Deliverable No. 1.4

Project acronym:

PrimeFish

Project title:

„Developing Innovative Market Orientated Prediction Toolbox to Strengthen the Economic Sustainability and Competitiveness of European Seafood on Local and Global markets"

Grant agreement No: **635761**

This project has received funding from European Union´s Horizon 2020 research and innovation program.

Start date of project: **1st March 2015**

Duration: **48 months**

Due date of deliverable :	28/02/2018
Submission date:	31/05/2017
File Name:	PrimeFish_D1_4ance
Revision number:	01
Document status:	Final[1]
Dissemination Level:	PU[2]

[1] Document will be a draft until it was approved by the coordinator

[2] PU: Public, PP: Restricted to other programme participants (including the Commission Services), RE: Restricted to a group specified by the consortium (including the Commission Services), CO: Confidential, only for members of the consortium (including the Commission Services)

Revision Control

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Deliverable 1.4

PrimeDSF methods compendium, including sample data, test runs, and comparative analysis

February 22nd 2018

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Executive Summary

The data used in the various tasks of PrimeFish comes from many sources. The approach taken in the analysis within each task depends both on the objective of the task at hand, as well as the data available. The methodology used in PrimeFish therefore spans a wide range of methods; from quantitative and qualitative analysis of interview data and simple descriptive statistics to state-of-the-art advanced statistical models.

This deliverable discusses the various methods used in the various tasks and deliverables. Following a short introductory section, Sections 2-4 present the methodology used in work package 2 (WP2). Section 2 presents the growth accounting used to assess productivity in the harvesting sectors of Denmark, the Faroe Islands, Iceland, Newfoundland and Norway, while Section 3 describes the data envelopment analysis to study efficiency and productivity in aquaculture in several European countries and Vietnam. Section 4 presents the Kalman filter method which is used to study the occurrence of boom-and-bust cycles in various seafood markets. Section 5 discusses the method of co-integration which is used to analyse price transmission and market integration. The global value chain analysis, upon which most of the analysis in WP3 is based, in presented in Section 6 and Sections 7 and Section 8 present the approach taken to study the how market institutions and labelling and certification affect seafood and aquaculture firms. The analysis of European seafood products innovations is discussed in Section 10, while the microeconomic models applied in WP4 are illustrated in Sections 11 and 12. The methods chosen to analyse social awareness, attempts to stimulate fish consumption, and negative press, are presented in Section 13. The choice experiments conducted in WP4 are described in Section 14, while the fisheries and aquaculture competitiveness index developed in WP5 is visited in Section 15. The methodology behind the boom-and-bust model developed in WP5 is presented in Section 16 and the latent class analysis and multinomial logistic regression used in WP5 is discussed in Section 17.

The wide variety of approaches shown in this deliverable show the breadth of the analysis undertaken in PrimeFish, and the range of tools used to study the competitiveness of the European seafood and aquaculture industries in this project.

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1 Introduction

The overall objective of PrimeFish is to enhance the economic sustainability of European fisheries and aquaculture sectors through new knowledge and insights about competitive performance. The main aim of the project is to develop an innovative decision support framework, PrimeDSF, which contains economic models and a decision support system, PrimeDSS, that can be used by the industry and policymakers to better predict consequences based on existing knowledge and simulation/forecasting models. The actual data collection and analysis takes place in work packages (WP) 2-4, with the models making up the PrimeDSS developed in WP 5.

WP1 is responsible for producing guidelines for consistent application of methods across the project and also for collecting and collating usage reports from the different sectors, cases and method users. The present deliverable, D1.4, brings together all the methods used in PrimeFish and thus gives an overview of the different methodology applied in PrimeFish.

The data used in the various tasks comes from many sources. These include public national and international agencies, sensitive firm-level data, interviews with business leaders and consumers, consumer surveys and scanner-data on French consumers. The approach taken in the analysis within each task depends both on the objective of the task at hand, as well as the data available. The methodology used in PrimeFish therefore spans a wide range of methods; from quantitative and qualitative analysis of interview data and simple descriptive statistics to state-of-the-art advanced statistical models.

This deliverable discusses each of the different methods used. The methodology applied to the different tasks is presented, sometimes in considerable detail, and where applicable the pros and cons of using the approach chosen discussed. In some cases, examples are provided of the data used, and the output obtained from using the models.

2 Growth accounting

Deliverable D2.2 analysed recent productivity developments in some of the most important capture fisheries in Europe. The growth accounting representation chosen for this analysis was introduced into the literature by Solow (1957) and later employed in empirical analysis of productivity growth by several authors (Kendrick, 1961), (Jorgenson & Griliches, 1967) and (Denison, 1972).

In the simple production process when one input is used to produce one output, output produced per unit of input yields a comprehensive measure of productivity. However, matters become a bit more complicated when several inputs are used to produce several outputs. Focusing on the productivity on one input will then only yield partial productivity measures, such as for instance output per worker per hour worked or output per unit of capital or machine hour. Although commonly used, such measures provide an incomplete picture and may even "mislead and misrepresent the performance of a firm" (Coelli, Rao, O'Donnell, & Battese, 2005, p. 62). Labour productivity can, for instance, improve because of more skilled labour or because of the additional usage of other inputs, such as capital.

To counter this, measures of multifactor or total factor productivity (MFP or TFP) have been developed and applied to cases where a multitude of inputs are employed to produce several outputs. By thus taking into account the changes that utilisation of all inputs has on production, these measures provide a more accurate picture of productivity. Total factor productivity may then be defined as the ratio of aggregate output produced relative to aggregate input used.

Following Arnason (2003) and Eggert and Tveterås (2013), the Törnqvist approximation of total factor productivity change in fisheries in discrete time may be defined as

$$(1) \qquad TFP = (ln\, Y_t - ln\, Y_{t-1}) - \gamma\delta\frac{1}{2}(s_{kt} + s_{kt-1})(\ln K_t - ln\, K_{t-1})$$

$$-\gamma_t\delta_t\frac{1}{2}(s_{lt} + s_{lt-1})(\ln L_t - ln\, L_{t-1}) - \frac{1}{2}(s_{at} + s_{at-1})(\ln S_t - ln\, S_{t-1}).$$

Here, Y represents landings which are measured in tons. Although fishermen may target one specific species, there is also some bycatch of other species, which in many cases may be considerable. In fisheries analysed in D2.2, Y is therefore always defined as aggregate of the most important species targeted by fleet segment in question. In the case of demersal fisheries, Y may therefore represent the combined catches of cod, haddock and saithe, and in the pelagic cases Y may represent the combined catches of herring, mackerel and capelin. The precise definition of Y does, however, differ between cases. K is defined as a capacity index that is usually measured as the product of average vessel length, average engine size (in kW) and number of vessels. This measure does therefore both take into account changes in the number of vessels and harvesting capacity of the fleet. L is defined as the number of employed fishermen or full-time equivalents. The value of the share of labour (s_l) and capital (s_k) in value-added is taken from the economic accounts of the fishery. Finally, s_a, represents the elasticity of output with respect to stock, i.e. to the catchability of individual stocks which may differ substantially between pelagic and demersal species, reflecting different distribution patterns of stocks. Thus, while pelagic species tend to form schools, many demersal species tend to be more evenly distributed. In the case of pelagic species the stock elasticity of output will therefore take a value close to zero, indicating that even if stocks are large the schooling behaviour of the specie in question may reduce its catchability, while in the case of demersal species the elasticity may take a value close to unity. Empirical studies (Bjørndal, 1987; Sandberg, 2006), have revealed a weak stock effect for pelagic species such as herring, implying a value of close to zero for the stock elasticity, but a value close to unity for demersal species (Hannesson, 1983; Hannesson, 2007a;Hannesson, 2007b; Sandberg, 2006).

As explained above, Y represents the total catches of the most important species of the relevant fleet segment. In the Icelandic case, for instance, catches of cod, haddock, saithe, redfish, wolffish and ling made on average up 89% of the total catches of the demersal fleet during the period 2002-2014. If it can be assumed that harvesting of all species is equally capital- and labour-intensive, which is a questionable assumption, it follows that capital and labour was only utilised 89% of the time on the harvesting of these six species. In the productivity analysis, this can be "corrected" by multiplying K and L by the parameter γ which takes on a value of unity if Y includes catches of all the species harvested by the relevant fleet, but a value below unity if catches of some species are excluded. In the Icelandic case, γ would therefore on average take a value of 0.89.

In some of the cases included in D2.2, information exists on the number of days-at-sea, i.e. the number of days spent searching for fishable quantities of the target species and time spent on fishing. Where such information is available, it may be used to adjust the utilisation of capital and labour, by multiplying K and L by the ratio of actual number of days-at-sea divided by 300, i.e.

$$\delta = \frac{number\ of\ days\ at\ sea}{300}.$$

The denominator is set at 300 rather than 365 (the number of days in a year) to make allowance for the fact that vessels may spend some day in harbour between fishing trips and to allow for time for necessary refurbishment and maintenance. Both γ and δ will in general vary between years, i.e. not take on fixed values.

Finally, in eq. (1) S represents an aggregate measure of the same stocks as included in Y. For the Icelandic case, mentioned above, S would therefore be defined as the sum of the stocks of cod, haddock, saithe, redfish, wolffish and ling. Stocks are usually defined as spawning stock biomass (SSB) or fishable biomass if information on SSB is unavailable. The output elasticity, s_a, is set at 0.85 for all demersal species and 0.1 for all pelagic species.

Provided data are available on landings, capital, labour and stocks, as well as the share of capital and labour, eq. (1) can then be used to calculate annual changes in total factor productivity for the fishery in question. As stated in eq. (1), productivity growth will depend on changes in landings, changes in the capital and labour, and changes in stocks. While increased landings have a positive effect on productivity growth, decreased landings will retard productivity growth. Increases in capital and labour will, *ceteris paribus*, decrease productivity growth, but decreases in these control inputs will have a positive effect. It should be remembered that in the studies included in D2.2, K is defined as a three dimensional capacity index that allows for changes in the number of vessels, average length and average engine size. Thus, scrapping programs that are aimed at reducing the number of vessels will encourage productivity growth. However, the harvesting capacity of the vessels remaining in the fleet may increase enough to compensate for the fall in vessel number. The end result could thus be an increase in K. In eq. (1), stocks are treated just like a traditional input. Increases in stock size will then, ceteris paribus, decrease productivity growth, while decreases in stocks enhance productivity growth. In this analysis, fishing stocks is therefore considered a viable way to promote productivity. This counterintuitive argument does though only hold in the short run, i.e. in the same year. In the long-run fishing down stocks will decrease catches and may of course jeopardize the existence of the fish species in question.

The growth accounting methodology was primarily chosen for two reasons. First, the models can be applied in data-poor cases, i.e. when the data may only span a few years. Second, the models are easy to implement, understand and interpret.

This methodology has though only been used relative infrequently. To date, there are only a couple of other studies (Arnason, 2003; Eggert and Tveterås, 2013). Other studies are either based on traditional micro economic models or DEA.

The main strength of this method is that it can be applied when there are relatively few data points, much fewer than would be need for parametric or non-parametric analysis. The method is also rather easy to implement and use, and interpret. The method is, however, based on rather stringent assumptions, and cannot be used for out-of-sample predictions.

The data at hand clearly limited the choice of methods and dictated the use of growth accounting. Better data would have allowed the use of other, more flexible methods that could have allowed for decomposition into changes in efficiency, productivity and returns-to-scale.

Example of data used

	Output	Labour share	Capital share	Labour	Fleet	Stocks
1993	100.0	0.54	0.46	100.0	100.0	100.0
1994	110.0	0.54	0.46	98.9	97.9	105.1
1995	120.9	0.56	0.44	101.3	97.6	114.7
1996	148.7	0.55	0.45	97.7	99.2	168.7
1997	174.0	0.59	0.41	101.6	103.1	199.5
1998	175.1	0.63	0.37	103.4	100.0	182.2
1999	166.5	0.64	0.36	102.4	100.7	159.4
2000	179.9	0.66	0.34	97.4	94.3	154.0
2001	213.7	0.60	0.40	98.3	95.1	175.2
2002	283.3	0.62	0.38	95.4	90.9	191.3
2003	263.6	0.65	0.35	110.0	110.5	201.7

Output sample

	Prod	Output	Inputs	Stocks
1993				
1994	6.1	9.6	-1.6	5.0
1995	-0.5	9.4	1.2	8.7
1996	-16.6	20.7	-1.3	38.6
1997	-4.9	15.7	3.9	16.7
1998	9.8	0.6	-0.1	-9.1
1999	8.6	-5.0	-0.3	-13.3
2000	16.8	7.7	-5.6	-3.5
2001	3.5	17.3	0.9	12.9
2002	22.9	28.2	-3.6	8.8
2003	-28.6	-7.2	16.1	5.3

Further description of the growth-accounting methods and its use may be found in D2.2 "Report on the economic performance of selected European and Canadian fisheries".

3 Data envelopment analysis

Data envelopment analysis (DEA) was used in deliverable 2.3 (D2.3) in WP2. The objective of D2.3 is to provide an overall picture of economic performance of aquaculture firm included in some of the case studies in PrimeFish. In order to examine and understand the competitiveness of key EU aquaculture industries, it was decided to compare the performance of two key fish farming activities within the EU - Scottish salmon firms and Mediterranean sea bass and sea bream firms – with two important international competitors – Norwegian salmon firms and Vietnamese pangasius firms.

Economic performance may be defined in various ways, but it is most common to focus either on financial indicators or productivity. D2.3 follows the latter approach and examine economic performance using an advanced-methods named Data Envelope Analysis (DEA). DEA is a non-parametric technique which allows productivity growth to be decomposed into changes in efficiency and technology. Efficiency here refers to how well firms manage to utilise their inputs to produce output, in this case farmed fish. Using DEA it is possible to construct an efficiency frontier, which is made up of the most efficient firms, and calculate how far other firms are from that frontier. The method also makes it possible to analyse shifts in the frontier, which is taken to represent technical change. Firms can then either improve their productivity by moving close to the efficiency frontier at each point in time, and/or take advantage of the technical progress which shifts the frontier out. DEA also makes it possible to decompose technical efficiency into pure technical efficiency and scale efficiency which measure how well firms are able to utilise the scale economies available.

Technical efficiency is one component of overall economic efficiency, which is referred to as the ability of a firm to obtain either maximal output from a given set of inputs (output-orientation) or the optimal combination of inputs to achieve a given level of output (an input-orientation), given the production technology (Coelli et al., 2005, p.51-56). Both input and output measures can be used in order to compare technical efficiency between firms and over time (Kumbhakar and Lovell, 2000, Coelli et al., 2005).

Following Farrell (1957), the input-orientation can be illustrated using a firm producing a single output (Q) with two inputs (X_1 and X_2) under an assumption of constant returns to scale (CRS). The isoquant of a fully efficient firm is given by SS' in Figure 19a. If a given firm uses quantities of inputs, defined by the point P, to produce a unit of output, the technical inefficiency of that firm could be represented by the distance QP, which is the amount by which all inputs could be proportionally reduced without a reduction in output. This is usually expressed in percentage terms by the ratio QP/OP, which represents the percentage by which all inputs need to be reduced to achieve technically efficient production. The technical efficiency *(TE)* of a firm is most commonly measured by the ratio OQ/OP, which is equal to one minus QP/OP. It takes a value between zero and one, and, hence, provides an indicator of the degree of technical efficiency of the firm. A value of one implies that the firm is fully technically efficient. For example, the point Q is technically efficient because it lies on the efficient isoquant.

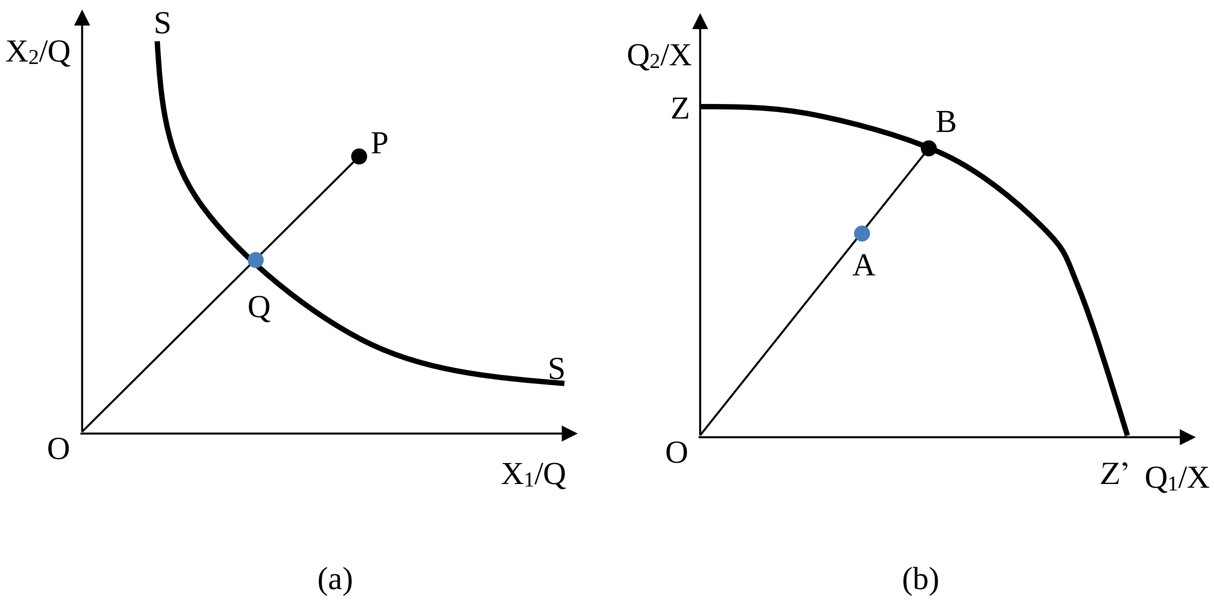


Figure 1 Technical efficiency from input (a) and output (b) orientations.

Now consider a firm which uses a single input (X) to produce two outputs, Q_1 and Q_2.The production possibility curve is shown as *ZZ'* in Figure 1b. Given the current input employed by the firm, the current production (denoted by point A) can be expanded radially to point B. The output-orientated measure of *TE* is given by OA/OB. The output and input measures will be equivalent under constant returns to scale.

Scale efficiency is a simple concept that is easy to understand in a one-input, one-output case. Hence, a one-input, one-output variable return to scale (VRS) production technology is depicted in Figure 2, where the production set, S, is the area between the VRS production frontier, *f(x)*, and the X-axis, inclusive of these bounds. The technically inefficient firm operates at point D., It is clear that the productivity of firm D (as reflected by the slope of the ray from the origin) could be improved by moving from point D to point E on the VRS frontier (i.e., removing technical inefficiency), and it could be further improved by moving from the point E to the point B (i.e., removing scale inefficiency) – the technically optimal productive scale is at point B.

The ratio of the slope of the ray OD to the slope of the ray OE is equal to the ratio GE/GD, and the ratio of the slope of the ray OE to the slope of the ray OF (which also equals the slope of the ray OB) is equal to the ratio GF/GE. Thus, distance measures can be used to calculate these efficiency differences. In particular, it is possible to calculate the technical efficiency with respect to both CRS and VRS, and then specify scale efficiency as the ratio between these measures. The technical efficiency of firm D relates to the distance from the observed data point to the VRS technology and is equal to the ratio TE_{VRS} = GE/GD. Likewise, the distance from the observed data point to the CRS technology is defined as TE_{CRS} = GF/GD. Scale efficiency is then defined as:

$SE = TE_{CRS} / TE_{VRS}$ = (GF/GD)/(GE/GD) = GF/GE.

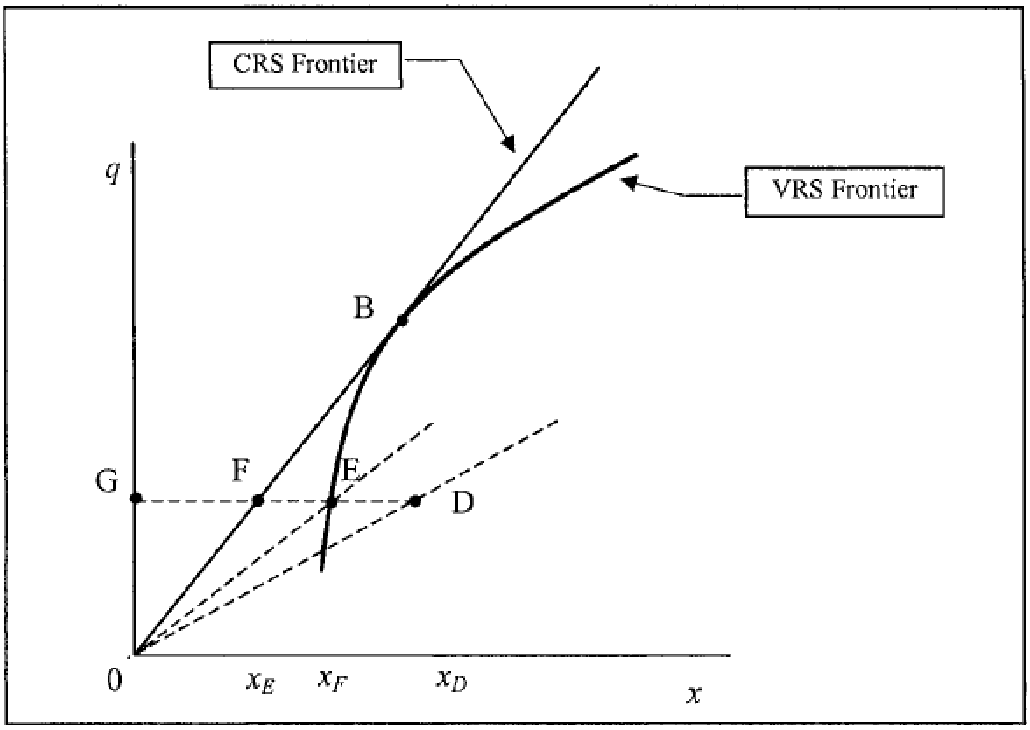


Figure 1 Scale efficiency. Source: Coelli et al. (2005).

The basic data envelopment analysis (DEA) model was defined by Charnes et al. (1978), based on Farrell (1957). DEA models can be formulated for input minimization or output maximization problems. As the calculations in this deliverable are all based on input minimization, we will in what follows only outline that approach.

TE scores of decision-making units (DMU) are derived by estimating each separate frontier for each year, by solving the following input-oriented DEA models:

Input-oriented DEA model under CRS assumption

$$\begin{aligned} &\mathrm{TE} = \mathrm{Min}_{\theta,\lambda} \quad \theta \\ &\text{Subject to} \quad \theta x_{ij} - \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, \quad i = 1, \dots, M, \\ &\qquad -y_{rj} + \textstyle\sum_{j=1}^{n} \lambda_j y_{rj} \geq 0, \quad r = 1, \dots, N, \\ &\qquad \lambda_j \geq 0, \quad j = 1, \dots, n, \end{aligned} \tag{2}$$

Input-oriented DEA models under VRS assumption

$$\begin{aligned} &\mathrm{TE} = \mathrm{Min}_{\theta,\lambda} \quad \theta \\ &\text{Subject to} \quad \theta x_{ij} - \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, \quad i = 1, \dots, M, \\ &\qquad -y_{rj} + \textstyle\sum_{j=1}^{n} \lambda_j y_{rj} \geq 0, \quad r = 1, \dots, N, \\ &\qquad \textstyle\sum_{j=1}^{n} \lambda_j = 1, \\ &\qquad \lambda_j \geq 0, \quad j = 1, \dots, n, \end{aligned} \tag{3}$$

where x_{ij} is the level of input i used by DMU_j, y_{rj} is output r of the DMU_j and n is the number of observed companies. The value of θ obtained is the efficiency score for the *j-th* firm. It satisfies: $\theta \leq 1$, with a value of 1 indicating a point on the frontier and hence a technically efficient firm.

The Malmquist Index (MI) is used to measure the total factor productivity (TFP) change of a company or an industry over time, which is known as the Malmquist TFP index. If the MI equals one, it represents no change in productivity; a value greater than one indicates positive TFP growth; and an MI smaller than one indicates a TFP decline. The MI will be defined by distance functions. The input distance function, which involves the scaling of the input vector, is defined on the input set, L(**q**), as:

$$d_i(\boldsymbol{x}, \boldsymbol{q}) = \max\left\{\rho : \left(\frac{\boldsymbol{x}}{\rho}\right) \in L(\boldsymbol{q})\right\}, \qquad (4)$$

where the input set L(**q**) represents the set of all input vectors, **x**, which can produce the output vector, **q**. The input distance function is illustrated using using Figure 19a. The value of the distance function for the point, *P*, is equal to the ratio ρ=OP/OQ (Figure 19a). The input-orientated TE measure of a firm like (1) can be expressed in terms of input-distance function

$$d_i(\boldsymbol{x}, \boldsymbol{q}) \text{ as: } TE = 1/d_i(\boldsymbol{x}, \boldsymbol{q}).$$

The input-orientated productivity measures focus on the level of inputs necessary to produce observed output vectors $\boldsymbol{q_t}$ and $\boldsymbol{q_{t+1}}$ under a reference technology. The input-orientated MI is defined as:

$$M_i(\boldsymbol{q}_t, \boldsymbol{q}_{t+1}, \boldsymbol{x}_t, \boldsymbol{x}_{t+1}) = [M_i^t(\boldsymbol{q}_t, \boldsymbol{q}_{t+1}, \boldsymbol{x}_t, \boldsymbol{x}_{t+1}) M_i^{t+1}(\boldsymbol{q}_t, \boldsymbol{q}_{t+1}, \boldsymbol{x}_t, \boldsymbol{x}_{t+1})]^{\frac{1}{2}}$$

$$= \left[\frac{d_i^t(\boldsymbol{q}_{t+1}, \boldsymbol{x}_{t+1})}{d_i^t(\boldsymbol{q}_t, \boldsymbol{x}_t)} \times \frac{d_i^{t+1}(\boldsymbol{q}_{t+1}, \boldsymbol{x}_{t+1})}{d_i^{t+1}(\boldsymbol{q}_t, \boldsymbol{x}_t)}\right]^{\frac{1}{2}} \qquad (5)$$

The MI in (4) is defined in terms of four input distance functions, and a separate M_i will be calculated for every DMU. The MI formula can be decomposed in a common way as follow:

$$M_i(\boldsymbol{q}_t, \boldsymbol{q}_{t+1}, \boldsymbol{x}_t, \boldsymbol{x}_{t+1}) = \frac{d_i^{t+1}(\boldsymbol{q}_{t+1}, \boldsymbol{x}_{t+1})}{d_i^t(\boldsymbol{q}_t, \boldsymbol{x}_t)} \left[\frac{d_i^t(\boldsymbol{q}_{t+1}, \boldsymbol{x}_{t+1})}{d_i^{t+1}(\boldsymbol{q}_{t+1}, \boldsymbol{x}_{t+1})} \times \frac{d_i^t(\boldsymbol{q}_t, \boldsymbol{x}_t)}{d_i^{t+1}(\boldsymbol{q}_t, \boldsymbol{x}_t)}\right]^{\frac{1}{2}} \qquad (6)$$

or

$$MI = EC \times TC,$$

where

$$EC = \frac{d_i^{t+1}(\boldsymbol{q}_{t+1}, \boldsymbol{x}_{t+1})}{d_i^t(\boldsymbol{q}_t, \boldsymbol{x}_t)} \qquad (7)$$

$$TC = \left[\frac{d_i^t(\boldsymbol{q}_{t+1}, \boldsymbol{x}_{t+1})}{d_i^{t+1}(\boldsymbol{q}_{t+1}, \boldsymbol{x}_{t+1})} \times \frac{d_i^t(\boldsymbol{q}_t, \boldsymbol{x}_t)}{d_i^{t+1}(\boldsymbol{q}_t, \boldsymbol{x}_t)}\right]^{\frac{1}{2}} \qquad (8)$$

The decomposition given in (6) identifies two sources of productivity change. The first part is technical efficiency change (EC) in (7). The second part is a measure of technical change (TC) in (7), the movements of the frontier technologies between the two periods, and its contribution to total productivity change.

Technical efficiency change (EC) be decomposed into scale efficiency change (SEC) and pure technical efficiency change (PEC). This can only be done when the distance functions in the above equations are estimated relative to a CRS technology (Fare et al.1994).

For the calculations, four different DEA models must be solved for each DMU. Assuming constant returns to scale (CRS) to start with, the following input-orientated linear programs are used:

$$\begin{aligned}
&[d_i^t(\boldsymbol{q}_t, \boldsymbol{x}_t)]^{-1} = \text{Min}_{\theta,\lambda} \quad \theta \\
&\quad \text{Subject to} \quad \theta x_{ij,t} - \textstyle\sum_{j=1}^{n} \lambda_j x_{ij,t} \geq 0, \quad i = 1, \dots, M, \\
&\qquad\qquad -y_{rj,t} + \textstyle\sum_{j=1}^{n} \lambda_j y_{rj,t} \geq 0, \quad r = 1, \dots, N, \\
&\qquad\qquad \lambda_j \geq 0, \quad j = 1, \dots, n,
\end{aligned} \tag{9}$$

$$\begin{aligned}
&[d_i^{t+1}(\boldsymbol{q}_{t+1}, \boldsymbol{x}_{t+1})]^{-1} = \text{Min}_{\theta,\lambda} \quad \theta \\
&\quad \text{Subject to} \quad \theta x_{ij,t+1} - \textstyle\sum_{j=1}^{n} \lambda_j x_{ij,t+1} \geq 0, \quad i = 1, \dots, M, \\
&\qquad\qquad -y_{rj,t+1} + \textstyle\sum_{j=1}^{n} \lambda_j y_{rj,t+1} \geq 0, \quad r = 1, \dots, N, \\
&\qquad\qquad \lambda_j \geq 0, \quad j = 1, \dots, n,
\end{aligned} \tag{10}$$

$$\begin{aligned}
&[d_i^{t+1}(\boldsymbol{q}_t, \boldsymbol{x}_t)]^{-1} = \text{Min}_{\theta,\lambda} \quad \theta \\
&\quad \text{Subject to} \quad \theta x_{ij,t} - \textstyle\sum_{j=1}^{n} \lambda_j x_{ij,t+1} \geq 0, \quad i = 1, \dots, M, \\
&\qquad\qquad -y_{rj,t} + \textstyle\sum_{j=1}^{n} \lambda_j y_{rj,t+1} \geq 0, \quad r = 1, \dots, N, \\
&\qquad\qquad \lambda_j \geq 0, \quad j = 1, \dots, n,
\end{aligned} \tag{11}$$

$$\begin{aligned}
&[d_i^t(\boldsymbol{q}_{t+1}, \boldsymbol{x}_{t+1})]^{-1} = \text{Min}_{\theta,\lambda} \quad \theta \\
&\quad \text{Subject to} \quad \theta x_{ij,t+1} - \textstyle\sum_{j=1}^{n} \lambda_j x_{ij,t} \geq 0, \quad i = 1, \dots, M, \\
&\qquad\qquad -y_{rj,t+1} + \textstyle\sum_{j=1}^{n} \lambda_j y_{rj,t} \geq 0, \quad r = 1, \dots, N, \\
&\qquad\qquad \lambda_j \geq 0, \quad j = 1, \dots, n,
\end{aligned} \tag{12}$$

The first two linear programs in (9) and (10) are where the technology and the observation to be evaluated are from the same period, and the solution value is less than or equal to unity. The second two linear programs in (11) and (12) occur where the reference technology is constructed from data in one period, whereas the observation to be evaluated is from another period.

DEA fits well the datasets used in D2.3 and meets one of the tasks of the work package's aim to understand economic performance at firm level. It is possible to apply another method such as stochastic frontier analysis (SFA), which is a method of economic modeling that applies regression technique to estimate parameters of production inputs. However, DEA has the following important advantages:

- Can handle multiple input and multiple output models.
- Does require an assumption of a functional form relating inputs to outputs.
- Firms are directly compared against other firms or combination of firms. In this case, DEA provides clear results for comparing efficiency among pangasius, salmon and seabass/seabream firms.
- Inputs and outputs can have very different units.

The same characteristics that make DEA a powerful tool can also create problems. Thus:

- Since DEA is an extreme point technique, noise (even symmetrical noise with zero mean) such as measurement error can cause significant problems.
- DEA is good at estimating "relative" efficiency of a firm but it converges very slowly to "absolute" efficiency. In other words, it can tell you how well you are doing compared to your peers but not compared to a "theoretical maximum."
- Since DEA is a nonparametric technique, statistical hypothesis tests are difficult and are the focus of ongoing research.
- Since a standard formulation of DEA creates a separate linear program for each firm, large problems can be computationally intensive.

The farmed fish-datasets at firm level have a number of weaknesses that limit the choice of methodology as well the analysis undertaken. The datasets do not include equal number of firms (decision making units), time periods are not the same for all datasets, and inputs and outputs vary between data sets. This makes it impossible to compare the DEA results across case studies.

Future research may apply DEA for another datasets. For example, DEA is now sometimes used for analysis of survey data at firm level. The firm questionnaire can be generated with identical output and input variables deployed for different case studies. The identical input and output variable enable the comparisons of economic performance between aquaculture sectors as well as across firms within sectors. The surveyed data are also more recent than the time series data. However, surveyed data can rarely be used to analyse changes in productivity and efficiency over times.

Example of data used for DEA

Year	Firm	Operating revenue	Current assets	Fixed assets	Non-current	Current liabilities
1	1	50.3	22.3	30.0	0.0	13.7
1	2	5.6	12.5	7.1	4.4	12.1
1	3	45.0	43.7	25.7	8.8	50.8
1	4	15.1	11.7	5.8	2.6	11.4
1	5	73.3	45.2	11.2	0.0	47.2
1	6	12.3	9.3	9.0	2.4	13.8
1	7	26.3	25.1	9.1	1.8	22.5
1	8	19.3	5.9	4.1	0.4	4.5
1	9	0.2	3.9	8.7	4.1	0.8
1	10	0.1	1.3	11.3	3.8	5.5
1	11	1.8	2.0	0.2	0.0	0.9
1	12	18.8	20.5	8.2	1.0	21.0
1	13	14.7	22.1	3.6	0.7	20.4
1	14	25.8	23.1	25.1	6.0	27.2
1	15	16.0	20.9	6.8	0.8	19.8
1	16	19.4	9.2	12.0	5.6	10.8
1	17	17.2	28.4	6.8	4.2	18.3
1	18	11.4	13.7	8.2	4.2	13.1
1	19	17.7	10.1	7.2	2.4	12.6
1	20	94.3	41.0	30.4	13.9	34.5
2	1	91.2	37.2	40.9	3.9	38.3
2	2	16.9	15.8	7.6	3.0	16.5
2	3	62.7	54.0	25.0	6.6	53.9
2	4	17.2	11.5	5.7	2.6	11.2
2	5	27.2	29.9	11.3	0.9	29.9
2	6	18.2	15.4	10.3	4.7	16.3
2	7	42.4	27.3	10.4	1.0	24.8
2	8	28.2	12.4	6.0	0.6	9.4
2	9	15.1	12.4	9.4	2.9	9.3
2	10	2.0	7.9	12.6	6.5	6.1
2	11	2.1	2.0	6.1	2.5	1.0
2	12	21.3	20.1	8.1	0.9	20.7
2	13	19.2	30.4	3.1	0.3	28.5
2	14	37.3	44.0	23.5	4.5	36.6
2	15	27.9	29.7	8.6	2.6	27.8
2	16	31.2	15.7	14.6	4.0	15.9
2	17	27.6	34.3	8.2	2.8	28.3
2	18	21.4	17.3	9.3	3.3	16.5
2	19	23.5	8.2	6.3	1.5	10.7
2	20	115.0	50.2	33.0	13.5	34.0

Example of model output

Average technical efficiency and scale efficiency

Year	CRS-TE (1)	VRS-TE (2)	SE (3)=(1)/(2)
2009	0.515	0.646	0.836
2010	0.660	0.775	0.838
2011	0.823	0.883	0.928
2012	0.723	0.863	0.844
2013	0.662	0.782	0.864
2014	0.676	0.814	0.820
Mean	0.677	0.794	0.855

Annual mean changes in productivity (TFP) decomposed into changes in pure technical efficiency (PE), scale efficiency (SE), technical efficiency (TE) and technology (TC).

Year	PE (1)	SE (2)	TE (3)=(1)*(2)	TC (4)	TFP (5)=(3)*(4)
2010	1.274	1.181	1.504	0.597	0.898
2011	1.159	1.147	1.329	1.066	1.417
2012	0.969	0.898	0.870	1.603	1.396
2013	0.887	0.988	0.877	1.255	1.101
2014	1.035	0.935	0.968	1.022	0.989
Mean	1.065	1.030	1.110	1.109	1.160

4 Kalman filter

The methodology discussed in this section was used in two deliverables, D2.4 and D5.2, both of whom deal with the analysis of "boom-and-bust cycles". The statistical model used for the identification of cycles in the time series is the Kalman filter. The starting approach is to look at a time series with the approach of structural models (Harvey, 1989). The traditional approach to the analysis of time series is to decompose the observed values as the sum of a linear or quadratic trend, a fixed cycle and a seasonal component modelled using a set of dummy variables or harmonics and an irregular component and eventually a set of fixed explanatory variables. However, when these components are not stable this formulation becomes inadequate and it is necessary to allow them to change over time. This flexibility is possible with structural models, such that "they are not more than regression models in which explanatory variables are a function of time and the parameters change with time" (Harvey, 1989). One peculiarity of a structural model is its flexibility in recognizing changes in the behaviour of a given series, by taking its different components as stochastic processes governed by random disturbances.

The Kalman filter decomposes the time series into elementary parts such as trend, cycle, seasonality and irregular component. Trend is defined as any long term tendency. By extension, the trend is the fundamental tendency (towards the increasing, the reduction or even to price stability) that the activities of the fisheries sector in periods of varying length (but always groups of years), apart from accidental variations (irregularities or outliers), seasonal and cyclical. The cycle (or cyclical component) is defined as alternation of different sign fluctuations around the trend. Seasonal component consists of changes that occur with similar intensity in the same periods every year, but with different intensity in the course of a year (for example, production is falling every year in the summer following the holiday closure of many companies, but it increases every year as Christmas approaches to and greater consumption). The irregular component represents unforeseeable and accidental variations related to all the most varied types of events. This component in some cases, may include extreme values or outliers.

The Kalman filter as well as break down the price trend in building blocks may be allocated to each member of the characteristics of stochasticity and determination. The classification of a component as a stochastic or deterministic is of particular importance since it allows to understand more in detail what inside on the price trend analysis can be considered as "fixed" or "probabilistic". The Kalman filter also allows to determine if the individual components are stochastic or deterministic

In order to estimate the parameters of the structural time series models it is necessary to put them inside the so called state-space form and then apply the Kalman filter. The filter has its origin in Kalman's (1960) paper who describes a recursive solution to the linear filtering problem of discrete data. Kalman's derivation took place within the context of state-space models, whose core is the recursive least squares estimation. The state-space representation is essentially a convenient notation to estimate stochastic models in which one assumes measurement errors in the system which allows handling a large set of time series models. The filter is a mathematical tool which operates by means of a prediction and correction mechanism. Essentially, this algorithm predicts the new state (which contains all information up to that point in time) starting from a previous estimation and adding a proportional correcting term to the prediction error, such that the latter is statistically minimized. The complete estimation procedure is as follows: the model is formulated in state-space form and for a set of initial parameters, the model prediction errors are generated from the filter. These are then used to recursively evaluate the likelihood function until it is maximized. The Kalman filter comprises a set of mathematical equations which result from an optimal recursive solution given by the least squares method. The purpose of this solution consists in computing a linear, unbiased and optimal estimator of a system's state at time t, based on information available at t - 1 and update, with the additional information at t, these estimates (Clark et al. 1998). The filter's performance assumes that a system can be described through a stochastic linear model with an associated error following a normal distribution with mean zero and known variance. The solution is optimal provided the filter combines all observed information and previous knowledge about the system's behaviour such that the state estimation minimizes the statistical error. The recursive term means that the filter re-computes the solution each time a new observation is incorporated into the system.

The Kalman filter is the main algorithm to estimate all structural models written in state-space form (Harvey and Proietti, 2005). This representation of the system is described by a set of state variables. The state contains all information relative to that system at a given point in time. This information allows to infer about the past behaviour of the system, aiming at predict its future behaviour. What makes the Kalman filter so interesting is its ability to predict the past, present and future state of a system, even when the precise nature of the modelled system is unknown. In practical terms, the individual state variables of a dynamic system cannot be exactly determined through a direct measurement. In this context, their measurement is done by means of stochastic processes involving some degree of uncertainty.

Data were also used in the report to analyze the price transmittion and market integration for selected species. Price transmission refers to the process in which upstream (producer) prices affect downstream (retail) prices. The relationships between different stages in the value chain (upstream and downstream), based on a simultaneous equilibrium, have been described by the theory of derived demand. The absence of complete pass-through of price changes and costs from one market to another has important implications for economic welfare. Price transmission studies provide important insights into how changes in one market are transmitted to another, and consequently reflect the extent to which markets function efficiently.

The main objective of D2.4 was to estimate the presence of boom and bust cycles and the best model for cycle analysis using the Kalman filter due to its ability to isolate the cycle component from other components. In addition, the filter highlights the irregular component of the cycle that allows us to determine how much what we are observing is stochastic or deterministic, allowing us to evaluate the goodness of the results obtained.

With the support of the economics literature (Gerdesmeier et al., 2012), and through many tests performed on the data, it seemed reasonable to argue that we can talk about boom or bust if prices are greater than the 85th percentile or below the 15th percentile. Furthermore, in order to avoid false signals, we classify a set of values beyond thresholds as a group if inside the set we do not have more than three consecutive monthly observations below the thresholds. This method allows avoidance of the formation of two booms or two busts in close periods just because there is a single value in the set that falls inside the percentiles used as a threshold. The classification method used to reduce the false signals produces smoother cycles.

The methodology applied is coherent with the current development of the international research in this field. However, other methodology could have been applied. Some examples include:

- ARCH (autoregressive conditionally heteroscedastic) model is a model for the variance of a time series. ARCH models are used to describe a changing, possibly volatile variance. Although an ARCH model could possibly be used to describe a gradually increasing variance over time, most often it is used in situations in which there may be short periods of increased variation.

- GARCH (generalized autoregressive conditionally heteroscedastic) model uses values of the past squared observations and past variances to model the variance at time t.

The algorithm of the Kalman filter has several advantages. This is a statistical technique that adequately describes the random structure of experimental measurements. This filter is able to take into account quantities that are partially or completely neglected in other techniques (such as the variance of the initial estimate of the state and the variance of the model error). It provides information about the quality of the estimation by providing, in addition to the best estimate, the variance of the estimation error.

The Kalman filter is very useful in this contest as it is able to identify the cycles, if they exist, to determine their length and to provide a diagnostic index of statistical significance.

The disadvantages of the method are mainly that it provides accurate results only for Gaussian and linear models.

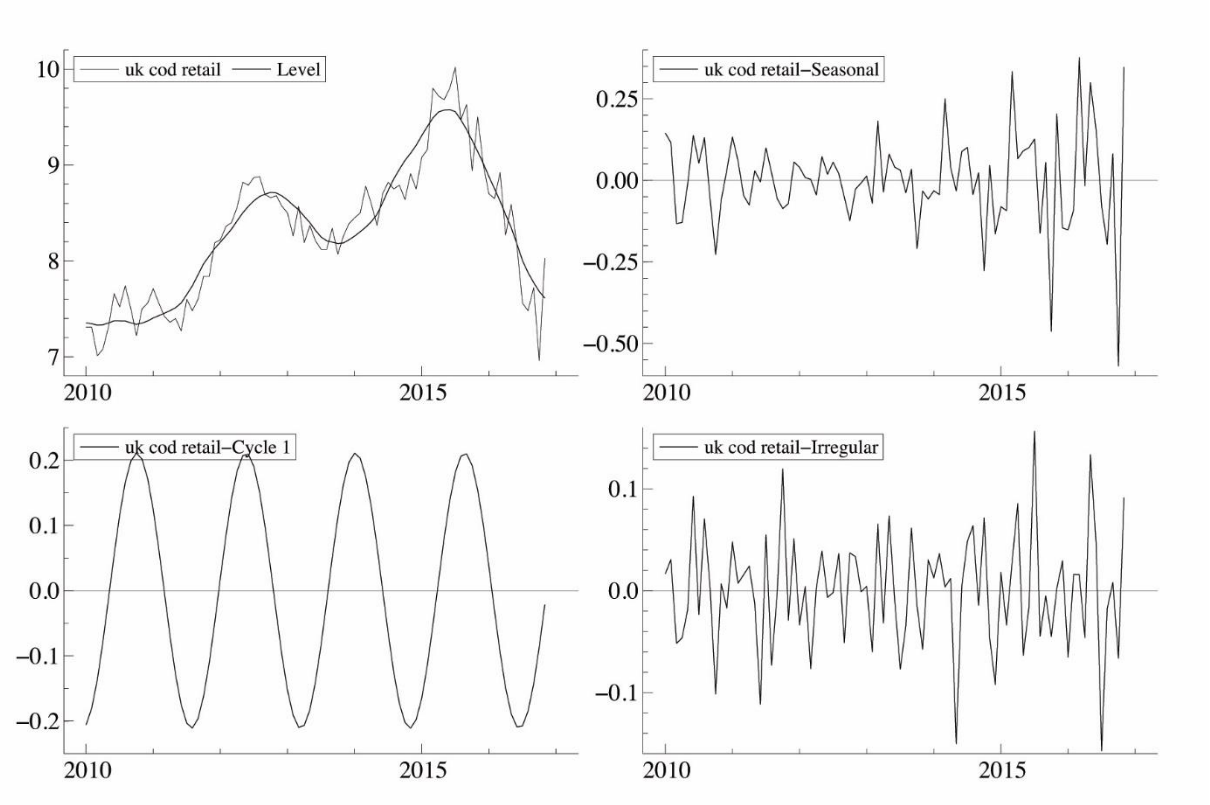
The methodology applied in D2.4 was directly based on the type of data collected and based on the objective of the task. The model applied, in our opinion, provides the best possible estimate for the cycle in prices time series for the species analysed.

The methods used in the D2.4 are quite robust and applied widely. However, there are still rooms to improve the application. For example, data are sufficient to investigate deeply the price transmission and market integration by advanced techniques such as cointegration analysis. Cointegration analysis can be applied to develop an empirical model that aims to test market integration and price leadership between actors in the value chain of seafood species. It is also possibly applied to test the horizontal market integration and market leadership among species. In addition, the quantile regression technique may be extended to empirical model by involving the deterministic variables of macro-economic factors (e.g., average income, interest rate, exchange rate, and national economic growth). The Kalman filter method may be applied more intensively by further investigating the stochastic components of the prices. These recommendations are suggested for future studies.

Example of data collected

year	month_of_year	year-month	country	main_commercial_species	weighted_price	market
2010	1	2010-1	United Kingdom	Cod	7,31	retail
2010	2	2010-2	United Kingdom	Cod	7,31	retail
2010	3	2010-3	United Kingdom	Cod	7,01	retail
2010	4	2010-4	United Kingdom	Cod	7,08	retail
2010	5	2010-5	United Kingdom	Cod	7,31	retail
2010	6	2010-6	United Kingdom	Cod	7,66	retail
2010	7	2010-7	United Kingdom	Cod	7,52	retail
2010	8	2010-8	United Kingdom	Cod	7,74	retail
2010	9	2010-9	United Kingdom	Cod	7,5	retail
2010	10	2010-10	United Kingdom	Cod	7,22	retail
2010	11	2010-11	United Kingdom	Cod	7,5	retail
2010	12	2010-12	United Kingdom	Cod	7,56	retail
2011	1	2011-1	United Kingdom	Cod	7,71	retail
2011	2	2011-2	United Kingdom	Cod	7,56	retail
2011	3	2011-3	United Kingdom	Cod	7,42	retail
2011	4	2011-4	United Kingdom	Cod	7,36	retail
2011	5	2011-5	United Kingdom	Cod	7,4	retail
2011	6	2011-6	United Kingdom	Cod	7,27	retail
2011	7	2011-7	United Kingdom	Cod	7,6	retail
2011	8	2011-8	United Kingdom	Cod	7,48	retail
2011	9	2011-9	United Kingdom	Cod	7,6	retail
2011	10	2011-10	United Kingdom	Cod	7,84	retail
2011	11	2011-11	United Kingdom	Cod	7,84	retail
2011	12	2011-12	United Kingdom	Cod	8,19	retail

Example of model output from Kalman filter.



Level	0.00180910 (0.1752)
Slope	0.00125137 (0.1212)
Seasonal	0.000203698 (0.01972)
Cycle	5.16005e-008 (4.996e-006)
Irregular	0.0103280 (1.000)
Cycle period	19.5 months

5 Price transmission and market integration

In Task 2.3.3, price co-integration was employed to analyse price transmission and market integration between species, among markets and along the value chains, i.e. between farming and processing sectors. The methodology is based on Nielsen et al. (2009)

The general formulation is driven by the empirical evidence is that there is strong support to use a Granger causal model (mixed with Autoregressive Moving Average [ARMA] model) However the effect of lagged causality of X(t-1) over Y(t) can be hidden as absorbed by the time-evolution modelled with the ARMA model. The formal definition of the ARMA model with the explanatory variable is

$$Y_t = c + \phi_1 Y_{\{t-1\}} + \theta_1 \epsilon_{\{t-1\}} + \gamma_0 X_t + \gamma_1 X_{\{t-1\}} + \epsilon_t,$$

where ϵ_t is a White Noise (assumed Gaussian) error term. The model can be used only when first sale price and retail price are both available for a sufficiently long time period (with monthly data) and no missing data. So, in the sequel, only combinations of fish/country where these restrictions are met will be under investigation.

Under the model assumptions it is expected that changes in X will cause changes in Y. This cause-effect transmision works if the time series share, at least, a mild common pattern (i.e. Y is large when X is large and vice-versa) and have a kind of long-term steady mean-stationary.

The parameter c and γ_0 are probably the two most important in terms of economic interpretation. The constant c is the fixed mark-up and γ_0 is the proportional mark-up (elasticity). Price transmission elasticity is defined as "the relative change in retail price to the relative change in producers' price when other factors affecting processors behaviour are held constant". So, the elasticity of price transmission measures the percentage change in the price at a downstream stage of the market chain, in relation to the relative change in the price of the same product at an upstream stage in the market chain.

The statistical hypothesis will assess the significance of the parameters via their p-value and only relevant parameters will be included. The comments to parameters will be mostly economical referred to the magnitude at which the prices are transmitted from first sale to retail. When common trend are found a modification to the above model will take into account the cointegration term.

The methodology was chosen because it is an advanced generalization to causal models that were analysed in the literature cited below. It exploits cause-and-effect and uses robust estimations.

This is the standard methodology used for this type of analysis, but has been enhanced by new robust estimators. Other methodologies could rely on a fully complete state-space representation to deal with irregularly samples time series.

The model is flexible enough to deal with seasonal, cyclical and erratic behaviours. Good out-of-sample forecasts and ease of interpretation. However, it can only be applied to regularly based time-series. Missing values create troubles and restrict the analysis to some datasets.

The objective of the task and the type of data collected dictated the methodology used. The model applied provided, in our opinion, the best possible results.

Future studies using similar methodology should take car to collect the data using a proper pre-defined methodology in a well organised database. The data used in this study are taken from EUMOFA and include the following variables: year, month of year, average monthly prices.

6 Global value chain analysis

Global value chain (GVC) analysis has been used as the underlying framework for the deliverables undertaken in work package 3. GVC mapping and quantification of "input-output structure" are standard initial steps of value chain analysis (Kaplinsky & Morris, 2001). A holistic VCA is conceived in PrimeFish as four inter-linked elements with focus on competitiveness (see T3.4 Deliverable Protocol). D3.1 represents the first of these steps, while the other linked elements of VCA can be found in D3.2 value chain governance, D3.3 market based governance, D3.4 Industry dynamics, opportunities and threats and to some extent in D4.1 product innovation case studies.

The initial data analysis was performed by each partner institution responsible for the value chain case and detailed in the form of a report on the structure of the respective value chain. Each report separately describes the main material flow in the supply chain (mapping and input-output structure escription) for one of the six commodity species (or species groups) that are the focus of PrimeFish; four farmed and two capture: (i) Atlantic Salmon, (ii) Rainbow Trout, (iii) European Sea bass (*Dicentrarchus labrax*) and gilthead sea bream (*Sparus aurata*) (iv) Pangasius catfish (*Pangasius hypophthalmus*) (v) Atllantic Cod (*Gadus morhua*) (vi) Atlantic Herring (*Clupea herrengus*). The latter two species are selected as examples of demersal and pelagic fisheries. Sea bass and sea bass are treated as a single group as almost perfect substitutes, sharing very similar production and post-harvest value-chain characteristics.

The value chain mapping started at the production node of the VC in the selected country of interest to Primefish (reasons for selection of countries detailed elsewhere), and traced the material downstream to processing (primary and/or secondary), marketing and consumption within the domestic portion of the value chain, exports to other markets and imports. As a first step the analysis positions the producer country on the global scene, particularly relevant for internationally traded commodities. Then it covers the volume and value of outputs from each major node in the value chain (raw material production, processing, distribution, retail and food-service, where data were available). The analysis was furthered through quantifying the additional elements of the VC detailed below.

1. Supply of material
    a. Landing/production

i. structure – for national fleet: number of vessels, size and capacity, employment, if possible with relevance to the type of fisheries (demersal or pelagic); for aquaculture - number of plants (possibly types within the production chain: hatcheries, nurseries, and for consumption/restocking; sizes, employment
ii. Landings (LWE and/or landed weight for domestic and foreign fleet); volume and value, price per kg; production capacity of aquaculture: eggs laid, seed (fry, fingerling) produced, fish for consumption - volume and value, price per kg

b. Imports
   i. Eggs and seed (for aquaculture) – number and value
   ii. Raw material/products imported (by category) – volume and value
   iii. Main exporting countries – volumes and value

2. Processing
   a. Types of raw materials raw materials supplied, volumes, values and prices for different processor types (primary, secondary, mixed)
   b. Outputs – types of products, volumes and value
   c. Gross value added (GVA)

3. Consumption and Export
   a. Retail sector – retail volumes, value of sales, average retail prices, GVA where available
   b. Food Service sector - retail volumes, value of sales, average retail prices, GVA where available
   c. Export – types of products exported, volumes and values, countries of destination.

Since the aim of this exploratory analysis was to summarize and visualize data, only simple data manipulations were performed e.g. totals, proportion, growth rate etc.

In most of cases the available data covered the period 2000-2014 at annual intervals, the analysis allowed identification of major trends in time and patterns across locations. A further synthesis was performed of the 17 individual value-chain descriptions, utilising a cross-case analyses i.e. each case (country VC) is compared to the other cases of the same type (species) in order to draw broad conclusions as to what the important aspects of this value chain were which define its structure, which forms and can be found in D3.1. The identification of these components served as a guide to further analysis and in-depth exploration of these issues in D3.4 with particular focus on competitiveness.

Competition is a complex, dynamic and multi-dimensional concept, while the global economy is increasingly structured around global value chains (GVCs) that account for a rising share of international trade, global GDP and employment (Gereffi & Fernandez-Stark, 2011). The major outputs of the EU‘s fisheries and aquaculture industries are no exception: the selected species of focus to Primefish represent internationally (globally) traded commodities. The multi-dimensionality and international scope of competition of EU fisheries and aquaculture, call for a systems thinking approach (Wächter, 2011) which lies at the core GVC analysis.

The activities that comprise a value chain can be contained within a single firm or divided among different firms (globalvaluechains.org, 2011). In the context of globalization, the activities that constitute a value chain have generally been carried out in inter-firm networks on a global scale.

Gereffi & Fernandez-Stark (2011) describe six basic dimensions that GVC methodology explores, divided into global and local elements. The analysis of this dataset comprises the first two dimensions (1) an input-output structure, which describes the process of transforming raw materials into final products and (2) the geographic scope, which explain how the industry is globally dispersed and in what countries the different GVC activities are carried out. These dimensions are concerned primarily with a 'global' analysis level of analysis (a more 'local' level analysis i.e. at national industry and company level is covered in D3.4)

Primarily descriptive statistical approaches were used since the aim of this initial analysis was collation/ exploration of available data including identification of major trends.

Globalization has given rise to a new era of international competition that is best understood by looking at the global organization of industries and how countries rise and fall within these industries. The global value chain framework has evolved from its academic origins to become a major paradigm used by a wide range of country governments and international organizations, including the World Bank, the International Labor Organization, the U.K. Department for International Development, and the U.S. Agency for International Development. Global value chain analysis highlights how new patterns of international trade, production, and employment shape the prospects for development and competitiveness, using core concepts like "governance" and "upgrading" (Gereffi & Fernandez-Stark, 2011).

The GVC is a framework for analysis which is flexible and allow addition of different „lenses" (e.g. competition, gender, environment) to suit the needs of the analysis and the intended users of the research (Bolwig, Ponte, du Toit Riisgaard, Lone, & Halberg, 2010). It is also flexible in terms of the choice of qualitative or qualitative methods, or a combination thereof.

The integrated framework underpinning this WP combine elements from the Global value chain school (primarily Gereffi) and the Strategic Management and industrial economics schools (e.g. (McGahan, 2000; Porter, 1980, 1998; Rumelt, 1991). The flexibility of the GVC framework makes is particularly suitable for this type of analysis, and a better candidate to narrower approaches such as single industries.

In value chain mapping it is important to generate data over time, showing the trajectory of change as well as the position in any one point in time. An alternative approach would have been a more qualitative analysis of trends, however, that would have not allowed graphical visualisation of trends.

Apart from the advantages of GVC mentioned above, the comprehensive nature of the framework allows policy makers to answer questions regarding development issues that have not been addressed by previous paradigms. It allows holistic understanding of how global industries are organized by examining the structure and dynamics of different actors involved in a given industry. GVC is a predominantly qualitative approach; the range validation steps routinely applied in social research are therefore requirement to verify the robustness of findings.

Initial scanning of data sources available in the public domain indicated GVC was a suitable framework for the consequent collection and analysis of data. The flexibility of GVC allows extending the analysis to different areas of interest where data are available, as well as adapting to the contingent circumstances of the research investigation, recognising that not in all researchers in the project will have equal access to data and importantly, the same quality of access to the subjects of the research.

The use of framework approaches requires deep understanding of the underpinning theory and ideally some level of relevant prior experience by all members of the team. Thus, extensive training is required by to align the perspectives of what in cases may be a diverse range of specialists. As such, this approach could be resource intensive in terms of supervision time. To ameliorate this, where possible the elements of the approach should be standardized and used in a prescriptive way.

Attempts to get access to internal company data on production (cut offs, waste etc.) or economic data for the company quickly showed to close the open dialogue. When asking to this type of information, the reaction were that this is confidential information, which could be used by competitors. Bringing this up would close for the open dialogue about e.g. relations in the value chain including relations to competitors and customers. – It is important not to mix too much in approach. This seems to confuse the interview person in understanding the purpose of the interview.

The economic/production data seems to be confidential for outsiders of the company. This type of data can probably only be accessed based on long-term trust relation (the company trust the interviewer not to share information with others unless real anonymised – e.g. in a form that cannot be identified by persons knowing the industry and companies) or based on official data collection under law and public guaranteed discretion.

7 Value-chains: Market institutional analysis

This analysis was used in D3.2. The data set used for this analysis were contained partly in value chain mapping in D3.1 and in specific national working papers summarising the legal institutional framework for fisheries and aquaculture. Further international (WTO) and EU documents on trade agreements (including tariffs) as well as other regulation were used.

The national reports from partners were mainly based on literature review and limited number of interviews with key informants. Themes for interviews (and literature reviews) were developed in the project, but a common coding system was not developed. At national level the interviews were coded for analysis. The common thematic focus was seen as productive for ensuring comparable information between countries. Local coding allowed for openness for including possible local aspects and perspectives. The national perspectives were used to further focus (and in some cases broaden) the supranational analysis.

The supranational analysis was based on reports, legal documents including e.g. tariff databases. Data from reports and other "grey" documents, interpretation of legal documents, databases and the national interpretation of the supranational legal framework influencing the competitiveness of the national seafood industry where combined in the analysis process. In this process triangulation, using different sources and types of sources to enlighten the subject, were used to substantiate the conclusions.

8 Value-chains: Labelling and certification

A holistic VCA is conceived in this project of four inter-linked elements with focus on competitiveness (see T3.4 Deliverable Protocol), of which this task and associated database represents D3.3 market based governance. The other linked elements of VCA can be found in D3.1 Value chain descriptions, D3.2 value chain governance, D3.4 Industry dynamics, opportunities and threats and to some extent in D4.1 product innovation case studies.

D3.3 addressed the current use and potential of voluntary market-based labelling and certification schemes for different actors of the value-chain. Growth in the market for social and environmentally assured seafood products has been driven by lead brands in the sector adopting third-party certification and eco-labelling as a strategic-option for outsourcing reputational risk management. This therefore represents an increasingly important facet in competition strategy at company and sectoral levels.

The dataset compiled for this task comprises publicly available data from various sources (including farm audit reports, certification websites and for the salmon sector, industry Global Salmon Initiative (GSI) 'sustainability reports') on the aquaculture production node of the value chain. It covers the following certification schemes:

- Aquaculture Stewardship Council (ASC)
- GlobalG.A.P.
- Best Aquaculture Practices (BAP)
- Friends of the Sea

And the following species groups and locations

- Samonids (Atlantic salmon, coho salmon, rainbow trout, Arctic charr, brown trout) - globally
- Sea bass and sea bream - globally
- Pangasius catfish – Viet Nam

Data from diverse sources were curated, standardized and organized in a relational database which allowed using query functionality in addressing the research questions.

The analytical approach is descriptive in nature and includes trends analysis, market share estimations, and strategy analysis, which are summarized and visualized in graphs, tables and maps.

Based on a review of literature and media reports; the task also looks at the political economy of the growing certification sector. Specifically market-failures associated with the dominance of single scheme that achieved clear 'first-mover' advantage in the fisheries sector and the proliferation of aquaculture standards and associated imposition of multiple-audit costs on producers. Approaches for dealing with these market failures are also reviewed.

These analyses and interpretation of quantitative data was supported by semi-structured interviews with representatives of industry and certification bodies.

Publicly available data on seafood certification is dispersed among a number of sources. A holistic analysis is only possible when pooling the data together and standardizing them, in order to uncover broader trends.

By positioning market-based governance as an element of value chain analysis we can build on chain and network conceptualisations to better understand how private governance arrangements are structured, and how such governance mechanisms can engage with chain actors in influences over sustainability (Bush, Oosterveer, Bailey, & Mol, 2015).

The methodological mix was deemed to be most consistent with the research questions of this task.

Collection of data from a diverse resource base, curation and standardisation is a time consuming process. However, it allows the analysis of data otherwise existing in a non-analysable form. The method also allows incorporation of further data (e.g. other species and other certification schemes) into a standardised format for analysis.

The analysis as part of broader GVC framework allows holistic understanding of how global industries are organized by examining the structure and dynamics of different actors involved in a given industry.

The choice of methodology has been used in line with the research questions in this task. Nevertheless more complete data would have allowed increasing the depth of analysis, through answering further questions which are at this point not possible to answer because of data limitations.

Request for data from relevant institutions met with mixed success. Lack of timely geographical (GPS) data increased reliance on less time-efficient and potentially less accurate interpolation of from publically available 'certification maps'. Conversely industry contacts provided generous access to GSI data-sets which would otherwise have had to be extracted piecemeal from the GSI website.

9 Discrete choice analysis

This section describes the methodology applied in carrying out deliverable 3.5 on population assessment and valuation of non-market effects (McFadden 1974; Hensher, Rose and Greene, 2007; Train, 2009; Hanley and Barbier, 2009).

Externalities are defined as "unintended effects of production (or consumption), which are costly for the producer to neutralize". Externalities can be of both positive and negative character. An example of a negative externality of European fish production is the overfishing of some fish stocks, which disturb the ecosystem these stocks are part of and thus these ecosystems may be less productive than without overfishing. An example of a positive externality we can find in some types of fish farming, where the waste from e.g. salmon production can be used by scallops farms. While the outcome of the mentioned positive externality is captured by economic agents and thus partly internalized, it is of less concern to society than the negative externality, which imply costs inflicted upon the whole society, without being compensated for. Hence, although we also will treat positive externalities, the main focus will be on negative externalities of fish production.

We use two case study fish industries to exemplify the role and extent of externalities in European fish production. These are production of farmed Atlantic salmon, and production (harvest) of wild cod. By the use of a methodology called choice experiment, we analyze to what extent case study producers are willing to internalise a few widely recognized externalities. The results of this analysis should be seen in relation to results from WP4.4, which is a choice experiment among European fish consumers. Taken together, the results from the two surveys will convey information of whether consumers and producers of fish agree on which are the important environmental issues in the European fish industry. Are fish producers focusing on the "right" environmental issues, and are consumers willing to pay more for the fish to encourage the producers to take environmental considerations?

For this deliverable, data is collected by the use of a survey questionnaire. Focal in this questionnaire is a set of choice cards, asking the respondents to choose between three alternatives for production of fish, where the alternatives are described by a combination of economic and environmental attributes. Based on the choices the respondents make on the cards the attributes characterizing the production process, which the respondents find most or least important can be elicited. This is done by the use of statistical methods in the form of bi- or multinomial logit models. The resulting, preference intensities for the attributes describing the production process can be further developed to express willingness to pay (WTP), which indicate what producers are willing to pay to improve each of the attributes describing the production alternatives.

We have applied a combination of qualitative semi-structured interviews and quantitative monetary valuation of sets of externalities relevant for each of the two fisheries production in question (farmed Atlantic salmon and wild cod).

For each fishery we derived a choice experiment survey, including both qualitative questions about main environmental issues, and choice cards. In the choice cards respondents were asked to choose between three production alternatives, one of which describes a generalized present situation and two which describes alternatives with lower environmental footprints, but higher production costs.

Based on the choice cards it is possible to derive monetary valuation of the environmental issues (named attributes). We do this by using the random utility model, assuming that the utility to a fisher/fish farmer of a production alternative depends on a set of attributes describing the environmental and other characteristics, including production costs. To take into account the influence of random components on individual utility we also add an idiosyncratic i.i.d. error term. Hence, utility of a production alternative j to respondent i can be formulated as follows;

$$U_{ijt}(b|\, X) = b * X_{jt} + \in_{ijt} \tag{1}$$

where b is a vector of preference parameters to be estimated, X is a vector of attributes and $\in$ is an i.i.d. distributed error term.

A utility maximizing agent will chose alternative when $U_{ijt} > U_{ikt}, \forall k \neq j$. Hence, production alternative j is chosen by respondent i when $b\left(X_{jt} - X_{kt}\right) > (\in_{kt} - \in_{jt})$. When the error terms are extreme value distributed, we have that the right hand side of this inequality is logistically distributed.

With logistically distributed error terms the probability for the probability for the inequality (substituted by equality) above to be fulfilled is given by

$$P_{ijt} = \frac{exp^{b\prime Xijt}}{\sum exp^{bXikt}} \tag{2}$$

Equation (2) is the probability for respondent i to choose production alternative j in choice situation t. With T choice situations and N respondents, the aggregate probability for all observed choices is given by

$$L = \sum_{i=1}^{N} \sum_{t=1}^{T} P_{ijt}{}^{y} \qquad (3)$$

where y is a dummy taking the value 1 if alternative j was chosen by individual i in choice situation t, and 0 otherwise.

Taking the log of (3) yields the log likelihood function, which is maximized to yield estimates for the b-vector. This vector of estimates can be interpreted as marginal utilities for each of the attributes.

Dividing each non-cost attribute by the cost-attribute estimate we can interpret the resulting term as marginal willingness to pay (WTP) for a change in each of the non-cost attributes. Hence,

$$WTP_m = \frac{b_m}{b_c} \qquad (4)$$

where b_m is the estimate of a non-cost attribute and b_c is the estimate of the cost attribute.

This is an indirect elicitation method which is important if we assume that respondents may have reasons for answering strategically. Regarding environmental effects, most producers aim at avoiding effects of their production harmful to the physical environment. However, when they have to trade this off against higher production costs and other elements important in the production process, it is no longer obvious that the production alternative with the lowest environmental impact will be chosen. This methodology forces the respondents to trade-off between various elements in the production process, and in our survey these are economic elements on one hand and environmental elements on the other.

Choice experiments have so far mainly been used in consumer surveys, i.e. to elicit consumer preferences. There are only a few examples where it has been used to elicit producer preferences.

The strength of the method is that it makes it more difficult for respondents to answer strategically, and thus give the "expected" answers, while the disadvantage is the hypothetical bias, i.e. the fact that respondents answer hypothetical questions, which may not be what they would have answered in a real situation.

The number of respondents is very limited, altogether 23 for the salmon case study. Hence, in addition to statistical treatment of the responses, we also do some qualitative analysis.

List of variables used in study

Indi												
land	1=Norway	2=Scotland										
type	1=producer	2=other										
card	1 through 9											
alternative	1 through 3											
sealice	attribute 1 level											
FIFO	attribute 2 level											
escape	attribute 3 level											
certifi	attribute 4 level											
cost	attribute 5 level											
choice	choice of alternative made on choice card											
sex	1=male	2=female										
age	1=born befo	2=born 1950-5	3=born 19	4=born 19	5=born 19	6=born 19	7=born 19	8=born 19	9=born 19	10=born 1	11=born 1	12=born 2000 and aft
ENGO	1=yes	0=no	member of environmental organisation									
Org	1=yes	0=no	member of business organisation									
edu	1=primary	2=secondary	3=lower U	4=higher Uni								
young	no of children in household											
old	No of adults in household											
income	1=<10k GBP	2=10-20 GBP	3=20-30 GBP									
establ	1=before 197	2=70-74	3=75-79	4=80-84	5=85-89	6=90-94	7=95-99	8=2000-20	9=05-10	10=10-15	11 after 2015	
county												
prodloc	1=1				5=5					10=10	11= >10	
license	1=1-3	2=4-6	3=7-9	4=10-14	5=15-19	6=20-24	7=25-29	8=30-34	9=35-39	10=40-44	11=45-49	12=50 and above
species	1=salmon	2=trout	3=sea trou	4=other								
green	0=no	1=yes, some	2=yes, all									
P2014	production measured in tonnes in 2014											
P2015												
P2016												
smolt	0=no	1=yes										
feed												
viktig1-escapees	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						
viktig2-FIFO	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						
viktig3-certification	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						
viktig4-cost	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						
viktig5-sealice	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						
reg	1=very good	2=good	3=OK	4=bad	5=very ba	6=don't know						
inforeg	1=very good	2=good	3=OK	4=bad	5=very ba	6=don't know						
suff	1=yes	2=no	0=don't know									
foravfall												
lus												
romme												
sykd												
ansvOpp	1=not resp	2=little resp	3=some re	4=quite re	5=respons	6=very resp						
ansvPO	1=not resp	2=little resp	3=some re	4=quite re	5=respons	6=very resp						
ansvKons	1=not resp	2=little resp	3=some re	4=quite re	5=respons	6=very resp						
ansvENGO	1=not resp	2=little resp	3=some re	4=quite re	5=respons	6=very resp						
ansvCert	1=not resp	2=little resp	3=some re	4=quite re	5=respons	6=very resp						
ansvMynd	1=not resp	2=little resp	3=some re	4=quite re	5=respons	6=very resp						
ansvEU	1=not resp	2=little resp	3=some re	4=quite re	5=respons	6=very resp						
vikMTB	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						
vikEsc	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						
vikBunn	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						
vikLus	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						
vikFIFO	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						
vikCert	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						
vikGreen	1=not imp	2=little imp	3=some in	4=quite in	5=importa	6=very imp						

This project has received funding from the European Union's Horizon 2020 research and innovation program under

Example of data collected through survey

Variable	Observations								
Indi	1	1	1	1	1	1	1	1	1
land	1	1	1	1	1	1	1	1	1
type	1	1	1	1	1	1	1	1	1
card	1	1	1	2	2	2	3	3	3
alternative	1	2	3	1	2	3	1	2	3
sealice	30	20	30	30	10	30	10	30	30
FIFO	1	0.6	1.4	1	1.4	1.4	1.4	0.6	1.4
escape	7	20	7	7	20	7	20	15	7
certifi	1	0	0	0	0	0	1	1	0
cost	28.75	31.38	26.15	30.05	27.45	26.15	28.75	28.75	26.15
choice	0	1	0	0	1	0	1	0	0
sex	1	1	1	1	1	1	1	1	1
age	6	6	6	6	6	6	6	6	6
ENGO	0	0	0	0	0	0	0	0	0
Org	0	0	0	0	0	0	0	0	0
edu	3	3	3	3	3	3	3	3	3
young	2	2	2	2	2	2	2	2	2
old	2	2	2	2	2	2	2	2	2
income	13	13	13	13	13	13	13	13	13
establ	5	5	5	5	5	5	5	5	5
county	3	3	3	3	3	3	3	3	3
prodloc	4	4	4	4	4	4	4	4	4
license	1	1	1	1	1	1	1	1	1
species	1	1	1	1	1	1	1	1	1
green	0	0	0	0	0	0	0	0	0
P2014	2300	2300	2300	2300	2300	2300	2300	2300	2300
P2015	2500	2500	2500	2500	2500	2500	2500	2500	2500
P2016	2700	2700	2700	2700	2700	2700	2700	2700	2700
smolt	1	1	1	1	1	1	1	1	1
feed	2700	2700	2700	2700	2700	2700	2700	2700	2700
viktig1	6	6	6	6	6	6	6	6	6
viktig2	5	5	5	5	5	5	5	5	5
viktig3	6	6	6	6	6	6	6	6	6
viktig4	4	4	4	4	4	4	4	4	4
viktig5	5	5	5	5	5	5	5	5	5
reg	3	3	3	3	3	3	3	3	3
inforeg	1	1	1	1	1	1	1	1	1
suff	1	1	1	1	1	1	1	1	1
foravfall									
lus	1	1	1	1	1	1	1	1	1
romme	1	1	1	1	1	1	1	1	1
sykd	1	1	1	1	1	1	1	1	1
ansvOpp	6	6	6	6	6	6	6	6	6
ansvPO	4	4	4	4	4	4	4	4	4
ansvKons	4	4	4	4	4	4	4	4	4
ansvENGO	3	3	3	3	3	3	3	3	3
ansvCert	5	5	5	5	5	5	5	5	5
ansvMynd	6	6	6	6	6	6	6	6	6
ansvEU	4	4	4	4	4	4	4	4	4
vikMTB	1	1	1	1	1	1	1	1	1
vikEsc	3	3	3	3	3	3	3	3	3
vikBunn	5	5	5	5	5	5	5	5	5
vikLus	3	3	3	3	3	3	3	3	3
vikFIFO	5	5	5	5	5	5	5	5	5
vikCert	5	5	5	5	5	5	5	5	5
vikGreen	3	3	3	3	3	3	3	3	3

10 Analysis of European seafood products innovations

This section discussed the methodology used in deliverable 4.1 Industry study cases report: A collection of marketing successes and failures in the world based on clever product innovations and/or marketing activities.

To analyse the trend of sustainable seafood products in European markets, we look at the evolution of the number of seafood products by categories of product (species, brand, claims…) at the European level and then we focused on major species in the project: cod, herring, trout, salmon, pangasius, seabass and seabream. Mostly descriptive statistics have been calculated with mean comparison test (t-test) to ensure the statistical significance of trends and differences. To have an accurate description of innovation trends in the European seafood market, we look at trends in innovation between 2010 and 2015 across Europe. Nonetheless, we cannot be sure that those trends are due to a real increase in seafood products innovation, as they could also be caused by an extension in coverage of EU markets by Mintel. To solve this problem, we look at the evolution of each classification of products in importance (by claims and type of launch).

Descriptive statistics and trend analyses were the most accurate methodologies in order to analyse time series data. This is the standard methodology used for this type of analysis

The main strength of this approach is that by analysing the evolution of each classification of products in importance, we avoid biases linked to data collection, and thus are able to analyse real trends. The main weakness is that for some sub-categories the number of observations is too low to reach definite conclusions.

11 Microeconomic demand analysis

This section reports the results of D4.3 entitled "Report on the development of fish consumption and demand in France and Finland," and D4.4, "Report on the impacts of increased fish consumption on economic, health and environmental attributes" which are two of the quantitative studies included in WP4 on "Products, consumers and seafood market trends."

The economic theory of consumer choice provides the conceptual underpinning of the analysis. Accordingly, consumers are assumed to choose the goods that they consume and their quantities so as to maximize their well-being, or utility, subject to a budget constraint. Minimal assumptions on preferences over combinations of goods are imposed to ensure the rationality of choices. For instance, transitivity requires that if bundle A is strictly preferred to bundle B, and bundle B to bundle C, then bundle A is also strictly preferred to bundle C. The budget constraint arises because, for given levels of income and prices, only certain combinations of goods (i.e., consumption bundles) can be afforded.

The main purpose of the analysis of demand is then to characterise consumer preferences from observed consumption choices or, in other words, to let the data "reveal" preferences. This differentiates the approach from the group of "stated preferences" methods that are also widely used to investigate consumer behaviour, including in PrimeFish WP4. Both groups of methods have their strengths and weaknesses, but in cases where markets exist, revealed preference methods are usually considered superior because they do not suffer from the hypothetical biases that plague stated preference methods (Murphy et al., 2005). On the other hand, revealed preference methods are less suited to assess demand for a new product that is not currently available to consumers, or to shed light on the cognitive and psychological processes underlying choices.

In our framework, the theory guides the empirical inquiry first by identifying the variables that should be legitimately included in the demand equations. Hence, the generic form of the demand function for good i, denoted $x_i(\mathbf{p}, m, \mathbf{z})$ takes several arguments:

- A vector of prices **p**, which means that demand for a good is a function of its own price, but also the prices of substitute and complement goods.
- Income, or total expenditure, m, which defines the level of the budget constraint

- Socio-demographic variables **z** (e.g., education, age) that may be related in a systematic way to consumer preferences.

At the estimation stage, the theory establishes criteria to compare specifications, reduces the number of parameters to estimate, and ensures the realism of the simulations derived from the model (e.g., adjustments of consumption to a price change remain compatible with the budget constraint). In practice, three groups of restrictions follow from the axioms imposed on consumer preferences (Deaton and Muellbauer, 1980): 1) Adding-up, which ensures that the total value of demand exhausts the available budget; 2) Homogeneity, which imposes the absence of money illusion (i.e., the fact that the same proportional increase in all prices and total budget does not modify choices); and 3) Symmetry, which is less intuitive and relates to the derivatives of the compensated demand functions. The fourth theoretical property of negativity or concavity is usually not imposed but only checked expost.

The theoretical concepts of compensated (or Hicksian) demand and its difference with uncompensated (or Marshallian) demand, are important to understand the model and interpret its results. Marshallian demand denotes demand for a consumer operating under a budget constraint, while Hicksian demand denotes demand for a consumer operating under a utility constraint (i.e., holding his/her level of wellbeing constant). The first concept is of course closer to reality, but understanding what happens when a price changes requires knowledge of the second concept. For instance, assuming that the price of salmon increases, two different effects determine the adjustment in Marshallian demand of a given household: first, the substitution effect captures the reduction in consumption of salmon resulting from the fact that its price has suddenly become higher relative to that of substitute goods (e.g., trout). Empirically, that substitution effect is measured by the change in Hicksian demand, whose sign should be unambiguously negative (i.e., demand for a good decreases with its own price). However, the rise in the price of salmon also means that the real income/expenditure of the household has decreased, or in other words that that consumer has become poorer. The change in Marshallian demand also captures that second so-called income effect, and the above decomposition can sometimes be useful to explain seemingly paradoxical results, as illustrated in the results section.

The first step in the parametric estimation of demand relationships is the choice of a functional form for the demand system, in order to allow imposition of the theoretical restrictions while preserving flexibility (i.e., limit the restrictions on the system implicit in the functional form). Several competing systems have been proposed, as reviewed by Barnett and Serlettis (2008) with Deaton and Muelbauer's Almost Ideal Demand System, or AIDS, remaining the most popular one (Irz, 2010).

The AIDS model, however, presents two limiting features. First, it only allows income to influence demand in a linear or log-linear form, when it is now well established that Engel curves are often highly non-linear and vary widely in shapes across goods (Banks et al., 1997; Lewbel, 1991). Second, the AIDS model does not allow for preference heterogeneity, which unfortunately is recognized as a fundamental feature of consumer microdata (Crawford and Pendakur, 2013), as indicated by the typically relatively poor fit of statistical models estimated from such data.

As a way of addressing both issues, Lewbel and Pendakur (2009) have proposed the Exact Affine Stone Index (EASI) demand system. The system's Engel curves can be polynomials or splines of any order in real expenditures and are therefore highly flexible. Further, the EASI error terms equal random utility parameters, and the model therefore accounts for unobserved preference heterogeneity in a theoretically consistent manner.

However, estimation of the model is complicated by endogeneity and non-linearity issues, which means that iterative GMM or three-stage least squares procedures are called for. For demand systems with censored data as specified in this study, it is likely that the computational problems created by those procedures are insurmountable, and estimation of the full EASI model was therefore deemed too challenging. Thus, we only estimate a simplified – or approximate - version of the EASI model. Support for this simplification comes from Pendakur (2009), who provides evidence that both linearity and endogeneity are only relatively small issues in practice. In particular, that author finds that the linearized version of the model estimated by Ordinary Least Squares (OLS) performs almost as well as fully-efficient endogeneity-corrected nonlinear estimation.

Derivation of the EASI demand system starts from a dual representation of preferences in the form of a minimum cost function:

$$\ln C(p,u,z,\boldsymbol{\varepsilon}) = u + \sum_{j=1}^{J} m^j(u,z)\ln p^j + 1/2\sum_{j=1}^{J}\sum_{k=1}^{J} a^{jk}\ln p^j \ln p^k + \sum_{j=1}^{J}\boldsymbol{\varepsilon}^j \ln p^j$$

where **p** is the J-vector of good prices; u denotes utility; **z** is a vector of observed socio-economic characteristics (e.g., education); **ε** is a J-vector of unobserved preference heterogeneity parameters; and m^j (.) denotes an unrestricted function. Note that the specification of parameters a^{jk} as constants rather than a function of socio-demographic variables restricts the influence of those variables on price responsiveness. By application of Shephard's lemma, we obtain the Hicksian cost share equations:

$$\omega^j(p,u,z,\varepsilon) = m^j(u,z) + \sum_{k=1}^{J} a^{jk} \ln p^k + \varepsilon^j$$

A few manipulations generate the implicit utility or real income y:

$$y = u = \ln(x) - \sum_{j=1}^{J} \omega^j \ln p^j + 1/2 \sum_{j=1}^{J}\sum_{k=1}^{J} a^{jk} l\,\mathrm{n}\, p^j \ln p^k$$

That manipulation represents the key step of the approach, as it permits to replace the unobservable utility level u by y, which is solely a function of observables and parameters. The implicit Marshallian budget shares then follow by substituting y, as expressed in equation (3), for u in the Hicksian budget shares (2).

$$w^j(p,y,z,\varepsilon) = m^j(y,z) + \sum_{k=1}^{J} a^{jk} \ln p^k + \varepsilon^j$$

The advantages of the EASI model are evident in that expression. First, the functions $m^j(y, z)$ are completely unrestricted in their dependence on implicit utility y and observable demographic characteristics **z**. Thus, the model can accommodate homothetic preferences (i.e., independence of w from y), linear Engel curves as in the AIDS, quadratic Engel curves as in the quadratic-AIDS model (QAIDS), or much more complex geometries of Engel curves. Second, the unobserved preference heterogeneity parameters ε show up as error terms in the estimated equations and as cost shifters in the cost function, and are thus an integral part of the theoretical model.

We simplify the model further by assuming that the functions m^j(.) are additively separable in y and **z**, linear in **z** and polynomial of degree R in y:

$$m^j(y,z) = \sum_{r=1}^{R} b_r^j (y)^r + \sum_{t=0}^{T} g_t^j z_t$$

The Marshallian budget share equations become:

$$w^j = \underbrace{\sum_{r=1}^{R} b_r^j (y)^r + \sum_{t=0}^{T} g_t^j z_t}_{m^j(y,z)} + \sum_{k=1}^{J} a^{jk} \ln p^k + \varepsilon^j, \; j = 1,\dots,J$$

Let's note that a constant is introduced as the first **z** variable, so that there are only T real sociodemographic characteristics in the model. More importantly, real income y is itself a function of the parameters a^{jk} and the cost shares w through equation (3). This implies first that model (6) is nonlinear in parameters, which complicates estimation. This first issue is addressed by approximating implicit utility (3) by the value of expenditure deflated by a Stone price index:

$$y \approx \ln(x) - \sum_{j=1}^{J} w^j \ln p^j$$

However, that simplification does not address the endogeneity issue, since the right hand-side of equation (7) remains a function of vector w. To circumvent that problem, we replace those observation-specific shares with sample averages, denoted with a bar:

$$\hat{y} = \ln(x) - \sum_{j=1}^{J} \overline{w}^j \ln p^j$$

The system of equations (6), using (8) to approximate y, defines the unrestricted demand system, to which we impose the properties derived from microeconomic theory. One advantage of the EASI specification is that those theoretical constraints are linear in parameters. First, homogeneity implies

First, homogeneity implies J constraints:

$$\sum_{k=1}^{J} a^{jk} = 0, \;\; \mathrm{j} = 1,\dots,J$$

Thus, in each share equation, the price coefficients sum to zero. This property can be imposed on the coefficients of the unconstrained model or, alternatively, all prices can be expressed relative to the price of an arbitrarily chosen numeraire good.

The second theoretical property, symmetry, implies:

$$a^{jk} = a^{kj} \text{ for all } j, k.$$

Hence, with J share equations (i.e., goods), there are J*(J-1)/2 such restrictions (i.e., the number of non-diagonal elements of a J*J matrix divided by 2).

Finally, adding-up implies that the sum of the J coefficients associated with the constant of each share equation (denoted z0) is equal to unity:

$$\sum_{j=1}^{J} g_0^j = 1$$

and the sum of the J coefficients associated with any other variable (i.e., price, socio-demographic, or expenditure) is equal to zero:

$$\sum_{j=1}^{J} a^{jk} = 0, \;\; k = 1,\ldots,J \; ; \;\; \sum_{j=1}^{J} b_r^j = 0, \;\; r = 1,\ldots,R \; ; \;\; \sum_{j=1}^{J} g_t^j = 0, \;\; \mathrm{t} = 1,\ldots,T$$

Altogether, the model features JxJ price coefficients, Jx(T+1) socio-demographic coefficients (including the constant terms), and JxR income coefficients, for a total of Jx(J+T+R+1). There are J homogeneity constraints, Jx(J-1) /2 symmetry constraints, and R+J+T+1 adding-up constraints, but it is easy to show that, for the price coefficients, imposing symmetry together with any of the other two constraints implies that the third constraint is automatically satisfied. Thus, there are only J(J+1)/2+R+T+1 independent constraints, and (J-1)(R+T+1+J/2) independent coefficients to estimate.

The numerous parameters of the model are not interpretable directly, so that the next step in the analysis is to compute elasticities. In general, the elasticity of any endogenous variable x with respect to an exogenous variable p is defined as

$$\frac{\partial x / x}{\partial p / p} = \frac{\textbf{\% change in x}}{\textbf{\% change in p}}.$$

This unitless quantity thus measures the responsiveness of x to p. The results section of this report therefore presents the estimates of elasticities of demand with respect to prices, total expenditure (i.e., budget), and sociodemographic variables.

The food choices that real-world consumers make involve thousands of products, which cannot be modelled simultaneously within the framework of traditional demand theory. The usual solution to this problem is to make a priori assumptions about consumers' preferences and decision making processes (Edgerton et al., 1996, p. 69). Here, the simplifying assumption is that of multi-stage budgeting. Thus, it is assumed that, as depicted in Figure 1, the consumer's food budget is allocated in a first stage to broad categories of products, including an aggregate of all fish and seafood products. In Stage 2, the fish budget is itself allocated to different categories of fish products as defined by the type of processing method. For both countries, those categories include fresh fish, smoked/marinated fish, canned fish and frozen fish, but the French model also covers two additional categories: fish-based prepared dishes, as well as other fish-based preparations (e.g., seafood spread). The third stage brings the analysis to the level of the species.

At each stage, a demand system is estimated while holding total expenditure on the upper-level aggregate constant. That is, the demand system for fresh fish estimates demand functions for each species under the assumption that total expenditure on fresh fish remains constant, which generates conditional elasticities (i.e., conditional on a constant fresh fish budget). Obviously real consumers do not impose that sort of constraints upon themselves, so that in simulation exercises, realism requires knowledge of unconditional elasticities, i.e. elasticities reflecting the response of demand to a change when only total income (or expenditure, or the food budget) is held constant. Carpentier and Guyomard (2003) have derived formulae to combine stage-specific elasticities into unconditional elasticities, and the empirical section uses those formulas to calculate unconditional elasticities.

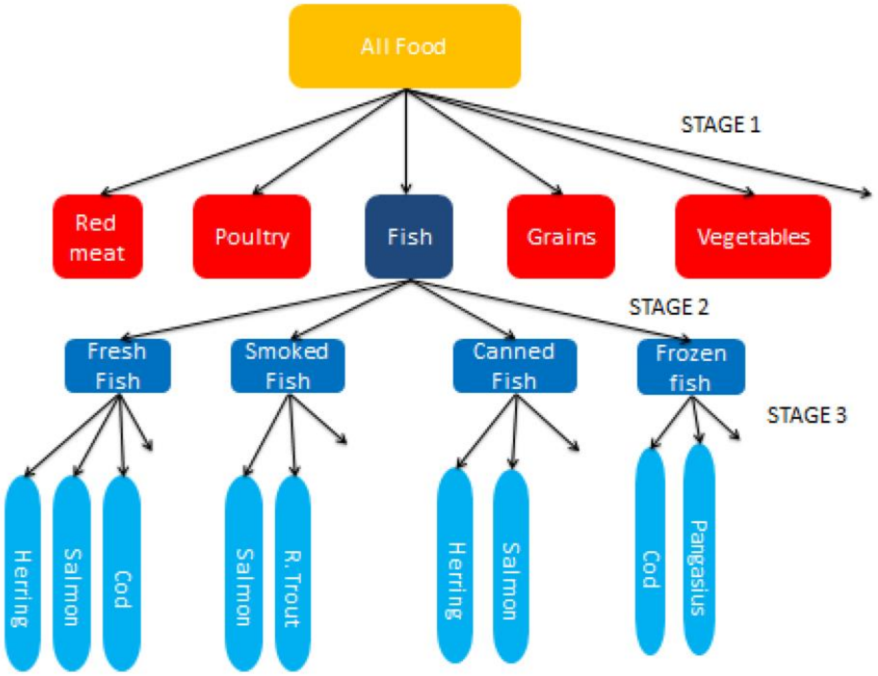


Figure 1. Multi-stage decomposition of the household's food budget.

At least since the seminal contribution of Theil (1952), it has been known that heterogeneous commodity aggregates cannot be treated as homogenous goods in demand models. In particular, as shown by Deaton (1988), unit values, defined as the ratio of expenditure to physical quantity for a product aggregate, do not measure prices accurately since they also reflect endogenous quality choices. For example, higher income may induce households to expand their consumption of a heterogeneous commodity, such as the aggregate "fish", by different means: either by consuming larger physical quantities of fish, or by switching to higher-priced fish (e.g., from herring to salmon, or from whole salmon to salmon filets). Consequently, the use of endogenous unit values in place of exogenous prices when estimating demand models results in biased elasticities. The level of the approximation that is made when considering that unit values measure prices depends of the level of product aggregation and inherent heterogeneity of the products gathered into a single aggregate. Thus, in the present study, the problem is likely to be more severe for the systems estimated in stages 1 and 2 than for those in stage 3. We also note that in addition to this quality adjustment issue, the use of unadjusted unit values as prices creates other problems related to sample selection (as only purchasing households are observed) and measurement errors.

Fortunately, the literature on the subject offers several options to correct unit values to make it possible to use them as price variables, as reviewed partially in Aepli (2014). Cox and Wohlgenant (1986) paved the way by showing how regressions of unit values on variables thought to influence quality choices (e.g., household size, education) can be used to "clean" unit values of their quality component. Their method, which is very close to that subsequently proposed by Park and Capps (1997), remains widely used in microeconometric analysis of household consumption. Based on the theoretical model of quantity versus quality choice of Houthakker (1952), a unit value equation is specified as relating the unit value to: 1- Forces with a strong influence on supply conditions (hence prices), which are of particular importance in order to identify demand relationships. Typically, regional, seasonal and, where appropriate, yearly dummies are included, or the unit value equation are expressed in terms of deviation from regional/seasonal/annual means; and 2- Variables thought to influence quality choices, such as household size, or income. More recent developments of the approach also include the physical amount of the category aggregate to accommodate the possibility that the same goods purchased in larger quantities entail lower unit values. In a second stage, adjusted prices are calculated by removing from unit values the estimated effect of all the variables in the second group (i.e., influencing quality choices) or, equivalently, by adding the household-specific residual to the estimated effect of the first group of variables. Given that residuals are not available for non-consuming households, they are simply assumed to be zero so as to allow estimation of demand relationships over the whole sample. The empirical analysis presented below used the Park and Capps (1997) approach to correct unit values.

The high prevalence of zero consumption observations in microeconomic data sets used to estimate demand systems is very common (Coelho et al., 2010). The fundamental problem that this creates results from the fact that an observation of zero consumption may not indicate that the household does not and will never consume the food concerned, since other possibilities are equally plausible. Zero consumption may be attributable to the infrequency of purchase of some food items, although this is less likely when consumption is recorded over a long period of time, as is the case with consumer panels. In addition to infrequency of purchase, an observation of zero consumption can also reflect a corner solution to the utility maximization problem: given its current income and prevailing prices, the household does not purchase the food item. However, under different economic circumstances, the household may opt to consume the good (Maddala, 1983).

Zero consumption explained by infrequency of purchase or corner solutions implies that the dependent variable, consumption, is censored, which creates an econometric problem particularly difficult to address in the case of multivariate models, such as demand systems. Ignoring censoring by treating zero values as any other value of the consumption variable produces estimates of demand models, and elasticities, which are known to be both biased and inconsistent. The most complete treatment of this issue considers the simultaneous estimation of the decision to consume each good (i.e., a binary problem) and the decision regarding the amount of the good that should be purchased. However, when a system of multiple equations is considered, direct estimation involves the resolution of multiple integrals in the likelihood functions, which proves computationally intensive and often intractable.

Thus, more tractable multi-stage estimation procedures of censored demand models have been developed. Heien and Wessels (1990) (henceforth HS) used the general Heckman procedure to propose an estimation in two simple steps. In the first step, a probit equation is estimated to model the binary decision to consume a food item and, in a second step, the demand equations are augmented by the inverse mills ratios extracted from the first-step regressions. Shonkwiler and Yen (1999) (henceforth SY), however, have demonstrated the inconsistency of the HS estimator before offering a consistent alternative. That procedure is still widely used in empirical demand analysis (e.g., Gustavsen and Rickertsen, 2014) and we adopt it as it represents a good compromise between theoretical soundness and empirical tractability. In a first step, as in the HS framework, the probabilities of consuming positive quantities of any given food item are estimated by probit models. The terms related to the first-stage probit equations are then introduced to correct the bias in the coefficients of the EASI model brought about by censoring. Thus, those corrected coefficients can be used as such in the expressions of the elasticities previously described.

The microeconomic analysis of demand for fish in D4.3 and D4.4 was carried out using the methodology presented above. The method proceeds in several steps:

- Descriptive statistics are used to characterize the market of interest and its evolution. This generates background and hypotheses but is insufficient to pinpoint the exact drivers of demand.
- Based on the economic theory of consumer choice, demand functions for different seafood products are derived, and the links among demand functions are made explicit. This allows one to specify three types of observables that influence

consumers' decisions to purchase fish, namely prices, income and socio-demographics related to tastes and preferences.

- A functional form is imposed to define empirically estimable demand relationships. In our case the approximate Exact Affine Stone Index (EASI) demand system was chosen because of its flexibility.
- The demand relationships are estimated as a system through appropriate econometric procedures.

The results of that analysis are summarized by elasticities measuring the response of demand to exogenous changes in the economic environment (prices, income) as well as the extent to which demand depends on socio-demographic variables. However, we developed the analysis further to produce simulations that make it easier to communicate the results effectively to non-specialists.

At a broad level, the method uses actual market transaction data (i.e., real purchases made by real consumers) to characterise consumers' preferences for fish. In other words, it lets the data "reveal" preferences. This differentiates the approach from the group of "stated preferences" methods that are also widely used to investigate consumer behaviour, including in PrimeFish WP4, and rely on consumers' statements about hypothetical situations. Both groups of methods have their strengths and weaknesses, but in cases where markets exist, revealed preference methods are usually considered superior because they do not suffer from the hypothetical biases that plague stated preference methods. On the other hand, revealed preference methods are less suited to assess demand for a new product that is not currently available to consumers, or to shed light on the cognitive and psychological processes underlying choices.

We used the most common method used to analyse the structure of demand in seafood markets, as stated for instance in this publication:

However, as mentioned above, stated preference methods can be used to analyse determinants of demand as well. Within the group of revealed preference methods, alternative approaches (e.g., random utility model) are available but they are more appropriate to investigate demand for highly differentiated products (e.g., different brands).

The main strength of the methodology applied is to rely on observations of what consumers actually do rather than what they say they will do. However, relying on secondary data has its drawbacks. First, the data are expensive to purchase. Second, some variables of interest, for instance regarding consumers' motivations to purchase fish, values and health status, are not measured in those data sets. Finally, the results are sometimes sensitive to the choice of estimation method.

The approach relies on very detailed data, i.e., "Big Data", which makes the analysis rather involved, technical and time consuming. While convenient tools exist to visualize and describe that type of data, going further to carry a full demand analysis remains difficult and requires specialist skills. However, tools may be developed in the future to limit the obstacles to that type of analysis.

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12 Frequency of purchases

The purpose of deliverable 4.5 report on frequencies of consumer purchases is to analyse what determines how frequently consumers buy seafood products. The methodology used is based on a system of demand equations, in terms of purchase frequencies, using a negative binomial model which is a modified version of the microeconomic model by Meghir and Robin (1992). In particular, the aim is to determine what types of consumers purchase the following seafood product categories; fresh salmon, frozen salmonids (salmon and trout), fresh cod, frozen white fish (cod, haddock, saithe etc.) and all other seafood products.

We approach the problem from the angle of purchasing freequencies, that is, how often households purchase various types of fish. The object is to combine aspects from the marketing literature and the economic demand literature, which have analysed consumer behavior from different angles, to utilise the strengths of both approaches in order to produce valuable information for those who wish to sell fish in France.

Conventional demand analysis aims at understanding markets by predicting consumption and understanding how demand relates to prices, expenditure, and socioeconomic variables. Various studies of the demand for fish exist in the literature. Thus, Asche et al. (2011) analyse demand for Atlantic salmon in the EU, especially France. Gobillon and Wolff (2015) investigate spatial variations in product prices in French fish markets, while Onozaka et al. (2014) analyse the relationship between consumer perception and salmon consumption frequencies. Xie and Myrland (2011) apply an empirical test for the aggregation levels of French household demand for salmon. The marketing literature has focused more on count data models which have been widely applied for different purposes, such as evaluating brand success, brand loyalty, and store choice. Kau and Ehrenberg (1984) use the negative binomial (NB) Dirichlet[4] model to predict store choice. Uncles et al. (1995) is a review paper on buyer regularities based on predictions from the NB Dirchlet model. Bhattacharya (1997) estimates deviations from brand loyalty and compares it with predictions from the Dirchlet model, and

[4] The negative binomial Dirichlet model has two stages; the first is a form of the multivariate beta distribution known as the Dirichlet distribution, and the second is a Poisson gamma mixture which produces a variant of the negative binomial model. The Dirichlet is assumed to be the data generating process (DGP) of some choice and the negative binomial is assumed to be the DGP of the frequency of the corresponding choice.

Uncles and Lee (2006) estimate the purchase frequency of different age groups using predictions from the NB Dirichlet model.[5]

A specific branch of the demand literature has applied count data models in demand analysis, where the key references are Meghir and Robin (1992) and Robin (1993). However, these studies do not use count data estimation as their main focus, but rather employ the estimated probabilities to adjust conventional demand models to account for the actual purchase frequency of consumers, instead of utilising only the observed choice to purchase or not. In general, though, the economics literature has only applied count data models to a very restricted set of problems, e.g. the estimation of recreational demand and demand for health care. The standard count data models are the Poisson and the negative binomial, where the negative binomial is a natural extension to the Poisson which allows for a variance which differs from the mean. The Poisson and negative binomial have been applied, for example, by Creel and Loomis (1990), and Hellerstein (19991) to estimate recreational demand. Munkin and Trivedi (1999), Deb and Trivedi (2002), and Wang (2003) estimate the demand for health care.

Consider a consumer that faces the following optimisation problem

$$\max_{l,c,n}\{U(l,c,n): wT + R = p'c + wl + wL(n), l > 0, c > 0, n > 0\} \tag{1}$$

where U denotes utility, l leisure, $c = (c_1, c_2, \dots, c_M)'$ is a vector of consumption goods and $n = (n_1, n_2, \dots, n_M)'$ represents the corresponding purchase frequency. We assume that the consumer's utility function, $u(l,c,n)$, is weakly separable and quasi-concave in l, c, and n. The consumer has income $y = wh$, where h is the hours spent working and w is the hourly wage rate, as well as other income through transfers and undeclared activities, R. Total available time is T, which is split into total hours worked h, time spent purchasing goods which is given by the function $L(n)$, which is increasing in n, and other non-market hours, l. From the aforementioned assumptions, the consumer's optimization problem can be expressed as follows:

[5] The Dirichlet distribution is generally not used in economics, but one example is Shonkwiler and Englin (2005) who use it to estimate the willingness to pay for removing grazing land from hiking trails.

$$\max_{l,c,n}\{u(l,c,n): wT + R = p'c + wl + wL(n), l > 0, c > 0, n > 0\} \qquad (1)$$

The solution to the optimization problem are three sets of Marshallian demand equations, $l(p,w,R)$, $n_i(p,w,R)$, and $c_i(p,w,R)$, where $i = 1,2,\dots,M$. This deliverable, however, only focuses on the purchase frequency decision. Let the number of shopping trips be generated by a discrete distribution with a probability mass function $f_N(n|Z_i)$ for $n = 0,1,2,\dots$ where Z_i is a matrix of exogenous variables, then the probability of observing $n = 0$ is given by $\Pr(N = 0|Z_i)$.

To be able to estimate the model it is necessary to specify the probability mass function of *n*. The usual starting point of count data estimation is to assume the Poisson distribution, which was used in Meghir and Robin (1992) to estimate their system of purchase frequency demand. This is a valid choice since quasi-maximum likelihood will lead to an unbiased estimation even though the distribution assumptions are incorrect as long as the mean is correctly specified. However, due to the Poisson limitations of equidispersion we assume instead the negative binomial distribution:

$$f(n_i|Z_i) = \frac{\Gamma(\theta + n_i) r^{\theta} (1-r)^{n_i}}{\Gamma(1+n_i)\Gamma(\theta)}, r = \frac{\theta}{\theta + \lambda}, 0,1,2,\dots \qquad (2)$$

The conditional mean of n_i is then $\mathrm{E}(n_i|Z_i) = \lambda_i$ and the conditional variance is $\mathrm{V}(n_i|Z_i) = \lambda\left(1 + \frac{1}{\theta}\lambda\right) = \lambda(1 + \kappa\lambda) = (\lambda + \kappa\lambda^2)$. This specification of the negative binomial model is known as the NB2, due to the square of the lambda parameter in the variance specification.[6] As in Meghir and Robin (1992) no stochastic relationship is assumed between different $\mathrm{E}(n_i|Z_i) = \lambda_i$. To be able to estimate a count data system with a dimension greater than two or three and an unrestricted covariance matrix one must use simulation based methods, see for example Chib and Winkelmann (2001).

The method chosen for this analysis represents state-of-the-art methodology. The models used are modified – and hopefully improved – version of the models proposed by Meghir and Robin (1992) and Robin (1993).

This is the standard methodology used in the field, but other, less statistically advanced, methods can certainly be employed to illustrate frequencies of purchases.

[6] See Cameron and Trivedi (2013) for details.

The method is typically used on consumer data such as scanner data which show "true" consumer behaviour as reflected by their purchases of goods and services. This yields a better picture of how consumers behave than surveys. However, the datasets – just like surveys – do not include all the variables researchers might be interested in using in their surveys. The models employed are based on classical microeconomic theory which has been criticised for its rather stringent assumption about homo economicus. The results of the methods are often sensitive to the choice of the estimation method and the restrictions imposed by theory. Finally, consumer data can be expensive to purchase.

The aim is to understand consumer behaviour in the French fish market using a frequency of purchase approach, which is significantly different from the standard demand system studies in the economics literature. The frequency of purchase approach, as we present it, models how often consumers purchase from each category of fish, as specified in the paper, and not how much quantity is purchased, or how much is spent in Euros on each category as is so often done in standard demand analysis. The strength of the frequency of purchase approach stems from the fact that purchasing behaviour is mainly determined by how often one purchases goods and not how much is purchased on each occasion. Furthermore, the results from the model show how prices, expenditure and socioeconomic variables relate to purchase frequencies, which then enables companies to construct their pricing strategy in such a way that each consumer purchases as frequently as possible. If the firm is a supermarket, which has a wide selection of products, and has fish on sale then customers who come to the supermarket with the aim of purchasing cheap fish are likely to purchase a range of other products as well, due to the opportunity cost of time.

The frequency of purchase approach, as we present it, has the flaw of not accounting for average purchased quantity. Even though the information that this addition would bring might be limited it would still improve the strength of the estimation. In comparison with the standard estimation framework where average quantity purchased and frequencies is lumped together in a variable such as total purchased quantity, expenditures on each category, or budget shares information is still lost, since frequencies of purchase are not modelled specifically. The two approaches both have their pros and cons and the choice of which model to use depends highly upon the problem at hand.

This project has received funding from the European Union's Horizon 2020 research and innovation program under

Example of scanner-data used

	Observations									
Variable	1	2	3	4	5	6	7	8	9	10
idfoyer	11644	11646	11646	11646	11662	11662	11662	11662	11684	11684
nf	1	2	2	2	1	1	1	1	1	1
cha	0	1	1	1	0	0	0	0	0	0
voit	0	1	1	1	0	0	0	0	0	0
cap1	0	1	1		0	1	1		1	1
cap2	0	0	0		0	0	0		0	0
agec	82	58	59	60	78	79	80	81	78	79
pq	4.20	48.03	131.57	128.70	119.24	110.46	87.97	79.82	28.62	17.78
p1	14.73	8.86	11.38	14.54	15.69	4.67	8.63	18.43	15.69	15.92
p2	15.94	15.46	17.25	15.88	14.13	15.46	15.94	15.88	14.13	15.46
p3	14.82	18.18	16.76	18.57	7.95	11.70	10.88	13.93	14.10	14.83
p4	9.47	9.11	7.50	14.92	9.43	9.70	9.47	10.10	9.43	9.70
p5	8.40	13.71	17.69	14.96	5.69	8.65	6.48	7.04	12.13	12.35
eq	1	1	1	1	1	1	1	1	1	1
edu1	0	0	0	0	1	1	1	1	0	0
edu2	1	0	0	0	0	0	0	0	0	0
edu3	0	1	1	1	0	0	0	0	1	1
bmi	23.875	23.529	23.529	23.529	20.240	21.504	21.926	21.926	24.342	24.342
home1	0	1	1	1	1	1	1	1	1	1
home2	1	0	0	0	0	0	0	0	0	0
home3	0	0	0	0	0	0	0	0	0	0
regs	0	0	0	0	0	0	0	0	0	0
regc	0	0	0	0	0	0	0	0	0	0
regpar	1	1	1	1	1	1	1	1	1	1
rege	0	0	0	0	0	0	0	0	0	0
regn	0	0	0	0	0	0	0	0	0	0
regw	0	0	0	0	0	0	0	0	0	0
dc1	0	0	0	0	0	0	0	0	0	0
dc2	0	1	0	0	0	0	0	0	1	1
dc3	1	0	1	1	1	1	1	1	0	0
dc4	0	0	0	0	0	0	0	0	0	0
n_freshsal	0	2	5	7	0	1	4	1	0	0
n_frozsalr	0	0	1	0	0	0	0	0	0	0
n_freshco	0	2	3	2	7	7	3	4	0	0
n_frozcod	0	1	1	1	0	0	0	0	0	0
n_other2	1	2	10	9	23	11	17	15	10	6
p1n	0.149	0.092	0.115	0.146	0.166	0.048	0.088	0.185	0.166	0.165
p2n	0.162	0.160	0.175	0.160	0.149	0.160	0.162	0.160	0.149	0.160
p3n	0.150	0.188	0.170	0.187	0.084	0.121	0.110	0.140	0.149	0.153
p4n	0.096	0.094	0.076	0.150	0.100	0.100	0.096	0.102	0.100	0.100
p5n	0.085	0.142	0.179	0.150	0.060	0.089	0.066	0.071	0.128	0.128
pqn	0.043	0.497	1.334	1.294	1.259	1.142	0.892	0.803	0.302	0.184
t2	0	1	0	0	0	1	0	0	0	1
t3	1	0	1	0	0	0	1	0	0	0
t4	0	0	0	1	0	0	0	1	0	0
pd1	0	0	0	0	0	0	0	0	0	0
pd2	0	0	0	0	0	0	0	0	0	0
pd3	0	0	0	0	0	0	0	0	0	0
pd4	0	0	0	0	0	0	0	0	0	0
pd5	0	0	0	0	0	0	0	0	0	0
d1	1	1	1	1	1	1	1	1	1	1
d2	0	0	0	0	0	0	0	0	0	0
d3	0	0	0	0	0	0	0	0	0	0
d4	0	0	0	0	0	0	0	0	0	0
d5	0	0	0	0	0	0	0	0	0	0
all	0	2	5	7	0	1	4	1	0	0

Example of output from the statistical software SAS

Negative binomial system estimation results: Fresh salmon, frozen Salmonidae, fresh cod, frozen white fish, and all other fish.								
Fit Statistics								
-2 Log Likelihood	872926							
AIC (smaller is better)	873158							
AICC (smaller is better)	873158							
BIC (smaller is better)	874405							
Parameter Estimates								
Parameter	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**	**95% Confidence Limits**		**Gradient**
b10	-0.5754	0.06008	350000	-9.58	<.0001	-0.6932	-0.4577	-0.89924
b11	-0.3686	0.1367	350000	-2.7	0.007	-0.6365	-0.1006	3.50294
b12	0.909	0.003744	350000	242.79	<.0001	0.9017	0.9164	2.24714
b13	-0.04777	0.006671	350000	-7.16	<.0001	-0.06085	-0.0347	-8.38614
b14	0.000035	0.000537	350000	0.07	0.9477	-0.00102	0.001088	-40.8148
b15	0.0507	0.02183	350000	2.32	0.0202	0.007925	0.09348	0.2526
b16	-0.1175	0.01716	350000	-6.85	<.0001	-0.1512	-0.08392	-3.25819
b17	-0.3104	0.02547	350000	-12.19	<.0001	-0.3603	-0.2605	1.90349
b18	-0.02683	0.007637	350000	-3.51	0.0004	-0.0418	-0.01187	-0.26943
b19	0.02947	0.01037	350000	2.84	0.0045	0.009148	0.04979	-2.73192
b110	0.0556	0.01979	350000	2.81	0.005	0.01681	0.09439	0.25346
b111	0.2304	0.01963	350000	11.74	<.0001	0.1919	0.2689	-0.64037
b112	0.1262	0.01958	350000	6.44	<.0001	0.0878	0.1645	0.13272
b113	0.03098	0.02467	350000	1.26	0.2092	-0.01738	0.07933	-0.18889
b114	0.1409	0.01555	350000	9.06	<.0001	0.1104	0.1713	-2.56933
b115	-0.077	0.0164	350000	-4.7	<.0001	-0.1091	-0.04486	1.5707
b116	0.05699	0.03851	350000	1.48	0.1389	-0.01849	0.1325	-0.33164
b117	-0.00339	0.001446	350000	-2.34	0.0191	-0.00622	-0.00055	-25.4972
b118	-0.1927	0.02133	350000	-9.04	<.0001	-0.2346	-0.1509	-0.88459
b119	0.1185	0.02604	350000	4.55	<.0001	0.06748	0.1696	-0.35162
b120	-0.1269	0.02756	350000	-4.6	<.0001	-0.1809	-0.07287	-0.79871
b121	0.04095	0.0213	350000	1.92	0.0545	-0.00079	0.08269	0.063161
b122	0.1316	0.02188	350000	6.02	<.0001	0.08872	0.1745	-0.66973

13 Analysis of social awareness

This section discusses the methodology applied in deliverable 4.6 Report on social awareness, attempts to stimulate fish consumption, and negative press.

The quantitative data was mainly analysed using different types of bivariate and multivariate data analysis. The purpose of these types of analysis is to determine the empirical relationship between two or several variables. The qualitative data is mainly based on literature review, but it also contains qualitative responses collected through questionnaire. The qualitative answers were analysed based on coding and qualitative comparative analysis.

These methodologies were used because they are simple to implement and because they correspond to the type of collected data. The bivariate and multivariate data analysis permitted to test the simple hypotheses of associations, especially between socio-demographic variables and fish consumption variables. Bivariate analysis was also used to analyse the impact of type of negative information on variables such as attitudes and intentions.

This type of analysis is a standard methodology used in the field. Another option could be structural equation model, that will be applied later in the scientific papers based on this data set.

The applied methodologies are simple to apply and robust. The weakness of the used methods, compared to structural equation model is the fact that it doesn't permit a fine analysis of latent variables.

The data didn't limit the choice of methodology, but on the basis of our experiment it might be better to base the analysis on both quantitative and qualitative data and to do statistical tests to check the quality of results. Furthermore, better analysis of latent variables (in our case: involvement, health sensitiveness and environmental sensitiveness) could be obtained by employing structural equation models.

14 Choice experiments

This section discusses the methodology employed for deliverable 4.7 Choice modelling report on innovative features and the consumers' willingness to pay.

According to Lancaster's consumer theory (1966), consumer utility stems from product attributes, not the products themselves. In other words, consumer utility can be separated into part-worth utilities. The part-worth utilities equal consumers' preference for corresponding attributes. In marketing research, the product attributes are classified into extrinsic and intrinsic attributes (Zeithaml, 1988; Olsen et al., 2008). Regardless of whether consumers are exposed to these attributes, they may be important signals of product quality and determinants of consumer preference.

The overall utility that a consumer obtains from consuming a seafood species j (U_j) can be expressed as:

$$u_{ij} = x'_{ij}\beta + \varepsilon_{ij} \qquad (1)$$

where: $i=1,....N$: Individual consumer i,

$j=1,....J$: product j among J products,

u_{ij}: utility obtained by individual i from product j,

x'_{ij}: product attributes,

β: vector of part-worth utility,

ε_{ij}: random effect.

It is generally assumed that an individual would choose a product alternative if the utility derived from this alternative is maximized compared to the other alternatives:

$$y_{ij} = \begin{cases} 1, & if\ u_{ij} \geq \max(u_i) \\ 0 & otherwise \end{cases} \qquad (2)$$

When facing a "basket" of seafood products, consumers assign a random utility to each product alternatives and select the one with the highest derived utility. Assuming that the stochastic components ε_j have independent and identical distributed (*iid*) forms, the probability of a consumer i choosing a fish product j ($P\left(y_{ij}=1\right)$) given by the multinomial logit (MNL) model (McFadden, 1974), is expressed in the following equation:

$$P\left(y_{ij}=1\right)=\frac{\exp(x'_{ij}\beta)}{\sum_{k=1}^{J}\exp(x'_{ik}\beta)} \qquad (3)$$

The MNL model presented in equation (3) is the basic choice model and has been approved to have several disadvantages such as assuming *iid* of the error and assuming the homogeneity of consumers' preference. To overcome the limitations of MNL, there many advanced discrete choice models suggested such as the mixed logit models (random coefficient, scaled-multinomial logit, and generalized-multinomial logit) and the latent class model (LCM) (see Fiebig et al., 2010; Greene & Hensher, 2003).

We estimated two types of models in this report to elicit the consumers' WTP for fish attributes that are specific to particular fish species and for individual consumers, named as fish species-specific effect model (FSSE) and random (i.e price) parameter effect model.

The fish species-specific effect (FSSE) model (fish j), is expressed as:

$$u_{ij} = \propto_j + \beta_{1j}Method_{ij} + \beta_{2j}Format_{ij} + \beta_{3j}Health_{ij} + \beta_{4j}Sustain_{ij} + \beta_{5j}Price_{ij} + \varepsilon_{ij} \qquad (4)$$

where β parameters are estimated for the *j-th* fish species and for the attributes production method (i.e. Method, as wild caught vs. farmed fish), product format (i.e. Format, as whole fish/round cut, fillet or ready-to-cook), nutritional and health claim (i.e. Health, as with/without nutritional and health claim), and sustainability label (i.e. Sustain, as with/without sustainability certification).

The Random price effect (RPE) model is specified so that the price coefficients includes two components, such as the average effect of price and the individual variance of price effects, expressed as:

$$u_{ij} = \propto_j + \beta_1 Method_{ij} + \beta_2 Format_{ij} + \beta_3 Health_{ij} + \beta_4 Sustain_{ij} + \beta_5 Price_{ij} + \gamma_{3i} Price_{ij} + \varepsilon_{ij} \qquad (5)$$

where αj, βk are fixed-effect coefficients, γ_3 is random coefficient of price estimated for individual i.

The specification of FSSE allows us to calculate the willingness to pay (WTP) for each of seven fish species in the choice experiment, while random price effect model allows us to elicit the WTP of each fish attributes at individual consumers' level. The WTP for a non-monetary attribute is the price premium that consumers are willing to pay for obtaining a desired attribute level. The WTP for an attribute level A (e.g. health) from FSSE model in equation (4) is calculated as:

$$WTP_{Aj} = -\frac{\beta_{Aj}}{\beta_{5j}} \qquad (6)$$

where WTP_{Aj} is the price premium paid for obtaining a desired level of attribute A (i.e., product with health claim) of the fish j, and β_{Aj} and β_{5j} are the estimated coefficients of attribute A and price attributes of fish j.

Similarly, the WTP for attribute A (not specific to fish species) at consumers' individual level (WTP_{Ai}) is calculated from model in equation (5) is:

$$WTP_{Ai} = \frac{\beta_A}{\beta_{5i}} \qquad (7)$$

We estimate the WTP specific to fish species with expectation that consumers' preference for fish quality attributes depends in specific species (Thong et al., 2015). For instance, consumers may prefer filleted cod to the whole fish cod, but they may prefer whole fish herring to the filleted herring. The WTP for fish quality attributes are calculated at individual consumers because the nature of heterogeneity of preference. The random price effect model also allows us to obtain choice probability for fish species at the individual consumer's level. The individual consumers' choice probability thus will be used for segmentations that are actionable for marketing strategy and developing the decision support system (DSS). The segments are derived in every country using SAS macros, and three parameter criterion: cubic clustering criterion (Sarle, 1983), Pseudo-F statistics (Calinski and Harabasz, 1974), and Pseudo-t squared statistics (Duda and Hart, 1973).

The main objective of Task 4.4 was to estimate the willingness to pay (WTP) for attributes (i.e. health and nutritional claim, production method, format and sustainability label) and for fish species (cod, seabass, seabream, pangasius, salmon, trout and herring).

The WTP estimate in our study is expected to be more accurate than those derived from studies based on single product alternatives because the model allows respondents to evaluate choice alternatives through both attribute judgment and alternative comparison.

Moreover, by estimating both the fish species-specific effects (FSSE) model and the random price effect (RPE) model, we could obtain WTP specific for the 7 species and segmentation, because of the individual estimates.

The methodology applied is coherent with the current development of the international research in this field. However, other methodology could have been applied. The basic MNL-fixed effect model could have been estimated, using the formula:

$$u_{ij} = \propto_j + \beta_1 Health_{ij} + \beta_2 Sustain_{ij} - \beta_3 Price_{ij} + \cdots + \varepsilon_{ij} \qquad (8)$$

where β parameters are only estimated for the attributes, without considering the fish species.

When facing a "basket" of seafood products, consumers assign a random utility to each product alternatives and select the one with the highest derived utility. Assuming that the stochastic components ε_j have independent and identical distributed (iid) forms, the probability of a consumer i choosing a fish product j ($P(y_{ij} = 1)$) given by the multinomial logit (MNL) model (McFadden, 1974), is expressed in the equation (3).

This means that with this model, it was not possible to estimate the specific parameters for fish species and for individuals (i.e. segmentation).

The WTP estimate in our study is expected to be accurate by estimating both the fish species-specific effects (FSSE) model and the random price effect (RPE) model, we could obtain WTP specific for the 7 species and segmentation, because of the individual estimates.

Applying the models to a number of fresh fish species allows us not only to understand consumers' evaluation of fish attributes within a product, but also to compare fish alternatives. Overall, many of the intrinsic values of the fish options emerged as important determinants of consumer choice.

Moreover, using the random price effect (RPE) model we have obtained individuals' estimates of the WTP for fish attributes alternatives, therefore allowing more deep analysis, including market segmentation based the consumers choices.

The main disadvantage of the method is related with the applied hypothetical choice experiment; in this case, the consumer choice may not be consistent with actual choices in the real market (i.e. the hypothetical bias, see Lusk et al. 2011). Therefore, the results of WTP may be overestimated. However, we have applied techniques to reduce the gap between hypothetical and real choice, i.e. including a cheap-talk script in the choice experiment. Moreover, the actual response task imposed respondents to select one single (fish) product only from each of the choice sets provided. With this simplification of the purchasing process we effectively eliminated the complexity of purchasing multiple goods. One further weakness in our study is associated with not including all potential quality attributes, in particular country of origin. We have decided to exclude the attribute origin because this attribute has already been deeply studied in the literature (Carlucci et al., 2015). Moreover, a huge effect of the domestic origin has been documented in previous studies: 145% WTP by Stefani et al. (2012), 108% by Mauracher et al. (2013), 100% by McClenachan et al. (2016). We have evaluated that this effect might have overwhelmed the impact of other attributes on the consumers' choices. Therefore, since other attributes have been studied much less, we have

The methodology applied (fish species-specific effects model and random price effect model) was directly based on the type of data collected. Based on the objective of the task (WTP estimated in 5 countries with online survey), the use of an online (hypothetical) choice experiment was straightforward. Therefore, the models applied, in our opinion, provide the best possible estimates for the attributes and species analysed.

We recommend that data be collected using proper methodology, in particular by evaluating carefully the choice of the attributes and levels to be analysed. Including more attributes would have increased the complexity of the choice task, which might have shifted the choice behaviours toward the choice of the "Non-option" rather than evaluating the attributes in the experiment.

Regarding the methodology used to analyse the data, we recommend to estimate mixed logit models, such as the fish species-specific effects (FSSE) model and the random price effect (RPE) model that we have estimated. In this way, it will be possible to obtain WTP estimates specific for the fish species and a market segmentation, because of the individual estimates.

15 Fisheries and aquaculture competitiveness index

The Fisheries and Aquaculture Competitiveness Index (FACI) developed in deliverable 5.1 is modelled on the Fisheries Competitive Index (FCI) developed by the Directorate of Fresh Fish Prices in Iceland and the Norwegian College of Fishery Science at the University of Tromsø in 2004-2005 (Verðlagsstofa skiptaverðs, 2009). The FACI though expands on the FCI in two directions. First, by developing a national-level FACI that also includes aquaculture. Second, by designing a firm-level index that is intended to capture the views of operators of individual firms and is therefore less complex.

The national-level FACI consists of 144 items, whereof 44 are taken from the WEF Global Competitiveness Index, 19 are based on data obtained from national, public sources and 81 are based on answers from a survey conducted among specialists in each country. Whereas the information taken from the GCI analyses the overall competitiveness of the nation, the other sources will throw light on the competitiveness of the fisheries and aquaculture sectors. The firm-level FACI is based on a survey which in the case of firms engaged in the harvesting, processing or marketing of wild capture fish consists of 40 questions, and in the case of aquaculture firms consists of 45 questions

The firm-level FACI builds heavily on the theories of Porter (1998), taking into consideration all five aspects of competition outlined by Porter. This index is mostly intended for operators of fisheries and aquaculture firms who wish to analyse the competitive standing of their firm. The index consists of 40 questions – 45 in the case of aquaculture – that together yield a solid measure of competitiveness. Here the results of a survey that was put to a limited number of firm operators are presented. Once the PrimeDSS in PrimeFish becomes operational it will be possible to access a computerised version of the firm-level FACI, complete the survey online and then obtain a measure of the competitiveness of the firm, both by analysing the data and comparing the competitive standing of the firm to that of other firms. Each question uses a seven-level Likert scale.

The national-level FACI is a comprehensive measure that includes both factors influencing each country's overall competitiveness, as well as factors that specifically relate to the fisheries and aquaculture sectors. Most of the indicators related to overall competitiveness are taken from the Global Competitiveness Index, published by the World Economic Forum (2016), but information on the other, more specific indicators was obtained through surveys and from public data collection agencies.

The national-level FACI consists of three pillars; (I) basic requirements, (II) efficiency enhancers, and (III) innovation and sophistication. In contrast to the firm-level FACI, the national-level FACI yields a weighted overall score for each country, as well as a weighted score for each pillar and the sub-indexes contain therein. Basic requirements weigh 30% of the total score, efficiency enhancers 50% and innovation and sophistication 20%.

16 Boom-and-bust model

This section discusses the methodology used in deliverable 5.2 "Boom-and-bust" model which aimed to develop simulation and prediction models that could be used to predict price hehaviour and give early-warning signals of a potential "boom-and-bust" cycle.

The statistical model used for the prices prediction is based on Robust Monitoring of Time Series approach. Time series often contain outliers and level shifts or structural changes, and these unexpected events are of the utmost importance in the forecasting of prices. The presence of such unusual events can easily mislead conventional time series analysis and yield erroneous conclusions. The model provides a unified framework for detecting outliers and level shifts in short time series that may have a seasonal pattern. The methodology was developed to detect potential fraud cases in time series of imports into the European Union, and we have borrowed it because it is particularly suited to the type of data and phenomena we have to manage (Barabesi et al, 2016; Fried et al., 2012; Galeano and Pena, 2013; Riani et al., 2012), Rousseeuw and van Driessen, 2006; Salini et al., 2015; FSDA).

The formal approach of the model is described in Perrotta et al. (2018), which contains methodology for robustly analysing a time series which contains a trend, a seasonal component (possibly time varying) and a level shift in an unknown position, as well as isolated or consecutive outliers.

The model is particularly suitable for the task at hand because it introduces a new robust approach to model and monitor nonlinear time series with a possible level shift. A fast algorithm was developed and applied to several real and artificial datasets. The automatic detection of level shift avoids the alternative and most common way of splitting in the parts before and after the break, after which each part can be analysed separately.

The model is especially relevant for this study because it can be applied to data sets which are not very long (less than 36 months), such as are frequently found in the fisheries sectors. The models also make it possible to manage any significant price changes over the period observed and therefore to make better forecasts. It is also quite easy to interpret the results for persons with non-statistical background. The model also offers the possibility to calculate robust confidence bands in the forecasts, therefore to define the risk linked to the forecasts. Finally, the model is innovative, as the method applied represents an improvement on previous models.

The methodology applied is coherent with the current development of the international research in this field. However, other methodologies could have been applied, such as ARCH and GARCH models. ARCH (autoregressive conditionally heteroscedastic) model is a model for the variance of a time series. ARCH models are used to describe a changing, possibly volatile variance. Although an ARCH model could possibly be used to describe a gradually increasing variance over time, most often it is used in situations in which there may be short periods of increased variation. GARCH (generalized autoregressive conditionally heteroscedastic) model uses values of the past squared observations and past variances to model the variance at time t.

The main strength of this method is that it works work well with not very long times series (less than 36 months), as are often found in fisheries, the ability to manage any significant price changes over the period observed and therefore to make better forecasts, the ease of interpretation of results for persons with non-statistical background and the possibility to calculate the confidence bands in the forecasts, therefore to define the risk linked to the forecasts and its robustness to the presence of isolated or consecutive outliers.

The weaknesses of the model, in relation to the aims of the project, are its inability to not foresee the boom and bust cycles in future periods compared to the observed data. This incapacity is not related to the model chosen in particular, but it is common to each statistical model.

The methodology applied was chosen to suit the task at hand and the nature of the data collected. The model applied provides, in our opinion, the best possible estimate of the cycle in prices time series for the species analysed.

Future work should be based on data collected using a well defined methodology and set up in a well organised database. This study was based on the following variables taken from EUMOFA; period (month, year), monthly prices, country, flow type (import or export), partner_country (imported from or exported to), fish species, market (first sale/landing, wholesale, retail).

17 Latent class analysis and multinomial logistic regression

Latent class analysis (LCA) (Lazarsfeld and Henry, 1968) was used in deliverable 5.4 which built on the demand and consumer analysis conducted in WP4. The deliverable introduced a robust model that could be used to analyse the likelihood that new seafood products launched will be successful by identifying certain consumer segments and matching them with products on offer.

Latent class analysis has been suggested as a model-based tool for regular market segmentation (Wedel & Kamakura, 2000) and international segmentation (Steenkamp & ter Hofstede, 2002). By "model-based," we mean that there is a statistical model that is assumed to come from the population from which the data was gathered (Vermunt and Magidson, 2002a; Vermunt and Magidson, 2002b). LCA is the state-of-the art segmentation method because of rigorous, objective and probabilistic results. Common areas of application include marketing research (eg. consumers segmentation), survey research, sociology, psychology and education. The most common use of LCA is to discover case subtypes (or confirm hypothesized subtypes) based on multivariate categorical data, a use which is perfectly in line with our objective.

LCA is a statistical method for finding subtypes of related cases, i.e. latent classes (they are called latent because a case's class membership is not directly observed) from multivariate categorical data (Marateb et al., 2014), in way analogous to cluster analysis. That is, given a sample of subjects (consumers) measured on several manifest (observed) variables (e.g. items), one wishes to know if there is a small number of basic groups into which cases fall (Uebersax, 2006). The latent class model seeks to stratify the cross-classification table of manifest variables by a latent unordered categorical variable that eliminates all confounding between the manifest variables (Jaspers et al., 2016).

Beyond LCA, traditional cluster analysis is used for the "segmentation" of sample data. Additionally, in identifying groups both methods aim at maximization which in the case of LCA concerns the log-likelihood function while in the case of traditional clustering a given criteria is maximized.

The advantages of LCA (probabilistic model) over cluster analysis (heuristic model) can be summarized as follows: less arbitrary choice of the grouping criterion; easier to use with different scales; flexibility in the choice of probability distributions; restraints can be rigorously defined and checked; formal criteria to decide number of classes (information criteria) and the possibility to insert covariates for the definition and description of classes (and for validation purposes); Vermunt and Magidson (2002a) in a comparsion between LCA and K-mean clustering have evidenced that LCA errors of classification are systematically lower than those of traditional cluster analysis.

Also, LCA is suitable for binary, ordered-category and Likert-scale, or nominal data and there is no technical barrier to analyzing models that combine categorical and continuous data (Lazarsfeld and Henry, 1968).

LCA supposes a simple parametric model and uses observed data to estimate parameter values for the model. The model parameters are (i) the prevalence of each latent classes, and (ii) conditional response probabilities, i.e. the probabilities, for each combination of latent class, item or variable (the items or variables are termed the manifest variables), and response level for the item or variable, that is a randomly selected member of that class will make that response to that item/variable (Collins and Lanza, 2010).

Essentially, LCA allows to obtain cross-classification tables of equal dimension to the observed table of manifest variables, and, following the assumption of conditional independence, the proportion of observations in each latent class, and the probabilities of observing each response to each manifest variable, conditional on latent class. Observations with similar sets of responses on the manifest variables will tend to cluster within the same latent classes (Hagenaars and McMutcheon, 2009). In this way, the LCA output will contains elements which enables quick comparisons of the observed cell counts to the cell counts predicted by the latent class model (Uebersax, 2006; Linzer and Lewis, 2011).

LCA defines latent classes by the criterion of conditional independence, that is conditional upon values of this latent variable, responses to all of the manifest variables are assumed to be statistically independent. This means that, within each latent class, each variable is statistically independent of every other variable (Magidson and Vermunt (2002). For example, within a latent class that corresponds to a distinct consumer segment the presence/absence of one preference is viewed as unrelated to presence/absence of all others. Paul Lazarsfeld (Lazarsfeld and Henry, 1968), the main originator of LCA, argued that this criterion leads to the most natural and useful groups.

An advantage of LCA as compared with other clustering techniques is the variety of tools available for assessing model fit and for determining the appropriate number of latent classes. (Linzer and Lewis, 2011).

In some applications, the number of latent classes will be selected for primarily theoretical reasons, in other cases, however, the analysis may be of a more exploratory nature, with the objective being to locate the best fitting or most parsimonious model. The researcher may then begin by fitting a complete "independence" model with C = 1, and then iteratively increasing the number of latent classes by one until a suitable fit has been achieved (Linzer and Lewis, 2011).

Parsimony criteria seek to strike a balance between over- and under-fitting the model to the data by penalizing the log-likelihood by a function of the number of parameters being estimated (Linzer and Lewis, 2011). The two most widely used parsimony measures are the Bayesian information criterion (BIC) (Schwartz, 1978) and Akaike information criterion (AIC) (Akaike, 1973). Preferred models are those that minimize values of the BIC and/or AIC.

The BIC will usually be more appropriate for basic latent class models because of their relative simplicity (Lin and Dayton 1997). Calculating Pearson's χ^2 goodness of fit and likelihood ratio chi-square (G^2) statistics for the observed versus predicted cell counts is another method to help determine how well a particular model fits the data (Goodman 1970).The entropy of a model is also used as a model selection criterion, either by itself or together with other statistics (Larose et al., 2016).

Problems related to the sample size, the adequate number of classes and the sparseness problem have been discussed in literature (for more details please see Muthen and Muthen (2002), W.H. Finch, K.C. Bronk (2011), Wurpts and Geiser (2014).

A LCA model can be expressed as follows. Let X represent the latent variable and Y_l one of the L observed or manifest variables, where $1 \leq l \leq L$. Moreover, let C be the number of latent classes and D_l the number of levels of Y_l. A particular LC (latent classes) is enumerated by the index x, x = 1, 2, ..., C, and a particular value of Y_l by y_l, y_l= 1, 2, ..., D_l. The vector notation Y and y is used to refer to a complete response pattern.

The basic idea underlying any type of LC model is that the probability of obtaining response pattern y, $P(\mathrm{Y} = \mathrm{y})$, is a weighted average of the C class-specific probabilities $P(\mathrm{Y} = \mathrm{y}|X = x)$; that is,

$$P(Y = y) = \sum_{x=1}^{C} P(X = x)P(\mathrm{Y} = \mathrm{y}|X = x) \tag{1}$$

Here, $P(X = x)$ denotes the proportion of persons belonging to LC x.

In the classical LC model, this basic idea is combined with the assumption of local independence. The L manifest variables are assumed to be mutually independent within each LC, which can be formulated as follows:

$$P(\mathbf{Y} = \mathbf{y}|X = x) = \prod_{l=1}^{L} P(Y_l = y_l\,|X = x) \tag{2}$$

After estimating the conditional response probabilities $P(Y_l = y_l|X = x)$, comparing these probabilities between classes shows how the classes differ from each other, which can be used to name the classes. Combining the two basic equations (1) and (2) yields the following model for $P(\mathbf{Y} = \mathbf{y})$ marginal probabilities:

$$P(\mathbf{Y} = \mathbf{y}) = \sum_{x=1}^{C} P(X = x) \prod_{l=1}^{L} P(Y_l = y_l\,|X = x) \tag{3}$$

The model is formulated for nominal indicators Y_l and consequently a multinominal logit distribution is hypothesized for the conditional probability to obtain y_l to l, given the affiliation to the latent class x, $P(Y_l = y_l|X = x)$.

The conditional probability is parameterized as follows

$$P(Y_l = y_l|X = x) = \frac{exp\left(\eta_{y_l|x}\right)}{\sum_{y_l'=1}^{D_l} exp\left(\eta_{y_l'|x}\right)} \tag{4}$$

Where the linear term $\eta_{y_l|x} = \beta_{y_l} + \beta_{y_l x}$, the parameter β_{y_l} is the intercept and $\beta_{y_l x}$ is the effect of the latent variable X on the indicator Y_l.

In the same way, the probability associated with the latent variable X has a nominal logit distribution:

$$P(X = x) = \frac{exp(\eta_x)}{\sum_{x'=1}^{C} exp(\eta_{x'})} \quad (5)$$

Similarly to cluster analysis, one of the purposes of LC analysis might be to assign individuals to latent classes. The probability of belonging to LC x – often referred to as posterior membership probability – can be obtained by the Bayes rule,

$$P(X = x|\mathbf{Y} = \mathbf{y}) = \frac{P(X = x)P(\mathbf{Y} = \mathbf{y}|X = x)}{P(\mathbf{Y} = \mathbf{y})} \quad (6)$$

The most common classification rule is modal assignment, which amounts to assigning each individual to the LC with the highest $P(X = x|\mathbf{Y} = \mathbf{y})$.

The parameters of LC models are typically estimated by means of maximum likelihood (ML):

$$\ln \mathcal{L} = \sum_{i=1}^{I} \ln P(Y|y_i) \quad (7)$$

Where i is a particular pattern of response, I is the number of all potential patterns of response, ($I = \prod_{l=1}^{L} D_l$) and $P(\mathbf{Y} = \mathbf{y}_i)$.

Among the most popular numerical methods for solving the Maximum Likelihood Estimation (MLE) problem is the Expectation-Maximization (EM) algorithm (Dempster et al., 1977). The EM algorithm treats the estimation of LC model parameters as an estimation problem similar to those for missing data (i.e. multiple imputation). More details about the model and the parameter estimation are provided in Lazarsfeld and Henry (1968), Goodman (1974); Haberman (1979), Clogg (1995), Agresti (2002) and Bartholomew, Knott and Moustaki (2011).

In most LC analysis applications, one not only wishes to build a classification model based on a set of responses, but also to relate the class membership to explanatory variables. In a more explanatory study, one may wish to build a predictive or structural model for class membership whereas in a more descriptive study the aim would be to simply profile the latent classes by investigating their association with external variables (Vermunt, 2010). The latent class regression model (LCRM) generalizes the basic latent class model by permitting the inclusion of covariates to predict individuals' latent class membership (Dayton and Macready, 1988; Hagenaars and McCutcheon, 2009).

In the LC analysis literature two ways for dealing with covariates have been proposed: a "one-step" and a "three-step" approach. The former involves simultaneous estimation of the LC (measurement) model of interest with a logistic regression (structural) model in which the latent classes are related to a set of covariates (Vermunt, 2010). Instead, the "three-step" approach estimates the basic latent class model, calculates the predicted posterior class membership probabilities and then uses these values as the dependent variable(s) in a regression model with the desired covariates. Since the "one-step" presents certain disadvantages – for example, it limits the number of covariates that can be considered in the model (please see Vermunt, 2010) - we use the "three-step" approach in order to avoid such limitation. In a subsequent step, this allows us to predict the consumer segment and perform a matching between segmentation and firms' characteristics, in order to detect the best segment for the firm. Accounting to this, the causal relationship firm-to-consumer segment will be explained by multinomial logistic regression models where the consumer segment will be the dependent variable and the selected covariates (es. organic, wild, cheap ...etc) will be the choice factors. Once the company has selected the variables (X) –the estimated coefficients of multinomial logistic regression will be employed:

$$logit(P) = \ln(Odds_i) = \left(ln\frac{P(class_i)}{P(class_r)}\right) = \mathbf{X}\beta_i$$

where $i = 1, \dots, k-1$, k = *number of classes discovered by* LCA, r = *reference class*, **X** *is the design matrix (with the independent variables) and* β_i*is the coefficients vector for the modality logit i*

Finally, we compute the membership probabilities $\hat{p}_i = \frac{e^{X\beta}}{1+e^{X\beta}}$ (by coefficients) for each *i* class in order to obtain the results in terms of best class, i.e. the best membership probability, in other terms, the "best" segment. From the algorithm we obtain the association between product characteristics and the segment, according to the best fit (highest membership probability).

The method described above was employed using primary data (cross-sectional) collected through an online survey in Summer 2017; including 800 consumers (no restrictions on frequency) of at least one of the target species (salmon, cod, seabream, seabass, herring, trout, and pangasius) and be fairly or completely involved in the fish buying process in their households in each country (Germany, Italy, France, Spain, UK) for a total of 4.000 representative responses along age, gender, education, geography. The survey was designed based on extant literature and in-depth consumer interviews done in WP 4.2.

Example of data collected

	Observations																			
Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
family_size	4	2	5	1	3	3	4	2	2	2	3	2	5	3	4	5	2	5	2	2
children_eat	yes	none	none	none	yes	yes	yes	none	none	none	yes	none	yes	yes	yes	yes	none	yes	none	none
age	27	30	28	57	41	53	41	29	36	30	43	35	39	41	38	42	69	39	48	45
gender	1	0	0	0	0	0	1	1	0	1	1	0	1	1	0	0	0	1	1	0
employment	3	1	1	3	1	1	3	2	1	1	4	3	1	2	1	1	5	4	3	1
income	4	6	6	2	5	3	4	5	5	3	2	7	6	1	6	4	6	3	4	4
education	2	3	2	2	4	2	3	3	4	3	2	5	4	2	5	4	5	2	2	2
sea	2	2	1	2	2	1	2	2	2	2	2	1	2	2	2	2	1	1	1	2
urban	1	1	1	3	3	3	3	1	1	1	3	2	3	2	2	2	1	3	3	1
purchase_food	400	200	5000	100	600	500	400	300	200	250	300	400	800	300	500	700	300	800	400	150
purchase_fish	150	65	1000	45	50	50	150	50	30	80	50	40	150	5	50	50	20	50	50	10
No_waste	5	3	7	7	6	5	7	4	4	5	4	na	6	7	4	4	6	4	6	7
Save_time	5	3	7	4	6	6	2	5	4	4	5	1	6	4	5	4	5	4	4	7
Fishing	2	2	7	3	7	6	5	5	6	5	4	6	5	7	4	4	6	5	7	5
Farming_effect	5	4	7	3	6	6	3	4	5	5	4	6	6	7	5	4	5	4	6	7
Omega3	5	3	7	5	7	5	5	6	6	5	7	7	6	6	6	5	6	5	5	7
Neg_substan	5	5	7	3	4	4	3	3	5	5	4	4	6	4	3	3	5	3	6	7
Evaluat_fish	5	4	7	5	7	5	6	5	5	5	7	5	6	4	5	4	3	5	5	7
Trust_cook	5	2	7	6	6	5	7	5	5	5	4	6	6	5	5	5	4	5	4	7
No_time.0	5	5	7	4	4	4	4	6	5	3	4	3	6	4	4	3	4	5	5	7
Ready_eat_charct	5	5	7	4	7	4	5	4	5	5	4	6	6	4	5	4	4	4	6	7
Fish_availa	5	4	7	5	6	4	4	6	7	5	5	5	6	5	5	4	5	5	4	7
Label.0	5	5	7	5	1	3	7	4	7	5	2	na	6	5	5	4	5	4	6	7
Local_com	5	6	7	5	4	3	5	3	4	5	2	6	6	4	5	4	5	4	5	7
Fridge_space	5	4	7	4	7	5	5	3	5	5	2	4	6	5	4	5	4	2	6	7
Nutrients.0	5	3	7	5	7	5	6	3	4	5	2	4	6	3	5	4	4	3	6	7
New_format	5	5	7	6	7	4	6	3	6	5	4	4	5	3	4	4	4	4	6	7
Taste_nutrition	5	4	7	5	7	5	5	5	5	5	7	2	3	5	5	4	4	6	6	6
Discount_effect	5	5	7	4	7	4	5	3	6	5	1	4	4	4	5	4	3	5	6	6
Versatile	5	5	7	5	7	4	5	5	7	5	7	7	4	5	5	5	5	5	6	7
Brand_pref	5	5	7	3	7	4	4	6	6	5	7	7	5	4	5	4	5	4	6	7
Brand_loyal	5	4	7	5	7	4	4	6	6	5	6	5	5	4	4	4	5	4	5	7
Low_price	5	6	7	5	6	5	6	3	4	3	4	3	5	4	3	4	4	4	3	2
Org_food	5	6	7	5	7	6	4	5	7	4	1	3	5	4	6	4	6	4	5	2
Creativity	5	7	7	4	7	6	7	3	6	5	4	7	5	5	4	4	5	5	6	2
Cook_like	5	4	7	7	7	4	6	3	6	5	6	7	5	6	6	6	4	5	6	1
Easy_cook	4	5	7	6	6	3	5	6	6	5	7	6	3	6	4	4	5	7	5	7
No_smell	7	5	7	7	7	3	6	4	5	5	4	5	3	4	5	4	5	5	6	5
N_calories	4	6	7	6	5	3	5	5	5	5	4	5	3	4	4	4	5	4	5	6
Conservation	4	7	7	6	6	4	5	5	6	5	7	6	1	6	5	5	5	6	5	7

Gen_appear	6	3	7	7	7	5	6	6	7	6	7	7	1	6	5	4	5	6	6	6
Easy_digest	6	6	7	7	5	3	5	5	6	5	4	7	3	4	4	4	5	4	5	7
Quality_price	6	4	7	7	7	4	6	6	7	5	7	7	1	6	5	4	6	7	6	6
Animal_welfare	5	5	7	6	7	4	6	4	5	5	4	5	1	6	5	4	5	5	5	5
No_time	5	5	7	6	7	4	5	4	5	5	4	5	1	6	5	4	3	5	5	7
Natural	6	4	7	6	7	4	6	5	6	5	7	7	1	6	5	4	6	6	6	6
Healthy	6	3	7	6	7	5	6	6	7	5	7	7	1	6	5	4	6	6	6	6
Discount	7	3	7	7	6	5	5	4	6	5	7	4	1	5	4	4	5	6	5	5
Environ_friend	7	4	7	6	7	5	5	4	5	5	4	5	1	5	4	4	5	5	5	3
Nutrients	5	5	7	6	7	5	6	4	5	5	4	6	1	4	4	4	5	5	6	7
Texture	5	6	7	7	7	5	6	4	6	5	7	7	1	6	5	5	6	5	6	7
Origin_guarant	5	7	7	7	6	5	6	4	7	5	4	7	1	5	5	5	5	na	5	7
Sust_certif	5	5	7	7	7	4	6	4	6	5	4	6	1	5	5	4	5	5	6	6
tot_consumption	5	5	5	4	5	5	6	6	5	6	5	4	5	2	5	4	5	5	5	5
Salmon	5	5	3	0	5	4	5	6	4	0	4	3	4	0	5	4	3	3	4	5
Seabream	0	4	0	0	0	0	5	0	2	5	0	2	4	0	0	0	0	0	0	0
Seabass	4	6	0	0	0	0	4	0	2	0	0	0	5	0	0	0	0	0	0	0
Trout	3	4	4	0	0	0	4	0	2	5	0	0	4	0	0	0	0	0	0	0
Cod	0	0	0	3	0	5	4	0	3	5	4	2	5	0	5	0	4	4	4	0
Herring	0	5	0	0	0	0	4	0	4	5	0	0	0	0	0	0	0	0	0	0
Pangasius	0	0	0	0	0	0	0	0	3	0	0	0	0	2	0	0	0	0	0	0
Whole_fish	3	4	0	2	0	0	5	0	3	6	0	0	5	0	0	0	0	0	3	5
Fresh_fillet	3	0	0	0	0	5	5	0	3	5	0	3	4	0	5	2	0	0	0	0
Fillet_frozen	0	0	4	2	4	0	0	6	3	6	3	0	5	2	0	3	4	3	3	0
Ready_eat	5	0	5	0	0	0	0	4	0	6	3	0	0	0	0	0	0	4	0	5
Ready_Cook	4	4	0	3	0	0	0	0	3	6	4	0	5	0	0	4	0	3	3	0
Marinated	0	5	0	0	0	0	0	0	0	5	0	0	0	0	0	4	0	0	0	0
Dry	0	6	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
Smoked	5	5	0	0	0	0	5	0	3	5	0	0	0	0	4	0	0	2	3	0
Salad	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0
Spread	6	0	0	0	0	0	5	4	4	6	0	0	0	0	5	0	0	5	0	0
Canned	0	0	0	0	0	0	0	0	0	5	4	0	0	0	0	0	4	0	2	0
Wild_farmed	3	5	1	6	1	4	4	5	3	6	4	1	2	4	2	5	2	2	1	2
Cheap_expensive	1	4	7	1	1	3	4	5	2	4	1	4	4	3	4	4	3	3	4	4
Natural_enchance	1	5	1	1	1	5	3	3	2	4	1	5	2	1	1	4	1	1	1	5
Bones_boneless	6	3	7	7	7	3	4	7	7	7	7	3	4	7	5	4	5	7	6	7
Fresh_frozen	4	3	1	1	7	4	1	5	4	3	7	2	2	4	1	3	6	4	3	5
Local_national	4	4	7	1	3	4	1	6	4	3	4	4	2	4	4	3	5	6	4	4
EU_NEU	4	4	7	1	1	5	3	2	3	1	4	1	4	4	1	2	6	1	4	4
Trustp_n	4	5	7	1	4	5	3	4	3	1	4	4	4	4	4	4	4	3	4	5
Brand_n	4	3	7	1	1	4	5	4	4	5	1	4	4	1	3	3	3	4	4	5
Organic_n	4	4	1	1	6	5	3	6	3	2	7	4	4	7	1	4	3	4	4	7
Prepared_n	4	4	7	7	7	3	6	6	6	5	4	7	4	4	7	4	6	4	6	2
Traditional_n	4	3	1	1	1	4	2	2	3	3	1	1	3	1	1	4	2	1	1	5

Family	3	4	7	1	1	6	4	2	5	4	1	2	4	1	3	2	3	2	3	1
Fishsaler	4	3	7	4	6	4	7	1	4	1	1	3	7	3	3	3	2	3	4	3
supermarket	5	4	7	2	4	3	7	3	4	1	1	2	6	1	3	3	1	2	5	6
Mass_adv	7	5	7	2	1	3	2	3	5	1	1	1	2	1	1	3	1	1	4	4
Social_media	5	6	7	2	1	3	1	1	4	1	1	1	2	1	1	1	1	1	3	1
Science	6	5	7	2	1	3	3	1	4	1	1	1	2	1	1	1	2	1	3	2
Doctor	6	4	7	3	1	4	4	1	3	1	1	1	2	1	1	1	2	1	3	3
Industry	5	3	7	2	1	4	5	1	4	1	1	1	6	4	1	1	1	1	2	3
Label	6	2	7	3	1	3	7	1	5	1	1	3	3	4	3	4	5	2	5	5
Friends	4	4	7	3	1	4	3	2	4	3	1	1	4	1	2	2	3	1	3	1
Consum_org	6	3	7	2	1	3	4	1	5	1	1	3	3	1	3	1	4	1	5	1
Salmon*_format__Fresh_fil*	0	0	0	0	0	0	1	0	1	0	0	1	0	0	1	1	0	0	0	0
Salmon_format__Frozen_fil	0	0	1	0	1	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0
Salmon_format__Ready_eat	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Salmon_format__Ready_cook	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
Salmon_format__Smoked	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0
Salmon_format__Canned	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Salmon_format__Marinated	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Salmon_format__Whole	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
Salmon_format__Dry	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Salmon_format__Salad	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Salmon_format__Spread_	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Evolution	5	5	7	4	5	4	2	6	5	4	4	5	5	4	5	4	5	4	3	5

*Data of formats available for all species.

Output of latent class analysis (LCA) and multinomial logistic regression (example for the Spanish dataset)

LCA was performed to obtain segmentations of markets (consumers side) based on a response to 27-items: Omega3, Fish evaluation, Trust to cook, No time, Ready to eat, Availability, Label, Local, New format, Taste over nutrition, Versatile, Value for money, Preferred brand, Brand loyalty, Creativity, Like to cook, Appearance, Conservation, Easy to cook, Easy to digest, Natural, Healthy, Environmental friendly, Nutrients, Texture, Traceability, Sustainability.

Example of output

R Output of the LCA

```
Conditional item response (column) probabilities,
 by outcome variable, for each class (row)

$Omega3
               1      2      3      4      5      6
class 1:  0.0000 0.0351 0.1567 0.7723 0.0359 0.0000
class 2:  0.0000 0.0000 0.0167 0.1116 0.7253 0.1464
class 3:  0.0683 0.1907 0.1104 0.1909 0.3019 0.1379
```

```
class 4:  0.0000 0.0000 0.0000 0.0160 0.1142 0.8698
class 5:  0.0054 0.0056 0.0486 0.1742 0.6259 0.1402
class 6:  0.0000 0.0000 0.0000 0.0408 0.2887 0.6705

$Evaluat_fish
               1      2      3      4      5      6
class 1:  0.0000 0.0351 0.0866 0.8783 0.0000 0.0000
class 2:  0.0000 0.0082 0.0395 0.1814 0.7442 0.0267
class 3:  0.0273 0.0819 0.2047 0.2339 0.3702 0.0820
class 4:  0.0160 0.0000 0.0321 0.1133 0.1600 0.6786
class 5:  0.0000 0.0218 0.0849 0.3301 0.5517 0.0115
class 6:  0.0050 0.0000 0.0248 0.0370 0.5062 0.4270

$Trust_cook
               1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0351 0.8756 0.0718 0.0175
class 2:  0.0042 0.0000 0.0234 0.1812 0.7606 0.0306
class 3:  0.0956 0.0000 0.1920 0.2049 0.4380 0.0695
class 4:  0.0160 0.0160 0.0000 0.0802 0.1982 0.6896
class 5:  0.0000 0.0325 0.0832 0.2360 0.6139 0.0344
class 6:  0.0000 0.0050 0.0149 0.0207 0.4518 0.5075

$No_time.0
               1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0513 0.8945 0.0543 0.0000
class 2:  0.0295 0.1395 0.1857 0.2611 0.3701 0.0141
class 3:  0.0149 0.1367 0.2047 0.2052 0.3019 0.1366
class 4:  0.3459 0.0819 0.0784 0.1168 0.1686 0.2084
class 5:  0.0318 0.1265 0.1649 0.2683 0.3943 0.0141
class 6:  0.2777 0.1762 0.1770 0.1188 0.1900 0.0603

$Ready_eat_charct
               1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0866 0.8961 0.0173 0.0000
class 2:  0.0000 0.0227 0.0461 0.2369 0.6562 0.0382
class 3:  0.0550 0.0951 0.1918 0.2743 0.3006 0.0831
class 4:  0.1282 0.0160 0.0160 0.1763 0.2081 0.4554
class 5:  0.0053 0.0111 0.0887 0.3080 0.5175 0.0694
class 6:  0.0151 0.0278 0.0332 0.2220 0.5036 0.1983

$Fish_availa
               1      2      3      4      5      6
class 1:  0.0000 0.0175 0.0865 0.8446 0.0513 0.0000
class 2:  0.0000 0.0083 0.0496 0.1159 0.7663 0.0599
class 3:  0.0819 0.0276 0.2327 0.2047 0.3710 0.0820
class 4:  0.0160 0.0160 0.0780 0.0481 0.1179 0.7240
class 5:  0.0000 0.0118 0.0550 0.1624 0.6697 0.1010
class 6:  0.0050 0.0240 0.0157 0.0510 0.4538 0.4504

$Label.0
               1      2      3      4      5      6
class 1:  0.0000 0.0351 0.0701 0.8581 0.0367 0.0000
class 2:  0.0000 0.0166 0.0202 0.1828 0.7346 0.0459
class 3:  0.0820 0.1101 0.1783 0.2459 0.2743 0.1094
class 4:  0.0000 0.0000 0.0000 0.1122 0.1302 0.7576
class 5:  0.0162 0.0214 0.0662 0.3199 0.5153 0.0609
class 6:  0.0000 0.0050 0.0095 0.0565 0.4651 0.4638

$Local_com
               1      2      3      4      5      6
class 1:  0.0000 0.0351 0.0702 0.8423 0.0524 0.0000
class 2:  0.0000 0.0000 0.0343 0.2696 0.6667 0.0294
class 3:  0.1093 0.0546 0.1228 0.2478 0.4245 0.0410
class 4:  0.0313 0.0000 0.0160 0.1732 0.1637 0.6157
class 5:  0.0000 0.0415 0.1071 0.4548 0.3620 0.0346
class 6:  0.0052 0.0117 0.0050 0.1732 0.5233 0.2816
```

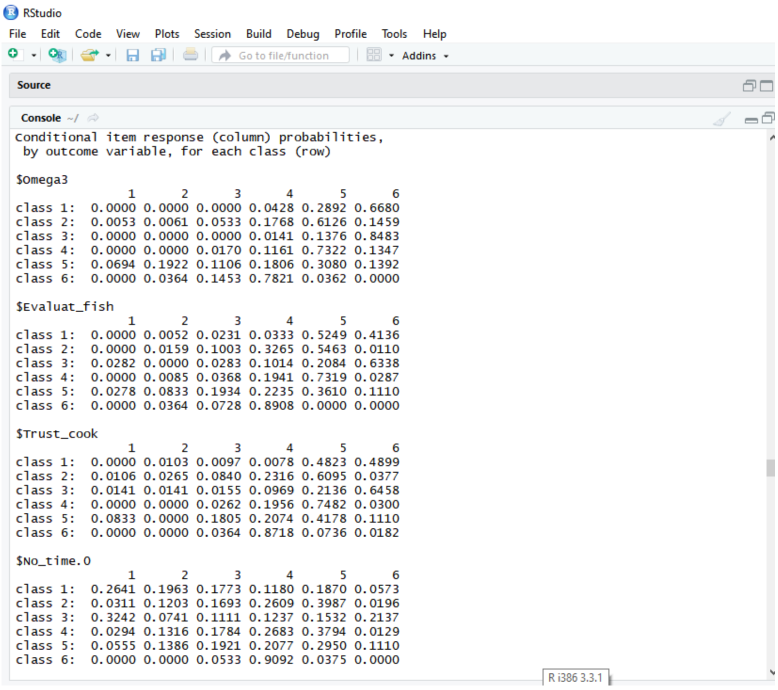
```
$New_format
               1      2      3      4      5      6
class 1:  0.0000 0.0175 0.0515 0.7538 0.1420 0.0351
class 2:  0.0041 0.0371 0.0224 0.1873 0.6873 0.0618
class 3:  0.0831 0.1231 0.1225 0.1507 0.4250 0.0956
class 4:  0.0802 0.0160 0.0466 0.1299 0.1335 0.5938
class 5:  0.0156 0.0291 0.1113 0.3198 0.4735 0.0505
class 6:  0.0203 0.0186 0.0164 0.1404 0.5142 0.2901

$Taste_nutrition
               1      2      3      4      5      6
class 1:  0.0000 0.0515 0.0877 0.7202 0.1407 0.0000
class 2:  0.0064 0.0622 0.1105 0.1930 0.6237 0.0042
class 3:  0.2050 0.1639 0.1091 0.1648 0.2752 0.0819
class 4:  0.1780 0.0801 0.0161 0.2065 0.3270 0.1923
class 5:  0.0223 0.0283 0.0811 0.2971 0.4947 0.0764
class 6:  0.0765 0.0699 0.1182 0.2255 0.4152 0.0947

$Versatile
               1     2      3      4      5      6
class 1:  0.0000 0.000 0.0690 0.7191 0.1576 0.0543
class 2:  0.0000 0.000 0.0287 0.0663 0.7346 0.1703
class 3:  0.0956 0.041 0.2465 0.0964 0.3565 0.1639
class 4:  0.0160 0.016 0.0000 0.0448 0.1117 0.8114
class 5:  0.0054 0.027 0.0495 0.1081 0.6291 0.1808
class 6:  0.0050 0.000 0.0000 0.0418 0.3358 0.6174

$Brand_pref
               1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0526 0.8245 0.0878 0.0351
class 2:  0.0000 0.0126 0.0184 0.1749 0.7434 0.0508
class 3:  0.0273 0.1089 0.1363 0.3018 0.3028 0.1229
class 4:  0.0641 0.0000 0.0167 0.0653 0.2413 0.6126
class 5:  0.0055 0.0272 0.0550 0.3060 0.5736 0.0327
class 6:  0.0200 0.0000 0.0171 0.1227 0.5765 0.2637

$Brand_loyal
               1      2      3      4      5      6
class 1:  0.0175 0.0000 0.0515 0.7906 0.1053 0.0351
class 2:  0.0000 0.0252 0.0263 0.2013 0.7002 0.0470
class 3:  0.0683 0.0817 0.3012 0.1241 0.3154 0.1093
class 4:  0.0641 0.0000 0.0480 0.1426 0.1168 0.6284
class 5:  0.0162 0.0433 0.1230 0.4243 0.3768 0.0164
class 6:  0.0201 0.0149 0.0350 0.1826 0.5390 0.2083

$Creativity
               1      2      3      4      5      6
class 1:  0.0000 0.0175 0.0350 0.7529 0.1770 0.0175
class 2:  0.0000 0.0122 0.0385 0.1774 0.7159 0.0560
class 3:  0.1229 0.0559 0.1907 0.2595 0.3573 0.0137
class 4:  0.0321 0.0160 0.0320 0.1123 0.1002 0.7074
class 5:  0.0000 0.0538 0.1016 0.3260 0.4673 0.0512
class 6:  0.0000 0.0103 0.0103 0.1125 0.4858 0.3811

$Cook_like
               1      2      3      4      5      6
class 1:  0.0000 0.0351 0.0526 0.6994 0.1603 0.0526
class 2:  0.0047 0.0230 0.0211 0.1262 0.7162 0.1088
class 3:  0.1366 0.0832 0.1497 0.1913 0.3554 0.0838
class 4:  0.0481 0.0321 0.0641 0.0657 0.0450 0.7450
class 5:  0.0279 0.0401 0.1181 0.2160 0.4557 0.1422
class 6:  0.0136 0.0000 0.0209 0.0448 0.3886 0.5321

$Quality_price
               1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0689 0.7719 0.1417 0.0175
class 2:  0.0000 0.0000 0.0000 0.0342 0.9025 0.0633
```

```
class 3:  0.0957 0.4110 0.1378 0.0956 0.2326 0.0273
class 4:  0.0160 0.0000 0.0000 0.0448 0.1196 0.8196
class 5:  0.0108 0.0054 0.0330 0.1328 0.7513 0.0666
class 6:  0.0050 0.0096 0.0195 0.0327 0.7357 0.1976

$Easy_cook
               1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0000 0.8439 0.1561 0.0000
class 2:  0.0000 0.0000 0.0043 0.1609 0.7971 0.0376
class 3:  0.1652 0.2049 0.2734 0.1232 0.2191 0.0143
class 4:  0.0641 0.0320 0.0000 0.0332 0.1728 0.6978
class 5:  0.0090 0.0000 0.0702 0.3962 0.5027 0.0219
class 6:  0.0513 0.0150 0.0451 0.1861 0.5651 0.1373

$Conservation
               1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0176 0.9468 0.0356 0.0000
class 2:  0.0000 0.0000 0.0071 0.0734 0.8782 0.0413
class 3:  0.0821 0.2185 0.2212 0.1641 0.2595 0.0546
class 4:  0.0641 0.0000 0.0000 0.0636 0.1338 0.7385
class 5:  0.0000 0.0165 0.0809 0.3623 0.5402 0.0000
class 6:  0.0200 0.0198 0.0208 0.1231 0.6506 0.1657

$Gen_appear
               1      2      3      4      5      6
class 1:  0.0000 0.0174 0.0526 0.8253 0.0872 0.0175
class 2:  0.0000 0.0000 0.0042 0.0727 0.7948 0.1283
class 3:  0.2731 0.2329 0.2336 0.0133 0.1924 0.0547
class 4:  0.0321 0.0000 0.0000 0.0643 0.0583 0.8454
class 5:  0.0162 0.0275 0.0428 0.2125 0.6438 0.0572
class 6:  0.0050 0.0144 0.0000 0.0518 0.4675 0.4613

$Easy_digest
               1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0174 0.9300 0.0526 0.0000
class 2:  0.0000 0.0000 0.0096 0.1292 0.8402 0.0210
class 3:  0.1647 0.2323 0.2462 0.1650 0.1091 0.0826
class 4:  0.0641 0.0000 0.0000 0.0340 0.1876 0.7143
class 5:  0.0266 0.0321 0.1010 0.4594 0.3735 0.0074
class 6:  0.0452 0.0153 0.0353 0.2158 0.5480 0.1404

$Natural
               1      2      3      4      5      6
class 1:  0.0000 0.0175 0.0175 0.9300 0.0349 0.0000
class 2:  0.0000 0.0000 0.0042 0.0148 0.8921 0.0889
class 3:  0.1361 0.1639 0.2869 0.2061 0.1374 0.0696
class 4:  0.0313 0.0000 0.0000 0.0161 0.0164 0.9362
class 5:  0.0056 0.0000 0.0324 0.3221 0.6057 0.0342
class 6:  0.0103 0.0050 0.0000 0.0394 0.4895 0.4559

$Healthy
               1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0526 0.8274 0.1200 0.0000
class 2:  0.0000 0.0000 0.0000 0.0079 0.8222 0.1699
class 3:  0.1366 0.1775 0.2731 0.1644 0.1800 0.0684
class 4:  0.0160 0.0000 0.0000 0.0000 0.0308 0.9532
class 5:  0.0000 0.0054 0.0109 0.1901 0.7351 0.0585
class 6:  0.0000 0.0000 0.0050 0.0141 0.3788 0.6021

$Environ_friend
               1      2      3      4      5      6
class 1:  0.0000 0.0174 0.0350 0.8949 0.0526 0.0000
class 2:  0.0000 0.0000 0.0000 0.0605 0.8901 0.0494
class 3:  0.0956 0.2607 0.3820 0.1094 0.1112 0.0411
class 4:  0.0481 0.0000 0.0000 0.0954 0.1171 0.7394
class 5:  0.0054 0.0000 0.0381 0.5678 0.3831 0.0056
class 6:  0.0000 0.0046 0.0100 0.0635 0.6660 0.2558
```

```
$Nutrients
                1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0688 0.8951 0.0186 0.0175
class 2:  0.0000 0.0000 0.0117 0.0327 0.8912 0.0645
class 3:  0.1366 0.2596 0.3154 0.0955 0.1382 0.0547
class 4:  0.0321 0.0000 0.0000 0.0481 0.0451 0.8748
class 5:  0.0000 0.0108 0.0618 0.4969 0.4140 0.0165
class 6:  0.0050 0.0050 0.0289 0.0471 0.6134 0.3005

$Texture
                1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0526 0.8598 0.0701 0.0175
class 2:  0.0000 0.0000 0.0046 0.0226 0.9161 0.0567
class 3:  0.0683 0.2322 0.2864 0.1780 0.2213 0.0138
class 4:  0.0321 0.0000 0.0000 0.0161 0.0153 0.9365
class 5:  0.0000 0.0054 0.0274 0.4105 0.5352 0.0215
class 6:  0.0000 0.0000 0.0093 0.0588 0.4955 0.4364

$Origin_guarant
                1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0515 0.9124 0.0361 0.0000
class 2:  0.0000 0.0000 0.0000 0.0435 0.9468 0.0097
class 3:  0.1093 0.2322 0.2186 0.1773 0.2489 0.0137
class 4:  0.0321 0.0000 0.0000 0.0160 0.0000 0.9519
class 5:  0.0054 0.0000 0.0653 0.4792 0.4172 0.0330
class 6:  0.0050 0.0000 0.0100 0.0355 0.6275 0.3219

$Sust_certif
                1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0175 0.9298 0.0527 0.0000
class 2:  0.0000 0.0000 0.0117 0.0464 0.9212 0.0206
class 3:  0.1502 0.2869 0.3956 0.0841 0.0558 0.0273
class 4:  0.0321 0.0000 0.0000 0.0481 0.1467 0.7732
class 5:  0.0216 0.0000 0.0607 0.5231 0.3853 0.0092
class 6:  0.0000 0.0050 0.0050 0.1309 0.6428 0.2163

Estimated class population shares
 0.0698 0.2932 0.0897 0.0765 0.2264 0.2444

Predicted class memberships (by modal posterior prob.)
 0.0699 0.3015 0.0895 0.0772 0.223 0.239

=========================================================
Fit for 6 latent classes:
=========================================================
number of observations: 816
number of estimated parameters: 815
residual degrees of freedom: 1
maximum log-likelihood: -22384.33

AIC(6): 46398.67
BIC(6): 50232.77
G^2(6): 34059.86 (Likelihood ratio/deviance statistic)
X^2(6): 5.176239e+23 (Chi-square goodness of fit)
```

This project has received funding from the European Union's Horizon 2020 research and innovation program under

Figure 1 Screen shot Rstudio output of LCA



```
RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
Go to file/function    Addins
Source
Console ~/
Conditional item response (column) probabilities,
 by outcome variable, for each class (row)

$Omega3
               1      2      3      4      5      6
class 1:  0.0000 0.0000 0.0000 0.0428 0.2892 0.6680
class 2:  0.0053 0.0061 0.0533 0.1768 0.6126 0.1459
class 3:  0.0000 0.0000 0.0000 0.0141 0.1376 0.8483
class 4:  0.0000 0.0000 0.0170 0.1161 0.7322 0.1347
class 5:  0.0694 0.1922 0.1106 0.1806 0.3080 0.1392
class 6:  0.0000 0.0364 0.1453 0.7821 0.0362 0.0000

$Evaluat_fish
               1      2      3      4      5      6
class 1:  0.0000 0.0052 0.0231 0.0333 0.5249 0.4136
class 2:  0.0000 0.0159 0.1003 0.3265 0.5463 0.0110
class 3:  0.0282 0.0000 0.0283 0.1014 0.2084 0.6338
class 4:  0.0000 0.0085 0.0368 0.1941 0.7319 0.0287
class 5:  0.0278 0.0833 0.1934 0.2235 0.3610 0.1110
class 6:  0.0000 0.0364 0.0728 0.8908 0.0000 0.0000

$Trust_cook
               1      2      3      4      5      6
class 1:  0.0000 0.0103 0.0097 0.0078 0.4823 0.4899
class 2:  0.0106 0.0265 0.0840 0.2316 0.6095 0.0377
class 3:  0.0141 0.0141 0.0155 0.0969 0.2136 0.6458
class 4:  0.0000 0.0000 0.0262 0.1956 0.7482 0.0300
class 5:  0.0833 0.0000 0.1805 0.2074 0.4178 0.1110
class 6:  0.0000 0.0000 0.0364 0.8718 0.0736 0.0182

$No_time.0
               1      2      3      4      5      6
class 1:  0.2641 0.1963 0.1773 0.1180 0.1870 0.0573
class 2:  0.0311 0.1203 0.1693 0.2609 0.3987 0.0196
class 3:  0.3242 0.0741 0.1111 0.1237 0.1532 0.2137
class 4:  0.0294 0.1316 0.1784 0.2683 0.3794 0.0129
class 5:  0.0555 0.1386 0.1921 0.2077 0.2950 0.1110
class 6:  0.0000 0.0000 0.0533 0.9092 0.0375 0.0000
R i386 3.3.1
```

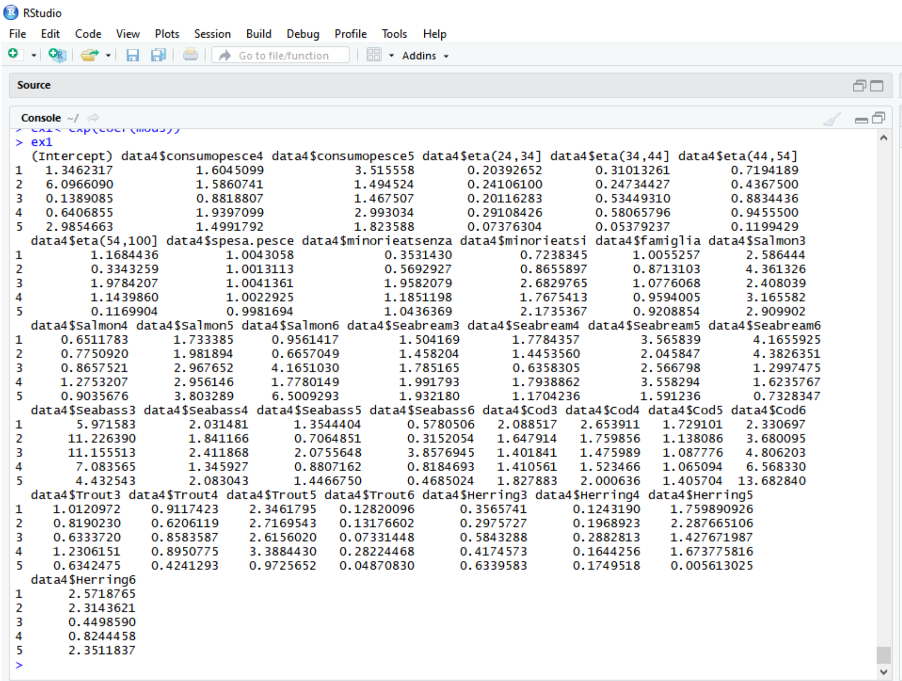
R Output of the multinomial logistic regression model – Example Spain

The multinomial logistic regression model is applied to evaluate the associations between classes predicted by LCA and the independent variables. In particular, the dependent variable was the membership class predicted by LCA (i.e. segment), while the independent variables were: family size, general consumption of fish, children eating fish, age, grocery shopping (euro), single fish species consumption (i.e., salmon, seabream, seabass, cod, trout, herring).

```
Coefficients:
  (Intercept) data4$consumopesce4 data4$consumopesce5 data4$eta(24,34] data4$eta(34,44] data4$eta(44,54]
1   0.2973094           0.4728183           1.2571982        -1.589996        -1.1707553      -0.32931153
2   1.8077327           0.4612619           0.4018079        -1.422705        -1.3969741      -0.82839439
3  -1.9739397          -0.1256985           0.3835648        -1.603641        -0.6264365      -0.12392784
4  -0.4452166           0.6625384           1.0962876        -1.234142        -0.5435934      -0.05598853
5   1.0937559           0.4049178           0.6008062        -2.606897        -2.9226236      -2.12073977
  data4$eta(54,100] data4$spesa.pesce data4$minorieatsenza data4$minorieatsi data4$famiglia data4$Salmon3
1         0.1556726       0.004296579          -1.04088212        -0.3231925     0.005510482     0.9502839
2        -1.0956389       0.001310460          -0.56336049        -0.1443443    -0.137757108     1.4727761
3         0.6822989       0.004127569           0.67202972         0.9869268     0.074742643     0.8788128
4         0.1345186       0.002289885           0.16984387         0.5695895    -0.041446718     1.1523369
5        -2.1456637      -0.001832283           0.04271162         0.7763557    -0.082419689     1.0681196
  data4$Salmon4 data4$Salmon5 data4$Salmon6 data4$Seabream3 data4$Seabream4 data4$Seabream5 data4$Seabream6
1    -0.4289717     0.5500763   -0.04484911       0.4082405       0.5757342       1.2713994       1.4268585
2    -0.2547735     0.6840531   -0.40690873       0.3772057       0.3683556       0.7158121       1.4776502
3    -0.1441567     1.0877711    1.42674101       0.5795108      -0.4528232       0.9426592       0.2621700
4     0.2431977     1.0838865    0.57549753       0.6890354       0.5843844       1.2692813       0.4846315
5    -0.1014043     1.3358663    1.87194514       0.6586487       0.1573657       0.4645108      -0.3108351
  data4$Seabass3 data4$Seabass4 data4$Seabass5 data4$Seabass6 data4$Cod3 data4$Cod4 data4$Cod5 data4$Cod6
1       1.787012      0.7087649      0.3033884     -0.5480939  0.7364542  0.9760344 0.54760175  0.8461675
```

```
2       2.418267      0.6103988      -0.3474532      -1.1545309  0.4995103  0.5652321 0.12934755  1.3029386
3       2.411934      0.8804017       0.7302333       1.3500697  0.3377865  0.3893280 0.08413534  1.5699073
4       1.957777      0.2970830      -0.1270199      -0.2003194  0.3439874  0.4209879 0.06306292  1.8822597
5       1.488974      0.7338300       0.3692678      -0.7582140  0.6031583  0.6934653 0.34053803  2.6161425
  data4$Trout3 data4$Trout4 data4$Trout5 data4$Trout6 data4$Herring3 data4$Herring4 data4$Herring5
1   0.01202464  -0.09239792   0.85278824    -2.054156     -1.0312133      -2.084904      0.5652518
2  -0.19964316  -0.47704943   0.99951152    -2.026728     -1.2120969      -1.625099      0.8275317
3  -0.45669736  -0.15273321   0.96149430    -2.612997     -0.5372914      -1.243819      0.3560451
4   0.20751409  -0.11084493   1.22037052    -1.264981     -0.8735731      -1.805297      0.5150820
5  -0.45531609  -0.85771683  -0.02781817    -3.021906     -0.4557721      -1.743245     -5.1826654
  data4$Herring6
1      0.9446358
2      0.8391341
3     -0.7988211
4     -0.1930439
5      0.8549189

Std. Errors:
  (Intercept) data4$consumopesce4 data4$consumopesce5 data4$eta(24,34] data4$eta(34,44] data4$eta(44,54]
1    1.563577           0.9220149           0.9980381        0.8080546        0.8085048        0.8003502
2    1.476542           0.8213385           0.9169525        0.7685004        0.7748194        0.7695325
3    2.020334           1.0734197           1.1520917        1.0085871        0.9777106        0.9752825
4    1.544234           0.8681334           0.9471116        0.7906524        0.7895953        0.7874976
5    1.752954           1.0551986           1.1481569        0.7996336        0.8304464        0.8110439
  data4$eta(54,100] data4$spesa.pesce data4$minorieatsenza data4$minorieatsi data4$famiglia data4$Salmon3
1         0.8048454       0.002592744            0.8081178         0.7842342       0.1691948     0.6401885
2         0.7825691       0.002685425            0.7883514         0.7707690       0.1673159     0.6188044
3         0.9633827       0.002813677            1.2636749         1.2413534       0.1967610     0.7523307
4         0.7910497       0.002583327            0.8481132         0.8296457       0.1647242     0.6292378
5         0.8320884       0.003290853            0.9985112         0.9734988       0.1924516     0.7188386
  data4$Salmon4 data4$Salmon5 data4$Salmon6 data4$Seabream3 data4$Seabream4 data4$Seabream5 data4$Seabream6
1     0.4301278     0.4987573      1.092470       0.6573433       0.4993213       0.5965440        1.017803
2     0.4261833     0.4932579      1.180985       0.6246743       0.4975014       0.6153992        1.068930
3     0.5330382     0.5803843      1.149629       0.7490687       0.6488793       0.6587961        1.156046
4     0.4145194     0.4858261      1.053722       0.6195433       0.4855465       0.5850670        1.025139
5     0.5325939     0.5708277      1.129700       0.7057845       0.5944129       0.6923235        1.217777
  data4$Seabass3 data4$Seabass4 data4$Seabass5 data4$Seabass6 data4$Cod3 data4$Cod4 data4$Cod5 data4$Cod6
1       1.122067      0.5339007      0.5304495      0.8697107  0.5314846  0.4746611  0.4637324   1.601206
2       1.099766      0.5327554      0.5593293      1.0206884  0.5069874  0.4672678  0.4643699   1.596846
3       1.173418      0.6490224      0.6050791      0.9122385  0.6271392  0.5569814  0.5376430   1.663850
4       1.097874      0.5239414      0.5260616      0.8209190  0.5080651  0.4570772  0.4483819   1.528825
5       1.188386      0.6262913      0.6239415      1.3378320  0.6111125  0.5555555  0.5383311   1.620966
  data4$Trout3 data4$Trout4 data4$Trout5 data4$Trout6 data4$Herring3 data4$Herring4 data4$Herring5
1    0.5980600    0.5045016    0.8296872     1.198188      0.9448573      0.6425214     1.10707366
2    0.5808465    0.5204504    0.8286506     1.310069      0.9467173      0.6394257     1.11816311
3    0.7392116    0.5979520    0.8864250     1.472868      1.0522261      0.7447944     1.20890106
4    0.5668671    0.4908278    0.8100199     1.122775      0.8970846      0.6123385     1.09779869
5    0.7412302    0.6542961    1.0097868     1.512587      1.0451688      0.9222532     0.04567071
  data4$Herring6
1       1.344623
2       1.397914
3       1.733318
4       1.370451
5       1.543647

Residual Deviance: 2389.768
AIC: 2739.768
```

Figur2 Screen shot of multinomial logistic regression model



```
> ex1
  (Intercept) data4$consumopesce4 data4$consumopesce5 data4$eta(24,34] data4$eta(34,44] data4$eta(44,54]
1   1.3462317           1.6045099            3.515558       0.20392652       0.31013261        0.7194189
2   6.0966090           1.5860741            1.494524       0.24106100       0.24734427        0.4367500
3   0.1389085           0.8818807            1.467507       0.20116283       0.53449310        0.8834436
4   0.6406855           1.9397099            2.993034       0.29108426       0.58065796        0.9455500
5   2.9854663           1.4991792            1.823588       0.07376304       0.05379237        0.1199429
  data4$eta(54,100] data4$spesa.pesce data4$minorieatsenza data4$minorieatsi data4$famiglia data4$Salmon3
1         1.1684436         1.0043058            0.3531430         0.7238345      1.0055257      2.586444
2         0.3343259         1.0013113            0.5692927         0.8655897      0.8713103      4.361326
3         1.9784207         1.0041361            1.9582079         2.6829765      1.0776068      2.408039
4         1.1439860         1.0022925            1.1851198         1.7675413      0.9594005      3.165582
5         0.1169904         0.9981694            1.0436369         2.1735367      0.9208854      2.909902
  data4$Salmon4 data4$Salmon5 data4$Salmon6 data4$Seabream3 data4$Seabream4 data4$Seabream5 data4$Seabream6
1     0.6511783      1.733385     0.9561417        1.504169       1.7784357        3.565839       4.1655925
2     0.7750920      1.981894     0.6657049        1.458204       1.4453560        2.045847       4.3826351
3     0.8657521      2.967652     4.1651030        1.785165       0.6358305        2.566798       1.2997475
4     1.2753207      2.956146     1.7780149        1.991793       1.7938862        3.558294       1.6235767
5     0.9035676      3.803289     6.5009293        1.932180       1.1704236        1.591236       0.7328347
  data4$Seabass3 data4$Seabass4 data4$Seabass5 data4$Seabass6 data4$Cod3 data4$Cod4 data4$Cod5 data4$Cod6
1       5.971583       2.031481      1.3544404      0.5780506   2.088517   2.653911   1.729101   2.330697
2      11.226390       1.841166      0.7064851      0.3152054   1.647914   1.759856   1.138086   3.680095
3      11.155513       2.411868      2.0755648      3.8576945   1.401841   1.475989   1.087776   4.806203
4       7.083565       1.345927      0.8807162      0.8184693   1.410561   1.523466   1.065094   6.568330
5       4.432543       2.083043      1.4466750      0.4685024   1.827883   2.000636   1.405704  13.682840
  data4$Trout3 data4$Trout4 data4$Trout5 data4$Trout6 data4$Herring3 data4$Herring4 data4$Herring5
1    1.0120972    0.9117423    2.3461795   0.12820096      0.3565741      0.1243190    1.759890926
2    0.8190230    0.6206119    2.7169543   0.13176602      0.2975727      0.1968923    2.287665106
3    0.6333720    0.8583587    2.6156020   0.07331448      0.5843288      0.2882813    1.427671987
4    1.2306151    0.8950775    3.3884430   0.28224468      0.4174573      0.1644256    1.673775816
5    0.6342475    0.4241293    0.9725652   0.04870830      0.6339583      0.1749518    0.005613025
  data4$Herring6
1      2.5718765
2      2.3143621
3      0.4498590
4      0.8244458
5      2.3511837
>
```

R Output of the matching "firm-to-segment " (Example Spain)

Multinomial logistic regression coefficients were employed for the match of segment (demand) and product/firm (supply side).

```
The best class is 2 (membership probability = 0.42)
```

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