UNDERSTANDING FRENCH CONSUMERS' PREFERENCES FOR FISH

- Eliciting Willingness to Pay by the Use of a Non-Hypothetical Choice Experiment

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Any remaining inaccuracies are ours and ours alone.

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Practical Information

This booklet consists of four parts; an article and three appendices.

The article is an independent document with a table of contents at the beginning and a list of references at the end.

Appendix I consists of an in-depth procedure of how the variables for the models in the article were chosen. The theory behind the random utility models, prior research and the theory behind the mixed logit models are also presented there. This appendix furthermore contains answers from the survey and regression outputs.

The sections, tables and figures in this appendix begin with an "A". In the article we refer to sections from this appendix as e.g. "(Appendix I, A.6.1.2.)". We refer to tables as e.g. "(Appendix I, Table A.11.2.)" .

This appendix is an independent document with a table of contents at the beginning and a list of references at the end.

Appendix II consists of the survey questions that were relevant for the article. We end a sentence with "(Appendix II)" when we refer to this document.

Appendix III consists of a table with statistics on Norwegian seafood exports. We end a sentence with "(Appendix III)" when we refer to something which is taken from this table.

Contents

Abstract

A Real Choice Experiment was used to examine French consumers' valuations of fresh salmon, farmed cod, wild cod, monk and pangasius. The study focuses on the willingness to pay for farmed cod. The participants were recruited by the French National Institute for Agricultural Research. Real economic incentives were introduced in the experiment by letting one randomly drawn choice scenario be binding.

By the use of a mixed logit model we study how consumers value the five fish types and their associated attributes, and how different consumer groups differ in their valuations. We find heterogeneous preferences for all the fish types. The preferences for pangasius are found to be most heterogeneous, while the preferences for salmon are found to be the most homogeneous. On average the participants are willing to pay more for wild cod than for farmed cod.

We further find that the participants value a piece of tail cut lower than a piece loin. Our results suggest that individuals with high income are willing to pay a price premium for both farmed and wild cod. The willingness to pay for salmon decreases with age, and the willingness to pay for wild cod and monk increases with age. Individuals living in single households are willing to pay a price premium for salmon, wild cod and pangasius.

Keywords: fish, aquaculture, consumer groups, real choice, willingness to pay, mixed logit

Sammendrag

Denne studien undersøker franske konsumenters preferanser for ferske fiskefileter av laks, villtorsk, oppdrettstorsk, breiflabb og pangasius ved hjelp av et valgeksperiment. Studien fokuserer på konsumenters betalingsvillighet for oppdrettstorsk. Deltakerne i eksperimentet ble rekruttert av Frankrikes Nasjonale Institutt for Landbruksforskning.

Økonomiske insentiver er introdusert i eksperimentet ved at ett valg er tilfeldig trukket ut til å være bindende. Ved å ta i bruk en mixed logit-modell, undersøker vi hvordan konsumenter verdsetter de fem fisketypene og deres tilhørende attributter, samt hvordan verdsettingen varierer mellom ulike konsumentgrupper.

Resultatene av analysen viser at det er heterogene preferanser for alle fiskeslagene. Videre viser analysen at preferansene for pangasius er de mest heterogene, mens preferansene for laks er de mest homogene. Deltakerne i eksperimentet er i snitt villige til å betale mer for villtorsk enn for oppdrettstorsk. Videre finner vi at deltakerne foretrekker fileter av loin framfor fileter av halestykker. Våre resultater tyder på at folk med høy inntekt er villige til å betale et prispåslag for både villfanget og oppdrettet torsk. Betalingsvilligheten for laks er avtakende med alder, og betalingsvilligheten for villtorsk og breiflabb er økende med alder. Personer i enslige husholdninger har høyere betalingsvillighet for laks, villtorsk og pangasius enn personer i samboende husholdninger.

Nøkkelord: fisk, akvakultur, konsumentgrupper, reelle valgeksperimenter, betalingsvillighet, mixed logit

1. Introduction

Norway has a long tradition as a fishing nation. A long coastline and many fjords provide good conditions for harvesting from the sea. France, on the other hand, is worldwide known for its quality cuisine. France is the second largest importer of Norwegian seafood, only surpassed by Russia (Appendix III). Salmon and cod are two of the most frequently eaten fish types in France (Willemsen 2003, p. 9).

Salmon farming has been very successful in Norway. The farming of cod, however, is still in its initial face and has not yet been able to achieve a similar success as the salmon farming industry. Since France is one of the main importers of Norwegian seafood, an up to date and well informed understanding of the French market is important. The objectives of this article are to study the French consumers' preferences and willingness to pay (WTP) for fish, and to examine how different consumer groups differ in their valuations.

1.1. Background

The success of the Norwegian salmon farming industry is visible through the almost hundredfold increase in exported volume over the last thirty years. In 1981 Norway exported 7.452 metric tons of salmon (and rainbow trout), and in 2010 the export volume was 714.484 (Statistics Norway 2012). Salmon was once regarded a high society food in France, but it is now accessible to everyone at an acceptable price (Nilssen & Monfort 2000). The reduction in price can be ascribed to low production costs resulting from improved technology and breeding techniques. In addition to price reductions there are many other advantages with fish farming. Modern breeding techniques can improve the fish's health, shape, texture, color, and nutritional content. Aquaculture can to some extent comply with the growing global problems of overfishing, since it is possible to control the amount being produced. Aquaculture can also provide jobs in rural areas.

Aquaculture does, however, interfere with the environment and wild populations of fish. This can cause negative externalities if farmed fish escape and spread diseases or genetic material to the wild stocks (Food and Agriculture Organization 2012). Aquaculture also interferes with alternative uses of the coast, which can lead to negative externalities in terms of, e.g. lost tourism.

The use of antibiotics in salmon and cod aquaculture has been highly controversial and has led to criticism from many consumers (see e.g., Gruben (2007), Tveterås (2003) and Food and Agriculture Organization (2012)). However, the preferences concerning controversial products are highly heterogeneous (Alfnes & Rickertsen 2011). This demonstrates the importance of understanding how consumer groups differ in their attitudes and retail behavior.

1.1.1. The Cod Farming Industry Today

Cod farming has not yet experienced a similar success as salmon farming. The cod farming industry still faces challenges in terms of understanding basic biological issues, and in finding production methods that ensure a stable and profitable production. “A boom-like investment period during 2000-2008 and rapid biomass build-up was followed by an almost collapse after the financial crisis in 2008” (Food and Agriculture Organization 2012). Despite the reduced access to capital in the wake of the financial crisis, the interest for cod farming has increased over the last years. The Norwegian production of farmed cod has risen from 300 metric tons in 2003 to about 20.000 metric tons in 2010 (Nereng 2011). Norway produces about 80% of the world’s farmed cod, nonetheless, this quantum was only about one tenth of the annual catch of Norwegian wild cod in 2009 (Olstad 2011).

The marketing channels for farmed cod have so far been the same as those for wild cod. Wild cod has its greatest supply in the springtime, and the farmed cod industry has focused on delivering in the autumn. Farmed cod can, to a greater extent than wild cod, deliver stable supplies to the major retail chains throughout the year. However, high production costs constitute a difficult starting point for competition. Other fish species are competitive in price and partly in quality, e.g. pangasius and tilapia. Moreover, the volume of wild cod to be supplied to the European market is expected to increase over the next years (Toften 2009). According to The Food and Agriculture Organization of the United Nations, it is likely that the growth in cod aquaculture production will be much slower than what was expected a few years ago. They also note that the structure of the industry is currently quite unclear (Food and Agriculture Organization 2012).

Asche (2009) argues that the future success of cod farming will depend on the industry’s ability to make use of its competitive advantages rather than to compete with wild cod on price. Furthermore, Nofima, Europe's largest institute for applied research within the fields of fisheries, aquaculture and food, presents the assessments of the strategic competiveness of the Norwegian cod farming industry in a report *Oppdrettstorsk – konkurransegrunnlag, marked og strategiske muligheter* (Toften 2009). They argue that cod farmers in reality have two choices: To position themselves at the higher price end of the market and create niche products, or to reduce production costs considerably and increase the production volume (Toften 2009, p. 17-18). It follows that an understanding of how French consumers value farmed cod compared to other fish types is important for the cod farming industry. It is also of interest to examine how consumer groups differ in their valuations of fish products.

1.2. The Experiment

To get a better understanding of the French consumers' preferences for fish, and accordingly their WTP, several kinds of experiments were conducted in Dijon in France, May 2008. Dijon is a city of 151 000 inhabitants. The fish consumption in Dijon is regarded to be representative for that of non-coastal France (Alfnes & Rickertsen 2008a). The experiments consisted of a tasting session, a Becker-DeGroot-Marschak (BDM)[1] bidding session, and a real choice (RC) experiment. 178 participants took part in the experiments and five types of fish were presented; salmon, farmed cod, wild cod, monk and pangasius. In both the BDM session and in the RC experiment the participants evaluated pre-packed fillets of fresh fish.

In the following a *fillet* of fish is defined as a piece of fresh fish. The experiments aimed to reveal what type of fish and fish attributes the French consumers find attractive, and to what extent they are willing to pay for these. The experiments were further meant to examine how different consumer groups differ in their WTP for the different fish types.

An understanding of French consumer preferences is important for several reasons. If farmed cod is regarded as undesirable to a great share of the French consumers, a cod farmer might wish to focus on other markets, like e.g. the Russian market. Furthermore, a fish fillet can have many attributes. One important attribute is price, a highly ranked decision criterion in most economic transactions. Knowledge about the effects of this key decision factor is important, both from a marketing point of view and from a production cost perspective. Another attribute of a fish fillet is the type of cut. A fillet can have different types of cut, e.g.

[1] For an explanation of the BDM, see Appendix I, section A.2.

loin (front cut), tail or round cut. A significant difference in preferences between the different types of cut is valuable information for a fish farmer.

It is also of importance to know how consumer groups differ in their WTP. For instance, if one is able to detect what types of fish people with high income value the most, one can address these products towards this group. Some types of fish, like e.g. wild cod and monk, have a long tradition in the French cuisine, while salmon became accessible at an acceptable price in the 90s (Nilssen & Monfort 2000). Hence, it is expected that older consumers differ in their preferences for the different types of fish compared to younger consumers.

Single people make up a non-negligible fraction of the French consumers. In 2009, 32% of the French lived in one-person households (Statistics Canada 2009). Their eating habits, and hence fish consumption habits, may differ from those of the cohabiting households. Fish consumption habits may also differ between genders, households with or without children, and consumers with different levels of education.

In addition to taking part in the tasting session, the BDM and the RC experiment, the participants answered a survey regarding fish likings, fish buying and eating habits, attitudes towards fish farming, demographics etc. This article focuses on the results from the RC experiment. The results will be compared with answers from the survey.

An RC experiment is meant to mimic a normal grocery store situation, which is a situation most people are familiar with. The participants made real, i.e., non-hypothetical, choices over 16 choice scenarios. Each choice scenario had three fillets of different type. Prices were posted in advance. For every choice scenario the participants chose which fillet they wanted to buy, or a non-of-these (NOT) alternative. Real economic incentives were introduced by letting one randomly drawn choice scenario be binding. This was done to remove the hypothetical bias that may arise from non-consequential choice experiments. RC experiments are a relatively new method for studying consumer preferences and eliciting WTP. This methodology is, however, increasingly utilized by researchers (Gracia et al. 2011).

1.2.1. Prior Research

Alfnes et al. (2006) study consumers' WTP for the color of salmon by the use of an RC experiment. Olesen et al. (2010) use an RC experiment to elicit consumers' WTP for organic and welfare-labeled salmon.

Some studies that have employed RC experiments have focused on the differences in WTP values between RC experiments and experimental auctions (EA). In EAs participants take part in a bidding session. There are many versions of EAs, for example a second-price sealed-bid auction, also known as a Vickrey auction. In a Vickrey auction participants submit sealed bids for a product, and the highest bidder buys the product for the price of the second highest bid (Alfnes & Rickertsen 2011). Gracia et al. (2011) find that valuations elicited from EAs can differ from those of RC experiments. Lusk and Schroeder (2006) find that EA bids were significantly lower than the estimated WTP from RC experiments.

Other literature including RC experiments focuses on the hypothetical bias, i.e., the differences in estimated WTP from hypothetical and non-hypothetical choice experiments. An example of a hypothetical choice experiment is the stated choice experiment. In stated choice experiments participants make hypothetical choices over a set of one or more choice scenarios. Participants are asked to pick the product they would have bought, given that it was a real life situation. Lusk and Schroeder (2004) found that WTP values obtained from a stated choice experiment exceeded the WTP values obtained from an RC experiment.

1.3. The Random Utility Model and Mixed Logit

Unlike Lusk and Schroeder (2004) who used beefsteak products that varied only in prices over choice scenarios, the experiment used for this study utilized fresh fillets of fish that varied in both prices and products over choice scenarios. By the use of a mixed logit model, we have estimated a random utility model (RUM) for each fish type used in the experiment. A RUM assumes that an individual's utility from choosing a product is a function of observable and, to the researcher, unobservable attributes of both the product and the individual.

Contrary to a standard logit model, a mixed logit model allows for heterogeneous preferences in the population (Train 2009, p. 134-137). In addition to estimating the utility an individual obtains from choosing a fillet of fish, we estimated a distribution that describes the preference heterogeneity in the population. Chang et al. (2009) find that mixed logit models can have superior performance over other discrete choice models in predicting actual retail shopping behavior. From the utility functions we estimated WTP.

To the best of our knowledge, no earlier research has used an RC experiment to study the preferences for salmon, farmed cod, wild cod, monk and pangasius by including both product attributes and consumer characteristics into the analysis.

The remainder of this article is organized as follows: First we present the sample data and describe the experimental design, before we introduce the econometric model used to analyze the data. The results and estimated WTP are then presented, followed by a discussion of how product attributes and consumer characteristics affect the WTP for fish. We also discuss possible factors that could bias WTP both upwards and downwards. We conclude with some thoughts about the future market potential for farmed cod.

2. Sample Data

The French National Institute for Agricultural Research (INRA) randomly drew 178 participants from their consumer panel to the take part in the experiments. A requirement to participate was that they ate fish at least once a month (Appendix II, p. 2).

Table 2.1 gives a descriptive summary of the participants. The participants' age ranged from 21 to 70 years. There were a few more women than men. About one third had children. A quarter of the participants' households' gross monthly income was more than 3000 EUR. The remaining had either less income or did not want to report it. 71% were married/cohabiting, the others were single. Approximately one third of the participants had higher education[2].

[2] See Appendix I, section A.6.1.2 for a detailed distribution of the education levels

Table 2.1. Consumer Characteristics of the 178 Participants

Variable Definition	
Gender	
Male	42 %
Female	58 %
Age (sample average)	46.86
Children	
No children	66 %
One or more children	34 %
Income	
Up to 3000 EUR per month	65 %
More than 3000 EUR per month	24 %
Do not know/Do not want to answer	11 %
Marital Status	
Married/Cohabiting	71 %
Single	29 %
Education	
No higher education	63 %
Higher education	37 %

3. Experimental Procedure

The experiment went over a period of seven days. There were two sessions each day, one at lunch time and one at dinner time. The experiment had nine steps. Step 1: The participants were explained the procedure. Step 2: They took part in a tasting session. The fish was heated to 70 degrees Celsius by a professional chef, and the participants were served a portion of 50 grams of each fish type. The order of the servings was randomized to avoid relative taste bias. As an example, an individual may perceive pangasius differently if served immediately after salmon than if he or she was served pangasius first. Step 3: The participants took part in the BDM bidding session and placed bids on a computer. Step 4: They marked on a questionnaire which alternative they wanted to buy in each choice scenario in the RC experiment. There were three alternatives in each scenario as well as the NOT option. See Figure 3.1 for an illustration of a choice scenario questionnaire and Figure 3.2 for an illustration of a choice set. Step 5: They drew a card to determine their binding scenario. The draw was done without replacement, so only one participant could be assigned to one scenario. Hence, there were maximum 16 participants in each session. The binding scenario was imposed to reveal true WTP and to avoid the hypothetical bias that may inflate WTP. Step 6: The participants answered the survey while being served dessert. Step 7: Each participant received the fish fillet he or she had chosen in the binding scenario. Step 8: They went to the cashier and got paid 25 EUR less the price of the fillet from the binding scenario.

Box 1	Alternative 1 € Salmon	Alternative 2 € Farmed Cod	Alternative 3 € Monk
I would choose (Check x one)	○	○	○
	None of these three alternatives		○

Figure 3.1. Example of Choice Scenario Questionnaire

Figure 3.2. An Example of a Choice Set

4. Products and Experimental Design

The experiment was intended to mimic a normal grocery store situation. The salmon and farmed cod was transported from Norway. The wild cod and the monk were caught in the Northern Atlantic and the pangasius was imported from Vietnam. Each fillet was cut into a 300 gram piece. Salmon, farmed cod and wild cod were either of tail cut or loin. Pangasius and monk did not have tail cuts, as this is not common for these fish types in French supermarkets.

The prices differed between 1.45 and 11.95 EUR for a 300 gram fillet, which corresponds to 4.83 and 39.83 EUR per kilogram. For a product attribute description, see Table 4.1. Pangasius and monk were included as cheap and expensive alternatives to cod, respectively. The participants were not informed about this to avoid framing effects. Framing effects implies giving clues to the participants about how they are supposed to value or perceive the products under scrutiny. If there was a negative focus on e.g. pangasius during the explanation of the procedure, this could have affected the participants' choices in the RC experiment and potentially bias WTP.

Each fillet was in a box laminated with plastic. The information provided on the packages was similar to what one usually finds in supermarkets: fish type, weight, production method (farmed or wild), price and region of origin. Since the participants had taken part in a tasting session before the experiment, they were familiar with the taste of the different fish. We did not have access to the taste scores while analyzing the data.

Table 4.1. Product Attributes of the Fish Fillets

	Average Price EUR/KG	Min Price EUR/KG	Max Price EUR/KG	Cut
Salmon	14.88	6.50	26.50	Loin and Tail
Farmed Cod	20.78	9.83	36.50	Loin and Tail
Wild Cod	20.79	9.83	36.50	Loin and Tail
Monk	27.88	18.17	39.83	Round Cut
Pangasius	10.82	4.83	16.50	Fillet

The table shows the average, the minimum and the maximum prices in EUR/KG of fish fillets over all choice scenarios, as well as the type of cut.

The same type of fillet did not occur more than once in each choice scenario. Note that there were five different types of fish and eight different types of fillets. Both prices and products varied among the scenarios. This differs from the design used by Lusk and Schroeder (2004), who used one set of products (five beefsteaks) that varied only in prices over choice scenarios. By letting each choice scenario contain a unique set of fillets, a coincidental, unattractive fillet would not have the same negative effect on WTP than would have been the case if the choice scenarios only varied in prices and not in products.

The variation in prices and products, as well as the positioning of the products in each scenario, was derived from a fractional factorial design. The fractional factorial design will, asymptotically, remove left – or right hand bias, i.e., the tendency to systematically choose a product that is positioned to the right or to the left of another product. The participants could start at any one of the 16 choice scenarios. This removed equal anchoring effects for all the participants and made the sessions take less time. Anchoring effects refers to affixing the prices one observes in the *first* choice scenario to the prices in the following choice scenarios. For instance, if the prices in the first scenario were very low, one is likely to compare the prices in the following scenarios with the first one. Hence one can obtain an unrealistic picture of the prices, and this can in turn affect WTP. Anchoring effects are commonly found in recent studies, see e.g. Ariely (2010, p. 25-53). Including only three alternatives in each choice scenario lessened the cognitive burden on the participants.

5. The Econometric Model

The theory underlying the utility functions in this study is based on Lancastrian consumer theory. Lancastrian consumer theory proposes that the utility associated with a good can be decomposed into separate utilities for the components of the attributes (Loureiro & Umberger 2004).

The utility an individual obtains from the different choices can be decomposed into observable and unobservable parts. The observable parts are known to both the individual and to the researcher. The observable parts are the known attributes of the fish as well as the known consumer characteristics. We assume the parameter estimates for the observable variables to be linear in parameters. The unobservable parts are known to the individual but not to the researcher. The unobservable part is represented by a stochastic error term, and hence utility is random. In other words we estimate *random* utility functions. The stochastic error term is assumed to be independent and identically distributed (iid) extreme value. The utility functions are estimated by mixed logit. Train (2009, p. 134-147) shows that a mixed logit model can approximate any random utility model.

5.1. How the Mixed Logit Model Obviates the Limitations of the Standard Logit Model

The mixed logit model obviates three restrictions from the standard logit model:

1. *It allows for random taste variation.* A mixed logit model can have both fixed and random parameters. The fixed parameters are to be interpreted as if they were standard logit. The random parameters have a distribution with a mean and a standard deviation. This is to capture preference heterogeneity for a product or a product attribute. It is up to the researcher to choose an appropriate distribution for the random parameters. The parameters for the variables representing each fish type are chosen to be the random in this article[3]. Hence, they take people's heterogeneous preferences into account and provide more information about consumer preferences than would have been the case with a standard logit model. We assume a normal distribution for the random parameters[4].

2. *Unrestricted substitution patterns.* In a standard logit model the relative probabilities of choosing one alternative over the other is the same, no matter what the other choice alternatives are (Train 2009, p. 34-75). This is known as the property of independence of irrelevant alternatives (IIA). Assuming that the relative probabilities between two alternatives are independent of other alternatives can, in many situations, be a strong assumption. The mixed logit model relaxes this assumption. In the mixed logit model the relative probabilities depend on all the data (Train 2009, p. 134-147). For example, the ratio of the probabilities of choosing farmed cod (*fc*) to salmon (sa), P_{fc}/P_{sa}, also depends on alternatives other than farmed cod and salmon, for example monk.

[3] Some interaction terms also includes the fish types. The parameter estimates for these interaction terms are not random.
[4] The log-normal distribution was not chosen, since we assumed that we may obtain "negative utility" from choosing some of the fish types.

3. *Correlations in unobserved factors over time or choice scenarios.* The mixed logit model can, in addition to estimating a distribution for each random parameter, also estimate the covariance between the random parameters. The dataset from the RC experiment is a panel dataset over sixteen choice scenarios. The choices an individual makes over the sixteen scenarios are likely to be correlated. Assume an individual has a strong preference for cod. Perhaps this person is likely to choose cod in every choice scenario where cod is present, no matter if it is farmed or wild. This implies a positive correlation between choosing farmed and wild cod. This correlation is captured by the covariance matrix. A positive and significant correlation between the preferences for the two types of fish indicates that these products might be substitutes. Allowing for correlations in unobserved factors over time or choice scenarios is an optional feature of the mixed logit model.

5.2. Utility as a Function of Observable and Unobservable Variables

Generally the utility an individual n obtains from choosing alternative i in a choice scenario s can be specified as;

$$(1) \qquad U_{nis} = \boldsymbol{\beta}\boldsymbol{x}_{nis} + \boldsymbol{\eta}_n\boldsymbol{z}_{nis} + \varepsilon_{nis},$$

where $\boldsymbol{x}_{nis}$ and $\boldsymbol{z}_{nis}$ are vectors of observed variables relating to individual n, alternative i and choice scenario s. $\boldsymbol{\beta}$ is a vector of fixed coefficients. $\boldsymbol{\eta}_n$ is a vector of random parameters with an estimated mean $\boldsymbol{\mu}_\eta$ and standard deviation $\boldsymbol{\sigma}$. ε_{nis} is a stochastic iid extreme value error term and varies over individuals and choices, with an expected value of zero.

The subscripts in the models we will present are defined as:

n = 1,2, …, 178 indices the participants in the experiment

i = 1,2, …, 5 are the fish types to choose from

i = 1: *Salmon (sa)*

i = 2: *Farmed Cod (fc)*

i = 3: *Wild Cod (wc)*

i = 4: *Monk (mo)*

i = 5: *Pangasius (pa)*

s = 1,2, …, 16 are the choice scenarios.

An individual n chooses alternative i if and only if $U_{nis} > U_{njs}$ for all $i \neq j$. Assume an individual faces a choice scenario. Assume this is a married female, 47 years of age, with higher education and two children. There are three fillets of fish in front of her, e.g. salmon, farmed cod and monk. Each fillet has a price and a cut. She will only choose farmed cod if the utility she obtains from choosing that specific fillet of farmed cod is higher than the utility she would obtain from choosing any other alternatives. Hence, utility is a function of the attributes of the fish fillets, as well as characteristics of the individual. In addition there might be attributes of the fish and characteristics of the individual that we do not observe that might affect her choice. This is captured by the error term ε_{nis}.

5.2.1. The Distribution of the Random Parameters

To better understand how the distributions of the random parameters are derived, we rewrite equation (1) as:

$$(2) \qquad U_{nis} = \boldsymbol{\beta x}_{nis} + \boldsymbol{\mu}_{\eta}\boldsymbol{z}_{nis} + (\boldsymbol{\eta}_{n} - \boldsymbol{\mu}_{\eta})\boldsymbol{z}_{nis} + \varepsilon_{nis}$$

The $\boldsymbol{\mu}_{\eta}$ is a vector of coefficients representing the expected (average) value of the random parameters. Given fish type i, every individual n has his or her estimated preference, η_n. This may differ from the estimated mean preference μ_{η}. However, the *expected* difference from the mean is zero; hence the term inside the parentheses in equation (2) has an expected value of zero. Since there are 178 participants in the experiment, there are 178 such differences from the mean. These differences make up a distribution, assumed to be normally distributed. Hence:

$$\left(\eta_n - \mu_{\eta}\right) \sim N(0, W)$$

from which it follows that

$$\eta_n \sim N(\mu_{\eta}, W),$$

where W denotes the covariance matrix for the random parameters. The square roots of the diagonal elements of the covariance matrix are the standard deviations of the random parameters (see Table 5.2.2.1). Large standard deviations imply a great extent of heterogeneity. Small standard deviations imply relatively homogenous preferences in the population. Since we have assumed a normal distribution for the random parameters, they can be illustrated as in Figure 5.2.1.1.

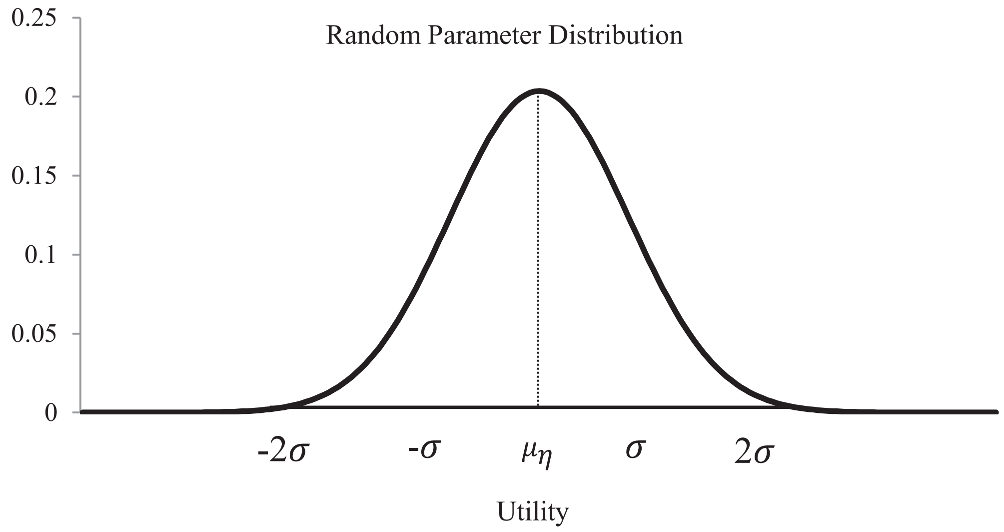

Figure 5.2.1.1. An Example of a Random Parameter Distribution

Assume Figure 5.2.1.1 displays the estimated utility for farmed cod. The parameter estimate, μ_η, is the expected value. The area to the left of the vertical line represents the share of the population who obtains a below average utility from choosing farmed cod, while the area to the right of the vertical line represents the share of the population who obtains an above average utility from choosing farmed cod.

5.2.2. Correlations between the Random Parameters

The off-diagonal elements of the covariance matrix W provide information about the correlations in preferences between the various fish types. A positive and significant covariance between e.g. salmon and monk implies that an individual who is likely to choose salmon is also likely to choose monk. Table 5.2.2.1 shows an example of a covariance matrix.

Table 5.2.2.1. An Example of a Covariance Matrix of the Random Parameters

	Salmon	*Farmed Cod*	*Wild Cod*	*Monk*	*Pangasius*
Salmon	σ_{11}^2				
Farmed Cod	σ_{21}^2	σ_{22}^2			
Wild Cod	σ_{31}^2	σ_{32}^2	σ_{33}^2		
Monk	σ_{41}^2	σ_{42}^2	σ_{43}^2	σ_{44}^2	
Pangasius	σ_{51}^2	σ_{52}^2	σ_{53}^2	σ_{54}^2	σ_{55}^2

1 = sa = Salmon, 2 = fc = Farmed Cod, 3 = wc = Wild Cod, 4 = mo = Monk, 5 = pa = Pangasius

Since the covariance matrix is symmetric about its diagonal only the lower triangular matrix is displayed in Table 5.2.2.1. If all the ${\sigma^2}_{ii}$ are zero, the mixed logit collapses to a standard logit.

5.3. Model Specification

Two models are presented in this article. *Model 1* includes product attributes only. The two product attributes under scrutiny are the price and the type of cut, defined by the variables *Price* and *Tail*. *Price* captures the price sensitivity and its expected sign is negative. This parameter is set to be fixed, assuming homogenous price sensitivity in the population. *Tail* is a dummy variable taking the value of 1 if the fish is a tail cut, and 0 otherwise. Salmon, farmed cod and wild cod have tail cuts as well as loins. Pangasius and monk do not have tail cuts.

The second model, *Model 2*, also incorporates how the consumer characteristics income, age and marital status affect an individual's choice. These consumer characteristics are defined by the variables *Income*, *Age* and *Single* respectively.

Income is a dummy variable taking the value of 1 if the participant's household's gross monthly income is more than or equal to 3000 EUR, and 0 otherwise[5]. 43 out of the 178 participants (24%) belong to the high income group. *Age* is a continuous variable measured in years. The participants' age ranged from 21 to 70 years. *Single* is a dummy variable taking the value of 1 if the household consists of a single person with or without children, and 0 otherwise. Of the 178 participants in the experiment, 51 (29%) were single. The five types of fish are represented by the vectors $\boldsymbol{z}_i$, where i = {*1=Salmon, 2=Farmed Cod, 3=Wild Cod, 4=Monk, 5=Pangasius*}. Hence each vector has the form:

[5] In Appendix I, section A.6.6.1, there is an explanation of why *Income* was chosen as a dummy variable, and not as a continuous variable.

$$\boldsymbol{z}_1 = \boldsymbol{z}_{sa} = \begin{bmatrix}1\\0\\0\\0\\0\end{bmatrix}, \boldsymbol{z}_2 = \boldsymbol{z}_{fc} = \begin{bmatrix}0\\1\\0\\0\\0\end{bmatrix}, \boldsymbol{z}_3 = \boldsymbol{z}_{wc} = \begin{bmatrix}0\\0\\1\\0\\0\end{bmatrix}, \boldsymbol{z}_4 = \boldsymbol{z}_{mo} = \begin{bmatrix}0\\0\\0\\1\\0\end{bmatrix}, \boldsymbol{z}_5 = \boldsymbol{z}_{pa} = \begin{bmatrix}0\\0\\0\\0\\1\end{bmatrix}$$

To estimate the effect of the consumer characteristics on the preferences for fish, interaction terms with the variables representing the fish types, $\boldsymbol{z}_i$, are necessary. For example, to estimate the age effect on farmed cod, one must multiply the variable *Age* with the vector representing farmed cod, i.e., $\boldsymbol{z}_2 = \boldsymbol{z}_{fc} = [0,1,0,0,0]$. This is the structure of the mixed logit model. The fact that the consumer characteristics do not vary over choice scenarios makes the interaction terms necessary.

Since only *Salmon*, *Farmed Cod* and *Wild Cod* had two types of cut, the *Tail* variable could not be defined as an explanatory variable on its own. To capture the effect of the *Tail* variable, interaction terms with *Salmon*, *Farmed Cod* and *Wild Cod* were necessary. This is done by defining the $\boldsymbol{y}_i$-vectors, where $\boldsymbol{i}$ = {*1=Salmon, 2=Farmed Cod, 3=Wild Cod*}. For example, to estimate the tail effect of salmon, one must multiply the variable *Tail* with the vector representing salmon, i.e., $\boldsymbol{y}_1 = \boldsymbol{y}_{sa} = [1,0,0]$. For *Monk* and *Pangasius* the $\boldsymbol{y}$-vectors are zero by default. For a detailed outline of how the utility models are set up, see Appendix I, section A.4.

Both models presented in this article allow for correlations in unobserved factors over choice scenarios. Hence we estimate a covariance matrix for the random parameters instead of *only* the standard deviations.

In addition to *Model 1* and *Model 2* we estimated a third model, *Model 3*, that included the product attributes and consumer characteristics in *Model 2* as well as gender, presence of children in the household, and education. The additional consumer characteristics included in *Model 3* all turned out to be insignificant. The output and analysis for this model is left to the appendix (Appendix I, section A.9).

5.3.1. Expected Utility

Since we are interested in estimating the individual specific average utility over *all* choice scenarios, we leave out the subscript s from now on. Having defined the variables and the interaction terms, the expected utility from choosing a product is defined as:

Model 1:

(3) $E(U_i) = \alpha Price + \boldsymbol{\mu}_\eta \boldsymbol{z}_i + \boldsymbol{\delta} \boldsymbol{y}_i Tail$

Note that since no consumer characteristic interactions are included in *Model 1*, the subscript n is omitted. α is the price coefficient, $\boldsymbol{\mu}_\eta$ is a vector of the expected values of the random parameters, and $\boldsymbol{\delta}$ is a vector of coefficients for the tail interaction terms.

Model 2:

(4) $E(U_{ni}) = \alpha Price + \boldsymbol{\mu}_\eta \boldsymbol{z}_i + \boldsymbol{\delta} \boldsymbol{y}_i Tail + \boldsymbol{z}_i[\boldsymbol{\gamma}_1 Income_n + \boldsymbol{\gamma}_2 Age_n + \boldsymbol{\gamma}_3 Single_n]$

The $\boldsymbol{\gamma}$s are coefficient vectors for the interaction terms between the variables *Income*, *Age* and *Single* and the $\boldsymbol{z}_i$-vectors representing the fish types. Note that in equation (1) the $\boldsymbol{\beta}$-vector incorporates the coefficients α and $\boldsymbol{\delta}$, and in equation (2) the $\boldsymbol{\beta}$-vector incorporates the coefficients α, $\boldsymbol{\delta}$ and the $\boldsymbol{\gamma}$s.

5.3.2. Estimating WTP

The utility an individual *n* obtains from the NOT alternative is normalized to zero. Hence a positive utility indicates a willingness to pay for a product. Theoretically, a negative utility implies that an individual should be compensated from choosing a product. In practice it means that he or she does not want to buy it, i.e., he or she prefers NOT to choosing it.

From the estimated utility functions it is possible to estimate the WTP_{ni} for the various fish types i, given consumer characteristics of individual n. The maximum amount an individual is willing to pay for a product is the price at which he or she is indifferent about buying the product and not buying it. To estimate this, we can set the utility to equal zero in equations (3) and (4), i.e., $E(U_i) = 0$ and $E(U_{ni}) = 0$, and solve with respect to *Price*.

WTP *Model 1*:

(5) $WTP_i = -\frac{1}{\alpha}(\boldsymbol{\mu}_\eta \boldsymbol{z}_i + \boldsymbol{\delta y}_i Tail)$

WTP *Model 2*:

(6) $WTP_{ni} = -\frac{1}{\alpha}\left(\boldsymbol{\mu}_\eta \boldsymbol{z}_i + \boldsymbol{\delta y}_i Tail + \boldsymbol{z}_i[\boldsymbol{\gamma}_1 Income_n + \boldsymbol{\gamma}_2 Age_n + \boldsymbol{\gamma}_3 Single_n]\right)$

The estimated WTP individual n obtains from choosing product *i* is a function of the observable variables scaled down by the negative inverse of the price sensitivity parameter α.

6. Results

In the following "significant" refers to significance at the 5% level, unless otherwise stated. The terms "utility from choosing" and "preferences" will be used interchangeably.

The results from *Model 1* and *Model 2* are presented in Table 6.1. The information of interest from the estimated parameters is the sign (positive or negative), the level of significance (*p*-value) and the relative magnitude between the parameter estimates.

First we focus on the *utility* obtained from the different fish types and their associated attributes. We begin by presenting the results that are common for both models, before we focus on the results from *Model 1* and *Model 2* separately. Thereafter we present the estimated WTP from both models.

Table 6.1. Empirical Estimates for *Model 1* and *Model 2*

	Model 1 Product Attribute Model			*Model 2* Product Attribute and Consumer Characteristics Interaction Model		
Variables	Estimate		Std.Err	Estimate		Std.Err
Price	-0.219	***	*(0.010)*	-0.220	***	*(0.010)*
Salmon	2.995	***	*(0.237)*	3.726	***	*(0.586)*
Farmed_Cod	2.359	***	*(0.328)*	0.928		*(0.830)*
Wild_Cod	2.922	***	*(0.286)*	1.121		*(0.687)*
Monk	2.793	***	*(0.357)*	1.050		*(1.027)*
Pangasius	-1.518	***	*(0.520)*	-1.525		*(1.269)*
*Tail * Salmon*	-0.430	***	*(0.117)*	-0.431	***	*(0.118)*
*Tail * Farmed_Cod*	-1.434	***	*(0.193)*	-1.449	***	*(0.192)*
*Tail * Wild_Cod*	-0.667	***	*(0.152)*	-0.672	***	*(0.152)*
*Income * Salmon*				0.529		*(0.354)*
*Income * Farmed_Cod*				0.862	*	*(0.475)*
*Income * Wild_Cod*				1.237	***	*(0.393)*
*Income * Monk*				0.302		*(0.585)*
*Income * Pangasius*				0.924		*(0.708)*
*Age * Salmon*				-0.022	**	*(0.011)*
*Age * Farmed_Cod*				0.023		*(0.015)*
*Age * Wild_Cod*				0.029	**	*(0.013)*
*Age * Monk*				0.038	**	*(0.019)*
*Age * Pangasius*				-0.010		*(0.024)*
*Single * Salmon*				0.974	***	*(0.320)*
*Single * Farmed_Cod*				0.639		*(0.421)*
*Single * Wild_Cod*				0.676	*	*(0.363)*
*Single * Monk*				0.238		*(0.527)*
*Single * Pangasius*				1.212	*	*(0.663)*
Standard Deviations						
Salmon	1.759	***	*(0.146)*	1.680	***	*(0.134)*
Farmed_Cod	2.229	***	*(0.222)*	2.138	***	*(0.199)*
Wild_Cod	2.093	***	*(0.173)*	1.888	***	*(0.160)*
Monk	2.652	***	*(0.362)*	2.499	***	*(0.287)*
Pangasius	3.260	***	*(0.466)*	3.186	***	*(0.479)*
Number of observations	11380			11380		
Number of participants	178			178		
LR Chi-Squared	961.61			854.21		
Log-likelihood	-2534.4973			-2508.7689		
AIC	5126.9946			5105.5378		

Significance codes: α=0.01 *** α=0.05** α=0.1 *

6.1. Preference Heterogeneity

The parameter estimates for *Salmon* are positive and significant in both models. The standard deviations for all the fish types are significantly different from zero at the 1% level. This suggests heterogeneous preferences for all the fish types, despite controlling for correlations in preferences. *Salmon* has, in addition to the highest expected utility, the narrowest distribution. This can be seen from the relatively low standard deviation in Table 6.1, indicating more homogeneous preferences for salmon relative to the other fish types. Pangasius has the lowest expected utility and the widest distribution. This can be seen from the relatively large standard deviation in Table 6.1. This indicates more heterogeneous preferences for pangasius relative to the other fish types.

6.2. Price Effect

The price parameter is negative and significant at the 1% level in both models. This implies that when the price of the product increases, the utility an individual obtains from choosing it decreases. This is expected, and in accordance with classical microeconomic theory of demand. This also supports Nilssen and Monfort (2000) findings of French consumers being price conservative.

6.3. Tail Effect

In both models there are significant negative signs on the parameters for the tail interaction terms. The participants are most negative to tail cuts of farmed cod and least negative to tail cuts of salmon. The parameter estimates for the tail interaction terms are quite similar in the two models. This implies that the interaction terms including *Tail* are not correlated with the interaction terms including the consumer characteristics. The unambiguous negative parameter estimates for fillets of tail cut could raise questions to producers on how to most profitably utilize the tail fillets.

6.4. *Model 1* – Product Attribute Model

In *Model 1*, where no consumer characteristics interaction terms are included, we find positive and significant utility from choosing salmon, farmed cod, wild cod and monk. The coefficient for *Pangasius* is negative. Hence, on average the participants prefer to choose the NOT alternative over pangasius. The parameter estimates for *Farmed Cod*, *Wild Cod* and *Monk* are positive and significant. The parameter estimate for *Monk* is not significantly different from those of neither *Farmed Cod* (Wald *p*-value 0.2081) nor *Wild Cod* (Wald *p*-value 0.6657). This indicates that the utility from choosing monk is not significantly different from the utility from choosing cod. The parameter estimate for *Wild Cod* is significantly higher than that of *Farmed Cod* (Wald *p*-value 0.0329). Hence, they value wild cod higher than farmed cod. Also, the coefficient for a tail fillet of wild cod is significantly higher than the coefficient for a tail fillet of farmed cod (Wald *p*-value 0.0007).

6.5. *Model 2* – Product Attribute and Consumer Characteristics Interaction Model

Contrary to the results from *Model 1*, the parameter estimates for *Farmed Cod*, *Wild Cod* and *Monk* are positive but <u>not</u> significantly different from zero, when *Income*, *Age* and *Single* are controlled for.

6.5.1. Income Effect

Higher income positively affects the preferences for farmed cod at the 10% level and wild cod at the 1% level. This indicates that higher income groups have a higher preference for cod relative to those with lower income. Apart from farmed cod and wild cod, there are no significant differences in the preferences for fish between the low and high income groups. Since 92% of the respondents eat fish for lunch or dinner at home weekly (Appendix I, Table A.11.1), fish may be regarded as a basis food, and this may explain why the income effect for fish is relatively low.

6.5.2. Age Effect

The preferences for salmon are decreasing with age. Farmed salmon was introduced to the French market in the late 1970s, but did not become common until the 1990s (Nilssen & Monfort 2000). Hence, it is likely that a greater share of young people relative to old people has adopted salmon as part of their eating habits. Older people tend to have higher preferences for wild cod and monk relative to younger people. Farmed cod appears to appeal equally to young and old people.

These results accord well with the findings of Alfnes and Rickertsen (2008b) from an experiment in Dijon in December 2007. They find that people below the age of 60 years gave higher taste scores to salmon relative to people over 60. They also find that both wild cod and monk is higher ranked among older consumers compared to younger consumers.

6.5.3. Single versus Married/Cohabiting

Single people obtain a higher utility from choosing salmon compared to married/cohabiting people. The survey results show that the majority thinks salmon and cod are easier to prepare than monk and pangasius (93%, 85%, 43% and 33% respectively (Appendix I, Table A.11.2)). It is likely to believe that single households prefer to cook food that is easy and fast to prepare. Hence, it comes as no surprise that single people have higher preferences for salmon relative to married/cohabiting people. However, time spent on preparing meals is decreasing in the whole French population (Nilssen & Monfort 2000). Seen from another perspective, salmon is regarded to be more expensive than both cod and pangasius (Table 6.7.1, column 7), and it is likely that single households have less disposable income than cohabiting households. In fact, the majority of the singles (86%) in the experiment belong to the low income group. Single people are also more positive to pangasius relative to married/cohabiting people. This is expected since pangasius is cheaper than the other fish types.

Of particular interest is that single people obtained a higher utility from choosing wild cod relative to married/cohabiting people. This is odd, since a greater fraction of the single people perceives farmed fish as healthier (45%) than do the married/cohabiting people (25%) (Appendix I, Table A.11.3). Additionally, more married/cohabiting people agree to the statement that *wild* fish is healthy food (87%) than do single people (73%) (Appendix I, Table A.11.3). From the survey responses, single people appear to have higher confidence in farmed fish than married/cohabiting people do. Farmed cod, however, appears to appeal equally to both single and married/cohabiting people.

6.6. Correlations in Preferences – The Covariance Matrices

The correlations in preferences for the fish types are displayed in Table 6.6.1. In both models many significant and positive correlations between the preferences for the fish types occur. This implies that those who get an above average utility from choosing e.g. salmon also get an above average utility from choosing e.g. farmed cod, wild cod and pangasius. Particularly high is the correlation between wild cod and monk, suggesting that these are good substitutes for each other. The correlation between farmed cod and wild cod is also relatively high.

Table 6.6.1. Covariance Matrices for *Model 1* and *Model 2*

Model 1	*Salmon*	*Farmed Cod*	*Wild Cod*	*Monk*	*Pangasius*
Salmon	3.096***				
Farmed Cod	2.006***	4.971***			
Wild Cod	1.519***	3.579***	4.380***		
Monk	0.995**	3.757***	4.358***	7.034***	
Pangasius	2.701***	1.253	0.0661	1.277	10.625***

Model 2	*Salmon*	*Farmed Cod*	*Wild Cod*	*Monk*	*Pangasius*
Salmon	2.823***				
Farmed Cod	1.784***	4.572***			
Wild Cod	1.276***	3.153***	3.564***		
Monk	0.546	3.113***	3.802***	6.244***	
Pangasius	2.423***	1.199*	0.443	0.819	10.152***

Significance codes: α=0.01*** α=0.05** α=0.1*

The tables show the correlations in unobserved factors over choice scenarios between the fish types, expressed by covariances.

The significant positive correlations may reflect that the participants, who chose fish instead of NOT in one choice scenario, were likely to do likewise in other choice scenarios. And the participants, who were likely to choose NOT in one choice scenario, were likely to do so in the other choice scenarios. Hence, these results must be interpreted with caution. For a distribution of how frequently the participants chose NOT, see Figure 6.6.1 below.

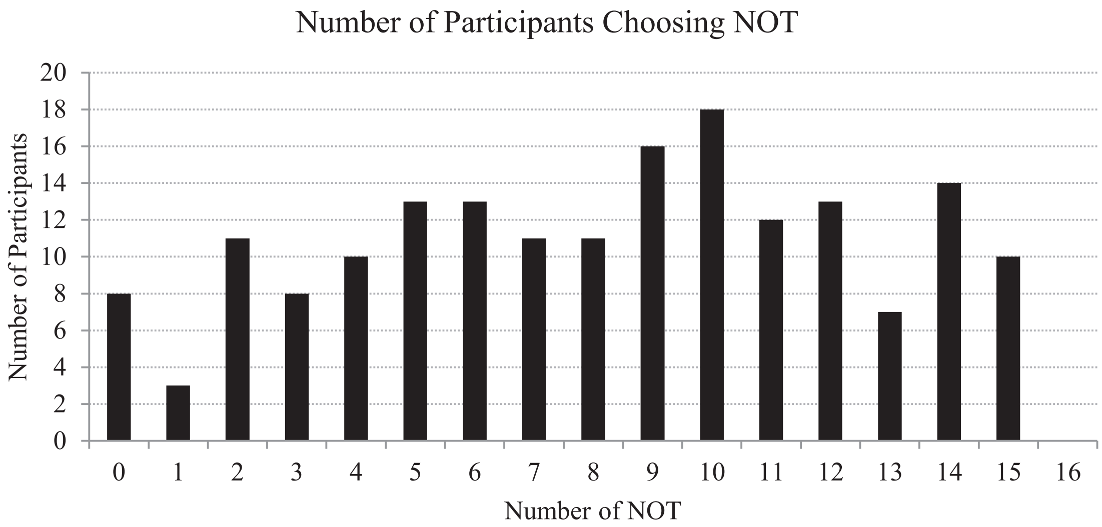

Figure 6.6.1. Distribution of How Frequently the Participants Chose the NOT Alternative

6.7. WTP Estimates for *Model 1* – Product Attribute Model

Of more economic interest than the somewhat vague concepts of "utility" and "preferences," is the willingness to pay. The second column of Table 6.7.1 shows the estimated WTP values from *Model 1*, where no consumer characteristics are controlled for. The third and fourth columns show the lower and upper limits of the 95% confidence intervals for the WTP values. The fifth column shows prices per kilogram of the five fish types found in grocery stores in Dijon in May 2008[6]. The sixth column shows the weighted average price of the fish over all choice scenarios in the experiment. The last column shows the average price per kilogram guessed by the participants when asked about this in the survey.

Table 6.7.1. WTP Values for *Model 1* Compared with Prices Found in Grocery Stores, Average Price Over Scenarios, and Average Guess by the Participants

		95% Confidence Interval				
Variables	Mean WTP/KG	Lower Limit	Upper Limit	Average Price/KG Found in Grocery Stores	Weighted Average Price/KG Over all Choice Scenarios	Guessed Price/KG by the Participants
Salmon	13.69	12.19	15.18	16.00	14.88	14.72
Farmed cod	10.78	8.36	13.20	24.25*	20.78	13.67
Wild cod	13.35	11.45	15.25	24.25*	20.79	13.67
Monk	12.76	10.03	15.49	34.00	27.88	21.17
Pangasius	-6.94	-11.72	-2.15	10.00**	10.82	9.34
*Tail * Salmon*	-1.97	-2.96	-0.97			
*Tail * Farmed Cod*	-6.55	-8.15	-4.96			
*Tail * Wild Cod*	-3.05	-4.33	-1.77			

The confidence interval is of 95% confidence level.
** It is unclear whether the prices found for cod were farmed or wild.*
*** The price for pangasius were the price for frozen pangasius.*

The estimated WTP for salmon is 13.69 EUR per kilogram. This price is fairly close to the average price of 16.00 EUR per kilogram of an equivalent fillet of salmon found in grocery stores in Dijon at the time of the experiment. The estimated WTP for salmon is also close to the weighted average price for salmon over all choice scenarios (14.88 EUR/KG) and the

[6] The prices for salmon ranged from 7 to 25 EUR/KG. The prices for cod ranged from 9 to 23 EUR/KG, but the prices for loin fillets similar to the ones used in the experiment ranged from 29 to 36 EUR/KG. The prices for monk ranged from 28 to 40 EUR/KG. Fresh fillets of pangasius were not found in grocery stores, but the price for frozen pangasius was 10 EUR/KG. The prices referred to as the "prices found in grocery stores" are the average of the minimum and the maximum value.

average price guessed by the participants (14.72 EUR/KG). For all the other fish types the WTP values are below the prices found in grocery stores.

Estimated WTP for pangasius is -6.94 EUR per kilogram. Theoretically this means that an individual, on average, should be compensated 6.94 EUR to accept one kilogram of pangasius. In practice it means that, on average, an individual prefers the NOT alternative to buying pangasius at the given prices. A possible reason for the low WTP estimates is that quite many participants chose the NOT alternative in many choice scenarios (Figure 6.6.1). This will pull the price parameter downwards. None of the participants, however, chose the NOT alternative in *all* choice scenarios.

By converting the estimated utility distributions, i.e., the estimated average utilities and standard deviations, into WTP values, we can graphically see the preference heterogeneity for each fish type. In Figure 6.7.1 the distributions for salmon, farmed cod and pangasius are found in the graph to the left. The distributions for farmed cod, wild cod and monk are found in the graph to the right.

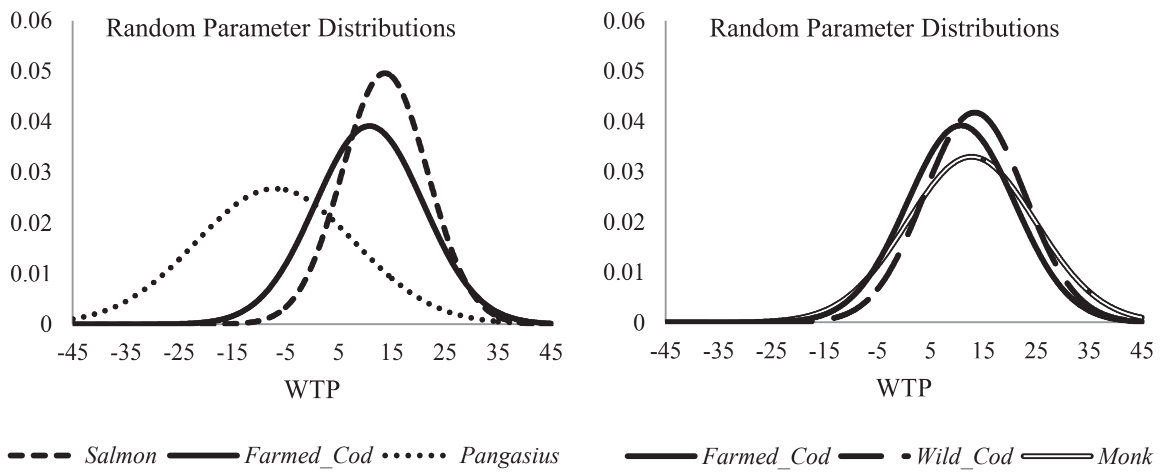

Figure 6.7.1. Distributions for the Random Parameters from *Model 1* Converted to WTP Values

As the graph to the left in Figure 6.7.1 illustrates, the WTP for pangasius is lower than that of farmed cod and salmon. The large heterogeneity in WTP values for pangasius is reflected by the wide distribution. The relatively homogenous WTP values for salmon are illustrated by the narrower curve. As shown in the graph to the right in Figure 6.7.1, the estimated WTP for farmed cod, wild cod and monk are quite similar. Their distributions are also relatively similar, indicating that the share of the population that is willing to pay more than average and the share of the population that is willing to pay less than average for these fish types, are relatively equally distributed in the population.

6.8. WTP Estimates for *Model 2* – Product Attribute and Consumer Characteristics Interaction Model

The WTP values obtained from *Model 2*, which includes the consumer characteristics *Income*, *Age* and *Single*, are presented in Table 6.8.1.

Table 6.8.1. WTP Results for *Model 2* – Product Attribute and Consumer Characteristics Interaction Model

Variables	Mean WTP/KG	95% Confidence Interval Lower Limit	95% Confidence Interval Upper Limit
Salmon	16.94	11.96	21.92
Farmed_Cod	4.22	-3.10	11.54
Wild_Cod	5.09	-0.92	11.11
Monk	4.77	-4.31	13.86
Pangasius	-6.93	-18.30	4.44
*Tail * Salmon*	-1.96	-2.95	-0.97
*Tail * Farmed_Cod*	-6.59	-8.17	-5.00
*Tail * Wild_Cod*	-3.06	-4.33	-1.78
*Income * Salmon*	2.40	-0.76	5.56
*Income * Farmed_Cod*	3.92	-0.32	8.15
*Income * Wild_Cod*	5.62	2.11	9.14
*Income * Monk*	1.37	-3.84	6.58
*Income * Pangasius*	4.20	-2.11	10.51
*Age * Salmon*	-0.10	-0.20	0.00
*Age * Farmed_Cod*	0.10	-0.03	0.24
*Age * Wild_Cod*	0.13	0.02	0.25
*Age * Monk*	0.17	0.00	0.34
*Age * Pangasius*	-0.05	-0.26	0.16
*Single * Salmon*	4.43	1.56	7.29
*Single * Farmed_Cod*	2.91	-0.85	6.66
*Single * Wild_Cod*	3.07	-0.17	6.32
*Single * Monk*	1.08	-3.62	5.78
*Single * Pangasius*	5.51	-0.40	11.42

As an example, the estimated WTP for a kilogram of loin of farmed cod for a 45 year old, single person, who belongs to the *low* income group, is:

$4.22 - 6.59 * 0 + 3.92 * 0 + 0.10 * 45 + 2.91 * 1 = 11.63$ EUR/KG.

Table 6.8.2 shows WTP values for different consumer groups. *Age* is set to 47, which is the sample average. The most striking features of Table 6.8.2 are the large differences in WTP values between fillets of loin and fillets of tail cut of farmed cod. All consumer groups, given that *Age* is 47, are willing to pay about twice as much for a loin of farmed cod than a tail fillet of farmed cod.

Another interesting finding is that people in the high income group, regardless of marital status, and given that *Age* is 47, are willing to pay more for a loin of wild cod than a loin of salmon. This again demonstrates the positive income effect on wild cod found in Table 6.1.

All WTP values for farmed cod are below the prices found in grocery stores in Dijon in May 2008, given that *Age* is 47.

Table 6.8.2. Examples of WTP Values in EUR/KG per Consumer Group (*Age* = 47)

	Low Income Single	High Income Single	Low Income Married	High Income Married
Salmon Loin	16.57	18.97	12.14	14.55
Salmon Tail	14.61	17.01	10.18	12.59
Farmed Cod Loin	12.00	15.92	9.10	13.01
Farmed Cod Tail	5.42	9.33	2.51	6.43
Wild Cod Loin	14.41	20.03	11.34	16.96
Wild Cod Tail	11.35	16.98	8.28	13.90
Monk	14.02	15.39	12.94	14.31
Pangasius	-3.64	0.56	-9.15	-4.95

By dividing consumers into age groups, we can see differences in WTP values between younger and older consumers. In Table 6.8.3 the consumers are divided into one group where *Age* is set to 30, and another group where *Age* is set to 60. All consumers are assumed to be married/cohabiting, that is, *Single* = 0.

Older consumers have higher WTP values for both farmed and wild cod relative to younger consumers. However, from Table 6.1 we find no significant age effect on farmed cod, but the *p*-value is 0.12, hence *close* to significance at the 10% level (Appendix I, Table A.12.2.1). The married/cohabiting participants aged 60 have, regardless of income, higher WTP values for loins of wild cod than loins of salmon.

All WTP values for farmed cod are below the prices found in grocery stores in Dijon in May 2008.

Table 6.8.3. Examples of WTP Values in EUR/KG per Consumer Group (*Single* = 0)

	Age 30 Low Income	Age 60 Low Income	Age 30 High Income	Age 60 High Income
Salmon Loin	13.88	10.82	16.28	13.22
Salmon Tail	11.92	8.86	14.32	11.26
Farmed Cod Loin	7.33	10.45	11.25	14.36
Farmed Cod Tail	0.75	3.86	4.66	7.78
Wild Cod Loin	9.08	13.06	14.70	18.69
Wild Cod Tail	6.02	10.01	11.64	15.63
Monk	9.98	15.19	11.36	16.57
Pangasius	-8.35	-9.77	-4.15	-5.57

It is worth noting that the 95% confidence intervals for the WTP estimates in *Model 2* (Table 6.8.1) are wide. The WTP values for all fish types but salmon range from a negative to a positive value. This indicates that there is uncertainty related to the estimates, and the results must be interpreted with caution.

7. Discussion

In the next sections we discuss the results and relate them to the answers from the survey. The terms "survey respondents" and "participants" are used interchangeably.

Generally, the preferences and the WTP values for farmed cod are lower than those of wild cod. Could attitudes towards production method (fish farming vs. wild catching) and environmental concerns be underlying factors determining these differences? In the survey, 83% agrees to the statement that wild fish is *healthy* food, but only 31% agrees to the equivalent statement for *farmed* fish (Appendix I, Table A.11.3). This implies that the participants regard wild cod to be healthier than farmed cod, and perhaps they are willing to pay a price premium for the fish they consider the healthier. This suggests that producers of farmed cod potentially could improve the image of farmed fish by focusing on healthiness.

60% of the survey respondents agrees to the statement that *wild* fish is *safe* to eat, but only one third (33%) agrees to the equivalent statement for *farmed* fish (Appendix I, Table A.11.3). However, this contradicts the unambiguous positive attitudes towards salmon, since almost all salmon sold on the French market is farmed. To which extent the participants (and French consumers in general) are aware of the salmon being farmed is unclear.

7.1. Environment and Animal Welfare – Attitude-Behavior Gap?

More people have reported that they are concerned about the environmental impact of the production of *wild* fish (77%) than of *farmed* fish (60%) (Appendix I, Table A.11.3). This suggests that the participants do not refrain from eating farmed fish on environmental grounds. When it comes to environmental sustainability, 76% reported that they are concerned about the environmental sustainability of fisheries, and 70% reported the same for fish farming (Appendix I, Table A.11.3).

Regarding animal welfare, the survey responses reveal no significant difference in the attitudes towards the welfare of farmed fish and the welfare of wild fish (Welch *p*-value = 0.3779) (Appendix I, Table A.11.1.1). This indicates that the attitudes towards fish farming are not significantly stronger than the attitudes towards wild fish catching.

However, more than half of the participants report that they are concerned about the welfare of farmed as well as wild fish. This comes as no surprise, since it is easy to agree to such a statement when answering a survey (Appendix I, Table A.11.3). Verbeke et al. (2007) found in a survey conducted on Flemish women that although consumers attach high perceived importance to sustainability and ethics related to fish, this perceived importance is not correlated with fish consumption or attitudes towards fish eating. Attitudes alone are often a poor predictor of marketplace behavior. The survey responses from this experiment indicate that beliefs about food safety and health perceptions are the main determinants for favoring wild fish to farmed fish. Hence, we might find an attitude-behavior gap among the French consumers as well.

7.2. Region of Origin

In general there is a positive view of fresh farmed fish from France (76%) and Northern Europe (72%) and wild fish from the Atlantic North (86%) (Appendix I, Table A.11.1). There is attached high skepticism towards fresh farmed fish from third world countries. 65% does not have a positive view of fresh farmed fish from third world countries (Appendix I, Table A.11.1). According to a marketing survey conducted by *Marint Verdiskapingsprogram*, it is unheard of to write on a restaurant menu in France that the fish is farmed. It is, however, common to write the country of origin on the menu (Solheim 2010). This supports the notion that knowledge about the origin of the fish is a highly valued criterion in France.

7.3. Competition from Pangasius

From the RC results and the survey answers it is evident that the preferences and WTP for cod are greater than those of pangasius. Two thirds of the respondents agree to the statement that cod tastes good, while only 19% agrees to the equivalent statement for pangasius. In fact, 61% *disagrees* to the statement that pangasius tastes good (Appendix I, Table A.11.2). About half of the respondents regard cod as safe to eat, but only 10% regards pangasius as safe to eat (Appendix I, Table A.11.2). This may be because pangasius is from Vietnam, as the majority does not have a positive view of fresh farmed fish from third world countries.

The correlations in preferences between salmon, wild cod, farmed cod and monk were generally positive and significant (Table 6.6.1). However, the results from *Model 1* suggest no correlations in the preferences between pangasius and farmed cod and wild cod. This suggests that those who obtain an above average utility from choosing farmed or wild cod do not necessarily obtain an above average utility from choosing pangasius.

Despite the somewhat unenthusiastic attitudes towards pangasius among the sample in this experiment, it is worth noting that pangasius is the ninth most consumed fish in the US today. A great advantage the pangasius has relative to other fish species is that it can breathe air; hence it can be produced in great volumes with little space (Greenberg 2011). Asian labor costs are in general lower, and the environmental restrictions are often more lax than in Europe. Hence, European fish farmers may face real challenges from the Asian fish farming industry.

7.4. Competition from Salmon

Knowledge about substitution effects between salmon and cod are important for both salmon and cod farmers. Our results suggest that, on average, the preferences for salmon outweigh those of both farmed and wild cod, despite the perceived relative higher price of salmon (Table 6.7.1, column 7). The significant and positive correlations between salmon, farmed cod and wild cod do, however, indicate that those who like salmon also like cod (Table 6.6.1). This may imply that salmon and cod could be substitutes. On the other hand, the correlations between farmed cod, wild cod and monk are even higher, indicating that cod (both farmed and wild) faces stronger competition from monk than from salmon.

Asche and Hannesson (1997) find that salmon does not compete on the whitefish market in France. They argue that salmon is often consumed as luncheons and as starters, while whitefish are more traditionally consumed as main dishes. Since salmon and whitefish are not consumed in similar product forms, they do not compete with each other. These findings are from 1997, and are based on data from 1983 to 1995. The consumption patterns in France may have changed considerably since then.

7.5. Farmed Cod versus Wild Cod – External Validity?

Through the tasting session, the BDM, and the RC experiment the participants were exposed to a distinction between farmed and wild cod. However, neither *wild* salmon nor *wild* pangasius were alternatives. Had wild salmon been an option, it may be that the WTP values for wild salmon would have been even higher than the WTP values already obtained for (farmed) salmon.

Despite the fractional factorial design, the visible distinction between wild and farmed cod may have biased the choices towards preferring wild to farmed cod. In an ordinary supermarket situation though, consumers make choices based on habits, and may pay less attention to the production method. It is likely that the distinction between farmed and wild cod is not that clear in the field, i.e., outside the laboratory. Hence this experiment may suffer from some lack of external validity. However, Chang et al. (2009) found a high level of external validity in non-hypothetical methods when comparing different preference elicitation methods for the product categories ground beef, wheat flour and dishwashing liquid. It is also worth noting that in a tasting session of a similar experiment in Dijon in December 2007, Alfnes and Rickertsen (2008b) found that 55% of the participants gave farmed cod a higher taste score than wild cod.

7.6. Factors That May Bias WTP

In this RC experiment the only choice options were *fish* or NOT. This enabled us to examine the relative WTP for one fish type over the other. In an ordinary supermarket situation there are also other options like meat, egg, chicken, vegetables etc. How will this absence of outside options influence the results? Alfnes et al. (2006) argue that this may cause the participants to choose the NOT alternative too seldom. This may affect the price parameter and bias the WTP upwards. Even though real economic incentives were introduced by letting one choice scenario be binding, the price of the binding scenario makes up a very small fraction of a total household budget, especially when the participants knew they would get paid to participate. It follows that the binding scenario might not outweigh the upward bias from the absence of outside options.

Another aspect of this experiment is that many participants may find it exiting to take part in an experiment like this. Taking part in such an experiment may temporarily increase their desire for fish. This "new desire" may increase their motivation to buy fish that specific day, and bias WTP upwards. But when they go to the grocery store the next day, the "new desire" might be gone, and WTP might be at a lower level than during the experiment. The absence of outside options, and a possible new earned "desire" for fish, could be possible reasons for an upward bias of WTP.

On the other hand, it is probable that a great share of the participants did not intend to purchase fish on the exact day of the experiment. Corrigan and Rousu (2008) found that consumers who intended to buy bananas on the same day they took part in an experiment, had WTP values closer to the market price than the consumers who did not intend to buy bananas the same day. Those who intended to buy bananas on the day of the experiment had WTP values *above* those who did not intend to buy bananas. Hence, it is likely that the majority of the 178 participants behaved as non-buyers at the time of the experiment. A fresh fillet of fish is liable to rot if not refrigerated shortly after acquisition. The participants might find bringing with them a fresh fillet of fish as unpractical, and only choose a fillet in a choice scenario if they felt it were a remarkably good deal. This may explain why many participants chose the NOT alternative in many choice scenarios, which biases WTP downwards. Had the experiment involved a nonperishable good, e.g. chocolate bars, which could easily be stored until its consumption value is higher, we might obtain higher WTP values.

Alfnes and Rickertsen (2011) recommend not including participants with a nonresponse to all alternatives, because those participants do not reveal anything about their relative valuations of the products included in the experiment. According to microeconomic theory, only relative prices matter. In our experiment there were no non-responses, but ten participants chose a fillet only once and chose NOT in all other choice scenarios (Figure 6.6.1). This may have biased the WTP results somewhat downwards.

7.7. Comparing RC with Other WTP Elicitation Methods

As mentioned in the introduction, other WTP elicitation methods are available, such as EA and stated choice experiments. In an EA participants are asked to be price makers, while in an RC experiment they are asked to be price takers. Being a price maker may deflate WTP, whereas being a price taker may inflate WTP. As Alfnes and Rickertsen (2011) point out, a weakness with the RC method compared with the EA is that the WTP is not directly observable. The WTP must be estimated based on the choices *all* the participants make. "Hence, the estimated WTP for each participant is affected by the responses of other participants and sensitive to the model specification" (Alfnes & Rickertsen 2011). For instance, if one participant obtains an infinitely high utility from choosing salmon and does not consider price in his or her choices, the WTP values of the other participants will be affected. However, the WTP values from this experiment were lower than the prices found in grocery stores. This indicates that the results are not inflated above market price.

In stated choice experiments the respondents are, like in an RC experiment, price takers. Stated choice experiments differ from RC experiments in that each choice is hypothetical or non-consequential, hence real economic incentives are absent. Chang et al. (2009) find that non-hypothetical elicitation methods outperform hypothetical experiments. WTP values from non-consequential experiments are found to almost always exceed WTP values from consequential elicitation methods (Gracia et al. 2011). This is known as the hypothetical bias.

When respondents are aware of the fact that the choices they make have no economic consequences, they tend to accept higher prices than when they make inconsequential choices. Hence, the results from this experiment have empirical support of being closer to the true WTP of the consumers than would have been the case in a stated choice experiment.

7.8. Alternative Model Specifications

This experiment's main objectives were to study consumer preferences and WTP for the five fish types, and examine how different consumer groups value these. To study this, several approaches are available. For an even better understanding of how individuals value one fish type relative to another fish type, participants that answered NOT in more than a certain number of choice scenarios could be omitted from the analysis (see e.g. Figure 6.6.1). The downside of this is that the dataset would be reduced.

In our analysis the *Tail* variable was not interacted with the different consumer groups. A further investigation of how the different consumer groups value a fillet of tail cut could be a topic for further research.

Of the five fish types presented, three were farmed and two were wild. To better understand French consumers' attitudes towards *farmed* fish, one could include a variable indicating if the fish is farmed or not.

The survey answers revealed that the participants did care about the region of origin of the fish. Hence including variables relating to region of origin could be of interest.

Before the RC experiment took place, the participants had been through a tasting session. Hence they were familiar with the taste of the different types of fish. Including taste scores as variables could also possibly lead to some interesting findings.

8. Conclusion

In this article we have analyzed data from an RC experiment. We investigated the French consumer preferences and WTP for fish. We estimated random utility functions by mixed logit to capture preference heterogeneity in the population. We estimated one product attribute model *(Model 1*) and one model which included both products attributes and consumer characteristics (*Model 2*).

WTP values varied both with the attributes of the fish and with the consumer characteristics. The participants were willing to pay less for a fillet of tail than for a loin. Particularly low was the WTP for a tail fillet of farmed cod.

The WTP for wild cod appears to be slightly higher than that of farmed cod. Salmon was found to be the most desirable choice among the participants. On average, we found positive WTP values for all the fish types except for pangasius. The preferences for all the fish types were heterogeneous, which implies that certain segments of the population have WTP values above average, whereas other segments have WTP values below average. People with higher income are willing to pay a price premium for both farmed and wild cod. Higher age is associated with higher WTP for wild cod and monk, and lower WTP for salmon. Single households are willing to pay a price premium for salmon, wild cod and pangasius.

Predominantly, all WTP values were below the average price of the five fish types found in grocery stores in Dijon at the time of the experiment. Gender, education and presence of children in the household did not significantly affect the participants' choices, and accordingly, had no effect on WTP.

The participants in the experiment also answered a survey on fish likings, fish buying habits, attitudes toward production methods etc. The answers from the survey corresponded well to the results obtained from the RC experiment.

In the introduction we referred to two possible strategies for the future of the cod farming industry. The first strategy is to position itself at the higher price end of the market and create niche products. A second approach is to reduce production costs considerably, and increase the production volume. Our results indicate that the high income group is willing to pay a price premium for both farmed and wild cod. This speaks in favor of choosing the first strategy. However, the survey results suggest that the participants regard cod as both safer to eat and tastier than pangasius. Hence, if cod farmers were able to reduce the price considerably, cod has a competitive advantage over pangasius. This speaks in favor of choosing the second strategy. Since it is unrealistic to assume that the cod farming industry can compete with the Asian whitefish farming industry on price, we believe the first strategy is more feasible.

References

Alfnes, F., Guttormsen, A. G., Steine, G. & Kolstad, K. (2006). Consumers' willingness to pay for the color of salmon: A choice experiment with real economic incentives. *American Journal of Agricultural Economics*, 88 (4): 1050-1061.

Alfnes, F. & Rickertsen, K. (2008a). Franske forbrukere ønsker oppdrettstorsken velkommen: Resultater fra fokusgrupper om fisk, pakking og merking. *Norsk Fiskeoppdrett*, 33 (4): 9-11.

Alfnes, F. & Rickertsen, K. (2008b). Franske smakstester av villtorsk og oppdrettstorsk: Klart skille mellom yngre og eldre forbrukere. *Norsk Fiskeoppdrett*, 33 (10): 8-10.

Alfnes, F. & Rickertsen, K. (2011). Nonmarket valuation: Experimental methods. In Lusk, J. L., Roosen, J. & Shogren, J. F. (eds) *The Oxford handbook of the economics of food consumption and policy*, pp. 215-242. New York: Oxford University Press Inc.

Ariely, D. (2010). *Predictably irrational: The hidden forces that shape our decisions*. New York: HarperCollins.

Asche, F. & Hannesson, R. (1997). *Market integration between whitefish and salmon in France*. Working Paper, vol. no. 40/97. Bergen: Institute for Research in Economics and Business Administration.

Asche, F. (2009). Oppdrettstorsk, hva nå? *Norsk Fiskeoppdrett*, 34 (6): 10-12.

Chang, J. B., Lusk, J. L. & Norwood, F. B. (2009). How closely do hypothetical surveys and laboratory experiments predict field behavior? *American Journal of Agricultural Economics*, 91 (2): 518-534.

Corrigan, J. R. & Rousu, M. C. (2008). Testing whether field auction experiments are demand revealing in practice. *Journal of Agricultural and Resource Economics*, 33 (2): 290-301.

Food and Agriculture Organization. (2012). *Fisheries and Aquaculture Department*: Food and Agriculture Organization of the United Nations. Available at: http://www.fao.org/fishery/culturedspecies/Gadus_morhua/en#tcNA00EA (accessed: 15.04.2012).

Gracia, A., Loureiro, M. L. & M. Nayga, R. (2011). Are valuations from nonhypothetical choice experiments different from those of experimental auctions? *American Journal of Agricultural Economics*, 93 (5).

Greenberg, P. (2011). *The whitefish's burden*. The New York Times. Available at: http://www.nytimes.com/2011/12/16/opinion/the-whitefishs-burden.html?_r=3&ref=fishfarming (accessed: 15.04.2012).

Gruben, M. H. (2007). *Etterspørsel etter laks: Når negativ medieomtale påvirker salget av laks*. Master's Thesis. Oslo: University of Oslo, Department of Economics.

Loureiro, M. L. & Umberger, W. J. (2004). A choice experiment model for beef attributes: What consumer preferences tell us. *Selected paper presented at the American Agricultural Economics Association annual meetings, Denver, Colorado August 1-4, 2004*.

Lusk, J. L. & Schroeder, T. C. (2004). Are choice experiments incentive compatible? A test with quality differentiated beef steaks. *American Journal of Agricultural Economics*, 86 (2): 467-482.

Lusk, J. L. & Schroeder, T. C. (2006). Auction bids and shopping choices. *Advances in Economic Analysis & Policy*, 6 (1): 1-37.

Nereng, M. (2011). *Mer fisk, takk!* In Forskningsrådet (ed.). Norsk mat fra sjø og land (Matprogrammet) Available at: http://www.forskningsradet.no/prognett-matprogrammet/Nyheter/Mer_fisk_takk/1253968930862?lang=no (accessed: 13.04.2012).

Nilssen, F. & Monfort, M. C. (2000). Some perspective on the future for farmed salmon in France. *Økonomisk Fiskeriforskning*, 10 (2): 105-114.

Olesen, I., Alfnes, F., Røra, M. & Kolstad, K. (2010). Eliciting consumers' willingness to pay for organic and welfare-labelled salmon in a non-hypothetical choice experiment. *Livestock Science*, 127 (2-3): 218 - 226.

Olstad, L. (2011). *Oppdrettstorsk ulik villtorsk* In Forskning.no (ed.). Available at: http://www.forskning.no/artikler/2011/mai/288677 (accessed: 13.04.2012).

Solheim, W. A. (2010). *Chefer liker oppdrettstorsk*. In Forskning.no (ed.). Available at: http://www.forskning.no/artikler/2010/mars/245368 (accessed: 13.04.2012).

Statistics Canada. (2009). *Proportion of one-person households in Canada similar to the United States but lower than some European countries*. In www.statcan.gc.ca, S. C. (ed.). Available at: http://www12.statcan.ca/census-recensement/2006/as-sa/97-553/figures/c5-eng.cfm (accessed: 23.04.2012).

Statistics Norway. (2012). *Tabell: 07681: Eksport av laks og regnbueørret, etter varegruppe* Available at: http://statbank.ssb.no/statistikkbanken/Default_FR.asp?Productid=10.05&PXSid=0&nvl=true&PLanguage=0&tilside=selecttable/MenuSelP.asp&SubjectCode=10 (accessed: 13.04.2012).

Toften, K. (2009). Oppdrettstorsk - Konkurransegrunnlag, market og strategiske muligheter. In Nofima (ed.). *Rapport 45/2009*. Tromsø: Nofima Marin.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge: Cambridge University Press.

Tveterås, S. (2003). *Value chains for primary goods: From wild to farmed fish*. Doctor Oeconomiae. Bergen: Norwegian School of Economics and Business Administration, Department of Economics.

Verbeke, W., Vanhonacker, F., Sioen, I., Van Camp, J. & De Henauw, S. (2007). Perceived importance of sustainability and ethics related to fish: A consumer behavior perspective. *Ambio*, 36 (7): 580-585.

Willemsen, F. (2003). Report on the seafood consumption data found in the European countries of the OT-SAFE Project. WP3. Risk assessment of TBT in seafood in Europe. Vrije Universiteit, 1081 HV Amsterdam: Institute for Environmental Studies.

Appendix I

Contents

A.1. A Short Introduction to Lancastrian Consumer Theory

The theory behind the utility models from the article is based on Lancastrian consumer theory. Traditional consumer theory postulates that the good itself generates utility for a consumer. Lancaster, on the other hand, proposes that the goods are components of different attributes, and that the summation of the utilities associated with the attributes determines a person's utility for the good. Following Lancaster (1966), "*the chief technical novelty lies in breaking away from the traditional approach that goods are the direct objects of utility and, instead, supposing that it is the properties or characteristics of the goods from which utility is derived.*" The attributes of fish in general are the fish types, and the five fish types used in our experiment had different cuts and prices. In the empirical specification of the utility functions in the article, we included product attributes and consumer characteristics. Although a consumer characteristic, like age, is not in itself an attribute of the product, a person's age may, however, affect how he or she perceives the product.

A.2. Other WTP Elicitation Methods and Prior Research

To study consumer preferences and elicit WTP, other methods than real choice (RC) experiments are available, for example experimental auctions (EA), Becker-DeGroot-Marschak (BDM) mechanisms or stated choice (SC) experiments. In EAs the participants take part in a bidding session. There are many versions of EAs, for example a second-price sealed-bid auction, also known as a Vickrey auction. In a Vickrey auction participants submit sealed bids for a product. The highest bidder buys the product for the price of the second highest bid (Alfnes & Rickertsen 2011).

The BDM mechanism is similar to an EA. A participant submits a sealed bid for a product. The sales price is determined by a draw from a distribution of numbers from zero to the highest anticipated bid. If the bid is higher than the drawn price, the participant buys the product for the price picked from the draw. Strategically a BDM is equal to an EA (Alfnes & Rickertsen 2011). A special feature of the BDM is that it is possible for only one person to participate. EAs and BDMs might seem like unfamiliar situations for consumers. No prices are posted in advance.

In SC experiments, participants make hypothetical choices over a set of one or more choice scenarios. Participants are asked to pick the product they would have bought; given that it was a real life situation. Prices are posted in advance.

Corrigan and Rousu (2008) study the differences in consumers' WTP for perishable and nonperishable goods by the use of EAs. Loureiro and Umberger (2004) use an SC experiment to study which beef attributes that affect consumer preferences, and the corresponding effect on WTP. Wolf et al. (2011) use an SC experiment to estimate consumers' WTP for half and whole gallons of milk. They study consumers' responses on attributes such as labeling with information on rbST-content. Another SC experiment that studies consumers' response on product labeling is James et al. (2009). They assess WTP values of organic, local and nutrition attributes on applesauce. A study of consumers' responses to animal welfare was conducted by Tonsor et al. (2009). They use an SC experiment with labeling on the use of gestation crates in the production as an attribute.

A.3. The Mixed Logit Model

The standard logit model estimates the logarithm of the odds of an outcome as:

$$(1)\ \log\left(\frac{\pi_j}{\pi_J}\right) = \beta_{j0} + \beta_{j1}x_1 + \beta_{j2}x_2 +, \dots, + \beta_{jk}x_k, \qquad j = 1, \dots, J-1,$$

where J is the baseline category, and π_j are the outcome probabilities given by:

$$(2)\ \pi_j = \frac{e^{\beta_j x}}{\sum_{j=1}^{J} e^{\beta_j x}}.$$

(Agresti 2007, p. 174-176)

When estimating a discrete choice random utility model, and assuming it is linear in parameters, one can interpret the logarithm of the odds as the utility an individual obtains from making a choice. The linear and ordinal nature of the logarithm of the odds makes a utility model straight forward to interpret.

The mixed logit model is more flexible than the standard logit. It obviates the limitations of the standard logit model in three ways: It allows for random taste variation, it takes unrestricted substitution patterns into account, and it allows for correlations in unobserved factors over time or choice scenarios (Train 2009, p. 134).

Any random utility model (RUM) can, to any degree of accuracy, be approximated by a mixed logit model with the right choice of variables and distribution for the random parameters (Train 2009, p. 142). The random parameters have, in addition to their expected values, a distribution chosen by the researcher (chosen to be normal in the article). Mixed logit probabilities are the integrals of logit probabilities over the density of the random parameters (Train 2009, p. 135). The probability that individual n chooses alternative i in one given choice scenario is given by:

$$(3)\ P_{ni}(\boldsymbol{\beta}, \boldsymbol{\eta}) = \int L_{ni}(\boldsymbol{\beta}, \boldsymbol{\eta}) f(\boldsymbol{\eta}) d\boldsymbol{\eta},$$

where $\boldsymbol{\beta}$ is a vector of the fixed parameters and $\boldsymbol{\eta}$ is a vector of the random parameters. The βs are to be interpreted as if they were standard logit. $f(\boldsymbol{\eta})$ is the density function of the random parameters and $L_{ni}(\boldsymbol{\beta}, \boldsymbol{\eta})$ is the standard logit probability evaluated at parameters $\boldsymbol{\beta}$ and $\boldsymbol{\eta}$:

$$(4)\ L_{ni}(\boldsymbol{\beta}, \boldsymbol{\eta}) = \frac{e^{\beta x_{ni} + \eta_n z_{ni}}}{\sum_{j=1}^{J} e^{\beta x_{nj} + \eta_n z_{nj}}}.$$

Note that i is an element in the array $j = 1,2, \dots, J$. In the models presented in the article i represents the five fish types. Equation (3) can be extended to allow for repeated choices over time or choice scenarios s (Train 2009, p. 145). Consider a sequence of choices $\boldsymbol{i} = \{i_1, i_2, \dots, i_S\}$. The probability that an individual makes this exact sequence of choices over a set of choice scenarios is:

$$(5)\ P_{ni}(\boldsymbol{\beta},\boldsymbol{\eta}) = \int L_{ni}(\boldsymbol{\beta},\boldsymbol{\eta}) f(\boldsymbol{\eta}) d\boldsymbol{\eta},$$

where $L_{ni}(\boldsymbol{\beta},\boldsymbol{\eta})$ is the product of the logit probabilities evaluated at parameters $\boldsymbol{\beta}$ and $\boldsymbol{\eta}$:

$$(6)\ L_{ni}(\boldsymbol{\beta},\boldsymbol{\eta}) = \prod_{s=1}^{S} \left[\frac{e^{\beta x_{nis}+\eta_n z_{nis}}}{\sum_{j=1}^{J} e^{\beta x_{njs}+\eta_n z_{njs}}}\right].$$

There were sixteen choice scenarios in the RC experiment presented in the article. The data is therefore treated as panel data. The estimated models contain both fixed and random parameters. Since we have assumed the random parameters to be normally distributed with mean $\boldsymbol{\mu}_\eta$, and covariance matrix W, the density of the random parameters are given by $\phi(\boldsymbol{\eta}|\boldsymbol{\mu}_\eta, W)$. Allowing for correlations in unobserved factors over choice scenarios makes W a covariance matrix, rather than just the standard deviations of the random parameters. The standard deviations can be obtained by taking the square root of the diagonal elements of the covariance matrix. The probability of a given sequence over the sixteen choice scenarios $\boldsymbol{i} = \{i_1, i_2, \dots, i_{16}\}$ is given by:

$$(7)\ P_{ni}(\boldsymbol{\beta},\boldsymbol{\eta}) = \int L_{ni}(\boldsymbol{\beta},\boldsymbol{\eta}) \phi(\boldsymbol{\eta}|\boldsymbol{\mu}_\eta, W) d\boldsymbol{\eta},$$

where $L_{ni}(\boldsymbol{\beta},\boldsymbol{\eta})$ is the standard logit probability evaluated at parameters $\boldsymbol{\beta}$ and $\boldsymbol{\eta}$:

$$(8)\ L_{ni}(\boldsymbol{\beta},\boldsymbol{\eta}) = \prod_{s=1}^{16} \left[\frac{e^{\beta x_{nis}+\eta_n z_{nis}}}{\sum_{j=1}^{5} e^{\beta x_{njs}+\eta_n z_{njs}}}\right].$$

Note that the sum in the denominator in equation (8) ranges from one to five since there are five different fish types in the experiment. The vector for the random parameters has an estimated mean $\boldsymbol{\mu}_\eta$, and covariance matrix W. Since the chosen distribution for the random parameters is normal, equation (7) must be integrated over all values of $\boldsymbol{\eta}$, that is, from minus infinity to plus infinity. The density $\phi(\boldsymbol{\eta}|\boldsymbol{\mu}_\eta, W)$ is given by the normal distribution. Mixed logit probabilities cannot be calculated analytically. A numerical approach is necessary (Train 2009, p. 144).

A.4. The Econometric Model and Model Setup

The utility model in the article can be thought of as five different utility functions; one for each fish type i. Each fish type is assigned a number from one to five, that is, i = {*1=Salmon, 2=Farmed Cod, 3=Wild Cod, 4=Monk, 5=Pangasius*}. The utility of choosing NOT is normalized to zero. Hence, the utility one obtains from choosing the different fish types is the utility one obtains compared to choosing NOT.

The socio-demographic variables (the consumer characteristics) do not vary over choice scenarios. To capture the effect of the consumer characteristics variables, one must multiply them with the variables representing the fish types. This accords well with thinking of the utility functions as one for each fish type.

The variables representing each fish type are defined by the $\boldsymbol{z}_i$-vectors:

$$\boldsymbol{z}_1 = \boldsymbol{z}_{sa} = \begin{bmatrix}1\\0\\0\\0\\0\end{bmatrix}, \boldsymbol{z}_2 = \boldsymbol{z}_{fc} = \begin{bmatrix}0\\1\\0\\0\\0\end{bmatrix}, \boldsymbol{z}_3 = \boldsymbol{z}_{wc} = \begin{bmatrix}0\\0\\1\\0\\0\end{bmatrix}, \boldsymbol{z}_4 = \boldsymbol{z}_{mo} = \begin{bmatrix}0\\0\\0\\1\\0\end{bmatrix}, \boldsymbol{z}_5 = \boldsymbol{z}_{pa} = \begin{bmatrix}0\\0\\0\\0\\1\end{bmatrix}$$

To estimate the consumer characteristics effect on the preferences for fish, interaction terms are necessary. For example, to estimate the age effect, one must multiply the variable *Age* with the $\boldsymbol{z}_i$-vectors. That is:

$$Age * \boldsymbol{z}_1 = Age * \boldsymbol{z}_{sa} = Age \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

$$Age * \boldsymbol{z}_2 = Age * \boldsymbol{z}_{fc} = Age \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

$$Age * \boldsymbol{z}_3 = Age * \boldsymbol{z}_{wc} = Age \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix},$$

$$Age * \boldsymbol{z}_4 = Age * \boldsymbol{z}_{mo} = Age \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix},$$

$$Age * \boldsymbol{z}_5 = Age * \boldsymbol{z}_{pa} = Age \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}.$$

For salmon, farmed cod and wild cod the cut was either a tail cut or a loin (front cut). Thus we get three vectors $\boldsymbol{y}_i$ representing the three fish types that had either tail cut or loin:

$$\boldsymbol{y}_1 = \boldsymbol{y}_{sa} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \boldsymbol{y}_2 = \boldsymbol{y}_{fc} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \boldsymbol{y}_3 = \boldsymbol{y}_{wc} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix},$$

To estimate the tail effect on preferences for fish, one must multiply the $\boldsymbol{y}_i$-vectors with the *Tail* variable:

$$Tail * \boldsymbol{y}_1 = Tail * \boldsymbol{y}_{sa} = Tail \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix},$$

$$Tail * \boldsymbol{y}_2 = Tail * \boldsymbol{y}_{fc} = Tail \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix},$$

$$Tail * \boldsymbol{y}_3 = Tail * \boldsymbol{y}_{wc} = Tail \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}.$$

Model 1 in the article, with no consumer characteristics included, is specified as:

(9) $E(U_i) = \alpha Price + \boldsymbol{\mu}_\eta \boldsymbol{z}_i + \boldsymbol{\delta} \boldsymbol{y}_i Tail,$

where α is the price coefficient, $\boldsymbol{\mu}_\eta$ is a vector of the expected values of the random parameters and $\boldsymbol{\delta}$ is a vector of coefficients for the interaction terms including *Tail*. Note that the n subscript is omitted in equation (1) since no consumer characteristics are included in *Model 1*.

Model 2 in the article, which includes the consumer characteristics *Income*, *Age* and *Single*, is specified as:

(10) $E(U_{ni}) = \alpha Price + \boldsymbol{\mu}_\eta \boldsymbol{z}_i + \boldsymbol{\delta} \boldsymbol{y}_i Tail + \boldsymbol{z}_i[\boldsymbol{\gamma}_1 Income_n + \boldsymbol{\gamma}_2 Age_n + \boldsymbol{\gamma}_3 Single_n + \boldsymbol{\gamma}_4 DNWA_n],$

where the $\boldsymbol{\gamma}$s are coefficient vectors for the socio-demographic interactions with each fish type. Since the consumer characteristics *Income*, *DNWA*, *Age* and *Single* are interacted with variables representing each fish type, they are multiplied by the $\boldsymbol{z}_i$ vector. The variable *DNWA* (*Do Not Want to Answer*) represents the people in the income group that did not want to reveal their income. This variable is included in every model where *Income* is a variable.

However, its parameter estimates are of limited interest and they are thus not presented in the article. For a thorough discussion of the *DNWA* variable, see section A.6.1.1.

A.4.1. A Numerical Example – Utility for Farmed Cod

Assume we are interested in the utility for farmed cod. Farmed cod was assigned the number 2, i.e., $i = 2$. The $\boldsymbol{y}$ and $\boldsymbol{z}$-vectors thus have the form:

$$\boldsymbol{y}_2 = \boldsymbol{y}_{fc} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \text{ and } \boldsymbol{z}_2 = \boldsymbol{z}_{fc} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Expected utility obtained from *Model 1* would be expressed as:

$$(11) \qquad E(U_{fc}) = \alpha Price + \boldsymbol{\mu}_\eta \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \boldsymbol{\delta} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} Tail,$$

and the expected utility obtained from *Model 2* would be expressed as:

$$(12) \qquad E\left(U_{n,fc}\right) = \alpha Price + \boldsymbol{\mu}_\eta \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \boldsymbol{\delta} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} Tail + \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} [\boldsymbol{\gamma}_1 Income_n + \boldsymbol{\gamma}_2 Age_n + \boldsymbol{\gamma}_3 Single_n + \boldsymbol{\gamma}_4 DNWA_n],$$

where $\boldsymbol{\delta}$, the $\boldsymbol{\gamma}$s and $\boldsymbol{\mu}_\eta$ are the coefficient vectors, and α is the price coefficient. If we omit the vector notation in equation (11), i.e.: extract the coefficients for farmed cod in the vectors

$\boldsymbol{\mu}_\eta$ and $\boldsymbol{\delta}$, and setting $\boldsymbol{z}_2 = \boldsymbol{z}_{fc} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = 1$ and $\boldsymbol{y}_2 = \boldsymbol{y}_{fc} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} = 1,$ *Model 1* can be rewritten as:

(13) $$E(U_{fc}) = \alpha Price + \mu_{\eta,fc} + \delta_{fc} Tail.$$

By omitting the vector notation in equation (12), *Model 2* can be rewritten as:

(14) $$E(U_{n,fc}) = \alpha Price + \mu_{\eta,fc} + \delta_{fc} Tail + \left[\gamma_{1fc} Income_n + \gamma_{2fc} DNWA_n + \gamma_{3fc} Age_n + \gamma_{4fc} Single_n\right]$$

From the output of *Model 1* in the article (Table 6.1) we obtain the following results:

(15) $$E(U_{fc}) = -.219[Price] + 2.36 - 1.434[Tail]$$

This is the logarithm of the odds of choosing farmed cod, and is to be interpreted as utility. The standard deviation for the random parameter is 2.229 and it is significant at the 1% level. This suggests preference heterogeneity for farmed cod. Figure A.4.1 shows the estimated distribution for the *Farmed_Cod* parameter. It is assumed that the fillet is a loin (*Tail* = 0).

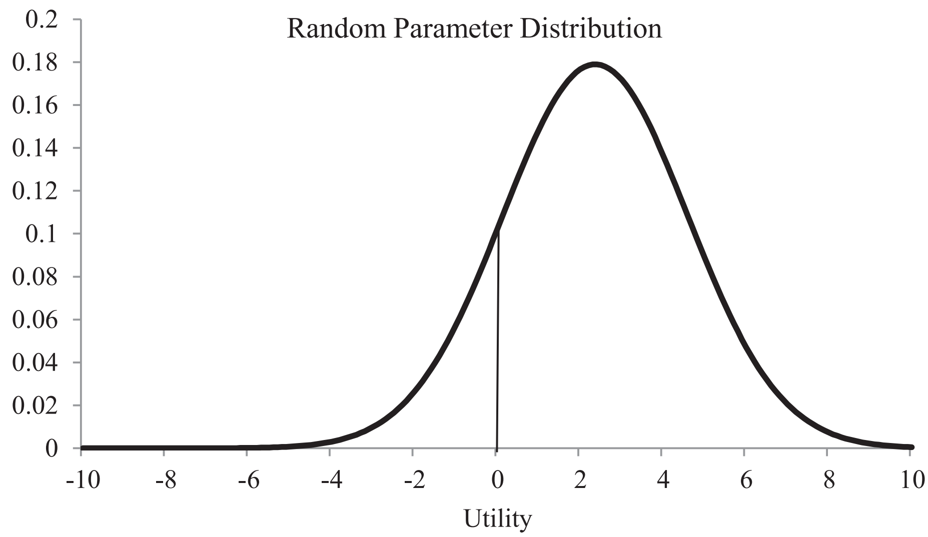

Figure A.4.1. The Random Parameter Distribution for *Farmed_Cod* in *Model 1*.

Following Hole (2007b), we can estimate the percentage of the population that is positive to farmed cod by the formula:

$$(16) \qquad 100 * \phi(-\frac{\mu_{\eta i}}{\sigma_i})$$

The estimated proportion of those who are positive to farmed cod, given that the fillet is a loin, is:

$$(17) \qquad 100 * \phi\left(-\frac{2.36}{2.229}\right) = 85.5\%,$$

which is the area to the right of the vertical line in Figure A.4.1. The estimated proportion being negative to farmed cod is $100\%(1 - 0.855) = 14.5\%$. Note that by "positive to farmed cod," we mean that an individual would rather choose farmed cod than the NOT alternative. The distribution displayed in Figure A.4.1 is the same distribution presented for *Farmed_Cod* in the article, but in the article the numbers on the horizontal axis are converted to WTP values, while they are expressed as utility in the appendix.

From the output of *Model 2* in the article we obtain the following results:

$$(18) \qquad E(U_{n,fc}) = -.22[Price] + .93 - 1.449[Tail] + .86[Income_n]$$
$$-.74[DNWA_n] + .023[Age_n] + .64[Single_n]$$

The estimated utility a single 55 year old person with *high* income obtains from choosing a loin of farmed cod priced 9.83 EUR/KG is thus;

$$-.22 * 9.83 + .93 * 1 - 1.449 * 0 + .86 * 1 - .74 * 0 + .023 * 55 + .64 * 1 = 1.5324.$$

The information of interest is the sign (positive or negative), the significance level (*p*-value) and the relative magnitude between the parameter estimates.

A.5. Generalized Extreme Value Distribution

The error term ε_{nis} in the random utility function is assumed to be independent and identically distributed (iid) extreme value. For a thorough review of extreme value distributions, see Coles (2011) and Train (2009, p. 76-96).

A.6. The Variables

The variables of interest in the RC experiment were the fish attributes and the consumer characteristics. The attributes of the five fish types were; the cut (tail or loin) and the price. Salmon, farmed cod and wild cod have loin as well as tail cuts. Monk and pangasius did not have tail cuts.

The consumer characteristics of interest were income, gender, age, marital status, children in the household, and education. *Model 1* in the article focuses on fish attributes only. It is meant to examine what attributes that affect people's preferences when no consumer characteristics have been controlled for. The fish attributes are included in all models. *Model 2* in the article includes the consumer characteristics; income, age and marital status. Section A.7 explains how the consumer characteristics included in *Model 2* were chosen.

Gender, presence of children in the household and level of education, which were the other consumer characteristics of interest, were not analyzed in the article. *Model 3* includes gender, presence of children in the household, and level of education in addition to the consumer characteristics from *Model 2*. This model is not presented in the article. See section A.9 for an analysis of *Model 3*.

A.6.1. Specification of the Consumer Characteristics

The consumer characteristics of interest were included by the following variables, that each was interacted with the variables representing the fish types:

Income:

Income was included by a dummy variable called *Income*, taking the value 1 if the participant's household's gross monthly income was above 3000 EUR, and 0 otherwise. 43 out of the 178 participants (24%) belonged to this group. Section A.6.1.1 explains why *Income* was chosen as a dummy variable, and not as a continuous variable.

Age:

Age was included as a continuous variable, called *Age*. The age of the participants ranged from 21 to 70 years.

Single:

Marital status was included as a dummy variable, *Single*, taking the value 1 is the participant was living in a single household with or without children, and 0 otherwise. Of the 178 participants in the experiment, 51 (29%) were single.

Female:

Gender was included as a dummy variable, *Female*, taking the value 1 if a participant is female, and 0 otherwise. 103 out of the 178 (58%) participants were women.

Children:

Presence of children in the household was included by a dummy variable, *Children*, taking the value 1 if a participant had children under the age of 18 in the household, and 0 otherwise. 61 out of the 178 (34%) participants had children in the household.

Education:

The level of education was included by a dummy variable, *Education*, taking the value 1 if a participant had two or more years of higher education, and 0 otherwise. 66 out of the 178 participants (37%) belonged to this group. An explanation of why *Education* was defined as a dummy variable rather than as a continuous variable is described in section A.6.1.2.

As explained in Section A.4, to capture the effects of the consumer characteristics, interaction terms with the $\boldsymbol{z}_i$-vectors were necessary. By including one extra consumer characteristic variable, the mixed logit model estimates five more parameters (since there were five fish types). Adding many consumer characteristics would quickly consume many degrees of freedom, and potentially reduce the robustness of the model. There are many observations in the dataset, since each participant made 16 choices in which there were 4 choice alternatives, but the number of participants (178 in total) is relatively small. Hence, it is desirable to limit the number of consumer characteristics to reduce the number of coefficients.

Not all variables were of a desired format. Particularly two variables of interest caused problems; *Income* and *Education*. The next two sections explain why *Income* and *Education* were defined as dummy variables rather than as continuous variables. In section A.7 we explain why *Income*, *Age* and *Single* were the socio-demographic variables included in *Model 2* presented in the article, in addition to *Model 1*.

A.6.1.1. The *Income* Variable

A household's gross monthly income had four categories in the survey questionnaire (Appendix II, p. 9):

Table A.6.1.1.1. Income Groups of the Participants

Income group	Definition	# of Participants	Share
1	Less than 2000 EUR a month	49	27.53 %
2	From 2000 to 3000 EUR a month	67	37.64 %
3	Over 3000 EUR a month	43	24.16 %
4	Do not know/Do not want to answer	19	10.67 %

As few as three income groups and one do-not-want-to-answer (*DNWA*) group, made this variable inappropriate as a continuous variable. Income group 3 could include all values above 3000 EUR a month. Large income variation within this group is a reasonable assumption. Participants in the *DNWA* group could belong to any level on the income spectrum, which made the income variable even harder to interpret. To get a meaningful variable for income, there were two options; (1) to include a dummy variable for each income group, or (2) to divide income into two groups; *low* and *high*. The former option would consume five more degrees of freedom than the latter, and potentially reduce the robustness of the model. As a first step to decide which options to choose, we estimated a model that included a dummy variable for each income group (*Model 4* – Income as Dummies for all Income Groups). That is, income group 1 was defined as the base category, and income groups 2, 3 and *DNWA* were defined by a dummy variable each. No other consumer characteristics but income were included in *Model 4*. To test the overall significance of the different income groups, the following hypotheses were postulated:

Hypothesis 1

$$Salmon * IncGr2 = Farmed\ Cod * IncGr2 = Wild\ Cod * IncGr2 = Monk * incGr2 = Pangasius * IncGr2 = 0$$

Hypothesis 2

$$Salmon * IncGr3 = Farmed\ Cod * IncGr3 = Wild\ Cod * IncGr3 = Monk * incGr3 = Pangasius * IncGr3 = 0$$

Hypothesis 3

$$Salmon * DNWA = Farmed\ Cod * DNWA = Wild\ Cod * DNWA = Monk * DNWA = Pangasius * DNWA = 0$$

The Wald test results are:

Table A.6.1.1.2. Wald Tests for the Income Groups

Hypothesis	Consumer Interaction Variable	Chi-Sq	Df	*p*-value
1	*IncGr2*	8.19	5	0.1461
2	*IncGr3*	9.08	5	0.1060
3	*DNWA*	11.94	5	0.0356

The difference between income group 1 and 2 is insignificant at the 10% level (*p*-value 0.146). The difference between group 1 and 3 is almost significant at the 10% level (*p*-value 0.106). Since the income group *DNWA* can contain both low and high income levels, its test result is of limited interest. It was included for the sake of clarity and tidiness.

The next step was to estimate a model that divided income into *low* and *high* by including a dummy variable for income group 3 only (*Model 5* Income as *Low* and *High*). This dummy variable was called *Income*. A dummy variable for *DNWA* was included to avoid income bias (see below in this section); however, its test result is not of importance. To test if there is a significant difference between the *low* and the *high* income groups, the following hypotheses were postulated:

Hypothesis 1

$$Salmon * Income = Farmed\ Cod * Income = Wild\ Cod * Income = Monk * income = Pangasius * Income = 0$$

Hypothesis 2

$$Salmon * DNWA = Farmed\ Cod * DNWA = Wild\ Cod * DNWA = Monk * DNWA = Pangasius * DNWA = 0$$

The Wald test results are:

Table A.6.1.1.3. Wald Tests for *Model 5*- Income as *High* or *Low*

Hypothesis	Consumer Interaction Variable	Chi-Sq	Df	*p*-value
1	*Income* (Above 3000 EUR a month)	13.75	5	0.0173
2	*DNWA* (Do not want to answer)	9.45	5	0.0925

The variable *Income* is significant at the 5% level (p-value 0.0173). The model with *Income* only, (*Model 5* Income as *Low* and *High*) is a special case of the more complex model that includes a dummy variable for each income group (*Model 4* – Income as Dummies for all Income Groups). To examine whether model *Model 5* had a significantly poorer fit than *Model* 4, a likelihood ratio test between the models was conducted. The test statistic is given by:

$$-2[Log\ likelihood_{Model4} - Log\ likelihood_{Model5}]$$

For large samples the test statistic has an approximate chi-squared distribution, with df equal to the difference in numbers of parameters between the two models (Agresti 2007, p. 86). The null hypothesis is: There is no significant difference between the models in explaining the data. The likelihood ratio test result is:

Table A.6.1.1.4. Likelihood Ratio Test between *Model 4* and *Model 5*

Model	Log-likelihood	# of coef.	AIC	Df	Chi-Sq Statistic	*p*-value
Model 4 – Income as Dummies *(2,3,4)*	-2517.5306	39	5113.061			
Model 5 – Income as *Low* and *High*	-2521.5856	34	5111.171	5	8.11	0.1502

The p-value of 0.1502 indicates that there is no significant improvement in model fit, by having each income group as a dummy variable of its own. Table A.6.1.1.4 also includes the AIC of the two models. AIC is a measure of model fit that penalizes a model for having many parameters (Agresti 2007, p. 141). A lower AIC number indicates a better fit. AIC is given by:

$$AIC = -2[Log\ likelihood - number\ of\ parameters\ in\ model]$$

Model 4 has the lower AIC of the two models, indicating a better fit. Thus we concluded to continue the analysis by having income as a dummy variable. The fact that income group 3 can include all values above 3000 EUR, also makes it natural to divide income into *low* and *high*.

The dummy variable for the income group *DNWA* was included in both models (and in all other models where *Income* is included). Its estimated parameters and test statistics provide limited information since individuals from all income levels can belong to this group. A non-negligible fraction of the participants (10.37%) belonged to this group. Omitting this variable would reduce the dataset somewhat. It is impossible to know what type of people who did not want to reveal their income are. For all we know, this could be people with strong preferences for monk or pangasius, or something else. Thus leaving them out of the analysis could potentially cause a bias. Another option was to simply place the whole group into one of the other income groups, by assuming they would either have low or high income. This could also cause a potential bias. Assume they were to be placed in the *high* income group. The high income group would then consist of the people who had high income as well as everyone from the *DNWA* group. If many respondents in the *DNWA* group actually had low income, the *Income* variable (which is a dummy variable for *high* income) would be very imprecise. If many people from the *DNWA* group had strong preferences for pangasius, it would seem like people with high income had strong preferences for pangasius. Hence, an income bias towards pangasius.

The *DNWA* estimates are omitted from the outputs presented in the article, since their parameter estimates were of no importance for our analysis. If the parameter estimates of the *DNWA* variable are of interest to the reader, see the regression outputs in section A.12.

A.6.1.2. The *Education* Variable

The variable for education consisted of seven levels of dubious ordinal and cardinal order (Appendix II, p. 1). Therefore we found it inappropriate to use it as a continuous variable.

Table A.6.1.2.1. The Level of Education Among the Participants

Education Level	# of Participants	Share	*Education* Dummy
No diploma	7	3.93 %	0
Brevet des colleges	21	11.80 %	0
CAP ou BEP	36	20.22 %	0
Baccaulaureat (BAC)	48	26.97 %	0
BAC + 2 or 3	41	23.03 %	1
BAC + 3 or 4	22	12.36 %	1
BAC + 6	3	1.69 %	1

Having a dummy variable for each of the seven education levels (six dummy variables in addition to the base category) would consume many degrees of freedom, since one would have to estimate $(\text{\# of dummy variables}) * (\text{\# of fish types}) = 6 * 5 = 30$ extra parameters. We therefore defined education as *low* and *high*, by creating a dummy variable, *Education*. This variable takes the value 1 if the participant has at least 2 years of education after completing BAC, and 0 otherwise. (That is, *Education* =1 if a participant has “BAC + 2 or 3” or “BAC +3 or 4” or “BAC +6”.) A total of 66 participants (37%) belonged to this group. Education is expected to be correlated with income. 79.46% of the participants who belonged to the *low* education group (i.e.: lower than BAC +2 or 3) also belonged to the *low* income group (i.e.: income less than 3000 EUR a month). Including both variables might not be necessary. To test for this we estimated a model that included both *Income* and *Education*, and postulated the following hypotheses:

Hypothesis 1

$$Salmon * Income = Farmed\ Cod * Income = Wild\ Cod * Income = Monk * income = Pangasius * Income = 0$$

Hypothesis 2

$$Salmon * DNWA = Farmed\ Cod * DNWA = Wild\ Cod * DNWA = Monk * DNWA = Pangasius * DNWA = 0$$

Hypothesis 3

$$Salmon * Education = Farmed\ Cod * Education = Wild\ Cod * Education = Monk * Education = Pangasius * Education = 0$$

The Wald test results are:

Table A.6.1.2.2. Wald Test for *Income* and *Education*

Test	Consumer Characteristics Interaction	Chi-Sq	Df	*p*-value
1	*Income*	14.15	5	0.0147
2	*DNWA*	10.78	5	0.056
3	*Education*	6.52	5	0.2590

The *p*-value of 0.2590 suggests that *Education* does not have a significant influence on the preferences for fish, when *Income* is controlled for. A likelihood ratio test to examine whether the more complex model, which includes both *Income* and *Education*, explains the data significantly better than its in-nested model, which includes only *Income*, gave the following result:

Table A.6.1.2.3. Likelihood Ratio Test between *Model 5* and *Model 6*

Model	Log-likelihood	# of coef.	AIC	Df	Chi-Sq. Statistic	*p*-value
Model 6 – Income and Education	-2518.3447	39	5114.6894			
Model 5 - Income	-2521.5856	34	5111.1712	5	6.4818	0.2621

The null hypothesis of no difference between the models is retained. *Model 6,* which includes both *Income* and *Education*, does not describe the data significantly better than *Model 5* that only includes *Income*. The AIC is lower for *Model 5* than *Model 6*, suggesting a better fit.

The variable *Education* shows no significant effect on the preferences for fish, and it is likely to be collinear with income. It was of dubious ordinal and cardinal order, and had many levels, which made it inconvenient to divide it into separate dummy variables. On the basis of this, and the elimination procedure to be explained in the next section (A.7), *Education* was omitted as a variable in the article.

A.7. Choice of Consumer Characteristics

Having defined the variables *Income* and *Education* in the previous sections (A.6.1.1 and A.6.1.2) we wanted to find the simplest model that best fits the data. That is, a model that would not have a significantly poorer fit than a larger model, but at the same time get a significantly poorer fit if a variable were to be removed. To find this model the following procedure was used: (1) Estimate a model with all relevant variables of interest, interacted with the variables representing the fish types, the $\boldsymbol{z}_i$-vectors. (2) Find the most insignificant variable interactions with a Wald-test. (3) Estimate a new model that excludes the most insignificant consumer characteristics interactions found in step (2). (4) Run a likelihood ratio test between the two models. (5) If there is no significant difference between the models, keep the simpler model, and repeat the procedure.

The procedure was repeated until we were left with a model that had a significantly better fit than its nested model and that did not have a significantly poorer fit than the model it was nested in. This procedure is quite similar to the technique of backward elimination (see Agresti (2007, p. 141)). The result of this procedure is found in Table A.7.1. Even though *Education* already has proven to be a poor explanatory variable, we included it in the procedure. Not surprisingly it was the first variable to be omitted.

Table A.7.1. Likelihood Ratio Tests to Find the Variables that Best Describe the Data

Model	Consumer Characteristics	Variable with Highest Wald *p*-value	Log-likelihood	# of Coef.	AIC	Models Compared	Df	Chi-Sq Statistic	*p*-value
Model 3	*Income, Age, Single, Female, Children, Education*	*Education (0.9144)*	-2505	59	5129				
Model 9	*Income, Age, Single, Female, Children*	*Children (0.8437)*	-2506	54	5120	3-9	5	0.839	0.9745
Model 8	*Income, Age, Single, Female*	*Female (0.5586)*	-2507	49	5112	9-8	5	2.016	0.8469
Model 2	*Income, Age, Single*	*Single (0.0499)*	-2509	44	5106	8-2	5	3.893	0.5649
Model 7	*Income, Age*		-2518	39	5114	2-7	5	18.264	0.0026

Children was the second variable to be removed. The likelihood ratio test between *Model 9* and *Model 8* had a *p*-value of 0.8469. A model that includes the variable C*hildren*, does not explain the data significantly better than a model without it. Having children in the household is an ambiguous measure. As an example; there is a big difference between having a three year old girl and two teenage boys in the household. It is likely that the purchase pattern of the former family constellation is quite different from that of the latter. Purchase of fish is no exception. Hence, *Children*'s limited impact on the preferences for fish comes as no surprise.

The next variable to be removed was *Female*. The likelihood ratio test between *Model 8* and *Model 2* gave a *p*-value of 0.5649. Including *Female* does not significantly describe the data better, than omitting it.

After *Female* had been removed, *Single* was the variable with the highest *p*-value from the Wald-test (*p*-value = 0.0499). The likelihood ratio test showed that removing *Single* from the model would lead to a significantly poorer fit (*p*-value = 0.0026).

The variables left to be presented in the article were thus *Income*, *Age* and *Single*. Even if *Education*, *Children* and *Female* were omitted from the models presented in the article, some interesting findings were made. Neither higher education, the presence of children in the household or gender significantly affects the WTP for fish.

A.8. Correlations in Preferences over Choice Scenarios

All models were estimated both with and without allowing for correlations in unobserved factors over choice scenarios. To test which of the two methods that gave the best fit, each model pair (one with and the other without correlations) was tested against each other with a likelihood ratio test. Since there are 10 coefficients on the off-diagonal part of the covariance matrix, the difference in estimated coefficients is 10 for each model pair. Hence, $df = 10$. The test results can be found below.

Table A.8.1. Likelihood Ratio Tests Between Models that Allow for Correlations in Unobserved Factors over Choice Scenarios and Models that do not Allow for Correlations in Unobserved Factors over Choice Scenarios

Consumer Characteristics Interactions	Models Compared	Log Likelihood Non-Corr	Log Likelihood Corr	Chi-Sq Statistic	Df	*p*-value
Fish Attributes Only	B.1 - 1	-2620.026	-2534.497	171.0580	10	1.68E-31
Income, *Age*, *Single*	B.2 - 2	-2584.737	-2508.769	151.9360	10	1.49E-27
Income, Age, Single, Female, Children, Education	B.3 - 3	-2578.085	-2505.395	145.3800	10	3.32E-26
Income as dummies (2, 3 and 4)	B.4 - 4	-2598.592	-2517.531	162.1220	10	1.18E-29
Income	B.5 - 5	-2600.926	-2521.586	158.6800	10	6.07E-29
Income, *Education*	B.6 - 6	-2598.7433	-2518.3447	160.7972	10	2.22E-29
Income, *Age*	B.7 - 7	-2591.82	-2517.901	147.8380	10	1.04E-26
Income, Age, Single, Female	B.8 - 8	-2582.376	-2506.822	151.1080	10	2.21E-27
Income, Age, Single, Female, Children	B.9 - 9	-2581.152	-2505.814	150.6760	10	2.71E-27

Every single model that allowed for correlations in unobserved factors over choice scenarios explained the data significantly better than those that did not allow for correlations in unobserved factors over choice scenarios, even at the 1% level. The two models presented in the article allow for correlations over choice scenarios, providing more information about the structure of the data.

A.9. *Model 3* – Product Attribute and Full Set of Consumer Characteristics Interaction Model

The output for *Model 3* includes *Female*, *Children* and *Education* in addition to the consumer characteristics included in *Model 2*.

Table A.9.1. Empirical Estimates for *Model 3* - Product Attribute and Full Set of Consumer Characteristics Model

Variable Name	Estimate		Std.Err
Price	-0.219	***	*(0.010)*
Salmon	3.335	***	*(0.752)*
Farmed_Cod	1.144		*(1.113)*
Wild_Cod	1.532		*(0.952)*
Monk	1.428		*(1.408)*
Pangasius	-1.663		*(1.757)*
*Tail * Salmon*	-0.429	***	*(0.118)*
*Tail * Farmed_Cod*	-1.440	***	*(0.193)*
*Tail * Wild_Cod*	-0.661	***	*(0.152)*
*Income * Salmon*	0.487		*(0.389)*
*Income * Farmed_Cod*	0.815		*(0.527)*
*Income * Wild_Cod*	1.093	**	*(0.442)*
*Income * Monk*	0.094		*(0.653)*
*Income * Pangasius*	0.592		*(0.868)*
*DNWA * Salmon*	-0.977	**	*(0.483)*
*DNWA * Farmed_Cod*	-0.713		*(0.704)*
*DNWA * Wild_Cod*	-0.883		*(0.568)*
*DNWA * Monk*	-2.414	**	*(0.956)*
*DNWA * Pangasius*	-0.868		*(1.013)*
*Age * Salmon*	-0.017		*(0.013)*
*Age * Farmed_Cod*	0.024		*(0.018)*
*Age * Wild_Cod*	0.027	*	*(0.016)*
*Age * Monk*	0.037		*(0.023)*
*Age * Pangasius*	-0.003		*(0.028)*
*Single * Salmon*	0.911	**	*(0.362)*
*Single * Farmed_Cod*	0.514		*(0.483)*
*Single * Wild_Cod*	0.382		*(0.431)*
*Single * Monk*	-0.073		*(0.635)*
*Single * Pangasius*	0.819		*(0.727)*
*Female * Salmon*	0.187		*(0.290)*
*Female * Farmed_Cod*	-0.514		*(0.370)*
*Female * Wild_Cod*	-0.292		*(0.320)*
*Female * Monk*	-0.273		*(0.473)*
*Female * Pangasius*	-0.178		*(0.601)*
*Children * Salmon*	-0.042		*(0.322)*

*Children * Farmed_Cod*	-0.032		*(0.528)*
*Children * Wild_Cod*	-0.457		*(0.441)*
*Children * Monk*	-0.511		*(0.632)*
*Children * Pangasius*	0.038		*(0.661)*
*High_Educ * Salmon*	0.241		*(0.349)*
*High_Educ * Farmed_Cod*	0.287		*(0.430)*
*High_Educ * Wild_Cod*	0.366		*(0.351)*
*High_Educ * Monk*	0.356		*(0.552)*
*High_Educ * Pangasius*	0.481		*(0.783)*
Standard Deviations			
Salmon	1.645	***	*(0.138)*
Farmed_Cod	2.134	***	*(0.231)*
Wild_Cod	1.872	***	*(0.189)*
Monk	2.448	***	*(0.328)*
Pangasius	2.967	***	*(0.403)*
N		11380	
LR Chi-Squared		830.14	
Log-likelihood		-2505.3946	
AIC		5128.7892	
Significance codes:	α=0.01***	α=0.05**	α=0.1 *

57% of the participants were female and 34% of the participants had children less than 18 years of age in the household. 37% of the participants had higher education. Neither by t-tests, Wald-tests nor Likelihood Ratio tests do these variables have any significant impact on the utility obtained from choosing the different fish types. Women's utility obtained from choosing a given type of fish does not differ from that of men. Presence of children in the household does not affect the utility obtained from choosing the different fish types. Hence, farmed cod can appeal equally to men and woman, to families with and without children, and to individuals with or without higher education. Some of the *DNWA* (Do not want to answer) coefficient estimates are significant. The only information they provide is that people that did not want to reveal their income had significant negative parameter estimates for *Salmon* and *Monk*.

A.10. Chi-squared Tests between Parameter Estimates

For both *Model 1* and *Model 2* we conducted several tests. The test results can be found in the matrices below. The chi-squared statistics and the corresponding *p*-value can be found for every test conducted. The null hypothesis in each test is that the sum of the coefficient for a certain type of fish and one or more consumer characteristic interactions with the same fish type is equal to a similar expression, but for another type of fish. For example, to test whether the coefficients for salmon and farmed cod in *Model 1* are significantly different from each other the null hypothesis is:

$$H_0: \mu_{\eta,sa} = \mu_{\eta,fc}$$

The test result is found as the top left result in Table A.10.1, i.e., the chi-squared statistic is 5.69 and the corresponding *p*-value is 0.0171. Hence we reject the null hypothesis that the coefficients are equal.

As another example; at the top left test result of Table A.10.5, the null hypothesis is:

$$H_0: \mu_{\eta,sa} + \gamma_{income} * \mu_{\eta,sa} = \mu_{fc} + \gamma_{income} * \mu_{\eta,fc}$$

The chi-squared statistic is 8.03 and the corresponding *p*-value is 0.005. Hence the null hypothesis is rejected.

In the matrices below are all the Chi-Squared tests we conducted. The header of each table says which consumer characteristic interaction coefficients, in addition to the coefficients for the fish types, which were tested against each other (except Table A.10.2). For example, in Table A.10.6 we test whether the sum of the coefficients for a fish type plus the coefficient for the interaction between *Single* and the same type of fish is equal to a similar expression for another fish type.

Table A.10.1. Chi-Squared Tests for *Model 1*

		Salmon	*Farmed Cod*	*Wild Cod*	*Monk*
Farmed Cod	Chi-Sq.	5.69			
	p-value	0.0171			
Wild Cod	Chi-Sq.	0.1	4.55		
	p-value	0.7503	0.0329		
Monk	Chi-Sq.	0.37	1.58	0.19	
	p-value	0.5434	0.2081	0.6657	
Pangasius	Chi-Sq.	75.06	46.43	62.7	51.51
	p-value	0.0000	0.0000	0.0000	0.0000

Table A.10.2. Chi-Squared Tests for *Model 1* The *Tail* Coefficients only

		Salmon	*Farmed Cod*
Farmed Cod	Chi-Sq.	51.51	
	p-value	0.0000	
Wild Cod	Chi-Sq.	1.76	11.5
	p-value	0.1848	0.0007

Table A.10.3. Chi-Squared Tests for *Model 1* The *Tail* + Fish Coefficients

		Salmon	*Farmed Cod*
Farmed Cod	Chi-Sq.	41.69	
	p-value	0.0000	
Wild Cod	Chi-Sq.	2.2	25.59
	p-value	0.1384	0.0000

All the below matrices are Chi-Squared tests conducted for *Model 2*.

Table A.10.4. *Model 2* Chi-Squared Tests for the Random Parameters only

		Salmon	*Farmed Cod*	*Wild Cod*	*Monk*
Farmed Cod	Chi-Sq.	12.39			
	p-value	0.0000			
Wild Cod	Chi-Sq.	13.93	0.07		
	p-value	0.0000	0.7930		
Monk	Chi-Sq.	6.29	0.01	0.012	
	p-value	0.0010	0.9070	0.9350	
Pangasius	Chi-Sq.	18.21	3.14	3.87	2.9
	p-value	0.0000	0.0760	0.0490	0.0870

Table A.10.5. *Model 2* Chi-Squared Tests Consumer Characteristics Interaction: *Income*

		Salmon	*Farmed Cod*	*Wild Cod*	*Monk*
Farmed Cod	Chi-Sq.	8.03			
	p-value	0.005			
Wild Cod	Chi-Sq.	6.42	0.55		
	p-value	0.011	0.457		
Monk	Chi-Sq.	6.11	0.15	1.14	
	p-value	0.013	0.695	0.286	
Pangasius	Chi-Sq.	17.47	3.32	5.62	1.75
	p-value	0.0000	0.0690	0.0180	0.1860

Table A.10.6. *Model 2* Chi-Squared Tests Consumer Characteristics Interaction: *Single*

		Salmon	*Farmed Cod*	*Wild Cod*	*Monk*
Farmed Cod	Chi-Sq.	16.55			
	p-value	0.000			
Wild Cod	Chi-Sq.	17.97	0.11		
	p-value	0.000	0.7403		
Monk	Chi-Sq.	10.01	0.08	0.35	
	p-value	0.0016	0.7822	0.5523	
Pangasius	Chi-Sq.	16.5	2.01	2.51	1.13
	p-value	0.000	0.1563	0.1135	0.287

Table A.10.7. *Model 2* Chi-Squared Tests Consumer Characteristics Interaction: *Age*

		Salmon	*Farmed Cod*	*Wild Cod*	*Monk*
Farmed Cod	Chi-Sq.	12.39			
	p-value	0.0004			
Wild Cod	Chi-Sq.	13.85	0.08		
	p-value	0.0002	0.783		
Monk	Chi-Sq.	6.22	0.02	0.10	
	p-value	0.0126	0.894	0.9421	
Pangasius	Chi-Sq.	18.72	3.33	4.12	3.11
	p-value	0.0000	0.0681	0.0424	0.0779

Table A.10.8. *Model 2* Chi-Squared Tests Consumer Characteristics Interaction: *Income* and *Age*

		Salmon	*Farmed Cod*	*Wild Cod*	*Monk*
Farmed Cod	Chi-Sq.	7.97			
	p-value	0.0047			
Wild Cod	Chi-Sq.	6.27	0.58		
	p-value	0.0123	0.4451		
Monk	Chi-Sq.	6.04	0.15	1.15	
	p-value	0.014	0.701	0.2833	
Pangasius	Chi-Sq.	17.95	3.52	5.96	1.9
	p-value	0.0000	0.0607	0.0146	0.1680

Table A.10.9. *Model 2* Chi-Squared Tests Consumer Characteristics Interaction: *Income* and *Single*

		Salmon	*Farmed Cod*	*Wild Cod*	*Monk*
Farmed Cod	Chi-Sq.	9.02			
	p-value	0.0027			
Wild Cod	Chi-Sq.	7.25	0.57		
	p-value	0.0071	0.4494		
Monk	Chi-Sq.	8.06	0.51	2.06	
	p-value	0.0045	0.4763	0.1513	
Pangasius	Chi-Sq.	13.52	1.75	3.23	0.38
	p-value	0.0002	0.1853	0.0724	0.5395

Table A.10.10. *Model 2* Chi-Squared Tests Consumer Characteristics Interaction: *Income, Age* and *Single*

		Salmon	*Farmed Cod*	*Wild Cod*	*Monk*
Farmed Cod	Chi-Sq.	8.95			
	p-value	0.0028			
Wild Cod	Chi-Sq.	7.09	0.6		
	p-value	0.0078	0.4389		
Monk	Chi-Sq.	7.99	0.51	2.08	
	p-value	0.0047	0.4762	0.1488	
Pangasius	Chi-Sq.	13.83	1.87	3.43	0.43
	p-value	0.0002	0.1716	0.0642	0.514

A.11. Survey Results - Definition of *Agree* and *Disagree*

The survey questions 2.1-2.8, 3.1-3.5, 6.1-6.8, 12.1-12.11, 13.1-13.11, 14.1-14.11, 15.1.-15.11, and 17.1-17.10 are categorized from 1-10 or 1-10 in addition to 11, "Do not know".

As an example, question 17 is categorized like this:

Attitudes toward fish farming and environmental aspects

17. On a scale from 1 to 10, where 1 means you very strongly DISAGREE and 10 means you very strongly AGREE, how much do you agree with the following statements?
Check one box per line.

		Very strongly disagree 1	2	3	4	5	6	7	8	9	Very strongly agree 10	Do not know 11
(17.1)	Farmed fish is healthy food.................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.2)	Wild fish is healthy food....................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.3)	Farmed fish is safe to eat....................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.4)	Wild fish is safe to eat........................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.5)	I am concerned about the environmental impact of the production of farmed fish...................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.6)	I am concerned about the environmental impact of cashing wild fish...	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.7)	I am concerned about the environmental sustainability of fish farming...	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.8)	I am concerned about the environmental sustainability of fisheries of wild fish...........................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.9)	I am concerned about the welfare of farmed fish....................................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.10)	I am concerned about the welfare of wild caught fish..............................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Figure A.11.1. An Example of a Survey Question

We have defined "disagree" to be the values 1-4. We have defined "agree" to be the values 7-10. Whenever we write that a certain percentage of the respondents "agrees to the statement that..," we refer to the percentage of the respondents that have answered 7, 8, 9 or 10. Equivalently, whenever we write that a certain percentage of the respondents "does not agree to the statement that…" we refer to the percentage of the respondents that answered 1, 2, 3 or

4. We have followed this definition throughout the whole article. The definition is arbitrary. We chose it for convenience.

When we analyzed the survey results the cross section version of the dataset has been convenient (See section A.13.10). This implies that the dataset consists of one row for each participant, that is, 178 rows. The original dataset has 64 rows for each participant, since each participant made 16 choices, and there were 4 choice alternatives in each choice set (3 fillets of fish and NOT). Since consumer characteristics do not vary over choice scenarios, the cross section dataset has been suitable for the survey analysis.

The survey questions used in the article are summarized in the tables below. Each variable is tabulated in STATA 12, and from there the share (in percentage) of respondents in category 1-4 and 7-10 are summarized. Some questions are summarized conditional on income group or marital status.

Table A.11.1. Survey Responses on Fish Likings, Fish Buying Habits and Origin of the Fish

			All respondents							
		How often would you say you eat the following items for lunch or dinner at home? Check one box per line.	Twice a week or more %	Once a week %	2-3 times a month %	Once a month %	Every second month %	2-4 times a year %	More seldom %	Never %
R4_	5		51.12	41.01	3.93	3.93				

			All respondents			High income		Low income		Single		Married/Cohabiting	
		Fish likings	Like %	Dislike %	Do not know %	Like %	Dislike %	Like %	Dislike %	Like %	Dislike %	Like %	Dislike %
q2_	1	Salmon (non-smoked)	78.65	10.11									
q2_	2	Cod	63.27	10.17									
q2_	3	Monk	74.71	15.74									
q2_	4	Pangasius	17.42	68.54									

			All respondents			High income		Low income		Single		Married/Cohabiting	
		Buying fish	Agree %	Disagree %	Do not know %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %
q3_	1	I have always decided which type of fish to buy before I go to the store	24.15	58.42									
q3_	2	I prefer to buy pre-packed filets of fish	25.83	48.33									
q3_	3	I most often choose the type of fish that is discounted	56.74	21.35									
q3_	4	It is important to know where the fish has been caught/produced	63.27	15.81									
q3_	5	I always ask how fresh the fish is before I make a decision	48.87	32.03									

			All respondents			High income		Low income		Single		Married/Cohabiting	
		Origin of the fish	Agree %	Disagree %	Do not know %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %
		I have a very positive view of fresh farmed fish from:											
q6_	1	France	75.57	5.68									
q6_	2	Countries in Northern Europe	72.16	6.25									
q6_	3	Countries in Southern Europe	34.65	18.75									
q6_	4	Other developed countries	14.45	23.7									
q6_	5	Third world countries	5.12	64.77	21.02								
		I have a very positive view of fresh wild fish from:											
q6_	6	The Atlantic North	86.36	1.14									
q6_	7	The Mediterranean	63.07	3.98									
q6_	8	The Pacific	54.54	10.79	12.5								

Table A.11.2. Survey Responses on Attitudes Towards Fresh Salmon, Fresh Cod, Fresh Monk and Pangasius

			All respondents			*High income*		*Low income*		*Single*		*Married/Cohabiting*	
		Attitudes towards fresh salmon	Agree %	Disagree %	Do not know %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %
q12_	1	salmon tastes good.	79.77	7.31						90.19	7.84	75.59	7.08
q12_	2	salmon gives you good value for money	68.54	8.43						70.58	9.8	67.72	7.87
q12_	3	It is easy to make different dishes with salmon.	84.83	6.74						84.32	3.92	85.05	7.87
q12_	4	Salmon is healthy food	83.52	1.71									
q12_	5	Salmon is fat food..	73.03	14.61									
q12_	6	Salmon is safe to eat	50.56	15.92									
q12_	7	Salmon is easy to prepare	93.26	2.24						94.11	1.96	92.91	2.37
q12_	8	Salmon is an expensive fish	53.94	18.53									
q12_	9	The whole family likes salmon	72	13.15									
q12_	10	Salmon can be served on special occasions	75.27	17.41									
q12_	11	Salmon is a Monday-to-Friday fish	50.56	26.96									

			All respondents			*High income*		*Low income*		*Single*		*Married/Cohabiting*	
		Attitudes towards fresh cod	Agree %	Disagree %	Do not know %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %
q13_	1	Cod tastes good.	67.79	10.73		76.73	9.31	64.34	11.31	62.75	11.76	69.85	10.31
q13_	2	Cod gives you good value for money	52.82	17.97									
q13_	3	It is easy to make different dishes with cod.	58.52	11.93									
q13_	4	Cod is healthy food	74.16	0.56		88.38	0	68.11	0				
q13_	5	Cod is fat food..	11.85	51.41									
q13_	6	Cod is safe to eat	47.45	15.25		53.49	9.3	46.95	17.4				
q13_	7	Cod is easy to prepare	84.84	2.24						80.39	1.96	86.62	2.36
q13_	8	Cod is an expensive fish	51.4	24.29		65.12	18.61	43.1	28.45	38	18	56.69	26.77
q13_	9	The whole family likes cod	67.97	10.12									
q13_	10	Cod can be served on special occasions	26.86	49.72									
q13_	11	Cod is a Monday-to-Friday fish	71.19	16.94									

			All respondents	
		Attitudes towards fresh monk	Agree %	Disagree%
q14_	7	Monk is easy to prepare	42.86	24.58

			All respondents			*High income*		*Low income*		*Single*		*Married/Cohabiting*	
		Attitudes towards pangasius	Agree %	Disagree %	Do not know %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %
q15_	1	Pangasius tastes good	18.54	60.68	10.11								
q15_	2	Pangasius gives you good value for money	32.76	21.47	37.85								
q15_	3	It is easy to make different dishes with Pangasius	11.86	24.29	53.67								
q15_	4	Pangasius is healthy food	18.63	23.72	47.46								
q15_	5	Pangasius is fat food	12.42	28.24	49.15								
q15_	6	Pangasius is safe to eat	10.22	32.39	49.43								
q15_	7	Pangasius is easy to prepare	32.59	11.24	47.75								
q15_	8	Pangasius is an expensive fish	10.22	42.61	38.07								
q15_	9	The whole family likes Pangasius	11.86	32.19	45.76								
q15_	10	Pangasius can be served on special occasions	12.42	48.58	31.07								
q15_	11	Pangasius is a Monday-to-Friday fish	30.34	28.65	32.02								

Table A.11.3. Survey Responses on Attitudes Toward Fish Farming and Environmental Aspects

			All respondents			*High income*		*Low income*		*Single*		*Married/Cohabiting*	
		Attitudes towards fish farming and environmental aspects	Agree %	Disagree %	Do not know %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %	Agree %	Disagree %
q17_	1	Farmed fish is healthy food	30.9	30.9									
q17_	2	Wild fish is healthy food	83.14	2.81									
q17_	3	Farmed fish is safe to eat	33.14	33.15	11.8								
q17_	4	Wild fish is safe to eat	60.45	10.72									
q17_	5	I am concerned about the environmental impact of the production of farmed fish	59.55	10.11									
q17_	6	I am concerned about the environmental impact of cashing wild fish	76.96	5.06									
q17_	7	I am concerned about the environmental sustainability of fish farming	69.66	9.54									
q17_	8	I am concerned about the environmental sustainability of fisheries of wild fish	76.27	6.21									
q17_	9	I am concerned about the welfare of farmed fish	51.68	20.22									
q17_	10	I am concerned about the welfare of wild caught fish	56.74	19.11									

A.11.1. Welch Two Sample t-test

A Welch Two Sample t-test was conducted to test whether the participants significantly differed in their concerns about the welfare of farmed and wild fish. The STATA output for the test follows in Table A.11.1.1.

Table A.11.1.1. Welch Two Sample t-test Regarding Concerns on Animal Welfare

```
Two-sample t test with unequal variances
------------------------------------------------------------------------------
Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
 q17_9xx |     166    6.698795    .2093942    2.697855    6.285358    7.112233
q17_10xx |     167    6.958084    .2058507    2.660178    6.551661    7.364507
---------+--------------------------------------------------------------------
combined |     333    6.828829     .146761    2.678137     6.54013    7.117528
---------+--------------------------------------------------------------------
    diff |           -.2592887    .2936332               -.8368993     .318322
------------------------------------------------------------------------------
    diff = mean(q17_9xx) - mean(q17_10xx)                         t =  -0.8830
Ho: diff = 0                                Welch's degrees of freedom =  332.865

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.1889         Pr(|T| > |t|) = 0.3779          Pr(T > t) = 0.8111
```

A.12. Regression Outputs

This section contains all the regressions we ran. For some relevant models the corresponding covariance matrix and standard deviations follow. *Model 1* and *Model 2* are the models presented in the article. These two models, and *Model 3* are the only models that have been given names in addition to a model number.

Model 1 – Product Attribute Model

Model 2 – Product Attribute and Consumer Characteristics Interaction Model

Model 3 – Product Attribute and Full Set of Consumer Characteristics Interaction Model

All models but *Model 1* contain consumer characteristics interaction terms. The consumer characteristics that are included in the models are given in the header. For example, in *Model 6 – Income and Education*, the fish types, represented by the $\boldsymbol{z_i}$-vectors, are interacted with the consumer characteristics *Income* and *Education*.

Each model was estimated by both allowing for correlations in unobserved factors over choice scenarios and not allowing for it. A model that allows for it is simply assigned a number, e.g.: *Model 4* or *Model 5*. The corresponding model that does not allow for correlations in unobserved factors over choice scenarios is given the same number, but with a "B" in front of the number, e.g.: *Model B.4* or *Model B.5*. All the models that allow for correlations in unobserved factors over choice scenarios are presented first. The corresponding models that do not allow for it follow after. The variable names in the regression outputs are different from those presented in the article. Table A.12.1 presents the variable names used in STATA for each variable and interaction term.

We used STATA 12 to analyze the data. We used two extensions to STATA 12, namely *mixlogit* and *wtp*. Both extensions are created by Arne Risa Hole (see Hole (2007b) and Hole (2007a)). The *wtp* extension was "delta" by default (see Hole (2007a)). We chose to use 500 Halton draws for the simulations by the *mixlogit* program. Hole (2007b) suggests using 500 Halton draws for the final model.

Table A.12.1. The Variable Names and Interaction Terms as Defined in STATA

Article Output Label	STATA Output Label	Article Output Label	STATA Output Label
Price	p1000	*Age * Salmon*	sa_age
Salmon	sa	*Age * Farmed_Cod*	fc_age
Farmed_Cod	fc	*Age * Wild_Cod*	wc_age
Wild_Cod	wc	*Age * Monk*	mo_age
Monk	mo	*Age * Pangasius*	pa_age
Pangasius	pa	*Single * Salmon*	sa_single
*Tail * Salmon*	sa_tail	*Single * Farmed_Cod*	fc_single
*Tail * Farmed_Cod*	wc_tail	*Single * Wild_Cod*	wc_single
*Tail * Wild_Cod*	fc_tail	*Single * Monk*	mo_single
*Income * Salmon*	sa_inc3	*Single * Pangasius*	pa_single
*Income * Farmed_Cod*	wc_inc3	*High_ Educ * Salmon*	sa_educUNI
*Income * Wild_Cod*	fc_inc3	*High_ Educ * Farmed_Cod*	fc_educUNI
*Income * Monk*	mo_inc3	*High_ Educ * Wild_Cod*	wc_educUNI
*Income * Pangasius*	pa_inc3	*High_ Educ * Monk*	mo_educUNI
*DNWA * Salmon*	sa_nonInc	*High_ Educ * Pangasius*	pa_educUNI
*DNWA * Farmed_Cod*	fc_nonInc	*Female * Salmon*	femaleSA
*DNWA * Wild_Cod*	wc_nonInc	*Female * Farmed_Cod*	femaleFC
*DNWA * Monk*	mo_nonInc	*Female * Wild_Cod*	femaleWC
*DNWA * Pangasius*	pa_nonInc	*Female * Monk*	femaleMO
*IncGroup2 * Salmon*	sa_inc_2	*Female * Pangasius*	femalePA
*IncGroup2 * Farmed_Cod*	fc_inc_2	*Children * Salmon*	childrenSA
*IncGroup2 * Wild_Cod*	wc_inc_2	*Children * Farmed_Cod*	childrenFC
*IncGroup2 * Monk*	mo_inc_2	*Children * Wild_Cod*	childrenWC
*IncGroup2 * Pangasius*	pa_inc_2	*Children * Monk*	childrenMO
		*Children * Pangasius*	childrenPA

A.12.1. *Model 1* – Product Attribute Model

Table A.12.1.1. *Model 1* – Product Attribute Model

```
Mixed logit model                                 Number of obs    =      11380
                                                  LR chi2(15)      =     961.61
Log likelihood = -2534.4973                       Prob > chi2      =     0.0000
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
p1000	-.2188413	.0102833	-21.28	0.000	-.2389962	-.1986865
sa_tail	-.430106	.1173051	-3.67	0.000	-.6600197	-.2001923
fc_tail	-1.434241	.1926131	-7.45	0.000	-1.811756	-1.056726
wc_tail	-.6670915	.1518392	-4.39	0.000	-.9646908	-.3694922
sa	2.995393	.2373191	12.62	0.000	2.530256	3.46053
fc	2.35932	.3280094	7.19	0.000	1.716434	3.002207
wc	2.921614	.2861402	10.21	0.000	2.360789	3.482438
pa	-1.518473	.5202391	-2.92	0.004	-2.538123	-.4988233
mo	2.792521	.3566915	7.83	0.000	2.093418	3.491623
/l11	1.759491	.1460412	12.05	0.000	1.473255	2.045726
/l21	1.140172	.1902552	5.99	0.000	.7672788	1.513066
/l31	.8636004	.1591278	5.43	0.000	.5517157	1.175485
/l41	1.535279	.3820067	4.02	0.000	.78656	2.283999
/l51	.5657018	.2583786	2.19	0.029	.0592892	1.072115
/l22	1.915893	.1909485	10.03	0.000	1.54164	2.290145
/l32	1.354149	.1579902	8.57	0.000	1.044494	1.663804
/l42	-.2595905	.381021	-0.68	0.496	-1.006378	.4871971
/l52	1.624456	.3162735	5.14	0.000	1.004571	2.244341
/l33	1.341704	.1534776	8.74	0.000	1.040894	1.642515
/l43	-.2332015	.4076972	-0.57	0.567	-1.032273	.5658703
/l53	1.244728	.3780116	3.29	0.001	.5038388	1.985617
/l44	2.854223	.5216802	5.47	0.000	1.831749	3.876698
/l54	.3926977	.3602321	1.09	0.276	-.3133443	1.09874
/l55	1.540034	.3402592	4.53	0.000	.8731382	2.20693

Table A.12.1.2. Covariance Matrix *Model 1*

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
v11	3.095808	.5139164	6.02	0.000	2.08855	4.103066
v21	2.006123	.3854116	5.21	0.000	1.25073	2.761515
v31	1.519497	.3147228	4.83	0.000	.9026516	2.136342
v41	2.70131	.7478071	3.61	0.000	1.235635	4.166985
v51	.9953472	.4599499	2.16	0.030	.0938619	1.896833
v22	4.970637	.9918143	5.01	0.000	3.026716	6.914557
v32	3.579057	.622302	5.75	0.000	2.359367	4.798746
v42	1.253135	.9090898	1.38	0.168	-.5286479	3.034919
v52	3.757281	.950221	3.95	0.000	1.894882	5.61968
v33	4.379695	.7231669	6.06	0.000	2.962314	5.797077
v43	.6614561	.8292742	0.80	0.425	-.9638915	2.286804
v53	4.358352	1.000834	4.35	0.000	2.396754	6.319951
v44	10.62544	3.041254	3.49	0.000	4.664696	16.58619
v54	1.277392	1.250936	1.02	0.307	-1.174397	3.72918
v55	7.03414	1.922035	3.66	0.000	3.267021	10.80126

Table A.12.1.3. Standard Deviations *Model 1*

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sa	1.759491	.1460412	12.05	0.000	1.473255	2.045726
fc	2.229492	.2224305	10.02	0.000	1.793537	2.665448
wc	2.092772	.1727773	12.11	0.000	1.754135	2.431409
pa	3.259669	.4664973	6.99	0.000	2.345351	4.173987
mo	2.652195	.3623479	7.32	0.000	1.942007	3.362384

Table A.12.1.4. WTP Table *Model 1*

```
. wtp p1000 sa fc wc mo pa sa_tail fc_tail wc_tail
```

	sa	fc	wc	mo	pa	sa_tail	fc_tail	wc_tail
wtp	13.687511	10.780963	13.350375	12.760482	-6.9386952	-1.9653784	-6.5537952	-3.0482884
ll	12.19247	8.3596955	11.454519	10.028299	-11.723679	-2.9614462	-8.1472395	-4.330633
ul	15.182552	13.202231	15.246232	15.492666	-2.1537117	-.96931054	-4.9603509	-1.7659438

A.12.2. *Model 2* – Product Attribute and Consumer Characteristics Interaction Model

Table A.12.2.1. *Model 2* – Product Attribute and Consumer Characteristics Interaction Model

```
Mixed logit model                                 Number of obs   =      11380
                                                  LR chi2(15)     =     854.21
Log likelihood = -2508.7689                       Prob > chi2     =     0.0000
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
p1000	-.219978	.010311	-21.33	0.000	-.2401873	-.1997687
sa_inc3	.528525	.3539879	1.49	0.135	-.1652786	1.222329
fc_inc3	.8618281	.475021	1.81	0.070	-.0691959	1.792852
wc_inc3	1.236745	.3926081	3.15	0.002	.467247	2.006242
mo_inc3	.3017439	.5849782	0.52	0.606	-.8447924	1.44828
pa_inc3	.9237724	.708125	1.30	0.192	-.464127	2.311672
sa_nonInc	-.9915482	.5349978	-1.85	0.064	-2.040124	.0570282
fc_nonInc	-.7489834	.7534443	-0.99	0.320	-2.225707	.7277402
wc_nonInc	-.8696943	.6040494	-1.44	0.150	-2.053609	.3142208
mo_nonInc	-2.463191	.9685813	-2.54	0.011	-4.361576	-.5648067
pa_nonInc	-1.037424	1.522705	-0.68	0.496	-4.021871	1.947024
sa_age	-.0224303	.0111221	-2.02	0.044	-.0442292	-.0006315
fc_age	.0228385	.0148552	1.54	0.124	-.0062771	.0519541
wc_age	.0292154	.0127577	2.29	0.022	.0042107	.05422
mo_age	.0382112	.0191481	2.00	0.046	.0006816	.0757408
pa_age	-.0103976	.0237843	-0.44	0.662	-.0570139	.0362188
sa_single	.9735092	.3200324	3.04	0.002	.3462572	1.600761
fc_single	.6391808	.4214307	1.52	0.129	-.1868082	1.46517
wc_single	.6762973	.3629847	1.86	0.062	-.0351395	1.387734
mo_single	.2381692	.5271793	0.45	0.651	-.7950832	1.271422
pa_single	1.212427	.6631813	1.83	0.068	-.0873842	2.512239
sa_tail	-.4313246	.1175423	-3.67	0.000	-.6617032	-.200946
fc_tail	-1.448939	.1923479	-7.53	0.000	-1.825934	-1.071945
wc_tail	-.6723534	.1517063	-4.43	0.000	-.9696923	-.3750146
sa	3.725824	.5862372	6.36	0.000	2.57682	4.874828
fc	.9277656	.8300922	1.12	0.264	-.6991852	2.554716
wc	1.120692	.686663	1.63	0.103	-.2251426	2.466527
pa	-1.524687	1.268955	-1.20	0.230	-4.011794	.9624204
mo	1.04982	1.026786	1.02	0.307	-.9626433	3.062282
/l11	1.680169	.1344787	12.49	0.000	1.416595	1.943742
/l21	1.061857	.180278	5.89	0.000	.7085182	1.415195
/l31	.759574	.1639483	4.63	0.000	.4382412	1.080907
/l41	1.441953	.3693172	3.90	0.000	.7181046	2.165802
/l51	.3250907	.2367334	1.37	0.170	-.1388982	.7890796
/l22	1.855936	.1810191	10.25	0.000	1.501145	2.210727
/l32	1.264363	.1660389	7.61	0.000	.9389325	1.589793
/l42	-.1787437	.3426318	-0.52	0.602	-.8502898	.4928023
/l52	1.491522	.2810828	5.31	0.000	.9406094	2.042434
/l33	1.178368	.1448888	8.13	0.000	.8943914	1.462345
/l43	-.361482	.4596478	-0.79	0.432	-1.262375	.5394111
/l53	1.416616	.2985704	4.74	0.000	.8314283	2.001803
/l44	2.812452	.4608865	6.10	0.000	1.909131	3.715773
/l54	.4014945	.3072443	1.31	0.191	-.2006933	1.003682
/l55	1.321344	.2958673	4.47	0.000	.7414543	1.901233

Table A.12.2.2. Covariance Matrix *Model 2*

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
v11	2.822967	.4518939	6.25	0.000	1.937271	3.708663
v21	1.784098	.353448	5.05	0.000	1.091353	2.476844
v31	1.276213	.3063345	4.17	0.000	.6758079	1.876617
v41	2.422724	.6872761	3.53	0.000	1.075688	3.769761
v51	.5462072	.4020077	1.36	0.174	-.2417135	1.334128
v22	4.572038	.8510785	5.37	0.000	2.903955	6.240121
v32	3.153135	.5249271	6.01	0.000	2.124297	4.181973
v42	1.199411	.6952826	1.73	0.085	-.1633184	2.562139
v52	3.113368	.7121832	4.37	0.000	1.717515	4.509222
v33	3.564117	.604374	5.90	0.000	2.379566	4.748669
v43	.4433143	.7474009	0.59	0.553	-1.021565	1.908193
v53	3.802049	.692995	5.49	0.000	2.443804	5.160295
v44	10.15173	3.054783	3.32	0.001	4.16447	16.139
v54	.8192685	1.165263	0.70	0.482	-1.464605	3.103142
v55	6.244267	1.436091	4.35	0.000	3.429581	9.058952

Table A.12.2.3. Standard Deviation *Model 2*

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sa	1.680169	.1344787	12.49	0.000	1.416595	1.943742
fc	2.138232	.1990145	10.74	0.000	1.748171	2.528294
wc	1.887887	.1600662	11.79	0.000	1.574163	2.201611
pa	3.186179	.4793804	6.65	0.000	2.24661	4.125747
mo	2.498853	.2873499	8.70	0.000	1.935658	3.062049

Table A.12.2.4. WTP *Model 2*

	Mean	Lower limit	Upper limit
sa	16.937258	11.959101	21.915415
fc	4.2175381	-3.103475	11.538551
wc	5.0945647	-0.92297773	11.112107
mo	4.7723843	-4.3102845	13.855053
pa	-6.9310872	-18.30411	4.4419357
sa_inc3	2.4026267	-0.75510633	5.5603596
fc_inc3	3.9177922	-0.31656666	8.152151
wc_inc3	5.6221293	2.1085425	9.135716
mo_inc3	1.3717002	-3.839846	6.5832465
pa_inc3	4.1993857	-2.113995	10.512766
sa*nonInc	-4.507488	-9.2861818	0.27120574
fc*nonInc	-3.4048105	-10.125023	3.3154015
wc*nonInc	-3.9535512	-9.3440448	1.4369423
mo*nonInc	-11.197443	-19.836947	-2.55794
pa*nonInc	-4.716034	-18.283771	8.8517026
sa*age	-0.1019663	-0.20121554	-0.00271706
fc*age	0.10382196	-0.02863731	0.23628123
wc*age	0.13281048	0.01897163	0.24664934
mo*age	0.17370465	0.00273429	0.344675
pa*age	-0.04726644	-0.25905983	0.16452695
sa*single	4.4254843	1.5645142	7.2864545
fc*single	2.905658	-0.85362495	6.664941
wc*single	3.0743863	-0.16789544	6.3166681
mo*single	1.0826956	-3.6172375	5.7826288
pa*single	5.511584	-0.39932593	11.422494
sa*tail	-1.9607626	-2.9533725	-0.96815265
fc*tail	-6.5867473	-8.1686491	-5.0048456
wc*tail	-3.0564578	-4.3302702	-1.7826454

A.12.3. *Model 3* – Product Attribute and Full Set of Consumer Characteristics Interaction Model

Table A.12.3.1. *Model 3* – Product Attribute and Full Set of Consumer Characteristics Interaction Model

```
Mixed logit model                                 Number of obs   =      11380
                                                  LR chi2(15)     =     830.14
Log likelihood = -2505.3946                       Prob > chi2     =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       p1000 |  -.2194887    .010346   -21.21   0.000    -.2397665   -.1992109
    sa_inc3 |   .4867803   .3889622     1.25   0.211    -.2755716    1.249132
     fc_inc3 |   .8151295    .526986     1.55   0.122     -.217744    1.848003
     wc_inc3 |   1.093393   .4415729     2.48   0.013     .2279258     1.95886
     mo_inc3 |    .093985   .6532151     0.14   0.886    -1.186293    1.374263
     pa_inc3 |   .5917403   .8679535     0.68   0.495    -1.109417    2.292898
   sa_nonInc |  -.9771875   .4833835    -2.02   0.043    -1.924602   -.0297733
   fc_nonInc |  -.7126866   .7042876    -1.01   0.312    -2.093065    .6676916
   wc_nonInc |  -.8825129   .5675379    -1.55   0.120    -1.994867    .2298409
   mo_nonInc |  -2.413946    .955722    -2.53   0.012    -4.287126    -.540765
   pa_nonInc |  -.8682049   1.013254    -0.86   0.392    -2.854147    1.117737
  childrenSA |  -.0423645   .3224722    -0.13   0.895    -.6743985    .5896695
  childrenFC |  -.0322402   .5283185    -0.06   0.951    -1.067725    1.003245
  childrenWC |   -.457222   .4413726    -1.04   0.300    -1.322296    .4078524
  childrenMO |  -.5114613   .6321563    -0.81   0.418    -1.750465    .7275423
  childrenPA |   .0383729   .6608988     0.06   0.954    -1.256965    1.333711
    femaleSA |   .1866528   .2903716     0.64   0.520    -.3824651    .7557707
    femaleFC |  -.5143591   .3704646    -1.39   0.165    -1.240456    .2117381
    femaleWC |  -.2924441   .3198976    -0.91   0.361    -.9194319    .3345438
    femaleMO |  -.2733139   .4728027    -0.58   0.563     -1.19999    .6533624
    femalePA |  -.1784797   .6014022    -0.30   0.767    -1.357206    1.000247
      sa_age |  -.0170753   .0125096    -1.36   0.172    -.0415937    .0074431
      fc_age |   .0238793   .0180901     1.32   0.187    -.0115766    .0593352
      wc_age |   .0270251    .015737     1.72   0.086    -.0038189    .0578691
      mo_age |   .0374012   .0231314     1.62   0.106    -.0079354    .0827379
      pa_age |  -.0027111    .028183    -0.10   0.923    -.0579487    .0525265
   sa_single |   .9107461   .3615915     2.52   0.012     .2020399    1.619452
   fc_single |   .5142746   .4827878     1.07   0.287    -.4319721    1.460521
   wc_single |   .3818803   .4308048     0.89   0.375    -.4624817    1.226242
   mo_single |   -.073355   .6348796    -0.12   0.908    -1.317696    1.170986
   pa_single |   .8193952   .7271502     1.13   0.260     -.605793    2.244583
  sa_educUNI |   .2408917   .3488066     0.69   0.490    -.4427566    .9245401
  fc_educUNI |   .2873476    .429614     0.67   0.504    -.5546803    1.129375
  wc_educUNI |     .36613   .3512717     1.04   0.297    -.3223498     1.05461
  mo_educUNI |   .3559302   .5522768     0.64   0.519    -.7265125    1.438373
  pa_educUNI |   .4806885   .7825609     0.61   0.539    -1.053103     2.01448
     sa_tail |  -.4292298   .1176437    -3.65   0.000    -.6598072   -.1986524
     fc_tail |  -1.440224   .1928167    -7.47   0.000    -1.818138   -1.062311
     wc_tail |  -.6605438   .1517246    -4.35   0.000    -.9579186    -.363169
          sa |   3.334567   .7519284     4.43   0.000     1.860815     4.80832
          fc |   1.144092    1.11339     1.03   0.304    -1.038113    3.326298
          wc |   1.531906   .9517272     1.61   0.107    -.3334447    3.397257
          pa |  -1.662705   1.756757    -0.95   0.344    -5.105886    1.780476
          mo |   1.427556   1.407913     1.01   0.311    -1.331904    4.187015
-------------+----------------------------------------------------------------
        /l11 |    1.64493   .1376219    11.95   0.000     1.375196    1.914664
        /l21 |   1.090176   .2158634     5.05   0.000     .6670913     1.51326
        /l31 |    .804167   .1915132     4.20   0.000      .428808    1.179526
        /l41 |   1.190066   .4578423     2.60   0.009     .2927117     2.08742
        /l51 |   .3675639    .257511     1.43   0.153    -.1371484    .8722763
        /l22 |   1.835032   .1925291     9.53   0.000     1.457682    2.212382
        /l32 |   1.242848   .1714953     7.25   0.000     .9067232    1.578973
        /l42 |  -.2806761   .4464544    -0.63   0.530    -1.155711    .5943584
        /l52 |   1.482551   .2785503     5.32   0.000     .9366023    2.028499
        /l33 |   1.145908   .1529339     7.49   0.000     .8461625    1.445653
        /l43 |  -.7408717   .3854691    -1.92   0.055    -1.496377    .0146338
        /l53 |   1.348948   .3066513     4.40   0.000     .7479225    1.949974
        /l44 |   2.599921   .3769456     6.90   0.000     1.861121     3.33872
        /l54 |   .4064174   .2911178     1.40   0.163     -.164163    .9769977
        /l55 |    1.29493   .3328663     3.89   0.000     .6425239    1.947336
```

A.12.4. *Model 4* – Income as Dummies for all Income Groups

Table A.12.4.1. *Model 4* – Income as Dummies for all Income Groups

Mixed logit model		Number of obs =	11380
		LR chi2(15) =	897.63
Log likelihood = -2517.5306		Prob > chi2 =	0.0000

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
p1000	-.2195032	.0103191	-21.27	0.000	-.2397282	-.1992781
sa_inc_2	-.7769536	.3384176	-2.30	0.022	-1.44024	-.1136672
fc_inc_2	-.0612313	.452569	-0.14	0.892	-.9482502	.8257876
wc_inc_2	-.3891837	.4057793	-0.96	0.338	-1.184496	.4061291
mo_inc_2	.4058495	.5763738	0.70	0.481	-.7238224	1.535521
pa_inc_2	-.8115087	.7646674	-1.06	0.289	-2.310229	.6872118
sa_inc_3	-.3330455	.4038338	-0.82	0.410	-1.124545	.4584541
fc_inc_3	.8657054	.5353571	1.62	0.106	-.1835751	1.914986
wc_inc_3	1.038777	.4409634	2.36	0.018	.1745044	1.903049
mo_inc_3	.7465031	.690635	1.08	0.280	-.6071167	2.100123
pa_inc_3	-.0228213	.8905516	-0.03	0.980	-1.76827	1.722628
sa_nonInc	-1.498905	.5034964	-2.98	0.003	-2.485739	-.5120698
fc_nonInc	-.8279735	.8363707	-0.99	0.322	-2.46723	.8112828
wc_nonInc	-1.074317	.6855174	-1.57	0.117	-2.417906	.2692726
mo_nonInc	-2.165486	1.106372	-1.96	0.050	-4.333935	.0029635
pa_nonInc	-1.680657	1.244749	-1.35	0.177	-4.120321	.7590072
sa_tail	-.4325366	.1173489	-3.69	0.000	-.6625362	-.202537
fc_tail	-1.435866	.1928649	-7.44	0.000	-1.813875	-1.057858
wc_tail	-.6613276	.1517063	-4.36	0.000	-.9586664	-.3639888
sa	3.50687	.3177517	11.04	0.000	2.884088	4.129652
fc	2.26044	.4333511	5.22	0.000	1.411087	3.109792
wc	2.915238	.3795725	7.68	0.000	2.17129	3.659187
pa	-.9377152	.6343454	-1.48	0.139	-2.181009	.3055788
mo	2.657833	.5360118	4.96	0.000	1.607269	3.708397
/l11	1.693189	.1359409	12.46	0.000	1.42675	1.959628
/l21	1.128895	.1896172	5.95	0.000	.7572525	1.500538
/l31	.7689937	.1810062	4.25	0.000	.4142281	1.123759
/l41	1.296033	.3934924	3.29	0.001	.5248022	2.067264
/l51	.4136651	.2652549	1.56	0.119	-.106225	.9335551
/l22	1.918423	.1919702	9.99	0.000	1.542168	2.294677
/l32	1.320833	.1778442	7.43	0.000	.9722653	1.669402
/l42	-.3203226	.4305534	-0.74	0.457	-1.164192	.5235466
/l52	1.607423	.2750429	5.84	0.000	1.068349	2.146497
/l33	1.256884	.1520302	8.27	0.000	.9589107	1.554858
/l43	-.7159321	.4823603	-1.48	0.138	-1.661341	.2294767
/l53	1.494459	.2766224	5.40	0.000	.9522894	2.036629
/l44	2.6189	.4115005	6.36	0.000	1.812374	3.425426
/l54	.2747836	.2700698	1.02	0.309	-.2545435	.8041107
/l55	1.340948	.3087385	4.34	0.000	.7358322	1.946065

A.12.5. *Model 5* – Income as *Low* and *High*

Table A.12.5.1. *Model 5* – Income as *Low* and *High*

Mixed logit model Number of obs = 11380
LR chi2(15) = 902.57
Log likelihood = -2521.5856 Prob > chi2 = 0.0000

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
p1000	-.218674	.0103005	-21.23	0.000	-.2388626	-.1984854
sa_inc_3	.1101639	.3616211	0.30	0.761	-.5986005	.8189283
fc_inc_3	.8770205	.4730104	1.85	0.064	-.0500628	1.804104
wc_inc_3	1.236088	.3782625	3.27	0.001	.4947067	1.977468
mo_inc_3	.4897637	.5919796	0.83	0.408	-.670495	1.650022
pa_inc_3	.474978	.7421392	0.64	0.522	-.9795881	1.929544
sa_nonInc	-1.043095	.4669096	-2.23	0.025	-1.958221	-.1279686
fc_nonInc	-.794113	.7931808	-1.00	0.317	-2.348719	.7604928
wc_nonInc	-.8742903	.6460249	-1.35	0.176	-2.140476	.3918952
mo_nonInc	-2.415986	1.05691	-2.29	0.022	-4.487491	-.3444803
pa_nonInc	-1.128544	1.089826	-1.04	0.300	-3.264564	1.007475
sa_tail	-.430767	.1172108	-3.68	0.000	-.660496	-.201038
fc_tail	-1.430036	.1926131	-7.42	0.000	-1.80755	-1.052521
wc_tail	-.6610077	.1516627	-4.36	0.000	-.9582612	-.3637543
sa	3.046131	.2533444	12.02	0.000	2.549585	3.542677
fc	2.228137	.3579618	6.22	0.000	1.526544	2.929729
wc	2.697999	.3066245	8.80	0.000	2.097026	3.298972
pa	-1.402489	.5454625	-2.57	0.010	-2.471576	-.3334023
mo	2.93149	.4015716	7.30	0.000	2.144424	3.718556
/l11	1.70157	.1373827	12.39	0.000	1.432304	1.970835
/l21	1.135433	.1843261	6.16	0.000	.7741603	1.496705
/l31	.8115959	.1727103	4.70	0.000	.4730899	1.150102
/l41	1.408446	.4118279	3.42	0.001	.6012777	2.215613
/l51	.4179797	.2755433	1.52	0.129	-.1220752	.9580347
/l22	1.905966	.1910407	9.98	0.000	1.531533	2.280399
/l32	1.308158	.1787839	7.32	0.000	.957748	1.658568
/l42	-.2603717	.3507424	-0.74	0.458	-.9478142	.4270708
/l52	1.59451	.2871397	5.55	0.000	1.031726	2.157293
/l33	1.259543	.1520411	8.28	0.000	.9615477	1.557538
/l43	-.6958762	.4744297	-1.47	0.142	-1.625741	.233989
/l53	1.432153	.3091793	4.63	0.000	.826173	2.038134
/l44	2.552167	.3516405	7.26	0.000	1.862964	3.24137
/l54	.3714819	.3251436	1.14	0.253	-.2657879	1.008752
/l55	1.311247	.3268253	4.01	0.000	.6706813	1.951813

A.12.6. *Model 6* – Income and Education

Table A.12.6.1. *Model 6* – Income and Education

Mixed logit model				Number of obs	=	11380
				LR chi2(15)	=	897.81
Log likelihood = -2518.3447				Prob > chi2	=	0.0000

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
p1000	-.2196156	.0103334	-21.25	0.000	-.2398687	-.1993624
sa_inc3	-.0019033	.3769359	-0.01	0.996	-.7406841	.7368775
fc_inc3	.8979831	.4882901	1.84	0.066	-.0590479	1.855014
wc_inc3	1.251629	.3962915	3.16	0.002	.474912	2.028346
mo_inc3	.4714741	.5890864	0.80	0.424	-.6831141	1.626062
pa_inc3	.29817	.9351084	0.32	0.750	-1.534609	2.130949
sa_nonInc	-1.15059	.4704385	-2.45	0.014	-2.072632	-.2285475
fc_nonInc	-.8981883	.7865899	-1.14	0.254	-2.439876	.6434996
wc_nonInc	-.9567357	.6312696	-1.52	0.130	-2.194001	.2805299
mo_nonInc	-2.473886	1.039379	-2.38	0.017	-4.511031	-.4367417
pa_nonInc	-.9889031	.9649234	-1.02	0.305	-2.880118	.902312
sa_educUNI	.6808361	.2959201	2.30	0.021	.1008434	1.260829
fc_educUNI	.2644023	.4034684	0.66	0.512	-.5263812	1.055186
wc_educUNI	.1390699	.3415994	0.41	0.684	-.5304526	.8085924
mo_educUNI	-.0344771	.5334476	-0.06	0.948	-1.080015	1.011061
pa_educUNI	1.038035	.6327745	1.64	0.101	-.2021804	2.27825
sa_tail	-.433119	.1174052	-3.69	0.000	-.663229	-.2030091
fc_tail	-1.434653	.1925815	-7.45	0.000	-1.812106	-1.0572
wc_tail	-.6640525	.151663	-4.38	0.000	-.9613066	-.3667985
sa	2.868314	.2598693	11.04	0.000	2.35898	3.377648
fc	2.180555	.3869034	5.64	0.000	1.422238	2.938872
wc	2.683641	.3341939	8.03	0.000	2.028633	3.338649
pa	-1.909587	.6960943	-2.74	0.006	-3.273907	-.545267
mo	2.960718	.4338914	6.82	0.000	2.110307	3.81113
/l11	1.704832	.1368482	12.46	0.000	1.436614	1.97305
/l21	1.115313	.1865238	5.98	0.000	.7497327	1.480893
/l31	.7752552	.1775589	4.37	0.000	.4272461	1.123264
/l41	1.421549	.372526	3.82	0.000	.6914121	2.151687
/l51	.350716	.2741945	1.28	0.201	-.1866954	.8881275
/l22	1.914757	.1928645	9.93	0.000	1.53675	2.292765
/l32	1.310011	.1729235	7.58	0.000	.9710868	1.648934
/l42	-.2298261	.316432	-0.73	0.468	-.8500215	.3903692
/l52	1.60265	.2787617	5.75	0.000	1.056287	2.149013
/l33	1.251521	.1506425	8.31	0.000	.956267	1.546775
/l43	-.8857156	.3800422	-2.33	0.020	-1.630585	-.1408465
/l53	1.431985	.2817696	5.08	0.000	.8797267	1.984243
/l44	2.665041	.3584521	7.43	0.000	1.962488	3.367595
/l54	.326595	.2941819	1.11	0.267	-.249991	.903181
/l55	1.351829	.3207825	4.21	0.000	.7231066	1.980551

A.12.7. *Model 7* – Income and Age

Table A.12.7.1. *Model 7* – Income and Age

```
Mixed logit model                                 Number of obs   =      11380
                                                  LR chi2(15)     =     861.84
Log likelihood = -2517.9007                       Prob > chi2     =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       p1000 |  -.2151495    .010208   -21.08   0.000    -.2351568   -.1951422
     sa_inc3 |    .084258   .3358955     0.25   0.802    -.5740851    .7426011
     fc_inc3 |   .5862758   .4463335     1.31   0.189    -.2885219    1.461073
     wc_inc3 |   .9592396   .3709346     2.59   0.010     .2322211    1.686258
     mo_inc3 |   .1019458   .5292575     0.19   0.847    -.9353798    1.139271
     pa_inc3 |   .1590509   .6663165     0.24   0.811    -1.146905    1.465007
   sa_nonInc |  -1.052047   .4649799    -2.26   0.024     -1.96339   -.1407026
   fc_nonInc |  -.7570505   .6869432    -1.10   0.270    -2.103434    .5893335
   wc_nonInc |  -.9076407   .5611077    -1.62   0.106    -2.007392    .1921102
   mo_nonInc |  -2.350384    .961045    -2.45   0.014    -4.233998   -.4667707
   pa_nonInc |  -1.151207   1.135602    -1.01   0.311    -3.376946    1.074531
      sa_age |  -.0229618   .0110245    -2.08   0.037    -.0445694   -.0013543
      fc_age |   .0204164   .0145689     1.40   0.161    -.0081381    .0489708
      wc_age |   .0246466   .0125158     1.97   0.049     .0001161    .0491771
      mo_age |   .0266071   .0183842     1.45   0.148    -.0094252    .0626395
      pa_age |  -.0091755   .0214981    -0.43   0.670     -.051311    .0329599
     sa_tail |  -.4163712   .1169928    -3.56   0.000    -.6456729   -.1870695
     fc_tail |  -1.414978   .1915506    -7.39   0.000     -1.79041   -1.039546
     wc_tail |  -.6390379   .1506201    -4.24   0.000    -.9342479   -.3438279
          sa |   4.022472   .5688519     7.07   0.000     2.907543    5.137402
          fc |   1.258656   .7752828     1.62   0.104    -.2608707    2.778182
          wc |   1.527926   .6512656     2.35   0.019     .2514686    2.804383
          pa |  -1.003957   1.064403    -0.94   0.346    -3.090149    1.082236
          mo |    1.75693   .9416493     1.87   0.062    -.0886686    3.602529
-------------+----------------------------------------------------------------
        /l11 |   1.704267   .1313796    12.97   0.000     1.446767    1.961766
        /l21 |   1.004769   .2032118     4.94   0.000     .6064813    1.403057
        /l31 |   .8360079   .1906484     4.39   0.000     .4623439    1.209672
        /l41 |   1.497435   .3737926     4.01   0.000     .7648146    2.230055
        /l51 |   .2194099   .2978745     0.74   0.461    -.3644133    .8032331
        /l22 |   1.795573   .1867867     9.61   0.000     1.429478    2.161668
        /l32 |   1.168871   .1807858     6.47   0.000     .8145377    1.523205
        /l42 |  -.2323023   .4188673    -0.55   0.579    -1.053267    .5886626
        /l52 |   1.571337   .3555452     4.42   0.000      .874481    2.268192
        /l33 |   1.143012   .1406888     8.12   0.000     .8672675    1.418757
        /l43 |  -.4350394   .4027205    -1.08   0.280    -1.224357    .3542783
        /l53 |   1.370541   .3054398     4.49   0.000       .77189    1.969192
        /l44 |   2.738865   .5018014     5.46   0.000     1.755353    3.722378
        /l54 |   .6665772    .341615     1.95   0.051    -.0029759     1.33613
        /l55 |   -.770024   .5474523    -1.41   0.160    -1.843011    .3029627
------------------------------------------------------------------------------
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Table A.12.7.2. Covariance Matrix *Model 7*

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
v11	2.904525	.4478116	6.49	0.000	2.02683	3.782219
v21	1.712394	.3958005	4.33	0.000	.9366397	2.488149
v31	1.42478	.3631854	3.92	0.000	.7129501	2.136611
v41	2.552028	.7077866	3.61	0.000	1.164791	3.939264
v51	.373933	.5102991	0.73	0.464	-.6262348	1.374101
v22	4.233643	.7980914	5.30	0.000	2.669413	5.797874
v32	2.938789	.4711008	6.24	0.000	2.015448	3.86213
v42	1.08746	.6804656	1.60	0.110	-.2462279	2.421148
v52	3.041906	.6769487	4.49	0.000	1.715111	4.368701
v33	3.371647	.5593267	6.03	0.000	2.275387	4.467907
v43	.4830803	.6641188	0.73	0.467	-.8185686	1.784729
v53	3.586664	.6682135	5.37	0.000	2.27699	4.896339
v44	9.986917	3.35447	2.98	0.003	3.412276	16.56156
v54	1.192953	1.297021	0.92	0.358	-1.349162	3.735068
v55	5.432885	1.490515	3.64	0.000	2.511529	8.354241

Table A.12.7.3. Standard Deviations *Model 7*

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sa	1.704267	.1313796	12.97	0.000	1.446767	1.961766
fc	2.057582	.1939392	10.61	0.000	1.677468	2.437696
wc	1.836204	.1523051	12.06	0.000	1.537692	2.134717
pa	3.160208	.5307356	5.95	0.000	2.119986	4.200431
mo	2.330855	.3197357	7.29	0.000	1.704185	2.957525

A.12.8. *Model 8* – Income, Age, Single and Female

Table A.12.8.1. *Model 8* – Income, Age, Single and Female

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Mixed logit model                                 Number of obs    =      11380
                                                  LR chi2(15)      =     843.48
Log likelihood = -2506.8224                       Prob > chi2      =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       p1000 |  -.2197579    .010317   -21.30   0.000    -.2399788   -.1995371
    femaleSA |    .123874   .2741471     0.45   0.651    -.4134444    .6611924
    femaleWC |  -.2918723   .3121699    -0.93   0.350    -.9037141    .3199695
    femaleFC |   -.489887   .3538451    -1.38   0.166    -1.183411    .2036366
    femalePA |  -.5004762   .6189649    -0.81   0.419    -1.713625    .7126727
    femaleMO |  -.2102739   .4811883    -0.44   0.662    -1.153386    .7328379
     sa_inc3 |   .5477731   .3571898     1.53   0.125     -.152306    1.247852
     fc_inc3 |   .7990615   .4708823     1.70   0.090    -.1238509    1.721974
     wc_inc3 |   1.182974    .385728     3.07   0.002      .426961    1.938987
     mo_inc3 |   .2510835   .5856089     0.43   0.668    -.8966888    1.398856
     pa_inc3 |   .9620616   .7125767     1.35   0.177     -.434563    2.358686
   sa_nonInc |  -.9733456   .5079825    -1.92   0.055    -1.968973    .0222818
   fc_nonInc |  -.7136065   .7043145    -1.01   0.311    -2.094038    .6668245
   wc_nonInc |  -.8569513    .582229    -1.47   0.141    -1.998099    .2841966
   mo_nonInc |  -2.457975   .9724547    -2.53   0.011    -4.363951   -.5519988
   pa_nonInc |  -.9859304   1.403494    -0.70   0.482    -3.736728    1.764868
      sa_age |  -.0204871   .0111652    -1.83   0.067    -.0423705    .0013963
      fc_age |   .0219603   .0144203     1.52   0.128     -.006303    .0502236
      wc_age |   .0286662   .0128544     2.23   0.026     .0034721    .0538604
      mo_age |   .0385091   .0195852     1.97   0.049     .0001227    .0768954
      pa_age |  -.0168309   .0248467    -0.68   0.498    -.0655296    .0318678
   sa_single |   .9894323   .3199252     3.09   0.002     .3623905    1.616474
   fc_single |   .5867889    .416105     1.41   0.158     -.228762     1.40234
   wc_single |    .646393   .3637666     1.78   0.076    -.0665765    1.359362
   mo_single |   .2287842   .5304664     0.43   0.666    -.8109108    1.268479
   pa_single |   1.327733   .6594871     2.01   0.044     .0351623    2.620304
     sa_tail |  -.4309934    .117598    -3.66   0.000    -.6614812   -.2005056
     fc_tail |  -1.446216   .1925078    -7.51   0.000    -1.823524   -1.068908
     wc_tail |   -.670536   .1515113    -4.43   0.000    -.9674926   -.3735793
          sa |   3.555328   .6165059     5.77   0.000     2.346999    4.763657
          fc |   1.289367    .834272     1.55   0.122    -.3457757     2.92451
          wc |   1.337882   .7309043     1.83   0.067    -.0946645    2.770428
          pa |   -1.02774   1.343611    -0.76   0.444    -3.661169    1.605689
          mo |   1.178493    1.13043     1.04   0.297     -1.03711    3.394096
-------------+----------------------------------------------------------------
        /l11 |   1.671968   .1342072    12.46   0.000     1.408926    1.935009
        /l21 |   1.044116   .1703658     6.13   0.000     .7102052    1.378027
        /l31 |   .7654823   .1520872     5.03   0.000     .4673969    1.063568
        /l41 |   1.476313   .3613438     4.09   0.000     .7680923    2.184534
        /l51 |   .3503324   .2324277     1.51   0.132    -.1052175    .8058823
        /l22 |   1.820779   .1795855    10.14   0.000     1.468798     2.17276
        /l32 |   1.244632   .1613029     7.72   0.000     .9284837     1.56078
        /l42 |  -.2071591   .3209852    -0.65   0.519    -.8362784    .4219603
        /l52 |   1.494319   .2785776     5.36   0.000     .9483166    2.040321
        /l33 |   1.187707   .1445744     8.22   0.000     .9043465    1.471068
        /l43 |  -.3611484   .4134508    -0.87   0.382    -1.171497    .4492003
        /l53 |   1.395301   .3157498     4.42   0.000     .7764427    2.014159
        /l44 |   2.823938   .4231249     6.67   0.000     1.994629    3.653248
        /l54 |   .3863853   .3015725     1.28   0.200     -.204686    .9774566
        /l55 |   1.339671   .2977958     4.50   0.000     .7560024     1.92334
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A.12.9 *Model 9* – Income, Age, Single, Female and Children

Table A.12.9.1. *Model 9* – Income, Age, Single, Female and Children

Mixed logit model — Number of obs = 11380

LR chi2(15) = 839.06

Log likelihood = -2505.8142 — Prob > chi2 = 0.0000

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
p1000	-.2198589	.0103257	-21.29	0.000	-.2400968	-.1996209
femaleSA	.1454464	.277937	0.52	0.601	-.3993002	.690193
femaleWC	-.3010792	.3105315	-0.97	0.332	-.9097097	.3075514
femaleFC	-.4930745	.3567683	-1.38	0.167	-1.192328	.2061786
femalePA	-.4955184	.6307272	-0.79	0.432	-1.731721	.7406842
femaleMO	-.2295455	.4746401	-0.48	0.629	-1.159823	.700732
childrenSA	-.0353057	.3098367	-0.11	0.909	-.6425745	.571963
childrenWC	-.4000821	.39037	-1.02	0.305	-1.165193	.3650289
childrenFC	.0392318	.4543832	0.09	0.931	-.8513428	.9298065
childrenMO	-.466433	.6006921	-0.78	0.437	-1.643768	.7109019
childrenPA	.0419306	.6703024	0.06	0.950	-1.271838	1.355699
sa_inc3	.5174595	.3637826	1.42	0.155	-.1955414	1.23046
fc_inc3	.7992007	.4901997	1.63	0.103	-.1615731	1.759974
wc_inc3	1.090697	.4073208	2.68	0.007	.292363	1.889031
mo_inc3	.1529481	.6022155	0.25	0.800	-1.027373	1.333269
pa_inc3	.9002013	.7251458	1.24	0.214	-.5210584	2.321461
sa_nonInc	-.9846223	.5257765	-1.87	0.061	-2.015125	.0458807
fc_nonInc	-.6888907	.7003389	-0.98	0.325	-2.06153	.6837483
wc_nonInc	-.8673521	.5883962	-1.47	0.140	-2.020588	.2858834
mo_nonInc	-2.423003	.9853925	-2.46	0.014	-4.354337	-.491669
pa_nonInc	-.9948132	1.533486	-0.65	0.517	-4.00039	2.010764
sa_age	-.0204262	.0114437	-1.78	0.074	-.0428555	.0020032
fc_age	.0223059	.0151533	1.47	0.141	-.0073939	.0520058
wc_age	.0264057	.0131649	2.01	0.045	.000603	.0522084
mo_age	.0360115	.0201087	1.79	0.073	-.0034009	.0754238
pa_age	-.0178802	.0252722	-0.71	0.479	-.0674128	.0316525
sa_single	.9777347	.3396624	2.88	0.004	.3120086	1.643461
fc_single	.5545705	.4583864	1.21	0.226	-.3438503	1.452991
wc_single	.4419415	.4145492	1.07	0.286	-.37056	1.254443
mo_single	-.012237	.5993753	-0.02	0.984	-1.186991	1.162517
pa_single	1.360751	.7326088	1.86	0.063	-.0751361	2.796637
sa_tail	-.4313691	.1176515	-3.67	0.000	-.6619618	-.2007764
fc_tail	-1.449361	.1925822	-7.53	0.000	-1.826815	-1.071906
wc_tail	-.6720018	.1516148	-4.43	0.000	-.9691613	-.3748424
sa	3.578647	.6699721	5.34	0.000	2.265526	4.891768
fc	1.285368	.9302425	1.38	0.167	-.5378733	3.10861
wc	1.679327	.7879962	2.13	0.033	.1348828	3.223771
pa	-.9807675	1.454173	-0.67	0.500	-3.830895	1.86936
mo	1.561865	1.226682	1.27	0.203	-.8423887	3.966118
/l11	1.672621	.1363033	12.27	0.000	1.405471	1.93977
/l21	1.037736	.1786289	5.81	0.000	.6876297	1.387842
/l31	.7820718	.1635336	4.78	0.000	.4615519	1.102592
/l41	1.47799	.3718436	3.97	0.000	.7491897	2.20679
/l51	.372054	.2402698	1.55	0.122	-.0988661	.8429742
/l22	1.819196	.1811708	10.04	0.000	1.464108	2.174285
/l32	1.256885	.1603577	7.84	0.000	.9425899	1.571181
/l42	-.2241423	.3241843	-0.69	0.489	-.8595319	.4112474
/l52	1.515707	.279291	5.43	0.000	.9683065	2.063107
/l33	1.156679	.1482599	7.80	0.000	.8660946	1.447263
/l43	-.3139335	.4294761	-0.73	0.465	-1.155691	.5278241
/l53	1.326243	.3222482	4.12	0.000	.6946482	1.957838
/l44	2.823529	.415281	6.80	0.000	2.009593	3.637465
/l54	.3867206	.2928387	1.32	0.187	-.1872327	.9606738
/l55	1.354235	.2972452	4.56	0.000	.7716448	1.936825

Table A.12.9.2. Covariance Matrix *Model 9*

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
v11	2.79766	.4559675	6.14	0.000	1.90398	3.69134
v21	1.735739	.3503841	4.95	0.000	1.048999	2.422479
v31	1.30811	.3077424	4.25	0.000	.7049456	1.911273
v41	2.472116	.6911148	3.58	0.000	1.117556	3.826676
v51	.6223053	.4073731	1.53	0.127	-.1761312	1.420742
v22	4.386371	.8383722	5.23	0.000	2.743192	6.029551
v32	3.098105	.530076	5.84	0.000	2.059175	4.137035
v42	1.126004	.6408416	1.76	0.079	-.1300221	2.382031
v52	3.143462	.7224766	4.35	0.000	1.727434	4.55949
v33	3.529302	.631298	5.59	0.000	2.291981	4.766624
v43	.5110527	.6893628	0.74	0.458	-.8400735	1.862179
v53	3.73008	.7434865	5.02	0.000	2.272873	5.187286
v44	10.30556	2.914619	3.54	0.000	4.593017	16.01811
v54	.8857226	1.116484	0.79	0.428	-1.302545	3.07399
v55	6.178217	1.518608	4.07	0.000	3.2018	9.154634

Table A.12.9.3. Standard Deviations *Model 9*

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sa	1.672621	.1363033	12.27	0.000	1.405471	1.93977
fc	2.094367	.2001493	10.46	0.000	1.702081	2.486652
wc	1.878644	.1680196	11.18	0.000	1.549331	2.207956
pa	3.210228	.4539582	7.07	0.000	2.320486	4.09997
mo	2.485602	.305481	8.14	0.000	1.88687	3.084334

Below are the regression outputs for the models that did not allow for correlations in unobserved factors over choice scenarios.

A.12.10. *Model B.1* – Product Attribute Model (No Correlation)

Table A.12.10.1. *Model B.1* – Product Attribute Model (No Correlation)

```
Mixed logit model                                 Number of obs   =      11380
                                                  LR chi2(5)      =     790.55
Log likelihood = -2620.0261                       Prob > chi2     =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Mean         |
       p1000 |  -.2183171   .0101298   -21.55   0.000    -.2381712    -.198463
     sa_tail |   -.443177   .1173116    -3.78   0.000    -.6731036   -.2132505
     fc_tail |  -1.388286   .1939552    -7.16   0.000    -1.768431    -1.00814
     wc_tail |  -.6969278   .1521574    -4.58   0.000    -.9951507   -.3987048
          sa |   2.842205   .2230201    12.74   0.000     2.405094    3.279317
          fc |   2.192911   .3231926     6.79   0.000     1.559465    2.826357
          wc |   2.908765   .2767394    10.51   0.000     2.366366    3.451164
          pa |  -1.794719   .5269901    -3.41   0.001    -2.827601   -.7618378
          mo |    2.74399   .3510635     7.82   0.000     2.055918    3.432062
-------------+----------------------------------------------------------------
SD           |
          sa |   1.660869   .1332524    12.46   0.000       1.3997    1.922039
          fc |    1.98182   .1896768    10.45   0.000     1.610061     2.35358
          wc |   1.855863   .1627946    11.40   0.000     1.536791    2.174935
          pa |   3.454727   .4368955     7.91   0.000     2.598428    4.311027
          mo |   2.455705   .3164644     7.76   0.000     1.835446    3.075964
------------------------------------------------------------------------------
The sign of the estimated standard deviations is irrelevant: interpret them as
being positive
```

A.12.11. *Model B.2* – Product Attribute and Consumer Characteristics Interaction Model (No Correlation)

Table A.12.11.1. *Model B.2* – Product Attribute and Consumer Characteristics Interaction Model (No Correlation)

```
Mixed logit model                                 Number of obs   =      11380
                                                  LR chi2(5)      =     702.28
Log likelihood = -2584.7369                       Prob > chi2     =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Mean         |
       p1000 |  -.2212292    .010227   -21.63   0.000    -.2412738   -.2011846
     sa_inc3 |   .3073738   .3178855     0.97   0.334    -.3156704     .930418
     fc_inc3 |   .3155598   .4656275     0.68   0.498    -.5970534    1.228173
     wc_inc3 |   1.468236   .3909246     3.76   0.000      .702038    2.234434
     mo_inc3 |   .1343882   .5690834     0.24   0.813    -.9809947    1.249771
     pa_inc3 |   .6131615   .6661159     0.92   0.357    -.6924016    1.918725
   sa_nonInc |  -1.108815   .4207675    -2.64   0.008    -1.933505   -.2841261
   fc_nonInc |  -.9502941   .6198928    -1.53   0.125    -2.165262    .2646734
   wc_nonInc |  -.7946081   .4957299    -1.60   0.109    -1.766221    .1770046
   mo_nonInc |  -3.206712   1.157803    -2.77   0.006    -5.475963   -.9374608
   pa_nonInc |  -1.262539   1.068464    -1.18   0.237    -3.356689    .8316115
      sa_age |  -.0246155   .0099949    -2.46   0.014    -.0442052   -.0050259
      fc_age |   .0245569   .0144714     1.70   0.090    -.0038065    .0529204
      wc_age |   .0245614   .0118089     2.08   0.038     .0014164    .0477063
      mo_age |   .0438991   .0188639     2.33   0.020     .0069266    .0808716
      pa_age |   .0178701   .0238914     0.75   0.454    -.0289562    .0646964
   sa_single |   .7466991   .3018717     2.47   0.013     .1550414    1.338357
   fc_single |   .1833902   .4422272     0.41   0.678    -.6833593     1.05014
   wc_single |   .8986283   .3250911     2.76   0.006     .2614615    1.535795
   mo_single |   .5236316   .5420452     0.97   0.334    -.5387574    1.586021
   pa_single |   .7205517   .6089905     1.18   0.237    -.4730477    1.914151
     sa_tail |  -.4493796   .1176557    -3.82   0.000    -.6799806   -.2187786
     fc_tail |  -1.411387   .1946752    -7.25   0.000    -1.792943   -1.029831
     wc_tail |  -.7021076   .1523444    -4.61   0.000    -1.000697    -.403518
          sa |   3.887584   .5398025     7.20   0.000     2.829591    4.945578
          fc |     .93478   .7386395     1.27   0.206    -.5129268    2.382487
          wc |   1.322184   .6336908     2.09   0.037     .0801733    2.564195
          pa |  -2.786808   1.436408    -1.94   0.052    -5.602115    .0284993
          mo |   .7562164   1.036525     0.73   0.466    -1.275335    2.787768
-------------+----------------------------------------------------------------
SD           |
          sa |   1.589231   .1292428    12.30   0.000      1.33592    1.842543
          fc |   2.018708   .1987104    10.16   0.000     1.629243    2.408173
          wc |   1.691765   .1591437    10.63   0.000     1.379849    2.003681
          pa |   3.213147   .4172448     7.70   0.000     2.395363    4.030932
          mo |   2.346026   .2697847     8.70   0.000     1.817258    2.874794
------------------------------------------------------------------------------
The sign of the estimated standard deviations is irrelevant: interpret them as
being positive
```

A.12.12. *Model B.3* – Product Attribute and Full Set of Consumer Characteristics Interaction Model (No Correlation)

Table A.12.12.1. *Model B.3* – Product Attribute and Full Set of Consumer Characteristics Interaction Model (No Correlation)

```
Mixed logit model                                 Number of obs    =      11380
                                                  LR chi2(5)       =     684.76
Log likelihood = -2578.0853                       Prob > chi2      =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Mean         |
       p1000 |  -.2215241   .0102425   -21.63   0.000    -.2415989   -.2014493
    femaleSA |   .1523377   .2579517     0.59   0.555    -.3532384    .6579137
    femaleWC |  -.3599552   .2855836    -1.26   0.208    -.9196888    .1997783
    femaleFC |  -.5276143   .3560344    -1.48   0.138    -1.225429    .1702003
    femalePA |  -.2763563   .6935106    -0.40   0.690    -1.635612    1.082899
    femaleMO |  -.2224424   .4746677    -0.47   0.639    -1.152774    .7078892
  childrenSA |   .0963526   .2775494     0.35   0.728    -.4476342    .6403394
  childrenWC |  -.3353401   .3292031    -1.02   0.308    -.9805664    .3098861
  childrenFC |   .3582823   .4253617     0.84   0.400    -.4754113    1.191976
  childrenMO |  -.0993182   .5422773    -0.18   0.855    -1.162162    .9635258
  childrenPA |  -.1393065   .5944195    -0.23   0.815    -1.304347    1.025734
     sa_inc3 |   .2697931    .330294     0.82   0.414    -.3775713    .9171576
     fc_inc3 |   .5062941    .481602     1.05   0.293    -.4376284    1.450217
     wc_inc3 |   1.158924    .394308     2.94   0.003     .3860946    1.931754
     mo_inc3 |  -.0908324   .5971402    -0.15   0.879    -1.261206    1.079541
     pa_inc3 |   .4734794   .8208183     0.58   0.564    -1.135295    2.082254
   sa_nonInc |  -1.151898   .4286213    -2.69   0.007     -1.99198   -.3118151
   fc_nonInc |  -.7199096   .6016407    -1.20   0.231    -1.899104    .4592845
   wc_nonInc |  -.9616222   .5064621    -1.90   0.058     -1.95427    .0310252
   mo_nonInc |   -3.28597   1.165868    -2.82   0.005    -5.571029   -1.000911
   pa_nonInc |  -1.431559    1.12145    -1.28   0.202     -3.62956    .7664424
      sa_age |  -.0223535    .011377    -1.96   0.049     -.044652   -.0000549
      fc_age |   .0263532   .0158416     1.66   0.096    -.0046957    .0574021
      wc_age |   .0305456   .0128128     2.38   0.017      .005433    .0556583
      mo_age |   .0492182   .0208535     2.36   0.018     .0083462    .0900902
      pa_age |   .0200493   .0312931     0.64   0.522     -.041284    .0813826
   sa_single |   .7603386   .3132374     2.43   0.015     .1464047    1.374273
   fc_single |   .4164262   .4698776     0.89   0.375    -.5045171    1.337369
   wc_single |   .6787391   .3336888     2.03   0.042      .024721    1.332757
   mo_single |    .301425   .5871436     0.51   0.608    -.8493553    1.452205
   pa_single |   .6236462   .6621538     0.94   0.346    -.6741515    1.921444
  sa_educUNI |   .1683996   .2940309     0.57   0.567    -.4078904    .7446897
  fc_educUNI |   .1105826   .3894419     0.28   0.776    -.6527094    .8738747
  wc_educUNI |   .7045497   .3181663     2.21   0.027     .0809552    1.328144
  mo_educUNI |   .5494157   .5195217     1.06   0.290    -.4688281     1.56766
  pa_educUNI |   .3616289   .8779494     0.41   0.680     -1.35912    2.082378
     sa_tail |  -.4505488   .1177751    -3.83   0.000    -.6813838   -.2197139
     fc_tail |  -1.415659   .1947666    -7.27   0.000    -1.797394   -1.033923
     wc_tail |  -.6965502    .152476    -4.57   0.000    -.9953976   -.3977028
          sa |   3.638391    .694099     5.24   0.000     2.277982      4.9988
          fc |   .8676914   .9791223     0.89   0.376    -1.051353    2.786736
          wc |   1.224319   .7854852     1.56   0.119    -.3152033    2.763842
          pa |  -2.759517   1.995734    -1.38   0.167    -6.671084    1.152051
          mo |     .62174   1.307349     0.48   0.634    -1.940617    3.184097
-------------+----------------------------------------------------------------
SD           |
          sa |    1.59422   .1304183    12.22   0.000     1.338605    1.849835
          fc |   1.910997   .1842664    10.37   0.000     1.549842    2.272153
          wc |   1.669651   .1554217    10.74   0.000      1.36503    1.974272
          pa |   3.198915   .4190679     7.63   0.000     2.377557    4.020273
          mo |   2.351558   .2721999     8.64   0.000     1.818056     2.88506
------------------------------------------------------------------------------
```

A.12.13. *Model B.4* – Income as Dummies for all Income Groups (No Correlation)

Table A.12.13.1. *Model B.4* – Income as Dummies for all Income Groups (No Correlation)

```
Mixed logit model                               Number of obs   =      11380
                                                LR chi2(5)      =     735.51
Log likelihood = -2598.5923                     Prob > chi2     =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Mean         |
       p1000 |   -.219856   .0101862   -21.58   0.000    -.2398205   -.1998915
    sa_inc_2 |  -.6841889    .334804    -2.04   0.041    -1.340393   -.0279852
    fc_inc_2 |  -.0675287   .4497447    -0.15   0.881    -.9490121    .8139547
    wc_inc_2 |  -.2161896   .3666145    -0.59   0.555    -.9347408    .5023616
    mo_inc_2 |   .3106629    .553082     0.56   0.574    -.7733579    1.394684
    pa_inc_2 |   .1229592   .6816385     0.18   0.857    -1.213028    1.458946
    sa_inc_3 |  -.3773299   .3532255    -1.07   0.285    -1.069639    .3149793
    fc_inc_3 |     .41684   .4630084     0.90   0.368    -.4906397     1.32432
    wc_inc_3 |   1.141192   .4131423     2.76   0.006      .331448    1.950936
    mo_inc_3 |   .4804879   .6153413     0.78   0.435    -.7255589    1.686535
    pa_inc_3 |   .4865697   .7452895     0.65   0.514    -.9741709     1.94731
   sa_nonInc |  -1.428753   .4924436    -2.90   0.004    -2.393925   -.4635817
   fc_nonInc |  -.9627322   .6811442    -1.41   0.158     -2.29775     .372286
   wc_nonInc |  -.9005184   .5448797    -1.65   0.098    -1.968463    .1674263
   mo_nonInc |  -3.160799   1.179365    -2.68   0.007    -5.472312   -.8492862
   pa_nonInc |  -1.439794    1.16649    -1.23   0.217    -3.726071     .846484
     sa_tail |  -.4503267   .1173973    -3.84   0.000    -.6804212   -.2202323
     fc_tail |  -1.406411   .1945408    -7.23   0.000    -1.787704   -1.025118
     wc_tail |  -.7001743   .1523458    -4.60   0.000    -.9987665   -.4015821
          sa |   3.351534   .3061855    10.95   0.000     2.751422    3.951647
          fc |    2.17417   .4194548     5.18   0.000     1.352054    2.996287
          wc |   2.851576   .3618144     7.88   0.000     2.142432    3.560719
          pa |  -1.675943   .6921601    -2.42   0.015    -3.032552   -.3193344
          mo |   2.766191   .4836106     5.72   0.000     1.818331     3.71405
-------------+----------------------------------------------------------------
SD           |
          sa |   1.612733   .1335779    12.07   0.000     1.350925    1.874541
          fc |   2.021616   .1960755    10.31   0.000     1.637315    2.405916
          wc |   1.756827   .1649001    10.65   0.000     1.433629    2.080025
          pa |   3.267303   .4152486     7.87   0.000     2.453431    4.081175
          mo |   2.375785   .2876498     8.26   0.000     1.812001    2.939568
------------------------------------------------------------------------------
The sign of the estimated standard deviations is irrelevant: interpret them as
being positive
```

A.12.14. *Model B.5* – Income as *Low* and *High* (No Correlation)

Table A.12.14.1. *Model B.5* – Income as *Low* and *High* (No Correlation)

```
Mixed logit model                                 Number of obs   =      11380
                                                  LR chi2(5)      =     743.89
Log likelihood = -2600.9263                       Prob > chi2     =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Mean         |
       p1000 |  -.2195481   .0101798   -21.57   0.000    -.2395002    -.199596
    sa_inc_3 |  -.0216635   .3077729    -0.07   0.944    -.6248873    .5815604
    fc_inc_3 |   .4074428   .4064897     1.00   0.316    -.3892624    1.204148
    wc_inc_3 |   1.244787   .3522805     3.53   0.000     .5543299    1.935244
    mo_inc_3 |   .3338106   .5276616     0.63   0.527    -.7003872    1.368008
    pa_inc_3 |   .3785514   .6348926     0.60   0.551    -.8658152    1.622918
   sa_nonInc |  -1.078228   .4633911    -2.33   0.020    -1.986458   -.1699982
   fc_nonInc |  -.9684699   .6443967    -1.50   0.133    -2.231464    .2945245
   wc_nonInc |  -.7896183   .5018907    -1.57   0.116    -1.773306    .1940694
   mo_nonInc |  -3.287969   1.127289    -2.92   0.004    -5.497416   -1.078522
   pa_nonInc |   -1.56151   1.109459    -1.41   0.159    -3.736009    .6129886
     sa_tail |  -.4484326   .1175008    -3.82   0.000      -.67873   -.2181352
     fc_tail |  -1.402456   .1943569    -7.22   0.000    -1.783389   -1.021523
     wc_tail |  -.7007592   .1522095    -4.60   0.000    -.9990843   -.4024341
          sa |   2.989869   .2484562    12.03   0.000     2.502904    3.476834
          fc |   2.170754   .3483924     6.23   0.000     1.487918    2.853591
          wc |   2.742532    .292987     9.36   0.000     2.168288    3.316776
          pa |  -1.622422   .5547049    -2.92   0.003    -2.709624   -.5352208
          mo |   2.917453   .3764427     7.75   0.000     2.179639    3.655268
-------------+----------------------------------------------------------------
SD           |
          sa |   1.628168   .1347938    12.08   0.000     1.363977    1.892359
          fc |   2.025007   .1957236    10.35   0.000     1.641396    2.408618
          wc |    1.74891   .1655058    10.57   0.000     1.424525    2.073296
          pa |    3.32771   .4225854     7.87   0.000     2.499458    4.155963
          mo |   2.356607   .2856305     8.25   0.000     1.796782    2.916433
------------------------------------------------------------------------------
The sign of the estimated standard deviations is irrelevant: interpret them as
being positive
```

A.12.15. *Model B.6* – Income and Education (No Correlation)

Table A.12.15.1. *Model B.6* – Income and Education (No Correlation)

```
Mixed logit model                               Number of obs   =      11380
                                                LR chi2(5)      =     737.01
Log likelihood = -2598.7433                     Prob > chi2     =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Mean         |
       p1000 |  -.2203148   .0101673   -21.67   0.000    -.2402424   -.2003872
     sa_inc3 |    .078514   .2979559     0.26   0.792    -.5054688    .6624968
     fc_inc3 |   .3532082   .3768075     0.94   0.349     -.385321    1.091737
     wc_inc3 |   1.037666   .3339709     3.11   0.002     .3830955    1.692237
     mo_inc3 |   .4419055   .5391451     0.82   0.412    -.6147994     1.49861
     pa_inc3 |   .0100179   .6907666     0.01   0.988     -1.34386    1.363895
   sa_nonInc |  -1.084602   .4902046    -2.21   0.027    -2.045385   -.1238186
   fc_nonInc |  -.6200244   .5565419    -1.11   0.265    -1.710827    .4707778
   wc_nonInc |  -.8757121   .5059726    -1.73   0.083      -1.8674    .1159761
   mo_nonInc |  -3.948041   1.479365    -2.67   0.008    -6.847542   -1.048539
   pa_nonInc |  -1.702773   1.422221    -1.20   0.231    -4.490276    1.084729
  sa_educUNI |   .4180674   .2720922     1.54   0.124    -.1152234    .9513583
  fc_educUNI |  -.0418893   .3434526    -0.12   0.903    -.7150441    .6312655
  wc_educUNI |   .2259001   .3111504     0.73   0.468    -.3839435    .8357438
  mo_educUNI |   .5017562   .5174348     0.97   0.332    -.5123974     1.51591
  pa_educUNI |   .9041553    .639378     1.41   0.157    -.3490025    2.157313
     sa_tail |   -.436933   .1173321    -3.72   0.000    -.6668996   -.2069663
     fc_tail |  -1.413537    .193639    -7.30   0.000    -1.793063   -1.034012
     wc_tail |  -.6967348    .152745    -4.56   0.000    -.9961094   -.3973601
          sa |   2.774276   .2551275    10.87   0.000     2.274236    3.274317
          fc |   2.172743   .3408331     6.37   0.000     1.504723    2.840764
          wc |   2.639184   .3202668     8.24   0.000     2.011473    3.266896
          mo |   2.777158   .4372442     6.35   0.000     1.920175     3.63414
          pa |  -2.058678   .6883157    -2.99   0.003    -3.407752   -.7096038
-------------+----------------------------------------------------------------
SD           |
          sa |   1.619028   .1290835    12.54   0.000     1.366029    1.872027
          fc |   1.752635   .1538991    11.39   0.000     1.450998    2.054272
          wc |   1.733166   .1456031    11.90   0.000     1.447789    2.018543
          mo |   2.646609   .3470805     7.63   0.000     1.966344    3.326874
          pa |    3.50803   .4823208     7.27   0.000     2.562698    4.453361
------------------------------------------------------------------------------
```

A.12.16. *Model B.7* – Income and Age (No Correlation)

Table A.12.16.1. *Model B.7* – Income and Age (No Correlation)

```
Mixed logit model                                 Number of obs   =      11380
                                                  LR chi2(5)      =     714.00
Log likelihood = -2591.8197                       Prob > chi2     =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Mean         |
       p1000 |  -.2201406   .0101888   -21.61   0.000    -.2401103    -.200171
    sa_inc3 |   .0522675   .3068436     0.17   0.865    -.5491349      .65367
    fc_inc3 |   .3011282   .4372212     0.69   0.491    -.5558097    1.158066
    wc_inc3 |   1.110882   .3598264     3.09   0.002     .4056354    1.816129
    mo_inc3 |  -.0347357   .5346324    -0.06   0.948    -1.082596    1.013125
    pa_inc3 |    .299782   .7123258     0.42   0.674    -1.096351    1.695915
  sa_nonInc |  -1.096145   .4471846    -2.45   0.014     -1.97261    -.219679
  fc_nonInc |  -.9388788   .6151484    -1.53   0.127    -2.144548      .26679
  wc_nonInc |  -.8862412     .49811    -1.78   0.075    -1.862519    .0900364
  mo_nonInc |   -3.16453   1.139066    -2.78   0.005    -5.397059   -.9320013
  pa_nonInc |  -1.464951   1.081396    -1.35   0.176    -3.584448     .654545
     sa_age |  -.0258103   .0105043    -2.46   0.014    -.0463983   -.0052223
     fc_age |   .0165338   .0153313     1.08   0.281     -.013515    .0465826
     wc_age |   .0253774   .0130292     1.95   0.051    -.0001594    .0509141
     mo_age |   .0399938   .0185816     2.15   0.031     .0035746     .076413
     pa_age |   .0094541   .0313285     0.30   0.763    -.0519486    .0708567
    sa_tail |   -.446634   .1174765    -3.80   0.000    -.6768836   -.2163844
    fc_tail |  -1.403053   .1942859    -7.22   0.000    -1.783846   -1.022259
    wc_tail |  -.7017746   .1522861    -4.61   0.000     -1.00025   -.4032994
          sa |   4.173266   .5559755     7.51   0.000     3.083574    5.262958
          fc |    1.41413   .7622067     1.86   0.064    -.0797672    2.908028
          wc |    1.62943   .6926236     2.35   0.019     .2719126    2.986947
          pa |  -2.109756   1.866338    -1.13   0.258    -5.767711    1.548199
          mo |   1.124268   .9691943     1.16   0.246    -.7753182    3.023854
-------------+----------------------------------------------------------------
SD           |
          sa |   1.605394   .1303048    12.32   0.000     1.350002    1.860787
          fc |   1.989765   .1971604    10.09   0.000     1.603338    2.376193
          wc |   1.685913   .1635229    10.31   0.000     1.365414    2.006412
          pa |   3.295532   .4185922     7.87   0.000     2.475106    4.115957
          mo |   2.335818   .2788206     8.38   0.000      1.78934    2.882297
------------------------------------------------------------------------------
The sign of the estimated standard deviations is irrelevant: interpret them as
being positive
```

A.12.17. *Model B.8* – Income, Age, Single and Female

Table A.12.17.1. *Model B.8* – Income, Age, Single and Female

```
Mixed logit model                                 Number of obs   =      11380
                                                  LR chi2(5)      =     692.37
Log likelihood = -2582.3759                       Prob > chi2     =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Mean         |
       p1000 |  -.2208827   .0102114   -21.63   0.000    -.2408966   -.2008688
    femaleSA |   .1632118   .2572894     0.63   0.526    -.3410662    .6674898
    femaleWC |  -.3971561   .2888523    -1.37   0.169    -.9632961     .168984
    femaleFC |  -.4653565   .3897295    -1.19   0.232    -1.229212    .2984992
    femalePA |  -.2499069   .6455539    -0.39   0.699    -1.515169    1.015355
    femaleMO |  -.2575745   .4706646    -0.55   0.584     -1.18006    .6649111
     sa_inc3 |   .3075114   .3154067     0.97   0.330    -.3106744    .9256971
     fc_inc3 |   .3720397    .451242     0.82   0.410    -.5123784    1.256458
     wc_inc3 |   1.387898   .3885756     3.57   0.000     .6263041    2.149492
     mo_inc3 |   .1108292   .5723893     0.19   0.846    -1.011033    1.232692
     pa_inc3 |   .6517143   .6598894     0.99   0.323    -.6416451    1.945074
   sa_nonInc |  -1.138633   .4229212    -2.69   0.007    -1.967543   -.3097227
   fc_nonInc |  -.8088386   .6066503    -1.33   0.182    -1.997851    .3801741
   wc_nonInc |   -.756146   .5009442    -1.51   0.131    -1.737979    .2256866
   mo_nonInc |   -3.32061   1.147699    -2.89   0.004     -5.57006   -1.071161
   pa_nonInc |  -1.261126    1.07545    -1.17   0.241    -3.368969    .8467169
      sa_age |  -.0232244   .0101892    -2.28   0.023    -.0431949    -.003254
      fc_age |   .0194326   .0158936     1.22   0.221    -.0117181    .0505834
      wc_age |   .0235107   .0118653     1.98   0.048     .0002552    .0467662
      mo_age |   .0415803   .0188602     2.20   0.027     .0046151    .0785456
      pa_age |   .0164734   .0273374     0.60   0.547     -.037107    .0700538
   sa_single |   .7574746   .2957595     2.56   0.010     .1777966    1.337153
   fc_single |   .2346478   .4454963     0.53   0.598    -.6385088    1.107804
   wc_single |   .8614223   .3248169     2.65   0.008     .2247929    1.498052
   mo_single |   .4750061   .5400075     0.88   0.379    -.5833891    1.533401
   pa_single |   .7251331   .6278271     1.15   0.248    -.5053855    1.955652
     sa_tail |  -.4488372   .1176786    -3.81   0.000     -.679483   -.2181915
     fc_tail |  -1.408806   .1945507    -7.24   0.000    -1.790118   -1.027494
     wc_tail |  -.7013171   .1522455    -4.61   0.000    -.9997128   -.4029213
          sa |   3.738725   .5824984     6.42   0.000     2.597049      4.8804
          fc |   1.401539    .870079     1.61   0.107    -.3037849    3.106862
          wc |   1.597881   .6736916     2.37   0.018       .27747    2.918293
          pa |   -2.62466   1.739215    -1.51   0.131    -6.033459    .7841384
          mo |   1.030966   1.104598     0.93   0.351    -1.134006    3.195938
-------------+----------------------------------------------------------------
SD           |
          sa |   1.599647    .130603    12.25   0.000      1.34367    1.855624
          fc |   1.945857   .1964055     9.91   0.000     1.560909    2.330805
          wc |   1.662154   .1562513    10.64   0.000     1.355907    1.968401
          pa |   3.198289   .4170934     7.67   0.000     2.380801    4.015778
          mo |   2.365593   .2710986     8.73   0.000      1.83425    2.896937
------------------------------------------------------------------------------
The sign of the estimated standard deviations is irrelevant: interpret them as
being positive
```

A.12.18. *Model B.9* – Income, Age, Single, Female and Children

Table A.12.18.1. *Model B.9* – Income, Age, Single, Female and Children

```
Mixed logit model                                 Number of obs   =      11380
                                                  LR chi2(5)      =     698.66
Log likelihood = -2586.9243                       Prob > chi2     =     0.0000
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Mean						
p1000	-.220397	.0101966	-21.61	0.000	-.240382	-.200412
femaleSA	.1801646	.2638824	0.68	0.495	-.3370355	.6973646
femaleWC	-.3479536	.2947852	-1.18	0.238	-.925722	.2298149
femaleFC	-.5368811	.3597864	-1.49	0.136	-1.24205	.1682873
femalePA	-.2357052	.6302945	-0.37	0.708	-1.47106	.9996494
femaleMO	-.1890896	.4644191	-0.41	0.684	-1.099334	.721155
childrenSA	-.0909577	.2721664	-0.33	0.738	-.624394	.4424787
childrenWC	-.605406	.3273796	-1.85	0.064	-1.247058	.0362463
childrenFC	.2745432	.3883422	0.71	0.480	-.4865936	1.03568
childrenMO	-.2557914	.5196562	-0.49	0.623	-1.274299	.7627161
childrenPA	-.3218319	.5736345	-0.56	0.575	-1.446135	.8024711
sa_inc3	.0063367	.3024831	0.02	0.983	-.5865193	.5991928
fc_inc3	.3372969	.4056579	0.83	0.406	-.457778	1.132372
wc_inc3	1.033631	.3679687	2.81	0.005	.3124253	1.754836
mo_inc3	-.1096397	.5398701	-0.20	0.839	-1.167766	.9484862
pa_inc3	.2896684	.6438659	0.45	0.653	-.9722856	1.551622
sa_nonInc	-1.140715	.4431486	-2.57	0.010	-2.00927	-.2721599
fc_nonInc	-.7659795	.572852	-1.34	0.181	-1.888749	.3567898
wc_nonInc	-.8369022	.4958371	-1.69	0.091	-1.808725	.1349205
mo_nonInc	-3.1943	1.140825	-2.80	0.005	-5.430275	-.9583243
pa_nonInc	-1.522231	1.12595	-1.35	0.176	-3.729052	.6845895
sa_age	-.0276973	.0106902	-2.59	0.010	-.0486496	-.0067449
fc_age	.0211555	.0168493	1.26	0.209	-.0118685	.0541796
wc_age	.0153362	.012833	1.20	0.232	-.0098161	.0404885
mo_age	.0412305	.0191139	2.16	0.031	.0037679	.0786931
pa_age	.012563	.0301801	0.42	0.677	-.046589	.071715
sa_tail	-.4465905	.1175884	-3.80	0.000	-.6770595	-.2161215
fc_tail	-1.409065	.1944567	-7.25	0.000	-1.790193	-1.027937
wc_tail	-.7001039	.1522529	-4.60	0.000	-.9985141	-.4016937
sa	4.24395	.6270329	6.77	0.000	3.014988	5.472912
fc	1.352996	1.007176	1.34	0.179	-.6210317	3.327025
wc	2.520255	.746319	3.38	0.001	1.057497	3.983013
pa	-2.048103	2.037356	-1.01	0.315	-6.041248	1.945042
mo	1.258962	1.11404	1.13	0.258	-.9245167	3.442441
SD						
sa	1.611091	.1309518	12.30	0.000	1.354431	1.867752
fc	1.876237	.1786408	10.50	0.000	1.526108	2.226367
wc	1.664036	.1621318	10.26	0.000	1.346263	1.981808
pa	3.25585	.420072	7.75	0.000	2.432524	4.079176
mo	2.367733	.281501	8.41	0.000	1.816001	2.919465

The sign of the estimated standard deviations is irrelevant: interpret them as being positive

A.13. STATA Do-Files

Below follow all the STATA Do-Files. They follow in the same order as the regression outputs did. Note that the Do-files for the regression outputs that did not allow for correlations in unobserved factors over choice scenarios are not included. They are exactly equal to the Do-files below except that the option “corr” is missing in the mixlogit command line.

A.13.1. STATA Do-File *Model 1* – Product Attribute Model

Table 13.1.1. STATA Do-File *Model 1* – Product Attribute Model

```
clear
use H:\Masteroppgave\RCData\RCdata.dta
* We create a new variable for group where we combine id and set to idset -
group(idset)
gen idset = 100*id+set

******************** fish  ************************
* Generate dummy variable for children. 1 = family have children under 18, 0
otherwise:
gen children = 0
replace children = 1 if q18_2 > 0


* Generate tail interactions with sa, fc and wc
gen sa_tail = sa*tail
gen fc_tail = fc*tail
gen wc_tail = wc*tail

* Four observations have missing values. We drop those:
drop if choice == 9

* Generate global random variables:
global randvars "sa fc wc pa mo"

* Define mixlogit model:
mixlogit y p1000 sa_tail fc_tail wc_tail, rand($randvars) group(idset) id(id)
nrep(500) corr
estimates store fish
test sa = wc
test sa = mo
test sa = pa
test wc = mo
test wc = pa
test mo = pa
test sa_tail = fc_tail
test sa_tail = wc_tail
test fc_tail = wc_tail
test sa + sa_tail = fc + fc_tail
test sa + sa_tail = wc + wc_tail
test fc + fc_tail = wc + wc_tail
mixlcov
mixlcov, sd
wtp p1000 sa fc wc mo pa sa_tail fc_tail wc_tail
************************** fish SLUTT **************************
```

A.13.2. STATA Do-File *Model 2* – Product Attribute and Consumer Characteristics Interaction Model

Table A.13.2.1. STATA Do-File *Model 2* – Product Attribute and Consumer Characteristics Interaction Model

```
clear
use H:\Masteroppgave\RCData\RCdata.dta
* We create a new variable for group where we combine id and set to idset -
group(idset)
gen idset = 100*id+set

******************* fish_inc3000_age_single  ***********************

* Generate dummy for "do no want to answer":
replace q20 = 0 if q20==4
replace q20 = 0 if q20==.
gen nonInc = 0
replace nonInc = 1 if q20 == 0

* Generate dummy for income group 3:
gen inc_3 = 0
replace inc_3 = 1 if q20 == 3

* Generate income variables for do not want to answer
gen sa_nonInc = sa*nonInc
gen fc_nonInc = fc*nonInc
gen wc_nonInc = wc*nonInc
gen mo_nonInc = mo*nonInc
gen pa_nonInc = pa*nonInc

* Generate income dummy for income group 3
gen sa_inc3 = sa*inc_3
gen fc_inc3 = fc*inc_3
gen wc_inc3 = wc*inc_3
gen mo_inc3 = mo*inc_3
gen pa_inc3 = pa*inc_3


* Generate age variables
gen sa_age = sa*age
gen fc_age = fc*age
gen mo_age = mo*age
gen wc_age = wc*age
gen pa_age = pa*age

* Generate single variable
gen single = 0
replace single = 1 if d3 == 1
gen sa_single = sa*single
gen fc_single = fc*single
gen mo_single = mo*single
gen wc_single = wc*single
gen pa_single = pa*single


* Generate tail interactions with sa, fc and wc
gen sa_tail = sa*tail
gen fc_tail = fc*tail
gen wc_tail = wc*tail

* Four observations have missing values. We drop those:
drop if choice == 9

* Generate global random variables:
global randvars "sa fc wc pa mo"
```

```
* Define mixlogit model:
mixlogit y p1000 sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3 sa_nonInc fc_nonInc
wc_nonInc mo_nonInc pa_nonInc sa_age fc_age wc_age mo_age pa_age sa_single
fc_single wc_single mo_single pa_single sa_tail fc_tail wc_tail, rand($randvars)
group(idset) id(id) nrep(500) corr
estimates store Model2_WTP
******************** TEST OVERALL SIGNIFICACE *****************
test sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3
test sa_nonInc fc_nonInc wc_nonInc mo_nonInc pa_nonInc
test sa_age fc_age wc_age mo_age pa_age
test sa_single fc_single wc_single mo_single pa_single
******************************** SINGLE TESTS *************************
test sa = wc
test sa = mo
test sa = pa
test wc = mo
test wc = pa
test mo = pa
**************************** INCOME TESTS ***************************
test sa+sa_inc3 = fc+fc_inc3
test sa+sa_inc3 = wc+wc_inc3
test sa+sa_inc3 = mo+mo_inc3
test sa+sa_inc3 = pa+pa_inc3
test fc+fc_inc3 = wc+wc_inc3
test fc+fc_inc3 = mo+mo_inc3
test fc+fc_inc3 = pa+pa_inc3
test wc+wc_inc3 = mo+mo_inc3
test wc+wc_inc3 = pa+pa_inc3
test mo+mo_inc3 = pa+pa_inc3
***************************** INCOME AGE TESTS ************************
test sa+sa_inc3+sa_age = fc+fc_inc3+fc_age
test sa+sa_inc3+sa_age = wc+wc_inc3+wc_age
test sa+sa_inc3+sa_age = mo+mo_inc3+mo_age
test sa+sa_inc3+sa_age = pa+pa_inc3+pa_age
test fc+fc_inc3+fc_age = wc+wc_inc3+wc_age
test fc+fc_inc3+fc_age = mo+mo_inc3+mo_age
test fc+fc_inc3+fc_age = pa+pa_inc3+pa_age
test wc+wc_inc3+wc_age = mo+mo_inc3+mo_age
test wc+wc_inc3+wc_age = pa+pa_inc3+pa_age
test mo+mo_inc3+mo_age = pa+pa_inc3+pa_age
***************************** INCOME SINGLE TESTS ************************
test sa+sa_inc3+sa_single = fc+fc_inc3+fc_single
test sa+sa_inc3+sa_single = wc+wc_inc3+wc_single
test sa+sa_inc3+sa_single = mo+mo_inc3+mo_single
test sa+sa_inc3+sa_single = pa+pa_inc3+pa_single
test fc+fc_inc3+fc_single = wc+wc_inc3+wc_single
test fc+fc_inc3+fc_single = mo+mo_inc3+mo_single
test fc+fc_inc3+fc_single = pa+pa_inc3+pa_single
test wc+wc_inc3+wc_single = mo+mo_inc3+mo_single
test wc+wc_inc3+wc_single = pa+pa_inc3+pa_single
test mo+mo_inc3+mo_single = pa+pa_inc3+pa_single

********************************* INCOME AGE SINGLE TESTS ******************
test sa+sa_inc3+sa_age+sa_single = fc+fc_inc3+fc_age+fc_single
test sa+sa_inc3+sa_age+sa_single = wc+wc_inc3+wc_age+wc_single
test sa+sa_inc3+sa_age+sa_single = mo+mo_inc3+mo_age+mo_single
test sa+sa_inc3+sa_age+sa_single = pa+pa_inc3+pa_age+pa_single
test fc+fc_inc3+fc_age+fc_single = wc+wc_inc3+wc_age+wc_single
test fc+fc_inc3+fc_age+fc_single = mo+mo_inc3+mo_age+mo_single
test fc+fc_inc3+fc_age+fc_single = pa+pa_inc3+pa_age+pa_single
test wc+wc_inc3+wc_age+wc_single = mo+mo_inc3+mo_age+mo_single
test wc+wc_inc3+wc_age+wc_single = pa+pa_inc3+pa_age+pa_single
test mo+mo_inc3+mo_age+mo_single = pa+pa_inc3+pa_age+pa_single

**************** ESTMATE WILLINGNESS TO PAY *****************************
wtp p1000 sa fc wc mo pa sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3 sa_nonInc
fc_nonInc wc_nonInc mo_nonInc pa_nonInc sa_age fc_age wc_age mo_age pa_age
```

```
sa_single fc_single wc_single mo_single pa_single sa_tail fc_tail wc_tail
wtp p1000 sa fc wc mo pa sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3 sa_age fc_age
wc_age mo_age pa_age sa_single fc_single wc_single mo_single pa_single sa_tail
fc_tail wc_tail

* nlcom
((_b[sa]+_b[fc]+_b[wc]+_b[mo]+_b[pa]+_b[sa_inc3]+_b[fc_inc3]+_b[wc_inc3]+_b[mo_inc3
]+_b[pa_inc3]+_b[sa_nonInc]+_b[fc_nonInc]+_b[wc_nonInc]+_b[mo_nonInc]+_b[pa_nonInc]
+_b[sa_age]+_b[fc_age]+_b[wc_age]+_b[mo_age]+_b[pa_age]+_b[sa_single]+_b[fc_single]
+_b[wc_single]+_b[mo_single]+_b[pa_single]+_b[sa_tail]+_b[fc_tail]+_b[wc_tail])/(_b
[p1000]))
mixlcov
mixlcov, sd


*************************** fish_inc3000_age_single SLUTT
***************************
```

A.13.3. STATA Do-File *Model 3* – Product Attribute and Full Set of Consumer Characteristics Interaction Model

Table A.13.3.1. STATA Do-File *Model 3* – Product Attribute and Full Set of Consumer Characteristics Interaction Model

```
clear
use H:\Masteroppgave\RCData\RCdata.dta
* We create a new variable for group where we combine id and set to idset -
group(idset)
gen idset = 100*id+set

******************* fish_inc3000_female_children_age_single_educDummy
************************
* Generate dummy variable for children. 1 = family have children udder 18, 0
otherwise:
gen children = 0
replace children = 1 if q18_2 > 0

* Generate dummy for "do no want to answer":
replace q20 = 0 if q20==4
replace q20 = 0 if q20==.
gen nonInc = 0
replace nonInc = 1 if q20 == 0

* Generate dummy for income group 3:
gen inc_3 = 0
replace inc_3 = 1 if q20 == 3

* Generate income variables for do not want to answer
gen sa_nonInc = sa*nonInc
gen fc_nonInc = fc*nonInc
gen wc_nonInc = wc*nonInc
gen mo_nonInc = mo*nonInc
gen pa_nonInc = pa*nonInc

* Generate income dummy for income group 3
gen sa_inc3 = sa*inc_3
gen fc_inc3 = fc*inc_3
gen wc_inc3 = wc*inc_3
gen mo_inc3 = mo*inc_3
gen pa_inc3 = pa*inc_3

* Generate children variable
gen childrenSA = children*sa
gen childrenWC = children*wc
gen childrenFC = children*fc
gen childrenPA = children*pa
gen childrenMO = children*mo

* Generate gender variables
gen femaleSA = female*sa
gen femaleWC = female*wc
gen femaleFC = female*fc
gen femalePA = female*pa
gen femaleMO = female*mo

* Generate age variables
gen sa_age = sa*age
gen fc_age = fc*age
gen mo_age = mo*age
gen wc_age = wc*age
gen pa_age = pa*age

* Generate single variable
gen single = 0
```

```
replace single = 1 if d3 == 1
gen sa_single = sa*single
gen fc_single = fc*single
gen mo_single = mo*single
gen wc_single = wc*single
gen pa_single = pa*single

* Generate education dummy for university degree :
gen educUNI = 0
replace educUNI = 1 if d7 > 4
gen sa_educUNI = sa*educUNI
gen fc_educUNI = fc*educUNI
gen mo_educUNI = mo*educUNI
gen wc_educUNI = wc*educUNI
gen pa_educUNI = pa*educUNI

* Generate tail interactions with sa, fc and wc
gen sa_tail = sa*tail
gen fc_tail = fc*tail
gen wc_tail = wc*tail

* Four observations have missing values. We drop those:
drop if choice == 9

* Generate global random variables:
global randvars "sa fc wc pa mo"

* Define mixlogit model:
mixlogit y p1000 femaleSA femaleWC femaleFC femalePA femaleMO childrenSA childrenWC
childrenFC childrenMO childrenPA sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3 sa_nonInc
fc_nonInc wc_nonInc mo_nonInc pa_nonInc sa_age fc_age wc_age mo_age pa_age
sa_single fc_single wc_single mo_single pa_single sa_educUNI fc_educUNI wc_educUNI
mo_educUNI pa_educUNI sa_tail fc_tail wc_tail, rand($randvars) group(idset) id(id)
nrep(500) corr
estimates store fish_inc3000_female_children_age_single
test femaleSA femaleWC femaleFC femalePA femaleMO
test childrenSA childrenWC childrenFC childrenMO childrenPA
test sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3
test sa_nonInc fc_nonInc wc_nonInc mo_nonInc pa_nonInc
test sa_age fc_age wc_age mo_age pa_age
test sa_single fc_single wc_single mo_single pa_single
test sa_educUNI fc_educUNI wc_educUNI mo_educUNI pa_educUNI

**************************** fish_inc3000_female_children_age_single_educDummy SLUTT
***************************
```

A.13.4. STATA Do-File *Model 4* – Income as Dummies for all Income Groups

Table A.13.4.1. STATA Do-File *Model 4* – Income as Dummies for all Income Groups

```
clear
use H:\Masteroppgave\RCData\RCdata.dta
* We create a new variable for group where we combine id and set to idset -
group(idset)
gen idset = 100*id+set

************************* fish_inc_dummy ********************************
* Generate dummy for "do no want to answer":
replace q20 = 0 if q20==4
replace q20 = 0 if q20==.
gen nonInc = 0
replace nonInc = 1 if q20 == 0

* Generate dummy for income group 1:
gen inc_1 = 0
replace inc_1 = 1 if q20 == 1

*Generate dummy for income group 2:
gen inc_2 = 0
replace inc_2 = 1 if q20 == 2

*Generate dummy for income group 3:
gen inc_3 = 0
replace inc_3 = 1 if q20 == 3


* Generate income variablesgen sa_no_answ = sa*no_answ
gen sa_nonInc = sa*nonInc
gen fc_nonInc = fc*nonInc
gen wc_nonInc = wc*nonInc
gen mo_nonInc = mo*nonInc
gen pa_nonInc = pa*nonInc

* Generate income dummy for group 1
*gen sa_inc_1 = sa*inc_1
*gen fc_inc_1 = fc*inc_1
*gen wc_inc_1 = wc*inc_1
*gen mo_inc_1 = mo*inc_1
*gen pa_inc_1 = pa*inc_1

* Generate income dummy for group 2
gen sa_inc_2 = sa*inc_2
gen fc_inc_2 = fc*inc_2
gen wc_inc_2 = wc*inc_2
gen mo_inc_2 = mo*inc_2
gen pa_inc_2 = pa*inc_2

* Generate income dummy for group 3
gen sa_inc_3 = sa*inc_3
gen fc_inc_3 = fc*inc_3
gen wc_inc_3 = wc*inc_3
gen mo_inc_3 = mo*inc_3
gen pa_inc_3 = pa*inc_3

* Generate tail interactions with sa, fc and wc
gen sa_tail = sa*tail
gen fc_tail = fc*tail
gen wc_tail = wc*tail

* Four observations have missing values. We drop those:
drop if choice == 9

* Generate global random variables:
```

```
global randvars "sa fc wc pa mo"

* Define mixlogit model:
mixlogit y p1000 sa_inc_2 fc_inc_2 wc_inc_2 mo_inc_2 pa_inc_2 sa_inc_3 fc_inc_3
wc_inc_3 mo_inc_3 pa_inc_3 sa_nonInc fc_nonInc wc_nonInc mo_nonInc pa_nonInc
sa_tail fc_tail wc_tail, rand($randvars) group(idset) id(id) nrep(500) corr
estimates store fish_inc_dummy
test sa_inc_2 fc_inc_2 wc_inc_2 mo_inc_2 pa_inc_2
test sa_inc_3 fc_inc_3 wc_inc_3 mo_inc_3 pa_inc_3
test sa_nonInc fc_nonInc wc_nonInc mo_nonInc pa_nonInc
*************************** fish_inc_dummy SLUTT ***************************
```

A.13.5. STATA Do-File *Model 5* – Income as *Low* and *High*

Table A.13.5.1. STATA Do-File *Model 5* – Income as *Low* and *High*

```
clear
use H:\Masteroppgave\RCData\RCdata.dta
* We create a new variable for group where we combine id and set to idset -
group(idset)
gen idset = 100*id+set

************************* fish_inc_dummy_3000EUR *********************************
* Generate dummy for "do not want to answer":
replace q20 = 0 if q20==4
replace q20 = 0 if q20==.
gen nonInc = 0
replace nonInc = 1 if q20 == 0

* Generate dummy for income group :
gen inc_3 = 0
replace inc_3 = 1 if q20 == 3

* Generate income variablesgen sa_no_answ = sa*no_answ
gen sa_nonInc = sa*nonInc
gen fc_nonInc = fc*nonInc
gen wc_nonInc = wc*nonInc
gen mo_nonInc = mo*nonInc
gen pa_nonInc = pa*nonInc


* Generate income dummy for group 3
gen sa_inc_3 = sa*inc_3
gen fc_inc_3 = fc*inc_3
gen wc_inc_3 = wc*inc_3
gen mo_inc_3 = mo*inc_3
gen pa_inc_3 = pa*inc_3

* Generate tail interactions with sa, fc and wc
gen sa_tail = sa*tail
gen fc_tail = fc*tail
gen wc_tail = wc*tail

* Four observations have missing values. We drop those:
drop if choice == 9

* Generate global random variables:
global randvars "sa fc wc pa mo"

* Define mixlogit model:
mixlogit y p1000 sa_inc_3 fc_inc_3 wc_inc_3 mo_inc_3 pa_inc_3 sa_nonInc fc_nonInc
wc_nonInc mo_nonInc pa_nonInc sa_tail fc_tail wc_tail, rand($randvars) group(idset)
id(id) nrep(500) corr
estimates store fish_inc_dummy_3000EUR
test sa_inc_3 fc_inc_3 wc_inc_3 mo_inc_3 pa_inc_3
test sa_nonInc fc_nonInc wc_nonInc mo_nonInc pa_nonInc
************************** fish_inc SLUTT **************************
```

A.13.6. STATA Do-File *Model 6* – Income and Education

Table A.13.6.1. STATA Do-File *Model 6* – Income and Education

```
clear
use H:\Masteroppgave\RCData\RCdata.dta
* We create a new variable for group where we combine id and set to idset -
group(idset)
gen idset = 100*id+set

******************* fish_inc3000_educDummy  ***********************
* Generate dummy variable for children. 1 = family have children under 18, 0
otherwise:
gen children = 0
replace children = 1 if q18_2 > 0

* Generate dummy for "do not want to answer":
replace q20 = 0 if q20==4
replace q20 = 0 if q20==.
gen nonInc = 0
replace nonInc = 1 if q20 == 0

* Generate dummy for income group 3:
gen inc_3 = 0
replace inc_3 = 1 if q20 == 3

* Generate income variables for do not want to answer
gen sa_nonInc = sa*nonInc
gen fc_nonInc = fc*nonInc
gen wc_nonInc = wc*nonInc
gen mo_nonInc = mo*nonInc
gen pa_nonInc = pa*nonInc

* Generate income dummy for income group 3
gen sa_inc3 = sa*inc_3
gen fc_inc3 = fc*inc_3
gen wc_inc3 = wc*inc_3
gen mo_inc3 = mo*inc_3
gen pa_inc3 = pa*inc_3


* Generate education dummy for university degree :
gen educUNI = 0
replace educUNI = 1 if d7 > 4
gen sa_educUNI = sa*educUNI
gen fc_educUNI = fc*educUNI
gen mo_educUNI = mo*educUNI
gen wc_educUNI = wc*educUNI
gen pa_educUNI = pa*educUNI

* Generate tail interactions with sa, fc and wc
gen sa_tail = sa*tail
gen fc_tail = fc*tail
gen wc_tail = wc*tail

* Four observations have missing values. We drop those:
drop if choice == 9

* Generate global random variables:
global randvars "sa fc wc pa mo"

* Define mixlogit model:
mixlogit y p1000 sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3 sa_nonInc fc_nonInc
wc_nonInc mo_nonInc pa_nonInc sa_educUNI fc_educUNI wc_educUNI mo_educUNI
pa_educUNI sa_tail fc_tail wc_tail, rand($randvars) group(idset) id(id) nrep(500)
corr
estimates store fish_inc3000_female_children_age_single
```

```
test sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3
test sa_nonInc fc_nonInc wc_nonInc mo_nonInc pa_nonInc
test sa_educUNI fc_educUNI wc_educUNI mo_educUNI pa_educUNI

*************************** fish_inc3000_educDummy SLUTT
***************************
```

A.13.7. STATA Do-File *Model 7* – Income and Age

Table A.13.7.1. STATA Do-File *Model 7* – Income and Age

```
clear
use H:\Masteroppgave\RCData\RCdata.dta
* We create a new variable for group where we combine id and set to idset -
group(idset)
gen idset = 100*id+set

******************* fish_inc3000_age ***********************
* Generate dummy variable for children. 1 = family have children under 18, 0
otherwise:
gen children = 0
replace children = 1 if q18_2 > 0

* Generate dummy for "do not want to answer":
replace q20 = 0 if q20==4
replace q20 = 0 if q20==.
gen nonInc = 0
replace nonInc = 1 if q20 == 0

* Generate dummy for income group 3:
gen inc_3 = 0
replace inc_3 = 1 if q20 == 3

* Generate income variables for do not want to answer
gen sa_nonInc = sa*nonInc
gen fc_nonInc = fc*nonInc
gen wc_nonInc = wc*nonInc
gen mo_nonInc = mo*nonInc
gen pa_nonInc = pa*nonInc

* Generate income dummy for income group 3
gen sa_inc3 = sa*inc_3
gen fc_inc3 = fc*inc_3
gen wc_inc3 = wc*inc_3
gen mo_inc3 = mo*inc_3
gen pa_inc3 = pa*inc_3


* Generate age variables
gen sa_age = sa*age
gen fc_age = fc*age
gen mo_age = mo*age
gen wc_age = wc*age
gen pa_age = pa*age


* Generate tail interactions with sa, fc and wc
gen sa_tail = sa*tail
gen fc_tail = fc*tail
gen wc_tail = wc*tail

* Four observations have missing values. We drop those:
drop if choice == 9

* Generate global random variables:
global randvars "sa fc wc pa mo"

* Define mixlogit model:
mixlogit y p1000 sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3 sa_nonInc fc_nonInc
wc_nonInc mo_nonInc pa_nonInc sa_age fc_age wc_age mo_age pa_age sa_single sa_tail
fc_tail wc_tail, rand($randvars) group(idset) id(id) nrep(500) corr
estimates store fish_inc3000_female_children_age_single
test sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3
test sa_nonInc fc_nonInc wc_nonInc mo_nonInc pa_nonInc
```

```
test sa_age fc_age wc_age mo_age pa_age

*************************** fish_inc3000_age_SLUTT
```

A.13.8. STATA Do-File *Model 8* – Income, Age, Single and Female

Table A.13.8.1. STATA Do-File *Model 8* – Income, Age, Single and Female

```
clear
use H:\Masteroppgave\RCData\RCdata.dta
* We create a new variable for group where we combine id and set to idset -
group(idset)
gen idset = 100*id+set

******************* fish_inc3000_female_age_single ***********************
* Generate dummy variable for children. 1 = family have children under 18, 0
otherwise:
gen children = 0
replace children = 1 if q18_2 > 0

* Generate dummy for "do not want to answer":
replace q20 = 0 if q20==4
replace q20 = 0 if q20==.
gen nonInc = 0
replace nonInc = 1 if q20 == 0

* Generate dummy for income group 3:
gen inc_3 = 0
replace inc_3 = 1 if q20 == 3

* Generate income variables for do not want to answer
gen sa_nonInc = sa*nonInc
gen fc_nonInc = fc*nonInc
gen wc_nonInc = wc*nonInc
gen mo_nonInc = mo*nonInc
gen pa_nonInc = pa*nonInc

* Generate income dummy for income group 3
gen sa_inc3 = sa*inc_3
gen fc_inc3 = fc*inc_3
gen wc_inc3 = wc*inc_3
gen mo_inc3 = mo*inc_3
gen pa_inc3 = pa*inc_3


* Generate gender variables
gen femaleSA = female*sa
gen femaleWC = female*wc
gen femaleFC = female*fc
gen femalePA = female*pa
gen femaleMO = female*mo

* Generate age variables
gen sa_age = sa*age
gen fc_age = fc*age
gen mo_age = mo*age
gen wc_age = wc*age
gen pa_age = pa*age

* Generate single variable
gen single = 0
replace single = 1 if d3 == 1
gen sa_single = sa*single
gen fc_single = fc*single
gen mo_single = mo*single
gen wc_single = wc*single
gen pa_single = pa*single


* Generate tail interactions with sa, fc and wc
gen sa_tail = sa*tail
```

```
gen fc_tail = fc*tail
gen wc_tail = wc*tail

* Four observations have missing values. We drop those:
drop if choice == 9

* Generate global random variables:
global randvars "sa fc wc pa mo"

* Define mixlogit model:
mixlogit y p1000 femaleSA femaleWC femaleFC femalePA femaleMO sa_inc3 fc_inc3
wc_inc3 mo_inc3 pa_inc3 sa_nonInc fc_nonInc wc_nonInc mo_nonInc pa_nonInc sa_age
fc_age wc_age mo_age pa_age sa_single fc_single wc_single mo_single pa_single
sa_tail fc_tail wc_tail, rand($randvars) group(idset) id(id) nrep(500) corr
estimates store fish_inc3000_female_children_age_single
test femaleSA femaleWC femaleFC femalePA femaleMO
test sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3
test sa_nonInc fc_nonInc wc_nonInc mo_nonInc pa_nonInc
test sa_age fc_age wc_age mo_age pa_age
test sa_single fc_single wc_single mo_single pa_single

*************************** fish_inc3000_female_age_single SLUTT
***************************
```

A.13.9. STATA Do-File *Model 9* – Income, Age, Single, Female and Children

Table A.13.9.1. STATA Do-File *Model 9* – Income, Age, Single, Female and Children

```
clear
use H:\Masteroppgave\RCData\RCdata.dta
* We create a new variable for group where we combine id and set to idset -
group(idset)
gen idset = 100*id+set

******************* fish_inc3000_female_children_age_single_educDummy
***********************
* Generate dummy variable for children. 1 = family have children under 18, 0
otherwise:
gen children = 0
replace children = 1 if q18_2 > 0

* Generate dummy for "do not want to answer":
replace q20 = 0 if q20==4
replace q20 = 0 if q20==.
gen nonInc = 0
replace nonInc = 1 if q20 == 0

* Generate dummy for income group 3:
gen inc_3 = 0
replace inc_3 = 1 if q20 == 3

* Generate income variables for do not want to answer
gen sa_nonInc = sa*nonInc
gen fc_nonInc = fc*nonInc
gen wc_nonInc = wc*nonInc
gen mo_nonInc = mo*nonInc
gen pa_nonInc = pa*nonInc

* Generate income dummy for income group 3
gen sa_inc3 = sa*inc_3
gen fc_inc3 = fc*inc_3
gen wc_inc3 = wc*inc_3
gen mo_inc3 = mo*inc_3
gen pa_inc3 = pa*inc_3

* Generate children variable
gen childrenSA = children*sa
gen childrenWC = children*wc
gen childrenFC = children*fc
gen childrenPA = children*pa
gen childrenMO = children*mo

* Generate gender variables
gen femaleSA = female*sa
gen femaleWC = female*wc
gen femaleFC = female*fc
gen femalePA = female*pa
gen femaleMO = female*mo

* Generate age variables
gen sa_age = sa*age
gen fc_age = fc*age
gen mo_age = mo*age
gen wc_age = wc*age
gen pa_age = pa*age

* Generate single variable
gen single = 0
replace single = 1 if d3 == 1
gen sa_single = sa*single
gen fc_single = fc*single
```

```
gen mo_single = mo*single
gen wc_single = wc*single
gen pa_single = pa*single


* Generate tail interactions with sa, fc and wc
gen sa_tail = sa*tail
gen fc_tail = fc*tail
gen wc_tail = wc*tail

* Four observations have missing values. We drop those:
drop if choice == 9

* Generate global random variables:
global randvars "sa fc wc pa mo"

* Define mixlogit model:
mixlogit y p1000 femaleSA femaleWC femaleFC femalePA femaleMO childrenSA childrenWC
childrenFC childrenMO childrenPA sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3 sa_nonInc
fc_nonInc wc_nonInc mo_nonInc pa_nonInc sa_age fc_age wc_age mo_age pa_age
sa_single fc_single wc_single mo_single pa_single sa_tail fc_tail wc_tail,
rand($randvars) group(idset) id(id) nrep(500) corr
estimates store fish_inc3000_female_children_age_single
test femaleSA femaleWC femaleFC femalePA femaleMO
test childrenSA childrenWC childrenFC childrenMO childrenPA
test sa_inc3 fc_inc3 wc_inc3 mo_inc3 pa_inc3
test sa_nonInc fc_nonInc wc_nonInc mo_nonInc pa_nonInc
test sa_age fc_age wc_age mo_age pa_age
test sa_single fc_single wc_single mo_single pa_single

*************************** fish_inc3000_female_children_age_single_educDummy SLUTT
***************************
```

A.13.10. STATA Do-File to Convert the Dataset to a Cross Section Dataset

Table A.13.10.1. Do-File to Convert the Dataset to a Cross Section Dataset

```
clear
use H:\Masteroppgave\RCData\RCdataCross\RCDataCross
*drop block set alt choice y sa fc wc pa mo tail p300 p1000
sort id
quietly by id: gen dup = cond(_N==1,0,_n)
drop if dup >1

* Generate dummy variable for children. 1 = family have children under 18, 0
otherwise:
gen children = 0
replace children = 1 if q18_2 > 0

* Generate single variable
gen single = 0
replace single = 1 if d3 == 1

* Generate inc3000 variable
gen inc_3 = 0
replace inc_3 = 1 if q20 == 3

* Generate educUni *****
gen educUNI = 0
replace educUNI = 1 if d7 > 4

* young
gen young = 0
replace young = 1 if age < 36

* middle
gen middle = 0
replace middle = 1 if age > 35 & age < 56
gen midAge = age if middle == 1

* old
gen old = 0
replace old = 1 if age > 55
```

A.13.11. STATA Do-File Unpaired Unequal Welch Tests

Table A.13.11.1. STATA Do-File Unpaired Unequal Welch Tests

```
clear
use H:\Masteroppgave\RCData\RCdataCross\RCDataCross
*drop block set alt choice y sa fc wc pa mo tail p300 p1000
sort id
quietly by id: gen dup = cond(_N==1,0,_n)
drop if dup >1

* Generelle sammenligninger av svar fra spørreundersøkelsen
gen q17_1xx = q17_1 if q17_1!=11
gen q17_2xx = q17_2 if q17_2!=11
ttest q17_1xx=q17_2xx, unpaired unequal welch
gen q6_1xx = q6_1 if q6_1!=11
gen q6_2xx = q6_2 if q6_2!=11
ttest q6_1xx=q6_2xx, unpaired unequal welch
gen q6_6xx = q6_6 if q6_6!=11
ttest q6_2xx=q6_6xx, unpaired unequal welch
gen q6_7xx = q6_7 if q6_7!=11
ttest q6_2xx=q6_7xx, unpaired unequal welch
gen q6_8xx = q6_8 if q6_8!=11
ttest q6_2xx=q6_8xx, unpaired unequal welch
ttest q17_1xx=q17_2xx, unpaired unequal welch
gen q17_3xx = q17_3 if q17_3!=11
ttest q17_1xx=q17_3xx, unpaired unequal welch
gen q17_4xx = q17_4 if q17_4!=11
ttest q17_3xx=q17_4xx, unpaired unequal welch
gen q17_5xx = q17_5 if q17_5!=11
gen q17_7xx = q17_7 if q17_7!=11
ttest q17_5xx=q17_7xx, unpaired unequal welch
gen q17_8xx = q17_8 if q17_8!=11
ttest q17_8xx=q17_7xx, unpaired unequal welch
ttest q17_7xx=q17_8xx, unpaired unequal welch
ttest q17_7=q17_8 if q17_7!=11 & q17_8!=11
ttest q17_7xx==q17_8xx, unpaired unequal welch
ttest q17_7xx==q17_8xx, unpaired unequal welch
ttest q17_7xx==q17_8xx, unpaired unequal
gen q17_6xx = q17_6 if q17_6!=11
ttest q17_6xx==q17_8xx, unpaired unequal welch
gen q17_9xx = q17_9 if q17_9!=11
gen q17_10xx = q17_10 if q17_10!=11
ttest q17_9xx==q17_10xx, unpaired unequal welch
```

References

Agresti, A. (2007). *An introduction to categorical data analysis*. Hoboken, N.J.: John Wiley & Sons, Inc.

Alfnes, F. & Rickertsen, K. (2011). Nonmarket valuation: Experimental methods. In Lusk, J. L., Roosen, J. & Shogren, J. F. (eds) *The Oxford handbook of the economics of food consumption and policy*, pp. 215-242. New York: Oxford University Press Inc.

Coles, S. (2011). *An introduction to statistical modeling of extreme values*. London: Springer.

Corrigan, J. R. & Rousu, M. C. (2008). Testing whether field auction experiments are demand revealing in practice. *Journal of Agricultural and Resource Economics*, 33 (2): 290-301.

Hole, A. R. (2007a). A comparison of approaches to estimating confidence intervals for willingness to pay measures. *Health Economics*, 16 (8): 827-840.

Hole, A. R. (2007b). Fitting mixed logit models by using maximum simulated likelihood. *The Stata Journal*, 7 (3): 388 - 401.

James, J. S., Rickard, B. J. & Rossman, W. J. (2009). Product differentiation and market segmentation in applesauce: Using a choice experiment to assess the value of organic, local, and nutrition attributes. *Agricultural and Resource Economics Review*, 38 (3): 357-370.

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74 (2): 132-157.

Loureiro, M. L. & Umberger, W. J. (2004). A choice experiment model for beef attributes: What consumer preferences tell us. *Selected paper presented at the American Agricultural Economics Association annual meetings, Denver, Colorado August 1-4, 2004*.

Tonsor, G. T., Olynk, N. & Wolf, C. (2009). Consumer preferences for animal welfare attributes: The case of gestation crates. *Journal of Agricultural and Applied Economics*, 41 (3): 713–730.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge: Cambridge University Press.

Wolf, C. A., Tonsor, G. T. & Olynk, N. J. (2011). Understanding US consumer demand for milk production attributes. *Journal of Agricultural and Resource Economics*, 36 (2): 326-342.

Appendix II

The survey questions answered by the participants are presented in this appendix.

FISH IN FRANCE MAY2008

Information from the database (D)

D1. What is your gender?

Male .... ☐1
Female .... ☐2

D2. How old are you?

Date of birth: ________

D3. Family status?

Single (with or without children) .... ☐1
Married or cohabiting (with or without children) .... ☐2
Living in collective home (residence for students
or elderly) .... ☐3

D7. Education level

No diploma .... ☐1
Brevet des collèges... ☐2
CAP ou BEP.. ☐3
Baccaulauréat (BAC) .... ☐4
BAC + 2 or 3 .... ☐5
BAC +4 or 5 .... ☐6
BAC + 6 .... ☐7

Questions to be asked at the recruitment stage (R)

R1. How often would you say you eat the following items for lunch or dinner at home?
Check one box per line.

		Twice a week or more	Once a week	2-3 times a month	Once a month	Every second month	2-4 times a year	More seldom	Never
(R1.1)	Poultry..................	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
(R1.2)	Beef......................	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
(R1.3)	Pork......................	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
(R1.4)	Lamb	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
(R1.5)	Fish.......................	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8

R2. Who in your household is deciding what food to shop?
Check <u>one or more</u> boxes.

(R2.1) Yourself.. ☐
(R2.1) Your partner .... ☐
(R2.1) Someone else... ☐

R3. How often would you say you buy the following fresh grocery products YOURSELF?
Check one box per line.

		Twice a week or more	Once a week	2-3 times a month	Once a month	Every second month	2-4 times a year	More seldom	Never
(R3.1)	Poultry..................	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
(R3.2)	Beef......................	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
(R3.3)	Pork......................	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
(R3.4)	Lamb	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
(R3.5)	Fresh Fish	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8

R4. How often would you say you eat the following items at home?
Check one box per line.

		Twice a week or more	Once a week	2-3 times a month	Once a month	Every second month	2-4 times a year	More seldom	Never
(R4.1)	Fish in a ready-made meal	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
(R4.2)	Canned fish	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
(R4.3)	Frozen fish............	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
(R4.4)	Fresh fish.............	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8

If they eat fish less than once a month and buy fresh fish less than every second month, then STOP.

FISH IN FRANCE

Thank you for taking part in this study of French consumers fish habits and preferences. The focus of this study is home consumption of fresh fish, and if noting else is specified we are asking about fresh fish for home consumption.

Fish likings

1. What is your favourite fish?______________________

2. On a scale from 1 to 10, where 1 means dislike very much and 10 means just as good as my favourite fish, how would you rate the following fish types? If you have never tasted a fish or do not remember how it tasted, please check Do not know.
Check one box per line.

		Dislike very much 1	2	3	4	5	6	7	8	9	Just as good my favourite fish 10	Do not know 11
(2.1)	Salmon (non-smoked)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(2.2)	Cod	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(2.3)	Monk	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(2.4)	Pangasius	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(2.5)	Mackerel	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(2.6)	Whiting	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(2.7)	Saithe	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(2.8)	Nile perce	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Buying fish

3. On a scale from 1 to 10, where 1 means you very strongly DISAGREE and 10 means you very strongly AGREE, how much do you agree with the following statements?
Check one box per line.

		Very strongly disagree 1	2	3	4	5	6	7	8	9	Very strongly agree 10
(3.1)	I have always decided which type of fish to buy before I go to the store	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(3.2)	I prefer to buy pre-packed filets of fish	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(3.3)	I most often choose the type of fish that is discounted	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(3.4)	It is important to know where the fish has been caught/produced	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(3.5)	I always ask how fresh the fish is before I make a decision	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

4. In what kind of store do you normally purchase the salmon, cod, monk and pangasius for consumption in your household?
Check one box per column.

	Salmon	Cod	Monk	Pangasius
Fish shop	☐1	☐1	☐1	☐1
Super- or Hypermarket..................	☐2	☐2	☐2	☐2
Traditional wet market	☐3	☐3	☐3	☐3
Other...	☐4	☐4	☐4	☐4
Don't know / Can't remember	☐5	☐5	☐5	☐5
Never bought.................................	☐6	☐6	☐6	☐6

5. In what form do you usually buy salmon, cod, monk and pangasius for home consumption?
Check one box per column.

	Salmon	Cod	Monk	Pangasius
Fresh whole fish	☐1	☐1	☐1	☐1
Fresh filets.....................................	☐2	☐2	☐2	☐2
Frozen filets..................................	☐3	☐3	☐3	☐3
Other...	☐4	☐4	☐4	☐4
Don't know/ Can't remember	☐5	☐5	☐5	☐5
Never bought.................................	☐6	☐6	☐6	☐6

Origin of the fish

6. On a scale from 1 to 10, where 1 means you very strongly DISAGREE and 10 means you very strongly AGREE, how much do you agree with following statements about the origin of fish?
Check one box per line.

	Very strongly disagree 1	2	3	4	5	6	7	8	9	Very strongly agree 10	Do not know 11
I have a very positive view of fresh farmed fish from:											
(6.1) France	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(6.2) Countries in Northern Europe	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(6.3) Countries in Southern Europe	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(6.4) Other developed countries..................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(6.5) Third world countries..........................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
I have a very positive view of fresh wild fish from:											
(6.6) The Atlantic North	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(6.7) The Mediterranean	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(6.8) The Pacific	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Last time you ate various types of fish

7. Do you remember when the last time you ate fish (whatever the fish and the place)?
Check one box

Less than 1 week ago	☐1
1-2 weeks ago	☐2
2-4 weeks ago	☐3
5-12 weeks ago	☐4
More than 3 months ago	☐5
Can't remember	☐6

8. Do you remember when the last time you ate salmon, cod, monk and pangasius?
Check one box per column.

	Salmon	Cod	Monk	Pangasius
Less than 2 weeks ago	☐1	☐1	☐1	☐1
2-4 weeks ago	☐2	☐2	☐2	☐2
5-12 weeks ago	☐3	☐3	☐3	☐3
More than 3 months ago	☐4	☐4	☐4	☐4
Can't remember	☐5	☐5	☐5	☐5
Never tasted	☐6	☐6	☐6	☐6

9. Where did you last time eat salmon, cod, monk and pangasius?
Check one box per column.

	Salmon	Cod	Monk	Pangasius
At home	☐1	☐1	☐1	☐1
At friends or family	☐2	☐2	☐2	☐2
At a brasserie or restaurant	☐3	☐3	☐3	☐3
At a cafeteria or staff canteen	☐4	☐4	☐4	☐4
Other	☐5	☐5	☐5	☐5
Can't remember	☐6	☐6	☐6	☐6
Never tasted	☐7	☐7	☐7	☐7

10. How often would you say you have salmon, cod, monk and pangasius at home?
Check one box per line.

	Twice a week or more	Once a week	2-3 times a month	Once a month	Every second month	2-4 times a year	More seldom	Never
Salmon	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
Cod	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
Monk	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
Pangasius	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8

11. Which of the following statements best describe your fish consumption at home?
Check one box.

I eat fish at home mainly on Monday to Thursday	☐1
I eat fish at home mainly Fridays, Saturdays and/or Sundays	☐2
I eat fish at home regularly all days of the week (Monday to Sunday)	☐3
I rarely eat fish at home	☐4

Attitudes towards fresh salmon

12. On a scale from 1 to 10, where 1 means you very strongly DISAGREE and 10 means you very strongly AGREE, how much do you agree with following statements about FRESH SALMON?
Check one box per line.

		Very strongly disagree 1	2	3	4	5	6	7	8	9	Very strongly agree 10	Do not know 11
(12.1)	**Salmon** tastes good	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(12.2)	Salmon gives you good value for money	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(12.3)	It is easy to make different dishes with salmon	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(12.4)	Salmon is healthy food	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(12.5)	Salmon is fat food	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(12.6)	Salmon is safe to eat	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(12.7)	Salmon is easy to prepare	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(12.8)	Salmon is an expensive fish	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(12.9)	The whole family likes salmon	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(12.10)	Salmon can be served on special occasions	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(12.11)	Salmon is a Monday-to-Friday fish	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Attitudes towards fresh cod

13. On a scale from 1 to 10, where 1 means you very strongly DISAGREE and 10 means you very strongly AGREE, how much do you agree with following statements about FRESH COD?
Check one box per line.

		Very strongly disagree 1	2	3	4	5	6	7	8	9	Very strongly agree 10	Do not know 11
(13.1)	**Cod** tastes good	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(13.2)	Cod gives you good value for money	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(13.3)	It is easy to make different dishes with cod	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(13.4)	Cod is healthy food	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(13.5)	Cod is fat food	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(13.6)	Cod is safe to eat	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(13.7)	Cod is easy to prepare	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(13.8)	Cod is an expensive fish	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(13.9)	The whole family likes cod	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(13.10)	Cod can be served on special occasions	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(13.11)	Cod is a Monday-to-Friday fish	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Attitudes towards fresh monk

14. On a scale from 1 to 10, where 1 means you very strongly DISAGREE and 10 means you very strongly AGREE, how much do you agree with following statements about FRESH MONK?
Check one box per line.

		Very strongly disagree 1	2	3	4	5	6	7	8	Very strongly agree 9	10	Do not know 11
(14.1)	**<u>Monk</u>** tastes good..............................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(14.2)	Monk gives you good value for money..	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(14.3)	It is easy to make different dishes with monk	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(14.4)	Monk is healthy food	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(14.5)	Monk is fat food................................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(14.6)	Monk is safe to eat	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(14.7)	Monk is easy to prepare	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(14.8)	Monk is an expensive fish	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(14.9)	The whole family likes monk.............	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(14.10)	Monk can be served on special occasions	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(14.11)	Monk is a Monday-to-Friday fish	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Attitudes towards Pangasius

15. On a scale from 1 to 10, where 1 means you very strongly DISAGREE and 10 means you very strongly AGREE, how much do you agree with following statements about PANGASIUS?
Check one box per line.

		Very strongly disagree 1	2	3	4	5	6	7	8	Very strongly agree 9	10	Do not know 11
(15.1)	**<u>Pangasius</u>** tastes good........................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(15.2)	Pangasius gives you good value for money..	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(15.3)	It is easy to make different dishes with Pangasius..................................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(15.4)	Pangasius is healthy food...................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(15.5)	Pangasius is fat food..........................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(15.6)	Pangasius is safe to eat......................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(15.7)	Pangasius is easy to prepare...............	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(15.8)	Pangasius is an expensive fish	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(15.9)	The whole family likes Pangasius.......	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(15.10)	Pangasius can be served on special occasions	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(15.11)	Pangasius is a Monday-to-Friday fish.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Fish prices

16. What is your best guess at the average market price for one kilogram of fresh salmon, cod, monk and pangasius fillets this week?
Check one box per line.

		Price per kilogram fillet											
		€3	€6	€9	€12	€15	€18	€21	€24	€27	€30	€33	€36
(16.1)	Salmon	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(16.2)	Cod	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(16.3)	Monk	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(16.4)	Pangasius....	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Attitudes toward fish farming and environmental aspects

17. On a scale from 1 to 10, where 1 means you very strongly DISAGREE and 10 means you very strongly AGREE, how much do you agree with the following statements?
Check one box per line.

		Very strongly disagree 1	2	3	4	5	6	7	8	9	**Very strongly agree** 10	**Do not know** 11
(17.1)	Farmed fish is healthy food................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.2)	Wild fish is healthy food....................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.3)	Farmed fish is safe to eat....................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.4)	Wild fish is safe to eat........................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.5)	I am concerned about the environmental impact of the production of farmed fish...................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.6)	I am concerned about the environmental impact of cashing wild fish..	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.7)	I am concerned about the environmental sustainability of fish farming..	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.8)	I am concerned about the environmental sustainability of fisheries of wild fish...........................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.9)	I am concerned about the welfare of farmed fish	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
(17.10)	I am concerned about the welfare of wild caught fish..............................	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Demographics

18. How many persons live in your household, - included yourself?

(18.1) Number of adults (>18): ________
(18.2) Number of children (≤18): _______

19. What is your current occupational situation?
Check one box.

- Paid work full time .... ☐1
- Paid work part time .... ☐2
- Unemployed for less than 3 month .... ☐3
- Unemployed for more than 3 month .... ☐4
- Housewife .... ☐5
- Student .... ☐6
- Retired or not able to work through illness............. ☐7
- Civil servant .... ☐8
- Working pensioner.. ☐9
- Other .... ☐0

20. What is your household's gross monthly income?
Check one box.

- Less than 2000 euros per month.............................. ☐1
- From 2000 to 3000 euros per month .... ☐2
- Over 3000 euros per month..................................... ☐3
- Do not now / Do not want to answer .... ☐4

Appendix III

The attached file is a part of a larger table that was sent to us personally us from Johan Kvalheim. Johan Kvalheim is currently a Representative of the Norwegian Seafood Council in France and the UK[1]. The file was sent to us on e-mail the 20th of April 2012.

The table consists of unrevised and preliminary data for Norwegian seafood exports for 2010 and 2011. The sources for the export statistics are from Statistics Norway (SSB) and Norwegian Customs (TAD). An explanation of the table is given in Norwegian. Since the data are preliminary and unrevised, they must be interpreted with caution.

[1] http://www.seafood.no/Om-oss/Organisasjon/Ansatte (accessed: 08.05.2012)

EKSPORTSTATISTIKK

Vedlagt følger statistikk over sjømateksporten for siste måned. Statistikken er basert på urettede og foreløpige tall. Den inneholder tabeller med detaljert eksportstatistikk av hovedprodukter. I tillegg til enkeltprodukter er også vedlagt samlestatistikk for noen produktgrupper.

Statistikken inneholder også importstatistikk som viser norsk import for de største produktgrupper og de viktigste land.

Importstatistikken inneholder tall som er to måneder gammel.

Datakilde for eksportstatistikken er Statistisk sentralbyrå (SSB) og Toll- og avgiftsdirektoratet (TAD) (siste måned). Statistikkgrunnlaget er data fra TAD med informasjon om eksporten av fiskeprodukter. Datasettene inneholder eksportmengde og verdi spesifisert på produkttype og eksportland. Denne statistikken inneholder tall for siste måned der datakilden er Toll- og avgiftsdirektoratet (urevidert) og hittil i år der kilden er SSB. Statistikken bør derfor brukes med varsomhet.

Norges sjømatråd samarbeider med SSB for å få statistikken så korrekt som mulig, men er i tillegg avhengig av eksportørene for å få en pålitelig statistikk. Vi ber brukere som finner feil eller urimeligheter i statistikken straks å ta dette opp med Norges sjømatråd, som vil gi beskjed videre til SSB.

Tabellene viser eksporten fordelt på samtlige markeder.

- for siste måned (mengde, verdi og pris, urettede tall).
-totalt hittil dette år (mengde, verdi og pris), foreløpige offisielle tall + urettede tall for siste måned
- mengde, verdi og kilopris for januar - siste måned i fjor, endelige tall.

Eksportverdiene er oppgitt FOB, mens importverdiene er oppgitt CIF.
Statistikken er laget bare til bruk for aktører innenfor næringen.

BRUK AV EKSPORTSTATISTIKKEN

Totaltabellene for fersk og frossen fisk inneholder ikke sild eller filet.

EU er ikke tatt med i totalen. Denne er kun ment som ekstra informasjon.

I den enkelte tabell er land ikke ført opp hvis eksportverdien er mindre enn kr 10.000,-. Hvis vekt er oppgitt til 0 betyr dette at vekt er under 1000 kg. I total mengde og verdi er all eksport inkludert.

Oversikt over eksporten hittil i år inneholder varegrupper som er utelatt fra den detaljerte oversiktstatistikken. Disse grupper er ofte lite spesifiserte varegrupper.

Grupper av annen (eks. annen filet) og ikke spesifisert (eks. fersk fisk - ikke spes.) inneholder varegrupper (restgrupper ol.) som av forskjellige grunner ikke er klassifisert som egne grupper.

Varenummeret refererer til HS-nummeret som benyttes i internasjonal toll- og statistikknomenklatur. Dette nummeret finnes bl.a. i TADs Statistisk varefortegnelse for utenrikshandelen.

Vennlig hilsen Norges sjømatråd:

Norsk eksport av fisk totalt per marked
Mengde i tonn, verdi i 1000 NOK

	Desember 2011 Ureviderte tall			Januar - Desember 2011 Ureviderte tall			Januar - Desember 2010 Foreløpige tall		
	Mengde	Verdi	Pris pr.kg	Mengde	Verdi	Pris pr.kg	Mengde	Verdi	Pris pr.kg
TOTALT	192.551	4.681.804	24,31	2.325.928	52.974.486	22,78	2.665.047	53.618.134	20,12
EU27	98.921	2.572.285	26,00	1.174.496	30.467.389	25,94	1.268.730	30.833.303	24,30
Russland	29.267	574.246	19,62	300.088	5.193.061	17,31	347.538	5.222.964	15,03
Frankrike	17.568	499.702	28,44	148.582	5.110.301	34,39	142.489	5.273.089	37,01
Danmark	10.924	262.480	24,03	176.091	3.599.272	20,44	196.800	4.098.816	20,83
Polen	13.387	328.546	24,54	135.577	3.525.376	26,00	153.820	4.111.669	26,73
Japan	9.084	243.812	26,84	140.057	2.877.206	20,54	135.673	2.473.652	18,23
Kina	9.406	169.365	18,01	166.740	2.525.259	15,14	152.071	2.341.106	15,39
Storbritannia	6.962	181.167	26,02	93.219	2.399.377	25,74	127.436	2.567.915	20,15
Sverige	6.087	204.263	33,56	71.571	2.375.811	33,20	69.692	2.265.240	32,50
Tyskland	10.462	236.477	22,60	104.854	2.282.603	21,77	99.544	2.115.907	21,26
Portugal	2.515	103.398	41,11	57.493	2.258.208	39,28	50.103	1.857.578	37,08
Spania	4.985	149.066	29,91	59.572	1.916.873	32,18	49.934	1.765.050	35,35
Nederland	6.426	139.409	21,69	97.258	1.881.566	19,35	94.245	1.819.536	19,31
U S A	4.992	178.005	35,66	39.164	1.683.341	42,98	56.764	2.726.193	48,03
Brasil	4.917	198.372	40,34	34.354	1.333.641	38,82	35.548	1.306.343	36,75
Italia	3.284	124.193	37,82	31.226	1.330.784	42,62	29.340	1.431.715	48,80
Ukraina	10.654	135.793	12,75	109.582	1.180.820	10,78	140.013	1.059.113	7,56
Finland	3.627	99.646	27,48	50.210	1.134.011	22,59	45.522	1.046.548	22,99
Litauen	5.794	96.066	16,58	72.298	1.031.928	14,27	71.416	976.931	13,68
Hong Kong	1.395	36.405	26,10	17.276	581.939	33,69	19.837	782.455	39,44
Sør-Korea	1.314	32.328	24,61	23.936	567.280	23,70	20.676	517.622	25,04
Vietnam	2.142	57.068	26,64	19.913	562.208	28,23	7.783	223.979	28,78
Nigeria	345	18.229	52,83	54.804	540.652	9,87	160.157	889.557	5,55
Tyrkia	3.316	39.094	11,79	42.873	539.442	12,58	53.531	504.028	9,42
Israel	1.464	40.182	27,44	14.805	483.608	32,66	11.799	388.303	32,91
Latvia	2.168	41.826	19,29	20.370	407.539	20,01	14.617	257.719	17,63
Taiwan	1.013	25.339	25,02	14.062	399.045	28,38	12.429	399.695	32,16
Thailand	1.440	42.946	29,81	14.795	386.628	26,13	13.021	417.388	32,05
Hellas	1.929	29.088	15,08	25.684	379.641	14,78	24.741	261.309	10,56
Belgia	935	30.377	32,48	10.371	365.699	35,26	11.841	417.227	35,24
Hviterussland	3.927	68.941	17,55	17.570	312.843	17,81	29.414	354.485	12,05
UKJENT	43	.	.	1.527	265.613	173,96	1.634	287.668	176,08
Canada	1.029	33.034	32,09	6.479	246.414	38,03	5.353	165.320	30,88
Sveits	486	26.936	55,43	4.423	241.158	54,52	4.453	232.620	52,24
Den Dominikanske Republikk	451	13.143	29,16	8.306	231.408	27,86	8.932	242.672	27,17
Singapore	588	18.611	31,66	6.457	222.982	34,54	5.495	220.399	40,11
Egypt	187	2.941	15,72	25.601	181.116	7,07	37.279	203.907	5,47
Kasakhstan	1.488	20.046	13,47	14.772	174.746	11,83	19.056	177.548	9,32
Australia	198	12.584	63,47	3.053	149.537	48,97	2.944	132.391	44,96
Kongo	585	16.827	28,76	5.466	145.525	26,63	4.819	119.588	24,82
Tsjekkia	682	18.872	27,66	4.959	135.232	27,27	2.126	71.931	33,84
Kongo, Brazzaville	266	7.539	28,30	5.218	132.742	25,44	3.603	88.143	24,46

Datakilde=Toll- og avgiftsdirektoratet (siste mnd.) og Statistisk Sentralbyrå