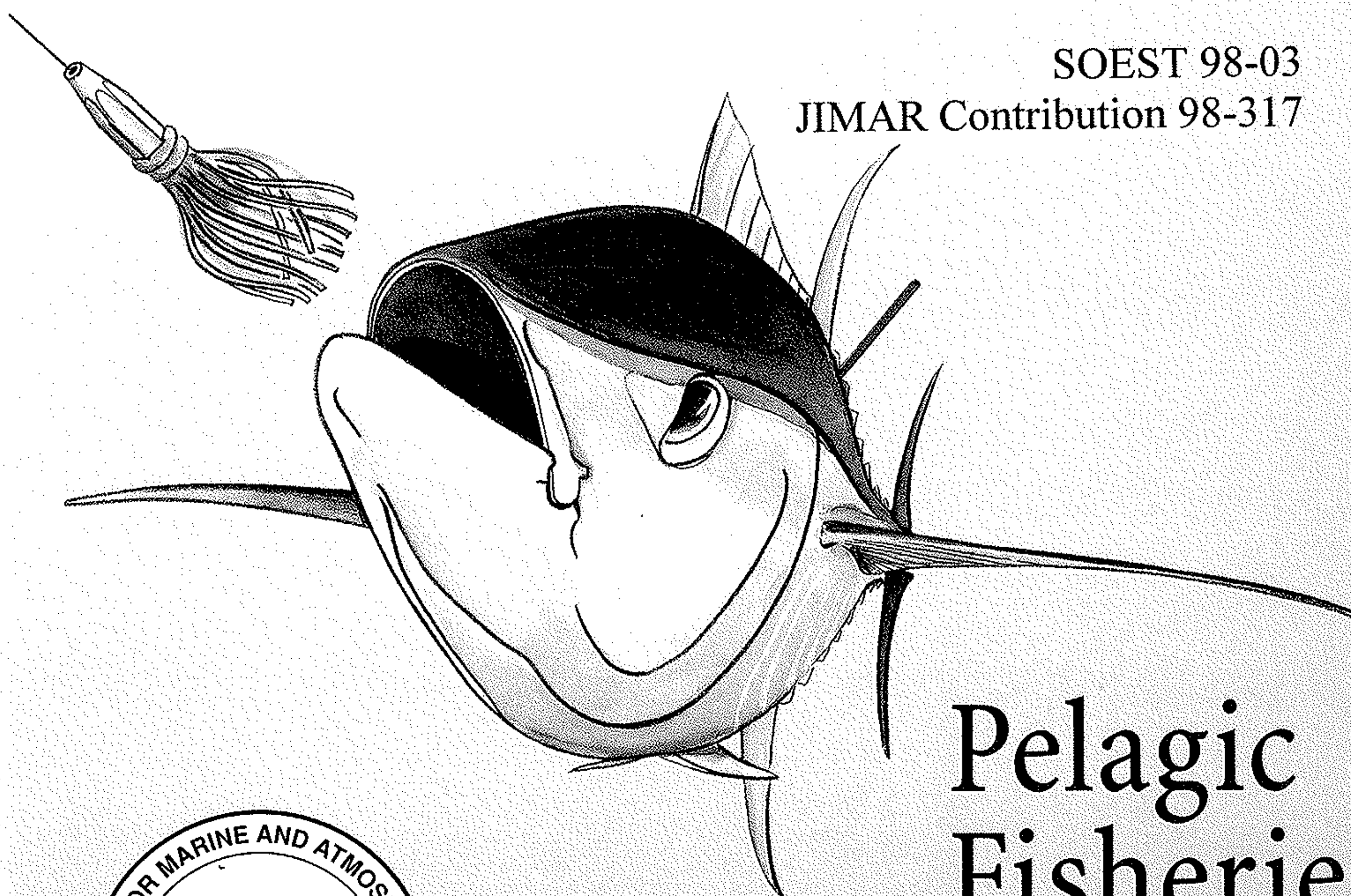
An Analysis of Auction Prices of Tuna in Hawaii: Hedonic Prices, Grading, and Aggregation

K.E. McConnell, I.E. Strand,
and R.E. Curtis

SOEST 98-03
JIMAR Contribution 98-317



JOINT INSTITUTE FOR MARINE AND ATMOSPHERIC RESEARCH ~UH-NOAA~
JIMAR

Pelagic Fisheries Research Program

An Analysis of Auction Prices of Tuna in Hawaii: Hedonic Prices, Grading, and Aggregation

K.E. McConnell,
I.E. Strand,
and R.E. Curtis

Bockstael, McConnell and Strand Inc.
3557 Church Road
Ellicott City, MD 21043

SOEST 98-03
JIMAR Contribution 98-317

This paper is funded in part by Cooperative Agreement Number NA67RJ0154 from the National Oceanic and Atmospheric Administration. The views expressed herein are those of the authors and do not necessarily reflect the views of NOAA or any of its subagencies.

McConnell, K. E., I. E. Strand, and R. E. Curtis, An Analysis of Auction Prices of Tuna in Hawaii: Hedonic Prices, Grading, and Aggregation, 27 pp., University of Hawaii, Joint Institute for Marine and Atmospheric Research, 1000 Pope Rd, Honolulu, HI, 1998.

The authors are with the Department of Agricultural and Resource Economics at the University of Maryland, College Park, MD 20742. We thank JIMAR for making the data available and for supporting this research. We thank Paul Bartram, Marcia Hamilton, Sam Pooley, John Sibert and Mike Travis for comments.

1. Introduction

Commercial harvesters of pelagic fish have the sale of these fish as their primary goal. In Hawaii fisheries, most tuna are sold in the two auctions, the United Fishing Auction in Honolulu and the Suisan Auction in Hilo. How prices paid for fish at these markets respond to increases in landings and the influence of different characteristics of fish are important inputs into fishermen's decisions and the determination of efficient landings. The understanding of price trends and variations in these prices is helpful in planning for investment decisions and in analyzing trends in the industry. The effect of management decisions on prices and hence revenues from fishing can be assessed better by understanding auction price behavior. Using a data series on auction prices gathered by Bartram, Garrod, and Kaneko, this report explores the determination of the price of tuna in Hawaii markets.

Recent analyses of fisheries markets have devoted more attention to the quality attributes of fish. This may be partly attributed to better data availability but the increased concern for managing fisheries (Blomo *et al.*, 1982; Wang and Kellogg, 1988) and the expansion of controlled production through aquaculture (Anderson and Kusakabe, 1989) may also be factors. Conjoint analysis is the most prevalent approach, relying on answers to survey questions from market participants regarding their preferences for seafood with differing characteristics (Anderson and Brooks, 1986; Anderson and Kusakabe, 1989; Wirth, *et al.*, 1991; Sylvia and Larkin, 1994). A major focus of conjoint analysis is the trade-off between the good's price and its attributes.

The Hawaiian markets offer a rare opportunity to reveal preferences for quality attributes of pelagic fish. The transactions in these markets show the trade-off between price and attributes of fish and hence do not rely on responses to hypothetical circumstances. Because the Japanese sashimi market for tuna is so discerning with regard to quality, most harvested tunas are auctioned individually, with their prices reflecting a willingness to pay for the quality attributes of the individual fish. Buyers act as middlemen to purchase tuna for resale in the Japanese market and other markets and they bid for tuna based on their knowledge of the willingness to pay for the fish, given its attributes, in subsequent markets.

The Pelagic Fisheries Research Program recognized the importance of studying the quality and price of tuna by commissioning the study "Quality and Product Determination as Price Determinants in the Marketing of Fresh Pacific Tuna and Marlin" (Bartram *et al.*, 1996). The researchers collected data from the Hawaii tuna and marlin auction, recording individual fish prices and the quality or characteristics of the fish. These data were collected during the two-week period at the end of June and beginning of July in both 1994 and 1995. The Bartram *et al.* study provides excellent descriptions of tuna product types and major markets. On the basis of average prices categorized by attributes, quality-differentiated market attributes were judged to be present. Based on their experience as seafood buyers (Bartram and Kaneko are buyers in the Honolulu market), Bartram *et al.* also provided their assessment of the "grade" of each tuna. The grading melds the individual attributes of each tuna into a numeric scale, ranging from a high of 1+ to a low of 4. Although the rating depends on the individual attributes of the fish, there is no simple "equation" that transforms the attributes into a grade (although we explore such an equation in this report), subjective judgments are inherent and the grade depends on market conditions. Average prices are observed to vary across grades (Figure 1).

We continue to explore the relationship between tuna prices, attributes and grades. Specifically, we examine in Section 2 the relationship between tuna prices and recorded attributes of the tuna using standard hedonic price methods. The relationship between the grades and the attributes will be examined in Section 3. The final section deals with the issue of whether aggregation across species is an appropriate procedure when estimating the demand for tuna. Our use of parametric statistical techniques rather than averages is the major methodological distinction between this report and the report by Bartram *et al.* (1996).

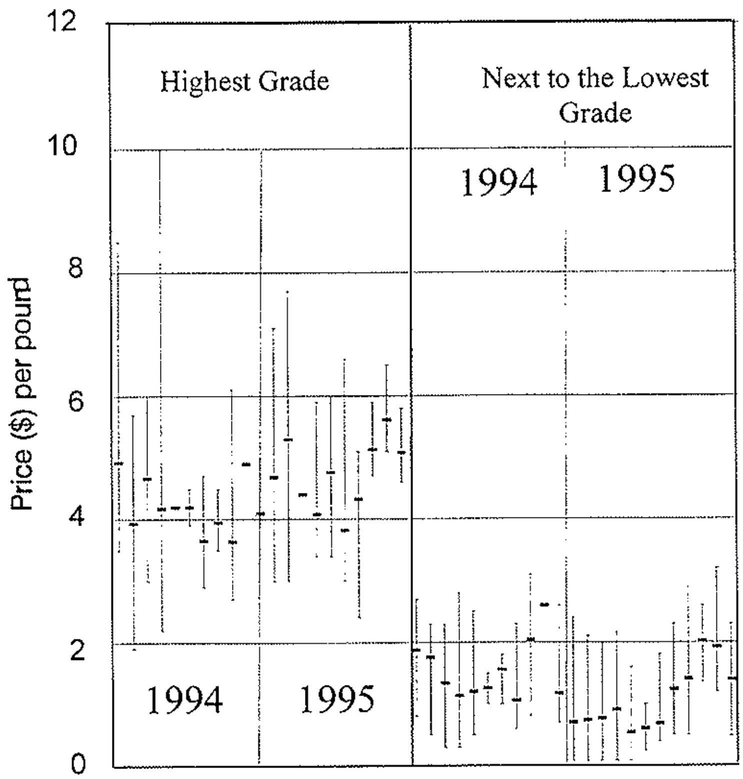


Figure 1. Average daily Hawaiian yellowfin tuna prices for highest and next to the lowest grades.

Three kinds of empirical results are found in this report. First, we estimate hedonic price functions for tuna that demonstrate empirically the value of characteristics and species of fish. Second we show how these characteristics influence the grading of fish. Third, by estimating demand curves on the basis of grades as well as species, we show that aggregation by grades may be more reasonable than aggregating by species, which is the traditional approach. Each empirical effort leaves us with unanswered questions, principally relating to the connection between the Hawaii markets and the world market for tuna.

The empirical results should not be considered as fixed but rather indicative of the kinds of empirical relations that hold. The results depend on the sampling period, late June and early July 1994 and 1995. This season has especially heavy landings of longline-caught fish. Further, during this time period prices are low relative to other times. Despite these shortcomings, the results help in understanding the marketing of tuna in Hawaii.

2. Hedonic Price Models

The prices that emerge in the auctioning of fish can be considered hedonic prices. The price of an individual fish depends on its characteristics, such as species, fat content, type of handling, and so forth. Hedonic prices of fish are similar in concept to hedonic prices of houses, which depend on characteristics such as location, square feet of floor space, lot size, etc., or hedonic prices of wine, which depend on the variety of the grape, year, sugar content, etc. There is a considerable literature on the hedonic prices of agricultural commodities, including tomatoes (Bierlen and Grunewald, 1995), apples (Tronstad *et al.*, 1992), wheat (Espinosa and Goodwin, 1991), cotton (Brown *et al.*, 1995), milk (Gillmeister

et al., 1996), beef (Brester *et al.*, 1993), and grapes (Golan and Shalit, 1993). However, there has been no hedonic study of the prices of fish, despite the growing awareness that the quality of fish is an important characteristic of seafood markets.

While the estimation of hedonic prices for fish is inherently interesting, this will illustrate the continued evolution of the role of quality in fisheries markets. This development has had a significant effect in the marketing of salmon, where the consistent quality of aquacultured fish has been influential in increasing the share of such fish in salmon markets. The role of quality must ultimately play a role in the management of tuna. Fisheries policy, designed in part to harvest fish in a socially efficient way, will be called upon to recognize that some forms of harvest provide more value added than other forms, because they create better products at the market. We provide some evidence of this phenomenon in the analysis of hedonic prices of tuna.

In the present analysis of the hedonic prices of tuna, we address three issues. The first pertains to the empirical content of the hedonic prices. What are the characteristics that determine these prices and what are the marginal values of these characteristics? The second issue concerns the grading of fish. Buyers provide an introspective or 'mental' grade when they examine a fish to determine its quality. How much information do these grades contain? Can the price of fish be explained exclusively by the grade of the fish, or do the characteristics of the fish provide additional information? Finally, we try to understand the degree to which the auction prices of fish are determined by quantities landed on the day the fish is sold. The question relates to Hawaii commercial fishing enterprises and landings. Do additional landings depress prices, and if so, by how much?

Our research finds evidence to support a market of fish by quality. Fish with better quality get higher prices. We show empirically the role of grading. Further, we show that the aggregation of fish by grade appears to provide results that are more consistent with consumer behavior than aggregation by species. These empirical findings, explained in detail below, are dependent on the nature of the datasets gathered. While these datasets are unique within fisheries research in providing grades and qualities, they were gathered during the summer, traditionally a time of low prices in Hawaii auctions. While there is no reason to believe that the qualitative findings would change if data were gathered during a time of more vigorous market activity, it is clear that higher prices would mean higher marginal values for many characteristics. In sum, our results are contingent on the nature of the data gathered.

A Simple Hedonic Price Equation and the Marginal Value of Characteristics of Tuna

The basic theory of hedonic prices explains the price of a commodity as a function of its characteristics. In this model, the increment in price due to increases in any characteristic will equal the buyers' marginal willingness to pay for the characteristic, as well as the marginal cost of producing the characteristic for sellers (Rosen, 1974). When buyers and sellers have time to adjust their responses, the marginal hedonic price equals the marginal value to consumers and the marginal cost to suppliers. In the very short run, such as prevails in fish auctions, equality between the marginal hedonic price and marginal willingness to pay of buyers holds. However, equality between prices and the marginal cost of production would require a longer horizon, perhaps a month or more, to accommodate.

To express the hedonic price analytically, let P_{it} represent the price of the i^{th} fish on the t^{th} day of the survey and let Z_i ($=Z_{i1}, Z_{i2}, \ldots Z_{iJ}$) be the J characteristics which determine the price of the fish. Then the hedonic price equation can be written

$$P_{it} = F(Z_i, t) \tag{1}$$

where F is the function which relates price P_{it} to the individual Z_{ij}. The marginal price of the jth characteristic, say Z_{ij}, is given by the partial derivative:

$$\partial P_{it} / \partial Z_{ij} = \partial F(Z_i, t) / \partial Z_{ij} \tag{2}$$

This shows how a characteristic influences the price as well as the marginal valuation of the characteristic by the buyer. Buyers are willing to pay more for fish with particular characteristics, ultimately reflecting consumer demand. To calculate the marginal price requires the estimation of the hedonic price equation.

The estimation of the hedonic price function is the subject of a vast literature. In estimation, we concentrate on the issues relating to marginal values. In particular, there is a considerable literature on the functional form (see Cropper *et al.*, 1988). In the analysis below, we will eschew the more complicated functional forms for two reasons. First, a simple linear form makes the results on marginal prices transparent. Second, the characteristics of fish tend to be measured quite well compared with other hedonic markets, and the very large number of observations reduces the influence of errors in measurement compared with the Cropper *et al.* analysis.

The linear form of the hedonic price equation is

$$P_{it} = \beta Z_i + \varepsilon_{it} \tag{3}$$

where β is the vector of J coefficients to be estimated, and ε_{it} is the random error term. To illustrate the effect of characteristics on hedonic prices, we choose from the set of characteristics in Table 1. Of the 8635 tuna in the analysis, 35 percent are yellowfin, 24 percent bigeye, and 41 percent albacore. Omitted from the analysis were 175 skipjack. Though not evident from Table 1, the categories of the data gathered for the two years were not exactly the same for both years. In particular, in 1994 more evidence on the flesh of the fish was obtained. The variables describing whether the fish was burned as well as the degree of fat were only available for 1994.

The estimated model includes all the variables in Table 1 except DUMSJ, BURN1, DSFAT, DUMTRL, and DGGILLED. These indicator variables cannot be included because they contain no additional information. The constant term in the regression includes the joint effects of the categories not included. They are the default cases: BURN1, DSFAT, DUMTRL, DGGILLED, and DUMSJ. Consequently the variables indicating the method of landing, species, method of handing or characteristics of the flesh should be interpreted as the increase or decrease over their default case.

Table 2 provides the coefficients for the ordinary least squares model of the hedonic price function. This model of 8635 observations on tuna prices explains 44 percent of the variation in prices, as given by the R^2. The *t*-statistics on the estimated coefficients tend to be quite large. Thirteen of the nineteen variables in the model are significant at the one-

percent level, implying a high level of confidence about most of the coefficients. Other functional forms would explain similar proportions of the variation in price, but would perhaps give different values for the marginal prices.

Table 1. Characteristics of Tuna Sold in the Hawaii Fish Auctions[a].

Variable	Description	Mean	Standard Deviation
SELLPRI	price per pound of fish	1.58	1.21
DUMYF	1 if yellowfin[b]	.35[c]	.48
DUMBE	1 if bigeye	.24	.43
DUMTM	1 if albacore	.41	.49
DUMLL	1 if landed on longliner	.83	.39
DUMHND	1 if landed on handliner	.12	.32
DUMTRL	1 if landed on troller	.05	.22
DUMWHL	1 if fish is whole	.76	.42
DHGUT	1 if fish is headed and gutted	.07	.26
DGGILLED	1 if fish is gutted and gilled, loined or other	.17	.38
WHOLEWT	whole weight of fish, in pounds	87.7	48.4
SUMWTBE	weight of bigeye landings for the day (in 10,000 pounds)	.927	.622
SUMWTTM	weight of albacore landings for the day (in 10,000 pounds)	1.213	.809
SUMWTYF	weight of yellowfin landings for the day (in 10,000 pounds)	1.75	.652
BURN0	1 if the fish is labeled not burned (1994 only)	.27	.44
BURN1	1 if the fish is labeled slight burn (1994 only)	.72	.27
BURN2	1 if the burn label is more severe (1994 only)	.005	.073
BURN3	1 if the burn is most severe (1994 only)	.004	.065
DNFAT	1 if the fish is labeled no fat (1994 only)	.804	.396
DSFAT	1 if the fish is neither labeled fat nor not fat (1994 only)	.178	.382
DFAT	1 if the fish is labeled fat (1994 only)	.018	.13

[a] There are 8635 complete observations for tuna in the dataset.
[b] These variables are 1 if the description is correct and 0 otherwise.
[c] The means are also proportions for 0, 1 variables.

In the hedonic models estimated, we have treated fish as a generic good. That is, all fish are pooled in the same model and the effect of the characteristics, such as species or grade, estimated. Another approach would be to estimate hedonic models for particular kinds of fish, such as yellowfin, bigeye, etc. Such a model would give somewhat different results, simply because it represents a slight variation in functional form. Another potential model would be to estimate hedonic models for each grade. We pool all the fish because evidence presented below (Section 4) suggests that markets appear to function with the quantities of different grades of fish as much as the quantities of different species of fish.

Table 2. Linear Hedonic Model of Tuna Prices.

	Coefficient	***t*-Statistic**
CONSTANT	-60.88	0.235
YEAR	0.030	0.235
DUMYF	0.919	28.65
DUMBE	0.931	33.47
BURN0	0.248	1.990
BURN2	-0.440	-2.462
BURN3	-0.941	-4.873
WHOLEWT	0.008	29.343
DHDGUT	1.007	21.173
DUMWHL	1.247	37.894
DUMLL	-0.241	-4.943
DUMHND	-0.093	-1.738
DNFAT	-0.335	-7.485
DFAT	1.001	12.973
SUMWTYF	-0.075	-3.911
SUMWTBE	-0.177	-9.309
SUMWTTM	0.008	0.468
Observations	8635	
R-bar squared	.446	

The coefficients represent the direct effect of the characteristics on the price of the fish, that is, the marginal value of characteristics. Most of the variables are categorical, explaining whether the fish being sold is in a particular category. The hedonic price coefficient of a characteristic is the price difference over the default case of the category not included. To illustrate, the coefficient on DUMYF represents the increase in price per pound paid for yellowfin over albacore, which in this case is estimated to be $0.919 per pound. The coefficient on DUMBE has the analogous interpretation; i.e., bigeye on average sells for $0.931 per pound more than albacore. The 'BURN' variables represent the influence of burns on the price of a fish. The default burn level is BURN1, which means that there is some burn of the muscle of the fish. The higher the BURN variable, the greater the burn. This is reflected in the prices, which show that the premium for no burn over some burn is $0.248 per pound (BURN0), while the discount for burn more serious than some burn is $0.44 to $0.94 per pound, depending on the severity of the burn. The variable WHOLEWT is the weight of the whole fish. As Bartram *et al.*, 1996, point out, there is a premium for larger fish. The coefficient on WHOLEWT measures this size premium. On average across all species, the price per pound increases by $0.008 (almost a cent a pound) for each pound increase in the weight of the fish. Thus, not only do bigger fish give more pounds, but also the price per pound goes up.

The fatness of the fish shows up in the coefficients DNFAT and DFAT. The default case is some fat, and the coefficients show the increment in price per pound over the 'some

fat' category. When there is no fat, the price falls by $0.335 per pound, and when the fat content is highest, the fish gets a premium of $1.001 because this is one of the characteristics of fish bound for the sashimi market.

The method of handling the fish, that is, how the fish is treated after harvest, influences how the fish can be used and hence to what market it will be sent. The default handling method is gilled and gutted and a variety of other methods, such as loined. The DHDGUT coefficient implies that the price per pound for headed and gutted fish is $1.007 higher than the default case. The premium per pound for whole fish comes from the coefficient on DUMWHL, which is more than a dollar—$1.247. The powerful influence of having a fish that is whole reflects greater certainty about the condition of the fish. Often fish are headed and gutted or loined when there is some question about the condition. The effect of these forms is especially strong and their significance is quite high, judging by the *t*-statistics.

The method of harvest, or gear type, reflects some expectation about the past handling of the fish, as well as characteristics that cannot be measured. The default case is trolling. The coefficients show that fish landed by longliners on average get $0.241 less per pound in the auction, while handliners get $0.093 less per pound, all other things being equal. This result is contrary to common expectations about the prices received by different gear types. It is also at odds with the simple means of published prices. This can be seen for mean prices in the current data set. Table 3 shows the mean prices and weights of yellowfin by gear type.

Table 3. Mean Price and Weight of Yellowfin, by Gear Type.

Gear type	**Mean price**	**Mean weight**
Longlining	$2.11 (.031)[a]	123.7 (1.29)
Trolling	2.04 (.035)	106.8 (7.78)
Handlining	2.55 (.042)	133.9 (2.35)

[a]Standard errors in parentheses.

Coefficients on bigeye landings, labeled SUMWTBE, and similarly named variables represent the influence of landings on prices. These variables are in units of 10,000 pounds to make the coefficients tractable. The bigeye price effect is the largest, showing that an increase of 10,000 pounds in landing per day reduces the price per pound of fish by $0.17. The coefficient on SUMWTBE is significantly different from zero at a high level of confidence. The coefficient on SUMWTYF is also negative (-0.075) suggesting that there is some depression of price, but it is smaller than the bigeye coefficient. The albacore coefficient (0.008) is not significantly different from zero. This is quite sensible, because there is a default world price for albacore for canning if it is not sold as fresh fish. The albacore result is consistent with the presence of a large world market for albacore. While many albacore go into outlets for fresh fish, equilibrium requires that prices are equal in both markets.

Two variables are important for policy considerations: the influence of WHOLEWT and the differential price effects of the method of handling, DUMHL or DUMLL. The size

of the fish is an important determinant of the price of the fish. Consequently, fish which grow bigger are proportionately more valuable, not in the sense of more pounds but more value per pound. Thus fish that can be saved potentially provide higher value, even though saving fish means harvesting them at a later date. A fish harvested in the future must be discounted by the market rate of interest to determine its current market value. For example a fish harvested one year from today would be worth $W_1P_1/(1+r)$ in present discounted revenues, where W_1 is the weight of the fish in pounds in one year, P_1 is the price received per pound in one year and r is the discount rate. If W_1P_1 grow faster than the interest rate, saving fish makes sense. The common property failure is clearly evident here, for no fisherman can hope to harvest in a year fish that he declines to catch today.

The categorical variables for method of capture or gear type suggest that fish caught by trollers are more valuable to consumers than fish caught by handliners or longliners. This does not necessarily mean that they are more valuable socially, because that depends in part on the cost of harvesting. However, other things being equal, it suggests that consumers, the ultimate users of the resource, are not indifferent to the allocation of catch to harvesting sectors.

A. Grading versus Characteristics

The role of buyers in the auction for fish is to grade fish on the basis of the characteristics of fish, and to bid for fish based on the grade of the fish. In the data set gathered by Bartram *et al.*, 1996, the authors of the report graded fish. In this section, we explore the degree to which the grades are 'sufficient statistics' for the price of fish. That is, can the price of fish be explained completely by the grades or do the characteristics provide additional information about the prices? We will examine this issue by estimating a series of increasingly inclusive models, beginning with a model that uses only the grades.

The basic hedonic model, equation (1) above, is

$$P_{it} = \beta Z_i + \varepsilon_{it} .$$

Note that the error is subscripted by i and t, where i is the individual fish and t represents the day on which the fish was sold. We accounted for the systematic variation over days (t) in the basic model by controlling for landings of tuna. This we will test below. To manage this error structure, we estimate a fixed effects model. Essentially this model specifies a different dummy variable for each day. Since there are 23 days of survey data, we will have 22 dummy variables representing the unmeasured events for each day of the survey. The fixed effects coefficients are suppressed in the following analysis.

To utilize the grades given by Bartram *et al.*, 1996, we have converted the two grades to one. In the Bartram *et al.* dataset, there are five grades, from 1 to 5, and a qualification, '+' or '-' or unrated for grade 2. However, there are no fish in grade 5. We have converted these grades into 6 consecutive grades in the following way:

Bartram *et al.* grade	Revised grade	Number of fish
1	0	393
2, '+'	1	4,297
2	2	665
2, '-'	3	1064
3	4	2042
4	5	405

Hence we have six grades based on the two-tier system.

To understand the influence of grading versus characteristics, we estimate the model sequentially, from the simplest model with grades only, to a model with grades and species, then the more complicated model with grades, species, and physical characteristics of the fish. This sequential estimation shows how partially specified models work, compared to the complete model. Table 4 presents the three basic models. The first model, with grades only, explains almost 39% of the variation in fish prices. The default grade is GRADE5, the lowest (worst) grade. Hence the coefficients on the grade variables represent the increment in the price of fish over the lowest grade. The grades are all significantly greater than zero, and they have the correct order, except for GRADE2. These coefficients show that GRADE0 gets a premium in price of $2.58 over the lowest grade. Although GRADE2 is higher than GRADE5 by $0.884, it receives a lower increment than GRADE3, which has a price higher by $1.332. The coefficients on the grades should decline monotonically from GRADE0 to GRADE4.

The obvious set of variables to include next is the species—the categorical variables for yellowfin and bigeye. As in the previous analysis, albacore will be the default case. The coefficients including both grades and species are found in column 2 of Table 4. Two things happen when species are included. First, the grades are sorted out in a logical way, so that the coefficient on each lower grade is significantly greater than zero but significantly less than the next higher grade. Consequently, including the species corrects the anomaly in the coefficients on grades. Further, the coefficients on the species conform with expectations, in that bigeye is the highest and yellowfin is the second highest. When the species are included, the model explains about 57% of the variation in price.

The third column of Table 4 includes the physical characteristics—the degree of burn, the fat content, and the means of handling. Here we can see that these variables are attempting to explain the same phenomena that graders have already observed and incorporated into the grade. The burn variables are not ordered in the right way and individually they are not significantly different from zero. Likewise, the coefficient on the variable for no fat, NFAT, is not significantly different from zero. However, the variables for handling the fish and method of landing are all significant. Further, the WHOLEWT variable indicates a premium for larger fish, at $0.005 per pound, independent of grade.

As in the previous model of hedonic prices, trolling is the default method of landing so that DUMLL and DUMHND represent the reduction in price over troll-caught fish. Although these physical characteristics appear significant, they only increase the explanation of the variation in price by six percentage points, from 57% to 64%.

A formal test of the significance of the additional variables is an F test. This is a test of the null hypothesis that all the parameters on the additional variables are zero. Table 5

Table 4. Fixed Effects Hedonic Model of Tuna Prices.

	Grade Only (*t*-statistic)[a]	**Grade & Species (*t*-statistic)**	**Grade, Species & Physical Characteristics (*t*-statistic)**
GRADE0	2.580 (37.66)	3.078 (53.24)	2.646 (47.41)
GRADE1	2.487 (40.45	2.630 (50.93)	2.237 (44.26)
GRADE2	0.884 (17.39	1.742 (38.91)	1.508 (34.68)
GRADE3	1.332 (23.54)	1.285 (27.18)	1.115 (24.60)
GRADE4	0.496 (9.36)	0.839 (18.30)	0.70 (16.37)
DUMYF		1.362 (55.93)	1.216 (42.40)
DUMBE		1.428 (53.09)	1.353 (51.87)
BURN0			-0.185 (-1.82)
BURN2			-0.172 (-1.19)
BURN3			-0.131 (-0.82)
WHOLEWT			0.005 (22.35)
DHDGUT			0.673 (16.73)
DUMWHL			0.917 (33.58)
DUMLL			-0.114 (2.76)
DUMHND			-0.110 (2.44)
DNFAT			0.043 (0.64)
DFAT			0.700 (10.60)
Observations	8635	8635	8635
R-bar squared	.39	.57	.64

gives three tests for the inclusion of the additional sets of variables. In the latter two models of Table 4, "Grade & Species," and "Grade, Species & Physical Characteristics," we can reject the hypothesis that the coefficients on the additional variables are all equal to zero.

This is true even when we consider the kinds of characteristics that go into grading, that is, fat content and the degree of burn on the fish.

Table 5. Tests of the Effect of Physical Attributes on Tuna Prices.

Variable Set	**F Statistic[a]**
DUMYF, DUMBE	1462.
BURN0, BURN2, BURN3, WHOLEWT, DHGUT, DUMWHL, DUMLL, DUMHND, DNFAT, DFAT	149.6
BURN0, BURN2, BURN3, NFAT, DFAT	31.8

[a] Critical values of the F-statistic at the 1 level of significance are, respectively, $F_3^{0.01} = 3.78$, $F_5^{0.01} = 3.02$, $F_{10}^{0.01} = 2.32$.

These tests isolate in a quantitative way what happens in the grading. As is described in Bartram *et al.*, 1996, grading is principally about the physical quality of the fish. Fish are graded primarily on their overt characteristics such as species, size and physical defects; potential shelf life,which is based on temperature, body condition, muscle texture and bloodline, and fishing and storage methods; and an evaluation of muscle quality based on texture, color, clarity and fat content. Additional quality is attributed to fish based on the size of the fish, its form, its species, and the method of harvesting. However, even these variables do not explain as much variation in the price of fish as the grades. We will return to the determinants of grading in the following section.

B. The Impact of Landings

In the previous section, we have used a fixed-effects model, which captures the influence of daily events through a dummy variable for the day. The variables most likely to change from one day to the next are the landings. However, if the Hawaii market were fully integrated into the world market for tuna, then daily landings would not influence local prices. Two conditions are required for landings in Hawaii not to influence Hawaii prices. First, landings in Hawaii must not be big enough to influence world prices. Second, handling and transportation capacity in Hawaii must be sufficient to accommodate increases in landings without raising costs or creating bottlenecks. In this section, we compare the fixed-effects model with a model in which landings replace the day-specific categorical variables.

The influence of landings on price is important for fisheries development and policy. From the development perspective, plans for increasing supply in Hawaii will not necessarily benefit the commercial harvesters if landings depress prices, unless harvests increase proportionately more than prices decline. From the point of view of fisheries policy, it is important to consider the price effects of seasonal and area restrictions on fisheries when these restrictions reduce harvest.

The fixed-effects model will be compared with a model using landings, conditional on the last specification in Table 4. When the landings specification is estimated, the set of variables that were significant in the fixed-effects model, shown in the last row of Table 5,

does change. However, we are more interested in the landings coefficients and the influence of landings on prices. The coefficients, mean daily landings and flexibilities, are given in Table 6. An intuitive indication of the role of landings versus the fixed-effects models can be gained by comparing the percent variation in price explained, the R^2. With the fixed-effects models, along with the other variables, the model explains 63.6% of the variation in price. When the landings are substituted for the fixed-effects variables, the model explains 62.3%. Consequently, it appears that the day-specific dummy variables are accounting chiefly for changes in landings.

Table 6. Effect of Landings on Tuna Prices.

Daily Landings of Species	Estimated Coefficient (Standard Error)	Mean Landings (10,000 lbs.)	Flexibility at Mean Landings and Prices
SUMWTYF (yellowfin)	-.086 (.016)	.649	-.035
SUMWTBE (bigeye)	-.187 (.019)	.624	-.074
SUMWTTM (albacore)	.019 (.014)	1.21	Coefficient not significantly different from zero

The flexibilities, percent changes in the price of all fish from a one percent change in landings of species i, are calculated as $(\bar{L}_i / \bar{P})\partial P_{it} / \partial L_{it}$ where the bars indicate means for landings or price over the sample period. The mean price per pound of all fish over all days of the auction was \$1.58. The last column contains the flexibilities. These are flexibilities in the sense that they represent the percent response in price to a percent increase in landings. For example, a 1000 pound increase in the landings of bigeye decreases the price of all fish by \$.0187 per pound. In principle, this response in price can occur because of insufficient capacity to ship fish out, because local consumers in Hawaii can only be induced to consume more fish with a lower price, or because Hawaii supply on the world market is large enough to influence world price. It seems unlikely that Hawaiian supply influences world prices, so the flexibilities probably stem from local conditions. This is borne out by the size of the flexibilities, which are generally quite low, the largest being for bigeye. The coefficient on albacore, which is positive but not significantly different from zero, can be understood in terms of the world market. Since albacore may potentially go into canning, it enters a very large world market. The coefficient not being significantly different from zero means that the market can accommodate large quantities of albacore without depressing the price. The world market effect holds even though much albacore now goes into markets for fresh fish because the fresh market for albacore must equilibrate with the world market for canning.

3. Grading and Landings

The empirical analysis above shows how the market accommodates grading. Empirically, grading accounts for some of the characteristics of the fish. In this section, we explore the relationship between grading, the characteristics of fish, and landings by focusing

on a model that explains grading rather than price. In particular, we try to separate the effects of the physical characteristics of fish from landings. It is of especial interest to determine whether landings affect the grading. This phenomenon is believed to occur in the crab industry in the sense that the definitions of jumbo, large, medium and small vary from season to season, depending on the supply of crabs. The question here is Do buyers downgrade fish when the market is flooded? Bartram *et al.*, 1996, who could observe the effects of landings on grading, raised this possibility.

A reasonable model for testing the influence of landings on grades is the ordered probit. This is a model that can be used with ranked data. Grading gives a categorical variable for each fish. We have converted the original categorical variables into six variables, ranging in value from 0 to 5, with the lowest numerical value being the highest quality. We motivate this analysis by supposing that the actual grade is a continuous variable that the buyers convert into a discrete value for the sake of convenience. For this model to work, buyers only need to rank fish. Then they can be shown to act as if their behavior were motivated by a continuous grade. Let the continuous grade be denoted y, where y depends on a set of variables Z according to the linear relationship

$$y = \gamma Z + \theta \tag{4}$$

where θ is a mean zero random error (assumed to be distributed N(0,1)) and γ is a vector of coefficients to be estimated. The y value would be the actual grade if it could be observed. Instead, we observe the grade g as follows:

$$\begin{aligned} g = 0 \text{ if } y \le \mu_0 \\ 1 \text{ if } \mu_0 \le y < \mu_1 \\ 2 \text{ if } \mu_1 \le y < \mu_2 \\ \dots \\ k \text{ if } \mu_{k-1} < y \end{aligned} \tag{5}$$

where in the current case k = 5. We observe the range in which the grade lies, which is described by g, but not the actual value of the grade as given by y. The idea is to use the information given by g and the assumed relationship between γZ and y to estimate γ. The probability of observing a particular grade is the probability that $y = \gamma Z + \theta$ falls in a particular range:

$$\Pr ob(g = j) \; = \; \Pr ob(\mu_{j-1} \le \gamma Z + \theta < \mu_j)$$

With six observed grades, we estimate four μ's and the vector of parameters γ. One of the μ's is embodied in the constant term and for practical purposes may be assumed to be zero. Since there are six categories there are four μ's. The μ's have meaning only in terms of their differences, in their absolute values. Hence μ_0 is set to zero. The estimation is by maximum likelihood, similar to a simple probit.

The idea of estimation is to explain the grading as a function of the characteristics of the fish, as well as test for the influence of landings on grades. Table 7 shows two sets of models. These models differ by specification, with two base specifications and two that omit

landings. Model A includes categorical variables for species, while Model B excludes these variables. For Models A and B, we also estimate a model that excludes the landings to test the hypothesis that landings influence grading.

The direction of the influence of the covariates can be explained through Equations (4) and (5). If the continuous grade were observed, then from (5) a positive coefficient would indicate that the covariate (one of the Z's) would increase the grade. Increasing grades means worse fish. Hence 'good' covariates, such as the weight of the fish, would decrease the grade and would imply a negative coefficient. Consequently, we expect desirable covariates, such as fat, to have negative coefficients, while undesirable covariates like burn should have positive coefficients.

Table 7 shows that most of the variables in Model A have the expected effect. The weight, whether the fish is whole, the presence of fat, the absence of burn all tend to lower the grade towards the best quality value of 1. The absence of fat and the degree of burn also influence the grading. The higher the degree of burn, the worse the rating—i.e., the rating becomes more positive. It is perverse that when a fish is identified as yellowfin or bigeye, the grading becomes higher, i.e., worse.

The influence of landings on the grading is a bit ambiguous. In Model B, landings of yellowfin and bigeye have a negative coefficient, meaning that, all other things being equal, fish sold on days when landings are high tend to be graded better than when landings are low. This is the opposite of the flooded market effect, which predicts worse grades when landings are high. However, when a variable reflecting the individual fish's species is included (Model A, column 1), there is no significant effect of landings on the grades.

To understand the influence of landings, and as a separate test, we asked, Suppose that the different gear types of fishing bring in fish with different reputations. In particular, suppose that tuna boats bring in tuna which is graded higher and that, on days when tuna boats land significant quantities, landings are higher and the quality of fish is better. Hence we classified all fish on the basis of the kind of boat/trip that landed them. The possible categories for trips are tuna, mixed, and broadbill. The estimated models include TUNA and BILL as categorical variables for the tuna and broadbill boats, with the default case being MIXED. In the estimated models, both of these categorical variables tend to improve the grade of the fish over fish from mixed boats. However, they do not explain the influence of landings on grades.

The finding on landings is weak however, because the coefficient on landings is so small, that even though it is significantly less than zero, very large changes in landings cannot change the grade. That is, from Table 1, mean yellowfin landings are 17,514 pounds and the coefficient on yellowfin landings is -0.015. Even a very large change in landings, say equal to the mean, will only produce a -0.026 change in the index. Given the μ's in Table 7, this is not large enough to change the grade of any fish. The coefficients are not large enough to matter, though the very large sample size may make them significant.

In sum, grading is well explained by the characteristics of fish. The chief anomaly in the grading of fish is the perverse influence of species. The apparently better species make the grade worse after we have controlled for the influence of other characteristics of the fish.

Table 7. The Influence of Landings on Grading.

	Model A--Species Included		Model B--Species Excluded	
	Unrestricted	**Restricted**	**Unrestricted**	**Restricted**
DUMYF	0.68 (16.43)	0.68 (16.42)	--	--
DUMBE	0.97 (26.29)	0.96 (26.68)	--	--
BURN0	-0.34 (-7.92)	-0.32 (-7.76)	-0.110 (-2.74)	-0.12 (-3.13)
BURN2	0.98 (3.39)	1.00 (3.44)	1.10 (3.56)	1.07 (3.58)
BURN3	2.82 (9.70)	2.83 (9.80)	2.96 (9.79)	2.91 (9.86)
WHOLEWT	-0.0068 (-22.38)	-.0068 (-22.51)	-.0030 (-11.43)	-0.0031 (-11.73)
DUMWHL	-0.61 (-16.86)	-0.60 (-16.90)	-0.69 (-19.06)	-0.70 (-19.20)
DHDGUT	-0.71 (-11.67)	-0.70 (-11.58)	-0.86 (-14.50)	-0.87 (-14.83)
DUMLL	0.21 (3.46)	0.21 (3.45)	0.079 (1.50)	0.082 (1.57)
DUMHND	-0.081 (-1.17)	-0.89 (-1.28)	-0.099 (-1.53)	-0.085 (-1.33)
DNFAT	0.34 (6.56)	0.34 (7.37)	0.37 (7.28)	0.48 (10.68)
DFAT	-0.68 (-7.07)	-0.68 (-7.09)	-.56 (-5.63)	-0.53 (-5.31)
BILL	-0.17 (-3.85)	-0.16 (-3.73)	--	--
TUNA	-0.15 (-4.91)	-0.15 (-4.98)	--	--
SUMWTYF (lbs * 10^{-4})	-0.015 (-0.72)	--	-0.068 (-3.17)	--
SUMWTBE (lbs * 10^{-4})	-0.034 (-1.48)	--	-0.082 (-3.74)	--
CONSTANT	2.34 (23.48)	2.28 (27.59)	2.42 (25.02)	2.30 (29.62)
μ_1	0.57 (26.84)	0.57 (26.85)	0.57 (27.29)	0.58 (27.32)
μ_2	2.20 (82.90)	2.20 (82.90)	2.13 (83.03)	2.13 (83.04)
μ_3	2.59 (96.73)	2.59 (96.74)	2.49 (93.60)	2.49 (93.54)
μ_4	3.87 (106.72)	3.87 (106.70)	3.68 (108.01)	3.67 (108.14)
Log-likelihood (# of observations)	-11216 8635	-11217 8635	-11668.02 8635	-11682.0 8635

4. Aggregating Data for Market-Level Analysis

There are many reasons to collect information on the Honolulu auction. For example, the large volume of tuna going through the market makes its price a critical determinant of Hawaiian commercial fishing revenue. Understanding trends and variations in these prices could help in planning for investment decisions. Also, allegations of price fixing among segments of the market cannot be examined without information on the impact of quantity on prices. Moreover, the effect of management decisions on fishermen and other industry participants can be assessed more definitively if auction data can be exploited to explain price-quantity interactions. The effect of total landings on prices is especially important.

However, data collection is expensive and care should be exercised to assure that maximum information content is obtained from the given data collection budget. At present, data are collected at the auction twice each week. A government agent records the price of each fish, the species, the weight, the name of the boat landing the fish and the buyer. A reasonable question is whether the previous analyses shed light on the cost efficiency of the information gathered. Since the data collection is largely a fixed expense (i.e., the agent walking around with auctioneer and buyers during the day of the sale), we want to know the subset of data that contains the most information.

But we need to determine the value of alternative forms of information. Obviously we are not interested in predicting the price of any one fish—there are too many fish in the auction. Rather, we are concerned with reducing the volume of information while still being able to predict effects on prices (and fishermen income) of those factors that NMFS influences. The most obvious one is the total harvest of a given species. NMFS policies such as area closures imply a change in composition of harvest (see Curtis, 1997) and this, in turn, implies different prices for the industry. Also, management that attempts to increase the minimum age of harvested fish necessarily alter the size and weight distribution of fish. We have seen that these factors influence fish prices and hence fishing revenues. One would like to be able to predict these effects in the deliberation over alternative policies.

A. Conditions for Aggregation

The previous sections demonstrate that the attributes of a fish do indeed affect the price that buyers are willing to pay for it. In addition to providing implicit prices for quality attributes, these results provide evidence that the traditional approach to the analysis of seafood demand may be inappropriate. Usually analysis is conducted as if the value and quantity were added up over all quality levels or grades of that species. This happens even when quality is not known, when aggregation takes place by species. Instead, a quality or grade-based grouping of fish may be in order. At issue is how to add-up (or aggregate) the weight and value of the fish harvested. It is costly to maintain and manipulate large data sets and, if there is an easy way of capturing the information related to 1000 fish into say four numbers, we should make the effort to do so. Most often, aggregation is done by adding up weights and values of individual (or lots) of fish on a species basis because fisheries management is most often directed toward species. However, if we are trying to understand what determines the general price in the auction, previous analysis suggests that it may be possible to capture more information if we were to aggregate according to grades, not species. That is, if one does not keep information on the grade of fish but only on the species, the factors affecting

price (i.e., the factors in product markets) are convoluted in the prices (by species) and it may be difficult to disentangle the effects.

As an example, average yellowfin tuna prices (shown as in Figure 1) vary substantially according to whether the fish are considered of a high grade going into the sashimi market or a low grade going into a cooked meat or canned market. However, if we consider the average price of all yellowfin tuna and compare it with the average price of all bigeye tuna, we do not see a great variation (Figure 2). By taking the average over all grades, we reduced the price variation and hence it is more difficult to "tease out" the causes of price change.

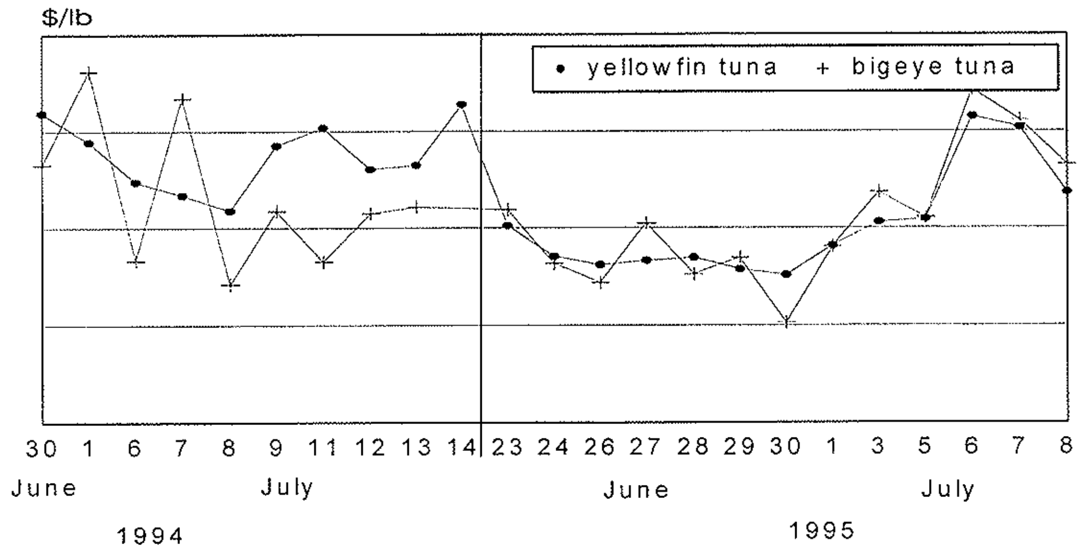


Figure 2. Average daily tuna prices by species.

Currently, however, data are commonly collected and analyzed on a **per-species.** Harvest is reported on a species basis by defining an aggregate output (e.g. pounds of bigeye) and summing the catch of each species, irrespective of grade. That is, suppose that we have fish, y^{sg}, where y is the weight of the fish, s is the species and g the grade, where there are M species (s=1,..,M) and T grades (g=1,...,T). Aggregation over species simply implies that

$$y^{s\bullet} = \sum_{g=1}^{T} y^{sg}$$

where s indexes the species of fish and g indexes the grade of fish. We are interested in which methods of adding up fish represent most closely the behavior of consumers of fish. Adding up, or summing, is a form of linear aggregation and places strong restrictions on consumer preferences. By using the above procedure, we presume that consumer's demand for seafood depends only on the species classification and that the distribution of catch of each species across quality levels does not affect the utility that the consumer derives from his expenditure on the species. This is not a bad assumption when the fish harvested are reasonably similar in quality and probably transformed into the same product line. In New England, auctions sell the entire catch of a species from a boat as one item because the fish have proven historically to be similar in quality. In addition, people seem to have formed

preferences on species (cod and haddock are preferred to whiting). In these instances, aggregation across species makes sense.

Instead, we could aggregate according to grade irrespective of the species of fish: i.e., create an aggregate weight,

$$\mathbf{y}^{\bullet g} = \sum_{s=1}^{M} y^{sg} \ .$$

Here we presume that consumer's demand for each grade of fish depends only upon the total catch of each grade and not upon the particular species. In this case, we are assuming that the important characteristics to the consumer are particular quality attributes (such as color of meat) and not the species. In a Japanese sushi bar, cubes of raw tuna fish are evaluated primarily on the texture, fat content, and color and less so on the species. In this case, aggregation across species may not make sense but across grade may be useful.

The purpose of this section is to define both types of aggregate outputs, one based on species classification, the other based on grade, and discuss the implications of linear aggregation for each output type. Can we aggregate the output, by species or by grade, so that a consumer who behaves rationally toward the individual species or grades acts the same way towards the aggregated groups? For this formal analysis, we are trying to find a method of aggregation that does not preclude its use in revealing rational individual behavior. Assume that consumers face the same prices, and except for differences in income, have the same parametric indirect utility function. A necessary and sufficient condition for aggregation is that the indirect-utility function can be expressed by the Gorman polar form.

For example, to define a series of aggregate outputs for each species, $\mathbf{y}^{s\bullet} = \sum_{g=1}^{T} y^{sg}$ s=1,2, . . . M, results in the following specification:

$$\begin{aligned} V^{s\bullet}(\mathbf{p}, M^{s\bullet}) &= b(\mathbf{p})M^{s\bullet} + a^{s\bullet}(\mathbf{p}) \\ &= b(\mathbf{p})\sum_{g=1}^{T} M^{sg} + \sum_{g=1}^{T} a^{sg}(\mathbf{p}) \\ &= \sum_{g=1}^{T} V^{sg}(\mathbf{p}, M^{sg}) \end{aligned} \qquad (6a)$$

where $\mathbf{V}^{s\bullet} = \sum_{g=1}^{T} V^{sg}$ is the indirect utility, $\mathbf{M}^{s\bullet} = \sum_{g=1}^{T} M^{sg}$ is the expenditure and $\mathbf{a}^{s\bullet} = \sum_{g=1}^{T} a^{sg}$ the price associated with the s[th] group of species-defined outputs. Equation (6a) describes a process of aggregation in which the macro-utility function, $\mathbf{V}^{s\bullet} = \sum_{g=1}^{T} V^{sg}$, is derived by adding up the micro-utility functions. Note that in this formulation, we are simplifying the problem by treating the buyers as simply passing through the preferences of consumers by moving (not transforming) their input (raw fish) into output to the consumer.

Alternatively, to define a series of aggregate outputs for each grade of fish, $\mathbf{y}^{\bullet g} = \sum_{s=1}^{M} y^{sg}$ g=1,2, . . . T, results in the following specification:

$$
\begin{aligned}
V^{\bullet g}(\mathbf{p}, M^{\bullet g}) &= b(\mathbf{p})M^{\bullet g} + a^{\bullet g}(\mathbf{p}) \\
&= b(\mathbf{p})\sum_{g=1}^{T} M^{sg} + \sum_{g=1}^{T} a^{sg}(\mathbf{p}) \\
&= \sum_{s=1}^{M} V^{sg}(\mathbf{p}, M^{sg})
\end{aligned}
\tag{6b}
$$

where $\mathbf{V}^{\bullet g} = \sum_{s=1}^{M} V^{sg}$ is the indirect utility, $\mathbf{M}^{\bullet g} = \sum_{s=1}^{M} M^{sg}$ is the expenditure and $\mathbf{a}^{\bullet g} = \sum_{s=1}^{M} a^{sg}$ the price associated with the g^{th} group of grade-defined outputs.

Consistent linear aggregation, whether over species or grades, not only requires that each consumer's preference function be quasi-homothetic, it also requires that each indirect utility function be affine in income or

$$V^{sg}(\mathbf{p}, M^{sg}) \quad = \quad b(\mathbf{p})\, \mathbf{M}^{sg} + a^{sg}(\mathbf{p})$$

where each V^{sg} is additively separable and homogeneous in expenditures. Differentiating (6a) and (6b) with respect to M^{sg} obtains

$$\frac{\partial V^{s\bullet}(\mathbf{p}, M^{s\bullet})}{\partial M^{sg}} = \frac{\partial V^{sg}(\mathbf{p}, M^{sg})}{\partial M^{sg}} = \frac{\partial V^{\bullet g}(\mathbf{p}, M^{\bullet g})}{\partial M^{sg}} \tag{7}$$

which implies that $\frac{\partial V^{sg}(\mathbf{p}, M^{sg})}{\partial M^{sg}}$ must be the same, and constant, across all levels of quality and species. The implication of linear output aggregation is that the distribution of outputs across quality levels or species is irrelevant and that the marginal utility of income spent on each quality differentiated species equals the aggregate (species or grade) marginal utility of income. For example, for a single species, the marginal utility of income derived from purchasing a high quality output is the same as the marginal utility of income of purchasing a low quality output. Alternatively stated, the increase in utility derived from the purchase of an additional unit of a high quality output concomitant to a reduction of one unit of low quality output does not affect expenditures.

Differentiating (7) with respect to M^{rf} ($r \neq s$, $f \neq g$) obtains

$$\frac{\partial^2 V^{s\bullet}(\mathbf{p}, M^{s\bullet})}{\partial M^{sg}\partial M^{rf}} = \frac{\partial^2 V^{sg}(\mathbf{p}, M^{sg})}{\partial M^{sg}\partial M^{rf}} = \frac{\partial^2 V^{\bullet g}(\mathbf{p}, M^{\bullet g})}{\partial M^{sg}\partial M^{rf}} = 0 \tag{8}$$

Equations (7) and (8) show why quality should not matter to consumers if the species approach to estimating aggregate demand functions is to be consistent with individual behavior. For consistency, linear aggregation requires that each species-defined marginal utility of income be independent of M^{sg} and equal to aggregate marginal utility of income, that is, also independent of aggregate income. Likewise, a grade-based aggregate output is also independent of income.

Returning to the present example, the implications of defining aggregate outputs based on species classifications suggests that the income elasticities of all quality levels of a tuna species are equal. This seems implausible because of the price differential between grade levels within a species classification: the average price per pound of high-grade bigeye tuna (grades 0 and 1) is $4.07 compared to an average $0.98 per pound for the low-grade bigeye tuna (grades 4 and 5). As noted by Gorman (1959), luxury goods should never be combined with necessary goods. Alternatively, defining aggregate outputs based on grading classifications may prove more plausible because the price range within a quality grouping is less stratified.

To summarize, the creation of aggregate outputs for each grade (species) requires that the total output of a given grade (species) is additively separable from other grades (species) in the representative consumer's preference function. Moreover, the sub-utility functions for each aggregate output are assumed to be additively separable and homogeneous in the outputs comprising each grouping. This requires that demand for each aggregate output be independent of expenditures and that the marginal utility of income for each species and quality-differentiated good be equal. Intuitively, this implies that a demand curve for a species does not shift with a change in the level and mix of grades that compose the catch of that species. Conversely, to define a demand curve for a particular grade requires that the demand curve does not shift with a change in the level and mix of species that compose the catch of that grade of fish.

Although the evidence from section 2.B suggests that both grades and species are important determinants of individual fish prices, we explore grade-based and species-based aggregation in the next section. Two empirical models are presented, one defining an aggregate output for each species classification, the other defining an aggregate output for each grade. Since linear aggregation is used to define both types of aggregate outputs, independence of demand for each output from expenditures cannot be tested and instead is imposed directly on both models. The emphasis of the comparison is, as in Section 2, on the marginal values and the degree of confidence that they can be estimated as well as the overall ability of the model to explain consumer choice.

B. Aggregating Outputs and Values

To explore the influence of aggregation across species and across grades, we have taken the nearly nine thousand observations for individual fish and summed for each day their weights and value to obtain twenty-two daily total quantities and values. We have done this twice, once on the basis of grades and once on the basis of species. An average daily price for aggregation scheme and day was created as the ratio of the value to the total quantity. The grades are defined as high grade (HG, if the fish's grade is in the best categories, 1+ to 2). These fish are destined for the sashimi market. All other fish are defined as low grade (LG, if the fish's grade was in any grade, 2- to 4). These fish are destined for the grilled or canned market. Average daily grades for the HG and LG product types were also created. For the tuna species, the data were limited for skipjack and therefore we did not consider it. This left three species—bigeye, yellowfin, and albacore—for which aggregate quantities and average prices were created.

Tables 8 and 9 contain the results of estimating price (or inverse demand) functions for the HG and LG tuna. Two models were estimated: complete specification, in which both

"own" and "cross" quantity and grades were included, and partial specification, in which only the "own" quantity and average grade were included. All price equations show sensitivity of price to "own" landings and "own" average grades. The estimated price flexibility at mean price/quantity levels for the HG and LG designation are -0.17 and –0.26, respectively. The prices, however, are insensitive to "cross" effect from either quantities marketed or grades. The 1994 dummy variable indicated a significantly higher price for the HG tuna in 1994 but no difference for the LG tuna.

Table 8. Price Equations for High-Grade[a] Tuna.

Variables		**Models** Complete Specification	Partial Specification
	Means	Coefficient (*t*-Statistic) \$2.29/lb	Coefficient (*t*-Statistic) \$2.29/lb
Q (High grade, in 10,000 lbs)	1.958	-.200 (-2.18)	-.081 (-2.34)
Q (Low grade, in 10,000 lbs)	1.066	.056 (0.30)	-
Mean Grade(HG)	1.68	-1.90 (-3.16)	-1.84 (-3.23)
Mean Grade (LG)	2.53	-.093 (-0.40)	-
Dummy1994	.43	.77 (2.26)	.56 (3.28)
Constant	1.0	5.74 (4.93)	5.51 (5.48)
Observations		22	22
R-bar squared		.78	.80

[a]Tuna in grade categories 0, 1 or 2 (1, 1-, 1+, 2+ or 2 from Bartram *et al.*, 1996).

The price (or inverse demand) curves for 1994 are drawn in Figure 3. The better tuna receives a higher price, one that is less sensitive to the quantity of fish on the market. One explanation for this result is that the volume of high grade tuna from Hawaii at this time of year is not large enough to have much of an effect on the world/Japanese markets. On the other hand, the lower grade tuna is more likely to be sold locally[1] and has a more responsive price.

[1] This is an example of sending the good apples out (Silberberg, 1978, p. 348).

Table 9. Price Equations for Low-Grade[a] Tuna.

Variables	Models: Means	Specification Complete Coefficient (*t*-Statistic)	Partial Coefficient (*t*-Statistic)
Q (High grade, in 10,000 lbs)	1.958	.017 (1.24)	-
Q (Low grade, in 10,000 lbs)	1.066	-.873 (-3.12)	-.673 (-2.99)
Mean Grade(HG)	1.68	.22 (0.24)	-
Mean Grade (LG)	2.53	-.043 (-0.20)	-.14 (-1.15)
Dummy1994	.43	-.35 (-.69)	-
Constant	1.0	2.08 (1.20)	2.67 (4.99)
Observations		22	22
R-bar squared		.27	.31

[a]Tuna in grades 3, 4, or 5 (2-, 3 or 4 for Bartram *et al.*).

In general, the results for the aggregated by grade case are encouraging, especially considering that the data are limited to a twenty-two day period. One should expect a longer time series to improve the results significantly. Next, we estimated a system of price or inverse demand function for the three species of tuna using seemingly unrelated regression.[2] The results are shown in Table 10 and are less encouraging. On the optimistic side, the prices are negatively related to "own" quantity but none are significantly different from 0 at the 5% level of confidence. The "cross" effects show that yellowfin and bigeye are substitutes whereas quantity of albacore has a complementary effect on the prices of the other two species, although none of the effects is convincing in a statistical sense. The year 1994 seems to have had a positive effect on yellowfin and albacore prices but not on bigeye. This would be inconsistent with the substitute relationship between bigeye and yellowfin.

These results show the difficulties of using species-based price equations. All of the various markets for the various product types lie behind the demand curve for each species. If our interest is in understanding the structure of the markets, little is gained by studying the price equations of species. However, if our interest is predicting species prices and their trends, then the species's price equations may be useful.

[2] We use the same technique on the aggregated by grade system but the inter-equation correlation was so small that the results did not change significantly.

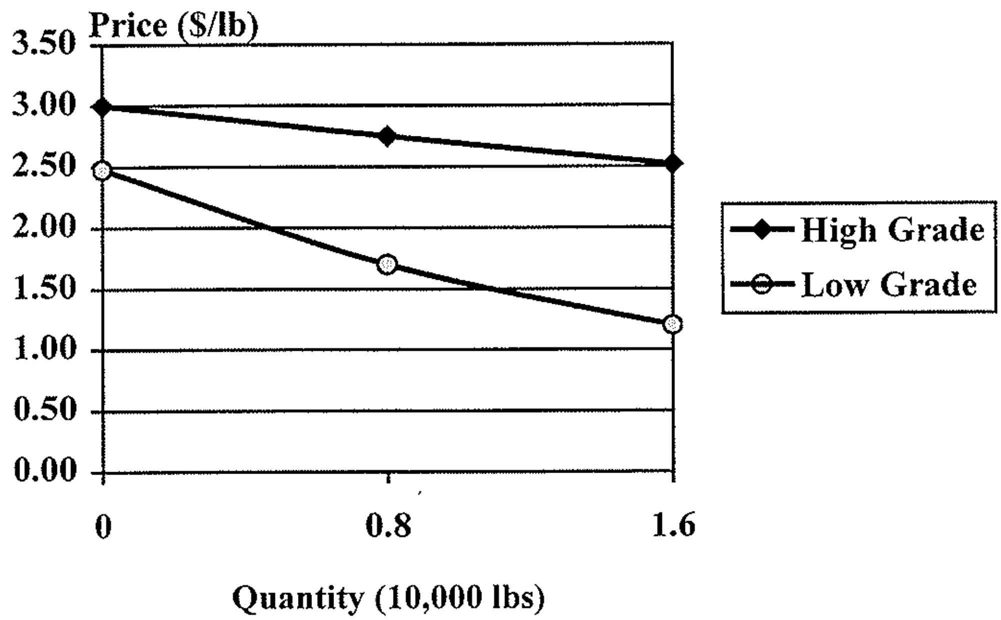


Figure 4. Inverse demand curves for tuna, by grade, 1994.

Table 10. Estimated Coefficients of Species' Inverse Demand Functions.

		Average Price ($/lb)		
		Bigeye	Yellowfin	Albacore
Variable	**Means**	2.18	2.30	1.06
Quantity of Bigeye Marketings (10,000 lbs)	.0815	-.470 (-1.63)	-.353 (-2.00)	.141 (1.92)
Quantity of Yellowfin Marketings (10,000 lbs)	1.701	.000 (.002)	-.280 (-1.89)	.059 (1.05)
Quantity of Albacore Marketings (10,000 lbs)	.887	.404 (1.69)	.300 (2.02)	-.11 (-1.87)
Dummy1994	.43	.34 (0.83)	.86 (3.37)	.42 (3.97)
Constant	1.0	2.06 (3.69)	2.44 (7.15)	.76 (5.37)
Observations		22	22	22
R-bar squared		.13	.49	.69

5. Conclusions

Prices in the Hawaii fish auctions are of prime concern to many. The livelihood of commercial fishermen obviously depends on them. Prices determine their incomes and strongly influence their production choices. Tuna consumers all over the world could be influenced by prices paid in Hawaii. Managers too should be aware of the tuna pricing system because their decisions implicitly influence prices and hence the welfare of fishermen and consumers.

In this report, we focused on understanding
the factors that influence the price of an individual tuna,
the marginal value of the different attributes of tuna,
the ability of a tuna's grade to reflect all other attributes' influence on the fish's price,
the factors that influence the grading of tuna,
and the ability to do market level analysis of auction prices.

Our analysis draws heavily on the data collected by Bartram *et al.* as well as their work. We have explored related issues, putting them in the context of research on other commodities, and exploiting common econometric techniques to understand additional issues.

The hedonic price analysis tell a logical story about price determination. The physical characteristics of fish determine the ex-vessel price. These characteristics, the degree of burn, fat, and the manner of harvesting and handling, all influence the grade of the fish. The grade itself can then be used as a means of aggregating information about the fish for wholesale marketing. This aggregation reduces the quantity of information needed to understand fish price determination, just as it reduces the information about the fish that buyers need to retain.

Subsequent analysis directly examines the factors that affect the grading of tuna. Essentially results of this analysis confirmed those found in the hedonic price analysis, i.e., fat, burn, fish size and processing characteristics all influenced grading. The grading seems to be based primarily on the characteristics of the fish. Landings have little ability to change the grading.

Further results of this study also indicated total daily landings of each species affected individual fish prices. This may have important implications for how the auction marketing process is currently structured. Currently, vessel decisions to land their harvest may be coordinated, but not always sufficiently to prevent a glut of fish on some days and a scarcity of fish on others, with prices varying accordingly. A policy that made public each vessel's decision to land its fish on a particular day could help smooth the supply, hence the price, of fish.

Results from a market-level analysis of the auction suggested that it is perhaps more useful to evaluate market demand for tuna on the basis of the grade of fish and not on a species basis as is typically done. This confirmed the hypothesis that for a quality differentiated good such as tuna for which there is a discerning market, aggregation across different grades of fish to analyze species demand may obscure market relationships.

This report is based exclusively on auction data in Hawaii for two-week periods in 1994 and 1995. It is evident that the links between the Hawaii auctions and prices in the rest of the world are important. The empirical influence of the rest of the world prices requires

data spread out over the year, so that seasonal adjustments in demand in other parts of the world can make their way through other markets and prices, and hence to Hawaii. This is research that follows logically from the current report, and could further aid in understanding the Hawaii market.

References

Anderson, J.L., and Y. Kusakabe, Analysis of the Japanese Salmon Market, Canadian Department of Fisheries and Oceans, Economic and Commercial Fisheries Report No. 56. D.F.O. Vancouver, BC, 1989.

Anderson, J.L., and P. Brooks, Conjoint Analysis of the New England Salmon Market, Report prepared for Canadian Department of Fisheries and Oceans, Vancouver, BC, 1986.

Bartram, P., P. Garrod, and J. Kaneko, Quality and Product Differentiation as Price Determinants in the Marketing of Fresh Pacific Tuna and Marlin, University of Hawaii, Joint Institute for Marine and Atmospheric Research, 1000 Pope Rd, Honolulu, HI, SOEST 96-06, JIMAR 96-304, 1996.

Bierlen, R., and O.C. Grunewald, Price Incentives for Commercial Fresh Tomatoes, *Journal of Agricultural and Applied Economics*, 27:138-48, 1995.

Blomo, V., J. Nichols, W. Griffin, and W. Grant, Dynamic Modeling of the Eastern Gulf of Mexico Shrimp Fishery, *American Journal of Agricultural Economics,* 64:475-482, 1982.

Brester, G.W., P.Lhermit, B.K. Goodwin, and M.C. Hunt, Quantifying the Effects of New Product Development: The Case of Low-Fat Ground Beef, *Journal of Agricultural and Resource Economics*, 18:239-50, 1993.

Brown, J.E., D. E. Ethridge, D. Hudson, and C. Engels, An Automated Econometric Approach for Estimating and Reporting Daily Cotton Prices, *Journal of Agricultural and Applied Economics*, 27:409-22, 1995.

Cropper, M., L.B. Deck, and K.E. McConnell, On the Choice of Functional Form for Hedonic Price Functions, *Review of Economics and Statistics*, 70:6688-675, 1988.

Curtis, R., The Effects of Aggregation in Fisheries Supply Models Working paper, Department of Agricultural and Resource Economics, University of Maryland, 1997.

Espinosa, J.A., and B.K.Goodwin, Hedonic Price Estimation for Kansas Wheat Characteristics, *Western Journal of Agricultural Economics*, 16:72-85, 1991.

Ethridge, D.E., Characteristic Supplies and Demands in a Hedonic Framework: U.S. Market for Cotton Fiber Attributes, *American Journal of Agricultural Economics*, 74 (1992): 991-1002.

Gillmeister, W.J., R.D.Yonkers, and J.W. Dunn, Hedonic Pricing of Milk Components at the Farm Level, *Review of Agricultural Economics*, 18:181-92, 1996.

Golan, A., and H. Shalit, Wine Quality Differentials in Hedonic Grape Pricing, *Journal of Agricultural Economics*, 44:311-321, 1993.

Gorman, W., Separable Utility and Aggregation, *Econometrica,* 27:469-481, 1959.

Lenz, J.E., R.C. Mittelhammer, and H. Shi, Retail-Level Hedonics and the Valuation of Milk Components, *American Journal of Agricultural Economics*, 76:492-503, 1994.

Mercier, S., C. Lyford, and V. Oliveira, The Effect of Quality on Corn Export Price Determination, *Review of Agricultural Economics*, 16:239-247, 1994.

Nelson, J.A., Quality Variation and Quantity Aggregation in Consumer Demand for Food, *American Journal of Agricultural Economics,* 73:1204-1212, 1991.

Parker, D.D., and D. Zilberman, Hedonic Estimation of Quality Factors Affecting the Farm Retail Margin, *American Journal of Agricultural Economics*, 75:458-466, 1993.

Parcell, J.L., T.C. Schroeder, and F.D. Hiner, Determinants of Cow-Calf Pair Prices, *Journal of Agricultural and Resource Economics*, 20:328-340, 1995.

Rosen, S., Hedonic Prices and Implicit Markets: Product Differentiation in Imperfect Competition, *Journal of Political Economy,* 82:34-55, 1974.

Silberberg, E., *The Structure of Economics: A Mathematical Analysis*, McGraw-Hill, 1978.

Sylvia, G., and S. Larkin, Wholesale, Firm-Level Demand for Whiting Products: A Multi-Attribute, Multi-Sector Analysis, *American Journal of Agricultural Economics*, 76(5):1242, 1994.

Tronstad, R., L.S. Huthoefer, and E.Monke, Market Windows and Hedonic Price Analyses: An Application to the Apple Industry, *Journal of Agricultural and Resource Economics*, 17:314-322, 1992.

Unnevehr, L., and S. Bard, Beef Quality: Will Consumers Pay For Less Fat?, *Journal of Agricultural and Resource Economics*, 18:288-295, 1993.

Wang, S.D., and C.B. Kellogg, An Econometric Model for American Lobster, *Marine Resource Economics,* 5:61-70, 1988.

Wirth, F.F., C.K. Halbrendt, and G.F Vaughn, Conjoint Analysis of the Mid-Atlantic Food-Fish Market for Farm-Raised Hybrid Striped Bass, *Southern Journal of Agricultural Economics*, 23:155-164, 1991.