondents with an advanced level of education is 25% in sample A compared to 27% in sample B. Fifty five percent in sample A are low-income households whereas this share is only 53% in sample B. The results further show that 47% (49%) of respondents in sample A (B) have a per capita income between 929 and 3418€ a month. There are no high-income households in sample A and only 1% of sample B respondents are high-income households. In order to test for significant differences in terms of the socioeconomic variables between samples A and B, *t*-tests are carried out. The two samples do not differ significantly with regard to the socioeconomic characteristics ensuring that willingness-to-pay (WTP) estimates between the two samples can be compared. This implies that potential differences in WTP between samples A and B are attributable to SPB and not to differences in socioeconomic characteristics such as different income levels.

5. Empirical Results

5.1 Introduction

This chapter presents the empirical results of the econometric modeling estimations of consumers' attribute preferences from the choice experiments. Estimation results of conditional logit, random parameter logit, and latent class models for all three dairy products are presented and discussed. Models were estimated using NLOGIT software version 4.0 (Econometric Software, Inc. 2007).

5.2 Conditional Logit Results

In order to derive initial start values for each of the parameters in the random parameter logit model, estimation of random parameter logit model first involves the estimation of a conditional logit model. Given that a two-split sample approach was employed, it is necessary to test if it is appropriate to estimate the model on the pooled data set or for samples A and B separately.

Following Swait and Louviere (1993), a sequential testing procedure (one-dimensional grid search) is applied using likelihood ratio tests. First of all, the analyst tests for differences in the preference parameter vector β by allowing for varying scale parameters λ between the two samples.³¹ Then a test for scale parameter equality is performed. This second test can only be conducted if the preference parameters are equal between the two samples because the confoundedness of preference and scale parameters prevents the attribution of observed differences to parameter vector inequality and scale equality ($\beta_A \neq \beta_B, \lambda_A = \lambda_B$) or to both parameter and scale inequality ($\beta_A \neq \beta_B, \lambda_A \neq \lambda_B$) (Swait and Louviere 1993). If the parameters are not equal between the two samples, the second test cannot be conducted, and as such the first test is a test of the joint hypothesis of equality of both preference parameters and scale (Lusk and Schroeder 2004). The likelihood ratio tests for all three dairy products reveal that the preference parameters are not equal between the two samples, i.e. the null hypothesis of preference parameter equality can be rejected.³² Therefore, the second test cannot be performed, implying that the models are different but it is not possible to attribute this

³¹ As indicated previously, the scale parameter λ is an inverse function of the standard deviation of the unobserved effects associated with an alternative, and as such positive (Louviere et al. 2000). The scale

parameter is equal to: $\lambda = \sqrt{\frac{\pi^2}{6\sigma^2}}$.

³² For instance, results from the likelihood ratio test for yoghurt are as follows: $LL_{\text{Sample A}} = -4569.291$ and $LL_{\text{Sample B}} = -4396.972$, that is, $LL_{\text{Sample A}} + LL_{\text{Sample B}} = -8966.263$ (unrestricted); $LL_{\text{Pooled (sample A + B)}} = -8986.139$ (restricted). Therefore, the value of the likelihood ratio is 39.752 with a critical value of $X^2_{(8,0.01)} = 20.1$, thus rejecting the null hypothesis of preference parameter equality.

difference to preference or scale parameter inequality. As a result, the two samples are considered separately. Given potentially different scale parameters in the choice models, it is significant to note that a direct comparison cannot be made with regard to the parameter estimates across models (Louviere et al. 2000).

The maximum likelihood estimates of the conditional logit model for yoghurt, cream cheese, and ice cream are presented in tables 22, 23, and 24, respectively. The results for all three dairy products reveal a strong statistical significance of the negative price parameter estimates in both samples A and B, implying that respondents prefer cheap dairy products. Omega-3 fatty acids parameter estimates are highly significant for yoghurt, cream cheese, and ice cream estimations and have a positive sign in both samples, indicating that respondents prefer dairy products enriched with omega-3 fatty acids. The positive preference for omega-3 fatty acids is consistent with the findings by Grunert et al. (2009), who found out that consumers have higher utilities for omega-3 fatty acids than for bioactive peptides. According to their study, enriching a product with a familiar ingredient is more likely to result in acceptance than enriching a product with an unfamiliar ingredient. Sample B also has a positive preference for yoghurt enriched with oligosaccharides, as indicated by the positive parameter estimate, which is significantly different from zero at the 5% level. Almost every model reveals that the parameter estimate for bioactive peptides is negative and significant. This implies that bioactive peptides are not preferred. The negative preference for bioactive peptides may be attributed to the fact that German consumers are not familiar with this functional ingredient because bioactive peptides are not on the market in Germany yet. As indicated earlier, consumers are more likely to accept functional ingredients they are familiar with (Grunert et al. 2009).

The results of all three dairy products further reveal a strong statistical significance of the parameter estimates for HC 1 (Supports healthy blood vessels.) and HC 2 (Supports healthy blood vessels and healthy metabolism.) in both samples, indicating that respondents have a negative preference for HC 1 and a positive preference for HC 2. Sample A also has a negative preference for cream cheese bearing HC 3 (one property depending on the ingredient), as indicated by the negative parameter estimate, which is significantly different from zero at the 5% level. As noted earlier, a conventional (non-functional) alternative has also been included in each choice set to act as a baseline alternative. The results for cream cheese and ice cream, presented in tables 23 and 24, reveal preference for the non-functional

alternative, as indicated by the positive and highly significant parameter estimates in both samples. The positive preference for non-functional ice cream may be attributed to the fact that ice cream represents a hedonic product and consumers probably prefer hedonic products without any healthy ingredients. More specifically, consumers want to eat hedonic products like ice cream and enjoy them without thinking about health related issues.

Table 22 Maximum likelihood estimates of the conditional logit model for yoghurt

Attributes	Sample A	Sample B
	Estimates	Estimates
Price (in €)	-1.762*** (0.086)	-2.220*** (0.091)
Omega-3 fatty acids	0.347*** (0.043)	0.263*** (0.045)
Oligosaccharides	0.010 (0.042)	0.096** (0.043)
Bioactive peptides	-0.081* (0.042)	-0.150*** (0.044)
HC 1	-0.476*** (0.048)	-0.380*** (0.049)
HC 2	0.263*** (0.041)	0.196*** (0.043)
HC 3	-0.033 (0.043)	-0.018 (0.045)
Non-functional alternative	0.030 (0.041)	0.049 (0.041)
Number of choice sets	4670	4703
Log likelihood	-4569.291	-4396.972
Hausman test statistic (restricted alternative B)	$X^2(8) = 27.9$ $p\text{-value} = 0.000$	$X^2(8) = 27.4$ $p\text{-value} = 0.001$

Standard errors are in parentheses. Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

Table 23 Maximum likelihood estimates of the conditional logit model for cream cheese

Attributes	Sample A	Sample B
	Estimates	Estimates
Price (in €)	-1.651*** (0.074)	-2.132*** (0.080)
Omega-3 fatty acids	0.400*** (0.045)	0.299*** (0.047)
Oligosaccharides	-0.058 (0.045)	0.065 (0.046)
Bioactive peptides	-0.097** (0.044)	-0.183*** (0.047)
HC 1	-0.369*** (0.050)	-0.316*** (0.051)
HC 2	0.247*** (0.043)	0.182*** (0.045)
HC 3	-0.098** (0.046)	-0.024 (0.047)
Non-functional alternative	0.212*** (0.040)	0.128*** (0.040)
Number of choice sets	4705	4690
Log likelihood	-4351.145	-4139.647
Hausman test statistic (restricted alternative B)	$X^2(8) = 19.4$ $p\text{-value} = 0.013$	$X^2(8) = 29.3$ $p\text{-value} = 0.000$

Standard errors are in parentheses. Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

Table 24 Maximum likelihood estimates of the conditional logit model for ice cream

Attributes	Sample A	Sample B
	Estimates	Estimates
Price (in €)	-1.402*** (0.064)	-1.833*** (0.068)
Omega-3 fatty acids	0.410*** (0.049)	0.222*** (0.052)
Oligosaccharides	-0.061 (0.050)	0.054 (0.050)
Bioactive peptides	-0.139*** (0.048)	-0.067 (0.049)
HC 1	-0.368*** (0.055)	-0.302*** (0.055)
HC 2	0.223*** (0.048)	0.139*** (0.049)
HC 3	-0.065 (0.050)	-0.040 (0.051)
Non-functional alternative	0.548*** (0.043)	0.315*** (0.042)
Number of choice sets	4717	4704
Log likelihood	-3892.384	-3801.510
Hausman test statistic (restricted alternative B)	$X^2(8) = 17.7$ $p\text{-value} = 0.024$	$X^2(8) = 19.4$ $p\text{-value} = 0.013$

Standard errors are in parentheses. Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

5.2.1 Price Elasticities

Price elasticities have been calculated using the conditional logit estimates in tables 22, 23, and 24. This provides useful information about the respondents' preferences for alternatives A (functional alternative), B (functional alternative), and C (non-functional alternative). Tables 25, 26, and 27 present the point elasticities of price for all alternatives for yoghurt, cream cheese, and ice cream, respectively.³³ The direct elasticities of alternatives A, B, and C are greater than one for all three dairy products, implying that they are relatively elastic. For instance, table 25 shows that a 1% price increase for functional yoghurt A will decrease the probability of selecting functional yoghurt A by 2.0% in sample A, all else being equal. Similarly, a 1% price increase for non-functional yoghurt will decrease the probability of selecting non-functional yoghurt by 1.1% in sample A. The results for yoghurt, cream cheese, and ice cream also reveal that the direct elasticities of the functional alternatives (alternatives A and B) are higher than the direct elasticities of the non-functional alternative (alternative C) in sample A as well as in sample B. Tables 25, 26, and 27 also present the cross-elasticities for alternatives A, B, and C for all three dairy products.³⁴ The results are in line with expectations, since an increase in the price for a good is likely to increase the demand for competing goods, *ceteris paribus*. For instance, table 27 shows that for sample A a 1% price increase for functional ice cream A will result in a 0.8% increase in the choice probability for functional ice cream B and an increase of 0.9% in the choice probability of non-functional ice cream.

³³ Probability weighted sample enumeration has been used in calculating the elasticities. This implies that the analyst calculates the elasticity for each individual decision maker and weights each individual elasticity by the decision maker's associated choice probability (Hensher et al. 2005).

³⁴ As noted by Hensher et al. (2005), the analyst is cautioned against the cross-elasticities in using the basic conditional logit model. While they are still of some use they are constrained by the IID condition for the conditional logit model.

Table 25 Price elasticities from conditional logit for yoghurt: effects on probabilities

	Sample A	Sample B
	Total effect (in %)	Total effect (in %)
Price increase of alternative A (functional)		
* Alternative = A	-1.980	-2.480
Alternative = B	0.623	0.688
Alternative = C	0.693	0.779
Price increase of alternative B (functional)		
Alternative = A	0.636	0.703
* Alternative = B	-1.949	-2.435
Alternative = C	0.700	0.792
Price increase of alternative C (non-functional)		
Alternative = A	1.065	1.431
Alternative = B	1.062	1.425
* Alternative = C	-1.110	-1.274

*indicates direct point elasticity effect of price

Table 26 Price elasticities from conditional logit for cream cheese: effects on probabilities

	Sample A	Sample B
	Total effect (in %)	Total effect (in %)
Price increase of alternative A (functional)		
* Alternative = A	-2.196	-2.733
Alternative = B	0.573	0.660
Alternative = C	0.652	0.771
Price increase of alternative B (functional)		
Alternative = A	0.586	0.673
* Alternative = B	-2.160	-2.682
Alternative = C	0.656	0.780
Price increase of alternative C (non-functional)		
Alternative = A	1.292	1.686
Alternative = B	1.282	1.673
* Alternative = C	-1.052	-1.276

*indicates direct point elasticity effect of price

Table 27 Price elasticities from conditional logit for ice cream: effects on probabilities

	Sample A	Sample B
	Total effect (in %)	Total effect (in %)
Price increase of alternative A (functional)		
* Alternative = A	-3.921	-4.813
Alternative = B	0.753	0.938
Alternative = C	0.852	1.097
Price increase of alternative B (functional)		
Alternative = A	0.771	0.967
* Alternative = B	-3.856	-4.729
Alternative = C	0.861	1.126
Price increase of alternative C (non-functional)		
Alternative = A	2.755	3.415
Alternative = B	2.729	3.394
* Alternative = C	-1.503	-1.982

*indicates direct point elasticity effect of price

5.2.2 Simulation Results

Simulations have been applied using the conditional logit estimates in tables 22, 23, and 24 as a basis of comparison to test how price changes impact upon the choice probabilities for each of the alternatives. More specifically, simulations are what-if scenarios and allow the analyst to use an existing model to test how changes in attributes (e.g., price) influence the choice probabilities for each of the alternatives (e.g., functional dairy product A, functional dairy product B, non-functional dairy product C) (Hensher et al. 2005). This requires a two-step process. First of all, the analyst estimates a choice model that will be used as a basis of comparison for subsequent simulations (step one). Then the stored parameter estimates are used and the simulation is performed in order to test how changes in an attribute affect the choice probabilities for the model estimated in step one (Hensher et al. 2005). For instance, it is possible to illustrate the impact upon individual choice probabilities given a 1€ increase in the prices of yoghurts (i.e. we change 1.29€/500g to 2.29€/500g and 1.49€/500g to 2.49€/500g and 1.79€/500g to 2.79€/500g and 2.09€/500g to 3.09€/500g).

Tables 28, 29, and 30 present the simulation results for yoghurt, cream cheese, and ice cream, respectively, if price levels are multiplied by 1.5 (e.g., for yoghurt we change 1.29€/500g to 1.935€/500g and 1.49€/500g to 2.235€/500g and 1.79€/500g to 2.685€/500g and 2.09€/500g to 3.135€/500g). Such an increase in the prices of yoghurts in sample A will produce an estimated market share for alternative A of 22.049, down from 25.262, *ceteris paribus*. The same change will produce market shares of 22.698 and 55.252 for alternatives B and C, respectively, *ceteris paribus*. The final columns of tables 28, 29, and 30 (scenario-base) provide the change in choice shares for each of the alternatives both as a percentage and in raw numbers for the sample. Thus, such an increase in the prices of yoghurts in sample A (if price levels are multiplied by 1.5), *ceteris paribus*, decreases the alternative A share as a percent by 3.213 which translates as 150 of the original 1180 choices for that alternative now switching to alternative C. Basically, such a price increase is predicted to decrease the shares of functional yoghurts A and B in sample A by 6.323% (3.213 + 3.110) which translates as 295 (150 + 145) of the original 2385 (1180 + 1205) choices for the two functional alternatives switching to the non-functional alternative (alternative C). In sample B, such a price increase for yoghurt results in a similar estimated share increase for non-functional yoghurt. The results for cream cheese and ice cream reveal similar changes in shares in both samples, implying that a price increase for dairy products results in a share decrease for functional

dairy products and a share increase for non-functional dairy products. This indicates that price is an important driver of choice behavior in terms of dairy products.

Table 28 Simulations of probability model for price (yoghurt)

Alternative	Base		Scenario		Scenario-Base	
	% Share	Number	% Share	Number	Δ Share	Δ Number
Sample A						
Alternative A (functional)	25.262	1180	22.049	1030	-3.213%	-150
Alternative B (functional)	25.808	1205	22.698	1060	-3.110%	-145
Alternative C (non-functional)	48.929	2285	55.252	2580	6.323%	295
Total	100.000	4670	100.000	4670	0.000%	0
Sample B						
Alternative A (functional)	23.237	1093	19.742	928	-3.495%	-165
Alternative B (functional)	23.903	1124	20.578	968	-3.324%	-156
Alternative C (non-functional)	52.860	2486	59.679	2807	6.819%	321
Total	100.000	4703	100.000	4703	0.000%	0

Table 29 Simulations of probability model for price (cream cheese)

Alternative	Base		Scenario		Scenario-Base	
	% Share	Number	% Share	Number	Δ Share	Δ Number
Sample A						
Alternative A (functional)	22.257	1047	19.168	902	-3.090%	-145
Alternative B (functional)	22.737	1070	19.723	928	-3.015%	-142
Alternative C (non-functional)	55.005	2588	61.110	2875	6.105%	287
Total	100.000	4705	100.000	4705	0.000%	0
Sample B						
Alternative A (functional)	21.308	999	18.020	845	-3.288%	-154
Alternative B (functional)	21.869	1026	18.743	879	-3.126%	-147
Alternative C (non-functional)	56.823	2665	63.237	2966	6.414%	301
Total	100.000	4690	100.000	4690	0.000%	0

Table 30 Simulations of probability model for price (ice cream)

Alternative	Base		Scenario		Scenario-Base	
	% Share	Number	% Share	Number	Δ Share	Δ Number
Sample A						
Alternative A (functional)	17.483	825	14.610	689	-2.872%	-136
Alternative B (functional)	17.921	845	15.150	715	-2.771%	-130
Alternative C (non-functional)	64.596	3047	70.240	3313	5.644%	266
Total	100.000	4717	100.000	4717	0.000%	0
Sample B						
Alternative A (functional)	18.061	850	14.976	704	-3.086%	-146
Alternative B (functional)	18.737	881	15.824	744	-2.914%	-137
Alternative C (non-functional)	63.202	2973	69.201	3255	5.999%	282
Total	100.000	4704	100.000	4703	0.000%	-1

5.2.3 Marginal Effects

In order to test how changes in the attribute levels influence the choice probabilities for each of the alternatives marginal effects for the categorical coded variables (functional ingredients and health claims) have been calculated employing the conditional logit estimates in tables 22, 23, and 24.³⁵ This provides information about respondents' preferences for the attribute levels, that is, for the functional ingredients and health claims. Table 31 presents the results for yoghurt for samples A and B if the functional ingredient levels are changed. Each marginal effect, presented in the last column of table 31, corresponds to an alternative (functional alternative A, functional alternative B or non-functional alternative C), the order of which is provided in the header of the table. Changing the functional ingredient in sample A from omega-3 fatty acids to polyphenols for alternatives A and B decreases the choice probabilities for alternative A and B by 0.07 and 0.08, respectively, *ceteris paribus*. This same change, however, increases the choice probability for alternative C (non-functional yoghurt) by 0.15. This implies that respondents prefer omega-3 fatty acids to polyphenols. The results also reveal that respondents prefer omega-3 fatty acids to both oligosaccharides and bioactive peptides, since changes from omega-3 fatty acids to oligosaccharides or bioactive peptides result in a decrease of the choice probabilities for the functional alternatives A and B and in a choice probability increase for the non-functional alternative C in both samples. Similar

³⁵ As noted by Hensher et al. (2005), a marginal effect for a choice model is interpreted as the change in probability given a unit change in a variable, *ceteris paribus* (e.g., a change from omega-3 fatty acids to oligosaccharides).

results are obtained for cream cheese and ice cream. The results for both dairy products are presented in appendix 3.

Table 31 Marginal effects: functional ingredients (yoghurt)

Attribute	Alternative	Coefficient (Wald statistic)	Marginal effect [A, B, C]
Sample A			
Non-functional	C	0.030 (0.729)	
Omega-3 fatty acids (Omega)	A, B	0.347 (8.100)	Δ from omega to olig: [-0.039, -0.040, 0.079]
Oligosaccharides (Olig)	A, B	0.010 (0.238)	Δ from omega to bio: [-0.050, -0.051, 0.101]
Bioactive peptides (Bio)	A, B	-0.081 (-1.942)	Δ from omega to poly ^a : [-0.073, -0.075, 0.148] Δ from olig to bio: [-0.011, -0.011, 0.022] Δ from olig to poly: [-0.034, -0.035, 0.068] Δ from bio to poly: [-0.023, -0.024, 0.047]
Sample B			
Non-functional	C	0.049 (1.183)	
Omega-3 fatty acids (Omega)	A, B	0.263 (5.877)	Δ from omega to olig: [-0.019, -0.020, 0.039]
Oligosaccharides (Olig)	A, B	0.096 (2.225)	Δ from omega to bio: [-0.048, -0.049, 0.097]
Bioactive peptides (Bio)	A, B	-0.150 (-3.412)	Δ from omega to poly: [-0.055, -0.056, 0.111] Δ from olig to bio: [-0.029, -0.029, 0.058] Δ from olig to poly: [-0.035, -0.036, 0.071] Δ from bio to poly: [-0.007, -0.007, 0.014]

^apoly = polyphenols

Table 32 presents the marginal effects for yoghurt for samples A and B if the health claim levels are changed. For instance, a health claim change in sample A from HC 1 (Supports healthy blood vessels.) to HC 2 (Supports healthy blood vessels and healthy metabolism.) for alternatives A and B increases the choice probabilities for alternative A and B by 0.09 and 0.09, respectively, *ceteris paribus*. Furthermore, this change leads to a decrease in the choice probability for the non-functional alternative (alternative C) of 0.18. This finding indicates that people favor HC 2 over HC 1. Similar results are obtained for sample B indicating that respondents prefer HC 2. Appendix 3 presents the results for cream cheese and ice cream which are quite similar.

Table 32 Marginal effects: health claims (yoghurt)

Attribute	Alternative	Coefficient (Wald statistic)	Marginal effect [A, B, C]
Sample A			
Non-functional	C	0.030 (0.729)	
HC 1	A, B	-0.476 (-9.952)	Δ from HC 1 to HC 2: [0.088, 0.089, -0.177]
HC 2	A, B	0.263 (6.361)	Δ from HC 1 to HC 3: [0.053, 0.053, -0.106]
HC 3	A, B	-0.033 (-0.767)	Δ from HC 1 to HC 4: [0.086, 0.087, -0.173] Δ from HC 2 to HC 3: [-0.036, -0.036, 0.071] Δ from HC 2 to HC 4: [-0.002, -0.002, 0.004] Δ from HC 3 to HC 4: [0.033, 0.034, -0.067]
Sample B			
Non-functional	C	0.049 (1.183)	
HC 1	A, B	-0.380 (-7.825)	Δ from HC 1 to HC 2: [0.067, 0.068, -0.135]
HC 2	A, B	0.196 (4.581)	Δ from HC 1 to HC 3: [0.042, 0.042, -0.084]
HC 3	A, B	-0.018 (-0.401)	Δ from HC 1 to HC 4: [0.067, 0.069, -0.136] Δ from HC 2 to HC 3: [-0.025, -0.026, 0.051] Δ from HC 2 to HC 4: [0.001, 0.001, -0.001] Δ from HC 3 to HC 4: [0.026, 0.026, -0.052]

5.2.4 Influence of Socioeconomic Characteristics on Attribute Preferences

A number of socioeconomic variables have been interacted with the attribute levels in order to measure their influence on attribute preferences using conditional logit models. This provides information about preference heterogeneity among consumers. The results for both samples are presented in tables 33, 34, and 35 for yoghurt, cream cheese, and ice cream, respectively. Some of the socioeconomic characteristics are statistically significant, implying that preferences are heterogeneous.

The results for yoghurt, presented in table 33, reveal a positive and highly significant interaction term between age and omega-3 fatty acids in both samples, indicating that older people tend to prefer yoghurt enriched with omega-3 fatty acids. This is probably because older people are more concerned with health than younger people and omega-3 fatty acids are well-known for their health benefits. The age of the respondent shows negative significant interaction with HC 1 (Supports healthy blood vessels.) in both samples at the 10% level of

significance as indicated in table 33. Furthermore, the results for sample A reveal that HC 2 (Supports healthy blood vessels and healthy metabolism.) interacts significantly and positively with age, while HC 3 (one property depending on the ingredient) interacts negatively with age, as indicated by the negative parameter estimate, which is significantly different from zero at the 1% level.

Gender shows positive significant interaction with oligosaccharides but negative interaction with bioactive peptides in sample A. This implies that women in sample A are more likely to choose yoghurt enriched with oligosaccharides but less likely to select yoghurt fortified with bioactive peptides relative to men. Respondents with higher per capita incomes in both samples tend to prefer yoghurt that bears HC 3 as indicated by the positive and statistically significant coefficient representing interaction of per capita income with HC 3. The results further reveal that per capita income interacts significantly and negatively with HC 1 and omega-3 fatty acids for samples A and B, respectively.

East Germany represents a variable consisting of the states Brandenburg, Mecklenburg-West Pomerania, Saxony, Saxony-Anhalt, and Thuringia. Respondents from East Germany in sample A are more likely to choose yoghurt enriched with bioactive peptides and bearing HC 1 or HC 3 relative to respondents living in the west of Germany. However, they are less likely to select yoghurt fortified with oligosaccharides or bearing HC 2. The results of sample B show that East Germany interacts significantly and negatively with HC 1. People in sample A who have an intermediate level of education are less likely to choose yoghurt that bears HC 1 and tend to prefer yoghurt that bears HC 2. Intermediate-educated people in sample B reveal preference for yoghurt enriched with oligosaccharides. Basic education shows a negative significant interaction with HC 1 in sample A but a positive interaction with HC 2 as indicated in table 33. The results for yoghurt also reveal preference for the non-functional alternative, as indicated by the positive and highly significant parameter estimates in both samples.

Table 33 Conditional logit estimates for yoghurt with socioeconomic characteristics

	Sample A	Sample B
	Estimates	Estimates
<i>Age</i>		
Omega-3 fatty acids	0.0057 (0.0021)***	0.0079 (0.0022)***
Oligosaccharides	-0.0030 (0.0021)	-0.0026 (0.0021)
Bioactive peptides	-0.0004 (0.0020)	-0.0019 (0.0021)
HC 1	-0.0041 (0.0024)*	-0.0046 (0.0024)*
HC 2	0.0036 (0.0021)*	0.0023 (0.0022)
HC 3	-0.0071 (0.0022)***	-0.0034 (0.0022)
<i>Gender</i>		
Omega-3 fatty acids	0.0230 (0.0875)	-0.0555 (0.0880)
Oligosaccharides	0.1476 (0.0859)*	0.0232 (0.0828)
Bioactive peptides	-0.1598 (0.0845)*	-0.0892 (0.0850)
HC 1	0.0712 (0.0967)	-0.0440 (0.0933)
HC 2	-0.1016 (0.0850)	0.0846 (0.0835)
HC 3	-0.0084 (0.0896)	-0.0109 (0.0875)
<i>Per capita income (€)</i>		
Omega-3 fatty acids	0.0000 (0.0000)	-0.0001 (0.0000)**
Oligosaccharides	0.0000 (0.0000)	0.0000 (0.0000)
Bioactive peptides	0.0000 (0.0000)	0.0000 (0.0000)
HC 1	-0.0001 (0.0000)*	0.0000 (0.0000)
HC 2	0.0001 (0.0000)	0.0000 (0.0000)
HC 3	0.0002 (0.0000)**	0.0001 (0.0000)**
<i>Children < 12</i>		
Omega-3 fatty acids	-0.1374 (0.1026)	0.0370 (0.1010)
Oligosaccharides	0.1229 (0.0980)	-0.0052 (0.1037)
Bioactive peptides	-0.0676 (0.0987)	-0.1492 (0.1081)
HC 1	0.0169 (0.1103)	-0.1267 (0.1195)
HC 2	0.1480 (0.0977)	0.1668 (0.1033)
HC 3	0.0312 (0.1032)	0.0224 (0.1104)
<i>East Germany</i>		
Omega-3 fatty acids	0.0348 (0.1081)	0.1376 (0.1249)
Oligosaccharides	-0.3172 (0.1104)***	0.0674 (0.1168)
Bioactive peptides	0.3868 (0.0905)***	0.1039 (0.1138)
HC 1	0.2916 (0.1308)**	-0.2448 (0.1459)*
HC 2	-0.7393 (0.1129)***	0.1196 (0.1165)
HC 3	0.3850 (0.0995)***	0.0158 (0.1251)
<i>Intermediate</i>		
Omega-3 fatty acids	0.0478 (0.0940)	-0.0701 (0.0951)
Oligosaccharides	-0.0391 (0.0916)	0.2593 (0.0903)***
Bioactive peptides	0.1448 (0.0884)	0.0630 (0.0919)
HC 1	-0.1827 (0.1027)*	-0.1160 (0.1018)
HC 2	0.1609 (0.0918)*	0.1310 (0.0911)
HC 3	-0.0042 (0.0945)	-0.0533 (0.0949)
<i>Basic</i>		
Omega-3 fatty acids	-0.0405 (0.1283)	-0.1286 (0.1342)
Oligosaccharides	0.0570 (0.1243)	0.0027 (0.1298)
Bioactive peptides	0.1187 (0.1222)	0.0864 (0.1308)
HC 1	-0.3394 (0.1432)**	-0.0159 (0.1422)
HC 2	0.2333 (0.1247)*	0.0080 (0.1293)
HC 3	0.0555 (0.1294)	-0.0751 (0.1351)
Non-functional alternative	0.6823 (0.0315)***	0.8266 (0.0309)***
Log likelihood	-4447.017	-4428.724
Number of choice sets	4386	4421

Standard errors are in parentheses. Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

The socioeconomic characteristics interactions with cream cheese attributes, presented in table 34, indicate positive interactions of age of the respondent with omega-3 fatty acids and HC 2 but negative interaction with HC 3 in both samples. This implies that older people tend to prefer cream cheese enriched with omega-3 fatty acids and bearing HC 2 but are reluctant to choose cream cheese that bears HC 3. Furthermore, age interacts significantly and negatively with oligosaccharides and HC 1 in sample A and with bioactive peptides in sample B.

Gender shows negative significant interaction with bioactive peptides and HC 2 in sample A, implying that women are less likely to purchase cream cheese fortified with bioactive peptides and bearing a health claim of support for healthy blood vessels and healthy metabolism relative to men. This is probably because women prefer to consume natural foods and may describe functional cream cheese as unnatural and potentially unsafe. The variable per capita income reveals positive significant interaction with HC 3 in samples A and B. This shows that respondents with higher per capita incomes prefer cream cheese that bears HC 3. However, it has a negative and significant interaction with omega-3 fatty acids in sample B.

Respondents in sample B with children under the age of 12 tend to prefer HC 2. The results further reveal that people from East Germany in sample A are less likely to choose cream cheese enriched with oligosaccharides and bearing HC 2 but more likely to select cream cheese fortified with bioactive peptides and bearing HC 1 or HC 3. Intermediate-educated respondents in both samples reveal preference for cream cheese fortified with bioactive peptides and bearing HC 2. Respondents with an intermediate level of education in sample B further prefer cream cheese enriched with oligosaccharides, as indicated by the positive parameter estimate in sample B, which is significantly different from zero at the 1% level. Basic-educated people in sample A prefer cream cheese bearing HC 2, while in sample B people with a basic level of education are reluctant to choose cream cheese enriched with omega-3 fatty acids. Both samples reveal preference for non-functional cream cheese, as indicated by the positive and highly significant parameter estimate.

Table 34 Conditional logit estimates for cream cheese with socioeconomic characteristics

	Sample A	Sample B
	Estimates	Estimates
<i>Age</i>		
Omega-3 fatty acids	0.0049 (0.0022)**	0.0080 (0.0023)***
Oligosaccharides	-0.0038 (0.0022)*	-0.0027 (0.0022)
Bioactive peptides	-0.0006 (0.0021)	-0.0048 (0.0023)**
HC 1	-0.0048 (0.0025)**	-0.0037 (0.0025)
HC 2	0.0072 (0.0022)***	0.0038 (0.0022)*
HC 3	-0.0094 (0.0023)***	-0.0046 (0.0023)**
<i>Gender</i>		
Omega-3 fatty acids	0.0210 (0.0912)	-0.0295 (0.0913)
Oligosaccharides	0.1046 (0.0902)	0.0664 (0.0854)
Bioactive peptides	-0.2491 (0.0888)***	-0.1250 (0.0880)
HC 1	0.0617 (0.0996)	-0.0141 (0.0955)
HC 2	-0.1561 (0.0889)*	-0.0126 (0.0868)
HC 3	0.0014 (0.0951)	0.0238 (0.0902)
<i>Per capita income (€)</i>		
Omega-3 fatty acids	0.0000 (0.0000)	-0.0001 (0.0000)*
Oligosaccharides	0.0000 (0.0000)	0.0000 (0.0000)
Bioactive peptides	0.0000 (0.0000)	0.0000 (0.0000)
HC 1	-0.0001 (0.0000)	0.0000 (0.0000)
HC 2	0.0000 (0.0000)	0.0000 (0.0000)
HC 3	0.0002 (0.0000)***	0.0001 (0.0000)*
<i>Children < 12</i>		
Omega-3 fatty acids	0.0134 (0.1060)	0.0048 (0.1144)
Oligosaccharides	0.1143 (0.1025)	-0.0075 (0.1064)
Bioactive peptides	-0.1287 (0.1045)	-0.1635 (0.1115)
HC 1	0.0536 (0.113)	-0.1569 (0.1226)
HC 2	0.0555 (0.1029)	0.1767 (0.1066)*
HC 3	0.1177 (0.1085)	0.0400 (0.1132)
<i>East Germany</i>		
Omega-3 fatty acids	-0.1274 (0.1127)	0.0723 (0.1297)
Oligosaccharides	-0.3446 (0.1159)***	0.1190 (0.1185)
Bioactive peptides	0.5770 (0.0942)***	0.1332 (0.1170)
HC 1	0.3023 (0.1356)**	-0.1931 (0.1463)
HC 2	-1.0364 (0.1189)***	0.0692 (0.1195)
HC 3	0.4919 (0.1036)***	-0.0944 (0.1291)
<i>Intermediate</i>		
Omega-3 fatty acids	-0.1087 (0.0979)	-0.0798 (0.0987)
Oligosaccharides	0.0171 (0.0964)	0.2429 (0.0935)***
Bioactive peptides	0.2623 (0.0926)***	0.2393 (0.0956)**
HC 1	0.0142 (0.1069)	-0.1556 (0.1039)
HC 2	0.1585 (0.0962)*	0.2102 (0.0943)**
HC 3	-0.1260 (0.0999)	-0.0072 (0.0984)
<i>Basic</i>		
Omega-3 fatty acids	0.0343 (0.1306)	-0.2350 (0.1403)*
Oligosaccharides	0.1326 (0.1285)	0.1107 (0.1323)
Bioactive peptides	-0.0081 (0.1296)	0.1955 (0.1360)
HC 1	-0.0797 (0.1451)	-0.0315 (0.1445)
HC 2	0.2375 (0.1288)*	-0.0751 (0.1354)
HC 3	-0.0285 (0.1353)	0.0756 (0.1377)
Non-functional alternative	0.9371 (0.0317)***	0.9819 (0.0311)***
Log likelihood	-4257.616	-4285.604
Number of choice sets	4415	4415

Standard errors are in parentheses. Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

The results of the socioeconomic characteristics interactions with ice cream attributes, presented in table 35, reveal that the respondent's age interacts significantly and positively with omega-3 fatty acids in sample B. As indicated previously, this implies that older respondents tend to prefer ice cream fortified with omega-3 fatty acids. The results of both samples further reveal that age shows negative interaction with HC 1 but positive interaction with HC 2. Furthermore, older respondents in sample A are less likely to choose ice cream that bears HC 3 relative to younger respondents.

Similar to the cream cheese interaction results, female respondents in sample A are less likely to select ice cream enriched with bioactive peptides and bearing HC 2 compared to males, as indicated by the negative and significant parameter estimates. Respondents with higher per capita income in sample A tend to prefer HC 3, whereas high income respondents in sample B reveal preference for HC 1. The significant and negative coefficient on the interaction term between bioactive peptides and the variable children under the age of 12 in sample A indicates that people with children are less likely to choose ice cream enriched with bioactive peptides relative to childless people. East Germany shows positive and highly significant interaction with bioactive peptides in both samples, indicating that respondents from East Germany are more likely to select ice cream fortified with bioactive peptides relative to respondents living in the western part of Germany. The results of sample A further show that respondents living in the east of Germany are less likely to purchase ice cream enriched with oligosaccharides and bearing HC 2. Furthermore, they are more likely to choose ice cream that bears HC 1 or HC 3, as indicated by the positive and highly significant parameter estimates in sample A. People in both samples who have an intermediate level of education reveal preference for bioactive peptides enriched ice cream. Intermediate-educated people in sample B are further reluctant to choose ice cream fortified with omega-3 fatty acids. Basic-educated respondents in sample B are similarly unwilling to select this kind of ice cream. The parameter estimate for the non-functional alternative is positive and highly significant in both samples, implying that respondents tend to prefer non-functional ice cream. The different dairy product attribute preference patterns exhibited through interactions with socioeconomic characteristics in tables 33, 34, and 35 are indicative of the potential sources of preference heterogeneity.

Table 35 Conditional logit estimates for ice cream with socioeconomic characteristics

	Sample A	Sample B
	Estimates	Estimates
<i>Age</i>		
Omega-3 fatty acids	0.0029 (0.0024)	0.0080 (0.0025)***
Oligosaccharides	-0.0032 (0.0024)	-0.0019 (0.0023)
Bioactive peptides	0.0000 (0.0023)	-0.0036 (0.0023)
HC 1	-0.0070 (0.0028)**	-0.0071 (0.0026)***
HC 2	0.0108 (0.0023)***	0.0061 (0.0024)**
HC 3	-0.0108 (0.0026)***	-0.0028 (0.0025)
<i>Gender</i>		
Omega-3 fatty acids	0.0186 (0.0994)	0.0601 (0.1001)
Oligosaccharides	0.0647 (0.0988)	0.0767 (0.0906)
Bioactive peptides	-0.2283 (0.0969)**	-0.1084 (0.0915)
HC 1	0.1429 (0.1105)	-0.0022 (0.1024)
HC 2	-0.1995 (0.0966)**	0.0727 (0.0922)
HC 3	0.1404 (0.1034)	0.0331 (0.0967)
<i>Per capita income (€)</i>		
Omega-3 fatty acids	0.0000 (0.0000)	-0.0001 (0.0000)
Oligosaccharides	0.0000 (0.0000)	0.0000 (0.0000)
Bioactive peptides	0.0000 (0.0000)	0.0000 (0.0000)
HC 1	0.0000 (0.0000)	0.0001 (0.0000)**
HC 2	0.0000 (0.0000)	0.0000 (0.0000)
HC 3	0.0002 (0.0000)***	0.0000 (0.0000)
<i>Children < 12</i>		
Omega-3 fatty acids	-0.0554 (0.1165)	-0.1317 (0.1276)
Oligosaccharides	0.1314 (0.1119)	-0.0575 (0.1142)
Bioactive peptides	-0.1919 (0.1158)*	-0.0048 (0.1136)
HC 1	0.0771 (0.1242)	-0.1054 (0.1312)
HC 2	0.1270 (0.1117)	-0.0087 (0.1158)
HC 3	0.0806 (0.1174)	0.1022 (0.1199)
<i>East Germany</i>		
Omega-3 fatty acids	0.0205 (0.1202)	0.0954 (0.1414)
Oligosaccharides	-0.4690 (0.1288)***	0.0507 (0.1273)
Bioactive peptides	0.5116 (0.1032)***	0.3228 (0.1192)***
HC 1	0.4640 (0.1497)***	-0.1358 (0.1561)
HC 2	-1.1078 (0.1308)***	-0.1043 (0.1293)
HC 3	0.4875 (0.1116)***	-0.0172 (0.1361)
<i>Intermediate</i>		
Omega-3 fatty acids	0.0238 (0.1067)	-0.2943 (0.1075)***
Oligosaccharides	0.0564 (0.1056)	0.1209 (0.0988)
Bioactive peptides	0.1952 (0.1010)*	0.2849 (0.0994)***
HC 1	0.0072 (0.1186)	-0.1775 (0.1113)
HC 2	0.0634 (0.1039)	0.0665 (0.1002)
HC 3	-0.1698 (0.1087)	0.0214 (0.1053)
<i>Basic</i>		
Omega-3 fatty acids	0.0701 (0.1428)	-0.5381 (0.1564)***
Oligosaccharides	0.0597 (0.1417)	0.0329 (0.1405)
Bioactive peptides	-0.0203 (0.1418)	0.2092 (0.1416)
HC 1	-0.0334 (0.1599)	-0.1663 (0.1574)
HC 2	0.0225 (0.1407)	-0.1597 (0.1440)
HC 3	0.1125 (0.1444)	0.0446 (0.1485)
Non-functional alternative	1.334 (0.0332)***	1.274 (0.0323)***
Log likelihood	-3831.504	-3973.610
Number of choice sets	4426	4422

Standard errors are in parentheses. Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

5.3 Random Parameter Logit Results

The simulated maximum likelihood estimates for the random parameter logit (RPL) model and associated willingness-to-pay (WTP) estimates are presented in the following sections. Based on these results, differences in WTP have been calculated to test whether WTP estimates are affected by starting point bias (SPB). Results presented in the following sections (Preference Heterogeneity, Willingness-to-Pay Measures, Differences in Willingness-to-Pay) refer to tables 36, 37, and 38.

5.3.1 Preference Heterogeneity

The Hausman test of the independence of irrelevant alternatives (IIA) assumption proposed by Hausman and McFadden (1984) has been conducted³⁶ and has shown that the random parameter logit model, which allows random taste variation, fits the data better than the conditional logit model, which assumes fixed parameters.³⁷ As indicated previously, the random parameter logit model is used to investigate the existence of preference heterogeneity and to test whether WTP estimates are subject to SPB. SPB is examined in the pooled sample, as well as in samples disaggregated according to gender, in order to investigate gender-specific SPB. The estimates from the random parameter logit models, which describe the elicited preferences for all three dairy products for samples A and B are presented in the second and fourth columns of tables 36, 37, and 38.³⁸ Thousand Halton draws have been utilized for the simulations. Also presented in the tables are the WTP estimates and the numerical differences between samples A and B in the WTP estimates. The estimates are based on the pooled sample (referred to as the main model), as well as on gender-specific samples. Following Hensher et al. (2005), a likelihood ratio test and a zero-based, asymptotic *t*-test for standard deviations have been used to identify random parameters. As a result, the attribute price has been entered as random parameter in the random parameter logit estimations, while functional ingredients and health claims have been entered as fixed parameters.

³⁶ In the following this test is described in terms of functional foods. According to the IIA assumption, the ratio of the choice probabilities of two alternatives (functional alternative A and non-functional alternative C) should not change when a third alternative (functional alternative B) is added. First, the analyst estimates an unrestricted model consisting of all three alternatives (functional alternative A, functional alternative B, and non-functional alternative C). The analyst then estimates a restricted model comprising two alternatives (functional alternative A and non-functional alternative C). If the resulting parameters of both models are approximately the same, the null hypothesis (which states the existence of IIA) cannot be rejected, and as such the conditional logit model is appropriate. If the null hypothesis is, however, rejected the analyst has to consider a less restrictive model specification (random parameter logit model).

³⁷ For instance, the Hausman test statistic (restricted alternative B) for yoghurt for the pooled sample A (B) is 27.9 (27.4) with a *p*-value of 0.000 (0.001).

³⁸ Standard errors are not reported in the interest of brevity.

Price is assumed to be drawn from a constrained triangular distribution, with the spread constrained to the mean. The triangular distribution has positive density that starts at $b - s$ (b is the mean and s the spread), rises linearly to b , and then drops linearly to $b + s$, taking the form of a tent or triangle. The mean b and spread s are estimated. The standard deviation is the spread divided by $\sqrt{6}$; hence the spread is the standard deviation times $\sqrt{6}$. Due to its form, the triangular (or tented) distribution has the advantage of being bounded on either side, and as such overcomes the long-tail problems of the lognormal distribution (Train 2003). The lognormal distribution has been widely used in past studies (e.g., Bhat 2000) for attributes with an explicit sign assumption such as price. However, the disadvantage of the lognormal distribution is that unreasonably large parameters for some share of decision makers can occur due to the long tail. Furthermore, there is very slow (or no) convergence of models using lognormally distributed parameters.

Likelihood ratio tests have been performed for all three dairy products testing the null hypothesis that the conditional logit model fits the data better than the random parameter logit model.³⁹ The results of all three dairy products for samples A and B, presented in tables 36, 37, and 38, reveal that the random parameter logit model is the preferred model for both the pooled sample as well as for gender-specific samples since the null hypothesis is rejected. The random parameter logit models also decrease the log likelihood values in samples A and B, in the main models, as well as in the gender-specific models.

The results of all three dairy products, presented in tables 36, 37, and 38, reveal a strong statistical significance of the mean parameter estimates for omega-3 fatty acids, HC 1 (Supports healthy blood vessels.), HC 2 (Supports healthy blood vessels and healthy metabolism.), and price in both samples, in the main models, as well as in most of the gender-specific models. The results indicate preference for dairy products that are cheap, enriched with omega-3 fatty acids and bearing HC 2. As indicated in the conditional logit results, the positive preference for omega-3 fatty acids is consistent with the findings by Grunert et al. (2009), who found that respondents have higher utilities for omega-3 fatty acids than for bioactive peptides. Dairy products that bear HC 1 are not preferred, as indicated by the negative parameter estimate, which is significantly different from zero at the 1% level. The parameter estimates for oligosaccharides, bioactive peptides, and HC 3 (one property

³⁹ The likelihood ratio test is given by $-2(LL_{CL}-LL_{RPL})$, where LL_{CL} is the restricted maximum log likelihood from the conditional logit model and LL_{RPL} is the unrestricted maximum log likelihood from the random parameter logit model. It has an asymptotic $X^2(k)$ distribution where k is the number of required restrictions.

depending on the ingredient) are partly significant for all three dairy products in both samples, in the main models, as well as in the gender-specific models, and reveal that bioactive peptides and HC 3 are not preferred. The results for oligosaccharides, however, indicate that women have a positive preference for oligosaccharides while men show a negative preference for them. As indicated in the conditional logit results, the negative preference for bioactive peptides is probably because German consumers are not very familiar with this functional ingredient due to the fact that bioactive peptides are not on the market in Germany yet. The results for ice cream, presented in table 38, also reveal preference for the non-functional alternative, as indicated by the positive and highly significant mean parameter estimates in both samples, in the main models, as well as in the gender-specific models. This finding is consistent with the results obtained from the conditional logit model and may be attributed to the fact that ice cream represents a hedonic product and consumers probably prefer hedonic products without any healthy ingredients. Women of both samples and the pooled sample A also reveal a positive preference for non-functional cream cheese, as indicated by the positive and highly significant mean parameter estimates presented in table 37. The results for yoghurt further indicate that women have a positive and men a negative preference for the non-functional alternative. The result is, however, only significant for sample B.

Associated with the mean parameter estimate of the random price parameter is the derived standard deviation calculated over the R Halton draws ($R = 1000$), revealing the amount of spread that exists around the sample population. The standard deviations, presented in tables 36, 37, and 38, are highly significant in terms of all three dairy products, indicating that the price parameter estimates are indeed heterogeneous in the population in both samples, in the main models, as well as in the gender-specific models.

Table 36 Comparison of estimates obtained from RPL model (yoghurt)

Parameter	Sample A		Sample B		Δ WTP ^b (<i>t</i> -test) ^c	Δ WTP (CC) ^d
	Estimates	WTP ^a (Std. dev.)	Estimates	WTP (Std. dev.)		
Omega-3 fatty acids						
Pooled	0.359***	0.26 (0.43)	0.273***	0.15 (0.25)	0.11 ⁺⁺⁺	0.11 ^{NS}
Men	0.408***	0.29 (0.34)	0.314***	0.19 (0.23)	0.10 ⁺⁺⁺	0.10 ^{NS}
Women	0.324***	0.23 (0.28)	0.230***	0.11 (0.14)	0.12 ⁺⁺⁺	0.12 ^{NS}
Oligosaccharides						
Pooled	0.005		0.098**	0.05 (0.09)		
Men	-0.120*	-0.08 (0.10)	0.038			
Women	0.099*	0.07 (0.08)	0.157**	0.08 (0.09)	-0.01 ⁺⁺⁺	-0.01 ^{NS}
Bioactive peptides						
Pooled	-0.086**	-0.06 (0.10)	-0.162***	-0.09 (0.15)	0.03 ⁺⁺⁺	0.03 ^{NS}
Men	0.002		-0.092			
Women	-0.154***	-0.11 (0.13)	-0.228***	-0.11 (0.13)	0.00 ^{NS}	0.00 ^{NS}
HC 1						
Pooled	-0.483***	-0.35 (0.57)	-0.390***	-0.22 (0.35)	-0.13 ⁺⁺⁺	-0.13 ^{NS}
Men	-0.462***	-0.33 (0.39)	-0.358***	-0.22 (0.26)	-0.11 ⁺⁺⁺	-0.11 ^{NS}
Women	-0.504***	-0.36 (0.43)	-0.428***	-0.21 (0.25)	-0.15 ⁺⁺⁺	-0.15 ^{NS}
HC 2						
Pooled	0.264***	0.19 (0.31)	0.198***	0.11 (0.18)	0.08 ⁺⁺⁺	0.08 ^{NS}
Men	0.321***	0.23 (0.27)	0.160**	0.10 (0.11)	0.13 ⁺⁺⁺	0.13 ^{NS}
Women	0.225***	0.16 (0.19)	0.234***	0.12 (0.14)	0.04 ⁺⁺⁺	0.04 ^{NS}
HC 3						
Pooled	-0.035		-0.021			
Men	-0.098		-0.013			
Women	0.011		-0.030			
Non-functional alternative						
Pooled	0.001		0.007			
Men	-0.093		-0.112*	-0.07 (0.08)		
Women	0.069		0.105*	0.05 (0.06)		
Price (in €)						
Pooled	-1.907***		-2.494***			
Men	-1.925***		-2.248***			
Women	-1.905***		-2.761***			
Derived standard deviation (price)						
Pooled	1.907***		2.494***			
Men	1.925***		2.248***			
Women	1.905***		2.761***			
No. of choice sets	4670, 2009, 2661		4696, 2159, 2537			
Halton draws	1000		1000			
LL at start values	-4569, -1974, -2588		-4383, -2098, -2265			
Simulated LL	-4566, -1972, -2586		-4379, -2097, -2262			
Pseudo-R ² adjusted	0.109, 0.105, 0.114		0.150, 0.114, 0.187			
Likelihood ratio test	13.2 ($X^2_{0.999}(1) = 10.8$)		13.6 ($X^2_{0.999}(1) = 10.8$)			
(pooled, men, women)	5.8 ($X^2_{0.950}(1) = 3.8$)		3.0 ($X^2_{0.900}(1) = 2.7$)			
	7.2 ($X^2_{0.990}(1) = 6.6$)		12.2 ($X^2_{0.999}(1) = 10.8$)			

Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

^aWTP values (€) are for 500g yoghurt.

^b Δ WTP denotes the numerical difference between WTP_{Sample A} and WTP_{Sample B}.

^cSignificance levels obtained from *t*-test. NS denotes no significant WTP differences, triple (+++) denotes significant WTP differences at 1% level.

^dSignificance levels obtained from the complete combinatorial (CC) method (Poe et al. 2005). This test determines whether the two WTP distributions overlap significantly. NS denotes no significant distribution differences.

Table 37 Comparison of estimates obtained from RPL model (cream cheese)

Parameter	Sample A		Sample B		Δ WTP ^b (<i>t</i> -test) ^c	Δ WTP (CC) ^d
	Estimates	WTP ^a (Std. dev.)	Estimates	WTP (Std. dev.)		
Omega-3 fatty acids						
Pooled	0.418***	0.31 (0.51)	0.318***	0.17 (0.28)	0.14 ⁺⁺⁺	0.14 ^{NS}
Men	0.459***	0.36 (0.43)	0.356***	0.21 (0.25)	0.15 ⁺⁺⁺	0.15 ^{NS}
Women	0.390***	0.26 (0.32)	0.291***	0.14 (0.16)	0.12 ⁺⁺⁺	0.12 ^{NS}
Oligosaccharides						
Pooled	-0.066		0.060			
Men	-0.186***	-0.15 (0.17)	-0.051			
Women	0.035		0.178***	0.08 (0.10)		
Bioactive peptides						
Pooled	-0.104**	-0.08 (0.13)	-0.197***	-0.11 (0.17)	0.03 ⁺⁺⁺	0.03 ^{NS}
Men	0.009		-0.122*	-0.07 (0.08)		
Women	-0.206***	-0.14 (0.17)	-0.279***	-0.13 (0.15)	-0.01 ⁺⁺⁺	-0.01 ^{NS}
HC 1						
Pooled	-0.376***	-0.28 (0.45)	-0.327***	-0.18 (0.29)	-0.10 ⁺⁺⁺	-0.10 ^{NS}
Men	-0.361***	-0.28 (0.33)	-0.310***	-0.18 (0.21)	-0.10 ⁺⁺⁺	-0.10 ^{NS}
Women	-0.402***	-0.27 (0.33)	-0.354***	-0.17 (0.19)	-0.10 ⁺⁺⁺	-0.10 ^{NS}
HC 2						
Pooled	0.248***	0.18 (0.30)	0.183***	0.10 (0.16)	0.08 ⁺⁺⁺	0.08 ^{NS}
Men	0.343***	0.27 (0.32)	0.231***	0.14 (0.16)	0.13 ⁺⁺⁺	0.13 ^{NS}
Women	0.169***	0.11 (0.14)	0.126*	0.06 (0.07)	0.05 ⁺⁺⁺	0.05 ^{NS}
HC 3						
Pooled	-0.103**	-0.08 (0.13)	-0.030			
Men	-0.168**	-0.13 (0.16)	-0.065			
Women	-0.045		0.009			
Non-functional alternative						
Pooled	0.167***	0.12 (0.20)	0.056			
Men	0.017		-0.068			
Women	0.276***	0.19 (0.22)	0.153***	0.07 (0.08)	0.12 ⁺⁺⁺	0.12 ^{NS}
Price (in €)						
Pooled	-1.873***		-2.571***			
Men	-1.734***		-2.332***			
Women	-2.024***		-2.868***			
Derived standard deviation (price)						
Pooled	1.873***		2.571***			
Men	1.734***		2.332***			
Women	2.024***		2.868***			
No. of choice sets	4705, 2042, 2663		4684, 2162, 2522			
Halton draws	1000		1000			
LL at start values	-4351, -1951, -2378		-4124, -1996, -2106			
Simulated LL	-4344, -1948, -2373		-4110, -1990, -2099			
Pseudo-R ² adjusted	0.159, 0.130, 0.188		0.201, 0.160, 0.241			
Likelihood ratio test	47.3 ($X^2_{0.999}(1) = 10.8$)		68.7 ($X^2_{0.999}(1) = 10.8$)			
(pooled, men, women)	17.2 ($X^2_{0.999}(1) = 10.8$)		36.7 ($X^2_{0.999}(1) = 10.8$)			
	29.6 ($X^2_{0.999}(1) = 10.8$)		30.8 ($X^2_{0.999}(1) = 10.8$)			

Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

^aWTP values (€) are for 200g cream cheese.

^b Δ WTP denotes the numerical difference between WTP_{Sample A} and WTP_{Sample B}.

^cSignificance levels obtained from *t*-test. Triple (⁺⁺⁺) denotes significant WTP differences at 1% level.

^dSignificance levels obtained from the complete combinatorial (CC) method (Poe et al. 2005). This test determines whether the two WTP distributions overlap significantly. NS denotes no significant distribution differences.

Table 38 Comparison of estimates obtained from RPL model (ice cream)

Parameter	Sample A		Sample B		Δ WTP ^b (<i>t</i> -test) ^c	Δ WTP (CC) ^d
	Estimates	WTP ^a (Std. dev.)	Estimates	WTP (Std. dev.)		
Omega-3 fatty acids						
Pooled	0.429***	0.36 (0.59)	0.233***	0.14 (0.24)	0.22 ⁺⁺⁺	0.22 ^{NS}
Men	0.451***	0.36 (0.43)	0.255***	0.18 (0.21)	0.18 ⁺⁺⁺	0.18 ^{NS}
Women	0.415***	0.35 (0.42)	0.224***	0.11 (0.13)	0.24 ⁺⁺⁺	0.24 ^{NS}
Oligosaccharides						
Pooled	-0.069		0.053			
Men	-0.155**	-0.13 (0.15)	-0.023			
Women	-0.005		0.144*	0.07 (0.08)		
Bioactive peptides						
Pooled	-0.147***	-0.12 (0.20)	-0.066			
Men	-0.036		-0.027			
Women	-0.239***	-0.20 (0.24)	-0.116			
HC 1						
Pooled	-0.374***	-0.32 (0.52)	-0.299***	-0.18 (0.30)	-0.14 ⁺⁺⁺	-0.14 ^{NS}
Men	-0.394***	-0.32 (0.38)	-0.310***	-0.22 (0.26)	-0.10 ⁺⁺⁺	-0.10 ^{NS}
Women	-0.349***	-0.30 (0.36)	-0.292***	-0.15 (0.17)	-0.15 ⁺⁺⁺	-0.15 ^{NS}
HC 2						
Pooled	0.221***	0.19 (0.31)	0.130***	0.08 (0.13)	0.11 ⁺⁺⁺	0.11 ^{NS}
Men	0.353***	0.28 (0.34)	0.184***	0.13 (0.15)	0.15 ⁺⁺⁺	0.15 ^{NS}
Women	0.102		0.060			
HC 3						
Pooled	-0.073		-0.059			
Men	-0.232***	-0.19 (0.22)	-0.097			
Women	0.058		-0.017			
Non-functional alternative						
Pooled	0.495***	0.42 (0.68)	0.245***	0.15 (0.25)	0.27 ⁺⁺⁺	0.27 ^{NS}
Men	0.289***	0.23 (0.27)	0.171***	0.12 (0.14)	0.11 ⁺⁺⁺	0.11 ^{NS}
Women	0.658***	0.56 (0.67)	0.296***	0.15 (0.17)	0.41 ⁺⁺⁺	0.41 ^{NS}
Price (in €)						
Pooled	-1.638***		-2.247***			
Men	-1.689***		-1.927***			
Women	-1.606***		-2.655***			
Derived standard deviation (price)						
Pooled	1.638***		2.247***			
Men	1.689***		1.927***			
Women	1.606***		2.655***			
No. of choice sets	4717, 2043, 2674		4697, 2181, 2516			
Halton draws	1000		1000			
LL at start values	-3892, -1751, -2118		-3788, -1878, -1889			
Simulated LL	-3884, -1747, -2114		-3776, -1873, -1882			
Pseudo-R ² adjusted	0.250, 0.220, 0.279		0.268, 0.217, 0.318			
Likelihood ratio test	53.7 ($X^2_{0.999}(1) = 10.8$)		43.8 ($X^2_{0.999}(1) = 10.8$)			
(pooled, men, women)	27.5 ($X^2_{0.999}(1) = 10.8$)		24.4 ($X^2_{0.999}(1) = 10.8$)			
	27.0 ($X^2_{0.999}(1) = 10.8$)		17.7 ($X^2_{0.999}(1) = 10.8$)			

Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

^aWTP values (€) are for 1000ml ice cream.

^b Δ WTP denotes the numerical difference between WTP_{Sample A} and WTP_{Sample B}.

^cSignificance levels obtained from *t*-test. Triple (⁺⁺⁺) denotes significant WTP differences at 1% level.

^dSignificance levels obtained from the complete combinatorial (CC) method (Poe et al. 2005). This test determines whether the two WTP distributions overlap significantly. NS denotes no significant distribution differences.

5.3.2 Willingness-To-Pay Measures

The derivation of the marginal rate of substitution between the attributes and the monetary parameter estimate (price in this analysis) provides an estimation of willingness-to-pay (WTP) for the attributes. Given that price is assumed to be drawn from a triangular distribution, the following formula is used to calculate the WTP (e.g., WTP for omega-3 fatty acids):

$$WTP_{\text{omega-3 fatty acids}} = - \left(\frac{\beta_{\text{omega-3 fatty acids}}}{\beta_{\text{price}} + \sigma_{\text{price}} * t} \right), \quad (40)$$

where β are the mean parameter estimates, σ is the standard deviation of the random price parameter and t is the triangular distribution. In order to calculate the WTP, a hypothetical sample for the random price parameter has to be simulated (Hensher et al. 2005). The possibility of negative WTP estimates is allowed to account for negative preferences associated with some attribute levels that provide disutility. As suggested by Hensher and Greene (2003), the triangular distribution from which the random price parameter is drawn has been constrained to derive behaviorally meaningful WTP values.⁴⁰ The results of all three dairy products are reported in the third and fifth columns of tables 36, 37, and 38. In order to establish meaningful WTP measures, it is important that both attributes to be used in the calculation are found to be statistically significant (Hensher et al. 2005), and as such only WTP values of significant attributes are presented. Given that the present study examines consumer goods, i.e. functional dairy products, consumers show several negative WTP values associated with attribute levels that reduce their utility.

In accordance with the results from the random parameter logit model reported earlier, respondents show a positive WTP for omega-3 fatty acids and HC 2 and a negative WTP for HC 1 for all three dairy products in both samples, in the main models, as well as in most of the gender-specific models. For instance, a yoghurt enriched with omega-3 fatty acids is valued at 0.26€ and 0.15€ more than a yoghurt without omega-3 fatty acids for samples A and B, respectively. These values appear plausible since functional yoghurts are sold at a premium from 0.10€ to 0.50€. The negative WTP for HC 1 indicates significant aversion to this attribute. Specifically, women in sample A (B) are willing to accept up to 0.36€ (0.21€) as compensation for utility reduction to choose yoghurt bearing HC 1. Furthermore, table 38

⁴⁰ In this analysis, the standard deviation parameter estimate is constrained to equal the mean of the random price parameter estimate. According to Hensher et al. (2005), this constraint is quite beneficial in terms of a triangular distribution.

shows a positive WTP for non-functional ice cream in both samples, in the main models, as well as in the gender-specific models. Almost every model reveals that respondents have the highest positive WTP for omega-3 fatty acids. For ice cream, women show a higher positive WTP for the non-functional alternative than for omega-3 fatty acids in both samples, as presented in table 38. The same tendency is apparent in the main models. The results for women reveal that non-functional ice cream is valued at 0.56€ and 0.15€ more than functional ice cream for samples A and B, respectively, indicating a strong dislike for ice cream enriched with functional ingredients and confirming the findings of the random parameter logit model.

5.3.3 Differences in Willingness-To-Pay

The numerical differences in willingness-to-pay estimates (Δ WTP) between samples A and B are presented in the last two columns of tables 36, 37, and 38. Given that the scale parameter does not affect the ratio of any two coefficients, since it drops out of the ratio, WTP estimates between the two samples can be directly compared (Train 2003). Both a *t*-test and the complete combinatorial (CC) method proposed by Poe et al. (2005) have been carried out for each of the WTP differences, testing the null hypothesis of identical WTP measures in the two samples. The results of the *t*-tests for all three dairy products, presented in the sixth columns of tables 36, 37, and 38, indicate that there are significant differences in WTP between samples A and B in the main models, as well as in the gender-specific models, suggesting the presence of starting point bias (SPB) in the data set.⁴¹ Given that the *t*-test imposes normality and considering the fact that the distributions being evaluated are not allowed to deviate substantially from normality, this test can lead to biased estimates of the significance of the difference of two distributions, and as such to erroneous decisions in hypothesis testing.

The complete combinatorial method, which provides an exact measure of the difference of two independent empirical distributions, imposes no normality assumptions, and as such is superior to the *t*-test (Poe et al. 2005). This test is used to compare the whole WTP distributions between samples A and B and determines whether the two WTP distributions overlap significantly. More specifically, the complete combinatorial approach is a non-parametric test that involves comparing differences in marginal WTP for all possible combinations of the WTP estimates. The complete combinatorial test results for all three dairy products, presented in the seventh columns of tables 36, 37, and 38, suggest that there are no significant differences in WTP between the two samples in the main models, as well as in the gender-specific models, indicating that WTP values are identical in samples A and B. More

⁴¹ Just one difference in WTP is not significant.

specifically, the complete combinatorial approach suggests that there is no SPB in the data set. This finding is in contrast to the results reported by Ladenburg and Olsen (2008), who found gender-specific SPB. It is, however, significant to mention that Ladenburg and Olsen (2008) employed a *t*-test in their analysis. A further explanation of the differences between the present findings and those of Ladenburg and Olsen (2008) might be that they investigated environmental goods, while market goods are investigated in this study. It is possible that respondents' WTP is affected by SPB when evaluating environmental goods as compared to market goods. The present findings are consistent with the findings by Carlsson and Martinsson (2008) who also focused on a market good and found no SPB in their choice experiment. However, they also employed a *t*-test to test the null hypothesis of equal WTP measures in two samples.

5.4 Latent Class Results

The maximum likelihood estimates for the best-fitting latent class model for yoghurt, cream cheese, and ice cream are presented in this section. As indicated previously, the latent class model is employed to examine the sources of heterogeneity in preferences across classes of consumers. Both socioeconomic and psychographic variables (perceptual and attitudinal indicators) represented by the eight components are included in the latent class estimation.

The basic approach for the latent class model estimation is to repeatedly estimate the model for different numbers of preference classes. Fit criteria are then used to identify the number of classes that best fits the data. Models with one through five classes have been estimated. The five class model for all three dairy products failed to converge. For each model the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and ρ^2 have been calculated in order to determine the optimal number of latent classes (Boxall and Adamowicz 2002). The aggregate statistics for these models are reported in table 39.

Table 39 Criteria for number of classes

Number of latent classes	Number of parameters (P)	Log likelihood at convergence (LL)	AIC ^b	BIC ^c	ρ^{2d}
<i>Yoghurt</i> ^a					
Conditional logit	8	-7309.3	14634.6	7338.0	0.073
2	28	-6090.1	12236.3	6190.6	0.227
3	48	-5949.6	11995.2	6121.8	0.245
4	68	-5976.1	12088.3	6220.1	0.242
<i>Cream cheese</i> ^a					
Conditional logit	8	-6924.4	13864.9	6953.1	0.090
2	27	-5818.3	11690.5	5915.2	0.235
3	46	-5660.6	11413.1	5825.7	0.256
4	65	-5595.4	11320.7	5828.7	0.264
<i>Ice cream</i> ^a					
Conditional logit	8	-6350.7	12717.3	6379.4	0.096
2	29	-5402.4	10862.8	5506.5	0.231
3	50	-5254.3	10608.6	5433.7	0.252
4	71	-5156.7	10455.5	5411.5	0.266

Optimal number of latent classes is three for all three dairy products. Sample size is 7642 choices for yoghurt, 7676 for cream cheese, and 7695 for ice cream from 1309 individuals (N).

^aThe value of the log likelihood evaluated at zero (LL(0)) is -7883.5, -7606.3, and -7024.3 for yoghurt, cream cheese, and ice cream, respectively.

^bAIC (Akaike Information Criterion) is calculated using $-2(LL-P)$.

^cBIC (Bayesian Information Criterion) is calculated using $-LL+[(P/2)*\ln(N)]$.

^d ρ^2 is calculated as $1-(LL/LL(0))$.

The log likelihood values at convergence (LL) reveal improvement in the model fit as classes are added to the procedure up to the three class model in terms of yoghurt. This is evident in the ρ^2 values which increase from the base of 0.073 to 0.245 with the three class model. Inspection of the AIC and BIC values also suggests that the three class model is the optimal solution for yoghurt, since the minimum BIC and AIC statistics are clearly associated with this class model. It is noteworthy that the BIC and AIC values rise when additional classes beyond three are added.

For cream cheese and ice cream, a similar pattern is observed with regard to the fit criteria. Once again, the log likelihood values at convergence reveal improvement in the model fit as classes are added to the model for both cream cheese and ice cream. Furthermore, the ρ^2 values increase rapidly up to the four class model also indicating improvement in the model fit. Given that the minimum BIC statistic is clearly associated with the three class model and considering the fact that the change in the AIC values is markedly smaller for the three to four class models than for the one to two and two to three class models, the three class model is the optimal solution for cream cheese. Similarly, the inspection of the AIC and BIC values for ice cream suggests that the three class model is more intuitive since the change in AIC and BIC is

also markedly smaller for the three to four class solutions than for the one to two and two to three class solutions, indicating that adding an additional class beyond the third may not be gaining much improvement in the model fit. Therefore, a three class latent class model for yoghurt, cream cheese, and ice cream has been estimated.

A likelihood ratio test has been employed to formally test the null hypothesis that the conditional logit model fits the data better than the latent class model. The sample values of the likelihood ratios are 2719.4, 2527.6, and 2192.8 with a critical value of $X^2_{(40,0.01)} = 63.7$, $X^2_{(40,0.01)} = 63.7$, and $X^2_{(50,0.01)} = 76.2$ for yoghurt, cream cheese, and ice cream attributes respectively, thus rejecting the null hypothesis. This implies that the latent class model fits the data better than the conditional logit model.

Having determined the model with the optimal number of classes, both the utility function and class membership estimates are now interpreted. The maximum likelihood estimates for all three dairy products are presented in tables 40, 41, and 42. The results indicate significant heterogeneity in preferences across latent classes as revealed by the differences in magnitude and significance of the utility function estimates. For instance, results for all three dairy products indicate a strongly negative price parameter estimate for class three in comparison to the other two classes, while the non-functional alternative estimate is strongly positive for class one and strongly negative for class two. Several likelihood ratio tests across competing models have been used in order to decide on the variables to be included in the model as determinants of class membership. The class membership estimates for the third class are equal to zero for all three dairy products due to their normalization during estimation. Thus, the other two classes must be described relative to the third class. The probability of being in a class is significantly related to the consumers' attitude towards functional foods, as indicated by the class membership estimates presented in tables 40, 41, and 42. Members of class one are likely to be functional food skeptics in terms of all three dairy products, since most of the functional food related component estimates are negatively significant relative to class three.⁴² For instance, the class membership estimate for the component "safety of functional foods" is negatively significant in class one for all three dairy products, indicating that members of class one perceive the consumption of functional foods as less safe than members of class three. Most of the functional food related component estimates for class two are, however, positively significant in terms of all three dairy products, implying that this

⁴² Reward from using functional foods, necessity for functional foods, confidence in functional foods, and safety of functional foods represent the functional food related components.

class is likely to be associated with being a functional food advocate. For example, class two believes more in the rewarding aspect of and in the necessity for functional foods compared to class three, as indicated by the positive and strongly significant class membership estimates for the components “reward from using functional foods” and “necessity for functional foods” with regard to yoghurt, cream cheese, and ice cream. Class three could subjectively be associated with functional food neutrals in terms of all three dairy products.

Table 40 shows that 21.5% of the respondents who participated in the choice experiment for yoghurt have a fitted probability to belong to class one, while 40.5% and 38% have a fitted probability to belong to class two and three, respectively. The estimation results reveal that members of class one have a preference for yoghurt that is cheap, enriched with omega-3 fatty acids, and non-functional. The class membership estimates for the components “reward from using functional foods” and “safety of functional foods” are negatively significant, indicating that class one is associated with respondents that perceive the consumption of functional foods as less rewarding and less safe than respondents of class three. Class two membership estimates for yoghurt reveal that members of this class believe more in the rewarding aspect of functional foods and in the necessity for these kinds of foods compared to class three, as indicated by the positive and strongly significant parameter estimates. Furthermore, members of class two are older, more interested in specific healthy diet related aspects, and show a higher likelihood to have an intermediate education than class three. Given that functional foods are products capable of generating health benefits and considering the fact that older people are more concerned with health than younger people (Roininen et al. 1999), the finding that members of class two are older is in line with expectations, since class two is associated with individuals with a positive attitude to functional foods. Class two has a preference for yoghurt that is cheap, fortified with omega-3 fatty acids or oligosaccharides, and bearing HC 2 (Supports healthy blood vessels and healthy metabolism.). Members of class two display a negative preference for yoghurt enriched with bioactive peptides, and bearing HC 1 (Supports healthy blood vessels.) or HC 3 (one property depending on the ingredient). Non-functional yoghurt also reduces their utility. Compared to class three, both class one and two are associated with individuals that are more interested in eating healthily in general and in eating natural foods. Furthermore, members of both classes are more hysterical with regard to food products than class three. Members of class three prefer cheap yoghurt fortified with omega-3 fatty acids or oligosaccharides, and bearing HC 3. They have a negative preference for yoghurt enriched with bioactive peptides, and bearing HC 1 or HC 2.

Table 40 Three latent class model: maximum likelihood estimates of yoghurt attributes

	Class 1	Class 2	Class 3
<i>Utility function estimates</i>			
Price (in €)	-4.905*** (1.693)	-1.524*** (0.069)	-11.367*** (0.500)
Omega-3 fatty acids	1.503*** (0.536)	0.369*** (0.034)	1.446*** (0.158)
Oligosaccharides	-0.072 (0.568)	0.150*** (0.035)	1.232*** (0.163)
Bioactive peptides	-0.965 (0.594)	-0.148*** (0.033)	-1.237*** (0.157)
HC 1	-0.404 (0.486)	-0.621*** (0.037)	-1.423*** (0.156)
HC 2	-0.620 (0.532)	0.351*** (0.036)	-0.943*** (0.164)
HC 3	0.809 (0.548)	-0.275*** (0.036)	1.258*** (0.153)
Non-functional alternative	2.312*** (0.313)	-2.700*** (0.078)	0.003 (0.052)
<i>Class membership estimates</i>			
Constant	-2.074*** (0.578)	-1.722*** (0.239)	
Age	0.004 (0.008)	0.035*** (0.004)	
Reward from using functional foods	-1.159*** (0.281)	0.820*** (0.095)	
Necessity for functional foods	-0.118 (0.196)	0.487*** (0.084)	
Confidence in functional foods	-0.233 (0.156)	0.110 (0.075)	
Safety of functional foods	-0.370** (0.168)	0.002 (0.071)	
General health interest	1.303*** (0.205)	0.656*** (0.093)	
Natural product interest	0.428*** (0.154)	0.290*** (0.073)	
Hysteria	0.814*** (0.148)	0.256*** (0.071)	
Specific health interest	0.051 (0.157)	0.227*** (0.075)	
Intermediate	0.382 (0.328)	0.298** (0.136)	
Advanced	0.180 (0.379)	-0.086 (0.174)	
Latent class probability	0.215	0.405	0.380
Number of choice sets	7642		
Log likelihood	-5949.6		
Likelihood ratio test = 2719.4 ($X^2_{0.990}(40) = 63.7$)			

Standard errors are in parentheses. Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

The likelihood ratio test is given by $-2(LL_{CL} - LL_{LC})$, where LL_{CL} is the restricted maximum log likelihood from the conditional logit model and LL_{LC} is the unrestricted maximum log likelihood from the latent class model. It has an asymptotic $X^2(k)$ distribution where k is the number of required restrictions.

Twenty five percent of the respondents who participated in the choice experiment for cream cheese have a fitted probability to belong to class one as indicated in table 41. The table also shows that 34% and 41% of the respondents have a fitted probability to belong to class two and three, respectively. The class membership estimates reveal that members of class one perceive the consumption of functional foods as less necessary and less safe than members of class three. Furthermore, class one is associated with respondents that have less confidence in functional foods than respondents of class three. Members of class one show a higher likelihood to have children under the age of 12 relative to members of class three. The utility function estimates reveal that class one has a preference for cream cheese that is cheap, enriched with omega-3 fatty acids, and non-functional. Members of class two prefer cheap cream cheese fortified with omega-3 fatty acids or oligosaccharides, and bearing HC 2. However, they display a negative preference for cream cheese enriched with bioactive peptides, and bearing HC 1 or HC 3. Furthermore, non-functional cream cheese reduces their utility. The class membership estimates for class two indicate that this class believes more in the rewarding aspect of functional foods and in the necessity for these kinds of foods compared to class three. Furthermore, members of class two are more likely to be male, more interested in specific healthy diet related aspects, have less confidence in functional foods and show a lower likelihood to have children under the age of 12 relative to class three. Members of class two as well as members of class one are associated with individuals that are more interested in eating healthily in general and in eating natural foods compared to class three members. Furthermore, both classes are more hysterical with regard to food products than class three. Members of class three have a preference for cheap cream cheese, as indicated by the negative parameter estimate which is significantly different from zero at the 1% level. They also display a negative preference for non-functional cream cheese.

Table 41 Three latent class model: maximum likelihood estimates of cream cheese attributes

	Class 1	Class 2	Class 3
<i>Utility function estimates</i>			
Price (in €)	-2.506*** (0.540)	-1.428*** (0.061)	-13.191*** (0.525)
Omega-3 fatty acids	0.885*** (0.260)	0.498*** (0.038)	0.734 (0.475)
Oligosaccharides	-0.377 (0.293)	0.071* (0.039)	0.596 (0.480)
Bioactive peptides	-0.132 (0.260)	-0.257*** (0.037)	-0.586 (0.476)
HC 1	0.059 (0.268)	-0.546*** (0.041)	-0.548 (0.474)
HC 2	0.124 (0.247)	0.345*** (0.041)	-0.512 (0.480)
HC 3	-0.155 (0.285)	-0.340*** (0.040)	0.459 (0.476)
Non-functional alternative	2.431*** (0.394)	-2.651*** (0.081)	-0.215*** (0.051)
<i>Class membership estimates</i>			
Constant	-1.617*** (0.341)	-0.114 (0.104)	
Gender	-0.062 (0.240)	-0.508*** (0.109)	
Reward from using functional foods	-0.112 (0.183)	1.129*** (0.084)	
Necessity for functional foods	-1.293*** (0.420)	0.241*** (0.080)	
Confidence in functional foods	-0.549** (0.263)	-0.125* (0.073)	
Safety of functional foods	-0.317** (0.149)	0.054 (0.068)	
General health interest	1.097*** (0.194)	0.501*** (0.077)	
Natural product interest	0.510*** (0.173)	0.189*** (0.068)	
Hysteria	0.584*** (0.152)	0.269*** (0.066)	
Specific health interest	0.169 (0.141)	0.279*** (0.067)	
Children < 12	0.545* (0.318)	-0.288** (0.139)	
Latent class probability	0.248	0.339	0.413
Number of choice sets	7676		
Log likelihood	-5660.6		
Likelihood ratio test = 2527.6 ($X^2_{0.990}(40) = 63.7$)			

Standard errors are in parentheses. Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

The likelihood ratio test is given by $-2(LL_{CL} - LL_{LC})$, where LL_{CL} is the restricted maximum log likelihood from the conditional logit model and LL_{LC} is the unrestricted maximum log likelihood from the latent class model. It has an asymptotic $X^2(k)$ distribution where k is the number of required restrictions.

Twenty six percent of the respondents who participated in the choice experiment for ice cream have a fitted probability to belong to class one as indicated in table 42. On the other hand, 27% and 47% of the respondents have a fitted probability to belong to class two and three, respectively. The utility function estimates for ice cream are consistent with those of yoghurt and cream cheese in terms of class one. Members of class one perceive the consumption of functional foods as less rewarding, less necessary, and less safe than members of class three. Furthermore, they have less confidence in functional foods and show a higher likelihood to have an intermediate education than respondents of class three. Class two membership estimates for ice cream indicate that compared to class three members of class two believe more in the rewarding aspect of functional foods and in the necessity for and safety of these kinds of foods. They are more likely to be male, more interested in specific healthy diet related aspects, and show a lower likelihood to have children under the age of 12 compared to class three. Members of class two prefer ice cream that is cheap, enriched with omega-3 fatty acids, and bearing HC 2. However, they have a negative preference for ice cream that is non-functional, enriched with bioactive peptides, and bearing HC 1 or HC 3. Both members of class one and two are more interested in eating healthily in general and more hysterical with regard to food products than class three. Table 42 indicates strongly negative price, bioactive peptides, HC 1, and HC 2 estimates for class three. Members of this class have a preference for ice cream fortified with omega-3 fatty acids or oligosaccharides, and bearing HC 3.

Table 42 Three latent class model: maximum likelihood estimates of ice cream attributes

	Class 1	Class 2	Class 3
<i>Utility function estimates</i>			
Price (in €)	-1.469*** (0.452)	-1.140*** (0.054)	-9.576*** (0.387)
Omega-3 fatty acids	0.810*** (0.279)	0.467*** (0.044)	1.535*** (0.235)
Oligosaccharides	-0.506 (0.391)	-0.005 (0.045)	1.501*** (0.243)
Bioactive peptides	0.137 (0.305)	-0.185*** (0.042)	-1.460*** (0.236)
HC 1	0.100 (0.303)	-0.526*** (0.046)	-1.346*** (0.231)
HC 2	0.402 (0.291)	0.311*** (0.046)	-1.440*** (0.244)
HC 3	-0.353 (0.378)	-0.458*** (0.046)	1.415*** (0.234)
Non-functional alternative	3.149*** (0.364)	-2.536*** (0.088)	-0.040 (0.050)
<i>Class membership estimates</i>			
Constant	-2.372*** (0.672)	-0.622*** (0.137)	
Gender	0.041 (0.262)	-0.430*** (0.100)	
Reward from using functional foods	-0.730* (0.400)	0.915*** (0.082)	
Necessity for functional foods	-1.123*** (0.265)	0.311*** (0.083)	
Confidence in functional foods	-0.361** (0.158)	-0.065 (0.068)	
Safety of functional foods	-0.599*** (0.208)	0.138** (0.060)	
General health interest	0.969*** (0.198)	0.403*** (0.071)	
Natural product interest	0.173 (0.139)	-0.030 (0.060)	
Hysteria	0.387** (0.158)	0.242*** (0.056)	
Specific health interest	0.164 (0.141)	0.215*** (0.060)	
Children < 12	-0.091 (0.360)	-0.460*** (0.124)	
Intermediate	1.048** (0.487)	-0.070 (0.117)	
Advanced	0.457 (0.426)	-0.161 (0.141)	
Latent class probability	0.260	0.267	0.473
Number of choice sets	7695		
Log likelihood	-5254.3		
Likelihood ratio test = 2192.8 ($X^2_{0.990}(50) = 76.2$)			

Standard errors are in parentheses. Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

The likelihood ratio test is given by $-2(LL_{CL}-LL_{LC})$, where LL_{CL} is the restricted maximum log likelihood from the conditional logit model and LL_{LC} is the unrestricted maximum log likelihood from the latent class model. It has an asymptotic $X^2(k)$ distribution where k is the number of required restrictions.

Class-specific willingness-to-pay (WTP) estimates and confidence intervals for the different dairy product attributes are presented in table 43. Following Layton and Brown (2000), 95% confidence intervals have been calculated using the Krinsky-Robb parametric bootstrapping method. Comparison of WTP estimates for the attributes across the latent classes shows notable differences in preference structure.

Consumers in class one attach a high value to dairy products enriched with omega-3 fatty acids. This finding is plausible, since functional food skeptics, the most likely members of this class, tend to prefer familiar ingredients like omega-3 fatty acids whose positive health related effects are well-known to consumers. Furthermore, non-functional products are highly valued in class one especially in terms of ice cream. The high valuations on non-functional dairy products, which are much higher than those of omega-3 fatty acids, may be attributed to the fact that members of class one regard functional food with distrust. Given that the remaining attribute levels are not statistically significant, this class does not attach great importance to these levels.

Class two, mainly associated with functional food advocates, places high value on dairy products enriched with omega-3 fatty acids and bearing HC 2. Furthermore, members of class two attach a high value on yoghurt and cream cheese enriched with oligosaccharides. However, they display a negative preference for non-functional dairy products and would be willing to accept up to 1.77€ (1.86€/2.23€) as compensation for utility reduction to choose non-functional yoghurt (cream cheese/ice cream). This is not surprising, since class two is associated with functional food advocates. Members of class two also show a negative WTP for dairy products enriched with bioactive peptides and bearing HC 1 or HC 3.

Given that class three displays a relatively high price estimate value (in absolute value terms) relative to the other two classes, WTP estimates for the third class tend to be lower in terms of all three dairy products, indicating that members of class three are price sensitive. This may be attributed to the fact that functional food neutrals, the most likely members of this class, base their functional food purchasing decision more on price than on functional food attributes. For yoghurt and ice cream, class three exhibits a similar preference structure, with omega-3 fatty acids, oligosaccharides, and HC 3 being similar highly valued and with bioactive peptides, HC 1, and HC 2 being similar low valued. The non-functional alternative is not statistically significant in terms of yoghurt and ice cream, suggesting that this attribute is not important for class three. The results for cream cheese, however, reveal that class three

has a negative preference for non-functional cream cheese and would be willing to accept up to 0.02€ as compensation for utility reduction to choose non-functional cream cheese.

Table 43 Class-specific WTP for attributes (€)

Attribute	Class 1	Class 2	Class 3
<i>Yoghurt</i>			
Omega-3 fatty acids	0.31 [-0.05 – 0.67]	0.24 [0.19 – 0.29]	0.13 [0.11 – 0.15]
Oligosaccharides	NS	0.10 [0.05 – 0.14]	0.11 [0.09 – 0.13]
Bioactive peptides	NS	-0.10 [-0.14 – -0.06]	-0.11 [-0.13 – -0.09]
HC 1	NS	-0.41 [-0.46 – -0.35]	-0.13 [-0.15 – -0.10]
HC 2	NS	0.23 [0.18 – 0.28]	-0.08 [-0.11 – -0.06]
HC 3	NS	-0.18 [-0.23 – -0.13]	0.11 [0.09 – 0.13]
Non-functional alternative	0.47 [-1.76 – 2.71]	-1.77 [-1.93 – -1.62]	NS
<i>Cream cheese</i>			
Omega-3 fatty acids	0.35 [0.06 – 0.64]	0.35 [0.29 – 0.41]	NS
Oligosaccharides	NS	0.05 [0.00 – 0.10]	NS
Bioactive peptides	NS	-0.18 [-0.23 – -0.13]	NS
HC 1	NS	-0.38 [-0.44 – -0.32]	NS
HC 2	NS	0.24 [0.18 – 0.30]	NS
HC 3	NS	-0.24 [-0.30 – -0.18]	NS
Non-functional alternative	0.97 [0.24 – 1.70]	-1.86 [-2.01 – -1.70]	-0.02 [-0.02 – -0.01]
<i>Ice cream</i>			
Omega-3 fatty acids	0.55 [-1.77 – 2.87]	0.41 [0.33 – 0.49]	0.16 [0.12 – 0.20]
Oligosaccharides	NS	NS	0.16 [0.11 – 0.20]
Bioactive peptides	NS	-0.16 [-0.23 – -0.09]	-0.15 [-0.19 – -0.11]
HC 1	NS	-0.46 [-0.54 – -0.38]	-0.14 [-0.18 – -0.10]
HC 2	NS	0.27 [0.19 – 0.35]	-0.15 [-0.19 – -0.11]
HC 3	NS	-0.40 [-0.49 – -0.32]	0.15 [0.11 – 0.19]
Non-functional alternative	2.14 [-7.16 – 11.44]	-2.23 [-2.43 – -2.02]	NS

95% confidence intervals are estimated using the Krinsky and Robb method with 2000 draws and are in parentheses.

NS: attribute level is not statistically significant.

6. Actual Choice Decisions on Functional Dairy Products

6.1 Introduction and Problem Setting

Several different hypothetical functional food attributes have been examined by using stated preference data within a choice experiment. As indicated in section 2.2.1, there are a number of compelling reasons why economists and other social scientists should be interested in stated preference data. On the other hand, stated preference data are hypothetical, and as such experience difficulty taking into account certain types of real market constraints. Revealed preference data, however, have high reliability and face validity due to the fact that these are real choices made by individuals who committed their actual, limited resources to make the choices possible (Louviere et al. 2000). More specifically, market and personal constraints (e.g., income, information availability) are reflected in revealed preference data. Furthermore, the majority of the existing market research on functional foods relies on survey data and stated preference methods. However, not much is known on the actual choice behavior towards these products and on the actual role of consumers' characteristics. Focusing on the German yoghurt and dairy drink market as a case study, the analyses presented in this section add to the scant literature by assessing the actual choice behavior towards functional and conventional dairy products. In order to achieve this objective, data from a home-scanned consumer panel is used. It is important to note that most functional yoghurts and functional dairy drinks which are sold in Germany are probiotic yoghurts and drinks that bear health claims aimed at improving gut health and general immunity. Some commercial examples of probiotic products are listed in table 44.

The chapter is organized as follows. The next section presents a review of extant literature on consumers' choice decisions with a special focus on functional food studies using revealed preference data. The econometric models that have been used to examine the choice decisions are also discussed. The theoretical framework for the actual choice behavior towards functional dairy products and the empirical models are then described, followed by a presentation of the empirical results. The chapter also makes some concluding remarks.

Table 44 Examples of probiotic products

Name	Description	Manufacturer (Country)
Actimel	Probiotic dairy drink with <i>L. casei</i> Imunitass cultures	Danone (France)
Activia	Creamy yoghurt containing Bifidus ActiRegularis	Danone (France)
Gefilus	A wide range of LGG products ^a	Valio (Finland)
Hellus	Dairy products containing <i>Lactobacillus fermentum</i> ME-3	Tallinna Piimatööstus AS (Estonia)
Jovita Probiotisch	Blend of cereals, fruit and probiotic yoghurt	H&J Bruggen (Germany)
Rela	Yoghurts, cultured milks and juices with <i>L. reuteri</i>	Ingman Foods (Finland)
Revital Active	Yoghurt and dairy drink with probiotics	Olma (Czech Republic)
Soytreat	Kefir type product with six probiotics	Lifeway (USA)
Vifit	Dairy drinks with LGG, vitamins and minerals	Campina (The Netherlands)
Vitality	Yoghurt with pre- and probiotics and omega-3 fatty acids	Müller (Germany)
Yakult	Dairy drink containing <i>Lactobacillus casei</i> Shirota	Yakult (Japan)

Source: Partially adapted from Table 2, Siró et al. (2008).

^aLGG = *Lactobacillus rhamnosus* GG.

6.2 Consumers' Choice Decisions on Functional Food: A Literature Review

Analyzing individuals' choices is fundamentally about modeling discrete outcomes of behavioral choices such as purchase decisions, for example whether or not to buy functional food. Decision makers are faced with a situation and reveal something about their underlying preferences by the choice that they make. The choices made will be affected by observable influences and by unobservable characteristics of the chooser (Greene 2008). Most studies on functional food choices have used survey data rather than data on actual consumer purchases. Many of these survey based studies have used probit or ordered probit models in order to examine the propensity for consumers to choose different types of functional food.

Henson et al. (2008) analyze the propensity of Canadian men to consume functional food and nutraceutical products containing lycopene as a means to reduce the risk of prostate cancer and collect data through face-to-face interviews. They use three separate probit models for three different products and find that two elements of protection motivation theory, namely threat appraisal and coping appraisal, have a positive influence on the propensity to purchase products containing lycopene.⁴³ Their results also reveal that older men exhibit a stronger intention to purchase functional foods and nutraceuticals. Based on data collected in a field survey, Del Giudice and Pascucci (2010) examine the factors influencing the acceptance of

⁴³ Protection motivation theory (Rogers 1975) was originally proposed to provide conceptual clarity to the understanding of fear appeals.

functional foods of three distinct groups of young Italian consumers and employ an ordered probit model. Their findings indicate that different sources of information and knowledge (e.g., internet, newspapers), judgments and motivations are important determinants of functional food acceptance. Moon et al. (2011) also use three ordered probit models in order to evaluate the impact of two soy-specific health claims on stated behavioral intentions toward soy-based food in the United States. Using a survey administered online by Ipsos-Observer, their results indicate that non-soy users and infrequent soy-users who were exposed to either FDA (Food and Drug Administration) health claim or general health claim are significantly more likely to eat soy-based food products.⁴⁴

As indicated previously, very few studies on functional food have used actual market data in order to examine functional food choices. For instance, Bonanno (2013) uses a scanner database (i.e. revealed preference data) in order to study demand, substitution pattern, and profitability of conventional and functional yoghurts in Italy. Using a modified Linear Approximated – Almost Ideal Demand System model, his results indicate that functional alternatives' demand is often less elastic than that of their conventional counterparts. His findings also suggest that brand loyalty plays a key role and that the profitability of the functional alternatives is, on average, larger than that of conventional ones. However, his findings describe a scenario prior to the implementation of the regulation on the use of nutrition and health claims for foods (EC 1924/2006; see section 1.2) which has so far resulted in many health claims being denied. His results are, therefore, unlikely to be representative of a highly regulated functional foods' market.

Similarly, Bonanno (2012) uses the same scanner database of yoghurt sales accounting for seven conventional and four functional yoghurt subcategories. He employs a discrete choice nested-logit demand model, where goods are grouped according to whether or not they present a functional attribute. His results reveal that high prices deter the market success of some functional alternatives. He further concludes that this finding does not apply to drinkable yoghurts, whose demand shows lower own-price and larger cross-price elasticities compared to the other functional alternatives. His results also suggest that an aging, increasingly health-conscious population is likely to provide fertile ground for the success of functional yoghurts. Yuan et al. (2009) also use scanner data in order to assess the demand for

⁴⁴ There are two further studies using survey data and employing probit or ordered probit models in order to examine the consumers' acceptance of functional food (Peng et al. 2006; Verbeke 2005). However, they are already described in section 2.3.2.

a phytosterol-enriched product⁴⁵ in the orange juice category in the United States and to examine possible cannibalization effects of its introduction.⁴⁶ Employing a synthetic demand-system approach, their results indicate that consumers view the phytosterol-enriched orange juice product differently from conventional products, implying that there is a strong substitutability among the conventional orange juice products and a weak substitutability between phytosterol and conventional orange juice products. Furthermore, they do not find any cannibalization effects.

The review of extant literature indicates that less effort has been made to investigate the observed choice decisions on functional dairy products in Germany. The present study uses a scanner database of yoghurt and dairy drink sales to assess the actual choice behavior towards functional yoghurts and functional dairy drinks in Germany. This is a further gap that this research study aims to fill. A bivariate probit model is employed to account for a possible correlation between the yoghurt and dairy drink decisions. An Almost Ideal Demand System (AIDS) model is then used to gain an understanding of household consumption patterns of functional and conventional (non-functional) dairy products.

6.3 Theoretical Framework for the Actual Choice Behavior towards Functional Dairy Products and the Empirical Models

This section presents a description of the bivariate probit model and the Almost Ideal Demand System (AIDS) model that have been used to examine the actual choice behavior towards functional and conventional dairy products. The bivariate probit model is employed to estimate the probability of a consumer to choose functional dairy drinks and the probability to purchase functional yoghurts, while the AIDS model is used to estimate the demand for functional and conventional (non-functional) dairy products.

6.3.1 Specification of the Bivariate Probit Model

In econometrics, researchers have been interested in explaining the variation of discrete random variables such as “participate, not participate” or “buy, not buy” by analyzing one single underlying outcome variable (e.g., Fisher 1962; Lee 1963; Thurow et al. 2001). However, the bivariate probit model provides a way of dealing with two separate binary dependent variables and allows for a correlation between the error terms of the two variables. The practical application discussed here estimates the probability of a consumer to purchase

⁴⁵ Phytosterol is a plant sterol being helpful in reducing blood cholesterol levels, one of the major risk factors of heart disease.

⁴⁶ Heskett (1976) defines cannibalization as “the process by which a new product gains sales by diverting them from existing products”.

functional dairy drinks and the probability to choose functional yoghurts, that is, each consumer makes two decisions. The bivariate probit model accounts for the fact that there may be unobservable characteristics of individuals that influence both functional food purchasing decisions. In particular, it is possible to examine whether households who are likely to buy functional dairy drinks are also likely to choose functional yoghurts.

The basis for the microeconomic model applied in the present context is the concept of random utility theory explained in section 3.1.3. More specifically, we take a random utility view of the choices that are observed. A consumer makes two choice decisions whether to purchase functional dairy drinks or not and whether to purchase functional yoghurts or not. The consumer's choice of purchasing functional dairy drinks and functional yoghurts versus conventional ones is then analyzed by assuming that a consumer derives utility by choosing dairy products. It is assumed that the consumer aims at maximizing his utility, that is, the consumer chooses dairy products with the highest utilities. The utility for the functional dairy drink is modeled as U_{FD} and the utility for the conventional dairy drink is defined as U_{CD} . The functional dairy drink will be chosen if

$$U_{FD} > U_{CD}. \quad (41)$$

Similarly, the utility for the functional yoghurt is represented as U_{FY} and the utility for the conventional yoghurt is modeled as U_{CY} . The consumer chooses functional yoghurts if $U_{FY} > U_{CY}$. The probabilities that the consumer chooses functional dairy drinks and functional yoghurts can therefore be written as:

$$P(Y_{FD}) = P(U_{FD} > U_{CD}) \quad \text{and}$$

$$P(Y_{FY}) = P(U_{FY} > U_{CY}), \quad (42)$$

where Y_{FD} is a binary choice variable for the functional dairy drink and Y_{FY} is a binary choice variable for the functional yoghurt. The consumer's utility associated with functional and conventional dairy products is unobserved and can be represented by the latent variable Y^* . For a consumer i , the general specification for the bivariate choice model may therefore be written as:

$$Y_{FDi}^* = X_{FDi}\beta_{FD} + \varepsilon_{FDi} \quad \text{and}$$

$$Y_{FYi}^* = X_{FYi}\beta_{FY} + \varepsilon_{FYi}, \tag{43}$$

$$\begin{pmatrix} \varepsilon_{FDi} \\ \varepsilon_{FYi} \end{pmatrix} | X_{FDi}, X_{FYi} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right], \quad -1 < \rho < 1.$$

Y_{FDi}^* and Y_{FYi}^* are unobservable to the analyst and denote the consumer's probability to choose functional dairy drinks (*FD*) and functional yoghurts (*FY*), respectively, X_{FDi} and X_{FYi} are vectors of household and other socioeconomic characteristics, β_{FD} and β_{FY} are vectors of unknown parameters to be estimated, and ε_{FDi} and ε_{FYi} are error terms following a bivariate normal distribution with zero means, unit variances and correlation ρ (Greene 2008). What is observed is whether the consumer i purchases functional dairy drinks or not and whether functional yoghurts are bought or not. The related observable variables Y_{FDi} and Y_{FYi} are defined as follows:

$$\begin{aligned} Y_{FDi} &= 1 \text{ if } Y_{FDi}^* > 0 \\ Y_{FDi} &= 0 \text{ otherwise and} \end{aligned} \tag{44}$$

$$\begin{aligned} Y_{FYi} &= 1 \text{ if } Y_{FYi}^* > 0 \\ Y_{FYi} &= 0 \text{ otherwise.} \end{aligned}$$

When $Y_{FDi}^* > 0$, consumer i decides to purchase functional dairy drinks and $Y_{FDi} = 1$ is observed; otherwise the consumer decides not to purchase functional dairy drinks and $Y_{FDi} = 0$ is observed. Similarly, we observe $Y_{FYi} = 1$ if consumer i decides to choose functional yoghurts, that is $Y_{FYi}^* > 0$, and $Y_{FYi} = 0$ if he/she decides not to choose functional yoghurts.

The correlation ρ as presented in equation (43) determines whether to use a bivariate probit model or to estimate two probit models separately. When $\rho = 0$, it indicates that the dairy drink and yoghurt decisions can be modeled using two separate probit models. However, when the error correlation ρ is not equal to zero ($\rho \neq 0$), it implies that the decisions are correlated, and as such the relationship between the error terms should be accounted for in order to improve the efficiency of the parameter estimation (Newburn et al. 2011). As a result, the bivariate probit model should be employed.

With two binary dependent variables, four possible outcomes can be observed, and as such it is possible to write down the probability of each of these four outcomes. From (43) and (44), the probability of consumer i choosing both functional dairy drinks and functional yoghurts is given by the following joint probability model:

$$P(Y_{FDi} = 1, Y_{FYi} = 1) = F(X_{FDi}\beta_{FD}, X_{FYi}\beta_{FY}; \rho), \quad (45)$$

where $F(, ; \rho)$ is the bivariate standard normal cumulative distribution function with correlation coefficient ρ (Ashford and Sowden 1970). The probability that consumer i decides to purchase functional dairy drinks but not to purchase functional yoghurts is specified as:

$$P(Y_{FDi} = 1, Y_{FYi} = 0) = \Phi(X_{FDi}\beta_{FD}) - F(X_{FDi}\beta_{FD}, X_{FYi}\beta_{FY}; \rho), \quad (46)$$

where $\Phi()$ denotes the univariate standard normal cumulative distribution function. The probability that consumer i chooses functional yoghurts but not functional dairy drinks can be defined in a similar way:

$$P(Y_{FDi} = 0, Y_{FYi} = 1) = \Phi(X_{FYi}\beta_{FY}) - F(X_{FDi}\beta_{FD}, X_{FYi}\beta_{FY}; \rho). \quad (47)$$

The probability that consumer i neither purchases functional dairy drinks nor functional yoghurts is then:

$$P(Y_{FDi} = 0, Y_{FYi} = 0) = 1 - \Phi(X_{FDi}\beta_{FD}) - \Phi(X_{FYi}\beta_{FY}) + F(X_{FDi}\beta_{FD}, X_{FYi}\beta_{FY}; \rho). \quad (48)$$

Given full observability of Y_{FDi} and Y_{FYi} (Meng and Schmidt 1985), the log likelihood function for the bivariate probit model is specified as:

$$\begin{aligned} \ln L(\beta_{FD}, \beta_{FY}, \rho) = & \sum_{i=1}^n \{ Y_{FDi} Y_{FYi} \ln F(X_{FDi}\beta_{FD}, X_{FYi}\beta_{FY}; \rho) \\ & + Y_{FDi}(1 - Y_{FYi}) \ln [\Phi(X_{FDi}\beta_{FD}) - F(X_{FDi}\beta_{FD}, X_{FYi}\beta_{FY}; \rho)] \\ & + (1 - Y_{FDi}) Y_{FYi} \ln [\Phi(X_{FYi}\beta_{FY}) - F(X_{FDi}\beta_{FD}, X_{FYi}\beta_{FY}; \rho)] \\ & + (1 - Y_{FDi})(1 - Y_{FYi}) \ln [1 - \Phi(X_{FDi}\beta_{FD}) - \Phi(X_{FYi}\beta_{FY}) \\ & + F(X_{FDi}\beta_{FD}, X_{FYi}\beta_{FY}; \rho)] \}, \end{aligned} \quad (49)$$

where $F(\cdot, \cdot; \rho)$ and $\Phi(\cdot)$ are given by (45) and (46); $i = 1, 2, \dots, N$ indexes the observations. Efficient parameter estimates for β_{FD} , β_{FY} and ρ that maximize equation (49) are obtained via Stata/MP 12.1 (StataCorp LP 2011).

One of the first applications of the bivariate probit model with full observability of both dependent variables dates back to Zellner and Lee (1965). They consider the example of a durable good purchase decision (purchase or not) and a credit decision (use installment credit or not). Their results show that a joint estimation for such a set of equations yields parameter estimates which are asymptotically more efficient than single equation parameter estimates, provided that the dependent variables being analyzed are correlated ($\rho \neq 0$). Similarly, Ashford and Sowden (1970) also employ a bivariate probit model with full observability and consider breathlessness and wheeze of a coal miner. In the area of food economics, Cranfield et al. (2012) use a bivariate probit model to examine Canadian consumers purchase intention for fresh and nonfresh locally produced foods, while Gracia and de Magistris (2008) employ this model to analyze consumers' choice for organic foods in Italy. Huang (1996) also formulates a two-equation bivariate probit model in order to analyze simultaneously consumers' preferences and attitudes toward organically grown produce in the United States.

6.3.2 Specification of the Almost Ideal Demand System

Since the development of the Almost Ideal Demand System (AIDS) model (Deaton and Muellbauer 1980), a number of studies have used it in estimating models of food demand which aim to be consistent with economic theory (e.g., Abdulai and Jain 1999; Asche et al. 1998; Tiffin and Tiffin 1999). The AIDS is a popular framework for examining price and income elasticities when expenditure or budget data are available. Furthermore, the AIDS model possesses many desirable properties. For instance, it satisfies the axioms of choice exactly; it aggregates perfectly over consumers without invoking parallel linear Engel curves; it has a functional form which is consistent with known household-budget data; and it can be employed to test the restrictions of homogeneity and symmetry through linear restrictions on fixed parameters (Deaton and Muellbauer 1980).

The linear approximation to the AIDS for n food commodities can be expressed with the following n expenditure share equations:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log \left(\frac{x}{p} \right) \quad \text{for } i = 1, \dots, n, \quad (50)$$

where w_i is the budget share (or expenditure share) of the i th good, p_j is the price of good j , x denotes total expenditure on the n goods for which the demand system is estimated, p is a price index, and α_i , β_i , and γ_{ij} are parameters. The price index p is a translog price index defined by:

$$\log p = \alpha_0 + \sum_i \alpha_i \log p_i + \frac{1}{2} \sum_j \sum_i \gamma_{ij} \log p_i \log p_j. \quad (51)$$

Economic theory implies the following three restrictions on the parameters of the AIDS equation (50):

$$\begin{aligned} \text{Adding up:} & \quad \sum_{i=1}^n \alpha_i = 1 & \quad \sum_{i=1}^n \gamma_{ij} = 0 & \quad \sum_{i=1}^n \beta_i = 0 \\ \text{Homogeneity:} & \quad \sum_j \gamma_{ij} = 0 \\ \text{Symmetry:} & \quad \gamma_{ij} = \gamma_{ji}. \end{aligned} \quad (52)$$

Equation (50) represents a system of demand functions which add up to total expenditure ($\sum w_i = 1$), are homogeneous of degree zero in prices and total expenditure, and which satisfy symmetry of the cross effects of demand functions. In line with Abdulai and Jain (1999), socioeconomic effects are allowed to influence preferences through the intercept in equation (50). The intercept can be specified as:

$$\alpha_i = \rho_{i0} + \sum_{j=1}^S \rho_{ij} d_j, \quad (53)$$

where d_j is the j th socioeconomic variable of which there are S . Given that this translating approach is simple and flexible, it is employed to include socioeconomic variables. For commodities like dairy products, which are consumed as daily subsistence goods, the approach represents an efficient way to model socioeconomic effects (Pollak and Wales 1978; Pollak and Wales 1981).

The translog price index as defined in equation (51) makes the system of equations (50) non-linear. In order to avoid non-linearity, Deaton and Muellbauer (1980) suggest that the price index can be approximated by a Stone price index:

$$\log p = \log p^* = \sum w_i \log p_i. \quad (54)$$

The AIDS model employing Stone's index is termed the Linear Approximate Almost Ideal Demand System (LA/AIDS). Most studies using the AIDS model have employed the Stone price index (e.g., Abdulai and Jain 1999; Tiffin and Tiffin 1999).

In this study, a three-stage budgeting process is assumed. More specifically, the consumer expenditure allocation problem is represented in three stages. In the first stage, the consumer is assumed to determine the expenditure to allocate to several commodity groupings, e.g. food, housing, clothing, transport and communication services etc. It is implicitly assumed that the food group is weakly separable from all the other commodities demanded by the consumer (Heien and Pompelli 1988). In the second stage, the expenditure is allocated among different food groups, e.g. dairy products, meat and fish, vegetable and fruit, bread and cereals. In the third stage, the consumer determines the allocation of his/her expenditure between different dairy products. This study deals with the third stage of the three-stage budgeting process by estimating a separable demand system for dairy products. We therefore focus on the effects of economic and socioeconomic variables within the third stage allocation.

Marshallian, expenditure, and Hicksian elasticities of demand for each category can be computed from the estimated parameters of the LA/AIDS model:

$$e_{ij}^m = \frac{\gamma_{ij}}{w_i} - \frac{\beta_i w_j}{w_i} - \delta_{ij} \quad \delta_{ij} = 1 \text{ if } i = j, \text{ otherwise } \delta_{ij} = 0 \quad (55)$$

$$e_i = 1 + \frac{\beta_i}{w_i} \quad (56)$$

$$e_{ij}^h = e_{ij}^m + w_j e_i, \quad (57)$$

where e_{ij}^m denotes Marshallian elasticities, e_i represents expenditure elasticities, and e_{ij}^h denotes the income-compensated, or Hicksian, measure of elasticity.

The AIDS has traditionally been applied within consumer research to estimate models of food demand. For instance, Abdulai and Jain (1999) use the LA/AIDS model to analyze economic and demographic effects on India's household demand for milk and milk products. Tiffin and Tiffin (1999) investigate estimates of food demand elasticities for Great Britain by employing

the LA/AIDS. In their study on salmon, Asche et al. (1998) use the AIDS to estimate the demand for fresh Atlantic salmon, frozen Atlantic salmon, and frozen Pacific salmon in the European Union. Surprisingly, only few studies have tried to examine the demand for functional foods. For instance, Bonanno (2013) employs the AIDS to assess the demand for functional and conventional yoghurts in Italy.

6.4 Data and Variable Description

The data used for the bivariate probit estimation are obtained from a home-scanned consumer panel surveyed by the German Society of Consumption Research (GfK = Gesellschaft für Konsumforschung). In this panel, over 39000 households in Germany record their daily purchasing activities with a home scanner. For the purpose of the present analysis, purchase information in 2009/2010 for two product categories (dairy drinks and yoghurts) has been extracted from this panel. Dairy drinks and yoghurts have been selected since functional alternatives within these two product categories are on the market in Germany yet.⁴⁷ The panel includes almost 2 million single purchase observations in terms of yoghurt and about 671000 single purchase observations in terms of dairy drinks.

Table 45 presents the definitions, means, and standard deviations of all the variables employed in the bivariate probit analysis. The two dependent variables are purchase of functional dairy drinks and functional yoghurts. Fifty seven percent of the households purchase functional dairy drinks, while 69% buy functional yoghurts. Given that people generally consume more yoghurts than dairy drinks, this finding is in line with expectations.

The independent variables also presented in table 45 include several household characteristics as well as information about the head of the household. The average household size is 2.5 which is slightly above the average household size in Germany which was 2.0 in 2011 (Statistische Ämter des Bundes und der Länder 2011). Given that functional foods tend to be more expensive than their conventional alternatives (Lähteenmäki et al. 2007), income may influence the functional food purchasing decision. If this hypothesis is true, then households with higher incomes will have a higher probability to choose functional dairy drinks and functional yoghurts. The average income of the sample population is 2263€. This is slightly below the average income in Germany which was 2922€ in 2010 (Statistisches Bundesamt 2013). Considering the fact that older people are more likely to be interested in and concerned with health than younger people, age may also influence the decision whether to purchase

⁴⁷ Dairy drinks used for the analysis consist of yoghurt drinks, whey, and buttermilk.

functional dairy products or not. Furthermore, older people may have a tendency to choose functional yoghurts but not functional dairy drinks since many people rather consume yoghurts than dairy drinks. Korzen-Bohr and O'Doherty Jensen (2006) note that older consumers are less likely to consume probiotic yoghurt drinks but more likely to choose functional foods that are part of a product category normally consumed (e.g., yoghurt). Different age groups have been used to examine the relationship between age and the probability of choosing functional dairy products. Twenty five percent of household heads are between the ages of 19 and 34, while there are 36% heads of the household aged between 35 and 49. The proportion of household heads aged between 50 and 64 is 25% and 14% are older than or equal to 65 years. Further descriptive statistics indicate that 20% of the people are living alone and 80% of the households are multi-person households consisting of at least two people. It may be expected that women who live alone have a higher probability to choose functional dairy products, since women are generally more health conscious than men (Rozin et al. 1999). Fifty eight percent of household heads are employees as indicated in table 45.

The size of a city determined by the number of inhabitants may also influence the decision whether or not a household purchases functional dairy products. It is hypothesized that households living in big cities have a higher probability of choosing functional dairy products, since new technologies are used to produce new functional foods and people in big cities can be regarded as more open-minded compared to people living in rural areas. Table 45 indicates that 15% of households live in country towns, 26% in small towns, 27% in middle towns and 24% in large towns. Only 8% of the sample population lives in cities with at least one million inhabitants.

Table 45 Variable definitions and descriptive statistics (GfK data)

Variable	Definition	Mean	Std. dev.
Dependent variables			
Functional dairy drinks	1 if household purchases functional dairy drinks, 0 otherwise	0.57	0.50
Functional yoghurts	1 if household purchases functional yoghurts, 0 otherwise	0.69	0.46
Independent variables			
Hhsize	Household size	2.52	1.21
Income	Total average net income in € (a month)	2263.36	930.25
Age19_34	1 if head of the household is between the ages of 19 and 34, 0 otherwise	0.25	0.43
Age35_49	1 if head of the household is between the ages of 35 and 49, 0 otherwise (reference)	0.36	0.48
Age50_64	1 if head of the household is between the ages of 50 and 64, 0 otherwise	0.25	0.43
Age65over	1 if head of the household is older than or equal to 65 years, 0 otherwise	0.14	0.35
Single-person hh (male)	1 if household is a man living alone, 0 otherwise	0.10	0.30
Single-person hh (female)	1 if household is a woman living alone, 0 otherwise	0.10	0.30
Multi-person hh	1 if two or more people live in the household, 0 otherwise (reference)	0.80	0.40
Employee	1 if head of the household is an employee, 0 otherwise	0.58	0.49
Country town ^a	1 if household lives in a town with < 5000 people, 0 otherwise	0.15	0.36
Small town	1 if household lives in a town with ≥ 5000 and < 20000 people, 0 otherwise	0.26	0.44
Middle town	1 if household lives in a town with ≥ 20000 and < 100000 people, 0 otherwise (reference)	0.27	0.44
Large town	1 if household lives in a town with ≥ 100000 and < 1m people, 0 otherwise	0.24	0.43
City $\geq 1m$	1 if household lives in a city with $\geq 1m$ people, 0 otherwise	0.08	0.27

Source: GfK data.

^aThe International Statistics Conference of 1887 defined different sizes of city/town based on their population size (country town, small town, middle town, large town, city $\geq 1m$).

Table 46 presents a bivariate frequency count for the two dependent binary variables in order to derive an initial impression in terms of their relationship (Greene 2008). For instance, 9451 households purchase functional yoghurts but not functional dairy drinks. In contrast, 4549 households buy functional dairy drinks, whereas functional yoghurts are not bought. These findings imply that people tend to purchase more functional yoghurts than functional dairy drinks. This may be attributed to the fact that people generally buy more yoghurts than dairy drinks.

Looking at the very large value in the lower-right cell (17675), one might surmise that these two binary variables are positively correlated. That is, households who show a high probability to choose functional yoghurts also reveal a high probability to choose functional dairy drinks.

Table 46 Consumption of (functional) dairy drinks and (functional) yoghurts

Functional dairy drinks	Functional yoghurts		Total
	0	1	
0	7466	9451	16917
1	4549	17675	22224
Total	12015	27126	39141

Source: GfK data.

The data used for the AIDS estimation are obtained from the home-scanned consumer panel previously employed for the bivariate probit estimation. For the purpose of the present analysis, purchase information in 2010 for several product groups of the category dairy products has been extracted from this panel.

The socioeconomic variables included in the LA/AIDS model are household size (total number of household members) and age of the household head (in years). These household characteristics are allowed to influence the α_i intercept parameters in each share equation. The average household size is 2.5. This is slightly above the average household size in Germany which was 2.0 in 2011 (Statistische Ämter des Bundes und der Länder 2011). The average age of household heads is 47. This compares well with the national average age of 44 in 2011 (Statistisches Bundesamt 2011).

The commodity items include household consumption quantity and expenditure on various dairy products. The demand system consists of five expenditure groups: functional yoghurts, functional dairy drinks, non-functional yoghurts, non-functional dairy drinks, and “other dairy products”. The “other dairy products” group comprises of all other dairy products, including liquid milk, butter, and cream.

The demand system for dairy products has been estimated by using the LA/AIDS model at the third stage. The equation for “other dairy products” has been omitted from the system estimation to avoid singularity of the variance-covariance matrix of the disturbance terms. Parameters of the deleted equation can be obtained through the adding up condition of demand parameters.

6.5 Estimation and Empirical Results

This section presents the empirical results of the econometric models that have been employed to examine the actual choice behavior towards functional dairy products. Estimation results of the bivariate probit model and the Linear Approximate Almost Ideal Demand System (LA/AIDS) model are presented and discussed. Models were estimated using Stata/MP 12.1 (StataCorp LP 2011).

6.5.1 Bivariate Probit Results

Table 47 presents the estimates of the maximum likelihood bivariate probit model explaining the probability of choosing functional dairy drinks and functional yoghurts. Also presented in the table are the marginal effects measuring the change in the probability of selecting functional dairy drinks (functional yoghurts) given a one-unit change in the independent variable.

The estimated model is first evaluated based on the log likelihood ratio test statistic and the ρ parameter. The results reveal that the estimate of ρ is significantly different from zero at the 1% level, indicating that the random disturbances of the functional purchasing decision of dairy drinks and yoghurts are not statistically independent. More specifically, errors for both equations are positively correlated, and as such inefficient parameter estimates may be obtained if the equations are estimated separately. The log likelihood ratio test statistic is significant at the 1% level, suggesting that the independent variables taken together influence the functional purchasing decision. This implies that one cannot defensibly estimate two separate probit models, thus supporting the simultaneous estimation method used here.

Product-specific parameter estimates are presented in the second and fourth columns of table 47. The results of both dairy products reveal a strong statistical significance of the parameter estimates for household size, income, age19_34, age50_64, age65over, single-person household (male), and employee. The relationship between income and the probability of choosing functional dairy products is positive, as revealed by the estimated coefficients on income, which are significantly different from zero at the 1% level. This implies that the probability of choosing functional dairy drinks and functional yoghurts increases as income increases. Given that functional dairy products tend to be more expensive than non-functional dairy products (Lähteenmäki et al. 2007), this result is consistent with the hypothesis that the decision whether to purchase functional dairy products or not is constrained by income. The coefficient on age19_34 is negative, indicating that younger people are less likely to choose functional dairy drinks and functional yoghurts. This finding is in line with expectations since functional products provide health benefits beyond basic nutrition and younger people are less concerned with health than older people (Roininen et al. 1999). The coefficients on age50_64 and age65over are negative in terms of functional dairy drinks but positive in terms of functional yoghurts, implying that people over the age of 49 have a lower probability of choosing functional dairy drinks but a higher probability of selecting functional yoghurts. To some extent this finding is consistent with the findings by Korzen-Bohr and O'Doherty Jensen (2006), who found that people over the age of 65 were less likely to consume probiotic yoghurt drinks and that older consumers were just interested in functional foods that were part of a product category normally consumed such as yoghurt.

Men living alone are less likely to choose functional dairy drinks and functional yoghurts relative to multi-person households, as indicated by the negative parameter estimates, which are significantly different from zero at the 1% level. The results also show that employees are more likely to select functional dairy drinks and functional yoghurts relative to non-employees. The coefficient on household size is positive in terms of functional dairy drinks but negative in terms of functional yoghurts, implying that an increasing household size leads to a higher probability of choosing functional dairy drinks and a lower probability of selecting functional yoghurts. The results further reveal that women living alone show a higher probability to choose functional dairy drinks compared to multi-person households, as indicated by the positive parameter estimate, which is significantly different from zero at the 1% level. Similarly, the probability of choosing functional dairy drinks is higher for people who live in cities with at least one million inhabitants.

Product-specific marginal effects are presented in the third and fifth columns of table 47. For instance, one additional household member increases the probability of selecting functional dairy drinks by 0.0351 and decreases the probability of choosing functional yoghurts by 0.0142. Being at least 65 years old, however, decreases the choice probability for functional dairy drinks by 0.1040 and increases the choice probability for functional yoghurts by 0.0512. The results further reveal that the probability of choosing functional dairy drinks and functional yoghurts is reduced by 0.0568 and 0.1145, respectively, if a person is male and lives alone.

Table 47 Bivariate probit model: estimates of the probability to choose functional dairy drinks and functional yoghurts

Variable	Functional dairy drinks (FD)		Functional yoghurts (FY)	
	Estimates	Marginal effects	Estimates	Marginal effects
Hhsize	0.0850*** (0.0076)	0.0351	-0.0259*** (0.0078)	-0.0142
Income ^a	0.1431*** (0.0321)	0.0347	0.2491*** (0.0330)	0.0633
Income squared	0.0000 (0.0000)	–	0.0000 (0.0000)	–
Age19_34	-0.1115*** (0.0170)	-0.0252	-0.2140*** (0.0173)	-0.0574
Age50_64	-0.1132*** (0.0179)	-0.0550	0.1292*** (0.0190)	0.0456
Age65over	-0.2363*** (0.0238)	-0.1040	0.1197*** (0.0251)	0.0512
Single-person hh (male)	-0.2365*** (0.0262)	-0.0568	-0.4062*** (0.0265)	-0.1145
Single-person hh (female)	0.0830*** (0.0264)	0.0286	0.0382 (0.0276)	0.0051
Employee	0.0797*** (0.0153)	0.0247	0.0743*** (0.0159)	0.0161
Country town	0.0006 (0.0207)	0.0005	-0.0033 (0.0216)	-0.0010
Small town	-0.0084 (0.0177)	-0.0027	-0.0064 (0.0185)	-0.0013
Large town	0.0110 (0.0181)	0.0053	-0.0123 (0.0189)	-0.0045
City ≥ 1m	0.0793*** (0.0261)	0.0325	-0.0272 (0.0270)	-0.0143
Constant	-1.0492*** (0.2278)		-1.3087*** (0.2336)	
ρ (FD, FY)			0.4009*** (0.0075)	
Observations			39141	
Log likelihood			-48557.49	
Likelihood ratio test				
χ^2 -statistic			2401.37	
p -value			0.0000	

Standard errors are in parentheses. Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively.

^aThe logarithm of income was used.

6.5.2 Almost Ideal Demand System Results

The Linear Approximate Almost Ideal Demand System (LA/AIDS) model was estimated by the non-linear seemingly unrelated regression method with homogeneity and symmetry imposed. The results for the parameter estimates are presented in table 48. Most of the parameter estimates, including socioeconomic variables, are significant at the 1% level, suggesting that household size and age of the household head influence household demand for dairy products. The coefficient for age is positive and highly significant for functional yoghurts, while it is negative and highly significant for non-functional yoghurts and non-functional dairy drinks. This indicates that older households allocate a higher share of expenditure to functional yoghurts, but a lower share of expenditure on non-functional yoghurts and non-functional dairy drinks. This finding is in line with expectations since functional foods are products capable of generating health benefits and older people are more concerned with health than younger people (Roininen et al. 1999). The coefficient for household size is negative and highly significant for functional yoghurts, functional dairy drinks, and non-functional dairy drinks, while it is positive and significant for non-functional yoghurts and other dairy products. Given that functional foods tend to be more expensive than their conventional (non-functional) alternatives (Lähteenmäki et al. 2007), this result can be given an intuitively appealing interpretation. As household size increases for a given level of expenditure and prices, households are compelled to adjust their pattern of demand towards relatively inexpensive commodities such as non-functional yoghurts and other dairy products, and away from more expensive commodities such as functional yoghurts, functional dairy drinks, and non-functional dairy drinks.

Food groups, or rather expenditure groups, with negative expenditure parameters, given in table 48, are income inelastic, and those with positive expenditure parameters are income elastic. This implies that yoghurts and dairy drinks (both functional and non-functional) are income inelastic, whereas the other dairy product group is income elastic. More specifically, the estimates of expenditure classify yoghurts and dairy drinks as necessities (both functional and non-functional), while the other dairy product group is a luxury, as indicated by the parameter estimates, which are significantly different from zero at the 1% level.

Table 48 Estimated coefficients for the LA/AIDS model for different dairy product items

	Mean Budget Share	Constant Term	FYO	FDD	NFYO	NFDD
FYO	0.0506	0.1730*** (0.0086)	0.0550*** (0.0020)	-0.0008 (0.0014)	-0.0305*** (0.0020)	-0.0064*** (0.0014)
FDD	0.0461	0.2176*** (0.0102)	-0.0008 (0.0014)	0.0545*** (0.0021)	-0.0188*** (0.0021)	-0.0115*** (0.0014)
NFYO	0.1588	0.2704*** (0.0118)	-0.0305*** (0.0020)	-0.0188*** (0.0021)	0.0504*** (0.0040)	0.0001 (0.0020)
NFDD	0.0537	0.2030*** (0.0090)	-0.0064*** (0.0014)	-0.0115*** (0.0014)	0.0001 (0.0020)	0.0364*** (0.0019)
ODP	0.6907	0.1359*** (0.0176)	-0.0172*** (0.0020)	-0.0233*** (0.0022)	-0.0011 (0.0030)	-0.0185*** (0.0021)
	ODP	EXP	AGE	HHSIZE		
FYO	-0.0172*** (0.0020)	-0.0194*** (0.0013)	0.0008*** (0.0001)	-0.0059*** (0.0009)		
FDD	-0.0233*** (0.0022)	-0.0199*** (0.0015)	0.0001 (0.0001)	-0.0058*** (0.0010)		
NFYO	-0.0011 (0.0030)	-0.0119*** (0.0018)	-0.0005*** (0.0001)	0.0028** (0.0012)		
NFDD	-0.0185*** (0.0021)	-0.0105*** (0.0013)	-0.0004*** (0.0001)	-0.0100*** (0.0009)		
ODP	0.0601*** (0.0045)	0.0617*** (0.0027)	0.0001 (0.0002)	0.0189*** (0.0017)		

Standard errors are in parentheses. Double (**) and triple (***) denote significant variables at 5% and 1% levels, respectively. FYO = functional yoghurts; FDD = functional dairy drinks; NFYO = non-functional yoghurts; NFDD = non-functional dairy drinks; ODP = other dairy products; EXP = expenditure; AGE = age of the household head (in years); HHSIZE = household size (total number of household members).

The interpretation of price and income effects is best discussed in terms of elasticities. Given that we used the expenditure on dairy products rather than total expenditure, the estimated compensated and uncompensated price and expenditure elasticities are conditional elasticities. The elasticities are therefore all third-stage estimates (Hayes et al. 1990). Table 49 presents both uncompensated and compensated price elasticities. Also presented in the table are expenditure elasticities and marginal expenditure shares.

The expenditure elasticities of all commodity groups are positive, ranging between 0.57 and 1.09. This indicates that all the commodities are normal goods, consumption of which will

increase with increased incomes. Yoghurts and dairy drinks (both functional and non-functional) have expenditure elasticities of less than one, while the other dairy product group has an expenditure elasticity above one. These findings suggest that as income increases consumers tend to spend proportionately less on yoghurts and dairy drinks and more on other dairy products, indicating that yoghurts and dairy drinks are necessities, while the other dairy product group is a luxury. This confirms the results presented in table 48 where yoghurts and dairy drinks revealed negative expenditure parameters, whereas the sign of the coefficient on the expenditure variable for other dairy products was found to be positive.

Following Powell (1974) the marginal expenditure shares have been calculated by multiplying the estimated expenditure elasticities presented in table 49 by the expenditure shares presented in table 48. The results reveal that for any increase in future expenditures, the largest percentage increase will be allocated to other dairy products (75%), followed by non-functional yoghurts (15%), non-functional dairy drinks (4%), functional yoghurts (3%), and functional dairy drinks (3%).

The uncompensated own-price elasticities for non-functional yoghurts, non-functional dairy drinks, and other dairy products presented in table 49 are found to be negative and range between -0.31 and -0.98. Demand is less price elastic for non-functional dairy drinks and non-functional yoghurts than for other dairy products. This indicates that a uniform percentage decrease in prices of all commodities would elicit a greater demand for other dairy products. The uncompensated own-price elasticities for functional yoghurts and functional dairy drinks are close to zero and even slightly positive, implying that the demand for these functional dairy products is price-independent. Functional dairy products provide health benefits beyond basic nutrition and consumers suffering from ill health purchase these products, regardless of market price behavior. Similar results are obtained for the compensated own-price elasticities.

The compensated cross-price elasticities provide an accurate picture of cross-price substitution between food groups, since they are a measure of substitution effects net of income (Molina 1994). Positive cross-price elasticities indicate that the relevant food groups are substitutes, negative cross-price elasticities suggest complementarity between the relevant food groups. The results reveal that non-functional yoghurts and non-functional dairy drinks are substitutes. However, the low magnitudes of the compensated cross-price elasticities between these food groups (0.05 and 0.16) suggest that substitution possibilities are quite

limited. All compensated cross-price elasticities of the other dairy product group are positive, indicating substitution effects between the other dairy product group and the other food groups. The compensated cross-price elasticities between functional and non-functional products indicate complementarity between the food groups. More specifically, there is complementarity between functional products (yoghurts and dairy drinks) and non-functional products (yoghurts and dairy drinks). This implies, for instance, that there are no substitution effects between functional yoghurts and non-functional yoghurts. It is important to note that the signs of some compensated elasticities are different from those of the uncompensated elasticities. This suggests that expenditure effects are significant in affecting consumer demand decisions. All uncompensated and compensated price elasticities are inelastic.

Comparison of our results to those of other authors is difficult and typically inconclusive since the models, data, and time periods are not the same. Nonetheless, comparison among studies may yield useful insights. For instance, Bonanno (2013) uses a scanner database of yoghurt sales for the period January 2004 – December 2005 in order to examine the demand for conventional and functional yoghurts in Italy. His results reveal that functional alternatives show lower own-price elasticities than their conventional counterparts. Our findings also indicate that, in the yoghurt (and dairy drink) market, functional alternatives' demand is less elastic than that of their conventional (i.e. non-functional) counterparts. Given that negative signs emerge for cross-price elasticities between functional and conventional yoghurts, Bonanno (2013) further concludes that functional and conventional products are not likely to be seen as substitutes, a finding that is consistent with our findings.

Bonanno (2012) uses the same scanner database of yoghurt sales in order to investigate seven conventional and four functional yoghurt subcategories and to assess also the role of demographic characteristics as potential contributors to the market success of functional yoghurts. His findings indicate that as health gets depleted by aging, the likelihood of consuming functional yoghurts in place of conventional ones increases. Our results show that older households allocate a higher share of expenditure to functional yoghurts, but a lower share of expenditure on non-functional yoghurts (and non-functional dairy drinks), and as such are consistent with Bonanno's results.

Table 49 Price and expenditure elasticities from the LA/AIDS model

	FYO	FDD	NFYO	NFDD	ODP	EXPEL	MEXPS
<i>Uncompensated</i>							
FYO	0.105*** (0.039)	0.001 (0.028)	-0.542*** (0.041)	-0.107*** (0.027)	-0.075* (0.040)	0.617*** (0.026)	0.031
FDD	0.004 (0.031)	0.201*** (0.045)	-0.340*** (0.046)	-0.226*** (0.031)	-0.207*** (0.049)	0.569*** (0.033)	0.026
NFYO	-0.188*** (0.013)	-0.115*** (0.013)	-0.671*** (0.025)	0.005 (0.013)	0.045** (0.018)	0.925*** (0.011)	0.147
NFDD	-0.110*** (0.026)	-0.205*** (0.027)	0.033 (0.038)	-0.313*** (0.035)	-0.210*** (0.038)	0.805*** (0.025)	0.043
ODP	-0.029*** (0.003)	-0.038*** (0.003)	-0.016*** (0.005)	-0.032*** (0.003)	-0.975*** (0.006)	1.089*** (0.004)	0.752
<i>Compensated</i>							
FYO	0.136*** (0.039)	0.030 (0.028)	-0.444*** (0.040)	-0.073*** (0.027)	0.352*** (0.040)		
FDD	0.033 (0.031)	0.227*** (0.045)	-0.250*** (0.045)	-0.196*** (0.031)	0.186*** (0.049)		
NFYO	-0.141*** (0.013)	-0.073*** (0.013)	-0.524*** (0.025)	0.054*** (0.012)	0.683*** (0.019)		
NFDD	-0.069*** (0.026)	-0.168*** (0.027)	0.161*** (0.037)	-0.269*** (0.035)	0.346*** (0.038)		
ODP	0.026*** (0.003)	0.012*** (0.003)	0.157*** (0.004)	0.027*** (0.003)	-0.222*** (0.007)		

Standard errors are in parentheses. Single (*), double (**), and triple (***) denote significant variables at 10%, 5%, and 1% levels, respectively. FYO = functional yoghurts; FDD = functional dairy drinks; NFYO = non-functional yoghurts; NFDD = non-functional dairy drinks; ODP = other dairy products; EXPEL = expenditure elasticities; MEXPS = marginal expenditure share.

6.6 Concluding Remarks

Given that consumers' interest in functional food grows, food manufacturers may see the development of functional products as an opportunity to revive mature markets. The success of functional food has initiated a large body of research (Siró et al. 2008) focusing on understanding consumers' acceptance of and preferences for functional foods. Most studies on functional food rely on survey data and stated preference methods. Surprisingly, little empirical analysis has so far used actual market data in order to examine consumers' actual choice behavior towards both conventional and functional food (Bonanno 2012). This study therefore used a scanner database of yoghurt and dairy drink sales, and as such tried to reveal consumers' real preferences for and choice decisions on functional dairy products.

The empirical results of the bivariate probit model indicate that income plays a major role, suggesting that high-income households are more likely to choose functional dairy drinks and functional yoghurts. This may be attributed to the fact that functional products tend to be more expensive than their conventional alternatives, and as such food manufacturers should take this finding into account. The findings also indicate that older people (i.e. people over the age of 49) are more likely to purchase functional yoghurts but have a lower probability of choosing functional dairy drinks. This is probably because people generally consume more yoghurts than dairy drinks, suggesting that older consumers are most likely to buy functional food that belongs to a product category they usually consume. Food manufacturers who want to target older people should take this finding into consideration. The finding that older consumers are more likely to select functional yoghurts is similar to the finding obtained from the latent class model for yoghurt which suggests that functional food advocates tend to be older. The results also indicate that men who live alone are neither likely to choose functional dairy drinks nor functional yoghurts. This finding is slightly different from the finding obtained from the latent class analyses for cream cheese and ice cream which suggest that functional food advocates are more likely to be male. Quite interesting is the finding that people who live in big cities reveal a higher probability of choosing functional dairy drinks. This may be attributed to the fact that new techniques are applied to produce functional foods and people in big cities tend to be more open-minded.

The results obtained from the linear approximate almost ideal demand system reveal that older households allocate a higher share of expenditure to functional yoghurts. This finding is similar to the findings obtained from the bivariate probit model as well as from the latent class

model which suggest that older consumers are more likely to select functional yoghurts and that functional food advocates tend to be older. The results also indicate that the share of expenditure on functional yoghurts, functional dairy drinks, and non-functional dairy drinks decreases as household size increases. This may be attributed to the fact that these products represent relative expensive commodities. The finding that the share of expenditure on functional yoghurts decreases as household size increases is similar to the finding obtained from the bivariate probit model which suggests that an increasing household size leads to a lower probability of selecting functional yoghurts. The demand for yoghurts and dairy drinks (both functional and non-functional) was found to be income inelastic, whereas the demand for the other dairy product group was found to be income elastic, suggesting that just the other dairy product group is quite responsive to expenditure changes. The results also reveal that all the commodities are normal goods, consumption of which will increase with increased incomes. This implies that income plays a major role, a finding that is consistent with the results of the bivariate probit model. The demand for non-functional yoghurts, non-functional dairy drinks, and other dairy products is quite responsive to price changes. Thus, as prices of the commodities increase, expenditure allocated to them is expected to decline. The demand for functional yoghurts and functional dairy drinks, however, tends to be price-independent. This is probably because functional products provide health benefits and people suffering from ill health purchase these products, regardless of market price behavior. Quite interesting is the finding that functional and non-functional dairy products (yoghurts and dairy drinks) are not likely to be seen as substitutes, a finding that is consistent with Bonanno (2013).

7. Conclusions

This study examined consumers' preferences and willingness-to-pay for functional dairy products in Germany using stated and revealed preference data. Given that the functional dairy market is continuously growing, the study was partly designed to provide a better understanding of consumers' preferences and willingness-to-pay for functional dairy products and to derive some implications for future development of these kinds of food products. Due to the fact that very few functional food studies have recently considered German consumers, the study makes a contribution to the literature by examining consumers' preferences for and attitudes towards functional dairy products in Germany, since Germany represents one of the most important countries within the functional food market in Europe. The study further aimed to examine whether willingness-to-pay values obtained from the analyses are subject to starting point bias, a hypothetical bias occurring in stated preference methods due to preference uncertainty. More specifically, different initial prices may lead to respondents stating different willingness-to-pay values. Due to the fact that very few studies have examined starting point bias in choice experiments, the study provides useful information, since it is tested whether choice experiments are able to reveal consumers' true willingness-to-pay values. Both stated and revealed preference data were used in order to get a deeper understanding of the consumers' preferences for and choice behavior towards functional dairy products. This chapter summarizes the focus and motivation of the study. A summary of the key results is then given, followed by a presentation of ideas for future research.

7.1 Study Focus

The analyses conducted in this study aimed at identifying consumers' preferences and willingness-to-pay values for several functional dairy product attributes in Germany. Furthermore, the study focused on analyzing the consumers' choice decisions on functional and conventional dairy products. The main motivation for studying the consumers' preference behavior in terms of functional food is the increasing significance of functional foods in dietary choices of consumers in industrialized countries. Primary data of a choice experiment were analyzed to investigate preferences for functional dairy product attributes on a random sample of 1309 consumers in Germany. Numerous factors motivate the use of choice experiments. First, choice experiments are useful because consumers can be asked about their willingness to purchase any product, including those currently not available on markets. Second, choice experiments are flexible because they allow for multiattribute valuation and enable the measurement of trade-offs among a number of attributes. Third, choice experiments are based on Lancaster's theory of consumer demand, which postulates that

preferences for goods are a function of the attributes possessed by the good, rather than the good per se. Fourth, choice experiment questions are typically framed in a way that is similar to actual purchasing situations.

Many functional food studies employing choice experiments have used conditional logit models to empirically model preference behavior. A restriction of these models is that consumers' preferences are assumed to be homogeneous, and as such it is just the average preference that is analyzed. However, it is reasonable to assume that different individuals will place a different value or importance on the different attributes defining the food choice alternatives due to different socioeconomic characteristics or attitudes. This study overcomes this limitation and accounts for heterogeneous preferences by employing random parameter logit models and latent class models.

The study also addressed the problem of starting point bias in stated preference methods. Starting point bias occurs when respondents are unsure about their true preferences for the good being valued. Consequently, they regard the presented price as an approximate value of the good's real value and anchor their willingness-to-pay in this value. Many economic studies have investigated the influence of starting point bias in dichotomous choice contingent valuation methods. The findings from these studies reveal that starting point bias significantly influences the derived willingness-to-pay. Given the close relationship between choice experiments and dichotomous choice contingent valuation methods, it may be expected that choice experiments are equally prone to starting point bias as in the case of dichotomous choice contingent valuation methods. Surprisingly, very little work has been undertaken to examine the possible existence of starting point bias in choice experiments. This study focuses on the possible influence of starting point bias in choice experiments by using a two-split sample approach and by accounting for gender-specific effects.

In order to assess the actual choice behavior towards functional and conventional dairy products, the study also used revealed preference data and examined individuals' real functional/conventional food choices in Germany. In particular, purchase information for several product groups of the category dairy products was extracted from a home-scanned consumer panel. To the extent that very few studies on functional food have used revealed preference data, this study makes a contribution to the empirical literature by examining the actual choice behavior towards functional dairy products. A bivariate probit model was used

to investigate factors that influence an individual's choice to purchase functional dairy drinks and functional yoghurts on a sample of 39141 households. Such information is useful in order to determine target groups and to develop successful functional products. An almost ideal demand system model was then employed to get an understanding of household consumption patterns of functional and conventional (non-functional) dairy products. This provides important information on how consumers react to changes in prices, how income changes affect the consumption of functional and non-functional dairy products, and how socioeconomic variables impact on household dairy product consumption.

7.2 Summary of Results

This section presents a summary of the empirical results. The findings of the choice experiment study are discussed, followed by a presentation of the empirical results dealing with the actual choice behavior towards functional dairy products.

7.2.1 Stated Preference Results

The empirical results obtained from random parameter logit and latent class model provide a number of insights to understanding consumers' choice behavior. The results of the random parameter logit model revealed significant preference heterogeneity among consumers with regard to price. In particular, dairy products fortified with omega-3 fatty acids and bearing a health claim of support for healthy blood vessels and healthy metabolism were found to be the most preferred attributes, whereas dairy products that bear a health claim of just support for healthy blood vessels were least preferred. The highest positive willingness-to-pay estimates were obtained for omega-3 fatty acids. This is probably because German consumers are familiar with this ingredient and its health related effects. It is widely known that fortifying a product with a familiar ingredient is more likely to result in acceptance than fortifying a product with an unfamiliar ingredient. This finding is also consistent with the finding that most respondents have a negative preference for bioactive peptides. German consumers are not very familiar with these kinds of ingredients due to the fact that bioactive peptides are not on the market in Germany yet. Quite significant and interesting was the finding that consumers prefer non-functional ice cream. This may be attributed to the fact that ice cream represents a hedonic product and consumers probably prefer hedonic products without any healthy ingredients. However, it might be that consumers prefer non-functional ice cream because functional ice cream is not on the market in Germany yet. Similarly, some consumers, particularly females, reveal a positive preference for non-functional cream cheese, implying that consumers do not accept functional cream cheese. This is not surprising since functional cream cheese is also not on the market in Germany yet. Basically, these findings

indicate that German consumers are skeptical consumers due to the fact that they prefer familiar ingredients like omega-3 fatty acids to unfamiliar ones like bioactive peptides and seem to reject unknown products such as functional ice cream and functional cream cheese. The future market development of functional foods in Germany is, therefore, influenced by the degree of familiarity of the functional products and their functional ingredients. It is, however, important to note that the regulatory situation of functional food in Europe will also strongly influence the development of functional foods in Germany, since a community list of approved functional health claims will be provided by the EFSA ensuring that any claim made on a food label in the EU is substantiated by scientific evidence. Given that companies have to spend a lot of money on clinical trials in order to get the scientific substantiation of the health claims verified, this may represent a big problem, particularly for small companies.

Based on the results of the random parameter logit model, differences in willingness-to-pay were calculated to test whether willingness-to-pay estimates are affected by starting point bias. The results suggested that willingness-to-pay estimates elicited in the choice experiment are not subject to starting point bias. Thus, employing different sets of price levels in the first choice set did not result in significantly different willingness-to-pay measures for functional dairy product attributes. Neither women nor men were affected by starting point bias. Quite significant and interesting was the finding that the method used to estimate the significance of the difference of the two willingness-to-pay measures had a big effect on the results, since a *t*-test provided biased estimates and led to erroneous decisions in hypothesis testing. More specifically, the complete combinatorial method provided an exact measure of the difference of the two willingness-to-pay distributions. These findings indicate that choice experiments have considerable merit over dichotomous choice contingent valuation methods, since dichotomous choice contingent valuation methods are susceptible to starting point bias.

In order to examine the sources of heterogeneity in preferences across classes of consumers, latent class models were employed. The results revealed heterogeneity of preferences relating to both the consumers' attitudes towards functional foods and healthy diet and socioeconomic characteristics. In particular, three distinct classes of consumers in the sample population, each displaying differing preferences for the same set of functional dairy product attributes, were identified. The classes mostly comprised functional food skeptics, functional food advocates, and functional food neutrals, since heterogeneous preferences were mainly driven by the consumer's attitude towards functional foods. Functional food skeptics placed high

value on dairy products enriched with omega-3 fatty acids and being non-functional. For the functional food advocates, dairy products fortified with omega-3 fatty acids and bearing a health claim of support for healthy blood vessels and healthy metabolism were found to be the most preferred attributes, whereas non-functional dairy products were least preferred. For the class comprising functional food neutrals, omega-3 fatty acids, oligosaccharides, and a health claim displaying an ingredient dependent property were the most important attributes in terms of yoghurt and ice cream.

Several conclusions can be drawn from the latent class results. First of all, the findings suggest that psychographic variables (e.g., attitudinal variables) are crucial in explaining class membership, and as such consumers' choice behavior. Furthermore, the results emphasize the importance of the familiarity of the functional ingredient, indicating that all consumers were willing to pay for functional dairy products enriched with known functional ingredients such as omega-3 fatty acids. This finding is consistent with the findings from the random parameter logit model. Finally, the results suggest that the same type of health claim does not appeal to everyone. In particular, functional food advocates and functional food neutrals revealed differing preferences for the same set of health benefits. Basically, these findings indicate that understanding preference heterogeneity requires more information about consumers than the simple socioeconomic characteristics typically collected by analysts.

7.2.2 Revealed Preference Results

The empirical results obtained from the bivariate probit model as well as from the almost ideal demand system model provide useful information about the consumers' actual choice behavior towards functional and conventional (non-functional) dairy products.

Factors influencing an individual's actual choice to buy functional dairy drinks and functional yoghurts were examined using a scanner database of dairy drink and yoghurt sales. Specifically, it was taken into consideration that there may be unobservable characteristics of individuals that influence both functional food purchasing decisions. The results of the bivariate probit model revealed that the functional purchasing decision of dairy drinks and yoghurts were not statistically independent. Furthermore, the results suggested that a number of socioeconomic characteristics play a significant role in explaining consumers' actual choice decisions on functional food. The results were consistent with the hypothesis that the decision whether to purchase functional dairy products or not is constrained by income. More specifically, households with higher incomes have a higher probability to choose functional

dairy drinks and functional yoghurts which can be explained by the fact that functional food tends to be more expensive than conventional food.

People between the ages of 19 and 34 were less likely to choose functional dairy drinks and functional yoghurts. This is not surprising since functional food aims at providing health benefits and younger people are generally less concerned with health than older people, implying that they do not feel the need to consume functional food. The results also revealed that older people (i.e. people over the age of 49) have a higher probability to purchase functional yoghurts. However, they are less likely to buy functional dairy drinks. Given that yoghurts are generally more consumed than dairy drinks, this finding implies that older consumers are just interested in functional foods that are part of a product category they normally consume. The finding that older people are more likely to choose functional yoghurts is consistent with the hypothesis that age influences the decision whether to purchase functional dairy products or not. Quite significant and interesting was the finding that male single-person households have a lower probability to purchase functional dairy drinks and functional yoghurts relative to multi-person households. This is probably because men tend to be less health conscious. The bivariate probit results also suggested that households living in big cities (i.e. cities with at least one million inhabitants) have a higher probability of choosing functional dairy drinks. This finding can be explained by the fact that people in big cities tend to be more open-minded, and as such are more willing to accept new technologies used to produce functional foods. These findings basically imply that food manufacturers should be aware of the relevant target group in order to develop successful functional dairy products since there are groups of consumers not willing to purchase these kinds of foods.

In order to estimate the demand for functional and conventional (non-functional) dairy products, the linear approximate almost ideal demand system model was further employed. The results revealed that age and household size affect the consumption of functional and non-functional dairy products. In particular, older households allocated a higher share of expenditure to functional yoghurts and the share of expenditure on functional yoghurts decreased as household size increased. Both findings are similar to the findings obtained from the bivariate probit model. Yoghurts and dairy drinks (both functional and non-functional) were found to be necessities, since the demand for these products was income inelastic. The almost ideal demand system results also suggested that the demand for non-functional yoghurts, non-functional dairy drinks, and other dairy products was quite responsive to price

changes, whereas the own-price elasticities for functional yoghurts and functional dairy drinks were close to zero. This implies that the demand for these functional dairy products tends to be price-independent which can be explained by the fact that functional dairy products provide health benefits and people suffering from ill health buy functional dairy products, regardless of market price behavior, since they feel the need to consume them. Furthermore, complementarity between functional and non-functional dairy products (yoghurts and dairy drinks) was found, indicating that there are no substitution effects.

7.3 Future Research

This study mainly examined consumers' preferences for several functional dairy product attributes in Germany using stated preference data. The willingness-to-pay values for the attributes derived from the choice experiment and the econometric analyses reflect the relative importance of the attributes to the consumers. The study also used revealed preference data in order to investigate the factors influencing an individual's decision whether to purchase functional dairy products or not as well as to gain an understanding of household consumption patterns of functional and non-functional dairy products.

Future research may try to combine revealed preference data from real markets with stated preference data from choice experiments or other sources of stated preference data using methods developed in the last two decades. Pooling both data sources implies, however, that at least some attributes of the products being analyzed are common to both data sets (Louviere et al. 2000).⁴⁸

Given that the choice experiment study was carried out using cross-sectional data and considering the fact that interesting results on consumers' attribute preferences were provided, it may be valuable to examine whether the preferences vary over time. In particular, this might be interesting due to the fact that consumers tend to prefer familiar ingredients which are on the market in Germany since several years.

There has been an extensive discussion about the possibility of eliciting preferences with stated preference methods and the extent of hypothetical bias. This study analyzed market goods and accounted for starting point bias in choice experiments. Given that only few economic studies have investigated the presence of starting point bias in choice experiments

⁴⁸ The process of pooling revealed preference and stated preference data and estimating a model from the pooled data is widely known as data enrichment (Louviere et al. 2000).

and considering the fact that the results obtained appear to differ, future research in this area may be necessary to shed more light on this phenomenon. Future studies may also consider other hypothetical bias problems such as attribute non-attendance (i.e. respondents ignore attributes in the choice sets) or context dependence of preferences (e.g., complexity of the choice situation).

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Appendices

Appendix 1: Choice Sets for Blocks Two, Three, and Four

Choice sets for all three dairy products (block two)

Choice set	Alt	Price (yoghurt/cream cheese/ice cream)	Omega	Olig	Bio	HC 1	HC 2	HC 3	Block
1	1	1.79€/2.09€/3.99€	-1	-1	-1	1	0	0	2
1	2	2.09€/2.49€/4.49€	0	0	1	1	0	0	2
1	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	2
2	1	1.49€/1.69€/3.49€	0	0	1	-1	-1	-1	2
2	2	2.09€/2.49€/4.49€	1	0	0	-1	-1	-1	2
2	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	2
3	1	2.09€/2.49€/4.49€	0	0	1	1	0	0	2
3	2	1.29€/1.49€/3.19€	-1	-1	-1	0	0	1	2
3	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	2
4	1	1.29€/1.49€/3.19€	-1	-1	-1	-1	-1	-1	2
4	2	1.29€/1.49€/3.19€	0	1	0	0	1	0	2
4	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	2
5	1	2.09€/2.49€/4.49€	1	0	0	0	0	1	2
5	2	1.79€/2.09€/3.99€	-1	-1	-1	1	0	0	2
5	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	2
6	1	1.29€/1.49€/3.19€	0	1	0	0	1	0	2
6	2	1.79€/2.09€/3.99€	0	1	0	-1	-1	-1	2
6	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	2
7	1	1.79€/2.09€/3.99€	0	1	0	0	0	1	2
7	2	1.49€/1.69€/3.49€	0	0	1	0	0	1	2
7	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	2

Choice sets for all three dairy products (block three)

Choice set	Alt	Price (yoghurt/cream cheese/ice cream)	Omega	Olig	Bio	HC 1	HC 2	HC 3	Block
1	1	2.09€/2.49€/4.49€	0	1	0	-1	-1	-1	3
1	2	1.49€/1.69€/3.49€	1	0	0	1	0	0	3
1	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	3
2	1	1.29€/1.49€/3.19€	1	0	0	1	0	0	3
2	2	1.49€/1.69€/3.49€	0	0	1	-1	-1	-1	3
2	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	3
3	1	1.49€/1.69€/3.49€	-1	-1	-1	0	0	1	3
3	2	1.29€/1.49€/3.19€	-1	-1	-1	-1	-1	-1	3
3	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	3
4	1	1.79€/2.09€/3.99€	0	0	1	0	1	0	3
4	2	1.29€/1.49€/3.19€	0	1	0	1	0	0	3
4	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	3
5	1	1.79€/2.09€/3.99€	1	0	0	-1	-1	-1	3
5	2	1.79€/2.09€/3.99€	0	1	0	0	0	1	3
5	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	3
6	1	1.29€/1.49€/3.19€	0	0	1	0	0	1	3
6	2	2.09€/2.49€/4.49€	0	0	1	0	1	0	3
6	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	3
7	1	1.49€/1.69€/3.49€	0	1	0	1	0	0	3
7	2	1.79€/2.09€/3.99€	-1	-1	-1	0	1	0	3
7	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	3

Choice sets for all three dairy products (block four)

Choice set	Alt	Price (yoghurt/cream cheese/ice cream)	Omega	Olig	Bio	HC 1	HC 2	HC 3	Block
1	1	1.79€/2.09€/3.99€	0	1	0	0	0	1	4
1	2	1.29€/1.49€/3.19€	1	0	0	0	1	0	4
1	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	4
2	1	1.49€/1.69€/3.49€	0	0	1	-1	-1	-1	4
2	2	1.79€/2.09€/3.99€	0	0	1	1	0	0	4
2	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	4
3	1	2.09€/2.49€/4.49€	1	0	0	0	0	1	4
3	2	2.09€/2.49€/4.49€	0	1	0	-1	-1	-1	4
3	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	4
4	1	2.09€/2.49€/4.49€	0	0	1	1	0	0	4
4	2	1.49€/1.69€/3.49€	0	1	0	0	1	0	4
4	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	4
5	1	1.79€/2.09€/3.99€	-1	-1	-1	1	0	0	4
5	2	1.79€/2.09€/3.99€	1	0	0	-1	-1	-1	4
5	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	4
6	1	1.49€/1.69€/3.49€	1	0	0	0	1	0	4
6	2	1.29€/1.49€/3.19€	0	0	1	0	0	1	4
6	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	4
7	1	1.29€/1.49€/3.19€	0	1	0	0	1	0	4
7	2	2.09€/2.49€/4.49€	-1	-1	-1	1	0	0	4
7	3	1.29€/1.49€/3.19€	0	0	0	0	0	0	4

Appendix 2: Questionnaire

University of Kiel

Department of Food Economics and Consumption Studies

Survey

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First of all I would like to provide you with a brief definition of the term functional food.

Please read the following text carefully before answering questions.

Functional foods are foods that have health benefits beyond basic nutrition, and as such improve health and general well-being or lower the risk of disease.

Functional foods are fortified with specific ingredients imparting the health benefits. Some examples for these ingredients are minerals, vitamins, peptides, fatty acids, dietary fibers or other bioactive substances such as secondary plant compounds or probiotics. Health claims are displayed on the product package explaining health benefits (e.g., “Strengthens immune system.” or “Lowers blood cholesterol.”). Examples of functional foods are dairy drinks strengthening the immune system or blood cholesterol lowering spreads.

1. Do you consume functional foods?

Please make a mark.

- Yes No Don't know

2. Some functional food related statements are listed below. Please indicate how much you agree or disagree with each of the following statements.

Please make a mark.

Scale:

1	2	3	4	5	6	7
Completely disagree	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Completely agree

	Completely disagree		Neutral			Completely agree	
	1	2	3	4	5	6	7
Functional foods help to improve my mood.	<input type="checkbox"/>						
My performance improves when I eat functional foods.	<input type="checkbox"/>						
Functional foods make it easier to follow a healthy lifestyle.	<input type="checkbox"/>						
I can prevent disease by eating functional foods regularly.	<input type="checkbox"/>						
The idea that I can take care of my health by eating functional foods gives me pleasure.	<input type="checkbox"/>						
Functional foods can repair the damage caused by an unhealthy diet.	<input type="checkbox"/>						
I am prepared to compromise on the taste of a food if the product is functional.	<input type="checkbox"/>						
I actively seek out information about functional foods.	<input type="checkbox"/>						
Functional foods are completely unnecessary.	<input type="checkbox"/>						
Functional foods are a total sham.	<input type="checkbox"/>						
The growing number of functional foods on the market is a bad trend for the future.	<input type="checkbox"/>						

	Completely disagree		Neutral			Completely agree	
	1	2	3	4	5	6	7
For a healthy person it is worthless to use functional foods.	<input type="checkbox"/>						
It is great that modern technology allows the development of functional foods.	<input type="checkbox"/>						
I only want to eat foods that do not have any medicine-like effects.	<input type="checkbox"/>						
Health effects are not appropriate in delicacies.	<input type="checkbox"/>						
Functional foods are consumed mostly by people who have no need for them.	<input type="checkbox"/>						
It is pointless to add health effects to otherwise unhealthy foods. (e.g., candies, potato chips)	<input type="checkbox"/>						
Functional foods promote my well-being.	<input type="checkbox"/>						
The safety of functional foods has been very thoroughly studied.	<input type="checkbox"/>						
I believe that functional foods fulfill their promises.	<input type="checkbox"/>						
Functional foods are science-based top products.	<input type="checkbox"/>						
If used in excess, functional foods can be harmful to health.	<input type="checkbox"/>						
In some cases functional foods may be harmful for healthy people.	<input type="checkbox"/>						
Using functional foods is completely safe.	<input type="checkbox"/>						
The new properties of functional foods carry unforeseen risks.	<input type="checkbox"/>						
Exaggerated information is given about health effects.	<input type="checkbox"/>						
I happily pay a higher price for foods with health claims.	<input type="checkbox"/>						

3. Some diet related statements are listed below. Please indicate how much you agree or disagree with each of the following statements.

Please make a mark.

Scale:

1	2	3	4	5	6	7
Completely disagree	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Completely agree

	Completely disagree			Neutral			Completely agree	
	1	2	3	4	5	6	7	
The healthiness of food has little impact on my food choices.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I am very particular about the healthiness of food I eat.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I eat what I like and I do not worry much about the healthiness of food.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
It is important for me that my diet is low in fat.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I always follow a healthy and balanced diet.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
It is important for me that my daily diet contains a lot of vitamins and minerals.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
The healthiness of snacks makes no difference to me.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I do not avoid foods, even if they may raise my cholesterol.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I try to eat foods that do not contain additives.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I do not care about additives in my daily diet.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I do not eat processed foods, because I do not know what they contain.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I would like to eat only organically grown vegetables.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
In my opinion, artificially flavoured foods are not harmful for my health.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
In my opinion, organically grown foods are no better for my health than those grown conventionally.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I always read the description displayed on the product package.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Below I provide you with some information about functional food.

Please read the following text carefully before continuing with the questionnaire. This may help you to answer the questions.

The following two attributes (functional ingredient and health claim) mentioned earlier are quite important in terms of functional food.

Functional ingredient

Functional foods are fortified with specific ingredients imparting the health benefits. Some examples for these ingredients are minerals, vitamins, peptides, fatty acids, dietary fibers or other bioactive substances such as secondary plant compounds or probiotics.

The present study accounts for four different functional ingredients: omega-3 fatty acids, oligosaccharides, bioactive peptides, and polyphenols. Omega-3 fatty acids are polyunsaturated fatty acids commonly found in fish. Oligosaccharides are classified as dietary fibers found in milk or produced synthetically. Bioactive peptides are protein fragments found in milk. Polyphenols are defined as secondary plant compounds and occur in fruits and vegetables.

The four functional ingredients listed above impart health benefits that are either quite different or similar.

Health claim

A health claim is a statement on the product package that explains the health benefit of the functional food (or rather the functional ingredient).

As indicated previously, the four functional ingredients listed above provide health benefits that are either quite different or similar. Furthermore, several different health benefits can be generated by the same functional ingredient.

You have received all necessary information in order to continue with the questionnaire. Different product combinations with varied functional ingredients, health claims, and prices are provided below.

First of all different yoghurts are presented in the following section (questions 4-10). Please indicate which yoghurt you would purchase even if you do not eat yoghurt. In this case, assume you are purchasing the yoghurt for your family or friends.

Please look at the different yoghurts. Yoghurts A and B are functional foods, while yoghurt C is non-functional. Each package contains 500 grams of yoghurt (= 4 cups). Taste, texture etc. are identical in terms of all three products. Please indicate which product you would purchase in each choice task.

4. Which product would you purchase?

Choose A, B or C.

Product	Yoghurt A	Yoghurt B	Yoghurt C
Price	2.09€/500g	1.79€/500g	1.29€/500g
Functional ingredient	Omega-3 fatty acids	Polyphenols	Conventional
Health claim	Supports healthy blood triglyceride levels.	Supports healthy blood vessels.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

5. Which product would you purchase?

Choose A, B or C.

Product	Yoghurt A	Yoghurt B	Yoghurt C
Price	1.79€/500g	2.09€/500g	1.29€/500g
Functional ingredient	Polyphenols	Bioactive peptides	Conventional
Health claim	Supports healthy blood vessels.	Supports healthy blood vessels.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

6. Which product would you purchase?

Choose A, B or C.

Product	Yoghurt A	Yoghurt B	Yoghurt C
Price	1.49€/500g	2.09€/500g	1.29€/500g
Functional ingredient	Bioactive peptides	Omega-3 fatty acids	Conventional
Health claim	Supports healthy blood vessels and healthy blood pressure.	Supports healthy blood vessels and healthy blood triglyceride levels.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

7. Which product would you purchase?

Choose A, B or C.

Product	Yoghurt A	Yoghurt B	Yoghurt C
Price	2.09€/500g	1.29€/500g	1.29€/500g
Functional ingredient	Bioactive peptides	Polyphenols	Conventional
Health claim	Supports healthy blood vessels.	Protects body's cells against free radicals.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

8. Which product would you purchase?*Choose A, B or C.*

Product	Yoghurt A	Yoghurt B	Yoghurt C
Price	1.29€/500g	1.29€/500g	1.29€/500g
Functional ingredient	Polyphenols	Oligosaccharides	Conventional
Health claim	Supports healthy blood vessels and protects body's cells against free radicals.	Supports healthy blood vessels and healthy metabolism.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

9. Which product would you purchase?*Choose A, B or C.*

Product	Yoghurt A	Yoghurt B	Yoghurt C
Price	1.29€/500g	1.79€/500g	1.29€/500g
Functional ingredient	Oligosaccharides	Oligosaccharides	Conventional
Health claim	Supports healthy blood vessels and healthy metabolism.	Supports healthy blood vessels and healthy digestion.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

10. Which product would you purchase?*Choose A, B or C.*

Product	Yoghurt A	Yoghurt B	Yoghurt C
Price	1.79€/500g	1.49€/500g	1.29€/500g
Functional ingredient	Oligosaccharides	Bioactive peptides	Conventional
Health claim	Supports healthy digestion.	Supports healthy blood pressure.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Now, it is about cream cheese. Different cream cheeses are presented in the following section (questions 11-17). Please indicate which cream cheese you would purchase even if you do not eat cream cheese. In this case, assume you are purchasing the cream cheese for your family or friends.

Please look at the different cream cheeses. Cream cheeses A and B are functional foods, while cream cheese C is non-functional. Each package contains 200 grams of cream cheese. Taste, texture etc. are identical in terms of all three products. Please indicate which product you would purchase in each choice task.

11. Which product would you purchase?

Choose A, B or C.

Product	Cream cheese A	Cream cheese B	Cream cheese C
Price	2.49€/200g	2.09€/200g	1.49€/200g
Functional ingredient	Omega-3 fatty acids	Polyphenols	
Health claim	Supports healthy blood triglyceride levels.	Supports healthy blood vessels.	Conventional
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

12. Which product would you purchase?

Choose A, B or C.

Product	Cream cheese A	Cream cheese B	Cream cheese C
Price	2.09€/200g	2.49€/200g	1.49€/200g
Functional ingredient	Polyphenols	Bioactive peptides	
Health claim	Supports healthy blood vessels.	Supports healthy blood vessels.	Conventional
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

13. Which product would you purchase?

Choose A, B or C.

Product	Cream cheese A	Cream cheese B	Cream cheese C
Price	1.69€/200g	2.49€/200g	1.49€/200g
Functional ingredient	Bioactive peptides	Omega-3 fatty acids	
Health claim	Supports healthy blood vessels and healthy blood pressure.	Supports healthy blood vessels and healthy blood triglyceride levels.	Conventional
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

14. Which product would you purchase?*Choose A, B or C.*

Product	Cream cheese A	Cream cheese B	Cream cheese C
Price	2.49€/200g	1.49€/200g	1.49€/200g
Functional ingredient	Bioactive peptides	Polyphenols	Conventional
Health claim	Supports healthy blood vessels.	Protects body's cells against free radicals.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

15. Which product would you purchase?*Choose A, B or C.*

Product	Cream cheese A	Cream cheese B	Cream cheese C
Price	1.49€/200g	1.49€/200g	1.49€/200g
Functional ingredient	Polyphenols	Oligosaccharides	Conventional
Health claim	Supports healthy blood vessels and protects body's cells against free radicals.	Supports healthy blood vessels and healthy metabolism.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

16. Which product would you purchase?*Choose A, B or C.*

Product	Cream cheese A	Cream cheese B	Cream cheese C
Price	1.49€/200g	2.09€/200g	1.49€/200g
Functional ingredient	Oligosaccharides	Oligosaccharides	Conventional
Health claim	Supports healthy blood vessels and healthy metabolism.	Supports healthy blood vessels and healthy digestion.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

17. Which product would you purchase?*Choose A, B or C.*

Product	Cream cheese A	Cream cheese B	Cream cheese C
Price	2.09€/200g	1.69€/200g	1.49€/200g
Functional ingredient	Oligosaccharides	Bioactive peptides	Conventional
Health claim	Supports healthy digestion.	Supports healthy blood pressure.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Finally, it is about ice cream. Different ice cream products are presented in the following section (questions 18-24). Please indicate which ice cream you would purchase even if you do not eat ice cream. In this case, assume you are purchasing the ice cream for your family or friends.

Please look at the different ice cream products. Ice cream products A and B are functional foods, while ice cream product C is non-functional. Each package contains 1000 milliliters of ice cream. Taste, texture etc. are identical in terms of all three products. Please indicate which product you would purchase in each choice task.

18. Which product would you purchase?

Choose A, B or C.

Product	Ice cream A	Ice cream B	Ice cream C
Price	4.49€/1000ml	3.99€/1000ml	3.19€/1000ml
Functional ingredient	Omega-3 fatty acids	Polyphenols	Conventional
Health claim	Supports healthy blood triglyceride levels.	Supports healthy blood vessels.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

19. Which product would you purchase?

Choose A, B or C.

Product	Ice cream A	Ice cream B	Ice cream C
Price	3.99€/1000ml	4.49€/1000ml	3.19€/1000ml
Functional ingredient	Polyphenols	Bioactive peptides	Conventional
Health claim	Supports healthy blood vessels.	Supports healthy blood vessels.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

20. Which product would you purchase?

Choose A, B or C.

Product	Ice cream A	Ice cream B	Ice cream C
Price	3.49€/1000ml	4.49€/1000ml	3.19€/1000ml
Functional ingredient	Bioactive peptides	Omega-3 fatty acids	Conventional
Health claim	Supports healthy blood vessels and healthy blood pressure.	Supports healthy blood vessels and healthy blood triglyceride levels.	
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

21. Which product would you purchase?*Choose A, B or C.*

Product	Ice cream A	Ice cream B	Ice cream C
Price	4.49€/1000ml	3.19€/1000ml	3.19€/1000ml
Functional ingredient	Bioactive peptides	Polyphenols	
Health claim	Supports healthy blood vessels.	Protects body's cells against free radicals.	Conventional
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

22. Which product would you purchase?*Choose A, B or C.*

Product	Ice cream A	Ice cream B	Ice cream C
Price	3.19€/1000ml	3.19€/1000ml	3.19€/1000ml
Functional ingredient	Polyphenols	Oligosaccharides	
Health claim	Supports healthy blood vessels and protects body's cells against free radicals.	Supports healthy blood vessels and healthy metabolism.	Conventional
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

23. Which product would you purchase?*Choose A, B or C.*

Product	Ice cream A	Ice cream B	Ice cream C
Price	3.19€/1000ml	3.99€/1000ml	3.19€/1000ml
Functional ingredient	Oligosaccharides	Oligosaccharides	
Health claim	Supports healthy blood vessels and healthy metabolism.	Supports healthy blood vessels and healthy digestion.	Conventional
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

24. Which product would you purchase?*Choose A, B or C.*

Product	Ice cream A	Ice cream B	Ice cream C
Price	3.99€/1000ml	3.49€/1000ml	3.19€/1000ml
Functional ingredient	Oligosaccharides	Bioactive peptides	
Health claim	Supports healthy digestion.	Supports healthy blood pressure.	Conventional
I would purchase...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Now, I would like to ask you some questions about your lifestyle.

25. How often do you normally consume the following foods and alcoholic drinks?

Please make a mark.

Scale:

1	2	3	4	5	6
Never	Seldom	Once or twice a month	Once a week	Several times a week	Daily

	Never					Daily
	1	2	3	4	5	6
Yoghurt	<input type="checkbox"/>					
Cream cheese	<input type="checkbox"/>					
Ice cream (consumption in summer only)	<input type="checkbox"/>					
Beer	<input type="checkbox"/>					
Wine	<input type="checkbox"/>					
Sparkling wine	<input type="checkbox"/>					
Spirits (“Schnapps”)	<input type="checkbox"/>					
Cocktails	<input type="checkbox"/>					

26. Do you smoke?

Please make a mark.

- Formerly
 Never
 Occasionally
 Daily

27. How often do you exercise for at least 30 minutes?

Please make a mark.

- Never
 Once a week
 Seldom
 Several times a week
 Once or twice a month
 Daily

28. In general, how would you describe your health?

Please make a mark.

- Very poor
 Poor
 Fair
 Good
 Excellent

29. Do you suffer or have suffered from any of the following diseases?

Please make a mark, multiple answers possible.

- | | |
|---|--|
| <input type="checkbox"/> Arteriosclerosis | <input type="checkbox"/> High blood pressure |
| <input type="checkbox"/> Arthritis | <input type="checkbox"/> High cholesterol levels |
| <input type="checkbox"/> Cancer | <input type="checkbox"/> Lactose intolerance |
| <input type="checkbox"/> Constipation | <input type="checkbox"/> Osteoporosis |
| <input type="checkbox"/> Coronary heart disease | <input type="checkbox"/> Overweight |
| <input type="checkbox"/> Dementia | <input type="checkbox"/> Rheumatism |
| <input type="checkbox"/> Diabetes | <input type="checkbox"/> Thrombosis |
| <input type="checkbox"/> Digestive problems | <input type="checkbox"/> Other: _____ |
| <input type="checkbox"/> Gluten sensitivity | |
| <hr/> | |
| <input type="checkbox"/> Gout | <input type="checkbox"/> I do not suffer from any disease. |

30. Does anyone in your family (all people genetically related to you) suffer or has suffered from any of the following diseases?

Please make a mark, multiple answers possible.

- | | |
|---|---|
| <input type="checkbox"/> Arteriosclerosis | <input type="checkbox"/> High blood pressure |
| <input type="checkbox"/> Arthritis | <input type="checkbox"/> High cholesterol levels |
| <input type="checkbox"/> Cancer | <input type="checkbox"/> Lactose intolerance |
| <input type="checkbox"/> Constipation | <input type="checkbox"/> Osteoporosis |
| <input type="checkbox"/> Coronary heart disease | <input type="checkbox"/> Overweight |
| <input type="checkbox"/> Dementia | <input type="checkbox"/> Rheumatism |
| <input type="checkbox"/> Diabetes | <input type="checkbox"/> Thrombosis |
| <input type="checkbox"/> Digestive problems | <input type="checkbox"/> Other: _____ |
| <input type="checkbox"/> Gluten sensitivity | |
| <hr/> | |
| <input type="checkbox"/> Gout | <input type="checkbox"/> Nobody suffers from any disease. |

Finally, I would like to ask you some questions about your person. All information will be treated confidentially.

31. How many people live in your household, including yourself?

Please enter a number.

_____ People

32. Do you have children?

Please make a mark.

Yes No

33. If yes, how many children are under the age of 12?

Please enter a number.

_____ Child/Children

34. What is your highest level of education?

Please make a mark.

- | | |
|--|--|
| <input type="checkbox"/> Not graduated yet | <input type="checkbox"/> Professional training |
| <input type="checkbox"/> No school degree | <input type="checkbox"/> Master craftsman status |
| <input type="checkbox"/> GCSE | <input type="checkbox"/> University degree |
| <input type="checkbox"/> A-levels | <input type="checkbox"/> Ph.D. |

35. In what year were you born?

Please enter the year you were born.

19_____

36. What is your net monthly household income? *This is the income of all members living in your household after tax has been paid and including child benefit etc..*
Please make a mark.

- | | | |
|---|--|--|
| <input type="checkbox"/> Less than 500€ | <input type="checkbox"/> 1501 to 2000€ | <input type="checkbox"/> 3001 to 3500€ |
| <input type="checkbox"/> 501 to 1000€ | <input type="checkbox"/> 2001 to 2500€ | <input type="checkbox"/> 3501 to 5000€ |
| <input type="checkbox"/> 1001 to 1500€ | <input type="checkbox"/> 2501 to 3000€ | <input type="checkbox"/> 5001€ or more |

37. What is your gender?
Please make a mark.

- Female Male

38. Please enter your city, state, and zip code.
Please enter city, state, and zip code.

Zip code/City_____

State_____

39. Please enter the date when you filled out this questionnaire.
Please enter date.

____.____.____

Thank you very much for your help.

Please indicate to which organization you want to donate one Euro:

- | | |
|---|---------------------------------------|
| <input type="checkbox"/> Médecins Sans Frontières | <input type="checkbox"/> UNICEF |
| <input type="checkbox"/> German Cancer Foundation | <input type="checkbox"/> Kieler Tafel |

Appendix 3: Marginal Effects (Cream Cheese and Ice Cream)

Marginal effects: functional ingredients (cream cheese)

Attribute	Alternative	Coefficient (Wald statistic)	Marginal effect [A, B, C]
Sample A			
Non-functional	C	0.212 (5.248)	
Omega-3 fatty acids (Omega)	A, B	0.400 (8.888)	Δ from omega to olig: [-0.054, -0.055, 0.108]
Oligosaccharides (Olig)	A, B	-0.058 (-1.284)	Δ from omega to bio: [-0.058, -0.059, 0.117]
Bioactive peptides (Bio)	A, B	-0.097 (-2.224)	Δ from omega to poly ^a : [-0.075, -0.076, 0.151] Δ from olig to bio: [-0.005, -0.005, 0.009] Δ from olig to poly: [-0.021, -0.022, 0.043] Δ from bio to poly: [-0.017, -0.017, 0.034]
Sample B			
Non-functional	C	0.128 (3.173)	
Omega-3 fatty acids (Omega)	A, B	0.299 (6.320)	Δ from omega to olig: [-0.027, -0.027, 0.054]
Oligosaccharides (Olig)	A, B	0.065 (1.410)	Δ from omega to bio: [-0.054, -0.056, 0.110]
Bioactive peptides (Bio)	A, B	-0.183 (-3.920)	Δ from omega to poly: [-0.054, -0.056, 0.110] Δ from olig to bio: [-0.028, -0.028, 0.056] Δ from olig to poly: [-0.028, -0.028, 0.056] Δ from bio to poly: [0.000, 0.000, 0.000]

^apoly = polyphenols

Marginal effects: functional ingredients (ice cream)

Attribute	Alternative	Coefficient (Wald statistic)	Marginal effect [A, B, C]
Sample A			
Non-functional	C	0.548 (12.871)	
Omega-3 fatty acids (Omega)	A, B	0.410 (8.309)	Δ from omega to olig: [-0.052, -0.054, 0.106]
Oligosaccharides (Olig)	A, B	-0.061 (-1.227)	Δ from omega to bio: [-0.060, -0.062, 0.122]
Bioactive peptides (Bio)	A, B	-0.139 (-2.876)	Δ from omega to poly ^a : [-0.068, -0.069, 0.137] Δ from olig to bio: [-0.008, -0.008, 0.016] Δ from olig to poly: [-0.015, -0.016, 0.031] Δ from bio to poly: [-0.007, -0.007, 0.015]
Sample B			
Non-functional	C	0.315 (7.573)	
Omega-3 fatty acids (Omega)	A, B	0.222 (4.255)	Δ from omega to olig: [-0.018, -0.019, 0.037]
Oligosaccharides (Olig)	A, B	0.054 (1.080)	Δ from omega to bio: [-0.031, -0.032, 0.063]
Bioactive peptides (Bio)	A, B	-0.067 (-1.357)	Δ from omega to poly: [-0.045, -0.047, 0.092] Δ from olig to bio: [-0.013, -0.013, 0.026] Δ from olig to poly: [-0.027, -0.028, 0.055] Δ from bio to poly: [-0.014, -0.015, 0.029]

^apoly = polyphenols

Marginal effects: health claims (cream cheese)

Attribute	Alternative	Coefficient (Wald statistic)	Marginal effect [A, B, C]
Sample A			
Non-functional	C	0.212 (5.248)	
HC 1	A, B	-0.369 (-7.448)	Δ from HC 1 to HC 2: [0.072, 0.072, -0.144]
HC 2	A, B	0.247 (5.692)	Δ from HC 1 to HC 3: [0.031, 0.031, -0.062]
HC 3	A, B	-0.098 (-2.137)	Δ from HC 1 to HC 4: [0.069, 0.069, -0.138] Δ from HC 2 to HC 3: [-0.041, -0.041, 0.082] Δ from HC 2 to HC 4: [-0.003, -0.003, 0.006] Δ from HC 3 to HC 4: [0.038, 0.038, -0.076]
Sample B			
Non-functional	C	0.128 (3.173)	
HC 1	A, B	-0.316 (-6.247)	Δ from HC 1 to HC 2: [0.056, 0.057, -0.113]
HC 2	A, B	0.182 (4.024)	Δ from HC 1 to HC 3: [0.032, 0.033, -0.065]
HC 3	A, B	-0.024 (-0.500)	Δ from HC 1 to HC 4: [0.053, 0.054, -0.107] Δ from HC 2 to HC 3: [-0.024, -0.024, 0.047] Δ from HC 2 to HC 4: [-0.003, -0.003, 0.006] Δ from HC 3 to HC 4: [0.021, 0.021, -0.042]

Marginal effects: health claims (ice cream)

Attribute	Alternative	Coefficient (Wald statistic)	Marginal effect [A, B, C]
Sample A			
Non-functional	C	0.548 (12.871)	
HC 1	A, B	-0.368 (-6.663)	Δ from HC 1 to HC 2: [0.062, 0.063, -0.125]
HC 2	A, B	0.223 (4.682)	Δ from HC 1 to HC 3: [0.031, 0.031, -0.061]
HC 3	A, B	-0.065 (-1.305)	Δ from HC 1 to HC 4: [0.061, 0.061, -0.122] Δ from HC 2 to HC 3: [-0.032, -0.032, 0.064] Δ from HC 2 to HC 4: [-0.001, -0.001, 0.003] Δ from HC 3 to HC 4: [0.030, 0.031, -0.061]
Sample B			
Non-functional	C	0.315 (7.573)	
HC 1	A, B	-0.302 (-5.532)	Δ from HC 1 to HC 2: [0.046, 0.047, -0.093]
HC 2	A, B	0.139 (2.845)	Δ from HC 1 to HC 3: [0.027, 0.027, -0.054]
HC 3	A, B	-0.040 (-0.785)	Δ from HC 1 to HC 4: [0.053, 0.054, -0.107] Δ from HC 2 to HC 3: [-0.019, -0.020, 0.039] Δ from HC 2 to HC 4: [0.007, 0.007, -0.015] Δ from HC 3 to HC 4: [0.026, 0.027, -0.053]

Curriculum Vitae

Name	Kai-Brit Bechtold
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Employment Experience

Since 03/2010	Student Advisor for Food Economics at the Department of Food Economics and Consumption Studies. Christian-Albrechts-University of Kiel, Germany.
Since 03/2009	Research Assistant at the Department of Food Economics and Consumption Studies. Christian-Albrechts-University of Kiel, Germany.
08/2007 – 12/2007	Student Assistant at the Chair of Agribusiness & Food Marketing. Christian-Albrechts-University of Kiel, Germany.
08/2006 – 10/2006	Internship at Gruner + Jahr AG & Co KG at the Editorial Office “essen & trinken” in Hamburg, Germany.
08/2005 – 09/2005	Internship at Prof. Dr. Pieldner’s Institute (quality control, product development, public relations) in Stuttgart, Germany.

Education

04/2007 – 02/2009	M.Sc. in Food Economics. Christian-Albrechts-University of Kiel, Germany. Subject of the Thesis: Determinants of <i>Visual Fluency</i> on the Perception of Package Design.
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1994 – 2003	Max-Born-Gymnasium Backnang, Germany. Academic High School. Degree: Abitur.