An Inverse Demand System for Blue Crab in the Chesapeake Bay: Endogeneity and Seasonality

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Abstract

This paper studies the demand structure of the blue crab market in the Chesapeake Bay. In addition to providing empirical results regarding the economically important fishery, the paper offers a useful example of the potential for inverse demand system estimations for seafood where quantities are often defined prior to prices, and a variety of products are obtained from a single system. This is done with a nonlinear Inverse Almost Ideal Demand System coupled with seasonal patterns and controlling for endogeneity. The model used in this paper is able to address seasonality in demand in terms of varying flexibilities over seasons and deals with endogeneity in accordance with biological stock assessment data. Empirical results show significant season-varying market behaviors. The results also indicate the presence of endogeneity in the demand system. The flexibilities are calculated according to the estimates before and after controlling for endogeneity. Most market categories are price inflexible across seasons. The #1 Male, #2 Male, Female, and Mixed categories are necessities, while the Soft and Peeler category is a luxuary. Cross-category flexibilities suggest that most categories are quantity substitutes.

Key words: endogeneity, seasonality, blue crab

Introduction

Inverse demand systems have become a popular approach for fish and vegetable demand analysis in recent decades, in which the commodities usually have highly inelastic supplies in the short term (Barten and Bettendorf 1989; Burton 1992; Eales and Unnevehr 1994; Holt and Bishop 2002; Park, Thurman, and Easley 2004; Lee and Kennedy 2008; Grant, Lambert, and Foster 2010; Dedah, Keithly, and Kazmierczak 2011; Thong 2012). In this sense, inverse demand systems are appropriate for most agricultural products (Holt 2002). In this paper, a demand analysis is undertaken for an important species in the Chesapeake Bay using an Inverse Almost Ideal Demand System (IAIDS). Blue crab is not only a crucial component of the Chesapeake Bay ecosystem, but also the largest source of crabs in the U.S., accounting for 50 percent of the total blue crab harvests with values ranging from \$46–103 million annually (Bunnell, Lipton, and Miller 2010; Miller et al. 2011).

This paper concentrates on a local fishery market that comprises five categories based on sizes and sexes. Since fish of different sizes generate differing market values, they should be treated differently in economic studies instead of a unified biomass (Asche et al. 2012). The recent trend of fishery research suggests that fisheries management should implement policies that are responsive to fish sizes and ages (Smith 2012). The estimated flexibilities from the demand analysis on differentiated products of a species can help fisheries managers with the process of policy making. The own-category flexibilities tell the direct effects of policies targeting a specific market category, while the cross-category flexibilities indicate the indirect effects on other market categories.

One of the challenges in estimating inverse demand systems is the existence of endogeneity. The common practice in these studies is to treat quantities as exogenously determined and, therefore, fishers do not take actions based on their price expectations (Burton 1992; Eales and Unnevehr 1994; Holt and Bishop 2002;

Dedah, Keithly, and Kazmierczak 2011; Xie and Myrland 2011; Thong 2012). However, an endogeneity issue can arise when the quantity formulation process is, to some extent, linked to market prices. This might happen in fish demand when harvest decisions are based on price expectations in the current period, which tends to jeopardize the demand relationship. Failure to account for endogeneity may bias parameter estimates, which could provide misleading information to policy makers. In recent decades, the endogeneity problem in demand estimation has been considered and tested (LaFrance 1993; Kadiyali, Vilcassim, and Chintagunta 1996; Dhar, Chavas, and Gould 2003; Park, Thurman, and Easley 2004; Grant, Lambert, and Foster 2010), but there are only a few researches addressing this problem in fish demand (Park, Thurman, and Easley 2004).

This study accounts for potential endogeneity in fish demand with the biological content of the species. The most common approach to control for endogeneity is to use instuments that are correlated with the endogenous variables but independent of the error terms in the estimated demand equations. Within the context of fisheries, the stock assessment for a fishery provides a good instrument for dealing with endogeneity since it is an objective measure of the stock status that is correlated with harvests, but clearly exogenous to the market in the year following the assessment. This study follows an approach that specifies the explicit quantity equations from the supply side, and jointly estimates the demand and supply equations (Kadiyali, Vilcassim, and Chintagunta 1996; Villas-Boas and Winer 1999; Dhar, Chavas, and Gould 2003). The resulting model generates unbiased estimates based on biological properties of a nature resource system.

This paper also addresses seasonality issues that arise because of changing consumption patterns over the year, changing biological processes, and seasonal variation in the weather. These factors may cause demand cycles for fish with different sizes and genders. The existence of cycles in prices and quantities in the market may suggest season-varying demand. During the last decade, a number of studies have recognized the importance of seasonality in the demand for agricultural products (Herrmann, Mittelhammer, and Lin 1992; Eales and Unnevehr 1994; Johnson, Durham, and Wessells 1998; Grant, Lambert, and Foster 2010). In these studies, seasonal patterns are examined by including binary variables for shifting the demand equations, or the number of season-varying elasticity estimates are limited. In this paper, the seasonal effects are illustrated by estimating season-specific flexibilities.

The article is organized as follows. The next section discusses the Chesapeake Bay blue crab fishery and regulations imposed on it. Then, the extended IAIDS model is described, including how seasonal effects and endogeneity are addressed. This is followed by an overview of the data and how they are treated in this study. The estimation results are then discussed in the next section, followed by the last section, which draws some conclusions.

Background

The blue crab fishery in the Chesapeake Bay is regulated under three jurisdictions, Maryland, Virginia, and the Potomac River Fisheries Commission. A number of policies have been proposed to protect the abundance of blue crabs. Given the effectiveness of current policies in reserving biological population, associated economic implications to the area are of interest when evaluating fishery policies. The bio-economic model developed by Bunnell, Lipton, and Miller (2010) uses a set of inverse demand equations that regress market prices on quantities, seasonal dummies, and disposable income for blue crabs in the Chesapeake Bay. However, the demand equations are with constant slope forms, making it impossible to test economic theories and examine the relationships between various market categories.

Harvested blue crabs in the Chesapeake Bay are divided into five market categories based on sizes and sexes labeled as #1 Male, #2 Male, Female, Soft and Peeler (SP hereafter), and Mixed. Blue crabs in the #1 Male category are larger than those in the #2 Male category. Female crabs constitute an individual category; they are smaller than those in the #1 Male, but similar to ones in the #2 Male. Crabs that are less marketable and gender unclassified are reported as Mixed. They are similar in size to those in Female. SP is the most valuable category in the market, with prices much higher than other categories.

To illustrate how the market changes over seasons, average prices, quantities, and market shares from April to November, during which the fishing season for blue crabs in the Chesapeake Bay is regulated, are presented in the three figures. This provides preliminary insights into how the blue crab fishery market changes on an annual basis. By looking at the real price data in Figure 1, we see that the #1 Male receives higher prices than the #2 Male or Female due to larger sizes. The SP category receives the highest prices compared to others. The prices for the #1 Male, #2 Male, Female, and Mixed demonstrate a decreasing trend over a fishing season. Figure 1 also shows that prices for the #2 Male, Female, and Mixed move together during a season, which may imply close relationships among the three categories.

Growing patterns over a year may result in changing quantities for categories, as shown in Figure 2. In the Chesapeake Bay, blue crabs grow discontinuously through a series of molts; a process that is highly dependent on water temperature (Bunnell, Lipton, and Miller 2010). Prior to molting, blue crabs become peelers as they prepare to separate their hard shells from their bodies. After molting, there are 24 to 48 hours for crabs to harden their shells, which is the perfect timing for harvesting soft shell crabs. Late spring and early summer is the mating season for mature males and maturing females, during which females are experiencing their last soft shell stage (Bunnell and Miller 2005). This explains the peak of SP harvests occurring in the mating season, May and June, as indicated in Figure 2. After the maturity molt, females cease molting, but males do not stop (Hines et al. 2003).

Figure 2 illustrates that quantities for all market categories are not uniformly distributed across periods, showing evident seasonality. Summer, from June to August, is the most favorable growing period for male crabs since warm water is crucial for crab molting and growing. Most males grow up to the size of the #1 Male and are harvested in summer months. The largest number of females are harvested in September and October, which are also the highest monthly quantities for all categories. This may be attributed to fishery policies that are intended to protect adult female crabs during the summer spawning period. Figure 2 also indicates that quantities for the #2 Male and Mixed have small magnitudes, implying that the #2 Male and Mixed categories have little impacts on the whole market.

Figure 3 presents the average monthly expenditure shares for the five market categories, which also illustrate seasonality of the blue crab market. At the beginning of a fishing season, the #1 Male accounts for the largest expenditure share up to 60 percent due to its relative large harvest. The #1 Male category is surmounted by the SP in May. This is because majority of soft and peeler crabs are harvested in late spring and early summer. The expenditure share for the Female peaks in October and November.

Model Specifications

Inverse Almost Ideal Demand System

Eales and Unnevehr (1994) develop the IAIDS model that holds most of the desirable properties of the famous Almost Ideal Demand System (AIDS) by Deaton and Muellbauer (1980). The IAIDS system has gained popularity for studying fish and agricultural products in recent years (Grant, Lambert, and Foster 2010; Dedah, Keithly, and Kazmierczak 2011; Thong 2012). Here the IAIDS is used to analyze the blue crab demand because the nonlinear structure provides a way of investigating season-varying behaviors in the market.

The derivations of the IAIDS model are presented in Eales and Unnevehr (1994). The functional form that will be estimated is given by:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \ln q_j + \beta_i \ln Q, \tag{1}$$

where w_i is the expenditure share for commodity i; $\ln q_j$ is the logarithm of quantity for the j^{th} commodity; the translog term $\ln Q$ is expressed as:

$$\ln Q = \alpha_0 + \sum_j \alpha_j \ln q_j + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \ln q_i \ln q_j.$$

Equation 1 forms a nonlinear system of equations.[1] To avoid estimation complexity, the translog index, $\ln Q$ is usually replaced with the Stone's quantity index, $\ln Q^* = \sum_i w_i \ln q_i$. This is similar to the Stone's price index in the AIDS model suggested by Deaton and Muellbauer (1980). Although this approximation results in a favorable linear system of equations, potential bias may arise due to collinearity of variables (Deaton and Muellbauer 1980). As with other demand systems, the adding-up, homogeneity, and symmetry restrictions can be imposed and tested. These restrictions are expressed as: $\sum_i \alpha_i = 1$, $\sum_i \gamma_{ij} = 0$, $\sum_i \beta_i = 0$ (adding-up); $\sum_j \gamma_{ij} = 0$ (homogeneity); $\gamma_{ij} = \gamma_{ji}, \forall i \neq j$ (symmetry).

The behavioral response parameters in ordinary demand are defined as elasticities. The counterparts in inverse demand systems are flexibilities, denoting how prices change in response to quantity changes. Differentiating equation (1) with

[1] There is difficulty in estimating the parameter α_0 in the nonlinear model due to the flatness of maximum likelihood function in α_0 (Deaton and Muellbauer 1980; Moschini, Moro, and Green 1994). In this study, α_0 is set to zero, since Moschini, Moro, and Green (1994) argue that zero value of α_0 has minimal impact on elasticity/flexibility estimates (Dhar, Chavas, and Gould 2003).

respect to $\ln q_j$, $\forall j$ yields the own- and cross-category flexibilities:[2]

$$f_{ij} = -\delta_{ij} + \frac{\gamma_{ij} + \beta_i \left(w_j - \beta_j \ln Q\right)}{w_i}, \tag{2}$$

where δ_{ij} is the Kronecker delta ($\delta_{ij} = 1$ if $i = j$, and $\delta_{ij} = 0$ otherwise). The scale flexibility is the sum of f_{ij} over j under the homogeneity restriction:

$$f_i = -1 + \frac{\beta_i}{w_i}. \tag{3}$$

Interpretations of flexibilities are similar to elasticities in ordinary demand. Demand for a commodity is said to be flexible if the own-category flexibility is less than -1 and inflexible if it is greater than -1 and less than zero. For cross-category flexibility, the negative number indicates gross quantity substitutes between goods, while the positive number denotes gross quantity complements. The scale flexibility is interpreted as the percentage change in a normalized price (i.e., price divided by expenditure) due to a scale expansion in the consumption bundle (Park and Thurman 1999). A commodity is classified as a necessity if its scale flexibility is less than -1, or defined as a luxury if greater than -1 and less than zero (Eales and Unnevehr 1994).

Seasonality

The strategy of capturing seasonality in the IAIDS model is proposed by Eales and Unnevehr (1994). However, the corresponding flexibilities are not seasonally adjusted in their study. In this paper, season-varying flexibilities are reflected by estimated coefficients associated with seasonal variables, indicating different market behaviors over the year.

Following Eales and Unnevehr (1994), the intercept α_i and α_j in equation (1)

[2] The steps of flexibility derivations are presented in Eales and Unnevehr (1994).

can be decomposed into different parts including seasonal dummies D_s, $s = 1, 2$. The modified functional form of IAIDS is:

$$w_i = \alpha_i + \sum_s \lambda_{is} D_s + \sum_j \gamma_{ij} \ln q_j + \beta_i \ln Q, \tag{4}$$

where

$$\ln Q = \alpha_0 + \sum_j \left(\alpha_j + \sum_s \lambda_{js} D_s \right) \ln q_j + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \ln q_i \ln q_j.$$

In practice, the intercept α_i and α_j can include any relevant dummy variables. For example, Dedah, Keithly, and Kazmierczak (2011) study external effects of policy regulations and health information on demand. Additional restrictions, $\sum_i \lambda_{is} = 0, \forall s$, are required to meet the adding-up constraint.

In this paper, the flexibilities are then adjusted to capture seasonal effects:

$$f_{ijs} = -\delta_{ij} + \frac{\gamma_{ij} + \beta_i \left(\alpha_j + \lambda_{js} + \sum_k \gamma_{kj} \ln q_{ks} \right)}{w_{is}}, \tag{5}$$

$$f_{is} = -1 + \frac{\beta_i}{w_{is}}, \tag{6}$$

where w_{is} and $\ln q_{ks}$ are seasonal expenditure share and logarithm of quantity, respectively.

Endogeneity

As indicated earlier, an endogeneity problem arises when a set of explanatory variables become endogenous in equation (4). Whenever there are unaccounted factors affecting harvest quantities and related to price formation, treating quantities as exogenous variables would result in biased estimates.

To control for potential endogeneity, an approach is used that a system of equations is jointly estimated, including both the inverse demand equations and the explicit quantity equations using instruments from the supply side (Kadiyali, Vilcassim, and Chintagunta 1996; Villas-Boas and Winer 1999; Dhar, Chavas, and Gould 2003). The quantity equation for the i^{th} product is represented as:

$$q_{it} = \boldsymbol{\eta}_i^T \mathbf{x}_{it}, \tag{7}$$

where q_{it} is the quantity for product i at time t; $\mathbf{x}_{it}$ contains a set of instruments that illustrate the quantity formation; $\boldsymbol{\eta}_i$ are the coefficients. The assumption associated with this specification is that the quantity can be exogenously explained by specific shifters (instruments) from the supply side. In this study, the quantity equations (7) are assumed to take reduced forms similar to Dhar, Chavas, and Gould (2003). This specification can generate consistent estimates of the parameters in the correctly specified demand equations (4) (Villas-Boas and Winer 1999).

A common choice of instruments $\mathbf{x}_{it}$ is to use lagged terms of endogenous variables, since they are easily obtained by researchers (Villas-Boas and Winer 1999; Park, Thurman, and Easley 2004; Grant, Lambert, and Foster 2010). This strategy might be challenged due to potential correlations between the previous quantities and current prices. One would argue that fishers may make their harvest decisions in a present period based on their price expectations in future periods. However, this correlation could be small for a local fishery because the short-term supply is inelastic.

Besides lagged terms, equation (7) can also include other explanatory variables. Fish stock variables could be a good instrument choice. In classical fisheries economics, harvest is usually modeled as a function of fish stock and fishing effort (Gordon 1954; Smith 1969). The rationale behind this choice is that harvest is dependent on the amount of fish in the stock that is predetermined at the beginning of each period.

The empirical form of equation (7) in this study includes current fish stock and harvest in previous period to represent the supply side. The reduced function form is:

$$\ln q_{it} = \eta_{i0} + \eta_{i1} \mathbb{1}_{(m \in i)} \ln S_{mt} + \eta_{i2} \mathbb{1}_{(f \in i)} \ln S_{ft} + \eta_{i3} \ln q_{it-1}, \tag{8}$$

where S_{mt} and S_{ft} are estimated fish stocks for males and females at time t, respectively; q_{it-1} is the harvest in a previous period; $\mathbb{1}_{(m \in i)}$ ($\mathbb{1}_{(f \in i)}$) is an indicator function that equals one if the i^{th} market category includes males (females), and zero otherwise. The joint estimation with raw stock data lacks of convergence maybe because the magnitudes of fish stocks are much larger than the logarithms of quantites in the demand equations (4). Here all fish stock data were converted to logarithms in equation (8). Given the specified quantity equations, we can jointly estimate the system of equaions (4) and (8). The resulting parameters are estimated from the model controlling for endogeneity.

The next step is to test if endogeneity problem exists in the inverse demand system. Following Dhar, Chavas, and Gould (2003) and LaFrance (1993), the Durbin, Wu and Hausman (DWH) approach is used to test for endogeneity. The test is represented as the difference between the estimates from the controlled and uncontrolled models. The DWH statistic is specified as:

$$DWH = (\boldsymbol{\theta}_u - \boldsymbol{\theta}_c)^T \left[Var(\boldsymbol{\theta}_u) - Var(\boldsymbol{\theta}_c) \right]^{-1} (\boldsymbol{\theta}_u - \boldsymbol{\theta}_c), \tag{9}$$

where $\boldsymbol{\theta}_u$ is the parameter vector estimated from the endogeneity-uncontrolled model, and $\boldsymbol{\theta}_c$ is the vector of estimates from the endogeneity-controlled model. The null hypothesis of DWH test is that there is no endogeneity issue in the original model. Under the null hypothesis, DWH statistics is asymptotically distributed as $\chi^2(k)$, where k is the number of potential endogenous variables.

Data

Data used in the analysis are monthly time series from 1994 to 2007 for five market categories of blue crabs: #1 Male, #2 Male, Female, SP, and Mixed. The number of total observations is 111. The study period after 1994 was chosen because of the change in the blue crab fishery management in Maryland. In 1994, Maryland Department of Natural Resources (MDNR) implemented a mandatory reporting scheme for fishers (Miller et al. 2011). Pre 1994 data are considered to be less reliable.

The quantity of landings and prices are obtained from the MDNR. The monthly harvest data are combined from logbook records of crab fishers, and the monthly price data are from the MDNR monthly survey of seafood dealers. Since this is the demand analysis for the Chesapeake Bay region, ideally we could also use data from Virginia and the Potomac River Fisheries Commission. However, there is no category-specific data for these management agencies. The assumption is made that the demand for blue crabs in Maryland is representative for the whole Chesapeake Bay area (Bunnell, Lipton, and Miller 2010).

Prices are converted to real terms using the consumer price index (CPI) with the base CPI = 100 in 1982. Since there are only combined quantity of landings for soft shell crabs and peelers in the data set, averages of the prices were taken to represent the prices for the combined market category, SP. The monthly quantity and price data range from April to November for each year. To account for seasonality in the model, April and May were grouped as Spring, June to August as Summer, and September to November as Fall.

As mentioned before, the stock assessment estimates are used as instruments to control for endogeneity. For the blue crab fishery, the Winter Dredge Survey is conducted during inactive fishing periods in the Chesapeake Bay to assess the stock status each year (Miller et al. 2011). The survey estimates how many harvestable crabs are available before fishing season starts, and contains sex-specific stock assessment data. To make the annual stock data compatible with the monthly fishery data, the stock data were converted to monthly data by adjusting actual harvests in each month. For example, the stock status for April is the initial data from the stock assessment survey each year. The stock for later months is subtracted by the commercial, recreational harvests, and natural mortalities in the previous month.[3]

Empirical Results

Seasonal IAIDS Estimates and Tests

The nonlinear IAIDS model (4) is estimated using the nonlinear seemingly unrelated regression (NLSUR) method. Results are presented in Table 1: a base model that does not control for endogeneity, and a model in which endogeneity is corrected using the stock instruments.

To avoid singularity, the equation assocated with the Mixed category is dropped. The coefficients of this equation are recovered from the adding-up constraint. The system estimates are not invariant to the deleted equation in the presence of serial correlation when dealing with time series data. This problem may result in inconsistent estimates. To test for serial correlation, the Durbin-Watson (DW) statistics are calculated from the predicted residuals for the estimated equations in the base model, the model with the homogeneity constraint, and the model with both homogeneity and symmetry constraints (Durbin and Watson 1971). The results are presented in Table 2. It shows that the test statistics range from 1.589 to 2.091 in the three models, which are all higher than the lower critical value, 1.539, at the five percent significance level. The results indicate that there is little evidence of severe

[3] In most blue crab studies in the Chesapeake Bay, the recreational harvests are assumed as eight percent of the total harvests, and the natural mortality rate is assumed to take 0.9 (Bunnell, Lipton, and Miller 2010; Miller et al. 2011).

serial correlation in the residuals of the models.

By further looking at the results in Table 2, the DW statistics change for all categories when the homogeneity restriction is imposed. However, there are only slight changes on DW statistics when the symmetry restriction is imposed conditional on homogeneity. This implies that serial correlation may be introduced through the the imposition of homogeneity, which is also found in Deaton and Muellbauer (1980).

The economic constraints, homogeneity and symmetry, are tested using the likelihood ratio (LR) test.[4] Three different tests are conducted: the model with homogeneity verses the base model, the model with homogeneity and symmetry verses the base model, and the model with homogeneity and symmetry verses the model with homogeneity. The LR test results reject homogeneity ($\chi^2 = 24.61$), joint homogeneity and symmetry ($\chi^2 = 33.74$), but cannot reject the case of homogeneity and symmetry conditional on homogeneity ($\chi^2 = 9.13$) at the five percent significance level. It is not surprising since rejections of these economic restrictions also exist in other studies regarding fish demand (Xie and Myrland 2011; Thong 2012).

Although the data show evident seasonality, the seasonal IAIDS model is statistically tested against the non-seasonal IAIDS also using the LR test. The null hypothesis that the seasonal and non-seasonal models are statistically identical is rejected ($\chi^2 = 23.37$). This result suggests that seasonality does impact the blue crab demand.

Here we briefly discuss the coefficient estimates in the base model. Ten significant coefficient estimates out of eleven at the one percent significance level are associated with the #1 Male, Female, and SP. This indicates that these three cate-

[4]Two sets of economic restrictions were imposed on the seasonal IAIDS model. The first case only imposes homogeneity, while the second imposes joint homogeneity and symmetry. No consideration was given to the case with only the symmetry restriction, since it is equivalent to the case of joint homogeneity and symmetry given that the adding-up constraint must hold.

gories have more market influence than the others, not surprising since the three account for over 99 percent of the total expenditures. Each market category has a significant coefficient associated with its own equation. Not many seasonal coefficients show significance in the model. However, the sign and magnitude of the seasonal coefficients coincide with the trends in Figure 3.

The coefficient estimates from the model controlling for endogeneity are also presented in Table 1. The system of equations (4) and (8) are jointly estimated using the NLSUR method. The equations associated with the #1 Male, Female, and SP in the market have more significant estimates than the other two. The test for endogeneity relative to the base model according to equation (9) is implemented. The DWH statistic is 771.132, which is much higher than the critical value of χ^2 (5) at five percent significance level. The test rejects the null hypothesis that estimates from the base model are consistent, which indicates strong evidence of endogeneity in the inverse demand system for the blue crab fishery. This result also suggests that not considering the endogeneity issue may generate erroneous results.

According to the results of several tests, the economic constraints and the exogenous assumption are rejected. Hence, the estimates from the endogeneity-controlled model with seasonal patterns are more preferred than other models. In the following analysis, the flexibility resutls are interpreted based on the model correcting for endogeneity.

Seasonal Flexibility Estimates

The flexibilities are estimated by seasons based on the parameter estimates before and after controlling for endogeneity. The results are presented in Table 3 and Table 4. Following LaFrance (1993) and Dhar, Chavas, and Gould (2003), we can calculate the absolute percentage difference between the flexibility estimates from the two models to get:

$$APD = \frac{100|f_u - f_c|}{0.5|f_u + f_c|},$$

where f_u and f_c are flexibility estimates from the uncontrolled and controlled endogeneity models, respectively. The last row of Table 4 presents the mean APD (MAPD) by market category over seasons. The average of these MAPD is 349.6 percent, implying that there is significant difference between the flexibility estimates with and without accounting for endogeneity.

Comparing results from Table 3 and Table 4, 38 out of 60 cross-category flexibilities increase in magnitudes, which implies that the relationships between some categories become stronger after considering endogeneity. This finding has policy implications; a policy designed for protecting one category may have greater price effects on other categories than it would be suggested by a model that neglected endogeneity. When implementing fishery policies to target a specific category, managers should take into account the effects on other categories.

The estimated flexibilities vary across seasons, as shown in Table 4. Regarding scale flexibilities, blue crabs in the Chesapeake Bay appear to be necessities for all categories, except for the SP category in the spring and summer. It suggests that the SP category is a luxury in this market. Note that the scale flexibility for SP in the fall is the only one greater than zero. It is difficult to provide an economically resonable explanation for this result. This positive scale flexibility may not be very reliable due to the small quantities of SP in the fall.

The results in Table 4 show that most significant own-category flexibilities in three seasons are greater than -1, indicating inflexible demand for these market categories. These numbers mean that a one percent increase in quantity results in less than one percent decline in the corresponding normalized price. However, there are some unexpected results for own-category flexibilities, such as Female in the summer and SP in the fall.

The cross-category flexibilities show relationships between products. A negative flexibility implies quantity substitutes, while a positive flexibility indicates quantity complements. All significant cross-category flexibilities are negative except between #2 Male and Mixed. This complement pattern between #2 Male and Mixed may be because they have prices and quantites that move together over seasons in the blue crab market, as illustrated in Figure 1 and Figure 2.

Conclusions

Using both commercial harvest and price data and biological stock assessment data, this paper investigates the demand structure for the blue crab fishery in the Chesapeake Bay. This analysis of the market for this iconic species can be used to evaluate various fishery policies in terms of socio-economic outcomes.

Future research would benefit from collecting more data to cover all markets in the Chesapeake Bay, although the markets in the area are similar. In addition, the quantity equations used in the paper are reduced forms. It would be useful to develop structural forms of the quantity equations to deal with endogeneity. Such a practice would help build a bio-economic model based on a solid biological foundation. As pointed out by Smith (2012), fisheries economics is moving towards more complex ecosystem-based and biology-intrinsic approaches instead of simple models. Separating economic studies of natural resources from their own characteristics may potentially cause problems. Another direction is to extend the current work to welfare evaluations of fishery policies. Although current fishery policies do work for preserving fish populations, there are associated socio-economic costs due to harvest restrictions. It would be worth studying the overall effects from a broader perspective.

Although this paper can be improved in some ways, it still contributes to the fish demand literature. This study analyzes a local fishery in the Chesapeake Bay addressing two important issues, endogeneity and seasonality, that are common to most analysis for fish demand.

A potential problem in estimating inverse demand systems is the presence of endogeneity. It is likely that endogeneity exists in many fisheries. We found that accounting for endogeneity is important. Failure to do so can generate incorrect results. This paper follows the framework in Dhar, Chavas, and Gould (2003) to control for endogeneity by explicitly expressing quantity equations from the supply side. A system of demand and supply equations are jointly estimated. The quantity equations are assumed to be explained by a set of instrumental variables, using biological stock assessment data that are exogenous to the market. Empirical results show that there is strong evidence of endogeneity in the inverse demand system for blue crabs in the Chesapeake Bay.

For perishable products, there are seasonal variations in demand due to different growing patterns. The nonlinear form of the IAIDS model can be used to examine seasonal effects. In most studies that address seasonality, the market behavior estimates, elasticities or flexibilities are not seasonally adjusted. This study takes advantage of the nonlinear feature of the IAIDS model to estimate season-varying flexibilities. Specifically, the results show that most categories are price inflexible. All market categories are gross quantity substitutes over seasons except for the #2 Male and Mixed. The #1 Male, #2 Male, Female, and Mixed categories are classified as necessities, while the SP category is sorted as a luxury.

The results from this study have policy implications. The estimates from the demand system can provide insights into policy making for fishery managers. The Chesapeake Bay blue crab policies frequently target one or a subset of the market categories. For instance, a policy of fishing closure is used to protect female crabs during spawning seasons. This analysis shows that the effects of specific policies on other categories need to be taken into account, especially with the presence of endogeneity.

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References

Asche, Frank, Lori S Bennear, Atle Oglend, and Martin D Smith. 2012. US shrimp market integration. *Marine Resource Economics* 27 (2):181–192.

Barten, Anton P and Leon J Bettendorf. 1989. Price formation of fish: An application of an inverse demand system. *European Economic Review* 33 (8):1509–1525.

Bunnell, David B, Douglas W Lipton, and Thomas J Miller. 2010. The bioeconomic impact of different management regulations on the Chesapeake Bay blue crab fishery. *North American Journal of Fisheries Management* 30 (6):1505–1521.

Bunnell, David B and Thomas J Miller. 2005. An individual-based modeling approach to spawning-potential per-recruit models: an application to blue crab (Callinectes sapidus) in Chesapeake Bay. *Canadian Journal of Fisheries and Aquatic Sciences* 62 (11):2560–2572.

Burton, Michael. 1992. The demand for wet fish in Great Britain. *Marine Resource Economics* 7 (2):57–66.

Deaton, Angus and John Muellbauer. 1980. An almost ideal demand system. *The American Economic Review* 70 (3):312–326.

Dedah, Cheikhna, Walter R Keithly, Jr, and Richard F Kazmierczak, Jr. 2011. An analysis of US oyster demand and the influence of labeling requirements. *Marine Resource Economics* 26 (1):17–33.

Dhar, Tirtha, Jean-Paul Chavas, and Brian W Gould. 2003. An empirical assessment of endogeneity issues in demand analysis for differentiated products. *American Journal of Agricultural Economics* 85 (3):605–617.

Durbin, James and Geoffrey S Watson. 1971. Testing for serial correlation in least squares regression. III. *Biometrika* 58 (1):1–19.

Eales, James S and Laurian J Unnevehr. 1994. The inverse almost ideal demand system. *European Economic Review* 38 (1):101–115.

Gordon, H Scott. 1954. The economic theory of a common-property resource: the fishery. *The Journal of Political Economy* 62 (2):124–142.

Grant, Jason H, Dayton M Lambert, and Kenneth A Foster. 2010. A seasonal inverse almost ideal demand system for North American fresh tomatoes. *Canadian Journal of Agricultural Economics* 58 (2):215–234.

Herrmann, Mark, Ronald C Mittelhammer, and Biing-Hwan Lin. 1992. Applying almon-type polynomials in modeling seasonality of the Japanese demand for salmon. *Marine Resource Economics* 7 (1):3–13.

Hines, Anson H, Paul R Jivoff, Paul J Bushmann, Jacques van Montfrans, Sherry A Reed, Donna L Wolcott, and Thomas G Wolcott. 2003. Evidence for sperm limitation in the blue crab, Callinectes sapidus. *Bulletin of Marine Science* 72 (2):287–310.

Holt, Matthew T. 2002. Inverse demand systems and choice of functional form. *European Economic Review* 46 (1):117–142.

Holt, Matthew T and Richard C Bishop. 2002. A semiflexible normalized quadratic inverse demand system: An application to the price formation of fish. *Empirical Economics* 27 (1):23–47.

Johnson, Aaron J, Catherine A Durham, and Cathy R Wessells. 1998. Seasonality in Japanese household demand for meat and seafood. *Agribusiness* 14 (4):337–351.

Kadiyali, Vrinda, Nauel J Vilcassim, and Pradeep K Chintagunta. 1996. Empirical analysis of competitive product line pricing decisions: lead, follow, or move together? *Journal of Business* 69 (4):459–487.

LaFrance, Jeffrey T. 1993. Weak separability in applied welfare analysis. *American Journal of Agricultural Economics* 75 (3):770–775.

Lee, Youngjae and P Lynn Kennedy. 2008. An examination of inverse demand models: An application to the US crawfish industry. *Agricultural and Resource Economics Review* 37 (2):243–256.

Miller, Thomas J, Michael J Wilberg, Amanda R Colton, Glenn R Davis, Alexei Sharov, Romuald N Lipcius, Gina M Ralph, Eric G Johnson, and Anthony G Kaufman. 2011. Stock assessment of blue crab in Chesapeake Bay 2011. Tech. rep., NOAA Chesapeake Bay Office, Annapolis, Maryland.

Moschini, Giancarlo, Daniele Moro, and Richard D Green. 1994. Maintaining and testing separability in demand systems. *American Journal of Agricultural Economics* 76 (1):61–73.

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

Park, Hoanjae, Walter N Thurman, and James E Easley, Jr. 2004. Modeling inverse demands for fish: Empirical welfare measurement in Gulf and South Atlantic fisheries. *Marine Resource Economics* 19 (3):333–351.

Smith, Martin D. 2012. The new fisheries economics: Incentives across many margins. *Annual Review of Resource Economics* 4 (1):379–402.

Smith, Vernon L. 1969. On models of commercial fishing. *The Journal of Political Economy* 77 (2):181–198.

Thong, Nguyen Tien. 2012. An inverse almost ideal demand system for mussels in Europe. *Marine Resource Economics* 27 (2):149–164.

Villas-Boas, J Miguel and Russell S Winer. 1999. Endogeneity in brand choice models. *Management Science* 45 (10):1324–1338.

Xie, Jinghua and Øystein Myrland. 2011. Consistent aggregation in fish demand: A study of French salmon demand. *Marine Resource Economics* 26 (4):267–280.

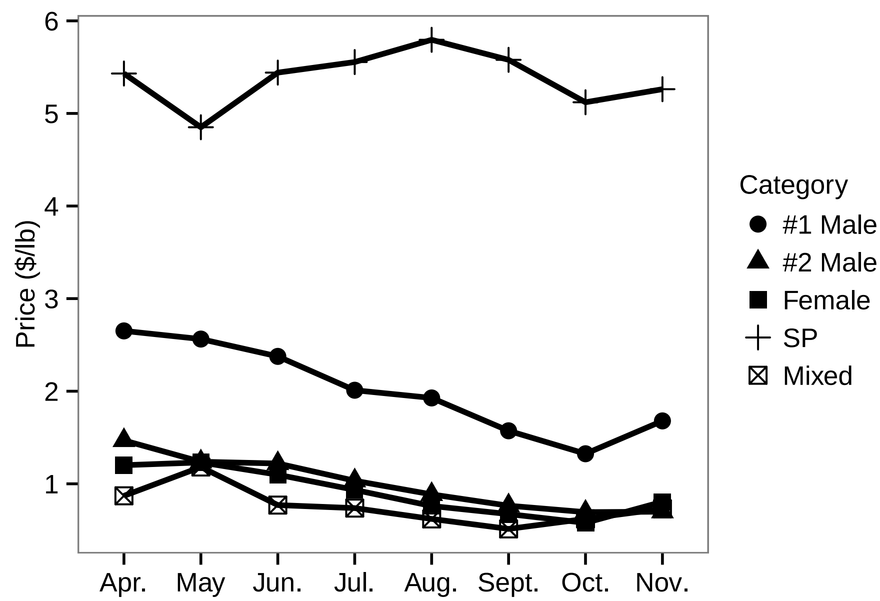

Figure 1: Average monthly prices over years for blue crab categories

Source: data from Maryland Department of Natural Resources (MDNR).

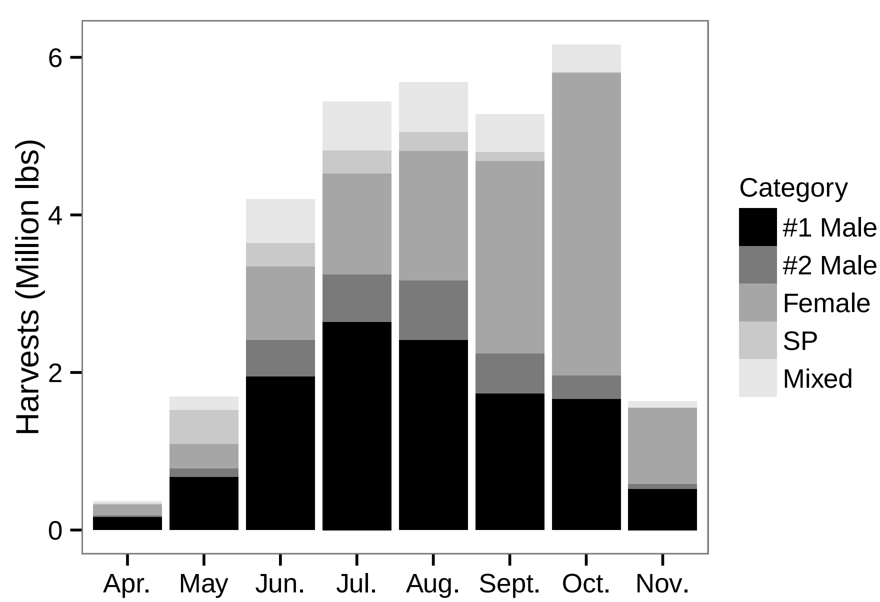

Figure 2: Average monthly harvests over years for blue crab categories

Source: data from Maryland Department of Natural Resources (MDNR).

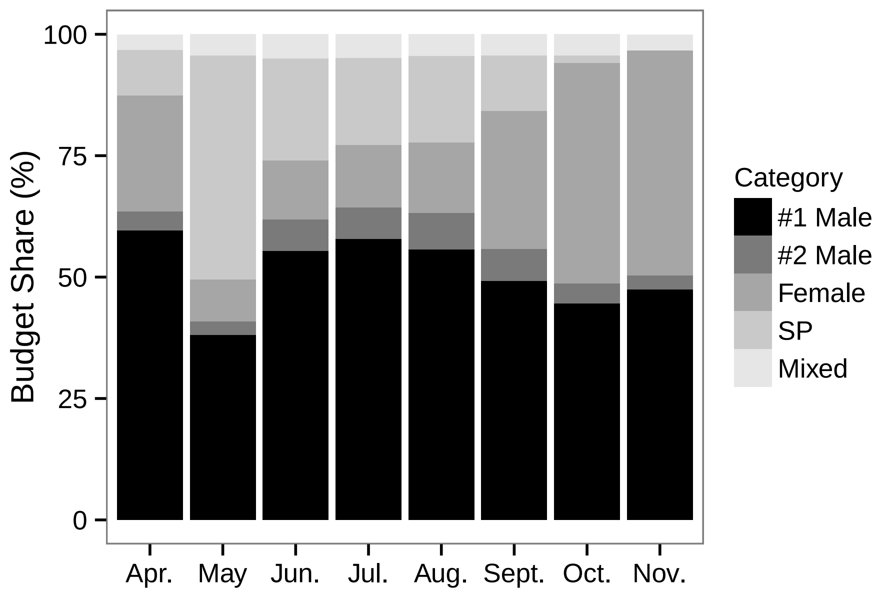

Figure 3: Average monthly expenditure shares over years for blue crab categories

Source: data from Maryland Department of Natural Resources (MDNR).

Table 1: The estimated parameters from the nonlinear IAIDS models

	Base Model					Model Controlling for Endogeneity				
	#1 Male	#2 Male	Female	SP	Mixed	#1 Male	#2 Male	Female	SP	Mixed
γ_{i1} (#1 Male)	0.233***	-0.029***	-0.059**	-0.124***	-0.022**	0.225***	-0.026***	-0.045	-0.113***	-0.041***
	(0.036)	(0.008)	(0.025)	(0.032)	(0.010)	(0.032)	(0.008)	(0.028)	(0.029)	(0.012)
γ_{i2} (#2 Male)	0.005	0.039***	-0.018*	-0.027*	0.001	0.007	0.031***	-0.021	-0.020	0.002
	(0.017)	(0.004)	(0.011)	(0.016)	(0.004)	(0.019)	(0.004)	(0.016)	(0.017)	(0.007)
γ_{i3} (Female)	-0.083***	-0.002	0.155***	-0.064***	-0.006	-0.097***	0.000	0.170***	-0.072***	-0.001
	(0.021)	(0.004)	(0.012)	(0.020)	(0.005)	(0.019)	(0.004)	(0.020)	(0.024)	(0.007)
γ_{i4} (SP)	-0.090***	-0.010***	-0.034***	0.134***	-0.000	-0.030***	-0.004	-0.040***	0.078***	-0.004
	(0.012)	(0.003)	(0.008)	(0.009)	(0.003)	(0.010)	(0.003)	(0.011)	(0.011)	(0.004)
γ_{i5} (Mixed)	-0.019	0.004	-0.019	0.010	0.024***	-0.029	0.016***	0.001	-0.032	0.045***
	(0.019)	(0.004)	(0.012)	(0.017)	(0.005)	(0.025)	(0.006)	(0.021)	(0.023)	(0.009)
β_i (Translog)	-0.066***	-0.007***	-0.017***	0.090***	-0.000	-0.041**	-0.005	-0.045***	0.096***	-0.005
	(0.007)	(0.002)	(0.006)	(0.005)	(0.002)	(0.016)	(0.004)	(0.013)	(0.010)	(0.006)
λ_{i1} (Spring)	-0.060	-0.001	-0.014	0.083**	-0.008	-0.151***	0.000	0.008	0.148***	-0.004
	(0.044)	(0.009)	(0.026)	(0.040)	(0.011)	(0.046)	(0.009)	(0.020)	(0.037)	(0.014)
λ_{i2} (Summer)	0.043	0.013**	-0.021	-0.033	-0.002	-0.015	0.007	-0.017	0.024	0.000
	(0.029)	(0.006)	(0.017)	(0.027)	(0.007)	(0.030)	(0.006)	(0.011)	(0.026)	(0.009)
α_i (Intercept)	0.601**	0.171***	0.033	0.073	0.122**	-0.047	-0.047	-0.093	1.018***	0.168*
	(0.238)	(0.049)	(0.143)	(0.218)	(0.059)	(-0.253)	(0.054)	(0.196)	(0.260)	(0.088)

*** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance.

Standard errors are presented in parentheses.

Table 2: Durbin–Watson tests in the base model and models with constraints

	#1 Male Equation	#2 Male Equation	Female Equation	SP Equation
Base Model	2.091	1.656	1.852	1.991
Homogeneity Imposed	1.878	1.609	1.933	1.623
Homogeneity and Symmetry Imposed	1.825	1.603	1.953	1.589

The Mixed equation is not reported because it is dropped in the process of estimation.

Table 3: Seasonal flexibilities for five blue crab categories estimated from the base model

	#1 Male			#2 Male			Female			SP			Mixed		
	Spring	Summer	Fall	Spring	Summer	Fall	Spring	Summer	Fall	Spring	Summer	Fall	Spring	Summer	Fall
#1 Male	-0.624***	-0.705***	-0.655***	-1.017***	-0.524***	-0.780***	-0.443***	-0.579***	-0.194***	-1.185***	-0.170	-0.614	-0.571**	-0.451**	-0.537**
	(0.085)	(0.070)	(0.082)	(0.233)	(0.109)	(0.158)	(0.135)	(0.160)	(0.051)	(0.313)	(0.185)	(0.723)	(0.246)	(0.188)	(0.223)
#2 Male	-0.006	-0.014	-0.016	0.147	-0.448***	-0.187**	-0.127*	-0.166**	-0.054**	-0.058	-0.048	-0.218	0.035	0.027	0.033
	(0.034)	(0.028)	(0.033)	(0.108)	(0.052)	(0.076)	(0.067)	(0.082)	(0.027)	(0.054)	(0.070)	(0.258)	(0.117)	(0.092)	(0.110)
Female	-0.167***	-0.155***	-0.227***	-0.067	-0.042	-0.107	-0.041	0.168*	-0.626***	-0.236***	-0.305***	-0.701*	-0.158	-0.125	-0.149
	(0.041)	(0.033)	(0.039)	(0.125)	(0.061)	(0.090)	(0.076)	(0.095)	(0.032)	(0.071)	(0.095)	(0.364)	(0.132)	(0.104)	(0.126)
SP	-0.199***	-0.135***	-0.135***	-0.308***	-0.117***	-0.143***	-0.224***	-0.234***	-0.070***	-0.481***	-0.390***	1.224***	-0.009	-0.006	-0.006
	(0.033)	(0.027)	(0.031)	(0.093)	(0.038)	(0.050)	(0.055)	(0.056)	(0.016)	(0.062)	(0.092)	(0.386)	(0.094)	(0.059)	(0.061)
Mixed	-0.049	-0.042	-0.045	0.092	0.045	0.072	-0.123*	-0.151*	-0.048*	0.061	0.088	0.301	-0.372***	-0.505***	-0.410***
	(0.037)	(0.030)	(0.035)	(0.118)	(0.057)	(0.083)	(0.072)	(0.089)	(0.029)	(0.059)	(0.076)	(0.280)	(0.126)	(0.099)	(0.118)
Scale flexibility	-1.136***	-1.118***	-1.141***	-1.216***	-1.105***	-1.155***	-1.104***	-1.128***	-1.042***	-0.674***	-0.521***	1.046***	-1.004***	-1.003***	-1.003***
	(0.015)	(0.013)	(0.016)	(0.056)	(0.027)	(0.040)	(0.035)	(0.044)	(0.014)	(0.018)	(0.027)	(0.113)	(0.062)	(0.049)	(0.058)
Mean share	0.489	0.563	0.471	0.033	0.068	0.047	0.162	0.132	0.398	0.278	0.189	0.044	0.038	0.048	0.040

*** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance.

Standard errors are presented in parentheses.

Table 4: Seasonal flexibilities for five blue crab categories estimated from the model controlling for endogeneity

	#1 Male			#2 Male			Female			SP			Mixed		
	Spring	Summer	Fall	Spring	Summer	Fall	Spring	Summer	Fall	Spring	Summer	Fall	Spring	Summer	Fall
#1 Male	-0.540***	-0.621***	-0.557***	-0.786***	-0.405***	-0.609***	-0.283*	-0.445**	-0.160***	-1.414***	-0.450**	-1.663**	-1.072***	-0.876***	-1.060***
	(0.078)	(0.062)	(0.073)	(0.225)	(0.103)	(0.150)	(0.157)	(0.185)	(0.057)	(0.346)	(0.186)	(0.727)	(0.323)	(0.239)	(0.279)
#2 Male	0.021	0.015	0.018	-0.047	-0.539***	-0.320***	-0.104	-0.146	-0.047	-0.101*	-0.121	-0.538**	0.067	0.047	0.057
	(0.039)	(0.033)	(0.039)	(0.131)	(0.064)	(0.093)	(0.102)	(0.124)	(0.039)	(0.058)	(0.074)	(0.267)	(0.187)	(0.147)	(0.175)
Female	-0.186***	-0.167***	-0.228***	0.028	0.007	-0.025	0.088	0.310*	-0.603***	-0.309**	-0.412**	-1.064	-0.015	-0.021	-0.068
	(0.044)	(0.037)	(0.042)	(0.149)	(0.070)	(0.093)	(0.157)	(0.184)	(0.053)	(0.130)	(0.180)	(0.710)	(0.199)	(0.151)	(0.163)
SP	-0.158**	-0.120**	-0.128**	-0.299	-0.128	-0.168	-0.564***	-0.611***	-0.182***	-0.320***	-0.123	2.365***	-0.267	-0.184	-0.196
	(0.061)	(0.047)	(0.053)	(0.208)	(0.088)	(0.116)	(0.153)	(0.167)	(0.049)	(0.098)	(0.145)	(0.619)	(0.288)	(0.197)	(0.210)
Mixed	-0.067	-0.063	-0.078	0.454***	0.217***	0.315***	-0.021	-0.049	-0.020	-0.086	-0.093	-0.319	0.179	-0.078	0.093
	(0.049)	(0.041)	(0.049)	(0.166)	(0.080)	(0.116)	(0.129)	(0.155)	(0.048)	(0.081)	(0.103)	(0.377)	(0.240)	(0.185)	(0.218)
Scale flexibility	-1.083***	-1.072***	-1.086***	-1.155***	-1.076***	-1.112***	-1.277***	-1.341***	-1.113***	-0.654***	-0.491***	1.174***	-1.140***	-1.111***	-1.132***
	(0.033)	(0.028)	(0.034)	(0.117)	(0.057)	(0.084)	(0.080)	(0.098)	(0.032)	(0.036)	(0.054)	(0.229)	(0.161)	(0.127)	(0.151)
MAPD (%)	73.996	979.348	580.089	173.586	77.833	57.570	142.570	51.149	35.774	219.619	1259.430	1196.989	176.613	100.774	118.506

*** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance.

Standard errors are presented in parentheses.

MAPD is the mean of absolute percentage difference by market category and season.