Efficient Estimation of Hedonic Inverse Input Demand Systems

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Abstract

The paper is concerned with efficient estimation of characteristics demand. We derive and estimate an inverse input demand system for quality characteristics by using 172,946 observations over 881 trading days in the Icelandic fish auctions. An improved estimation method based on an expanded random coefficient model is suggested as an alternative to the currently used two-stage method of Brown and Rosen (1982). The estimates demonstrate the improved efficiency of the suggested method. A number of empirical results emerge, including a general increase in the demand for quality.

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Introduction

The purpose of hedonic price analysis is to determine how the price of a unit of a commodity varies with its characteristics, i.e. to estimate the hedonic price function. Some recent examples on estimation of hedonic price functions are Nerlove (1995), Combris et al. (1997), and McConnell and Strand (2000). However, theory predicts that shifts in supply or demand affect the implicit price relationships between the overall price of the good and its individual characteristics, and so we need to estimate the underlying demand and supply functions for the characteristics. Rosen (1974) developed a two-stage method for analyzing hedonic markets. In the first stage, the hedonic price function is estimated and in the second stage a system of demand and supply functions for characteristics is estimated, using the shadow prices of the characteristics from the first stage as variables. Brown and Rosen (1982) showed that this procedure could yield estimates of demand and supply functions that are mere transformations of the coefficients in the hedonic function. They suggested the currently used two-stage method using data from multiple markets. This method utilizes the within-market variation to identify the marginal characteristic prices and the between-market variation to identify the demand and/or supply function.

Some econometric problems are associated with Brown and Rosen's two-stage method. First, the first-stage errors are generally heteroscedastic as is easily verified by substitution of the second-stage demand model into the first-stage hedonic model as discussed below[1]. Second, given that the supplies of characteristics are perfectly inelastic and an inverse demand structure is assumed, the second-stage dependent variables are the estimated marginal characteristics prices and the resulting second-stage estimates are unbiased but inefficient. Third, given that the supplies of characteristics are perfectly elastic and an ordinary demand structure is assumed, the estimated marginal characteristics prices will be used as the second-stage independent variables, resulting in biased and inconsistent second-stage estimates. Fourth, given that both the supplies and demands of characteristics are endogenous, they have to be estimated simultaneously using instrumental variable techniques. For further discussion about the econometric problems associated with characteristic demand analysis, see Epple (1987) and Bartik (1987).

In spite of these inherent problems, the two-stage method has frequently been used in environmental economics to assess welfare effects of externalities (see Zabel and Kiel (2000) for a recent example). The method has also been applied to characteristics of other products such as cotton fibers (Bowman and Ethridge, 1992), US automobiles (Bajic, 1993), baseball players (Stewart and Jones, 1998), and coal (Kolstad and Turnovsky, 1998).

The contributions of this paper are as follows. First, we derive an inverse input demand system for quality characteristics from a distance function under the assumption of perfectly inelastic supply of characteristics. In this case, the estimated implicit prices will reflect the market's valuation of the characteristics.

Second, we use a random coefficient model to estimate characteristics demand. In this model, the first-stage hedonic price function and the second-stage inverse input demand system are estimated simultaneously using the correct variance structure. This joint estimation method has been used to allow for spatial variation in hedonic parameter estimates (Jones, 1991 and Jones and Bullen, 1993). We use it to identify the demand structure for data from multiple markets. Our random coefficient model is expanded to include an inverse demand system as explanatory variables for the random coefficients[2]. The model solves the problem of a heteroscedastic first-stage covariance matrix and is more efficient than the currently used two-stage method. Efficiency is crucial for estimates used in welfare analysis, because imprecise estimates may result in misleading policy recommendations. The method is applicable when data from multiple markets are available and an inverse demand structure is appropriate; for example, in studies of welfare effects of environmental quality changes or characteristics demand for fish and perishable agricultural commodities.

Third, we apply the derived input demand system to the buyers in the Icelandic auction market for cod[3] and compare the efficiency of the random coefficient estimates with the traditional two-stage estimates. Fresh fish is a good example of a heterogeneous good whose price is determined by characteristics[4]. We use data for the cod sold in Icelandic fish auctions over the 1998-2000 period or more than 170,000 transactions. The fish auctions have evolved since 1987 when they were established as a part of the liberalization of the fish market. Today, buyers remotely purchase fresh fish in real time in one central daily auction connecting 19 auctions in 30 locations.

The Distance Function and Inverse Input Demand Functions

Kolstad and Turnovsky (1998) developed an input demand system for quality differentiated inputs and, for the most part, we follow their theoretical framework and notation. However, a major difference is that we treat the supplied quantities of characteristics as exogenous. In our case, the daily supplies of the characteristics of fresh fish are given at the start of each auction (see also Barten and Bettendorf, 1989). Under this assumption, the daily prices of characteristics are determined by demand, and we then derive an inverse instead of an ordinary input demand system for quality characteristics. We start with a production technology involving a vector of outputs, y. The firm uses conventional inputs aggregated into one composite input, x, and one heterogeneous input, q, available with a variety of per unit characteristics, z. We write the production set as

$$g\left(x,q,z,y\right)\leq 0. \tag{1}$$

Producers face the price, p_x, for the composite input and a price function $\rho(z;\alpha)$ for the heterogeneous input. Here α is a vector of marginal characteristics price parameters that allow for the existence of multiple markets with multiple price functions.

Let the characteristics vector, z, consist of two types of characteristics; "goods" and "bads." The two characteristics are bundled together in the heterogeneous input. They cannot be unbundled without incurring costs. For example, fresh fish includes the good fillet and the bad gut. We assume that only the total quantities of the good and the bad are of interest for the producer, and that mixing or repackaging different qualities of the heterogeneous input can produce these quantities. For example, to produce 100 kg of fillets you can either use 200 kg of gutted fish, 230 kg of non-gutted fish, or any combination of these two bundles[5]. We denote the total quantities of the characteristics, bad and good, as B and G. In a market, producers can choose between different (B,G) bundles with values given by the associated value function $V(B,G;\alpha)$ showing the minimum cost of obtaining a specific (B,G) bundle.

We assume that the value function has three properties. First, the value function is convex, or

$$V(\hat{B},\hat{G};\alpha)+V(\widetilde{B},\widetilde{G};\alpha)\geq V(\hat{B}+\widetilde{B},\hat{G}+\widetilde{G};\alpha) \tag{2}$$

where $(\hat{B},\hat{G})$ and $(\widetilde{B},\widetilde{G})$ are two bundles. Since $(\hat{B}+\widetilde{B},\hat{G}+\widetilde{G})$ can easily be assembled from the two bundles by repackaging, equation (2) holds. Second, the good is positively valued and the bad is negatively valued, implying that V is monotonically increasing in G and monotonically decreasing in B. Third, we assume that the cost of providing a bundle is independent of the scale of the bundle, implying that the value function is homogenous of degree one[6].

Let b and g denote the per unit (of input) quantities of the good and the bad, such that

$$b = B/q \quad \text{and} \quad g = G/q. \tag{3a}$$

The vector of per unit characteristics consists of the per unit quantities of the good and the bad, z=[b g], and the unit value function equals the unit price function or

$$V(z;\alpha)=V(b,g;\alpha)=\rho(b,g;\alpha)=\rho(z;\alpha). \tag{3b}$$

Given homogeneity of degree one, we use the heterogeneous input as a numeraire input and rewrite the value function $V(B,G;\alpha)$ as

$$V(B,G;\alpha)=V(qz;\alpha)=qV(z;\alpha)=q\rho(z;\alpha). \tag{3c}$$

Implementing the assumptions of repackaging on our production set (1) yields

$$g(x,qz,y)\leq 0. \tag{4}$$

The producers' cost minimization problem becomes

$$C(p_x,\alpha,y)\equiv \min_{x,qz}\left\{\left(V(qz;\alpha)+p_x x\right) \mid g(x,qz,y)\leq 0 \text{ and } qz,\, x\geq 0\right\} \tag{5}$$

where the cost function $C\left(p_x,\alpha,y\right)$ shows the minimum costs of producing the given vector of outputs, y. Input demand functions can be derived by using the envelope theorem on the cost function.

To derive our inverse input demand system, we define a distance function possessing properties corresponding to the cost function, i.e. the distance function is homogenous of degree one in input quantities, decreasing in output level, increasing in input quantities, and concave in input quantities. We normalize the prices in equation (5) so the minimum costs of producing the given level of output become unity, or $C\left(p_x,\alpha,y\right)=1$. The distance function is defined by the problem

$$D\left(x,qz,y\right)\equiv\min_{p_x,\alpha}\left\{\left(V\left(qz;\alpha\right)+p_x x\right)\middle|C\left(p_x,\alpha,y\right)=1\text{ and }p_x,\alpha\geq 0\right\}. \qquad (6)$$

Inverse input demand functions are derived from the distance function (6) by the envelope theorem

$$\frac{\partial D\left(x,qz,y\right)}{\partial x}=p_x* \qquad (7a)$$

$$\frac{\partial D\left(x,qz,y\right)}{\partial qz}=\frac{\partial V\left(qz;\alpha*\right)}{\partial qz}=\frac{\partial\rho\left(z;\alpha*\right)}{\partial z} \qquad (7b)$$

where p_x* and α* denote the optimal values of p_x and α. The last equality in equation (7b) follows from equation (3c) since

$$\begin{aligned}\frac{\partial V\left(qz;\alpha\right)}{\partial qz}&=\frac{\partial\left[q\rho\left(z;\alpha\right)\right]}{\partial qz}=\frac{\partial\left[q\rho\left(z;\alpha\right)\right]}{\partial z}\frac{\partial z}{\partial zq}\\&=q\frac{\partial\left[\rho\left(z;\alpha\right)\right]}{\partial z}\frac{1}{q}=\frac{\partial\rho\left(z;\alpha\right)}{\partial z}.\end{aligned} \qquad (8b)$$

The choice of functional form of hedonic models has been discussed by, for example, Cropper et al. (1988). However, theory provides no clear guidance for the choice of a "best" functional form. We use a linear form for two reasons. First, our panel data set is highly unbalanced and identification problems are more frequent for non-linear than linear models. Second, the parameter estimates of the linear hedonic model are the marginal prices, simplifying the second-stage estimation. Our linear hedonic price function has the form

$$p_{nt} = \sum_{k=1}^{K} \beta_{kt} z_{knt} \tag{9}$$

where p_{nt} is the price of transaction n in day (or sub market) t, β_{kt} is a time-varying parameter representing the marginal price of characteristic k, and z_{knt} is the level of characteristic k. The marginal price of each characteristic is given by

$$\frac{\partial p_{nt}}{\partial z_{knt}} = \beta_{kt}. \tag{10}$$

The translog, generalized Leontief, and generalized McFadden functional forms are commonly used to approximate cost functions. These forms can also be used to approximate distance functions. Since the quantity data include zero observations, we use the generalized McFadden form with a trend variable

$$D(q,y,t) \equiv \frac{y_t}{2q_{It}} \sum_{i=1}^{I-1} \sum_{j=1}^{J-1} c_{ij} q_{it} q_{jt} + \sum_{i=1}^{I} b_{iy} q_{it} y_t + \sum_{i=1}^{I} a_i q_{it} + \sum_{i=1}^{I} d_i q_{it} t \tag{11}$$

where symmetry implies that $c_{ij}=c_{ji.}$ Dividing all cross effects by a numeraire input, $q_{It,}$ imposes homogeneity. The q_i variables are defined in Table 1 and the quantity of cod from other sources than the fish auctions (i=9) is used as numeraire input. The trend variable, t, is added to allow for changes over time.

By using the envelope theorem (7b) on equations (9) and (11), the inverse input demand functions representing the marginal characteristic prices are

$$\beta_{kt} = \frac{\partial D}{\partial q_{kt}} = a_k + \frac{y_t}{q_{It}} \sum_{j=1}^{J-1} c_{kj} q_{jt} + b_{ky} y_t + d_k t. \qquad (12)$$

Data

Íslandsmarkaður, the Network of Icelandic fish auctions, provided the data set. It includes auction data for cod over the 1998 – 2000 period, covers 1008 auction days with 176,674 transactions, and includes a quantity of 138,776 tons with a market value of 17.1 billion ISK or about US$ 236 million[7].

Some observations were excluded due to extreme prices (174 observations) and missing observations of independent variables (2,814 observations). Furthermore, some days, especially Saturdays and Sundays, have few transactions. Unbalanced data represents no problem for the random coefficient model; however, Brown and Rosen's (1982) two-stage method uses OLS at stage one and requires a full rank hedonic model for each day. To facilitate comparison of the estimates of the random coefficient model with the estimates of the two-stage method, we excluded any day with fewer observations than twice the number of estimated parameters. In our case 127 days, including 36 Saturdays and 75 Sundays, with fewer than 14 observations were excluded[8]. Our final sample consisted of 172,946 observations, including 881 days.

The buyers know the weight class of the fish, whether the fish is gutted or not, and the storage time of the fish. We included these characteristics in the first-stage hedonic model and defined the good, fillet, and the bads, gut and storage. This is parameterized in the model as five dummy variables describing the five weight classes of fish sold in the auctions, a dummy variable indicating whether the fish was gutted or not, and a variable for the number of days of storage.

For the second-stage inverse input demand system, we included variables describing the daily supply of inputs. Our inputs included the total quantity of fish (minus gut) in each weight class and the total quantity of gut[9]. We included the product of the number of days of storage and quantity as a proxy variable for bacterial content and other quality factors associated with storage. Furthermore, Statistics Iceland provided data for the quantity of cod from other sources than the fish auctions, the number of workers in the Icelandic fish processing industry as a proxy variable for labor, and the output quantity measured as the value of the output in constant January 1998 prices.

The variables are defined, and the mean values are reported, in Table 1. The characteristics variables, z, belong to the first-stage hedonic price function while the other variables belong to the second-stage inverse input demand system. To ease the interpretation of the first level estimates, the second-stage variables are normalized at their means when the model is estimated.

(Table 1 here)

Estimation Method

Considerer a random coefficient model for the price of transaction n in sub market t, p_{nt}, specified as

$$\begin{gathered} p_{nt} = \mu + \alpha_t + \varepsilon_{nt} \\ \alpha_t \sim iid\ \mathrm{N}\left(0,\tau^2\right) \text{ and } \varepsilon_{nt} \sim iid\ \mathrm{N}\left(0,\sigma^2\right). \end{gathered} \tag{13}$$

The model has one fixed effect, μ, and two variance components. One variance component, τ^2, represents the variation in prices between different markets and the other, σ^2, represents the variation in prices within each market.

The random coefficient model can also be represented as a pair of linked models. This alternative representation is more easily generalized to more complex models. At level one, the price is expressed as the average price for sub market t, β_t, and an error term, ε_{nt}, such that

$$\begin{aligned} p_{nt} &= \beta_t + \varepsilon_{nt} \\ \varepsilon_{nt} &\sim iid\ \mathrm{N}\left(0,\sigma^2\right). \end{aligned} \tag{14}$$

At level two, the average price is expressed as the mean price of all sub markets, μ, and an error term representing random deviation of the average price in each sub market from that mean, α_t, or

$$\begin{aligned} \beta_t &= \mu + \alpha_t \\ \alpha_t &\sim iid\ \mathrm{N}\left(0,\tau^2\right). \end{aligned} \tag{15}$$

As is evident, substitution of equation (15) into equation (14) results in equation (13).

To explain the variation in marginal prices between markets, we replace the mean price, μ, in equation (15) by our inverse input demand system and the random deviation from the mean price, α_t, by a vector of errors, u_t, such that the second-level model becomes

$$\beta_t = \Gamma q_t + u_t \tag{16a}$$

$$u_t \sim iid\ \mathrm{N}\left(\vec{0},\Sigma_u\right) \tag{16b}$$

where q is a vector of variables explaining demand in sub market t, and Γ is the matrix of demand parameters.

Using matrix notation, the hedonic price function (9) in stochastic form may be written as

$$p_{nt} = z'_{nt}\beta_t + \varepsilon_{nt} \tag{17a}$$

$$\varepsilon_{nt} \sim iid\ \mathbf{N}\left(0,\sigma^2\right). \tag{17b}$$

By inserting equation (16a) into (17a), we get the reduced form model

$$p_{nt} = z'_{nt}\left(\Gamma q_t + u_t\right) + \varepsilon_{nt} = z'_{nt}\Gamma q_t + \left(z'_{nt}u_t + \varepsilon_{nt}\right). \tag{18}$$

Equation (18) is a random coefficient model (Bryk and Raudenbush, 1992). It is evident from equation (18) that the second level errors, u_t, are heteroscedastic in z.

Although the error terms given by equations (16b) and (17b) are assumed to be independent, the variance structure is quite complex. It has a first-level variance and a second-level variance-covariance matrix. The covariance terms allow the random prices to vary according to a higher-level joint distribution. The implicit prices are not defined as fixed, separate, and independent but as drawn from a higher-level distribution. If the elements in the second-level covariance matrix are zero, there is no gain in expanding the system beyond the first level (Bryk and Raudenbush, 1992).

Some restrictions are generally appropriate in demand analysis. Homogeneity and symmetry are imposed parametrically on the system. Let R be the matrix of restrictions and write equations (16a), (16b), (17b), and (18) as

$$\beta_t = \Gamma R q_t + u_t \tag{19a}$$

$$p_{nt} = z'_{nt}\left(\Gamma R q_t + u_t\right) + \varepsilon_{nt} = z'_{nt}\Gamma R q_t + \left(z_{nt}u_t + \varepsilon_{nt}\right) \tag{19b}$$

$$u_t \sim iid\ \mathrm{N}(\vec{0}, \Sigma_u) \text{ and } \varepsilon_{nt} \sim iid\ \mathbf{N}(0, \sigma^2). \tag{19c}$$

For simplicity, we assume that the covariance matrix Σ_u is diagonal.

The model specified by equations (19) contains more than one error term, and therefore cannot be estimated by ordinary least squares (OLS). We use iterative generalized least squares (IGLS) as implemented by the Proc Mixed procedure in SAS®. This algorithm simultaneously estimates the fixed and random parameters in a sequence of linear regressions until it reaches a convergence. This facilitates the estimation of a variety of random coefficient models. For a discussion, see Singer (1998).

Empirical Results

We present parameter estimates for the first-stage hedonic price function in Table 2. The OLS column shows the ordinary least squares (OLS) estimates for the data, pooled across sub markets (trading days). These estimates are only consistent in the unlikely case that the marginal prices are fixed across the sub markets; they are mainly presented as a comparison. The two-stage column gives the average parameter estimates of the single day hedonic functions that is the first stage of Brown and Rosen's two-stage method. The RC column shows the estimates from the random coefficient (RC) model. The *t* values are given in the parentheses.

The parameter estimates are in Icelandic crowns (ISK). The estimated parameters have the expected signs and are significantly different from zero. The goods, cod of different weight classes, have positive parameters while the bads, gut and storage, have negative parameters. The price of the smallest fish is lowest and the price of the largest fish is highest indicating a clear preference for larger fish. For example, the RC estimates show that the price per kilogram of cod larger than five kilos is 155.73 ISK, while it is 118.37 ISK for cod smaller than two kilos.

The parameters are not very different across the estimation methods, with the exception of the storage parameters. In most cases, the OLS estimates are numerically larger than the other estimates, but, as noted above, they are inconsistent given different characteristics prices in different sub markets. The *t* values suggest that the random coefficient model generally has higher *t* values than Brown and Rosen's two-stage method, demonstrating the increased efficiency of the estimates.

At the bottom of the table, the variance of the regressions, $\hat{\sigma}^2$, the value of the log-likelihood function, Logl, and Akaike's information criterion, AIC, are reported. The two-stage estimates are obtained by using a dataset consisting of parameter estimates and we do not report goodness of fit measures for this model. The random coefficient model has a substantially better fit than the pooled OLS model, demonstrating increased explanatory power.

(Table 2 here)

Variance component estimates for the random coefficient model without the second-level expansion, test statistics for the variance components being equal to zero (*Z* value), and the associated *P* values are reported in Table 3. We reject the hypothesis that the corresponding variance component for each characteristic is zero and conclude that the marginal characteristics prices vary from day to day. This conclusion indicates that the expanded random coefficient model is preferred to the OLS estimates. The variance component estimates also show that the variability of the marginal characteristics prices increases with the size of cod, and that this variability is larger within each weight class than for the characteristics gut and storage.

(Table 3 here)

The parameters of the inverse demand system (12) estimated by Brown and Rosen's two-stage method and by the expanded random coefficient model are presented in Tables 4 and 5. Except for the trend, the variables of the second-stage were normalized to the mean to facilitate interpretation. An increase of 1.0 in a normalized variable represents a 100% increase as compared with the mean values reported in Table 1. A parameter estimate of –1.0 implies that when quantity increases by 100%, the corresponding characteristic price decreases by 1.0 ISK. The trend was normalized such that the parameter estimates show the annual changes in characteristics prices.

The parameters of the random coefficient model have numerically higher t values in 38 of the 49 cases, indicating an increased efficiency. Moreover, 29 and 35 of the estimated parameters are significant at the 5% level in Tables 4 and 5, suggesting that small effects are more easily detected by using the random coefficient model. In addition, two of the significant parameters in Table 4 have unexpected signs. There are significant negative output effects for cod between 3.5 and 5 kilos (b_{4y}) and for cod larger than 5 kilos (b_{5y}) and, furthermore, an insignificant negative output effect for cod between 2.7 and 3.5 kilos (b_{3y}). None of these effects is significant in the random coefficient model.

The last column in Table 4 contains the adjusted R^2 values and the last column in Table 5 contains the relative reduction in the variance components; see Bryk and Raudenbush (1992) for a discussion of this measure. As expected, the values are quite different. In the two-stage method, the first-level errors associated with each day's marginal prices are assumed away, resulting in overestimated fit for two equations and underestimated fit for two equations. These results, as well as the differences in *t* values, indicate that the random coefficient model improves the estimates, especially for small and variable marginal prices.

Focusing on the estimates of the expanded random coefficient model in Table 5, all the own-quantity variables with the exception of the largest fish are significant and have the expected negative sign. The cross-quantity parameters indicate that cod from different weight classes are substitutes. As expected, the cross-quantity effects of gut and storage on the price of cod in different weight classes are positive. Increased labor supply has a negative effect on the price of each weight class, indicating substitution between labor and the size of the cod. The prices of gut and storage are negative, and the positive labor parameters for gut and storage also indicate substitutability. Two significant output effects are found; one positive for a good and one negative for a bad. The positive trends for all weight classes suggest price increases over the three-year period. On the other hand, the negative trends for gut and storage show increasingly negative prices for these characteristics. In most cases, the parameters suggest that the quantity effects are small, with decreases of less than 2 ISK for 100% increases in the quantities of characteristics, as compared with the mean values. However, there are some exceptions. The effects of increased labor supply on the price of the small and labor-intensive fish are –6.25 ISK

(<2 kg), -4.70 ISK (2-2.7 kg), and –3.03 ISK (2.7-3.5 kg). The effects lessen with increased size. The effect of labor supply on the marginal price of gut is also substantial and positive. As the labor supply increases, compensation for accepting gut is reduced. Among the largest parameter estimates are the trends for cod from different weight classes, with annual increases from 9.14 ISK to 28.04 ISK per kilogram and year.

(Tables 4 and 5 here)

To facilitate interpretation, the second-level flexibilities are reported in Table 6. The own-quantity flexibilities are negative and significant for all weight classes except the largest, for which the flexibility is not significantly different from zero. As expected, the different weight classes are substitutes. The substitution effect seems to be smaller, the greater the weight differences are. For example, the cross-quantity flexibility between medium-sized (2-2.7 kg) and small cod (<2 kg) is –0.03, while it is reduced to –0.01 between small cod and very large cod (>5 kg). As discussed above, labor is a substitute for cod but the substitution effect is reduced with increasing size. The substitutability between labor and gut is substantial, indicating that gutting is labor intensive. Trend flexibility is smallest for the smallest fish and largest for the largest fish, and there has been a shift in demand towards larger fish. The trend flexibilities for gut and storage are also substantial, indicating that the market has become more willing to pay for quality. The own-quantity flexibilities for gut and storage have the highest numerical values, suggesting that the demand for these characteristics is more responsive to supply.

(Table 6 here)

Conclusions and Implications

When data from multiple markets is available and an inverse demand structure is appropriate, we suggest using an expanded random coefficient model instead of the two-stage method of Brown and Rosen that is currently used. The estimated *t* values demonstrate that the suggested method results in more efficient estimates as compared with the less precise, and somewhat dubious, estimates from the two-stage method.

The own-quantity flexibilities for cod of different weight classes are small, showing that the quantities of characteristics supplied to the Icelandic market could be increased substantially without reducing prices. This result is not surprising since the buyers mainly export their final products to the world market and cannot affect domestic prices. The inelastic own-quantity flexibilities also underline the need for quota regulations in a fishery where prices will not regulate supply.

The own-quantity flexibilities of gut and storage are numerically larger than those of cod in different weight classes, showing that the market is more sensitive to the supply of bads than goods. Furthermore, there is a trend in demand away from the bads. This trend is especially clear for storage indicating an increased preference for fresh fish. Large quantity variations in the goods have small effects on prices, while small quantity variations in the bads have large effects on the prices. These results are not surprising in a market where supply is strictly regulated by a quota system and the world market sets prices. In such a market, the buyers can influence the price only through the quality characteristics they can change, in our case the bads, gut and storage.

The trend flexibilities suggest a shift in demand towards larger fish. The inelastic own-quantity flexibility for the largest and most expensive cod in combination with this increased demand for larger cod suggest that it is profitable for fishermen to catch large cod. The results indicate that the economic incentives to discard small cod at sea are substantial, increasing over the study period, and not affected by the supply. Given the practical surveillance problems in quota-regulated fisheries with many fishermen, dumping is potentially a serious problem and our results imply that the regulatory authorities should give this problem serious consideration.

Footnotes

1. See equation (18) below.

2. These explanatory variables may be termed higher level variables, hence the term multilevel hedonic model.

3. Atlantic cod (referred to as cod) is an interesting species from an economic point of view. Of the whitefish species, cods, hakes and haddocks, the Atlantic cod, with an annual catch of about one million metric tons, is the most important in a total whitefish catch of about nine million tons (FAO, 2002). Whitefish is the second largest group of fish traded in the world market after pelagic species such as anchovies and sardines.

4. For studies of fish, see McConnell and Strand (2000) on the Hawaiian auction market for tuna, and Carroll et al. (2001) on the Japanese tuna market.

5. Although repackaging may be an implausible assumption for goods such as houses, it is a plausible assumption for many types of inputs, for example, different grades of fuel

in energy production with pollution constraints or gutted and non-gutted fish in the production of fillets.

6. Homogeneity of degree one for the value function in *G* and *B* implies that the value doubles when the quantities of *G* and *B* double. For example, if the value of 100 kilos of fillets and 50 kilos of gut is 100, then the value of 200 kilos of fillets and 100 kilos of gut is 200. Homogeneity seems to be a plausible assumption in our case given the variety of different technologies coexisting in the Icelandic fishing industry, from one-man vessels to factory trawlers.

7. The exchange rate 01.01.2000 was 100 ISK = US$1.38.

8. The estimation results for the random coefficient model did not change substantially when the excluded observations were included.

9. According to Birgisson and Þorsteinsson (1997), gut in Icelandic cod is on average about 18% of the whole fish weight.

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Table 1. Definitions and Mean Values of Variables

Variable	Definition	Mean
p	The price of each lot in ISK deflated by January 2000 exchange rate index	124.55
z_1	Dummy variable, 1 for very small cod, < 2.0 kg	0.06
z_2	Dummy variable, 1 for small cod, 2.0 kg - 2.7 kg	0.24
z_3	Dummy variable, 1 for medium size cod, 2.7 kg - 3.5 kg	0.27
z_4	Dummy variable, 1 for large cod, 3.5 kg – 5.0 kg	0.17
z_5	Dummy variable, 1 for very large cod, > 5.0 kg	0.27
z_6	Dummy variable for gutting, 1 for non-gutted and 0 for gutted	0.62
z_7	Storage, days	0.49
q_1	Total daily quantity of cod having characteristic z_1, tons per day	10.16
q_2	Total daily quantity of cod having characteristic z_2, tons per day	49.84
q_3	Total daily quantity of cod having characteristic z_3, tons per day	58.46
q_4	Total daily quantity of cod having characteristic z_4, tons per day	28.52
q_5	Total daily quantity of cod having characteristic z_5, tons per day	49.71
q_6	Total daily quantity of gut, tons per day	21.60
q_7	Total daily quantity times storage, tons*days	117.85
q_8	Number of workers in the Icelandic fishing industry	7,447
q_9	Quantity of cod from other sources than the fish markets, tons per month[1]	9,856
y	Total output of the Icelandic fish industry, millions ISK per month[2]	2,359
t	Trend	-

[1] Monthly data including an unknown quantity of undersized cod and not directly comparable to the quantities from the auction markets.

[2] Measured in January 1998 value.

Table 2. Parameter Estimates of the Hedonic Price Function (in ISK)[1]

	OLS	Two Stage[2]	RC
Cod, < 2.0 kg	107.97	105.53	105.48
	(438.85)	(210.77)	(238.19)
Cod, 2.0-2.7 kg	119.22	118.37	118.37
	(734.05)	(228.06)	(276.56)
Cod, 2.7-3.5 kg	134.12	133.03	133.12
	(861.17)	(257.78)	(319.84)
Cod, 3.5-5.0 kg	138.62	138.70	138.90
	(810.10)	(264.78)	(361.99)
Cod, > 5.0 kg	157.93	155.77	155.73
	(1131.85)	(261.87)	(327.42)
Non-gutted cod	-17.37	-15.84	-15.93
	-(130.89)	-(42.93)	-(63.49)
Storage	-1.73	-0.81	-0.71
	-(21.01)	-(4.50)	-(5.76)
$\hat{\sigma}^2$	484	-	157
Logl	-784732	-	-690629
AIC	1569465	-	1381273

[1] Estimated *t* values in parentheses.

[2] Average parameter estimates.

Table 3. Variance Component Estimates

Variable	Estimate	*Z* value	*P* value
Cod, < 2.0 kg	199.2	17.71	0.000
Cod, 2.0 - 2.7 kg	231.0	19.68	0.000
Cod, 2.7 - 3.5 kg	317.5	20.14	0.000
Cod, 3.5 – 5.0 kg	365.4	19.81	0.000
Cod, > 5.0 kg	736.1	20.46	0.000
Non-gutted cod	51.3	17.43	0.000
Storage	8.7	13.98	0.000

Table 4. Estimated Parameters and Adjusted R^2 Using Two-Stage Method[1]

	c_{kj}								b_{ky}	d_k	$\bar{R}^2$
	1	2	3	4	5	6	7	8			
1	-1.49	-3.34	-1.35	-1.87	-1.88	2.02	0.30	-6.35	3.08	8.88	0.80
	(-2.65)	(-6.19)	(-2.67)	(-3.83)	(-3.66)	(4.78)	(1.36)	(-3.23)	(1.25)	(15.85)	-
2	-	-3.64	-2.11	-2.62	-0.93	2.72	1.64	-3.70	3.42	11.61	0.68
	-	(-3.03)	(-2.52)	(-3.47)	(-1.32)	(3.05)	(3.51)	(-1.77)	(1.35)	(20.55)	-
3	-	-	-1.60	-1.62	-0.87	1.15	0.91	-2.60	-1.23	16.94	0.64
	-	-	(-1.44)	(-2.22)	(-1.26)	(1.23)	(2.12)	(-1.29)	(-0.48)	(30.19)	-
4	-	-	-	-2.61	-1.74	3.08	1.35	1.04	-5.04	19.27	0.79
	-	-	-	(-2.78)	(-2.60)	(4.53)	(4.21)	(0.51)	(-1.96)	(33.54)	-
5	-	-	-	-	0.80	0.67	1.35	2.74	-7.34	28.80	0.77
	-	-	-	-	(0.84)	(1.03)	(4.21)	(1.14)	(-2.50)	(43.66)	-
6	-	-	-	-	-	-8.02	-3.82	8.08	-3.17	-2.95	0.14
	-	-	-	-	-	(-5.60)	(-6.47)	(5.46)	(-1.73)	(-7.23)	-
7	-	-	-	-	-	-	-0.73	-0.04	1.12	-1.22	0.07
	-	-	-	-	-	-	(-1.92)	(-0.06)	(1.26)	(-6.13)	-

[1] Estimated t values in parentheses.

Table 5. Estimated Parameters and R^2 Using Expanded Random Coefficient Model[1]

	c_{kj}								b_{ky}	d_k	R^2 [2]
	1	2	3	4	5	6	7	8			
1	-1.55	-3.13	-1.54	-1.58	-1.61	1.36	0.19	-6.25	3.00	9.14	0.43
	(-3.18)	(-6.98)	(-3.74)	(-4.18)	(-3.69)	(4.48)	(1.21)	(-3.33)	(1.32)	(17.21)	-
2	-	-3.28	-2.44	-2.27	-1.07	2.09	1.25	-4.70	5.27	11.23	0.52
	-	(-3.35)	(-3.63)	(-3.84)	(-1.83)	(3.13)	(3.61)	(-2.61)	(2.44)	(23.24)	-
3	-	-	-2.37	-1.38	-1.48	1.28	1.15	-3.03	1.10	16.56	0.66
	-	-	(-2.72)	(-2.47)	(-2.67)	(1.86)	(3.69)	(-1.80)	(0.53)	(35.30)	-
4	-	-	-	-2.02	-2.05	1.66	0.56	-0.76	-2.51	18.76	0.76
	-	-	-	(-2.93)	(-4.03)	(3.39)	(2.34)	(-0.48)	(-1.29)	(42.17)	-
5	-	-	-	-	0.14	1.20	0.30	2.03	-4.54	28.04	0.80
	-	-	-	-	(0.19)	(2.51)	(1.26)	(1.03)	(-1.91)	(52.00)	-
6	-	-	-	-	-	-6.25	-2.86	10.61	-5.58	-2.38	0.30
	-	-	-	-	-	(-5.88)	(-6.64)	(9.70)	(-4.27)	(-7.97)	-
7	-	-	-	-	-	-	-0.53	0.10	0.36	-1.37	0.12
	-	-	-	-	-	-	(-1.99)	(0.18)	(0.56)	(-9.08)	-

[1] Estimated t values in parentheses.

[2] Estimated as the relative reduction in estimated variance components due to expansion; see Bryk and Raudenbush (1992). The unexpanded variance component estimates are given in table 3.

Table 6. Flexibilities for the Second Level[1]

	e_{kj}								e_{ky}	e_{kt}
	1	2	3	4	5	6	7	8		
1	-0.01	-0.03	-0.01	-0.01	-0.01	0.01	0.00	-0.06	0.03	0.08
	(-3.18)	(-6.98)	(-3.74)	(-4.18)	(-3.69)	(4.48)	(1.21)	(-3.33)	(1.32)	(17.21)
2	-0.03	-0.03	-0.02	-0.02	-0.01	0.02	0.01	-0.04	0.04	0.09
	(-6.98)	(-3.35)	(-3.63)	(-3.84)	(-1.83)	(3.13)	(3.61)	(-2.61)	(2.44)	(23.24)
3	-0.01	-0.02	-0.02	-0.01	-0.01	0.01	0.01	-0.02	0.01	0.12
	(-3.74)	(-3.63)	(-2.72)	(-2.47)	(-2.67)	(1.86)	(3.69)	(-1.80)	(0.53)	(35.30)
4	-0.01	-0.02	-0.01	-0.01	-0.01	0.01	0.00	-0.01	-0.02	0.13
	(-4.18)	(-3.84)	(-2.47)	(-2.93)	(-4.03)	(3.39)	(2.34)	(-0.48)	(-1.29)	(42.17)
5	-0.01	-0.01	-0.01	-0.01	0.00	0.01	0.00	0.01	-0.03	0.18
	(-3.69)	(-1.83)	(-2.67)	(-4.03)	(0.19)	(2.51)	(1.26)	(1.03)	(-1.91)	(52.00)
6	-0.09	-0.13	-0.08	-0.11	-0.08	0.40	0.18	-0.69	0.36	0.15
	(-4.48)	(-3.13)	(-1.86)	(-3.39)	(-2.51)	(5.88)	(6.64)	(-9.70)	(4.27)	(7.97)
7	-0.28	-1.84	-1.71	-0.82	-0.44	4.23	0.79	-0.15	-0.54	2.03
	(-1.21)	(-3.61)	(-3.69)	(-2.34)	(-1.26)	(6.64)	(1.99)	(-0.18)	(-0.56)	(9.08)

[1] Estimated *t* values in parentheses.