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Pricing on the fish market – Does size matter?

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Keywords: Fish; Inverse demand, Size, Pricing;
JEL Classification: C51; Q11; Q22

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1 Introduction

Goods such as fish, meat, vegetables and fruit take time to produce. Once harvested, they are costly to store which means that they are supply constrained in the short run. For these kinds of goods, regular demand estimation, where price is a function of quantity, is inappropriate since price and not quantity is the variable that clears the market. Over the years, different inverse demand models have been suggested to estimate relationships between supply and demand of supply constrained goods. In this study, I use inverse demand models to estimate relationships between fish size and price per kilo.

The question of how changes in the catch composition affect prices is interesting for several reasons, many of which can be linked to the problem of overfishing, see e.g., Aps and Lassen (2010). First, the estimated price differences and flexibilities (inverse demand counterparts to elasticities) in this paper help explain the incentives for fishermen to engage in high-grading. High-grading is

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the procedure to discard less valuable fish in order to make room for more valuable fish and also to affect prices. The discarded fish usually have high mortality rates (Davis 2002). High-grading is more common for fish species where size is an important factor for price. The practice is illegal within the E.U. but monitoring is difficult for the authorities. Data on high-grading is unreliable due to the practice being illegal. Hence, few studies have been made that assess the magnitude of the problem but a few examples exist, see e.g. Kristofersson and Rickertsen (2009) who find evidence of high-grading by Icelandic fishermen and the Swedish Fishery Board (Fiskeriverket 2011) which estimates that 10 to 15 % of the yearly landings of shrimp, roughly 1000-2000 tons, go to waste due to high-grading.

Second, both biologists (Almroth et al. 2012) and economists (Diekert 2012 and Quaas et al. 2010) have recently called for new regulation where age and size of fish are taken into account. Traditional fishery models based on biomass have been criticized for being overly simplistic and for failing to take into account maturity and weight structures in fish stocks (Tahvonen 2009). Recently, more realistic age-structured models have been developed, see e.g., Diekert (2012), Tahvonen (2009) or Quaas et al. (2010). Based on the findings in these papers, the authors call for regulation based on age-structured models rather than traditional biomass models. Regulation based on age-structured models implies changed incentives for harvesting in the different size categories and a changed size composition of the stock. However, the prices in these models are fixed for each size. The results of this paper can be used to shed some light on how prices change due to changed harvesting patterns in different weight classes.

Third, growth overfishing is a serious problem for many species of fish (Diekert 2012). Growth overfishing is the practice to use gear to target fish of a more valuable size, usually larger specimen. Growth overfishing might thus disproportionally decline the share of fish of certain sizes in a stock and cause disturbances in recruitment, see e.g. Ottersen et al. (2006).[1] Flexibilities can be used to study what happens to market prices in instances of growth overfishing. Changing market prices further change the incentives of fishermen. In general, larger fish yield higher prices on the market. Growth overfishing leads to smaller specimen on average which, in the long run, may drive fishermen to larger catches in order to keep the revenue constant.

Fourth, climate change has been linked to changes in the composition of fish stocks in the case of herring (Casini et al. 2010). As in the case of growth overfishing, flexibilities can be used to predict the effect on market prices of changes in the stock size composition due to a changing climate.

In this paper, a new Swedish data set is used to study how the size composition of the catch is related to the price of fish. Fish landed and sold in Sweden are divided according to an EU standard into different size categories (weight classes) based on the weight of the specimen caught. Fish in the different categories are then sold separately at different prices per kilo. I use the

[1] Guttormsen et al. (2008) study optimal management of a fish stock with Darwinistic selection induced by harvesting.

methods proposed in Brown et al. (1995) and refined in later papers such as Lee and Kennedy (2008) and perform rigorous testing in order to find the most appropriate inverse demand model to estimate quantity and scale flexibilities for the different size categories. Scale flexibilities measure the percentage change in the price of a size category in response to a proportional increase in the catch of all categories, and are the inverse demand counterparts to income elasticities. Quantity flexibilities measure the percentage change in the price of category i in response to an increase in the catch of category j, and are analogues to price elasticities in regular demand.

Previewing the results, scale flexibilities are estimated to be close to -1 for most species and size categories implying homothetic preferences. However, quantity flexibilities vary across size categories and species. The estimates have some interesting implications. For example, the increased average price in saithe over the last few years can be explained not only by falling total catch but also by a very large decrease in the catch of small saithe which is estimated to be of great importance for the prices of all size categories. Another example is incentives for high-grading. Larger plaice and common sole yield much higher prices on the market than smaller fish of the same species. An increase in the catch of large plaice is estimated to have large negative effects on the prices of smaller plaice while an increase in the catch of large common sole is estimated to have a much smaller impact on the price of smaller common sole. Hence, the incentives for high-grading are relatively larger for plaice than for common sole. Finally, new theory on fishery management using age-structured models calls for regulation based on number of fish and not biomass. This would have an impact on the size composition of the catch since the incentives to catch larger fish increase. The estimates in this paper can be used to discuss the resulting effects on prices.

The history of inverse demand estimation goes back to the early 1980s. In a seminal paper, Anderson (1980) established important theoretical properties of inverse demand models, which inspired many applied papers. The earliest empirical papers in the field of inverse demand estimation studied flexibilities between broad categories of goods. One of the most cited papers is Barten and Bettendorf's (1989) empirical study of fish landed in Belgian ports. From a theoretical perspective, the general trend has been to move from estimating and improving upon single inverse demand models e.g., Moschini and Vissa (1992) and Holt and Goodwin (1997) to nesting existing inverse demand systems in more general models to see which one best fits the data e.g., Eales et al. (1997) and Brown et al. (1995). Besides fish, the most common markets that have been the subject of study under inverse demand are meat, fruit and vegetables.[2]

Over the years, the focus on these broad markets has been replaced by a focus on more narrow markets where certain characteristics of goods define the market. For example, using different inverse demand models, Muhammad and Hanson (2009) studied the importance of product cut and form for catfish demand in the U.S., Chiang et al. (2001) analyzed the impact of inventory on tuna prices and Galdeano (2009) studied quality effects on Spanish demand for fruit and vegetables.

[2]For fish, see e.g., Eales et al. (1997), Park et al. (2004) or Chiang et al. (2001), meat e.g., Holt (2002), fruit and vegetables e.g., Brown et al (1995) and Galdeano (2005).

What these studies have in common is that they use discrete characteristics of goods to define the markets. Just as meat can be divided into e.g., poultry and beef, quality markings of fruit can divide e.g., apples into different categories.

Researchers in the field of inverse demand estimation have thus become more and more interested in the flexibilities between different characteristics of goods rather than the flexibilities between broader categories of goods. Discrete characteristics have been used to separate goods into different categories and the flexibilities among the categories have been estimated and studied. In regular demand estimation, researchers often use other structural estimation methods such as hedonic regressions to study how quality aspects affect the demand of a good and to find elasticities between different characteristics. But for supply constrained goods with discrete characteristics, inverse demand estimation is also appropriate for a simple and straightforward estimation of flexibilities.

It is worth noting that hedonic regressions have also been used for studying the fish market. Both McConnell and Strand (2000) and Carroll et al. (2001) used hedonic models to look at how quality characteristics affected the price of tuna in the Hawaiian market and the U.S. and Japanese markets, respectively. Kristofersson and Rickertsen (2004) mixed a hedonic regression approach with an inverse demand model to study, among other things, the effect of quantity changes in different size categories on the price of cod. I will compare the flexibilities estimated with my inverse demand approach in this study to the estimates in Kristofersson and Rickertsen (2004) resulting from the hedonic regression framework.[3] In a broader context, this is interesting since I approach the question of the impact of the characteristics on demand from a different perspective. What further separates this study from Kristofersson and Rickertsen (2004) are the seven additional species of fish for which size flexibilities are estimated and the very different types of data sets used.

The rest of the paper is organized as follows. In section 2 the inverse demand models are derived. The data is presented in section 3. The procedure how to select the appropriate model and tests of the statistical and economic assumptions are presented and performed in section 4. Section 5 presents the results. The results are discussed in section 6 in relation to earlier papers, the theory of optimal management in age-structured fisheries and empirical relevance. Some final comments then conclude the paper in section 7.

2 The models

On a given market day, the supply of fish is fixed and the fishermen will sell their fish to wholesalers, restaurateurs etc. at the price that clears the market. Therefore, I assume the price to be a function of the quantity. There are many reasons for quantity being treated as an exogenous variable in fish demand estimation. Special gear is needed for different species of fish and changing gear on a

[3]Due to data limitations, discussed further in the paper, it is not possible to replicate Kristofersson and Rickertsen's model with my data.

fishing vessel is expensive. The fishermen do not know the price on a given market day when they catch the fish. There is also some evidence that it is difficult for fishermen to foresee the size of the catch (Asche et al. 1997, Salvanes and Steen 1994). When the fishermen have caught the fish, the quantity is fixed and storage is expensive due to the cold temperatures needed to keep the fish fresh. Therefore, the fishermen have no other incentives than to sell the catch once it is landed.

Since I assume price to be a function of the catch, inverse demand models are appropriate to estimate the exact relationship. The models are used to estimate quantity and scale effects. A quantity effect can be interpreted as a measurement of how the price of fish in size category i changes for a marginal change in the quantity of fish harvested in size category j. The scale effect can be interpreted as how the price of fish of size i is affected by a proportional increase in all other sizes caught.[4] From the quantity and scale effects, I will calculate flexibilities (inverse demand counterpart to elasticities) to facilitate the interpretation.

Four different inverse demand models are presented below. They are based on standard microeconomic theory and differ in how the quantity and scale effects are specified. The differences are whether the effects are assumed to be constant or dependent on the shares for each size category of the total catch. It is difficult to argue on theoretical grounds which of the four models is best suited to use. Therefore, I use a synthetic model, also presented below, as an indicator to see if some of the models are rejected by the data.

There are many ways of deriving the inverted demand models; see for example Brown et al. (1995) or Barten and Bettendorf (1989). I start with a standard consumer maximization problem. A species of fish is divided into n different size categories denoted $i = 1, 2, ..., n$. The consumer's problem can be formulated in the following way:

$$\max_{q_1, q_2, \ldots, q_n} u(q_1, q_2, ...q_n) \text{ s.t. } \sum_{i=1}^{n} p_i q_i = m. \tag{1}$$

Here, u is a utility function, q_i is the quantity of fish in size category i, p_i is the associated price and m is the total budget. Denote μ as the Lagrange multiplier. Then, the first-order condition for each size category i is

$$\frac{\partial u}{\partial q_i} = \mu p_i.$$

Summing across the first-order conditions and rewriting, inverse demand equations for each size category i expressed in relative prices, $\pi_i = \frac{p_i}{m}$, can be derived.

$$\pi_i = \frac{\frac{\partial u}{\partial q_i}}{\sum_j \frac{\partial u}{\partial q_j} q_j} \tag{2}$$

The next step is to use the distance (also transformation) function which is dual to the expenditure function in regular demand theory, see e.g., Deaton (1979) or McLaren and Wong (2005). The

[4]For more on quantity and scale effects and their relation to their regular demand counterparts, see Park and Thurman (1999) and Houck (1965).

distance function $D(\hat{u}, q_1, q_2, ..., q_n) \equiv D(\hat{u}, q)$ tells us how a vector of quantities must be scaled to reach a given utility level $\hat{u}$. It can be implicitly defined as

$$u\left(\frac{1}{D(\hat{u}, q)}(q_1, q_2, ..., q_n)\right) = \hat{u}.$$

The distance function is positive, continuous, linearly homogeneous, nondecreasing and concave in quantities and nonincreasing in utility. The distance function provides a convenient way of generating inverse demand systems since by the Shephard-Hanoch lemma, it is related to the inverse demand, expressions 2 (Deaton 1979):

$$\pi_i = \frac{\partial D}{\partial q_i} = \pi_i(u, q_1, q_2, ..., q_n). \tag{3}$$

To derive the models, the distance function must be defined. I start by deriving the Almost Ideal Inverse Demand system (AIIDS), analogous to the Almost Ideal Demand System (AIDS) created by Deaton and Muellbauer (1980).[5] Let q be the vector of quantities in each category. Define the distance function to be logarithmic (PIGLOG) and equal to:

$$\log D(u, q) = (1 - \hat{u}) \log a(q) + \hat{u} \log b(q) \tag{4}$$

where

$$\log a(q) = \sum_{j=1}^{n} \rho_j \log q_j + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \tilde{\eta}_{ij} \log q_i \log q_j$$
$$\log b(q) = \beta_0 \prod_{j=1}^{n} q_j^{-\beta_j} + \log a(q).$$

This specification is flexible and results in attractive testable properties in the final demand system; see Deaton and Muellbauer (1980) for its use in AIDS. Equation 3 can be manipulated by multiplying both sides with $\frac{q_i}{D(\hat{u},q)}$ and noting that $D(\hat{u}, q) = 1$ in optimum. By doing this and using the derivative of equation 4, we have that

$$\frac{\partial D(\hat{u}, q)}{\partial q_i} \frac{q}{1} = \frac{\partial \log D(\hat{u}, q)}{\partial \log q_i} = w_i = \rho_i + \sum_{j=1}^{n} \eta_{ij} \log q_j - \beta_i \hat{u} \beta_0 \prod_{j=1}^{n} q_j^{-\beta_j}. \tag{5}$$

$w_i = \frac{p_i q_i}{m}$ is category i's share of the total budget and $\eta_{ij} = \frac{\tilde{\eta}_{ij} + \tilde{\eta}_{ji}}{2}$.[6] Finally, inversion of 4 at the optimum and substituting for $\hat{u}$ in 5 gives the AIIDS.

$$w_i = \rho_i + \sum_{j=1}^{n} \eta_{ij} \log q_j - \beta_i \log Q \tag{6}$$

[5] See, for example, Eales and Unnevehr (1994) for further details.

[6] $\eta_{ij} = \frac{\tilde{\eta}_{ij} + \tilde{\eta}_{ji}}{2}$ will later mean that I have to assume symmetry of quantity effects in the models. This assumption can (and will) be tested.

where $\log Q = \sum_{j=1}^{n} \alpha_j \log q_j + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \eta_{ij} \log q_i + \log q_j$. I approximate $\log Q$ with the Divisia quantity index, $\log Q = \sum_{i=1}^{n} w_i \log q_i$, in order to simplify the estimation. This approximation has proved to work well in earlier work such as Eales and Unnevehr (1994) and Rickertsen (1998).

The restrictions on the model are adding up which implies $\sum_i \eta_{ij} = 0, \sum_i \beta_i = 0$, homogeneity $\sum_j \eta_{ij} = 0$ and symmetry $\eta_{ij} = \eta_{ji}$. Adding up is satisfied by construction. The homogeneity restriction comes from the fact that the distance function is assumed to be homogenous of degree one, and the symmetry restriction from the definitions of η_{ij}. Since the latter two are not satisfied by construction, they will both be tested for. Let d be the difference operator. Then, totally differentiate equation 6 for the differential version of AIIDS (Brown et al. 1995).

$$d(w_i) = \sum_{j=1}^{n} \eta_{ij} d(\log q_j) + \beta_i d(\log Q) \tag{7}$$

This was the derivation of the first of the four models which will be used. In this specification, the quantity and scale effects, η_{ij} and β_i, are allowed to vary with the shares. In the other models, either or both are treated as independent of the shares.

It is straightforward to derive the other three models from the AIIDS, equation 7. Subtracting $w_i (d(\log q_i) - d(\log Q))$ from both sides of equation 7 gives the model proposed by Laitinen and Theil (1979) and which Barten and Bettendorf (1989) later denoted as the Differential Inverse Central Bureau of Statistics (DICBS). This model has its analogue in ordinary demand estimation in the CBS model introduced by Keller and van Driel (1985). The model as proposed by Barten and Bettendorf (1989) in its differential form is:[7]

$$w_i d\left(\log \frac{p_i}{P}\right) = \sum_{j=1}^{n} \gamma_{ij} d(\log q_j) + \beta_i d(\log Q) \tag{8}$$

where P is the divisia price index analogous to the divisia quantity index above. DICBS and AIIDS share scale effects but the quantity effects differ since $\eta_{ij} = \gamma_{ij} + \delta_{ij} w_{ij} - w_{ii} w_{ij}$, where $\delta_{ij} = 0(1)$ if $i \neq (=) j$ (i.e., the Kronecker delta). The difference between AIIDS and DICBS is thus that for the DICBS, the quantity effects are treated as static but are allowed to vary with the shares for AIIDS. The restrictions on the $\gamma' s$ are analogous to the restrictions on the $\eta' s$; adding up, $\sum_i \gamma_{ij} = 0$ homogenity, $\sum_j \gamma_{ij} = 0$, and symmetry, $\gamma_{ij} = \gamma_{ji}$.

By subtracting $w_i d(\log Q)$ from both sides of equation 8, the Rotterdam Inverse Demand system (RIDS) can be obtained.[8]

$$w_i d(\log \pi_i) = \sum_{j=1}^{n} \gamma_{ij} d(\log q_j) + \alpha_i d(\log Q) \tag{9}$$

The RIDS share quantity effects with the DICBS but the scale effects differ. $\beta_i = \alpha_i + w_i$. The difference between RIDS and the DICBS is thus that not only the quantity but also the scale

[7]See Laitinen and Theil (1979) for details.

[8]See Brown et al. (1995) for a complete derivation.

effects, are treated as static. From the definitions of the scale effects, the adding up restriction must change accordingly, i.e., $\sum_i \alpha_i = -1$.

The last model is obtained by subtracting $w_i d(\log Q)$ from the left- and right-hand side of equation 7. The resulting model is denoted the differential inverse NBR (DINBR) and it corresponds to the NBR model in regular demand estimation (Neves 1994). As shown in Brown et al. (1995), the DINBR can be written in its differential form as:

$$d(w_i) - w_i d(\log Q) = \sum_{j=1}^{n} \eta_{ij} d(\log q_j) + \alpha_i d(\log Q). \tag{10}$$

The DINBR model shares quantity coefficients with AIIDS and scale coefficients with RIDS. Thus, in contrast to the other models, the scale effect is treated as static while the quantity effects are allowed to vary with the shares.

To sum up, all models share right-hand side variables. The differences between the specifications are whether or not the quantity and scale effects should also depend on the share of the size categories. Table 1 presents the relationships between the two different quantity and scale effects.

Table 1: Quantity and scale effects

	Quantity effects	Scale effect
RIDS	γ_{ij}	α_i
DICBS	γ_{ij}	β_i
AIIDS	η_{ij}	β_i
DINBR	η_{ij}	α_i
	$\eta_{ij} = \gamma_{ij} + \delta_{ij} w_i - w_i w_j$	
	$\beta_i = \alpha_i + w_i$	

DICBS and RIDS share quantity effects (the γ's) which are constant while the quantity effects for AIIDS and DINBR (the η's) are allowed to vary with the shares. Analogously, the scale effects of the RIDS and DINBR (the α's) are constant while the scale effects for the DICBS and AIIDS (the β's) are allowed to vary with the shares.

Theoretically, it is difficult to argue which of the models is the most appropriate one for different inverse demand systems. To see if any of the models could be rejected by the data, Brown et al. (1995) showed that the four models could be nested in a synthetic demand system. Tests on the parameters of this model could then sort out some inappropriate models. This nested model shares the dependent variable with the RIDS model. Define $e_i = (1-\theta_1)\alpha_i + \theta_1\beta_i$ and $e_{ij} = (1-\theta_2)\gamma_{ij} + \theta_2\eta_{ij}$. The nested model is then written as

$$w_i d(\log \pi_i) = \sum_{j=1}^{n} \left[e_{ij} - \theta_2 w_i (\delta_{ij} - w_j)\right] d(\log q_j) + (e_i - \theta_1 w_i) d(\log Q). \tag{11}$$

Putting restrictions on the right-hand side parameters transforms the nested model into the four different inverted demand models. Table 2 shows the assumptions on θ_1 and θ_2 that transform the nested model into each of the four inverted demand models. The adding up, homogeneity and symmetry restrictions still hold, $\sum_i e_i = \theta_1 - 1$, $\sum_i e_{ij} = 0$, $\sum_j e_{ij} = 0$ and $e_{ij} = e_{ji}$.

Table 2: Restrictions on nested model

θ_1	θ_2	Model
0	0	RIDS
1	0	DICBS
1	1	AIIDS
0	1	DINBR

Estimating the nested model and then testing the restrictions in table 2 might reject some of the models. However, this only sorts out some models that are rejected by the data. Each model still has underlying assumptions that need to be tested for. First, the economic assumptions of homogeneity and symmetry are not satisfied by construction. Second, there is a range of econometric issues that need to be dealt with. It is not clear that the exogeneity of quantities is appropriate. Moreover, since this is a panel data set, there might be some problem of autocorrelation. These issues will also be tested for and potentially corrected. The methods are described in section 4. The model selection and estimation procedures follow Brown et al. (1995) and Lee and Kennedy (2008).

3 Data

The data on prices and harvest in this study is monthly data ranging from January 2003 to May 2010.[9] Data was obtained from the website of the Swedish Fishery Board where it was also publicly available. The Swedish Fishery Board merged with other government agencies in June 2011 into the Swedish Agency for Marine and Water Management where the data is now available.[10] The Swedish Fishery Board gathered the data from auctions, the refinement industry, wholesalers and retailers who buy the fish straight from the fishermen. All prices used in this paper have been deflated by the monthly Swedish consumer price index from Statistics Sweden. Hence, all prices in the text refer to 2003 prices.

Eight species will be the subject of this study. The reasons for these eight species to be chosen are that they are sold in size categories, the major part of the quantity traded is landed in Sweden (although this varies across species and season) and the season is long enough to provide a reasonably large number of observations. The different species are cod, common sole, haddock,

[9] Due to the seasonality of fishing, the number of observations differs between the different species estimated. For some species that are harvested all year, the number of observations is close to 89 but for a few species, the number of observations is substantially smaller. For all species, data is missing in October and November of 2009.

[10] It is also available from the author upon request.

Table 3: Price and landings[a]

		1	2	3	4	5
Cod	Price	34.89	24.96	19.66	16.64	13.83
	Tons	42.0	165.2	701.0	3,449	6,169
Common Sole	Price	122.50	100.86	81.53	66.94	63.92
	Tons	4.5	5.1	5.8	3.7	1.1
Haddock	Price	26.66	25.87	17.54	13.08	
	Tons	14.8	36.2	44.3	16.0	
Hake	Price	54.53	44.34	33.37	24.35	20.71
	Tons	3.5	11.4	9.3	7.3	5.2
Lemon Sole	Price	58.66	49.42	39.35		
	Tons	1.6	4.8	8.1		
Plaice	Price	35.19	32.03	23.50	14.15	
	Tons	13.6	52.1	117.0	133.9	
Saithe	Price	13.85	12.19	9.96	9.22	
	Tons	4.7	29.9	152.9	314.6	
Whiting	Price	15.41	12.99	17.85	17.03	
	Tons	19.9	25.2	17.5	31.9	

[a] Average price and landing per year in all size categories.

hake, lemon sole, plaice, saithe and whiting. Figure 1 below shows the trends of harvested fish and average prices over the years 2003 - 2010.

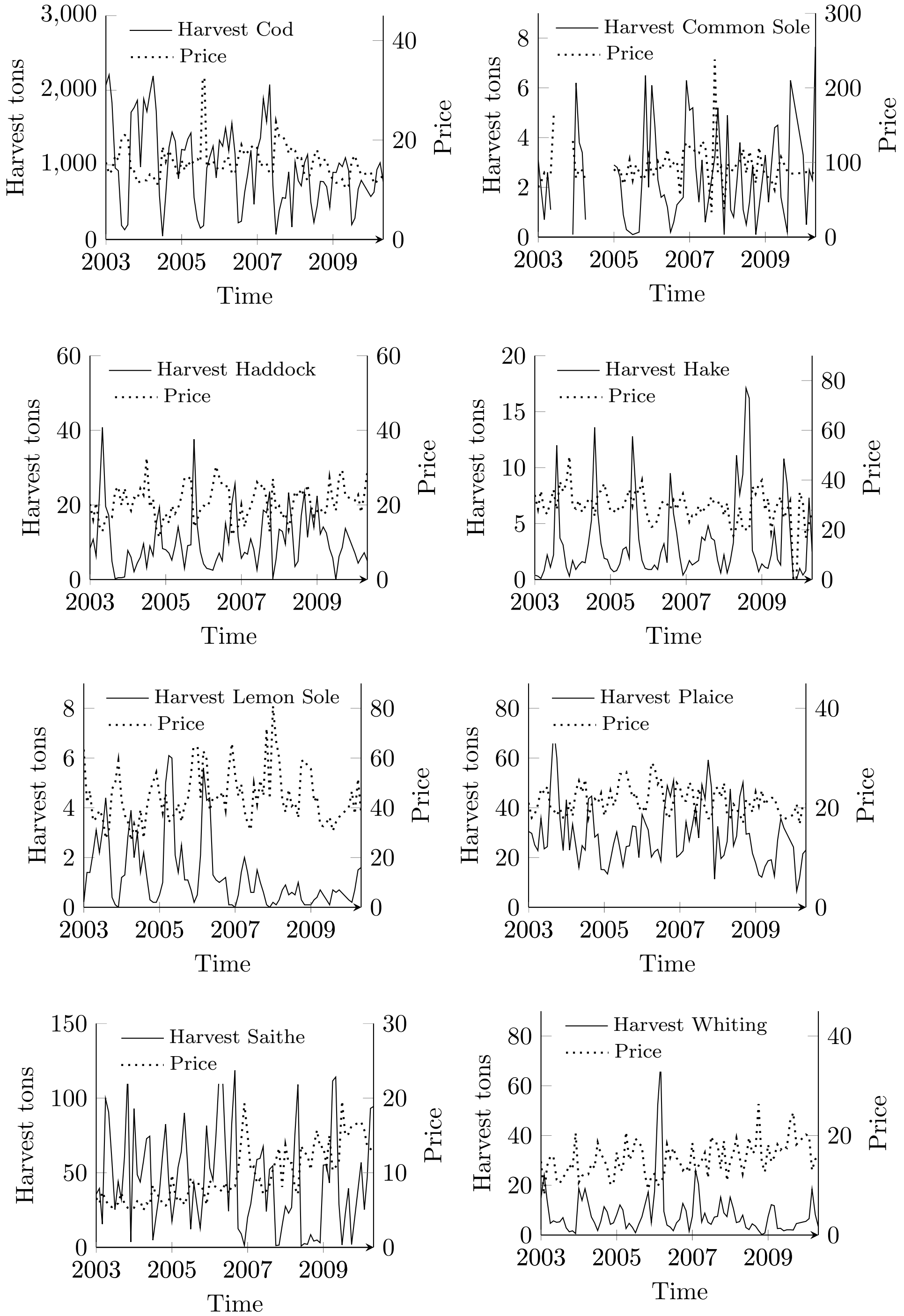
Most species show a cyclical pattern (with the exception of whiting) in total harvest but with a large variation for a given month across years. A cyclical pattern is most apparent for hake and cod. There is a downward trend in harvested quantities for both lemon sole and cod and maybe also for haddock and plaice. For all species, prices are negatively correlated with quantity. For most species, average prices do not seem to have changed to any considerable extent during the investigated period. There is a small decreasing trend in the average price for hake and plaice and what seems to be a quite substantial increase in the average price for saithe.

Fish are divided into size categories according to weight. There are three to five categories depending on the species. Each species has specific categories so a category 1 specimen of cod is not necessarily of the same size as a category 1 specimen of haddock. The different categories are presented in table 14 in the appendix. Table 3 presents average price and quantity (yearly in tons) per size category for each species.

4 Model selection

In this section, I explain how a model is selected for a given species. This is done by estimating the nested model, equation 11, and testing which, if any, of the models that is not rejected by the data. The underlying economic (homogeneity and symmetry) and statistical (exogeneity and

Figure 1: Trends in price and total harvest



autocorrelation) assumptions of the selected model are then tested. The procedure follows both Brown (1995) and Lee and Kennedy (2008).

I assume that all coefficients are constant over time and that there is weak separability across species. Estimating a model using all species and categories simultaneously is not feasible due to data limitations. Weak separability is a strong assumption. Asche et al. (2005) find that fish is weakly separable from meat. Some concern may be raised whether one can restrict a demand system to contain only one species of fish. This assumption is common in fish demand, see e.g., Angrist et al. (2000, whiting), Muhammad and Hanson (2009, catfish), Lee and Kennedy (2008, crawfish) and Chiang et al. (2001, tuna). In this study, testing for exogeneity of the quantities using instruments, see below, does not reject this assumption. However, this does not necessarily mean that there is no interaction between the different species, it can instead mean that the harvest of one species is not correlated with the harvest of others to any greater extent.

The selected model will produce quantity and scale effects which can be used to derive the uncompensated quantity and scale flexibilities. I outline the selection procedure below and motivate each test using whiting as the leading example, but I will also present and discuss the results of the other species.

Whiting is a popular food fish that is mostly caught and landed off the western coast of Sweden. It is divided into four different size categories, see table 3. Although it is possible to estimate the equation for each size category separately, it is likely that the error terms are correlated across equations at a given point in time. A random shock in demand at time t is likely to affect all size categories. Therefore, to increase the efficiency, an iterative seemingly unrelated regression (SUR) procedure was used in Stata 11.

For all models, one observation in category i at time t is indexed by *it*. The inverse demand models are written in differential form and need to be transformed into discrete time. Hence, all differential variables are transformed into discrete form s.t. $d(\log x_{it}) = \log x_{it} - \log x_{it-1} \equiv \log \tilde{x}_{it}$. The shares are also approximated by the moving average of the last two consecutive months, $\bar{w}_{it} = \frac{w_{it} - w_{it-1}}{2}$. Finally, an error term, ϵ_{it}, is added to each equation 8-10 and 11.

The error terms are subject to adding up. This makes the residual covariance matrix singular which makes it impossible to estimate the equations for all categories simultaneously. Hence, in order to estimate the models using SUR, one of the equations must be deleted during the estimation, but the results are invariant to which equation (Barten 1969). The parameters for the missing equation can then be obtained from the restrictions of the model. Then, another equation can be deleted in order to obtain standard errors for the parameters of the deleted equation.

Nested model

The models from section 2 are related and based on the same microeconomic theory but differ in the specification of quantity and scale effects. To select the most appropriate model, I start by estimating equation 11 and test the restrictions from table 2. As discussed above, the combination of the restrictions on θ_1 and θ_2 gives the four inverted demand models.

Formally, to test the restrictions, I first estimate the unrestricted version of 11 with homogeneity and symmetry imposed. Then, I estimate the four restricted versions of 11, corresponding to RIDS, DICBS, AIIDS and DINBR, and use a log likelihood ratio test to see which models are rejected to be nested in the unrestricted model. Table 4 gives the parameter values of θ_1 and θ_2 in the unrestricted model as well as the log likelihood values for each model. The test statistic is $\xi = -2(L^{UR} - L^R)$. ξ has asymptotically a χ^2_2 distribution, and L^{UR} and L^R are the log likelihood values from the unrestricted and restricted model, respectively. This is to be compared with the 5 % critical value of 5.99. A star indicates significance and means that the model is rejected by the data. Table 4 presents the results of this test for whiting and all other species.

Table 4: Model specification[a]

		θ_1	θ_2	L^b	ξ^c		θ_1	θ_2	L^b	ξ^c
	Common Sole					*Cod*				
Unrestricted		0.94	-0.02	498.2			1.03	0.01	1289.6	
		0.03	*0.03*				*0.02*	*0.01*		
RIDS		0	0	317.9	360*		0	0	1028.4	522*
DICBS		1	0	496.5	3.55		1	0	1288.3	2.53
AIIDS		1	1	415.2	166*		1	1	940.0	699*
DINBR		0	1	298.6	399*		0	1	824.8	929*
	Haddock					*Hake*				
Unrestricted		0.97	-0.02	544.3			0.94	-0.08	712.4	
		0.04	*0.03*				*0.04*	*0.03*		
RIDS		0	0	331.9	424*		0	0	404.6	615*
DICBS		1	0	544.1	0.39		1	0	709.7	5.5
AIIDS		1	1	316.4	455*		1	1	360.1	704*
DINBR		0	1	200.3	688*		0	1	203.7	1017*
	Lemon Sole					*Plaice*				
Unrestricted		0.97	-0.07	206.7			1.02	-0.01	639.5	
		0.04	*0.05*				*0.08*	*0.06*		
RIDS		0	0	115.5	182*		0	0	534.3	210*
DICBS		1	0	205.4	2.53		1	0	639.2	0.52
AIIDS		1	1	132.2	149*		1	1	487.8	303*
DINBR		0	1	87.5	238*		0	1	407.2	464*
	Whiting					*Saithe*				
Unrestricted		0.94	-0.02	453.4			0.95	-0.01	543.3	
		0.03	*0.03*				*0.02*	*0.02*		
RIDS		0	0	222.7	461*		0	0	373.4	340*
DICBS		1	0	450.5	5.77		1	0	541.0	4.44
AIIDS		1	1	224.4	458*		1	1	306.2	474*
DINBR		0	1	103.7	699*		0	0	265.5	555*

[a] Log likelihood ratio test of unrestricted and restricted estimation of equation 11. Standard errors in italics.

[b] Log likelihood values.

[c] Log likelihood ratio test of the restrictions on θ_1 and θ_2, $t = -2(L^{UR} - L^R) \sim \chi^2_2$. 5 % cutoff value is 5.99.

For whiting, RIDS, AIIDS and DINBR are all rejected. DICBS is, however, a much more relevant candidate. Thus, for whiting, DICBS will be used for estimation. This is actually the case for all species as can be seen in table 4. That DICBS is the inverse model that best fits the data is not uncommon in this kind of studies, see e.g., Fousekis and Karagiannis (2001) or Brown et al. (1995).

As described in section 2, DICBS relies on economic and statistical assumptions which may not be appropriate. Before moving on to estimating the quantity and scale flexibilities, these assumptions will now be tested.

Exogeneity of quantity

I have argued intuitively for why quantity is and should be treated as an exogenous variable. I tested this assumption formally by performing a Hausman test. The estimates from the SUR estimation were compared to an alternative estimator that is assumed to be consistent notwithstanding if the hypothesis of exogenous quantities is true. For a comparison of estimates, the three-stage least square (3SLS) estimator was used. The 3SLS estimator is a combination of a two-stage least square (2SLS) estimator and the SUR estimator.

The quality of this test depends on how good the instruments are. One instrument that has been used historically is weather conditions, see e.g. Angrist et al. (2000). However, matching historical weather data from weather stations to certain fish stocks at a given point in time proved to be infeasible. I used other standard variables in the literature as instruments, namely diesel prices, twelve-month lagged variables and monthly dummies, see e.g., Eales and Unnevehr (1993), Eales et al. (1997), Matsuda (2005) or Park et al. (2004). The coefficient estimates from the 3SLS estimator were then compared with the estimates from the SUR estimator and systematic differences were tested for. If systematic differences were to be found, exogeneity of quantity would be rejected and the 3SLS estimates would be used for those species.

Thus, equation 8 was estimated for each category using 3SLS. The procedure was then repeated but using SUR. The coefficients from both estimation methods were then compared in a Hausman test. The resulting p-value from the Hausman test (where H_0 was no systematic differences in coefficients) were 0.186. Hence, exogeneity was not rejected for DICBS at conventional significance levels. Since no systematic differences were found, the SUR estimates were used for whiting. Repeating the same procedure for all other species showed that exogeneity of quantities was not rejected in any instance.

Autocorrelation

To address autocorrelation, I use the procedure suggested in Park et al. (2004). Equation 8 is estimated for all size categories in an unrestricted system using SUR. The residuals ϵ_{it} are then stored for each category i. The correlation coefficient ρ between the residuals was then estimated using the following equation:

$$\epsilon_{it} = \rho\epsilon_{it-1} + v_{it} \quad (12)$$

Note that ρ is independent of size category. This is necessary to preserve the adding up feature of the data. Hence, ρ is imposed to be the same when estimating equation 12 for each category 1-4. Finally, ρ is used to transform all variables according to $\tilde{x}_{it} = x_{it} - \rho x_{it-1}$. Once this is done, the original strategy to apply SUR on the autocorrelation corrected data is restored. A Breusch-Godfrey test for each size category does not reject the null hypothesis of no autocorrelation in the transformed model.

Homogeneity and symmetry

As shown in section 2, the homogeneity and symmetry restrictions stem from the economic assumptions underlying the model. Both restrictions will be imposed during estimation. However, since they are assumptions, they can also be inappropriate. Therefore, the variables corrected for autocorrelation are used to estimate both an unrestricted DICBS and a restricted DICBS model where homogeneity and symmetry are both imposed.

The same log likelihood ratio test as for the model selection was performed to test if the restricted model is rejected to be nested in the unrestricted model. Equation 8 is thus estimated for each size category using SUR with and without the restrictions of homogeneity and symmetry. The test statistic is $\xi = -2(L^{UR} - L^{R})$, where L^{UR} and L^{R} are the log likelihood values from the unrestricted and restricted model, respectively. ξ follows asymptotically a χ^2_n distribution where n is the number of restrictions depending on the number of size categories. Table 5 reports the log likelihood values from the unrestricted and restricted models L^{UR} and L^{R}, respectively. A * on the test statistic indicates that it is above the 5 % cut off level.

Table 5: Homogeneity and symmetry[d]

	L^{UR}	L^{R}	ξ		L^{UR}	L^{R}	ξ
Common sole[c]	497.10	488.11	17.97	Cod[c]	1303.50	1286.42	34.16*
Haddock[b]	555.97	549.81	12.33	Hake[c]	738.8	729.43	18.74*
Lemon sole[a]	206.18	204.95	2.46	Plaice[b]	656.6	649.62	13.96*
Whiting[b]	456.21	452.10	8.22	Saithe[b]	581.22	578.23	5.97

95 % cutoff value is $^a\chi^2_3$: 7.81, $^b\chi^2_6$: 12.59, $^c\chi^2_{10}$: 18.31.

[d]Log likelihood ratio test of restricted DICBS model nested in unrestricted model.

Neither symmetry nor homogeneity is systematically rejected for whiting. For hake and plaice, the test statistic is just above the 95 % cut off value. For cod, homogeneity and symmetry is strongly rejected when imposed jointly. Testing the restrictions of homogeneity and symmetry separately, only symmetry is rejected for cod and plaice, and neither is rejected for hake. For all other species, imposing homogeneity and symmetry is not rejected by the log likelihood ratio test.

Both symmetry and exogeneity will be imposed during the estimation with the saving clause that symmetry might not be an appropriate assumption for cod and plaice.

Statistical tests

Some statistical tests were also performed to test the appropriateness of DICBS. The tests are summarized in table 6. A Shapiro-Wilks test showed that normal distribution of the residuals could not be rejected at any conventional significance levels for any size category. The residuals also summed to zero at each time t. A RESET test for misspecification was performed by including second and third power of the explanatory variables. The F-statistics did not reject any omitted variables for any category. The p-values from the Shapiro-Wilks and RESET test are presented in table 6.

Table 6: Shapiro-Wilks and RESET test[a]

	P-values	
	Shapiro Wilks	RESET
Category 1	0.34	0.48
Category 2	0.42	0.88
Category 3	0.37	0.44
Category 4	0.52	0.12

[a]Shapiro Wilks test for normally distributed errors and RESET test for misspecification.

The results of these tests for all other species were similar. With this final statistical test, it is now time to estimate the full DICBS model with homogeneity and symmetry imposed, the result of which is presented in the next section.

5 Results

The final goal is to estimate quantity and scale flexibilities. Whiting can still serve as an example of how these are obtained. Equation 8 is estimated for each size category of whiting using SUR with both homogeneity and symmetry imposed. This gives the quantity and scale effects which are presented in table 7.

The quantity and scale effects are difficult to interpret. Hence, they are transformed into quantity and scale flexibilities, f_{ij} and ϕ_i respectively, the analogues to price and income elasticities. In general, using the terms from the nested model (equation 11), the relationships between the quantity and scale effects and the quantity and scale flexibilities are the following.

Table 7: Quantity and Scale Effects, Whiting[a]

	$\bar{w}_1 \log \frac{\tilde{p}_1}{\tilde{P}}$	$\bar{w}_2 \log \frac{\tilde{p}_2}{\tilde{P}}$	$\bar{w}_3 \log \frac{\tilde{p}_3}{\tilde{P}}$	$\bar{w}_4 \log \frac{\tilde{p}_4}{\tilde{P}}$
$\log \tilde{Q}$	0.00349	0.0133	-0.00461	-0.0118
	0.00357	*0.00503*	*0.00448*	*0.00539*
$\log \tilde{q}_1$	-0.00801			
	0.00213			
$\log \tilde{q}_2$	0.00212	-0.00884		
	0.00231	*0.00486*		
$\log \tilde{q}_3$	0.00004	0.00240	-0.0266	
	0.00230	*0.00387*	*0.00553*	
$\log \tilde{q}_4$	0.00585	0.00432	0.0242	-0.0341
	0.00272	*0.00412*	*0.00490*	*0.00634*
Obs.	63	63	63	63
$\bar{R}^2$	0.197	0.125	0.272	0.276

[a]Estimation of the DICBS model, equation 8 for all categories using SUR. Standard errors in italics, the first row is scale effects, the dependent variable for category i at the top of column i.

$$f_{ij} = \frac{e_{ij}}{w_i} - \theta_2(\delta_{ij} - w_j) + w_j\phi_i \tag{13}$$

$$\phi_i = \frac{e_i}{w_i} - \theta_1 \tag{14}$$

Thus, for the DICBS model, the quantity and scale flexibilities are calculated as

$$f_{ij} = \frac{\gamma_{ij}}{w_i} + w_j\phi_i$$
$$\phi_i = \frac{\beta_i}{w_i} - 1.$$

The uncompensated quantity flexibility is interpreted as the percentage change in price of category i when a one percent change in the quantity of category j occurs. The scale flexibility is the percentage change in price of category i when all quantities increase proportionally by one percent. A scale flexibility for a good equal to -1 implies homothetic preferences. That is, a one percentage increase in all quantities would result in approximately a one percent decrease in the normalized price for the good. Scale flexibilities of less than -1 imply necessities and a value greater than -1 implies luxuries. Table 8 presents the different flexibilities for the size categories of whiting.[11]

[11]Average shares are used when calculating quantity and scale flexibilities.

Table 8: Flexibilities, Whiting

	Quantity Flexibilities				Scale Flexibilities
	Category 1	Category 2	Category 3	Category 4	
C1	-0.191	-0.120	-0.138	-0.125	-0.974
	-0.220, -0.162	*-0.137, -0.102*	*-0.156, -0.120*	*-0.138, -0.112*	*-1.026, -0.922*
C2	-0.229	-0.273	-0.246	-0.248	-0.947
	-0.264, -0.194	*-0.311, -0.235*	*-0.278, -0.215*	*-0.268, -0.228*	*-0.986, -0.908*
C3	-0.238	-0.222	-0.358	-0.192	-1.019
	-0.273, -0.202	*-0.253, -0.190*	*-0.402, -0.314*	*-0.215, -0.168*	*-1.055, -0.983*
C4	-0.352	-0.367	-0.313	-0.501	-1.029
	-0.402, -0.302	*-0.406, -0.327*	*-0.359, -0.267*	*-0.537, -0.465*	*-1.055, -1.003*

95 % confidence intervals in italics.

A 1 % increase in the quantity of the own category is estimated to decrease the price between 0.19 and 0.5 %, depending on category. The cross-quantity effects are estimated to between 0.12 and 0.37 %. The effects are fairly precisely estimated. Some trends are worth noting.

The own quantity flexibility is estimated to be larger than any cross-quantity flexibility. That is, a percentage change in category i affects the price of whiting in category i more than the price in any other category j. Whiting in category 4 is estimated to have a larger impact on the price of larger fish than vice versa. But while the cross-quantity flexibilities differ across categories, one striking feature is the similarity of the different cross-quantity flexibilities within a category. E.g., changes in category i seem to have a relatively similar effect on all categories $j \neq i$.

Regarding the scale flexibilities, larger whiting are estimated to be more of a luxury good than smaller whiting. But all estimates are close to -1, a value which is also covered by all 95 % confidence intervals except category 2. This implies close to homothetic preferences for each different category. That is, a proportional increase in all categories decreases the price with the same proportion.

For whiting, even though small specimen have a larger effect on prices than large specimen, the average price is fairly equal (table 3) across categories. Small fish are, however, somewhat more expensive. Hence, for whiting, high-grading would imply discarding larger fish to make room for smaller fish. The positive effect on price of discarding large fish is smaller than the negative effect on price of replacing it with smaller fish. High-grading can be curbed through regulation. This is discussed in section 6.

Flexibilities of other species

In section 4, I discussed how the appropriate inverted demand model was selected for each species. The models were then used to estimate quantity and scale effects which are transformed into flexibilities to facilitate the interpretation. The analogues of table 8 are presented in tables 9 - 13 for the other species except cod and plaice, for which symmetry was rejected. The tables for cod and plaice are found in the appendix. The results are discussed below.

Table 9: Flexibilities, Common Sole

	Quantity Flexibilities					Scale Flexibilities
	Category 1	Category 2	Category 3	Category 4	Category 5	
C1	-0.307	-0.303	-0.301	-0.241	-0.251	-0.999
	-0.375, -0.238	*-0.365, -0.241*	*-0.353, -0.248*	*-0.330, -0.152*	*-0.447, -0.054*	*-1.032, -0.966*
C2	-0.317	-0.404	-0.223	-0.210	-0.377	-1.010
	-0.387, -0.248	*-0.488, -0.321*	*-0.286, -0.160*	*-0.310, -0.109*	*-0.605, -0.149*	*-1.042, -0.977*
C3	-0.241	-0.172	-0.225	-0.426	-0.090	-0.989
	-0.284, -0.198	*-0.218, -0.125*	*-0.311, -0.140*	*-0.539, -0.313*	*-0.287, -0.107*	*-1.016, -0.963*
C4	-0.103	-0.086	-0.227	-0.082	-0.103	-0.989
	-0.142, -0.064	*-0.126, -0.047*	*-0.288, -0.166*	*-0.192, 0.028*	*-0.269, 0.062*	*-1.041, -0.937*
C5	-0.031	-0.045	-0.013	-0.030	-0.212	-1.030
	-0.057, -0.005	*-0.072, -0.018*	*-0.045, 0.019*	*-0.079, 0.020*	*-0.362, -0.061*	*-1.143, -0.917*

95 % confidence intervals in italics.

Table 10: Flexibilities, Haddock

	Quantity Flexibilities				Scale Flexibilities
	Category 1	Category 2	Category 3	Category 4	
C1	-0.196	-0.184	-0.170	-0.180	-0.937
	-0.219, -0.173	*-0.196, -0.171*	*-0.186, -0.154*	*-0.216, -0.145*	*-0.967, -0.908*
C2	-0.407	-0.449	-0.384	-0.435	-0.979
	-0.438, -0.377	*-0.473, -0.425*	*-0.413, -0.355*	*-0.501, -0.369*	*-1.003, -0.955*
C3	-0.276	-0.282	-0.421	-0.328	-1.040
	-0.305, -0.247	*-0.304, -0.260*	*-0.460, -0.382*	*-0.403, -0.252*	*-1.073, -1.008*
C4	-0.073	-0.080	-0.082	-0.155	-1.081
	-0.088, -0.058	*-0.091, -0.069*	*-0.100, -0.064*	*-0.210, -0.100*	*-1.178, -0.983*

95 % confidence intervals in italics.

For each species, there are one or two adjacent size categories that have the largest effect on the prices of the other categories. The point estimates of the largest cross-quantity flexibilities are roughly between 0.25 % and 0,6 % depending on species. It is not the case that large or small fish in general have the largest effect, this is dependent on species. For example, small saithe have a much larger effect on the price of the other categories than larger fish, but for common sole, the largest cross-quantity flexibilities belong to the larger fish in size categories 1 and 2. The cross-quantity flexibilities are also relatively stable across categories i.e., the effect of a change in category i has more or less the same effect on all categories $j \neq i$.

In general, but not without exception, $f_{ii} > f_{ij} \forall i \neq j$, that is, a change in catch of category i

Table 11: Flexibilities, Hake

	Quantity Flexibilities					Scale Flexibilities
	Category 1	Category 2	Category 3	Category 4	Category 5	
C1	-0.221	-0.124	-0.110	-0.100	-0.101	-0.992
	-0.269, -0.172	*-0.151, -0.097*	*-0.132, -0.087*	*-0.127, -0.073*	*-0.128, -0.074*	*-1.033, -0.950*
C2	-0.255	-0.263	-0.263	-0.260	-0.237	-1.008
	-0.305, -0.204	*-0.304, -0.222*	*-0.295, -0.231*	*-0.295, -0.226*	*-0.272, -0.202*	*-1.040, -0.976*
C3	-0.230	-0.268	-0.279	-0.240	-0.247	-0.987
	-0.278, -0.181	*-0.304, -0.232*	*-0.323, -0.235*	*-0.279, -0.202*	*-0.285, -0.209*	*-1.013, -0.961*
C4	-0.166	-0.211	-0.191	-0.207	-0.256	-1.002
	-0.212, -0.12	*-0.242, -0.180*	*-0.221, -0.160*	*-0.255, -0.158*	*-0.297, -0.215*	*-1.035, -0.970*
C5	-0.138	-0.159	-0.162	-0.212	-0.187	-1.011
	-0.177, -0.098	*-0.186, -0.131*	*-0.188, -0.135*	*-0.247, -0.176*	*-0.233, -0.141*	*-1.050, -0.971*

95 % confidence intervals in italics.

Table 12: Flexibilities, Lemon Sole

	Quantity Flexibilities			Scale Flexibilities
	Category 1	Category 2	Category 3	
C1	-0.068	-0.127	-0.143	-0.920
	-0.132,-0.004	*-0.151, -0.104*	*-0.162, -0.125*	*-1.011, -0.828*
C2	-0.385	-0.380	-0.426	-0.961
	-0.468, -0.302	*-0.430, -0.330*	*-0.463, -0.388*	*-1.004, -0.918*
C3	-0.501	-0.489	-0.522	-1.051
	-0.586, -0.417	*-0.534, -0.444*	*-0.564, -0.479*	*-1.089, -1.014*

95 % confidence intervals in italics.

has a larger effect on the price of i than any other category j. However, own quantity flexibilities do not necessarily have the largest effect on the price. This seems natural since different size categories are close substitutes.

For most species and categories, the scale flexibilities are relatively close to -1, implying homotheticity. For haddock, lemon sole and saithe, the high categories have larger scale flexibilities. For those species, proportional changes in landings have larger effects on the prices of small fish. It also implies that larger fish are more of a luxury good which agrees with the descriptive data (table 3) where it can be seen that for these species, larger fish constitute a smaller share of the catch and are also significantly more expensive per kilo. Common sole and hake have no clear pattern.

Symmetry was rejected for cod and plaice. It is interesting to note that both are species that have a very skewed distribution towards smaller weight classes (table 3). Furthermore, some of the results for cod, table 15 in the appendix, are contrary to intuition as some flexibilities are estimated

Table 13: Flexibilities, Saithe

	Quantity Flexibilities				Scale Flexibilities
	Category 1	Category 2	Category 3	Category 4	
C1	-0.115	0.010	-0.018	-0.010	-0.821
	-0.175, -0.054	*-0.004, 0.024*	*-0.021, -0.014*	*-0.013, -0.008*	*-0.964, -0.678*
C2	0.060	-0.203	-0.053	-0.057	-0.976
	-0.010, 0.131	*-0.233, -0.173*	*-0.060, -0.047*	*-0.061, -0.053*	*-1.022, -0.930*
C3	-0.347	-0.226	-0.275	-0.276	-0.984
	-0.421, -0.272	*-0.250, -0.202*	*-0.284, -0.266*	*-0.280, -0.271*	*-1.000, -0.969*
C4	-0.429	-0.567	-0.649	-0.680	-1.012
	-0.608, -0.249	*-0.629, -0.504*	*-0.669, -0.628*	*-0.693, -0.666*	*-1.022, -1.003*

95 % confidence intervals in italics.

to be positive. The estimated flexibilities for plaice, table 16 in the appendix, do not stand out relative to the other species in any particular way. However, since symmetry was rejected for both these species, the estimates should be interpreted with some care.

Even though the appropriateness of the model was doubtful for cod, I want to briefly discuss my estimates in relation to the estimates from Kristofersson and Rickertsen (2004) who studied the relationship between cod size and price using a mixed hedonic regression and inverse demand approach. Kristofersson and Rickertsen found much smaller flexibilities, between -0.03 and -0.01, for all cross and own quantity flexibilities across all categories. They used daily auction data from Iceland, which is a much more export oriented market. Furthermore, in my study, monthly data was used while Kristofersson and Rickertsen used daily data which might help explain the discrepancies between the flexibilities since short-run variation in quantities might not have as large an impact on price due to inventory effects. But since symmetry was rejected for cod, the estimates should be taken with a grain of salt. Thus, it is not appropriate to make a direct comparison of the estimates in Kristofersson and Rickertsen (2004) and the estimates obtained in this paper for cod.

It would be an interesting future project to explicitly compare the two methods on the same data set. Due to data limitations, it is not possible to replicate their results with my data. Kristofersson and Rickertsen use a two-stage hedonic regression method where in the first stage, prices and their standard deviations of category prices are estimated for each day from every single auction that took place. Since my data is already aggregated on a monthly level, it is not possible to use this method.

Overall, the results show that size is an important quality characteristic when estimating fish demand. There are few general conclusions to be made for the different species. The relationship between size and price is highly dependent on the species of fish.

6 Discussion

In general, large fish are more expensive than small fish (table 3) for several reasons. Economies of scale is of course one reason, filleting a fish of 2 kilos takes less time than two fish of 1 kilo while the quantity of the finished product is about the same. It could also be demand driven, consumers are willing to pay for larger fish. In a meeting with Ilona Miglacs, a marine biologist at the Gothenburg Fish Auction which is the largest trading place for fish in Sweden, she stated that "*larger fish means less work and a more delicious result in the kitchen*". However, that price differs so much for different size categories means that the average price for a species can vary, not only due to changes in total harvest, but also due to long- or short-term variation in the size composition of the stock, which can be induced both by endogenous and exogenous factors.

The price structure might be a sufficient incentive for high grading. But for species that are traded in small quantities, such as common sole, it is also likely that the single fishermen can make an impact on the price. For these species, the incentives for high-grading are larger when increasing the catch of more expensive fish has little effect on the prices of other fish, and the effect of the discarded fish on the prices of other fish is large. For example, larger plaice are much more expensive than small. High-grading would mean that smaller plaice are discarded to make room for larger plaice. The effects of an increase in the catch of large plaice on the price of smaller plaice are small while the effects of a decrease in the catch of small plaice on larger fish are large. Hence, engaging in high-grading by discarding small plaice to make room for larger specimen is much more profitable than the high-grading of e.g. common sole where the relationship is the opposite.

Unfortunately, there is no data on what species are subject to high grading in Sweden. One of the main motivations of high grading is to increase the value of the catch, especially for the species where size is of importance such as shrimp where around 15 % of the yearly catch are estimated to be thrown back into the water (Fiskeriverket 2011). The results from this paper highlight the differences in price, and also how changes in the size composition affect the prices in different size categories and can thus be used as indicators for the species where the incentives for high-grading are high. Since fish that are thrown back into the sea have high mortality rates, high-grading does not only have an effect on the size composition of today's harvest but also an indirect effect on that of tomorrow. The simple fact that price differs per kilo for fish of different sizes also says something about the problems growth overfishing might create. For example, if growth overfishing of large, more valuable fish eventually decreases the average size of each fish, a given biomass will yield less on the market. This may either incentivize fishermen to harvest more fish to increase their income which can have potentially harmful consequences, or if the species have a binding cap, make fishing less profitable and further diminish the ranks of fishermen in Sweden.

Since fishermen are allowed to throw some fish back into the water, for example bycatch for which the vessel does not have any quota, it is difficult to observe high-grading. High-grading has been illegal since 2010 but the authorities cannot check whether it still occurs and early estimates indicate that it still is a problem (Fiskeriverket 2011). To combat high-grading one could change the incentives for the fishermen. Through the selection of gear and the practice of high-grading, fishermen can influence the size of the fish they catch. So how can the incentives for fishermen to engage in high-grading and growth overfishing be reduced? To discuss this, I summarize the recent literature on regulation in age-structured fishery models in the next sub section.

Age structured fishery models

Traditional fishery biomass models, see for example Clark (1990), have been criticized for being too blunt to be used for studying optimal management, see e.g., Quaas et al. (2010) or Tahvonen (2009). Competing models that take into account the growth and aging of stocks are not new, see e.g., Beverton and Holt (1957), but have been used more sparsely than the less complex biomass models based on Schaefer (1957). Age structured models are closer to reality in that they, for example, allow prices to differ for different sizes of fish. They also allow for the use of differentiated fishing gear such as different mesh sizes which only target parts of the fish stock.

The marginalized use of age-structured models can be attributed by the increased complexity of the models. For example, in his seminal book on managing renewable resources, Clark writes that "*including age structure in the analysis introduces significant new mathematical difficulties, Indeed, the problem of the optimal harvesting of age-distributed populations remains unsolved in general*" (Clark 1990 p. 267). However, there are earlier studies that have solved age-structured models (see Getz and Haight 1989 for a summary) but these have been criticized for relying too heavily on ad hoc assumptions for tractable numerical solutions, see Quaas et al. (2010). But with better programs and computers, these complex models can be solved with less restrictions using numerical methods, see Tahvonen (2009). So what are the conclusions for optimal harvesting and regulation from these more recent theoretical models?

Tahvonen (2009) sets up an age-structured fishery model in a discrete setting to study optimal harvesting.[12] He finds that the lessons learnt on optimal extraction from the use of biomass models do not necessarily carry over to the age-structured model. The main differences between optimal harvesting in biomass and age-structured models, and hence also the reasons for why it is important to base regulation on age-structured models, are the following. The optimal harvest of age-structured models does not only depend on biological factors such as in the biomass model but also on fishing technology. The conditions for the existence of optimal steady states are different. Transition paths are different in that they are always monotonic for the biomass model but may be non-monotonic for age-structured models. Pulse fishing might prove to be optimal in age-structured models but never for biomass models. Hence, basing regulation on biomass models can lead to suboptimal outcomes.

Quaas et al. (2010) use a discrete age-structured fishery model to look at the optimal harvest

[12] Tahvonen 2009 also serves as an excellent survey of prior models of age-structured fishery models.

and discuss the consequences for regulation. They suggest that optimal harvest can be implemented by setting a single total allowable catch (TAC) and then tradable harvest quotas. Harmful overfishing is divided into two categories, growth overfishing and recruitment overfishing, which means that immature fish have been over harvested. To implement optimality in this age-structured model, the quotas should be traded in numbers of fish harvested and not on biomass. Quotas based on biomass prove not to be able to solve the problem of growth and recruitment overfishing simultaneously. Alternative instruments which can also yield first-best solutions are harvesting fees for the number of fish harvested. The fees should then differ over maturity levels (weight).

The most recent development (to my knowledge) is by Diekert (2012) who sets up a continuous age-structured model to look at harvest and regulation. Diekert confirms and strengthens the conclusions of Quaas et al. (2010), namely that any regulation should be based on the number of fish caught and not biomass. However, Diekert finds that in a continuous setting, even though ITQs based on numbers are superior to other regulation methods, it does not implement the first-best solution. Thus, he argues for complementary regulation methods such as size restrictions.

As in Tahvonen (2009) and Quaas et al. (2010), the price is dependent on fish size in Diekert (2012). However, the prices are implicitly assumed to be constant for different harvest levels. The authors argue strongly and convincingly that age-structured fishery models are better alternatives than biomass models. The conclusion for regulation is that restrictions should be based on numbers and not biomass for regulation purposes. If implemented, this would eventually change the size composition of the catch. However, in the models, there are no general equilibrium effects on price due to changed harvest patterns in different size categories. The results of my paper show clearly that the size of the catch in the different categories affects the prices which, in turn, affect optimal management and regulation. The estimates can shed some light on how size or number based regulation affect market prices.

7 Conclusion

In this study, I have used inverse demand models to study the relationship between size and the price of different fish species. After a selection procedure to find the most appropriate model, quantity and scale flexibilities for six species were estimated using a DICBS model. For two species, cod and plaice, the symmetry assumption of the quantity effects was rejected. Both these species have a skewed distribution towards smaller fish. This is interesting from an applied perspective as it might point to limitations of the usefulness of inverted models.

The estimates showed that size is a crucial determinant for price per kilo and also that variations of the catch in the different size categories have very different effects on the prices of other size categories. This is interesting since the stock composition and catch can change both due to exogenous and endogenous factors, such as growth overfishing, climate change and regulation. In the longer run, this of course also changes the incentives for the fishermen.

New theory in fishery management using age-structured models calls for regulation that takes maturity and size into account. This is emphasized both by biologists and economists. In a study on the aging of Atlantic cod, Almroth et al. (2012) conclude that "[t]*he results emphasize the importance of conserving old mature fish, in particular high egg-productive females, when managing fisheries*." To improve on the regulation, economists have studied age-structured models. The main lesson from these models is that quotas should be defined in numbers and not in biomass. This gives fishermen incentives to catch larger specimen of the different fish species and will, in turn, affect the size composition of the catch which has consequences for prices. The estimates from this paper shed some light on how prices might change for different types of regulations. For example, whiting has similar prices and landings in all size categories. Changing the incentives through regulation so that larger whiting are caught is estimated to have an increasing impact on the price on average since the effect of less small fish on price is estimated to be large and the effect of more large fish is estimated to be smaller.

The exact effect of changed incentives for fishermen on fish stocks due to new regulation is difficult to foresee. However, since the relationship between size and price is estimated to be strong and also dependent on the actual weight class, I conclude that size is an important aspect of fish demand. Biological reasons and a changing climate along with growth overfishing and high grading mean that the relationship between size and price deserves attention in future research and new regulation.

References

- Almroth, B.C., Sköld, M. and Nilsson Sköld, H., 2012. Gender differences in health and aging of Atlantic cod subject to size selective fishery. *Biology Open*, [online] Available at: http://bio.biologists.org/content/early/2012/07/30/bio.20121446.abstract?cited-by=yes&legid=biolopen;bio.20121446v1 [Accessed 4 September 2012].
- Anderson, R.W., 1980. Some theory of inverse demand for applied demand analysis. *European Economic Review*, 14, pp.281-290.
- Angrist, J.D., Graddy, K. and Imbens, G.W., 2000. The interpretation of instrumental variables estimators in simultaneous equation models with an application to the demand for fish. *The Review of Economic Studies*, 67(3), pp.499-527.
- Aps, R. and Lassen, H., 2010. Recovery of depleted Baltic Sea fish stocks: a review. *ICES Journal of Marine Science*, 67, pp.1856 - 1860.
- Asche, F., Bjørndal, T. and Gordon, D., 2005. Demand structure for fish. *SNF Working Paper* No. 37/05.
- Asche, F., Salvanes, K.G. and Steen, F. 1997. The curse of uncertainty in a fishery. *SNF report* No. 61/97
- Barten, A.P., 1969. Maximum likelihood estimation of a complete system of demand equations. *European Economic Review*, Fall, pp.7-73.
- Barten, A.P. and Bettendorf L.J., 1989. Price formation of fish. *European Economic Review*, 33, pp.1509-1525.

- Beverton, R. and Holt, S.J., 1957. *On the dynamics of exploited fish populations*, Fishery Investigation Series II, vol 19. London: Chapman & Hall.
- Brown, M.G., Lee, J.Y. and Seale, J.L., 1995. A family of inverse demand systems and choice of functional form. *Empirical Economics*, 20, pp.519-530.
- Carroll, M.T., Anderson, J.L. and Martínez-Garmendia, Josué, 2001. Pricing U.S. North Atlantic bluefin tuna and implications for management. *Agribusiness*, 17(2), pp.243-254.
- Casini, M., Bartolino, V., Molinero, J.C. and Kornilovs, G., 2010. Linking fisheries, trophic interactions and climate: threshold dynamics drive herring Clupea harengus growth in the central Baltic Sea. *Marine Ecology Progress Seriess*, 413, pp.241-252.
- Chiang, F.S., Lee, J.Y. and Brown, M.G., 2001. The impact of inventory on tuna price: an application of scaling in the rotterdam inverse demand system. *Journal of Agricultural and Applied Economics*, 33(3), pp.403-411.
- Clark, C.W., 1990. *Mathematical bioeconomics: Optimal management of renewable resources*. 2nd ed. Hoboken: John Wiley and Sons, Inc.
- Davis, M.W., 2002. Key principles for understanding fish bycatch discard mortality. *Canadian Journal of Fisheries and Aquatic Sciences*, 59(11), pp.1834-1843
- Deaton, A., 1979. The distance function in consumer behaviour with applications to index numbers and optimal taxation. *The Review of Economic Studies*, 46(3), pp.391-405.
- Deaton, A. and Muellbauer, J., 1980. An almost ideal demand system. *The American Economic Review*, 70(3), pp.312-326.
- Diekert, F.K., 2012. Growth overfishing: the race to fish extends to the dimension of size. *Environmental Resource Economics*, [online] Available at: http://www.springerlink.com/conten t/07g8612371833584/?MUD=MP [accessed 18 April 2012]
- Eales, J.S., Durham, C. and Wessells, C.R., 1997. Generalized models of Japanese demand for fish. *American Journal of Agricultural Economics*, 79(4), pp.1153-1163.
- Eales, J.S. and Unnevehr, L.J., 1993. Simultaneity and structural change in U.S. meat demand. *American Journal of Agricultural Economics*, 75(2), pp.259-268.
- Eales, J.S. and Unnevehr L.J., 1994. The inverse almost ideal demand system. *European Economic Review*, 38, pp.101-115.
- Fiskeriverket, 2011. *Fiskbestånd och miljö i hav och sötvatten*. Ödeshög: Fiskeriverket.
- Fousekis, P. and Karagiannis, G., 2001. Wholesale level demand for fish grades in Greece. *Applied Economics Letters*, 8, pp.479-482.
- Galdeano, E., 2005. An inverse demand analysis with introduction of quality effects: an application to Spanish consumption of fruit and vegetables. *Agricultural Economics*, 33, pp.163-177.
- Getz, W.M. and Haight, R.G., 1989. *Population harvesting: Demographic models of fish, forest, and animal resources*. Princeton: Princeton University Press.
- Guttormsen, A.G., Kristoffersson, D. and Nævdal, E., 2008. Optimal management of renewable resources with Darwinian selection induced by harvesting. *Journal of Environmental Economics and Management*, 56(2), pp.167-179.

– Holt, M.T., 2002. Inverse demand systems and choice of functional form. *European Economic Review*, 46, pp.117-142.

– Holt, M.T. and Goodwin, B.K., 1997. Generalized habit formation in an inverse almost ideal demand system: an application to meat expenditures in the U.S.. *Empirical Economics*, 22, pp.293-320.

– Houck, J.P., 1965. The relationship of direct price flexibilities to direct price elasticities. *Journal of Farm Economics*, 47(3), pp.789-792.

– Keller, W.J. and Van Driel, J., 1985. Differential consumer demand systems. *European Economic Review*, 27, pp.375-390.

– Kristofersson, D. and Rickertsen, K., 2004. Efficient estimation of hedonic inverse input demand systems. *American Journal of Agricultural Economics*, 86(4), pp.1127-1137.

– Kristofersson, D. and Rickertsen, K., 2009. Highgrading in quota-regulated fisheries: evidence from the icelandic cod fishery. *American Journal of Agricultural Economics*, 91(2), pp.335-346.

– Laitinen, K. and Theil, H., 1979. The Antonelli Matrix and the reciprocal slutsky matrix. *Economics Letters*, 3, pp.153-157.

– Lee, Y. and Kennedy, P.L., 2008. An examination of inverse demand models: an application to the U.S. crawfish industry. *Agricultural and Resource Economics review*, 37(2), pp.243-256.

– McConnell, K.E. and Strand, I.E., 2000. Hedonic prices for fish: Tuna prices in Hawaii. *American Journal of Agricultural Economics*, 82, pp. 133-144.

– McLaren, K.R. and Wong, K.K.G., 2005. Specification and estimation of regular inverse demand systems: a distance function approach. *American Journal of Agricultural Economics*, 87(4), pp.823-834.

– Moschini, G. and Vissa, A., 1992. A linear inverse demand system. *Journal of Agricultural and Resource Economics*, 17(2), pp.294-302.

– Muhammad, A. and Hanson, T.R., 2009. The importance of product cut and form when estimating fish demand: the case of U.S. catfish. *Agribusiness*, 25(4), pp.480-499.

– Neves, P.D., 1994. A class of differential demand systems. *Economics Letters*, 44, pp.83-86.

– Ottersen, G., Hjermann, D. and Stenseth, N., 2006. Changes in spawning stock structure strengthen the link between climate and recruitment in a heavily fished cod (Gadus morhua) stock. *Fisheries Oceanography*, 15(3), pp.230-243.

– Park, H. and Thurman, W.N., 1999. On interpreting inverse demand systems: a primal comparison of scale flexibilities and income elasticities. *American Journal of Agricultural Economics*, 81(4), pp.950-958.

– Park, H., Thurman, W.N. and Easley JR, J.E., 2004. Modeling inverse demands for fish: empirical welfare measurement in gulf and south atlantic fisheries.*Marine Resource Economics*, 19, pp.333-351.

– Quaas, M.F., Requate, T., Ruckes, K., Skonhoft, A., Vestergaard, N. and Voss, R., 2010. Incentives for optimal management of age-structured fish populations. In: WCERE 2012; Fourth world congress of environmental and resources economists; 2010, Montreal, Canada.

– Rickertsen, R., 1998. The effects of advertising in an inverse demand system: Norwegian vegetables revisited. *European Review of Agricultural Economics*, 25, pp.129-140.

– Salvanes, K.G. and Steen, F., 1994. Testing for relative performance between seasons in a fishery. *Land Economics*, 70(4), pp.431-447.

– Schaefer, M.B., 1957. Some considerations of the dynamics of populations important to the management of commercial marine fisheries. *Journal of the Fisheries Research Board of Canada*, 14, pp.669-681.

– Tahvonen, O., 2009. Optimal harvesting of age-structured fish populations. *Marine Resource Economics*, 24, pp.147-169.

Table 14: Size categories[a]

	Category 1	Category 2	Category 3	Category 4	Category 5
Cod	>7	7-4	4-2	2-1	1-0.3
Common sole	>0.5	0.5-0.33	0.33-0.25	0.25-0.17	0.17-0.12
Haddock	>1	1-0.57	0.57-0.37	0.37-0.17	
Hake	>2.5	2.5-1.2	1.2-0.6	0.6-0.28	0.28-0.2
Herring	>0.25	0.25-0.13	0.13-0.09	0.09-0.05	0.05-0.03
Lemon Sole	>0.6	0.6-0.35	0.35-0.18		
Plaice	>0.6	0.6-0.4	0.4-0.3	0.3-0.15	
Saithe	>5	5-3	3-1.5	1.5-0.3	
Whiting	>0.5	0.5-0.35	0.35-0.25	0.25-0.11	

[a] Average weight per fish in each size category.

Table 15: Flexibilities, Cod

	Quantity Flexibilities					Scale Flexibilities
	Category 1	Category 2	Category 3	Category 4	Category 5	
C1	-0.221	0.060	0.016	0.004	-0.026	-0.895
	-0.320, -0.122	*0.029, 0.090*	*-0.001, 0.033*	*-0.004, 0.013*	*-0.034, -0.019*	*-1.011, -0.779*
C2	0.153	-0.120	0.026	-0.018	-0.039	-0.983
	0.076, 0.230	*-0.250, -0.149*	*0.005, 0.047*	*-0.026, -0.009*	*-0.047, -0.031*	*-1.031, -0.936*
C3	0.134	0.082	-0.112	-0.085	-0.108	-0.996
	-0.007, 0.276	*-0.014, 0.151*	*-0.157, -0.068*	*-0.098, -0.059*	*-0.128, -0.090*	*-1.000, -0.936*
C4	0.173	-0.240	-0.320	-0.419	-0.363	-0.973
	-0.142, 0.487	*-0.364, -0.114*	*-0.403, -0.238*	*-0.497, -0.342*	*-0.434, -0.291*	*-1.001, -0.945*
C5	-1.134	-0.687	-0.576	-0.462	-0.491	-1.029
	-1.43, -0.837	*-0.811, -0.563*	*-0.662, -0.491*	*-0.539, -0.385*	*-0.567, -0.416*	*-1.056, -1.001*

95 % confidence intervals in italics.

Table 16: Flexibilities, Plaice

	Quantity Flexibilities				Scale Flexibilities
	Category 1	Category 2	Category 3	Category 4	
C1	-0.111	-0.017	-0.081	-0.095	-0.948
	-0.165, -0.056	*-0.039, 0.005*	*-0.093, -0.068*	*-0.114, -0.075*	*-1.050, -0.847*
C2	-0.064	-0.405	-0.169	-0.259	-0.920
	-0.146, 0.018	*-0.459, -0.351*	*-0.192, -0.145*	*-0.300, -0.217*	*-0.975, -0.866*
C3	-0.433	-0.241	-0.545	-0.352	-1.026
	-0.525, -0.342	*-0.287, -0.194*	*-0.584, -0.507*	*-0.403, -0.301*	*-1.053, -0.999*
C4	-0.341	-0.259	-0.232	-0.339	-1.045
	-0.421, -0.261	*-0.305, -0.212*	*-0.261, -0.203*	*-0.393, -0.286*	*-1.095, -0.995*

95 % confidence intervals in italics.