

Consumer demand for meat in Finland

Johannes Piipponen

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Faculty		Department						
Faculty of Agriculture and Forestry		Department of Economics and Management						
Author								
Johannes Piipponen								
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Abstract	•	•						

Abstract

This paper focuses on meat consumption patterns in Finland. Empirical analysis for this paper was based on the micro data of three Household Budget Surveys: 1998, 2006 and 2012. A censored linear approximation of the almost ideal demand system (LA-AIDS) model was employed in the study. The major outcomes of the study were the demand expenditure and price elasticities that were obtained from the parameter estimates of five different meat products. Since the data lacked price information, unit values were used as a price substitutes, which gave some insights into quality-quantity upgrading.

According to the results, pork expenditure was elastic and thus was luxury good during the study period, whereas ruminant meat and poultry were luxuries only in 2000s. In addition, the price of a good, household size, and income had a large influence on meat consumption. Additionally, other factors (such as age) affected the portion of the budget that was allocated to meat products. In order to obtain more information relating to the food sector, further research concerning disaggregate demand would be needed.

Keywords

meat, demand elasticities, Almost Ideal Demand System, LA-AIDS

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Further information

Supervisor: Xavier Irz, Natural Resources Institute Finland Reviewer: Antonios Rezitis, University of Helsinki



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Tiivistelmä Vaikka kasvisten ja vaihtoehtoisten proteiini saavuttaneen lakipistettään. Terveysongelr kasvihuonekaasuja tuottavana ympäristön rasi voida reagoida tehokkaasti ellei kulutukseen v	nien lisäksi korkea ittajana. Kulutuksessa	lihakulutustaso nä tapahtuviin muutoksi	ähdään biodiversiteettiä heikentävänä ja							
Tässä tutkimuksessa lihan kysyntää, ja siihe jaoteltiin ryhmiin (nauta ja lammas, sian Tilastokeskuksen kulutustutkimus-aineistoja menojoustot, jotka estimoitiin sensoroidun l lihatuotteet ovat hintavaihteluille ja paljastav kuinka sosio-ekonomiset muuttujat kuten tulo	iliha, siipikarjanliha, vuosilta 1998, 2006 lineaarisen moniyhtälö at ryhmien välisiä tul	prosessoitu liha, m ja 2012. Tutkielma omallin (LA-AIDS) a o- ja substituutiovaik	nuut lihatuotteet) ja aineistona käytettiin an päätuotoksena ovat kysynnän hinta- ja avulla. Joustot kertovat kuinka herkkiä eri autuksia. Lisäksi tutkimustulokset kertoivat,							
Kulutus ohjaa koko ruokaketjun toimintaa; laajentamista muille elintarvikesektoreille kor		vientiä. Jatkotutkimu	aksen tarvetta ja vastaavanlaisen analyysin							
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Muita tietoja Ohjaaja: Xavier Irz, Natural Resources Institt Tarkastaja: Antonios Rezitis, University of Ho										

Abbreviations list

AIDS Almost Ideal Demand System

CDF Cumulative Density Function

COICOP Classification of individual consumption by purpose

EASI Exact Affine Stone Index

FBS Food Balance Sheet

HBS Household Budget Survey

ITSUR Iterative Seemingly Unrelated Regression

LA-AIDS Linear Approximation Almost Ideal Demand System

LR Likelihood Ratio

PDF Probability Distribution Function

PIGLOG Price-Independent, Generalized Logarithmic

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1 Introduction

1.1 Background and aims of the study

In recent years, the trends and patterns of food consumption have been a topic of much discussion. While the demand for vegetables and environmentally friendly food products has increased, meat consumption has simultaneously increased. This raises questions regarding consumer trends in meat consumption – are meat consumption levels nearing their saturation point? Or will meat consumption continue to increase from some time to come? (Vranken et al., 2014.)

Because livestock production has a notable impact on the decrease of biodiversity and increase of greenhouse gases, the reduction of high-level meat consumption is often seen as a clear way to decelerate climate change (Stoll-Kleemann and Schmidt, 2017). In Finland, this has a great effect on the food sector, as the food sector in Finland is heavily based on animal production. Additionally, excessive meat consumption can increase the risk of developing certain health problems. Although decreasing meat consumption could be achieved by restricting the choices of consumers (Lombardini and Lankoski, 2013), taxation of meat products is considered to be a more effective method (Nordgren, 2012).

It is public knowledge that food consumption habits are driven by a multitude of factors including, but not limited to: income, age, economic status, price fluctuations, nutritional trends, etc. The degrees to which these various factors affect consumptions patterns, however, are less clear. From a political standpoint, numerical data relating to the amount of impact that each of these factors has on the consumption levels of food products would be very valuable. For example, Vinnari (2008) speculates that an increased taxation of meat products could effectively reduce meat consumption in Finland, but without concrete numerical data regarding the demand elasticity of meat products after increased taxation, Vinnari's speculation is just that – speculation. Attempts to guide consumer habits without a basis in consumer research are likely to prove ineffective.

Most recent studies pertaining to the demand for meat products (where household-level data is utilized) were done in Africa (Aborisade et al., 2017; Delport et al., 2017; Shibia et al., 2017) and in France (Dahlberg, 2017a). In Finland, this type of research has mostly been performed using Household Budget Survey data and has concentrated

on a more general food spectrum; research relating to a more specific food category (e.g. meat) does not exist. The first demand system approach to this type of research in Finland was conducted by Laurila (1994), followed by Irz (2017), who published a comprehensive demand analysis article where food consumption was aggregated into 19 categories. This means, of course, that the meat sector has also been extensively researched; however, a quantitative analysis that explains the drivers affecting changes in consumptive trends within the meat industry has yet to be performed. This study will investigate factors that affect household demands for meat products and will attempt to create a basis for future studies pertaining to this topic.

The main outcomes are demand elasticities, which provide information about the necessity of a food product – that is, it predicts the amount that demand for a certain commodity will fluctuate if the price of said product rises. Without an adequate understanding of the dynamics surrounding supply and demand in relation to the price of a product, it is impossible to enact effective policies for promoting or reducing the consumption of a certain product – the repercussions of such blind policymaking are far too uncertain.

After a general view of meat consumption is presented, common consumer theory is examined in Chapter 2 as well as the model used in this study. Chapter 3 examines the Household Budget Survey (HBS) data, describes preparations and corrections that must be made before estimation, and provides summary tables concerning variables defined in HBS. The estimation process is explained in Chapter 4, and Chapter 5 expresses and interprets the outcome of the estimation process. Chapter 6 contains the final summary of this thesis and recommends topics for future studies related to this study. This thesis is part of the RUOMU project at the Natural Resource Institute of Finland. This project produces information regarding the structure of Finnish food markets as well as the competitiveness and efficiency of the food sector in Finland.

1.2 Survey of meat consumption in Finland

According to national data provided by Statistics Finland (2017), private consumption expenditure for meat and meat products has increased by over 60 per cent from 1975 to 2015 when measured using reference prices from 2010. During the same time period, meat consumption per person has increased by almost 30 per cent, with the average being over 80 kilograms per person in 2016 according to Food Balance Sheets (Luke, 2017a). These changes are presented in graph form below (Figure 1; Figure 2). Although all classifications differ between the Food Balance Sheet (FBS) and national accounts, some observations can be made. In the 2000s, there is no clear sign that consumption levels of any meat product would obviously be falling, whereas rapid growth in poultry consumption is apparent. Beef and pork consumption remains stable, but, according to national accounts, the consumption of tinned and processed meat products is becoming more common. It is worth mentioning that the HBS covers only food consumed at home, while the FBS contains all food. In fact, just the inclusion of food consumed away from home may explain the divergence between HBS and FBS trends.

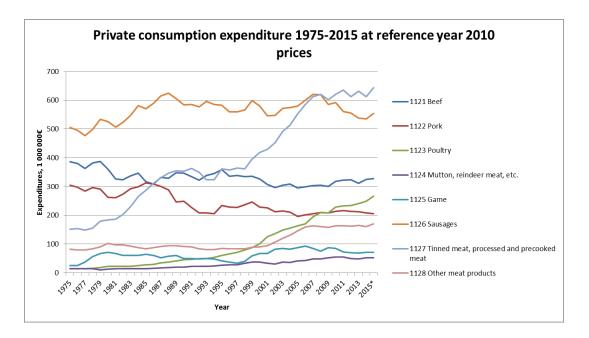


Figure 1. Meat consumption expenditure 1975-2015 at reference year 2010 prices (Statistics Finland, 2017)

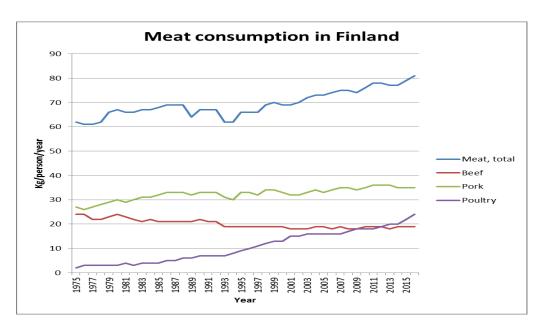


Figure 2. Meat consumption in Finland according to Food Balance Sheets (Luke, 2017b)

In spite of tremendous growth, the consumption of meat in Finland is still below the average consumption levels in the EU-area (Figure 3). In some countries meat consumption has exceeded 100 kilograms, which leads one to believe that an increase in meat consumption in Finland is still possible. The importance of meat consumption analysis cannot be undervalued, as intentions to reduce meat production will only provoke more discussion in the future. This will have a direct impact on the production, import, and export of meat products in Finland.

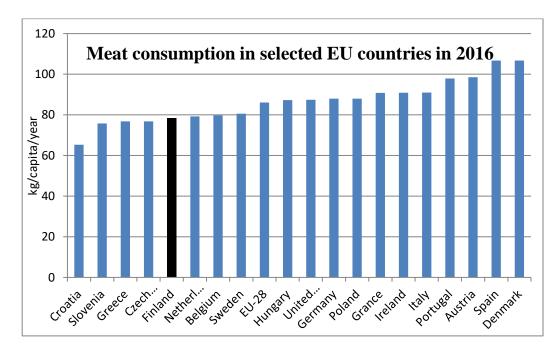


Figure 3. Meat consumption in selected EU countries in 2016. (TNS Gallup, 2017)

2 Theoretical Background

2.1 Consumer theory

This study will be utilizing an empirical model that is based on common consumer theory, which was explained in detail by Varian (2014). Classical micro theory attempts to explain consumer rationality by applying a set of rules to the thought processes that the consumer goes through when a purchase is being made. More specifically, the axioms considered in this definition of the consumer thought process are: completeness, transitivity, continuity, and monotonicity. The completeness axiom operates under the assumption that the consumer is always able to choose between two goods and determine which of those two goods is of equal or superior quality. The transitivity aspect considered when applying these rules assumes the consumer rationality that: if A is preferred to B, and B is preferred to C, then A is also preferred to C. The continuity axiom makes the application of the utility function possible, as continuity does not allow the possibility of open sets. Finally, monotonicity is based on the given that goods are desirable to the consumer, and can be explained simply using the phrase "more is better than less" – that is having more of a certain good is definitely better than having less of said good. (Varian, 2014.)

Now that the basic principles of consumer theory are understood, it is important to examine the functions used in analyzing cost and utility, as these are two of the key components that will be applied when using the demand system model. Consumers tend to maximize product utility in relation to their expenditure limitations (primal problem) and will react rationally to changes in this formula. The utility maximization or the primal problem can be defined as follows:

(1)
$$\max u = v(q)$$
, s.t. $pq = x$,

where v(q) denotes utility, q is a vector of quantities consumed, p is a corresponding price vector and x a is fixed budget. As an alternative to utility maximization, consumers can minimize their expenditure for a given utility level (dual problem):

(2)
$$\min x = pq$$
, s.t. $v(q) = u$

The primal and dual problems lead to Marshallian and Hicksian demand functions respectively. Furthermore, we can derive the indirect utility function as well as the expenditure function from these demand functions as they are closely interrelated

through the Slutsky equation. (Edgerton et al., 1996.) The demand systems presented later are based on these properties. The closer examination and derivation of these functions is presented in Deaton and Muellbauer (1980a, 1980b).

2.2 Theoretical restrictions of the demand models

There are some restrictions that must be implemented in demand models, as estimations without them are not consistent with theory. These restrictions control the parameters estimated from Marshallian demand equations. However, these restrictions are often violated in practice, which decreases the credibility of the obtained results (Deaton and Muellbauer, 1980a). Also, the restrictions have to be tested, as they are worthless otherwise (Shukur, 2002). In this section, information regarding these restrictions is presented generally, but restrictions linked to parameter estimation and testing procedures will be discussed in more depth in Chapter 4. The following definitions are based on the findings of Deaton and Muellbauer (1980b) and Edgerton et al. (1996).

The first frequently imposed restriction that must be discussed is adding-up, which means that sum of the Marshallian demand functions must result in total consumption. In other words, the consumer's budget must be totally used. The adding-up restriction is the result of the budget constraint and monotonicity assumptions. The second restriction, homogeneity, suggests an absence of money illusion, in which case only the relation between prices and the total budget is significant. Under these circumstances, even if we change the prices and expenditures proportionally in the primal problem (1), neither the utility function nor budget constraint will be changed. The third restriction is symmetry (Slutsky symmetry), which ensures consumer rationality. The symmetry property is linked to substitution matrices and derivatives of demand functions. The fourth, and most rarely observed property, is negativity. As the expenditure function is concave regarding prices, the substitution matrix is negative and semidefinite, and the diagonal elements of the matrix are negative as well. This restriction can be tested only after other calculations have been performed. While adding-up and homogeneity are required to satisfy the budget constraint, symmetry and negativity allow for utility maximization. Usually the homogeneity and symmetry properties are imposed on the demand model as they do not cause severe estimation difficulties, and their validity is easy to test.

2.3 Almost Ideal Demand System (AIDS)

The consumer theory gives guidelines for selecting functional form for empirical analysis of demand. Many functional forms have been proposed as alternatives for demand analysis tools. The first of these was developed in the 1950s, when Stone suggested his linear expenditure system (LES) that was derived from classical micro theory (Stone, 1954). Following the model presented by Stone, the Rotterdam model (Barten and Theil, 1964-1965) and the translog model (Christensen et al., 1975) rose in popularity as a marketing research tool until 1980, when the Almost Ideal Demand System (AIDS) was developed by Deaton and Muellbauer. Finally, as alternative to the AIDS model, the Exact Affine Stone Index (EASI) was suggested in 2007. (Clements and Selvanathan, 1988; Lewbel and Pendakur, 2007.)

Over the time the models became more flexible and later systems had advantages over older ones (Deaton and Muellbauer, 1980a). Nowadays different price indices and linear or non-linear approximations specify the models further and there is not mutual understanding which combination of these would produce most reliable results (Barnett and Serletis, 2008). Since the AIDS model is most commonly used in demand system analysis, it will be used in present study.

The AIDS model was created by Deaton and Muellbauer in 1980, and has since been the preferred method for product demand analysis, due to its flexibility and compatibility with household-level data. (Delport et al., 2017). The AIDS model satisfies the axioms of choice, aggregates over consumers and gives first-order approximation to any demand system. Also, as the homogeneity and symmetry depend only on the estimated parameters, these restrictions are easy to impose and test. Thus, the AIDS model has several desirable properties, some of which are missing from preliminary demand systems. The AIDS based on revealed preferences, which are often considered superior compared to stated preferences. (Deaton and Muellbauer, 1980a; Irz, 2017.)

The model consists of various demand functions that are used to calculate the correlation coefficient between the budget shares of different commodities, relative product prices, and total consumer expenditures (Lewbel and Pendakur, 2007). The AIDS model is derived from PIGLOG class cost function by using Shephard's lemma

and budget share functions are linear in parameters. Deaton and Muellbauer (1980) presented the basic form of the AIDS model as (3):

(3)
$$w_{ih} = \alpha_i + \sum_{j=1}^n \gamma_{ij} \ln P_j + \beta_i \ln \left(\frac{X_h}{P_h}\right) + u_{ih}$$
, where

- w_i is the expenditure share allocated to ith good (defined by $w_i = \frac{P_i Q_i}{X}$) in household h
- P_i is the price of jth good
- X_h is the total expenditures in household h
- α_i , γ_{ij} and β_i are parameters to be estimated, u_{ih} is the random error term
- P_h is a translog price index (defined in Appendix)

However the nature of the translog price index makes the model non-linear, which causes empirical problems – especially with aggregated data. By replacing price index P with Stone's price index P* the AIDS model can be linearized (Deaton and Muellbauer, 1980a; Green and Alston, 1990). This linear form is known as the Linear Approximation Almost Ideal Demand System (LA –AIDS). Formation of the model used in the study as well as Stone and translog price indices are presented in the Appendix.

Many researchers consider LA-AIDS model more suitable and easily estimated than traditional AIDS. For example Abodisade et al. (2017), Delport et al. (2017), Green and Alston (1990), Shibia et al. (2017) to name a few. Also in my thesis the LA-AIDS model is being used. Theoretical restrictions on the parameters of the LA-AIDS model include adding-up (4), homogeneity (5), and symmetry (6).

(4)
$$\sum_{i=1}^{n} \alpha_{i} = 1$$
 $\sum_{i=1}^{n} \beta_{i} = 0$ $\sum_{i=1}^{n} \gamma_{ij} = 0$ (5) $\sum_{j=1}^{n} \gamma_{ij} = 0$ (6) $\gamma_{ij} = \gamma_{ji}$

These restrictions in combination with equation (3) ensure that the sum of expenditure shares equals unity, and that the demand functions are homogenous and exhibit Slutsky symmetry. Restriction (5) holds for any i and (6) for any pair (i, j). (Deaton and Muellbauer, 1980a.)

2.4 Linear Approximation Almost Ideal Demand System

There are some difficulties associated with using the LA-AIDS model (or AIDS in the first place) in combination with data derived from the HBS. Firstly, while the Household Budget Survey contains ample information regarding consumer expenditures, it does not contain information regarding commodity prices. As can be seen in equation (3), good prices are an essential factor in this model, and, therefore, this information must be derived from somewhere. Secondly, the AIDS model assumes parallel in consumer preferences, which a close inspection of microdata and consumer theory will prove to be untrue. Finally, using the LA-AIDS model, income can only have an influence on demand in a log-linear or linear form; this greatly limits the production of Engel curves. In fact, empirical work with consumer expenditure data has revealed that Engel curves are often strictly non-linear. (Irz, 2017; Lewbel and Pendakur, 2007)

It should be noted that the LA-AIDS model has often been chosen just for the sake of its computational simplicity. In fact, by replacing translog price index e.g. by Stone's price index, we get only linear approximation, which is not as accurate as the original model (Blundell and Robin, 1999; Mizobuchi and Tanizaki, 2014). However, the LA-AIDS is frequently considered sufficiently good model and it has done pretty well in comparison to other models, for example quadratic or generalized AIDS (Alston et al., 1994; Asche and Wessells, 1997; Liu et al., 2003). Usually existing data gives guidelines to model selection but it is not so clear which model is appropriate in particular situation (Meyer et al., 2011; Smutná, 2016). A recent study that has utilized linear form of the AIDS model successfully was done by Bilgic and Yen (2013).

The Appendix shows the form of equations to be estimated for use with the Stone's price index. Other suitable price indices for the LA-AIDS model would be the Stone's price index with lagged shares, the loglinear analogue to the Paasche price index, the loglinear analogue to the Laspeyers price index, the simplified loglinear analogue to the Laspeyers price index, and the Tornqvist price index. (Henningsen, 2017a.) There have been discussions about reliability of Stone's price index in literature. (Pashardes, 1993) claims that Stone index approximation can lead to biased results. However, if the prices are normalized to one as done in present study, the Stone's price index is corrected and it corresponds to loglinear analogue to a Paasche index (Asche and Wessells, 1997).

Also, many studies bring out that coefficient obtained from LA-AIDS in the first place are biased according to demand theory. (Mizobuchi and Tanizaki, 2014; Pashardes, 1993). Still, the estimated results of linear and non-linear AIDS are often close to each other's (Bilgic and Yen, 2014; Smutná, 2016). As Asche and Wessells (1997) pointed out, if the prices are normalized to one, the results obtained from linear and non-linear AIDS are rather similar. In general quadratic form of the AIDS (QAIDS) is considered the best fitting AIDS model but Liu et al. (2003) specified that importance of quadratic term decreases when censored and demographic effects are taking into account.

One remarkable extension for future studies could be estimation with EASI model, which may achieve popularity in the future. As in the AIDS system, the budget share parameters in the EASI system are also linear. However, the EASI model allows for non-linear, and even S-shaped Engel curves; this, one might argue, gives a more accurate representation of data than the typically linear curves provided by the AIDS model. Another significant advantage of the EASI model is that it allows for heterogeneity in consumer preferences. Despite these obvious advantages of the EASI model, the non-linear and complex functions that the model applies can be troublesome; alternatively, the linear nature of the parameters found in the AIDS model can make that model more user-friendly. (Lewbel and Pendakur, 2007.)

3 The empirical model

3.1 Data

In Finland, as well as in many other countries, data concerning food consumption and the prices and quantities of purchased goods is not readily available to economists; however, the Household Budget Survey (HBS) conducted by Statistics Finland has long collected similar data in Finland. The HBS collects information regarding the estimated expenditures of consumers. From 1960 to 1990, this data was collected at five year intervals. Following this, data was collected yearly for the three years spanning from 1994 to 1996; and, since then, the survey has been conducted more sporadically, occurring in 1998, 2001, 2006 and 2012. The next HBS survey will be published at the end of 2017. The target group for this study consists of 8000 people who live permanently in Finland. People who live in institutions (e.g. hospitals, prisons, nursing homes) are excluded from these surveys. (Statistics Finland, 2017.)

The consumer survey from Statistics Finland offers information regarding changes in the consumption patterns of households and differences in the consumption patterns of different socio, -economic and age groups. The survey focuses mainly on consumer expenditures, but also contains quantitative information concerning the consumption of certain commodities as well as other background variables. (Statistics Finland 2016.) Changes in consumption patterns and changes in the physical quantities demanded, which are based on HBS data, were investigated by Aalto and Peltoniemi (2014).

In this thesis, the three most recent and comprehensive cross-sectional HBS data sets (from years 1998, 2006 and 2012) will be used. Price and quantity information of year 2001 are not sufficient and therefore it cannot be used in this analysis. The data must be prepared before it can be used to make any estimations, as – in its current state – it is lacking various important bits of information, such as commodity prices. In addition to this, the quantitative data in these data sets differs somewhat from that which is present in the Food Balance Sheet data. Consequently, the food consumption data contained in the HBS data sets is not readily comparable to the information in the public domain.

3.1.1 Aggregation over goods

As applied in many meat demand analysis (Cashin, 1991; Fulponi, 1989; Pace Guerrero et al., 2015; Taljaard et al., 2004), weak separability in consumers' preferences is assumed also in the presents study. Separability allows goods allocation into groups and, besides, in every group preferences are independent from goods in other groups. Correspondingly weak separability means that price changes in one group influence demand for every goods (in other groups) equally. (Laurila, 1994.) According to Xie and Myrland (2011) incorrect aggregation leads to biased research results. Besides, they remark that usually the aggregation does not rest upon empirical tests. The problem becomes more serious if aggregation level is large. Many meat studies (cited above) which have been used AIDS models and HBS data, have divided the meat commodities into four or five groups.

The HBS data contains numerous codes for meat and there is no reason to examine all of them separately. Due to zero observations, multicollinearity and lack of degrees of freedom, over 30 meat group would make estimation almost impossible and besides of that the obtained results would not be sensible (Xie and Myrland, 2011). The national COICOP classification provided by Eurostat gave framework for selecting five aggregate groups for the study (Table 1). Aggregation level used in this study is so small and even though it should be tested, the results are most likely reliable concerning aggregation. It is worth noticing that minced meat has been placed under "other meat products".

Table1. Aggregate groups for meat based on national COICOP codes.

	I Beef and lamb		IV Processed meat continues
112101	Meat of bovine animals, boneless	1126S1	Grilled, smoked, cooked and cured pork
112102	Meat of bovine animals, with bone	1126S2	Grilled, cured, etc. poultry
112103	Seasoned beef, uncooked	112605	Other cured meat
112301	Fresh, chilled or frozen meat of sheep	112606	Meat in aspic
	and goat		
	II Pork		V Other meat products
112201	Meat of swine, boneless	112701	Meat preserves
112202	Pork chops	112702	Other preserved meat preparations
112203	Ham, uncooked	112703	Cabbage rolls
112204	Other meat of swine with bone	112704	Meat cabbage and meat potato casseroles,
			etc.
112205	Seasoned pork, uncooked	1127S1	Meat balls, ground beef patties
	III Poultry	1127S2	Salads, ready-to-eat and frozen soups of meat
1124	Fresh, chilled or frozen poultry	1127S3	Blood pancakes, blood sausages, etc.
	IV Processed meat	1127S4	Ready-to-eat meals of meat and other meat preparations
112501	Salami	112801	Meat of reindeer
1125S1	Other sausages, cold cuts	112802	Other meat and game
112504	Liver pâté and pastes	112803	Liver and kidneys
112505	Frankfurters	112804	Blood, tongue, bone, knuckle, etc.
112506	Ring sausages	112805	Minced meat
112507	Other cooking sausages	112806	Mixed meat for Karelian stew
112508	Sausages n.e.c.	112807	Meat n.e.c.

3.1.2 Descriptive statistics

Average zero consumption, expenditure shares, unit values and quantities are presented below (Table 2). As can be seen, there is very little change in zero consumption, apart from poultry, where zero observations dropped drastically from 1998 to 2012. Expenditure shares given to beef and lamb, poultry, and composite dishes have been rising since 1998, whereas the portion of the food budget allotted to pork and processed meat have decreased.

Table 2. Summary of House	ehold Budget Survey	data. Years	1998, 2006	and 2012
included				

Meat	Beef and lamb	Pork	Poultry	Processed meat	Other meat	Total
zeros1998 (% of sample)	74.93	49.02	62.56	4.67	14.56	-
zeros2006 (% of sample)	76.93	50.46	51.32	4.47	13.54	-
zeros2012 (% of sample)	79.86	49.33	45.48	6.01	13.86	-
Exp.Share 1998 (%)	6.97	14.77	7.41	46.97	23.88	100
Exp.Share 2006 (%)	6.96	12.91	10.44	43.21	26.48	100
Exp.Share 2012 (%)	7.51	12.65	12.26	40.48	27.1	100
UV1998 (€/kg)	7.32	6.07	6.18	6.22	4.52	30.31
UV2006 (€/kg)	9.21	7.79	5.53	7.62	5.84	35.99
UV2012 (€/kg)	11.73	8.52	7.07	9.76	7.26	44.34
QTY 1998 (kg/capita)	3	8.7	4.5	22.9	14.2	53.3
QTY 2006 (kg/capita)	2.4	6.3	6.2	22.2	16.1	53.2
QTY 2012 (kg/capita)	2.6	6.6	8.9	20.2	16.9	55.2

Overall, all unit values have increased. The only decrease in unit values can be observed in poultry from 1998 to 2006, but the poultry unit value reaches a new high in 2012, and displays an overall all increase (Figure 4). As unit values are defined as physical expenditure divided by quantity, the slight decrease in the unit value of poultry was likely caused by a tremendous growth in the quantity of poultry that was demanded, which, in turn, exceeded the growth of poultry expenditures. These unit values will be discussed more carefully in the section that follows.

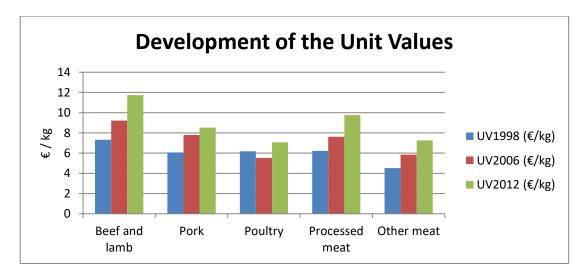


Figure 4. Development of the unit values in HBS data

In 1998 households marked their expenditures to consumption daybooks, whereas, in 2006 and 2012, households sent in receipts as records of their consumption patterns

for the survey. As the reliability of the daybooks was impossible to check, the physical quantities observed in 1998 may differ greatly from those in 2006 and 2012. Most likely, the consumption daybooks led to higher recorded quantities of unprocessed carcass meat (ruminant meat, pork, poultry) being consumed than receipts. (Aalto and Peltoniemi, 2014.) These quantities are not included in the probit equations, but since unit value equations also contain quantity variables, the "biased" quantities of 1998 may also affect elasticities.

Figure 5 very clearly displays this phenomenon. According to FBS (Figure 1), neither the physical quantity of ruminant meat nor that of pork has decreased from 1998 to 2006, which is the case when quantities are calculated from HBS data. Despite the fact that the consumed quantity of poultry has also increased from 1998 to 2006 in HBS, one can assume that in reality the growth might have been even larger. It is worth noting that the magnitudes of quantities are different in FBS and HBS data. The Food Balance Sheets calculate the amount of food that is available for consumers after imports and exports. The storage and food stuffs used for animal feed are also observed, but the FBS does not reveal how much of that food actually ends up in the home of the consumer. Therefore, HBS data is more reliable, despite omitting the proportion of food waste and being based on non-credible consumption daybooks.

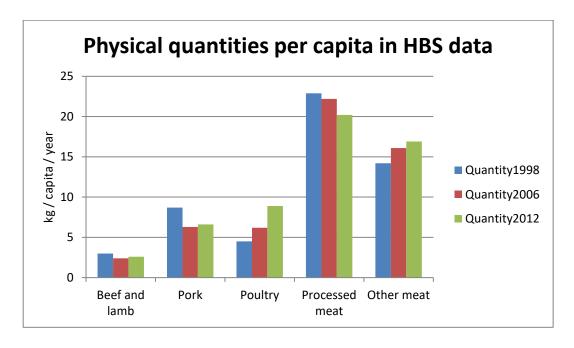


Figure 5. Development of physical quantities in HBS data.

Demand system modelling contains many indices, estimators, approximations and other corrections that must be accounted for in various stages. In order to work properly, the data has to be prepared carefully, as it may contain misspecifications, such as observations where the total expenditure of meat is zero or negative, or observations where the expenditure is zero even if the physical quantity is positive. Therefore, the observations described above must be deleted from the data sets. As is usual with demand analysis, some observations may have negative adjusted prices, leading to their removal as well. In total, nearly 200 observations were dropped from each data set (4129, 3823, 3377 observations in years 1998, 2006 and 2012 respectively).

3.1.3 Socio-economic variables

One important objective of the thesis is to identify demographic variables that influence consumption. The literature has adopted certain group of socio-demographic variables that are considered significant when speaking demand analysis (Khaliukova, 2013). Naturally, the selection of relevant variables depends on data. In this paper we utilize the model used by Irz (2017), who chose to incorporate the following socio-demographic variables after careful consideration: age, education, household size, number of kids, socio-professional status, income, region and season.

The socio-economic variables will be utilized in three different stages. First they explain consumers' choice problem in the probit model (discussed in section 3.3), then they help with estimating unit values (section 3.2) and finally they are used to estimate consumption in the LA-AIDS model (Irz, 2017). However the explanatory variables used in estimation are not entirely same in all estimation stages but the issue will be discussed later on. There are a couple of ways to include socio-demographic characteristic to demand system. The most frequently used methods are demographic scaling and demographic translating and according to Pollak and Wales (1981), the scaling method leads higher log-likelihood values. In the thesis demographic translating is adopted as it preserves linearity of the LA-AIDS model (Heien and Wessells, 1990).

Table 3 provides short survey of socio-economic variables. Age needs no definition, nor does household size. Still, it is interesting to see that average age has been increasing whereas households have become smaller. Other variables and definitions

based on demand analysis of Irz (2017). Dummy variables, which can get values one or zero, are compared to their reference group and, as usual in econometric analysis, reference variables are not used in the estimation process. With dummies, the mean column in the table reveals probability that a respondent belongs to that particular group.

Education was divided into three categories. Reference category refers basic education, which contains primary and lower secondary education, second category is intermediate grade and last group consist of tertiary education. Number of kids under or equal to the age of 16 has been decreasing, which is totally understandable when looking development in household size. Socio-economics groups are lower clerical and workers (known as blue collars), entrepreneurs and upper clerical (known as white collars), pensioners and finally students, farmers, unemployed and others. Proportion of pensioners has increased in study period, whereas number of people in other socioprofessional categories has remained steady. Income was divided into quartiles and then reported per consumption units. The consumption unit is calculated so that head of the household gets largest weighting coefficient, whereas other family members get smaller weight, which is further dependent on their age. The region characteristics were defined differently between 1998, 2006 and 2012, and therefore new universal definitions were formed for this study. The regions used in the study are Helsinki and southern Finland, western Finland, northern and eastern Finland and the reference group is Archipelago region. As one can see from the table, there are not many observations from that region but it does not cause problems with estimation or interpretation (Table 3). The seasonal variables divide calendar year approximately to quarters.

Table 3. Descriptive statistics of the socio-demographic variables used in analysis

	1	.998 (4	1129ob	s)		2006 (3823ob	s)	2012 (3377obs)			s)
	min	max	mean	SD	min	max	mean	SD	min	max	mean	SD
Age	17	97	49	16	17	96	51	17.00	18	95	53	17.00
Education (ed1, Low)												
Medium (ed2)	0	1	0.36	0.48	0	1	0.13	0.34	0	1	0.38	0.49
High (ed3)	0	1	0.27	0.44	0	1	0.19	0.40	0	1	0.39	0.49
HH size	1	18	2.6	1.4	1	19	2.5	1.40	1	12	2.4	1.30
kids16	0	1	0.32	0.47	0	1	0.29	0.45	0	1	0.26	0.44
Socio-profit (soscat1, Blue collar)												
White collar (soscat2)	0	1	0.2	0.4	0	1	0.26	0.44	0	1	0.25	0.44
Pensioners (soscat3)	0	1	0.24	0.43	0	1	0.27	0.45	0	1	0.3	0.46
Other (soscat4)	0	1	0.13	0.34	0	1	0.09	0.29	0	1	0.09	0.29
Income (inc1, Quartile 1)												
Quartile 2 (inc2)	0	1	0.25	0.43	0	1	0.25	0.43	0	1	0.25	0.43
Quartile 3 (inc3)	0	1	0.25	0.43	0	1	0.25	0.43	0	1	0.25	0.43
Quartile 4 (inc4)	0	1	0.25	0.43	0	1	0.25	0.43	0	1	0.25	0.43
Region (regdum4, Archipelago)												
Helsinki and southern Finland (regdum1)	0	1	0.42	0.49	0	1	0.44	0.50	0	1	0.47	0.50
Western Finland (regdum2)	0	1	0.27	0.44	0	1	0.26	0.44	0	1	0.25	0.43
Northern and eastern Finland	0	1	0.29	0.45	0	1	0.26	0.44	0	1	0.24	0.43
(regdum3)												
Annual quarter (seasdum4)												
seasdum1	0	1	0.26	0.44	0	1	0.26	0.44	0	1	0.27	0.44
seasdum2	0	1	0.22	0.42	0	1	0.22	0.41	0	1	0.22	0.42
seasdum3	0	1	0.22	0.42	0	1	0.23	0.42	0	1	0.23	0.42

3.2 Unit values as a price substitutes

HBS data do not contain information relating to prices; during the estimation process, this can be problematic. A quick look at the AIDS model will reveal that price information is an essential element of this process, so without that information, the information found using these prices must be obtained in another way. One alternative for finding this information would be to divide expenditures by physical quantities and use the obtained values as a substitute for the price variable. (Deaton, 1988.) There is, however a problem with this solution – the value obtained using this method and the market price value are not directly proportionate, as this value does not remove the uncontrolled variable of consumer preference. For example, using this solution, despite the fact that a higher-income household might consume less meat, their budget allocation for meat products might be equal to that of a lower-income household because they prefer to buy higher quality meat. Similarly, increases in meat prices may push a low-income household to consume larger quantities of minced meat while reducing their consumption of higher quality meats, all the while allowing them to maintain a fairly constant budget for meat expenditures. Taking these scenarios into consideration, it becomes clear that the situation imagined using this method as an alternative is incomplete and somewhat misleading. Additionally, Deaton (1988) states that both expenditure and quantity estimates are affected by measurement errors, and, consequently, any unit values obtained using this method are contaminated by those errors. Without accounting for those errors the estimations obtained are likely to be biased (Irz, 2017).

In order for the obtained value to be a viable replacement for the price value in demand estimates, the unit values must first be adjusted to dispel possible bias and complications such as those mentioned above. One solution to this issue that was suggested by Cox and Wohlgenant (1986) was the incorporation of dummy variables such as income, education and household size in the obtaining of and correcting of these values. Another suggestion from Majumder et al (2012) proposed the insertion of a regional variable. Yet another proposal from Aepli and Finger (2013) extended the correction model further still by incorporating a time variable. However, in spite of these adjustments, the unit values obtained from these calculations can still deliver biased results (Gibson, 2005). A more comprehensive analysis regarding the unit values is provided in the Appendix.

3.3 Zero consumption

One characteristic of data obtained from the HBS is its considerable proportion of zero values. The two-week survey period utilized in the survey may be shorter than the consumption cycle of a consumer, which could result in a household not consuming a certain food item at all. This infrequency of purchases is often reason for zero values. However, it is also a possibility that the zero consumption of a certain product reflects a true corner solution where the price of the product is too high and the consumer cannot afford it. Additionally, the "true" zeros may refer consumers that buy meat at no price. In other words, the expenditure allocated to beef liver might simply be zero because the household in question consists only of vegetarians, or beef liver might just be an otherwise undesirable commodity for that household at its current income level. (Gould, 1992.)

A data set with a significant amount of zero values is referred to as "censored". Positive data are usually utilized in the estimation process; however, the zero values must be accounted for, as any estimate made without regard for those zero values would be biased and inconsistent (Amemiya, 1985; Smutná, 2016). Researchers have often

approached censored data simply by ignoring zero values (Aborisade et al., 2017; Shibia et al., 2017), but this raises the question: Is that sample still random? Tiberti and Tiberti (2015) attempted to resolve the zero observation problem by adding one to each value in the data set and transform them into logarithms. Unfortunately, by generating information that is inaccurate and changing observations to one, one is assuming that a person actually bought meat, which is not the case with "true" zero observations.

There are a couple of ways how to approach censored data. Due to the complex nature of the multiple equations model, many straightforward one-stage systems that utilize maximum likelihood are not usable (Coelho et al., 2010). Therefore Haines, Guilkey and Popkin (1988) suggested two-stage methods for approaching a censored demand system. The Heckman two-step procedure was utilized by Heien and Wessells (1990) and for the sake of its simplicity it has been a popular tool in demand analysis. The first stage examines the dichotomous choice of the consumer: whether to buy certain good or not. Next, this probit model is used to make probability estimates of consumption for every household and food item being examined. In the second step, the inverse Mills ratio is calculated and is then added to each equation in the LA-AIDS model.

Later, Shonkwiler and Yen (1999) detected that the technique used by Heien and Wessel was theoretically inconsistent and could not be incorporated into Monte Carlo simulations well (Coelho et al., 2010, 2010; Heien and Wessells, 1990). While the method proposed by Shonkwiler and Yen (henceforth SY) has received criticism (Tauchmann, 2005), it is the method that will be utilized in this study. Like the Heien and Wessel method, the SY method also consists of two steps. Once again, the first step examines the consumer decision of whether to purchase a specific meat product or not. As many variables influence this decision, various socio-demographic variables must be considered in explaining the choice of the consumer (Shonkwiler and Yen, 1999). In the second step, the probability density function (PDF) ϕ and the cumulative probability function (CDF) ϕ obtained from fitted values of probit equations are introduced to the LA-AIDS model.

4 Estimation procedure

According to Akbay et al. (2008) "Estimation of a censored demand system with household survey data is one of the most challenging tasks in applied econometrics". The censored LA-AIDS model has to be estimated in two steps. First, the probit equations are used to determine whether a household consumes certain meat aggregate or not. The main outcomes of these equations are the cumulative distribution function (CDF) and the probability density function (PDF), which are used in the second step of the estimation process. In the second step, corrected unit values are also needed as substitutes for price variables. So, before the final estimation can be completed, both the probit equations and the unit value equations must be calculated separately. The LA-AIDS model, as presented below in equation (7), is in its final form, which will be used in this study:

(7)
$$w_i = \Phi_{ih} * \left[\alpha_i + \sum_{j=1}^n \gamma_{ij} \ln P_j + \beta_i (\ln X_h - \sum_i w_i \ln P_i) + \sum_k \lambda_k D_{kh} \right] + \delta_i \phi_{ih} + u_i$$

4.1 LA-AIDS in R

There are a couple of ways to approach the equations used in the LA-AIDS model. Once the unit values have been corrected, the simplest approach is to use R package "micEconAids" as authored by Henningsen (2017a). In order to fully understand what is happening here, it is essential to understand the procedures that are taking place when using this package. Unfortunately the R package does not make estimation with censored data possible, and therefore all the formulas have to be formed manually if one wants to take zero-consumption into account.

Step 1 Probit and unit value equations

After defining the socio-demographic variables, the first-step independent probit equations can be regressed for every meat aggregate. Regression as used in this paper is based on Irz (2017), and the procedure is presented in detail in the Appendix. It is worth noting that price variables are not included in the probit equations as they would disrupt the homogeneity assumption. Instead, in the probit equations, only socio-demographic variables are included as explanatory variables (Bilgic and Yen, 2013).

Additionally, the unit value equations are independent, and a separate regression can be run for each meat category "i". As Cox and Wohlgenant (1986) proposed, the

quality-adjusted prices, or the final price substitutes, consist of the corrected average prices and residuals. The residuals are obtained simply by applying an OLS regression, where the dependent variable (unit value) is explained by household characteristics and the physical quantity the chosen category. Physical quantity is defined according to Capacci and Mazzocchi (2011), where the larger the quantity purchased is, the lower the unit value will be. Due to zero consumption, the average prices for non-consuming households must also be taken into account. In order to correct for region and season linked differences in prices, fitted values were applied in the unit value equations. Without regional and seasonal correction, the average price substitutes that were obtained would be biased. (Cox and Wohlgenant, 1986; Irz, 2017; Park and Capps Jr, 1997.) The estimation process and the R codes used in the study are presented in greater detail in the Appendix.

Step 2 The LA-AIDS model with Iterative Seemingly Unrelated Regression

As this study examined five aggregated meat groups, the number of equations used was also five. In the second step, these equations had to be estimated simultaneously due to cooperative actions between the aggregate groups. In R, this can be done with help of a "systemfit" package (Henningsen and Hamann, 2007). The system of equations can be estimated using the seemingly unrelated regression (SUR) model, the ordinary least squares (OLS) model, or the weighted least squares (WLS) model if the regressors are exogenous (as was assumed earlier). If the disturbance terms are correlated, the estimates of foregoing models are biased and the two-stage least squares (2SLS), weighted two-stage least squares (W2SLS), or three-stage least squares (3SLS) estimation models should be used instead. (Henningsen and Hamann, 2007.)

When the number of iterations is larger than one, the SUR estimator is referred to as iterated seemingly unrelated regression (ITSUR or ISUR). Because ITSUR is well tested and frequently used in LA-AIDS estimation, it was utilized in this study. The SUR estimates are based on one-step covariances (obtained by OLS or 2SLS), whereas ITSUR calculates a new covariance matrix from previous estimations until the estimated coefficients converge. (Henningsen and Hamann, 2007.) Another frequently used estimator is the full information maximum likelihood (FIML) estimator, but according to Henningsen (2017b), ITSUR often converges to FIML.

As budget shares sum-up to one, the residual covariance matrix will be singular, which is problematic for estimations. As a result, one of the equations must be dropped from system; however, the missing coefficients can be obtained with the assistance of an adding-up restriction (Blanciforti and Green, 1983). However, after censoring, budget shares do not sum up to one anymore, making it possible to estimate all five equations simultaneously (Yen et al., 2002). Some studies actually recommend that estimations be calculated in this manner. Still, the majority of censored demand system studies drop one equation when estimating their model. This is because, according to Akbay et al. (2008), the results obtained using this method are typically similar despite the fact that the estimation was performed by omitting one equation.

This study utilized the method where one equation was dropped before running the system of equations in R. While an estimation using all five meat equations would have been possible, including the fifth equation led to coefficients that were very small, resulting in estimates that were uncomfortably close to minus unity or unity (depending on elasticities). Similarly, researchers utilizing all *n* equations in their estimations (Akbay et al., 2007; Yen et al., 2002) estimated only *n-1* equations in their later studies (Akbay et al., 2008; Bilgic and Yen, 2013). Because of this, it was decided that an estimation using only four meat aggregates would better suit this study. However, the selection of meat group that should be omitted is complicated, as the results are not quite invariant to the group selected (Bilgic and Yen, 2013; Boysen, 2016; Pudney, 1989).

Because there was no natural residual group, the beef and lamb group equation was dropped from the model. This group was dropped because it was heavily censored, which could have skewed the final results of the study. This decision was also based on a similar decision made by Yen and Lin (2006) who dropped the highly censored beef group from their study, as it would have affected the accuracy of the elasticities for the beef group obtained in their estimations. By comparing the results with beef and lamb omitted to models where some other meat was omitted, the expenditure elasticity of the beef and lamb group became higher. Coefficients of the LA-AIDS model are presented in the Appendix.

4.2 Testing linear restrictions.

The homogeneity and symmetry restrictions can be implemented beforehand and are easily testable. There are a few ways of testing the restrictions: the F test, Wald tests and the likelihood ratio (LR) test. The formulas of these tests were proposed by Henningsen and Hamann (2007) and in this thesis they are applied symbolically. The null hypothesis of the tests assumes homogeneity in expenditures and prices, which denotes that proportional changes in prices and expenditures have no effect on demand. So, this simply implies that the sum of the price parameters in all equations equals zero, as can be seen in (5).

Homogeneity can be implemented in every equation separately, which is not case with symmetry (Deaton and Muellbauer, 1980a). However, as the first equation is dropped from the system, homogeneity cannot be implemented for the beef and lamb category. The homogeneity restriction held in 2006 and 2012 as the likelihood ratio test was unable to reject the null hypothesis at a 95 % level of significance. In 1998 the homogeneity restriction held only for processed meat and other meat products. Both the symmetry restriction and symmetry with homogeneity were rejected (Table 4):

Table 4. Testing the restrictions. LR test results

	1998	2006	2012
Homogeneity imposed Pr(>Chisq)	0.695 (eq4, eq5)	0.213	0.073
Symmetry imposed Pr(>Chisq)	0.0310	0.0039	0.0240
Homogeneity and symmetry imposed Pr(>Chisq)	0.0028	0.0074	0.0001

The fourth - and rarely observed - property is negativity. When the expenditure function is concave in relation to prices, the substitution matrix is negative semidefinite, and the diagonal elements of the matrix are negative as well. This restriction can be tested only afterwards by, for example, checking whether the sum of the Marshallian own-price elasticities and the expenditure elasticities of multiple budget shares of a certain group are less than or equal to zero (Edgerton et al., 1996). In this paper, the negativity restriction holds true (Table 5):

Table 5. Testing the negativity restriction (Edgerton et al., 1996)

			Checking the negativity restriction										
I	$\epsilon_{ii} + w_i * E_i \leq 0$	Beef and lamb	Pork	Poultry	Processed meat	Other meat products							
I	1998	-0.9	-0.6	-0.4	-0.4	-0.4							
ĺ	2006	-0.7	-0.3	-0.5	-0.5	-0.4							
I	2012	-0.8	-0.5	-0.4	-0.5	-0.4							

4.3 Elasticities

Generally, the articles related to demand systems result in either Hicksian (compensated) or Marshallian (uncompensated) elasticities without exception. Own-price and expenditure elasticities are of particular interest. One could say that elasticities are the most important result of demand analyses, as the other coefficients and results of the AIDS model can be difficult to interpret. (Irz, 2017) Elasticities are determined using the parameter estimates found using the LA-AIDS model. Formulas of expenditure elasticities, Marshallian demand elasticities, and Hicksian demand elasticities are defined in the Appendix. In this analysis, elasticities have been calculated by using the unconditional means of the expenditure shares as proposed by Yen and Lin (2006).

Expenditure or income elasticity is defined as $e_i = \frac{\% \ change \ in \ demand}{\% \ change \ in \ income}$. Therefore, the elasticity reveals how much the quantity demanded changes as a result of a one per cent change in the total expenditure of meat products. In general expenditure elasticities divide goods to necessity, luxury or inferior goods. When the elasticity is larger than one, the good is luxury and changes in quantity demanded are larger than changes in expenditures. In the case that the elasticity is between zero and one, the good is known as a necessity. Together luxuries and necessities are known as normal goods, as quantity demanded rises when expenditure rises. Increasing expenditures can also lead to decreasing the quantity demanded when expenditure elasticity is negative and a good is inferior. (Varian, 2014.)

Cross-price elasticity reveals how much the demanded quantity of good "i" changes when price of good "j" changes by one per cent. In a case where the value of that elasticity is negative, goods "i" and "j" are complements, whereas a positive sign denotes substitution. Own-price elasticity measures the change in demand that occurs when a good's own price changes. Due to restrictions and consumer theory, own-price elasticities are negative unless the good is a Giffen good, in which case rises in price would increase the demand. (Deaton and Muellbauer, 1980a; Edgerton et al., 1996.) Demand elasticities are often defined as elastic or inelastic depending on the magnitude of elasticity. If the elasticity is smaller than minus one, the demand is elastic whereas demand is inelastic when the elasticity is between minus one and zero (Varian, 2014). Hicksian elasticities measure how good or bad the price changes are for those consumers they effect. For example, if the price of a good rises but this change would

be compensated to the consumer, the question is how much would s/he buy? Thus, Hicksian elasticities give information relating to what happens to consumers' demand due to price changes when holding utility constant. (Irz, 2017.)

Differences between Marshallian and Hicksian cross-price elasticities may be difficult to understand without adequate information regarding the substitution and income effects in general. Marshallian demand functions produce gross complements and substitutes, where gross denotes both the income and substitution effects. Consequently, Hicksian demand functions produce net complements (substitutes) when the effect of income is not present at all. Due to presence of the income effect, good "i" can be a gross substitute for good "j", and at the same time "j" can be a cross complement to "i". So, the gross definitions are not symmetric. Instead the net definitions are symmetric in sign. For example, if the price of the first meat group rises, and this has an effect on the consumption of the second group, the effect would be similar to the hypothetical price increasing in the second group that would affect the first group. Therefore, the price ratio is the only aspect that changes between those two goods when a price changes. (Varian, 2014.)

Meat elasticities obtained in different studies differ depending on county, culture, religion and income level. More so, the model used in an estimation analysis as well as the different specifications used can change elasticity values, and therefore the results may not be comparable. Gallet (2010) summarized the meat demand elasticities of different studies, and in general the price elasticity of poultry seemed to be the lowest whereas the elasticity of the beef and lamb category reached the highest values. However, sometimes the results are the opposite. Despite a median price elasticity of -0.77 from a sample of hundreds of studies, estimates varied greatly with a standard deviation of 1.28. According to Gallet (2010) price elasticity is strongly affected by the estimation method and specification of demand, whereas the location of demand and data characteristics have minor impact.

Literature provides a broad range of elasticity formulas, which differ greatly from one another. As with demand modelling, it is also preferable to use ready-made approximations and simplifications when calculating elasticities, so that the author does not need to derive elasticities from original expressions. While using ready-made approximations and simplifications accelerates the process, it also causes uncertainty

as the author knows neither where the elasticities come from nor which elasticities should be used. Expenditure elasticities are similar, but especially Marshallian elasticities with censored systems can cause problems. However, there are also clear mistakes with elasticity formulas. Many elasticity expressions are based on Green and Alston (1990), and while the elasticity formulas of the LA-AIDS model were determined to be incorrect later (Green and Alston, 1991), they are still present in some studies (Aborisade et al., 2017).

Yen and Lin (2006) suggested that in censored systems elasticities should be calculated using the unconditional means of the expenditure shares rather than sample means. In this study we utilize the derivations suggested by Bilgic and Yen (2013). The system used to calculate the means can greatly impact the final elasticities that are found. Values of the CDF can be computed for individuals and then averaged, or the CDF values can be calculated directly from the parameters of the corresponding exogenous variables. Derivations of the formulas are presented in the Appendix.

5 Results

5.1 Probit and unit value equations

The estimated coefficients from the first-stage probit equations aim at explaining a positive consumption by the consumer. The absolute value of the coefficients reveals to which degree the explanatory variables influence that choice. In other words, the coefficients identify the factors that increase or decrease the probability that a consumer will decide to buy a good belonging to a certain meat category. Thus, it is worth noting that these coefficients do not reveal how much consumption levels change due to household characteristics, but instead they reveal whether consumption becomes more or less probable. The significances of the factors have been marked with asterisks, and standard errors have been provided in parentheses. The coefficients of dummy variables (education, socio economic status, income, region and season) provide information pertaining to the probability effect in relation to the corresponding reference category, which has been excluded from the table. These determinants are presented for all three data sets used in the study. (Table 6.)

Table 6. Coefficients of estimated probit equations. (Significance levels *p<0.1; **p<0.05; ***p<0.01, standard errors in parentheses)

	Beef and lamb			Pork			Poultry			Processed meat			Other meat products		
	1998	2006	2012	1998	2006	2012	1998	2006	2012	1998	2006	2012	1998	2006	2012
age	0.01***	0.003	0.004*	0.01***	0.01***	0.01***	-0.002	-0.01***	-0.01**	0.01**	0.01**	0.02***	0.002	-0.01***	0.003
	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003	-0	-0	-0.002	-0.002	-0.002
ed2	0.01	-0.05	0.01	-0.06	-0.004	0.02	0.07	0.16**	0.16**	-0.11	-0.13	0.05	0.02	-0.14*	0.1
	-0.06	-0.07	-0.07	-0.05	-0.06	-0.06	-0.05	-0.06	-0.06	-0.09	-0.12	-0.1	-0.07	-0.08	-0.08
ed3	-0.06	0.05	0.03	-0.20***	-0.20***	-0.08	0.18***	0.07	0.12*	-0.13	-0.15	0.01	-0.06	-0.20**	0.06
	-0.06	-0.07	-0.07	-0.06	-0.06	-0.07	-0.06	-0.07	-0.07	-0.11	-0.12	-0.11	-0.07	-0.08	-0.08
HH size	0.17***	0.11***	0.09***	0.17***	0.23***	0.15***	0.11***	0.15***	0.25***	0.20***	0.31***	0.24***	0.29***	0.25***	0.29***
	-0.02	-0.02	-0.03	-0.02	-0.03	-0.03	-0.02	-0.03	-0.03	-0.05	-0.06	-0.05	-0.04	-0.04	-0.04
kids<=16	-0.08	-0.06	0.11	-0.01	-0.23***	0.003	0.12*	0.09	-0.01	-0.06	-0.08	-0.09	0.1	0.06	0.03
	-0.07	-0.08	-0.09	-0.07	-0.07	-0.08	-0.07	-0.07	-0.08	-0.13	-0.15	-0.14	-0.09	-0.11	-0.11
soscat2	0.14**	-0.06	0.06	0.07	-0.08	-0.07	0.02	0.13**	0.06	-0.07	0.03	-0.02	-0.14*	-0.03	-0.29***
	-0.06	-0.07	-0.07	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.11	-0.12	-0.11	-0.08	-0.08	-0.08
soscat3	0.002	0.01	0.03	-0.12	-0.12	-0.07	-0.12	-0.08	0.02	-0.23 [*]	0.02	-0.09	-0.26***	0.13	-0.18*
	-0.08	-0.09	-0.09	-0.08	-0.08	-0.08	-0.08	-0.08	-0.08	-0.13	-0.14	-0.13	-0.09	-0.1	-0.1
soscat4	0.09	-0.03	0.12	-0.01	-0.15*	-0.07	-0.1	-0.09	-0.01	-0.34***	-0.14	-0.23*	-0.17**	-0.21**	-0.11
	-0.08	-0.09	-0.1	-0.07	-0.08	-0.08	-0.07	-0.08	-0.09	-0.11	-0.13	-0.12	-0.09	-0.1	-0.11
inc2	0.18***	0.09	0.19**	0.14**	0.17***	0.16**	0.19***	0.16**	0.13*	0.04	0.29***	0.11	0.01	0.20***	0.11
	-0.07	-0.07	-0.08	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.1	-0.11	-0.1	-0.07	-0.08	-0.08
inc3	0.22***	0.23***	0.19**	0.24***	0.26***	0.21***	0.31***	0.29***	0.20***	0.16	0.42***	0.15	0.09	0.30***	0.26***
	-0.07	-0.07	-0.08	-0.06	-0.06	-0.07	-0.06	-0.06	-0.07	-0.11	-0.12	-0.11	-0.08	-0.08	-0.09
inc4	0.39***	0.42***	0.48***	0.22***	0.26***	0.14*	0.30***	0.30***	0.20***	0.27**	0.45***	0.17	0.05	0.24***	0.22**
	-0.07	-0.08	-0.08	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07	-0.12	-0.13	-0.12	-0.08	-0.09	-0.09
regdum1	-0.51***	-0.37***	-0.59***	-0.003	-0.09	-0.33***	0.39**	0.26**	0.13	0.45*	0.35*	0.08	-0.45*	0.39***	-0.01
	-0.17	-0.11	-0.12	-0.17	-0.11	-0.12	-0.18	-0.11	-0.12	-0.23	-0.18	-0.2	-0.26	-0.13	-0.15
regdum2	-0.58***	-0.42***	-0.59***	0.13	-0.18	-0.29**	0.35*	0.31***	0.17	0.58**	0.39**	0.15	-0.39	0.50***	0.11
	-0.17	-0.12	-0.12	-0.17	-0.11	-0.12	-0.18	-0.12	-0.12	-0.24	-0.19	-0.2	-0.26	-0.13	-0.16
regdum3	-0.80***	-0.48***	-0.67***	0.03	-0.16	-0.28**	0.34*	0.12	0.14	0.68***	0.27	0.17	-0.34	0.56***	0.16
	-0.17	-0.12	-0.12	-0.17	-0.11	-0.12	-0.18	-0.12	-0.12	-0.24	-0.19	-0.2	-0.27	-0.13	-0.16
seasdum1	0.09	0.15**	0.18***	-0.05	-0.07	0.04	0.09	-0.12**	0.07	0.15	0.06	-0.04	-0.02	0.04	0.08
	-0.06	-0.06	-0.07	-0.05	-0.06	-0.06	-0.05	-0.06	-0.06	-0.09	-0.1	-0.1	-0.07	-0.07	-0.08
seasdum2	0.10*	-0.08	0.05	0.03	0.08	0.24***	0.004	0.02	-0.01	0.17*	0.09	0.03	0.02	-0.11	-0.12
	-0.06	-0.07	-0.07	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.1	-0.11	-0.1	-0.07	-0.07	-0.08
seasdum3	0.02	0.03	-0.02	-0.04	0.04	0.03	0.15***	0.10*	0.08	0.19*	0.08	0.02	0.04	-0.01	-0.01
	-0.06	-0.06	-0.07	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.1	-0.1	-0.1	-0.07	-0.07	-0.08
Constant	-1.28***	-0.96***	-1.03***	-1.09***	-0.92***	-0.59***	-1.20***	-0.50***	-0.62***	0.33	0.12	0.01	0.74**	0.36*	0.17
	-0.22	-0.17	-0.19	-0.21	-0.16	-0.18	-0.22	-0.16	-0.18	-0.31	-0.25	-0.28	-0.3	-0.19	-0.22

Apart from a few observations, age was consistently a significant factor. Even though the effect of aging is not great, it allows for the assumption that young people are less likely to buy meat products (apart from poultry) than their older counterparts. However, the literature does not take a stand on this hypothesis. While the effects of education on meat product purchases seem to be minimal, there is some evidence that

highly educated people tend to choose poultry over pork; however, this purchase gap is shrinking. Naturally, household size increases the consumption probability of every meat aggregate significantly. This effect, however, is more apparent in the "processed meat" and "other meat products" categories than in the first three categories. During the years studied in this thesis, the effect of household size on beef and lamb consumption has decreased by half, while the effect on poultry consumption has doubled.

The number of kids (16 or younger) does not have notable effect one way or the other, nor does socio-economic status (except in the fourth social category, which probably includes more people who avoid processed meat and other meat products). Income also has a clear influence on non-zero consumption. Higher income increases the probability of positive consumption in every category, but the effects are not as significant in the last two categories. Other regions are compared to the archipelago region, which makes the interpretation of data problematic. However, the coefficients are significant, which reveals that there are apparent differences between regions, or at the least a great difference between the archipelago and other areas. The probability of consuming beef and lamb seems to decrease when going north and east. In 2006 the same phenomenon was observed in relation to other meat products, and in 2012 pork was most avoided in the southern part of Finland. Seasonal variables do not have a meaningful effect on non-zero consumption. The results found here are similar to those presented by Irz (2017), although the meat aggregates used in this analysis differ slightly.

UNIT VALUES

The estimated coefficients of the unit value equations are presented in Table 7. Before interpreting the results, it is important to recall that changes in unit values result in either changes in physical quantity or expenditures. Thus, the table also contains quality and quantity effects on consumer choices as discussed above in the unit value chapter, or in more detail by Irz (2017). The table reveals how much the unit value changes when the magnitude of a particular explanatory variable increases by one unit, or (with the dummy variables) what is the change compared to the reference group when moving to the next dummy level (for example ed2 to ed3).

Table 7. Coefficients of estimated unit value equations. (Significance levels *p<0.1; **p<0.05; ***p<0.01, standard errors in parentheses)

	Be	ef and lar	mb	Pork				Poultry			cessed m	eat	Other meat products		
	1998	2006	2012	1998	2006	2012	1998	2006	2012	1998	2006	2012	1998	2006	2012
age	0.01	0.02***	0.02	-0.01	-0.004	-0.005	-0.01*	0.003**	-0.01**	0.01***	-0.01**	-0.01***	0.003	-0.002	-0.004
	(0.01)	(0.01)	(0.02)	(0.005)	(0.003)	(0.004)	(0.01)	(0.001)	(0.01)	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)
ed2	-0.01	-0.06	0.10	0.19*	0.003	0.20*	0.27	-0.04	-0.08	0.19**	0.06	0.13	0.11*	0.05	0.04
	(0.26)	(0.24)	(0.72)	(0.11)	(0.09)	(0.10)	(0.19)	(0.04)	(0.17)	(0.09)	(0.09)	(0.11)	(0.06)	(0.07)	(0.09)
ed3	0.44	0.01	0.98	0.35***	0.15	0.41***	0.59***	0.04	0.14	0.34***	0.25***	0.40***	0.22***	0.01	0.11
	(0.29)	(0.23)	(0.72)	(0.13)	(0.10)	(0.11)	(0.20)	(0.04)	(0.17)	(0.10)	(0.09)	(0.11)	(0.07)	(0.07)	(0.09)
HH size	-0.19**	-0.13	0.20	-0.10**	-0.01	0.07*	0.09	0.01	0.23***	-0.03	0.06*	0.08	-0.03	0.04*	0.08**
	(0.10)	(0.08)	(0.30)	(0.05)	(0.03)	(0.04)	(0.08)	(0.02)	(0.06)	(0.04)	(0.03)	(0.05)	(0.03)	(0.02)	(0.04)
kids<=16	0.11	0.27	-0.77	0.14	0.11	-0.02	0.10	0.06	-0.14	-0.10	-0.28***	-0.27**	0.02	-0.17**	-0.07
	(0.30)	(0.25)	(0.87)	(0.14)	(0.10)	(0.13)	(0.22)	(0.04)	(0.18)	(0.11)	(0.10)	(0.14)	(0.07)	(0.07)	(0.11)
soscat2	1.03***	0.13	1.19*	0.30**	0.02	0.09	0.28	-0.002	0.49***	0.27***	0.14	0.03	-0.001	-0.04	-0.04
	(0.28)	(0.22)	(0.64)	(0.13)	(0.09)	(0.10)	(0.19)	(0.04)	(0.15)	(0.11)	(0.08)	(0.11)	(0.07)	(0.06)	(0.09)
soscat3	-0.33	-0.38	-0.60	-0.19	-0.11	-0.17	-0.18	-0.11*	0.35	-0.19	-0.01	0.04	-0.04	-0.09	-0.12
	(0.38)	(0.29)	(0.88)	(0.16)	(0.11)	(0.13)	(0.29)	(0.06)	(0.21)	(0.14)	(0.11)	(0.14)	(0.09)	(0.08)	(0.11)
soscat4	-1.37***	-1.65***	-5.11***	-0.85***	-0.24*	-0.41***	-0.84***	-0.06	0.22	-0.28**	0.12	-0.05	-0.24***	-0.16*	-0.18
	(0.35)	(0.32)	(0.97)	(0.15)	(0.13)	(0.15)	(0.25)	(0.05)	(0.22)	(0.12)	(0.11)	(0.15)	(0.08)	(0.08)	(0.12)
inc2	0.39	0.31	0.63	0.34***	0.09	0.09	0.35	0.03	0.11	0.27***	0.26***	-0.06	0.06	0.05	0.01
	(0.31)	(0.25)	(0.79)	(0.13)	(0.09)	(0.11)	(0.22)	(0.04)	(0.17)	(0.10)	(0.08)	(0.11)	(0.07)	(0.06)	(0.09)
inc3	0.27	0.25	2.48***	0.13	0.16	0.13	0.40*	0.02	0.15	0.40***	0.36***	0.06	0.12*	0.06	0.02
	(0.32)	(0.25)	(0.80)	(0.13)	(0.10)	(0.11)	(0.22)	(0.04)	(0.17)	(0.11)	(0.09)	(0.12)	(0.07)	(0.06)	(0.09)
inc4	0.95***	0.41	1.91**	0.63***	0.20*	0.03	0.84***	0.002	0.61***	0.77***	0.36***	0.31**	0.30***	0.14*	0.21**
	(0.33)	(0.27)	(0.81)	(0.14)	(0.11)	(0.12)	(0.24)	(0.05)	(0.19)	(0.12)	(0.10)	(0.13)	(0.08)	(0.07)	(0.10)
regdum1	-0.30	-0.16	-0.51	-0.97***	0.05	-0.08	1.06	0.18**	-0.27	-0.12	0.28*	0.24	-0.85***	-0.41***	0.04
	(0.62)	(0.33)	(0.91)	(0.36)	(0.15)	(0.18)	(0.70)	(0.08)	(0.31)	(0.31)	(0.16)	(0.20)	(0.19)	(0.12)	(0.16)
regdum2	-0.83	-0.80**	-3.01***	-1.21***	-0.01	-0.30	0.95	0.12	-0.54*	-0.26	0.06	-0.02	-0.86***	-0.54***	-0.21
	(0.63)	(0.35)	(0.98)	(0.37)	(0.16)	(0.18)	(0.71)	(0.08)	(0.32)	(0.32)	(0.16)	(0.21)	(0.20)	(0.12)	(0.17)
regdum3	-1.02	-1.41***	-2.55**	-1.30***	-0.17	-0.26	0.79	0.11	-0.60*	-0.35	0.20	0.14	-0.81***	-0.42***	-0.16
	(0.63)	(0.36)	(1.00)	(0.37)	(0.16)	(0.18)	(0.71)	(0.08)	(0.32)	(0.31)	(0.16)	(0.21)	(0.20)	(0.12)	(0.17)
seasdum1	0.45*	0.13	-0.31	0.24**	0.12	-0.02	0.23	0.03	-0.12	0.18	-0.02	-0.16	0.09	-0.03	-0.06
	(0.27)	(0.20)	(0.63)	(0.12)	(0.09)	(0.10)	(0.19)	(0.04)	(0.15)	(0.10)	(0.08)	(0.10)	(0.06)	(0.06)	(0.08)
seasdum2	0.43	0.09	-0.87	0.41***	0.29***	0.21**	0.03	0.32***	-0.08	-0.03	-0.53***	-0.24**	0.14**	-0.15**	-0.16*
	(0.28)	(0.23)	(0.69)	(0.12)	(0.09)	(0.10)	(0.20)	(0.04)	(0.16)	(0.10)	(0.08)	(0.11)	(0.07)	(0.06)	(0.09)
seasdum3	0.44	-0.18	-1.02	0.13	0.10	0.12	0.28	0.08**	-0.07	0.06	-0.14*	0.06	0.07	-0.08	0.04
	(0.29)	(0.22)	(0.71)	(0.12)	(0.09)	(0.11)	(0.19)	(0.04)	(0.16)	(0.10)	(0.08)	(0.11)	(0.07)	(0.06)	(0.09)
quantity	-0.003***	-0.001	-0.02***	-0.01***	-0.01***	-0.01***	-0.04***	0.002***	-0.03***	-0.01***	-0.01***	-0.01***	-0.001*	-0.001***	-0.01***
	(0.001)	(0.002)	(0.01)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.001)
Constant	7.65***	9.84***	13.75***	7.01***	7.70***	8.61***	5.12***	5.29***	7.53***	6.38***	7.58***	9.69***	5.28***	6.32***	7.36***
	(0.90)	(0.56)	(1.84)	(0.46)	(0.24)	(0.30)	(0.83)	(0.11)	(0.46)	(0.38)	(0.22)	(0.31)	(0.24)	(0.17)	(0.25)

The influence of age seems to be conflicting, but the data suggests that in 2012 aging reduced the unit values of processed meat and poultry. In regards to education, a more straightforward relation is suggested: a higher education level directly corresponds with a higher unit values, especially in relation with processed meat and pork (except 2006). In 2012, household size most notably corresponded with an increased unit value in poultry, but to a smaller degree corresponded with increases in unit value for pork and other meat products as well. In general, the effects were parallel, but in 1998

household size corresponded with a decrease in the unit values of beef and lamb and pork. The number of kids had a significant (and negative) effect only on the unit values for processed meat.

Socio-economic status can affect unit values in either direction. Entrepreneurs and upper-clerical workers, known as white-collar workers, produce high unit values in the beef and lamb category compared to the reference group. In 2012 the same can be observed in relation to poultry. One could say that second socio-economic group produces the highest unit values among the meat aggregates, apart from the other meat products category. The last group - containing students, farmers, unemployed and others - is notably heterogeneous. However, the unit values for beef and lamb and pork were significantly lower for this group.

Increases in unit values for all meat categories can clearly be seen in the highest income group. As Irz (2017) claimed, the well-educated and high-income classes are more likely to select better quality products than those in the reference category. Region has some impact on unit values, but that impact in of little significance. Surprisingly season two exhibits an increase the unit values of pork while simultaneously exhibiting a decrease in the unit values of processed meats and other meat products (except in 1998). The last factor of the table, physical quantity of the product group itself, is significant and reveals that unit values diminish when quantities increase (Irz 2017). In general, the constant term reveals the magnitude of the dependent variable when other independent variables are set to zero. However, the intercepting terms in the table are not equal to the final unit values, as the price variables used in the analysis consist of corrected average prices and residuals (Cox and Wohlgenant, 1986).

5.2 Demand elasticities

The definitions of elasticities were discussed above in Chapter 4. Parameter estimates of the LA-AIDS model were mostly significant, with the exception of a few socio-demographic variables that contained only some significant coefficients. For ensuring the reliability of elasticities, the delta method was used for calculating standard errors and the significances of elasticities. The interpretation below is based on the homogeneity-constrained model, which was deemed superior to the unrestricted model. However, due to the results of the F and Wald tests, in 1998 homogeneity was

implemented only for the processed meat and other meat products categories. In 2006 and 2012 homogeneity held for all meat categories.

Table 8 presents the expenditure, or income, elasticities for the meat aggregate groups. Because an increased amount of expenditure results in an increased demand in meat quantity, meat can be considered a normal good. The beef and lamb category was dropped during the estimation process, and was recovered using an adding-up constraint. Consequently, the elasticities of that group may be slightly biased and/or underestimated. When an equation other than that for the beef and lamb category was dropped, the expenditure elasticities for the first meat category increased, and conversely Marshallian price elasticities decreased.

The expenditure elasticity of the beef and lamb category exceeded unity in 2012, which means that ruminant meat was considered as a luxury good. Additionally, the demand for poultry is approximately as expenditure-elastic as ruminant meat, whereas pork is clearly considered more of a luxury good. Although this correlation has become weaker, pork is still most strongly affected by expenditure changes. In 2012, if income increased by 10 %, the demand for pork would increase by over 13 %. The processed meats and other meat products categories have the lowest expenditure elasticities, which makes them necessity goods. This is understandable, as the groups include minced meat, cold cuts and other base products. In 2012, if income was increased by 10 %, the demand for other meat products would increase by 9 %.

Table 8. Expenditure elasticities of meat aggregates. (Significance levels *p<0.1; **p<0.05; ***p<0.01, standard errors in parentheses)

	1998	2006	2012
Beef and lamb	0.976***	0.921***	1.013***
	(0.031)	(0.024)	(0.023)
Pork	1.412***	1.389***	1.341***
	(0.031)	(0.03)	(0.034)
Poultry	0.926***	1.086***	1.012***
	(0.039)	(0.03)	(0.031)
Processed meat	0.937***	0.876***	0.908***
	(0.011)	(0.011)	(0.013)
Other meat products	0.846***	0.925***	0.89***
	(0.019)	(0.018)	(0.019)

Conditional Marshallian elasticities are presented in Table 9. Own-price elasticities (diagonal elements of the matrices) are negative and significant at the 99 % level. Marshallian elasticities fulfill the necessary conditions of utility maximization and there are not any Giffen goods among the meats. The homogeneity restriction only changed Marshallian elasticity estimates to the hundredth decimal place. In the table, each column lists goods to be examined, whereas rows list goods whose prices change.

Table 9. Conditional Marshallian price elasticities. (Significance levels *p<0.1; **p<0.05; ***p<0.01, standard errors in parentheses)

									Prices							
		В	eef and lar	nb		Pork		Poultry		Processed meat			Other meat products			
		1998	2006	2012	1998	2006	2012	1998	2006	2012	1998	2006	2012	1998	2006	2012
Q	Beef and lamb	-1.003***	-0.796***	-0.863***	-0.173**	-0.282***	-0.175**	-0.27***	-0.088	-0.149***	0.258***	0.198***	0.293***	0.093	-0.032	-0.106
u a	beer and rains	(0.087)	(0.09)	(0.041)	(0.076)	(0.094)	(0.076)	(0.061)	(0.11)	(0.056)	(0.06)	(0.072)	(0.071)	(0.072)	(0.082)	(0.071)
n t	Pork	-0.182**	-0.009	0.035	-0.779***	-0.497***	-0.69***	-0.048	-0.31**	-0.111	-0.273***	-0.346***	-0.341***	-0.079	0.162	0.107
i t		(0.091)	(0.119)	(0.061)	(0.081)	(0.12)	(0.113)	(0.068)	(0.14)	(0.085)	(0.061)	(0.093)	(0.106)	(0.073)	(0.104)	(0.105)
i e	Davilan	0.096	-0.149	-0.14**	0.044	-0.202*	-0.14	-0.484***	-0.588***	-0.549***	-0.041	0.073	-0.069	-0.083	-0.133	-0.102
s	Poultry	(0.115)	(0.112)	(0.056)	(0.099)	(0.117)	(0.099)	(0.079)	(0.139)	(0.073)	(0.078)	(0.089)	(0.093)	(0.094)	(0.106)	(0.094)
d e	Dunnand mank	0.032	-0.058	-0.066***	-0.027	-0.032	0.086**	-0.026	0.092*	-0.005	-0.808***	-0.841***	-0.837***	-0.171***	-0.161***	-0.177***
m a	Processed meat	(0.03)	(0.044)	(0.024)	(0.028)	(0.044)	(0.043)	(0.024)	(0.052)	(0.033)	(0.02)	(0.033)	(0.04)	(0.024)	(0.039)	(0.039)
n d	Other meat products	0.026	0.05	0.063*	-0.031	0.039	-0.1	-0.066	-0.141*	-0.113**	-0.287***	-0.2***	-0.173***	-0.642***	-0.748***	-0.676***
e d		(0.051)	(0.068)	(0.034)	(0.047)	(0.07)	(0.061)	(0.04)	(0.082)	(0.046)	(0.035)	(0.053)	(0.057)	(0.042)	(0.062)	(0.056)

Under the circumstances that goods are complements, when the price of a good "i" increases, the demanded quantity of the good "j" decreases. Alternatively, if the demanded quantity of good "j" increases due to a higher price for good "i", the goods are substitutes. In the table, negative cross-price elasticities denote complement goods and positive elasticities illustrate substitution. As is typical in food demand, most of the food products (71 %) are gross complements and, except ruminant meat in 1998, all absolute values of the elasticities are smaller than one, meaning that the demand for meat is inelastic. The complementary nature of the Marshallian cross-price elasticities may result from the fact that the meat budget is fixed and goods are not individual, and, therefore, the income effects are large.

Only six cross-price elasticities are positive and significant. The substitution relationship is strongest between ruminant meat and processed meat, but evidence also suggests that processed meat was a substitute for pork and poultry. So, in 2012, when the price of the beef and lamb category rose by 10 %, the demand for processed meat

increased 3 %. In other words, when ruminant meat becomes too expensive, a consumer will substitute it for cheaper products, such as cold cuts and sausages. More than one third of the cross-price elasticities are negative and significant. Pork and processed meat, ruminant meat and pork, and other meat products and processed meat all exhibited strong complementary relationships during the study period.

The results of this study coincide with the results of Gallet (2010) in his broad meat analysis: in terms of own-price elasticities, poultry is the most inelastic group, and the beef and lamb and processed meat groups have the largest absolute values. From the unit value table (Table 7), it can be seen that ruminant meat and processed meat have the greatest unit values, while the unit values for poultry are much lower. Therefore, consumers tend to respond more readily to price fluctuations in expensive products. Furthermore, the processed meat and other meat products categories remained most steady during the study period, whereas ruminant meat and pork experienced notable changes from 1998 to 2006 and continued to do so from 2006 to 2012. But, because demand seems to be inelastic, the consumption of meat products is not greatly influenced by price changes.

The substitution effects are much more clearly visible when using Hicksian elasticities (Table 10) than it was with Marshallian elasticities. This is understandable as the income effect is not present in Hicksian net cross-price elasticities. Irz (2017) concluded that uncompensated elasticities are slightly more negative than compensated elasticities. Over half of all cross-price elasticities are positive, but even though the rest are negative, only two of those negative observations are significant. The beef and lamb category was substituted for the pork and poultry categories, but in 2012 the effect was no longer significant. The Hicksian substitution effect is most notable between the beef and lamb and processed meat categories, but the pork category is also a strong substitute to the other meat products category, and the poultry category is a strong substitute for the processed meat category.

Table 10. Conditional Hicksian price elasticities. (Significance levels *p<0.1; **p<0.05; ***p<0.01, standard errors in parentheses)

			Prices													
		В	eef and lar	mb	Pork			Poultry			Processed meat			Other meat products		
		1998	2006	2012	1998	2006	2012	1998	2006	2012	1998	2006	2012	1998	2006	2012
Q	Beef and lamb	-0.949***	-0.748***	-0.812***	-0.054	-0.184*	-0.065	-0.197***	0.005	-0.026	0.745***	0.63***	0.733***	0.336***	0.217***	0.183***
a	Beer and lamb	(0.087)	(0.09)	(0.041)	(0.076)	(0.094)	(0.076)	(0.061)	(0.11)	(0.056)	(0.062)	(0.072)	(0.072)	(0.072)	(0.083)	(0.071)
t	Pork	-0.104	0.062	0.102*	-0.608***	-0.348***	-0.543***	0.058	-0.169	0.051	0.433***	0.306***	0.241**	0.273***	0.537***	0.49***
t		(0.092)	(0.119)	(0.061)	(0.081)	(0.12)	(0.113)	(0.068)	(0.14)	(0.085)	(0.063)	(0.093)	(0.107)	(0.074)	(0.105)	(0.105)
e	Poultry	0.147	-0.093	-0.089	0.156	-0.086	-0.029	-0.415***	-0.478***	-0.427***	0.421***	0.583***	0.37***	0.148	0.161	0.186**
d	rounty	(0.115)	(0.112)	(0.056)	(0.1)	(0.117)	(0.099)	(0.079)	(0.139)	(0.073)	(80.0)	(0.09)	(0.095)	(0.095)	(0.106)	(0.094)
e m	Processed meat	0.084***	-0.013	-0.02	0.086***	0.062	0.185***	0.045*	0.181***	0.104***	-0.34***	-0.43***	-0.443***	0.063***	0.076*	0.082**
a n	Processed meat	(0.03)	(0.044)	(0.024)	(0.028)	(0.044)	(0.043)	(0.024)	(0.052)	(0.033)	(0.021)	(0.034)	(0.04)	(0.024)	(0.039)	(0.039)
d	Other meet products	0.072	0.098	0.107***	0.071	0.138**	-0.003	-0.002	-0.048	-0.006	0.136***	0.235***	0.213***	-0.431***	-0.498***	-0.422***
d	Other meat products	(0.051)	(0.068)	(0.034)	(0.047)	(0.07)	(0.061)	(0.04)	(0.082)	(0.046)	(0.037)	(0.054)	(0.057)	(0.042)	(0.062)	(0.056)

Demand elasticities regarding socio-demographic variables are presented in Table 11. The table displays how much percentage demand changes as the result of a socio-demographic variable increase of one unit; otherwise, the interpretation is similar to that contained in the probit table.

The budget share allocated to the beef and lamb category increases as the age of the focus group increases. Additionally, differences in consumption habits linked to region and income level are becoming less significant. In relation to the pork category, education and high income influence consumption negatively, and regional differences are smaller when compared to the beef and lamb category. Despite this, people tend to consume less pork in the north and east than elsewhere. The budget share allocated to poultry decreases with an aging focus group and increases as household size increases. As the significance of coefficients was not static throughout the course of the study, all factors that affect poultry consumption are still not known. All that can be said for certain is that poultry consumption rates are still changing. In addition to the age of the focus group, the budget share allotted for processed meats is positively influenced by region. Moving north on a map of Finland, consumers begin to spend more money on processed meat products; however, households with small children tend to spend less money on this category of meat. In the other meat products category, an increased age of the focus group leads to a decreased budget allocation for that group. Whitecollar workers and those living in southern Finland tend to avoid meat products from the other meat products category, whereas in west this category includes many traditional food stuffs, and consequently causes this category to form a greater part of the budget.

Table 11. Demographic elasticities. (Significance levels *p<0.1; **p<0.05; ***p<0.01, standard errors in parentheses)

	Ве	ef and la	mb	Pork			Poultry			Pro	cessed m	eat	Other meat products		
	1998	2006	2012	1998	2006	2012	1998	2006	2012	1998	2006	2012	1998	2006	2012
age	0.009**	0.004	0.006*	0	0.001	0.001	-0.01***	-0.008***	-0.014***	0.002***	0.005***	0.005***	-0.004***	-0.006***	-0.003**
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ed2	0.09*	0.139***	-0.087*	-0.097**	-0.102**	-0.082**	-0.048	-0.097***	0.062	-0.003	0.017	0.007	0.049**	0.009	0.066***
	(0.053)	(0.038)	(0.05)	(0.042)	(0.042)	(0.036)	(0.038)	(0.031)	(0.055)	(0.01)	(0.012)	(0.015)	(0.019)	(0.018)	(0.022)
ed3	-0.012	0.03	-0.076	-0.11**	0.037	-0.02	0.125	0.044	0.114	-0.045**	-0.049*	-0.041	0.094***	0	0.05
	(0.059)	(0.057)	(0.06)	(0.055)	(0.065)	(0.069)	(0.077)	(0.069)	(0.079)	(0.019)	(0.026)	(0.027)	(0.033)	(0.041)	(0.039)
HH size	-0.058	0.022	-0.063	-0.076	0.027	-0.025	0.208**	0.064	0.179**	-0.053**	-0.029	-0.072**	0.057	-0.031	0.043
	(0.089)	(0.07)	(0.06)	(0.081)	(0.081)	(0.074)	(0.097)	(0.064)	(0.078)	(0.022)	(0.026)	(0.028)	(0.038)	(0.042)	(0.041)
kids<=16	0.01	0.055	0.083	-0.038	-0.035	-0.043	0.042	-0.046	-0.002	-0.037	-0.029	-0.067*	0.062	0.061	0.062
	(0.072)	(0.068)	(0.054)	(0.065)	(0.076)	(0.084)	(0.087)	(0.069)	(0.07)	(0.024)	(0.028)	(0.034)	(0.041)	(0.044)	(0.047)
soscat2	0.038	0.025	0.097*	0.024	-0.036	-0.067	0.115	0.072	0.147**	-0.049**	-0.022	-0.008	-0.04	-0.007	-0.115**
	(0.06)	(0.055)	(0.057)	(0.063)	(0.065)	(0.071)	(0.07)	(0.062)	(0.059)	(0.022)	(0.024)	(0.027)	(0.038)	(0.038)	(0.042)
soscat3	-0.046	-0.054	0.112*	0.069	0.105	-0.026	0.127	-0.003	0.048	-0.076***	-0.067**	-0.038	0.029	0.073	-0.045
	(0.103)	(0.075)	(0.066)	(0.089)	(0.087)	(0.089)	(0.124)	(0.097)	(0.086)	(0.03)	(0.031)	(0.034)	(0.055)	(0.05)	(0.05)
soscat4	0.226***	-0.107	0.057	-0.036	0.002	-0.065	-0.141	0.081	0.061	-0.045	0.022	-0.044	0.037	-0.013	0.021
	(0.081)	(80.0)	(0.071)	(0.073)	(0.098)	(0.1)	(0.106)	(0.093)	(0.085)	(0.029)	(0.033)	(0.042)	(0.044)	(0.052)	(0.052)
inc2	0.147	0.248***	0.045	-0.101	-0.136*	0.003	0.043	-0.192**	-0.048	-0.01	0.046*	0.016	-0.04	-0.028	-0.025
	(0.101)	(0.069)	(0.065)	(0.073)	(0.079)	(0.08)	(0.108)	(0.078)	(0.077)	(0.022)	(0.027)	(0.028)	(0.038)	(0.041)	(0.041)
inc3	0.199	0.391***	0.019	-0.149	-0.205**	-0.087	0.047	-0.21**	-0.019	0.024	0.02	0.016	-0.103***	-0.031	0.032
	(0.139)	(0.083)	(0.078)	(0.091)	(0.089)	(0.086)	(0.131)	(0.092)	(0.088)	(0.024)	(0.031)	(0.031)	(0.04)	(0.046)	(0.047)
inc4	0.292**	0.52***	0.258***	-0.242***	-0.278***	-0.295***	0.058	-0.266***	-0.045	0.032	0.016	0.002	-0.119***	-0.028	0.029
	(0.137)	(0.088)	(0.078)	(0.092)	(0.096)	(0.089)	(0.136)	(0.099)	(0.094)	(0.027)	(0.034)	(0.033)	(0.043)	(0.049)	(0.049)
regdum1	-0.523**	-0.117	-0.168*	-0.26	-0.15	-0.096	0.556*	0.052	0.114	0.199***	0.053	0.046	-0.134	0.069	0.046
	(0.252)	(0.115)	(0.098)	(0.18)	(0.107)	(0.119)	(0.325)	(0.142)	(0.126)	(0.071)	(0.046)	(0.05)	(0.105)	(0.082)	(0.072)
regdum2	-0.562**	-0.171	-0.174*	-0.307*	-0.159	-0.092	0.55*	0.051	0.002	0.235***	0.057	0.063	-0.128	0.109	0.098
	(0.256)	(0.131)	(0.1)	(0.184)	(0.116)	(0.123)	(0.322)	(0.147)	(0.133)	(0.073)	(0.048)	(0.053)	(0.105)	(0.087)	(0.075)
regdum3	-0.611**	-0.186	-0.17*	-0.293	-0.191*	-0.206*	0.451	-0.041	0.006	0.266***	0.048	0.069	-0.09	0.218**	0.159**
	(0.249)	(0.118)	(0.097)	(0.181)	(0.116)	(0.123)	(0.321)	(0.14)	(0.131)	(0.074)	(0.047)	(0.053)	(0.104)	(0.089)	(0.075)

5.3 Elasticities without censoring, R package micEconAids

Elasticities for 2012 without correcting for censoring and without translating socio-demographic variables are presented in Table 12. After unit values are corrected, these demand elasticities can be obtained with help of R package "micEconAids" (Henningsen, 2017a). As Henningsen (2017) suggests, instead of the linear AIDS model one could use the nonlinear AIDS model, which is estimated using iterations of linear estimations. The name of this method is Iterated Linear Least Square Estimation (ILLE), and according to Henningsen it is a more controlled model than the LA-AIDS model, because the translog price index does not suffer from bias caused by price indices. With ILLE the share equations are estimated with linear techniques and the translog index remains fixed. Then, the translog index is updated with the coefficients obtained from the previous step. The process continues until the coefficients converge. (Henningsen, 2017b.) The package does not take zero observations into account, which has a definite effect on the outcome. In addition to homogeneity, a symmetry restriction was also imposed on the model. Monotonicity was fulfilled in 98 % of observations.

Table 12. Demand elasticities in 2012 without correcting for censoring, Iterated Linear Least Square Estimation in R package micEconAids. (Significance levels *p<0.1; **p<0.05; ***p<0.01)

EXPENDITURE ELASTICI	TIES WITHOUT CENSO	ORING			
	Beef and lamb	Pork	Poultry	Processed meat	Other meat products
	1.499***	1.285***	1.062***	0.913***	0.908***
CONDITIONAL MARHS	ALLIAN PRICE ELASTIC	ITIES WITHOU	JT CENSORIN	IG	
	Beef and lamb	Pork	Poultry	Processed meat	Other meat products
Beef and lamb	-0.563***	-0.167	-0.362***	-0.172	-0.235
Pork	-0.066	-0.696***	-0.139	-0.296**	-0.087
Poultry	-0.129**	-0.102	-0.498***	-0.134	-0.200*
Processed meat	0.01	-0.034	-0.019	-0.759***	-0.111**
Other meat products	-0.01	0.008	-0.066	-0.166**	-0.672***
CONDITIONAL HICKSIA	N PRICE ELASTICITIES	WITHOUT CE	ENSORING		
	Beef and lamb	Pork	Poultry	Processed meat	Other meat products
Beef and lamb	-0.487 ^{***}	-0.0028	-0.181	0.479**	0.193
Pork	-0.00158	-0.555***	0.016	0.261**	0.28**
Poultry	-0.075	0.014	-0.37***	0.327***	0.103
Processed meat	0.056**	0.066**	0.09***	-0.362***	0.15***
Other meat products	0.034	0.107**	0.044	0.228***	-0.413***

As can be seen, expenditure elasticities predict that pork will be higher when estimating without zero value correction (Table 12). The beef and lamb category diverges greatly from the norm, which is the result of a high amount of zero values in that category. The own-price elasticity of the beef and lamb category differs from that calculated in Tables 8 and 9, but the other own-price elasticities are rather similar. With the uncensored model there are no significant Hicksian complements, which was also case with censored model. Apart from the processed meat or beef and lamb categories, significant Hicksian substitutes presented in the uncensored model are also significant in the censored model.

Although the elasticities clearly differ between the censored and uncensored models, the estimation with the package micEconAids provides evidence that the results of this study are rather robust. The corrected unit values have a large impact on the outcome, and socio-demographic variables do not have as great an effect as might be expected.

5.4 Elasticities in other investigations

Because many factors - such as model specification and time lag - influence demand elasticities, they are not directly comparable. In Finland especially, the aggregation of meat products creates differences between elasticities, as the commodities included under various titles are not exactly same in different studies. However, in order to expand magnitude of the elasticities, Table 13 has been provided to compare the expenditure elasticities and uncompensated elasticities of different investigations conducted in Europe. The range of the elasticities is large and there are some outliers (e.g France) in the table, but, nonetheless, the table provides some insights into meat elasticities. The consumption of beef is inelastic in France and Sweden, which could signify that beef consumption is already at its saturation point and does not rise with a growing income. Consequently, for Finland, this means that there is still room for growth in the unprocessed meat category as its demand is elastic. (Table 13)

In the present study, the expenditure elasticity obtained for pork is the highest of all values, but otherwise the elasticities all fall within the same range (Table 13).

Table 13. Expenditure elasticities and conditional Marshallian own-price elasticities of different investigations conducted in Europe. (Dahlberg, 2017b; Irz, 2017; Rickertsen et al., 2003; Säll and Gren, 2015; Thiele and others, 2008)

	A	<u> </u>	e 10 1								
Country	Author	Data	Expenditure elasticity	Marshallian own-price elasticity							
			Beef								
Denmark	Rickertsen et al.	1966-1996	1	-0.71							
Finland	Irz	2012	1.13	-0.916							
Finland	Rickertsen et al.	1966-1996	1.03	-0.61							
Finland	Present study	2012	1.013	-0.863							
France	Dahlberg	1990-2016	0.806	-1.357							
Germany	Thiele	2003	1.23	-0.53							
Norway	Rickertsen et al.	1966-1996	1	-0.68							
Sweden	Rickertsen et al.	1966-1996	1	-0.57							
Sweden	Säll and Gren	1980-2012	0.786	-0.538							
Pork											
Denmark	Rickertsen et al.	1966-1996	1.09	-1							
Finland	Irz	2012	1.072	-1.064							
Finland	Rickertsen et al.	1966-1996	1.17	-0.74							
Finland	Present study	2012	1.341	-0.69							
France	Dahlberg	1990-2016	0.406	-0.629							
Germany	Thiele	2003	1.26	-0.82							
Norway	Rickertsen et al.	1966-1996	1.14	-0.72							
Sweden	Rickertsen et al.	1966-1996	1.13	-0.82							
Sweden	Säll and Gren	1980-2012	0.731	-0.37							
			Poultry								
Denmark	Rickertsen et al.	1966-1996	0.76	-0.54							
Finland	Irz	2012	1.147	-0.461							
Finland	Rickertsen et al.	1966-1996	0.78	-0.33							
Finland	Present study	2012	1.012	-0.549							
France	Dahlberg	1990-2016	0.367	-1.636							
Germany	Thiele	2003	1.03	-0.68							
Norway	Rickertsen et al.	1966-1996	0.7	-0.6							
Sweden	Rickertsen et al.	1966-1996	0.79	-0.8							
Sweden	Säll and Gren	1980-2012	0.959	-0.363							

Figure 6 presents uncompensated own-price elasticities obtained from Finnish data (Rickertsen et al., 2003; Irz, 2017; the present study), and compares them to the average elasticities measured in studies by Gallet (2010). Although Laurila (1994) has done demand analysis as well, the meat categories he used were not comparable to the studies mentioned above, and, therefore, the elasticities of that study are not present in the figure. Clearly, poultry is the most price inelastic product, but it is more difficult to determine whether beef or pork is more price elastic (Figure 6). Additionally, these elasticities reveal that the demand for carcass meat is more or less

inelastic. The expenditure elasticities of Finnish investigations are also presented in Table 13. The demand for beef and pork is expenditure elastic, and apart from data obtained by Rickertsen et al. (2003), the demand for poultry is also expenditure elastic in Finland (Table 13).

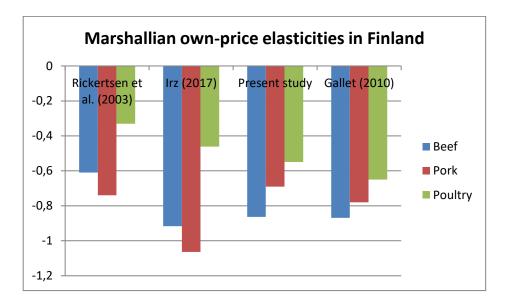


Figure 6. Conditional Marshallian own-price elasticities obtained from different studies (Gallet, 2010; Irz, 2017; Rickertsen et al., 2003)

5.5 Extension: consumers' response to food price increases

Consumers can react many ways to rising prices. Intuitively one could think that the expenditure for a certain category would fall if the price of said product rises, but often that is not the case. According to Irz (2010), consumers may use more money on food despite quantities and prices remaining constant. For example, by changing minced meat to fillet steaks, the value spent could increase even if the physical quantities consumed decreased. In the United Kingdom, the effects of food price increases were investigated by DEFRA (2017), and between 2007 and 2015 the consumers responded to the rising prices of meat simply by spending more. At the same time, the "quality" of the food (as well as the physical quantities) decreased in many meat categories.

In Finland, a deconstruction of consumption growth has been explored by Irz (2010). The consumption expenditure consists of a price component, a quality component and a quantity component. Therefore, changes in all of these factors can cause an increase in consumption. National accounts relay expenditures at current prices, E_G , and expenditures at constant prices, Q_G . A real price index can be written as: $P_G = \frac{E_G}{O_G}$ and

correspondingly $E_G = P_G Q_G$. Further, Irz (2010) explains that $Q_G = v_G q_G$, where q_G is the physical quantity (derived from HBS) and v_G is Theil's quality index, which measures how consumption can increase despite keeping prices and physical quantity constant. Thus, $E_G = P_G v_G q_G$ and the percentage change between two periods, t0 and t1, can be approximated as:

$$\ln(E_G(t1)) - \ln(E_G(t0)) = \ln(P_G(t1)) - \ln(P_G(t0)) + \ln(q_G(t1)) - \ln(q_G(t0)) + \ln(v_G(t1)) - \ln(v_G(t0)),$$

where $\ln(v_G(t1)) - \ln(v_G(t0))$ is the discrete approximation of a continuous rate of growth between years t0 and t1, also known by the quality adjustment term "trading-up/down".

Table 14. Impact of price changes on quantity, expenditure and quality choices of consumers

Percentage changes between 1998 and 2006											
Price rise	Quantity	Expenditure	Quality term								
(InP2006-InP1998)	(Inq2006-Inq1998)	(InE2006-InE1998)	(Inv2006-Inv1998)								
19.8 %	-22.3 %	10.6 %	13.1 %								
18.1 %	-32.3 %	-0.6 %	13.6 %								
-9.6 %	32.0 %	65.4 %	43.0 %								
2.9 %	-3.1 %	14.1 %	14.3 %								
-3.2 %	12.6 %	46.3 %	37.0 %								
Percentage changes between 1998 and 2012											
Price rise	Quantity	Expenditure	Quality term								
(InP2012-InP1998)	(Inq2012-Inq1998)	(InE2012-InE1998)	(Inv2012-Inv1998)								
38.9 %	-14.3 %	35.8 %	11.2 %								
41.7 %	-27.6 %	26.5 %	12.5 %								
-1.4 %	68.2 %	102.3 %	35.4 %								
29.0 %	-12.5 %	27.3 %	10.8 %								
15.9 %	17.4 %	66.6 %	33.2 %								
Percentage change	s between 2006 and	2012									
Price rise	Quantity	Expenditure	Quality term								
(InP2012-InP2006)	(Inq2012-Inq2006)	(InE2012-InE2006)	(Inv2012-Inv2006)								
19.1 %	8.0 %	25.2 %	-1.8 %								
23.6 %	4.7 %	27.1 %	-1.1 %								
8.2 %	36.2 %	36.8 %	-7.5 %								
26.1 %	-9.4 %	13.1 %	-3.5 %								
19.2 %	4.8 %	20.3 %	-3.8 %								

Table 14 reveals the effects of food-price increases in Finland. From 1998 to 2006, as well as from 1998 to 2012, consumers did not switch to cheaper products despite growth in prices and/or quantities. In the long run, changes in almost all categories seem to be in the form of an increase, apart from quality term, which refers to a change to a cheaper product within a food group. The trading up/down effect implies that the unit values of meat have been improved over time, but between 2006 and 2012 the exact opposite occurred. While the quality term is negative between 2006 and 2012 (this might be due to a recession), the response to the price rise in meat was to spend more money on meat purchases. A similar conclusion was come to by DEFRA (2017). As changes in prices and expenditures are derived from national accounts (Table 14), they are naturally in tune with Figure 1. With quantities, the changes are not completely different from what is displayed in Figure 2, which is encouraging, as the HBS covers only food consumed at home while the FBS contains all food. In fact, just the inclusion of food consumed away from home may explain the divergence between HBS and FBS trends.

6 Conclusions and recommendations for future research

In this study, meat demand was separated into five categories for analysis: beef and lamb, pork, poultry, processed meat, and other meat products. Meat consumption is influenced by a number of factors, the magnitude and importance of which were clarified throughout the duration of this study. Price and expenditure elasticities for this study were obtained using household level data, and incorporating that data into the linear demand system (LA-AIDS) model, which was extended by adding socio-demographic characteristics and zero-correction terms. The corrected unit values were used as price substitutes in this study, and consequently the quality-quantity aspect was also briefly examined. The results of this study were consistent with other investigations in this field, and great decreases in meat consumption cannot be assumed based on the results.

The demand for pork that was observed in this study clearly suggested that pork expenditure was elastic during the entirety of the study period, whereas ruminant meat and poultry have been showing signs of expenditure elasticity only since the 2000s. Since the consumption of these meat products will increase more than in relation to increased income levels, these meat groups would be considered luxury products. This means that there is still room for consumption growth in relation to unprocessed meats. The demand for processed meat and other meat products is inelastic, and collectively all meat groups can be considered normal goods. As almost 70 percent of the meat expenditure budget is exhausted by inelastic processed meats and other meat products, overall meat consumption will not increase in relation to an increasing income.

According to Marshallian cross-price elasticities, many of the meat products are complements but there is also evidence of a substitution effect. When utility is held constant (Hicksian elasticities), the substitution effect plays a major role. Processed meat and other meat products seem to be net substitutes for every other meat category, as rising prices in those groups increases the quantities demanded in every other category. The results in regard to own-price elasticities were similar to those found by Gallet (2010), who concluded that the demand for poultry is the most inelastic while the demands for beef/lamb and processed meats are the most elastic. This is to be expected, because, out of all the meat categories, poultry consumption levels are the most affected by factors other than price.

Demographically speaking, a high level of income tends to increase the consumption of ruminant meat but decrease the consumption of pork. This can be attributed to a consumer preference for higher quality meat when they have a larger amount of disposable income. Household size and age also affect consumption patterns, and therefore an aging population and an increase in the number of single-person households will have a great effect on consumption patterns in the future. Trends for larger households suggest that larger households tend to buy larger quantities of food when unit values are lower. Regional differences in consumer patterns decreased during the period from 1998 to 2012, and as a result of this, it is difficult to determine whether urbanization will affect consumption patterns.

Liu et al. (2009) presumed that the demand for meat can become elastic if the safety of meat cannot be secured. In this situation, consumers would substitute meat with other food products, such as vegetables. However, HBS data does not provide sufficient information for examining vegetarian habits, so that issue was disregarded in this study. In the future, this study could be extended to include newer methods of analysis such as the nonlinear EASI or QUAIDS models discussed above. It would, after all, be useful to investigate whether the censored model estimation should be conducted by estimating all n equations or only n-1 equations simultaneously, as this is an issue that researchers do not seem to fully understand currently. Also, the quality-quantity aspect, endogeneity issues, and unconditional elasticities aspects of this study all leave room for future studies in this field. Because the methods and procedures of this study are presented in detail, a comparable study of other food sectors could easily be replicated using the same methods.

After the latest HBS survey is published, this study will be easy to update, and the consumption trends described at the beginning of the study will be able to be explained more carefully. Still, the analysis obtained from HBS data does not explain everything regarding consumption behavior, as other factors such as health and values clearly have their own impact on consumption. Therefore, demand elasticities not only reveal changes caused by fluctuations in price or income, but also reflect trends that affect consumption levels behind the scenes. An interesting topic for additional research would be to perform the same study while including new sources of data (e.g. loyalty cards).

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Appendix

<u>Probit regression</u> (presented for first meat group)

 $glm(Y_{1h} \sim age + ed2 + ed3 + jasenia + kids16 + soscat2 + soscat3 + soscat4 + inc2 + inc4 + regdum1 + regdum2 + regdum3 + seasdum1 + seasdum2 + seasdum3, family = binomial(link = probit))$

The CDF and PDF values are extracted from the fitted values of the probit regression and saved for future use.

Unit value regression(presented for first meat group)

$$UVeq1 = lm(age + ed2 + ed3 + jasenia + kids16 + soscat2 + soscat3 + soscat4 + inc2 + inc + inc4 + regdum1 + regdum2 + regdum3 + seasdum1 + seasdum2 + seasdum3 + $q1$),$$

where lm denotes a "linear model" (OLS) estimation and q is the physical quantity of the first category. Then, the residuals obtained from the upper equation (uveq $1_{residual}$) are saved for next stage. Also the fitted values (uveq 1_i) must be selected for creating a constant portion of the price, which is linked to region and season and, most of all, takes zero observations into account:

$$\begin{aligned} UV const1 &= \text{uveq1}_{intercept} + \text{uveq1}_{regdum1} * \text{regdum1} + \text{uveq1}_{regdum2} * \text{regdum2} + \text{uveq1}_{regdum3} * \\ \text{regdum3} &+ \text{uveq1}_{seasdum1} * \text{seasdum1} + \text{uveq1}_{seasdum2} * \text{seasdum2} + \text{uveq1}_{seasdum3} * \text{seasdum3} \end{aligned}$$

The final price substitutes consist of corrected average prices and the error term:

$$UV1 = UVconst1 + uveq1_{residual} = P_1$$

Derivation of the LA-AIDS model:

(A1)
$$w_{ih} = \alpha_i + \sum_{j=1}^n \gamma_{ij} \ln P_j + \beta_i \ln \left(\frac{X_h}{P_h}\right) + u_{ih}$$
, where P_h is translog price index:
(A2) $\ln P_h = \alpha_0 + \sum_{i=1}^n \alpha_i \ln P_i + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \gamma_{ij} \ln P_i \ln P_j$, which can be replaced with Stone's price index:

(A3)
$$\ln P^* = \sum_{i=1}^{n} w_i \ln P_i$$

After Stone's's price index is imposed, the model is linearized and called LA-AIDS:

(A4)
$$w_{ih} = \alpha_i + \sum_{j=1}^n \gamma_{ij} \ln P_j + \beta_i (\ln X_h - \sum_i^n w_i \ln P_i) + u_{ih}$$

Then, socio-demographic variables, as well as the CDF and PDF values obtained from the first step, are added to the model:

$$(A5) \ E(w_i) = \Phi_{ih} * \left[\alpha_i + \sum_{j=1}^n \gamma_{ij} \ln P_j + \beta_i (\ln X_h - \sum_i w_i \ln P_i) + \sum_k \lambda_k D_{kh} \right] + \delta_i \phi_{ih}$$

The model presented in (A5) does not include the error term. $E(w_i)$ reflects the fitted values.

Elasticities

As presented above, censored LA-AIDS can be written as (A5) and elasticities can be derived by differentiating the unconditional means.

Expenditure elasticity:

$$\epsilon_{iX} = \left(\frac{\delta E(w_i)}{\delta \ln X_h}\right) \left(\frac{1}{E(w_i)}\right) + 1 = \left(\frac{\delta \Phi_{ih} \beta_i \ln X_h}{\delta \ln X_h}\right) \left(\frac{1}{E(w_i)}\right) + 1 = \frac{\Phi_{ih} \beta_i}{E(w_i)} + \mathbf{1}$$

Marshallian price elasticity:

$$\epsilon_{ij}^{M} = \left(\frac{\delta E(w_i)}{\delta \ln P_i}\right) \left(\frac{1}{E(w_i)}\right) - \delta_{ij} = \left(\frac{\delta \Phi_{ih} \sum_{j=1}^{n} \gamma_{ij} \ln P_j}{\delta \ln P_i}\right) \left(\frac{1}{E(w_i)}\right) - \delta_{ij} = \frac{\Phi_{ih} \gamma_{ij}}{E(w_i)} - \delta_{ij}$$

Socio-demographic elasticity:

$$\epsilon_{iD} = \left(\frac{\delta E(w_i)}{\delta D_{kh}}\right) \left(\frac{1}{E(w_i)}\right) = \left(\frac{\delta \Phi_{ih} \sum_k \lambda_k D_{kh}}{\delta D_{kh}}\right) \left(\frac{1}{E(w_i)}\right) = \frac{\Phi_{ih} \lambda_k}{E(w_i)}$$

Hicksian price elasticity

$$\epsilon_{ij}^H = \epsilon_{ij}^M + \epsilon_{iX} E(w_j)$$

Coefficients of the LA-AIDS model

	19	98	20	06	20	12		19	98	20	06	20	12
Variable	Estimate	Std. Error		Std. Error	Estimate	Std. Error	Variable	Estimate	Std. Error		Std. Error	Estimate	Std. Error
df1	0.303***	0.0680	0.294***	0.062	0.274***	0.088	cdf3:ed3	0.042**	0.02	0.013	0.013	0.04*	0.017
cdf1:const	0.028	0.2433	-0.138	0.109	0.227*	0.133	cdf3:kids16	0.008	0.017	-0.01	0.014	-0.0004	0.016
cdf1:lp1	-0.001	0.0191	0.046*	0.020	0.033***	0.010	cdf3:soscat2	0.023	0.014	0.015	0.013	0.032*	0.013
cdf1:lp2	-0.0379**			0.021	-0.042**	0.018	cdf3:soscat3	0.025	0.025	-0.001	0.02	0.011	0.019
cdf1:lp3	-0.059***	0.0133	-0.02	0.025	-0.036***	0.013	cdf3:soscat4	-0.028	0.023	0.017	0.019	0.011	0.019
cdf1:lp4	0.057***	0.0133	0.044***	0.016	0.030	0.017	cdf3:inc2	0.009	0.022	-0.04**	0.016	-0.011	0.017
cdf1:lp5	0.02	0.0157	-0.007	0.018	-0.026	0.017	cdf3:inc3	0.009	0.026	-0.044**	0.019	-0.004	0.02
cdf1:se	-0.005	0.0067		0.005	0.003	0.006	cdf3:inc4	0.012	0.027	-0.055***	0.021	-0.01	0.021
	0.002**	0.0009	0.001	0.001	0.003	0.001	cdf3:regdum1		0.065	0.011	0.029	0.025	0.021
	0.002	0.0116	0.031***	0.009	-0.021*	0.012	cdf3:regdum2		0.065	0.011	0.031	0.001	0.029
cdf1:jd3cilld	-0.003	0.0110	0.007	0.013	-0.018	0.012	cdf3:regdum3		0.064	-0.009	0.029	0.001	0.029
cdf1:ed3	-0.013	0.0195	0.005	0.016	-0.015	0.014	df4	0.557***	0.104	0.394***	0.103	0.259*	0.118
cdf1:kids16	0.002	0.0157	0.012	0.015	0.02	0.014	cdf4:const	0.545***	0.063	0.679***	0.058	0.582***	0.075
	0.002	0.0137	0.006	0.013	0.024*	0.013	cdf4:lp1	0.017	0.003	-0.028	0.038	-0.03**	0.073
cdf1:soscat2	-0.01	0.0227	-0.012	0.017	0.027*	0.014	cdf4:lp2	-0.014	0.014	-0.016	0.022	0.04*	0.02
cdf1:soscat4	0.05***	0.0178	-0.024	0.017	0.014	0.017	cdf4:lp3	-0.014	0.014	0.045*	0.025	-0.002	0.015
cdf1:inc2	0.032	0.0178	0.056***	0.015	0.014	0.017	cdf4:lp4	0.1***	0.012	0.043	0.023	0.002	0.013
cdf1:inc3	0.032	0.0222	0.030	0.019	0.005	0.010	cdf4:lp5	-0.09***	0.011	-0.079***	0.010	-0.082***	0.018
	0.044	0.0303	0.117***	0.013	0.063***	0.019	cdf4:se	-0.033***	0.006	-0.061***	0.015	-0.062	
cdf1:regdum1	-0.115**	0.0554	-0.0262	0.026	-0.041*	0.019		0.001***	0.0004	0.003***	0.003	0.002***	0.000
	-0.113	0.0554	-0.0202	0.020	-0.041	0.024	cdf4:iasonia	-0.001	0.0004	0.003	0.0004	0.002	0.001
	-0.123	0.0545	-0.038	0.025	-0.042	0.024	cdf4:jasenia cdf4:ed2	-0.001	0.003	-0.024*	0.000	-0.019*	0.007
cdf1:regdum3 df2	0.135	0.0343	0.076	0.026	0.208***	0.024	cdf4:ed2	-0.024	0.012	-0.024	0.013	-0.013	0.012
cdf2:const	-0.327*	0.172	-0.279**	0.074	-0.347***	0.002		-0.028	0.012	-0.014	0.013	-0.033	0.015
	-0.327*	0.172	-0.279	0.115	0.007	0.092	cdf4:kids16 cdf4:soscat2	-0.019	0.013	-0.014	0.014	-0.031.	0.016
cdf2:lp1	0.053***	0.022	0.109***	0.026	0.067**	0.013	cdf4:soscat2	-0.026**	0.012	-0.011	0.012	-0.004	0.012
cdf2:lp2	-0.011		-0.067**	0.026	-0.024				0.016	0.011	0.015	-0.018	0.016
cdf2:lp3 cdf2:lp4	-0.011	0.016		0.03	-0.024	0.018	cdf4:soscat4 cdf4:inc2	-0.023 -0.005	0.013	0.011	0.010	0.007	0.013
cdf2:lp4	-0.065	0.014	0.035	0.02	0.023	0.023	cdf4:inc3	0.012	0.011	0.023	0.015	0.007	0.013
cdf2:se	0.098***	0.017	0.033	0.023	0.023	0.023	cdf4:inc4	0.012	0.012	0.008	0.013	0.001	0.014
cdf2:age	0.0001	0.001	0.0002	0.007	0.0003	0.001	cdf4:regdum1		0.014	0.026	0.017	0.021	0.013
cdf2:jasenia	-0.023**	0.001	-0.022**	0.001	-0.018*	0.001	cdf4:regdum2		0.037	0.028	0.023	0.021	0.023
cdf2:ed2	-0.026**	0.013	0.008	0.014	-0.004	0.005		0.139***	0.039	0.023	0.024	0.032	0.024
cdf2:ed2	-0.018	0.013	0.006	0.014	-0.005	0.016	df5	0.207***	0.066	0.224***	0.023	0.396***	0.076
cdf2:kids16	-0.009	0.016	-0.008	0.016	-0.009	0.018	cdf5:const	0.579***	0.053	0.462***	0.054	0.444***	0.064
	0.006	0.015	-0.008	0.014	-0.015	0.015	cdf5:lp1	0.008	0.015	0.016	0.021	0.021 .	0.011
cdf2:soscat3	0.016	0.021	0.023	0.019	-0.006	0.019	cdf5:lp2	-0.009	0.013	0.012	0.022	-0.033.	0.02
cdf2:soscat4	-0.009	0.021	0.023	0.013	-0.014	0.022	cdf5:lp3	-0.019*	0.014	-0.044*	0.022	-0.037*	0.015
cdf2:inc2	-0.024	0.017	-0.029*	0.017	0.001		cdf5:lp4	-0.084***	0.012	-0.063***	0.017	-0.057**	0.019
cdf2:inc3	-0.036	0.022	-0.044**	0.019	-0.019	0.017	cdf5:lp5	0.104***	0.012	0.079***	0.019	0.107***	0.019
cdf2:inc4	-0.058***	0.022	-0.06***	0.021	-0.063***	0.019	cdf5:se		0.005	-0.023***	0.005	-0.036***	0.006
cdf2:regdum1	-0.062	0.043	-0.032	0.023	-0.021	0.026	cdf5:age	-0.001***	0.0004	-0.002***	0.0004	-0.001*	0.0004
	-0.073*	0.044	-0.034	0.025	-0.02	0.026	cdf5:jasenia	0.014**	0.006	0.002	0.006	0.022**	0.007
cdf2:regdum3	-0.07	0.044	-0.041	0.025	-0.02	0.026	cdf5:ed2	0.014	0.000	0.0001	0.000	0.016	0.007
	0.101	0.045	-0.023	0.023	0.275**	0.020	cdf5:ed2	0.017	0.003	-0.01	0.013	0.014	0.013
cdf3:const	0.175	0.169	0.275***	0.09	0.094	0.124	cdf5:kids16	0.018	0.011	0.019	0.013	0.02	0.015
	0.019	0.023	-0.031	0.023	-0.031*	0.012	cdf5:soscat2	-0.012	0.012	-0.002	0.014	-0.038**	0.013
cdf3:lp2	0.019	0.023	-0.031	0.023	-0.031	0.012	cdf5:soscat2	0.008	0.011	0.002	0.012	-0.038	0.014
cdf3:lp3	0.104***	0.02	0.086***	0.024	0.1***	0.022	cdf5:soscat4	0.008	0.010	-0.004	0.016	0.007	0.017
cdf3:lp4	-0.008	0.016	0.015	0.029	-0.015	0.016	cdf5:soscat4	-0.012	0.013	-0.004	0.016	-0.008	0.017
		0.016	-0.028	0.018	-0.013	0.021	cdf5:inc3	-0.012	0.011	-0.009	0.013	0.011	0.014
cdf3:lp5	-0.017 -0.015*	0.019	0.018***	0.022	0.003	0.021	cdf5:inc3		0.012	-0.01	0.014	0.011	0.015
cdf3:se			-0.002***			0.007							
cdf3:age	-0.002***	0.001		0.001	-0.003***			-0.039	0.031	0.021	0.026	0.015	0.024
cdf3:jasenia	-0.01	0.008	-0.02***	0.007	0.014	0.012	cdf5:regdum2	-0.037	0.031	0.034	0.027	0.033	0.025
cdf3:ed2	0.025	0.015	0.009	0.014	0.025	0.018	cdf5:regdum3	-0.026	0.03	0.068**	0.028	0.053*	0.025

The R codes used in the analysis

```
## NOTES:
#m denotes HBS data
#Quantity (q) and expenditure (ex) variables are per households
#Aggregation as presented in Table 1 and socio-demographic variables as presented in
chapter 3.1.3
n=5
m$ext <- apply(m[, c("ex1", "ex2", "ex3", "ex4", "ex5")], 1, sum)</pre>
m$age<-m$pika
# UNIT VALUES
for (i in 1:n) {
  v1<-paste0("uv", i)
  v2<-paste0("ex", i)
  v3<-paste0("q", i)
 m[v1] < -m[v2]/m[v3]
# Budget shares
for (i in 1:n) {
  v1<-paste0("ex", i)
  v2<-paste0("w", i)
 m[v2]<-m[v1]/m["ext"]}
ind <- which (m$ext == 0)
m=m[-ind,]
# PROBIT EQUATIONS (after defining sos.ec variables)
part<-function (y) {ifelse (y > 0, 1, 0)}
exall<-paste0("ex", 1:n)
binmat<-sapply(m[exall], part)</pre>
colnames(binmat) <-paste0("bin", 1:n)</pre>
m<-cbind(m, binmat)</pre>
f<-function(bivar) {glm(bivar ~ age + ed2 + ed3 +jasenia +kids16 + soscat2 + soscat3
+ soscat4 + inc2 + inc3 + inc4 + regdum1 + regdum2 + regdum3 +seasdum1 + seasdum2 +
seasdum3, family = binomial(link = "probit"), data=m) }
binall<-paste0("bin", 1:n)</pre>
prob<-lapply(m[binall], f)</pre>
for (i in 1:n) {
  v1<-paste0("bin", i)
  v2<-paste0("cdf", i)
 v3<-paste0("df", i)
 m[v2]<-prob[v1][[1]][[3]]
 m[v3] < -sapply(m[v2], qnorm)
 m[v3]<-sapply(m[v3], dnorm) }</pre>
# ADJUSTMENT OF PRICES
uvvar<-c("age","ed2","ed3","jasenia","kids16","soscat2","soscat3","soscat4",
"inc2","inc3","inc4","regdum1","regdum2","regdum3","seasdum1","seasdum2","seasdum3","
luvvar<-paste0(uvvar, collapse=" + ")</pre>
                                                      ~",
                                                                                   sep=""))),
                      as.formula( paste("uv1
                                                                         "q1",
uveq1<-lm(with(m,
                                                             luvvar,
na.action=na.exclude)
uveq2<-lm(with(m,
                      as.formula( paste("uv2
                                                                         "q2",
                                                                                   sep=""))),
                                                             luvvar,
na.action=na.exclude)
                                                      ~".
                                                                         "q3",
                                                                                   sep=""))),
uveq3<-lm(with(m,
                      as.formula(
                                    paste("uv3
                                                             luvvar,
na.action=na.exclude)
                                                      ~",
                                                                                   sep=""))),
uveq4<-lm(with(m,
                      as.formula(
                                     paste("uv4
                                                             luvvar,
                                                                         "q4",
na.action=na.exclude)
                                                                         "q5",
                                                                                   sep=""))),
uveq5<-lm(with(m,
                                      paste("uv5
                                                      ~".
                      as.formula(
                                                             luvvar,
na.action=na.exclude)
uvres1<-as.numeric(resid(uveq1))</pre>
uvres2<-as.numeric(resid(uveq2))</pre>
uvres3<-as.numeric(resid(uveq3))</pre>
uvres4<-as.numeric(resid(uveq4))</pre>
uvres5<-as.numeric(resid(uveq5))</pre>
resmat<-cbind(uvres1, uvres2, uvres3, uvres4, uvres5)
resmat<-matrix(resmat, nrow=dim(m)[1], ncol=n)</pre>
resmat[is.na(resmat)]<-0
colnames(resmat) <-paste0("uvres", 1:n)</pre>
m<-cbind(m, resmat)</pre>
```

```
oef(uveq1)["seasdum3"]*m$seasdum3
m$uvc2<-coef(uveq2)["(Intercept)"]+
coef(uveq2)["regdum1"]*m$regdum1+coef(uveq2)["regdum2"]*m$regdum2+coef(uveq2)["regdum
oef(uveq2)["seasdum3"]*m$seasdum3
 \begin{tabular}{ll} $\tt m\$uvc3<-coef(uveq3)["(Intercept)"]+coef(uveq3)["regdum1"]*m\$regdum1+coef(uveq3)["regdum2"]*m\$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef(uveq3)["regdum2"]*m$regdum2+coef["regdum2"]*m$regdum2+coef["regdum2"]*m$regdum2+coef["regdum2"]*m$regdum2+coef["regdum2"]*m$regdum2+
3"] *m$regdum3+coef(uveq3)["seasdum1"] *m$seasdum1+coef(uveq3)["seasdum2"] *m$seasdum2+c
oef(uveq3)["seasdum3"]*m$seasdum3
m$uvc4<-coef(uveq4)["(Intercept)"]+</pre>
coef(uveq4)["regdum1"]*m$regdum1+coef(uveq4)["regdum2"]*m$regdum2+coef(uveq4)["regdum
3"] *m$reqdum3+coef(uveq4)["seasdum1"] *m$seasdum1+coef(uveq4)["seasdum2"] *m$seasdum2+c
oef(uveq4)["seasdum3"] *m$seasdum3
m$uvc5<-coef(uveq5)["(Intercept)"]+</pre>
coef(uveq5)["regdum1"]*m$regdum1+coef(uveq5)["regdum2"]*m$regdum2+coef(uveq5)["regdum
3"] *m$regdum3+coef(uveq5)["seasdum1"] *m$seasdum1+coef(uveq5)["seasdum2"] *m$seasdum2+c
oef(uveq5)["seasdum3"]*m$seasdum3
m$p1<-m$uvc1+m$uvres1
m$p2<-m$uvc2+m$uvres2
m$p3<-m$uvc3+m$uvres3
m$p4<-m$uvc4+m$uvres4
m$p5<-m$uvc5+m$uvres5
for (i in 1:n) {
    temp<-paste0("p", i)</pre>
    print(c(sum(m[temp]<=0, na.rm=TRUE), i))</pre>
    print(which(m[temp]<=0))}</pre>
np<-which (m$p1<=0 | m$p2<=0 | m$p3<=0 | m$p4<=0 | m$p5<=0)
m < -m[-np,]
m$x<-m$ext
m$logx=log(m$x)
for (i in 1:n) {
   v1<-paste0("p", i)
   m[,v1] < -m[,v1]/mean(m[,v1])
flbis<-function (var) {</pre>
   var1<-with(m, get(var))</pre>
   mean(var1)/mean(m$ext)}
wb2<-sapply(dput(paste0("ex", 1:n)), f1bis)</pre>
for (i in 1:n) {
   v1<-paste0("w", i, "b")
    print(v1)
    assign(v1, print(wb2[i]))}
for (i in 1:n) {
    nam<-paste("p",i, sep="")
    lnam<-paste("lp",i, sep="")</pre>
    m[lnam]<-log(m[nam]) }</pre>
\label{lem:mean} \texttt{fmean} \texttt{<-function (v1) } \{ \texttt{mean} (\texttt{m[,v1]}) \, \}
cdfall<-paste0("cdf", 1:n)
cdfb<-sapply(cdfall, fmean)
pt<-""
for (i in 1:n) {
    v<-paste(" lp", i , " +", sep="")</pre>
    pt<-paste(pt, v, sep="")}</pre>
ldt<-c("age", "jasenia", "ed2", "ed3", "kids16", "soscat2", "soscat3", "soscat4",
```

```
"inc2", "inc3", "inc4", "regdum1", "regdum2", "regdum3")
dt<-paste0(ldt, collapse=" + ")</pre>
\verb|msse=mslogx-(mslp1*msw1+mslp2*msw2+mslp3*msw3+mslp4*msw4+mslp5*msw5)|
se=m$se
m$const. <- 1
\#\#\# censored LA-AIDS equations (first equation dropped)
eq1=with(m, as.formula(paste("w1 \sim 0 +cdf1:(const +", pt,"se","+", dt, ")", "+ df1",
sep=""))))
eq2=with(m, as.formula(paste("w2 \sim 0 +cdf2:(const +", pt,"se","+", dt, ")", "+ df2",
sep="")))
eq3=with(m, as.formula(paste("w3 \sim 0 +cdf3:(const +", pt,"se","+", dt, ")", "+ df3",
sep=""))))
eq4=with(m, as.formula(paste("w4 \sim 0 +cdf4:(const +", pt,"se","+", dt, ")", "+ df4",
sep="")))
eq5=with(m, as.formula(paste("w5 \sim 0 +cdf5:(const +", pt,"se","+", dt, ")", "+ df5",
sep=""))))
eqsys<-list(eq1=eq2, eq2=eq3, eq3=eq4, eq4=eq5)
## Homogeneity
restrict2 = "eq1\_cdf2:lp1+eq1\_cdf2:lp2+eq1\_cdf2:lp3+eq1\_cdf2:lp4+eq1\_cdf2:lp5=0"
restrict3="eq2_cdf3:lp1+eq2_cdf3:lp2+eq2_cdf3:lp3+eq2_cdf3:lp4+eq2_cdf3:lp5=0" restrict4="eq3_cdf4:lp1+eq3_cdf4:lp2+eq3_cdf4:lp3+eq3_cdf4:lp4+eq3_cdf4:lp5=0"
restrict5="eq4_cdf5:1p1+eq4_cdf5:1p2+eq4_cdf5:1p3+eq4_cdf5:1p4+eq4_cdf5:1p5=0"
homogeneity=c(restrict2, restrict3, restrict4, restrict5)
library("systemfit")
sysuunrest<-systemfit(eqsys, method="SUR", maxiter = 500)</pre>
sysu<-systemfit(eqsys, method="SUR",restrict.matrix = homogeneity, maxiter = 500)
linearHypothesis(sysuunrest, homogeneity, test = "Chisq")
lrtest(sysu,sysuunrest)
mod<-sysu
mcdf1=cdfb[1]
mcdf2=cdfb[2]
mcdf3=cdfb[3]
mcdf4=cdfb[4]
mcdf5=cdfb[5]
fmean < -function (v1) \{mean(m[,v1])\} \# with cdf we had same function
m$ew2=as.numeric(unlist(fitted(sysu)[1]))
m$ew3=as.numeric(unlist(fitted(sysu)[2]))
m$ew4=as.numeric(unlist(fitted(sysu)[3]))
m$ew5=as.numeric(unlist(fitted(sysu)[4]))
ewall<-paste0("ew", 2:n)
eb <- sapply (ewall, fmean)
mew2=eb[1]
mew3=eb[2]
mew4=eb[3]
mew5=eb[4]
mew1=1-sum(eb)
k=length(ldt)
ss=as.vector(t(cbind(paste0("df",
                                        2:n),paste0("co",2:n),
                                                                      outer(paste0("gamma",
2:n," "), 1:n, FUN=paste0), paste0("beta", 2:n),
                      outer(paste0("cd", 2:n,"_"), 1:k, FUN=paste0))))
cbind(names(coef(mod)), ss)
vv<-coef(mod)
names(vv)<-ss
vmat<-vcov (mod)
colnames(vmat)<-ss
rownames(vmat)<-ss
#ELASTICITIES
fiesta<-function(i){
  if(i=1) \{paste0("((0-(beta2+beta3+beta4+beta5))", "*mcdf", i, ")/mew", i, " + 1")\}
paste0("(beta", i, "*mcdf", i, ")/mew", i, " + 1")}
fie2<-function(i){    deltaMethod(vv, fiesta(i), vcov=vmat)}</pre>
temp1<-unlist(t(sapply(1:n, fie2)))</pre>
matrix(unlist(t(sapply(1:n, fie2))), nrow=n, ncol=2)
mee<-matrix(0, nrow=2*n, ncol=1)
for (i in 1:n) {
  v1<-temp1[i]
  v2 < -temp1[n+i]
  v3<-abs(v1/v2)
  if (v3>=2.57) {mee[2*(i-1)+1,1]<-paste0(round(v1, digit=3), "***")} else
```

```
if (v3>=1.96) {mee[2*(i-1)+1,1]<-paste0(round(v1, digit=3), "**")} else
       if (v3>=1.65) {mee[2*(i-1)+1,1]<-paste0(round(v1, digit=3), "*")} else
       \{mee[2*(i-1)+1,1] < -round(v1, digit=3)\}
  mee[2*i ,1]<-paste0("(", round(temp1[n+i], 3),")")}</pre>
#MARSHALLIAN PRICE elasticities
fiuu<-function(i, j) {
  v0<-ifelse(i==j, "-1", "")</pre>
  if(i==1){paste0("((0-
(gamma2_",j,"+gamma3_",j,"+gamma4_",j,"+gamma5_",j,"))*mcdf1)/mew1",v0)} else paste0("((gamma", i, "_", j, ")*mcdf", i,")/mew",i,v0))}
fme2<-function(i, j){</pre>
  deltaMethod(vv, fiuu(i,j), vcov=vmat)}
mind<-matrix(c(1:n), n, n, byrow=TRUE)
mmel=matrix(unlist(mapply(fme2, col(mind), row(mind))[1:2,]), nrow=2, ncol=2*n*n)
mme4<-matrix(0, nrow=2*n, ncol=n)
for(i in 1:(2*n)) {
  for (j in 1:n) {
    if(is.odd(i)){
       v1 < -mme1[1, (abs((i-1)/2))*n+j]
       v2 < -mme1[2, (abs((i-1)/2))*n+j]
       v3<-abs(v1/v2)
       if (v3>=2.57) {mme4[i,j]<-paste0(round(v1, digit=3), "***")} else</pre>
         if (v3>=1.96) {mme4[i,j]<-paste0(round(v1, digit=3), "**")} else
           if (v3>=1.65) {mme4[i,j]<-paste0(round(v1, digit=3), "*")} else
           {mme4[i,j]<-round(v1, digit=3)} }
    else {mme4[i,j]<-paste0("(", round(mme1[2, (i/2-1)*n+j], digit=3), ")")}}}
for (i in 1:n) {
 print(c(mme4[2*(i-1)+1, i], mme4[2*(i-1)+2, i]))}
mme4
# Hicksian
fhe=function(i, j) {
  v1=paste0(fiuu(i,j),"+mew", j,"*(",fiesta(i),")")
  v1}
fhe2<-function(i, j){</pre>
  deltaMethod(vv, fhe(i,j), vcov=vmat)}
mind<-matrix(c(1:n), n, n, byrow=TRUE)</pre>
mhel=matrix(unlist(mapply(fhe2, col(mind), row(mind))[1:2,]), nrow=2, ncol=2*n*n)
mhe4<-matrix(0, nrow=2*n, ncol=n)</pre>
for(i in 1:(2*n)) {
  for (j in 1:n) {
    if(is.odd(i)){
       v1 < -mhe1[1, (abs((i-1)/2))*n+j]
       v2 < -mhe1[2, (abs((i-1)/2))*n+j]
       v3<-abs(v1/v2)
       if (v3>=2.57) {mhe4[i,j]<-paste0(round(v1, digit=3), "***")} else
         if (v3>=1.96) {mhe4[i,j]<-paste0(round(v1, digit=3), "**")} else
           if (v3>=1.65) {mhe4[i,j]<-paste0(round(v1, digit=3), "*")} else
           \{mhe4[i,j] < -round(v1, digit=3)\}
    else \{mhe4[i,j] < -paste0("(", round(mhe1[2, (i/2-1)*n+j], digit=3), ")")\}\}
mhe4
# sos.dem elasticities
fsdd<-function(i, j){</pre>
  if(i==1){paste0("((0-(cd2_",j,"+cd3_",j,"+cd4_",j,"+cd5_",j,"))*mcdf1)/mew1")} else
   paste0("(cd", i, "_", j,"*mcdf",i,")/mew", i)}
fsdsd<-function(i, j){</pre>
\label{eq:deltaMethod} $$\det(vv, fsdd(i,j), vcov=vmat)$ $$nameg<-c("Beef and lamb", "Pork", "Poultry", "Processed meat", $$
          "Other meat products")
namegse<-numeric()</pre>
for (i in 1: length(nameg)) {namegse<-c(namegse, nameg[i], "SE")}</pre>
msd<-matrix(namegse, nrow=2*n, ncol=1)</pre>
for (jj in 1:k) {
  temp1<-unlist(t(sapply(1:n, fsdsd, j=jj)))</pre>
  mtemp<-matrix(0, nrow=2*n, ncol=1)</pre>
  for (i in 1:n) {
```

```
v1<-temp1[i]
v2<-temp1[n+i]
v3<-abs(v1/v2)
if (v3>=2.57) {mtemp[2*(i-1)+1,1]<-paste0(round(v1, digit=3), "***")} else
if (v3>=1.96) {mtemp[2*(i-1)+1,1]<-paste0(round(v1, digit=3), "**")} else
if (v3>=1.65) {mtemp[2*(i-1)+1,1]<-paste0(round(v1, digit=3), "*")} else
{mtemp[2*(i-1)+1,1]<-round(v1, digit=3)}
mtemp[2*i,1]<-paste0("(", round(temp1[n+i], 3), ")")}
msd<-cbind(msd, mtemp)}
msd</pre>
```