Marine Resource Economics, Volume 27, pp. 371–387
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ISSN 0738-1360

Analysis of a Demand System for Unbreaded Frozen Seafood in the United States Using Store-level Scanner Data

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Abstract *This article uses weekly national store-level scanner data acquired from A.C. Nielsen Inc., to analyze demand for 14 unbreaded frozen seafood products in the United States (U.S.). While utilization of scanner data for food demand analyses has become increasingly popular in the U.S., just a few studies of seafood demand have utilized scanner data. We used a log linear version of the Paasche's index with lagged shares as the price index in an Almost Ideal Demand System (AIDS) model and modified the intercept of a standard AIDS model to account for effects of the season and the lagged demand. Own-price, cross-price, and expenditure elasticities vary across species considerably, which highlights the importance of studying consumer demand behavior at disaggregated levels for seafood.*

Key words Seafood demand, scanner data, Almost Ideal Demand System, price and expenditure elasticity, Paasche's index, consumer demand behavior.

JEL Classification Codes C32, D12, Q21, Q22.

Introduction

During the 1980s scanning grocery prices via universal product codes on packages became common in supermarkets. Haller (1994) suggests that commercial market-level scanner databases are the most appropriate research tool for analyzing both demand and strategic interactions. The availability of commercial scanner data from food retailers is a potential improvement in data collection (Cheng and Capps 1988) and allows significant advances in understanding food marketing (Nayga 1992; Cotterill 1994; Sexton, Zhang, and Chalfant 2003; Li, Carman, and Sexton 2005; Roheim, Gardiner, and Asche 2007). Scanner data provide evidence of actual market choices that allow researchers to

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The work reported herein was supported in part by the Southern Regional Aquaculture Center through USDA/NIFA grant nos. 2006-38500-16977 and 2007-38500-18470 (Prime). The findings, opinions, and recommendations expressed are those of the authors and not necessarily those of the Southern Regional Aquaculture Center, the Mississippi Agricultural and Forestry Experiment Station, or the U.S. Department of Agriculture.

use revealed preference data and enhance the analyst's ability to understand consumer demand, particularly for food products (Capps and Love 2002).

Some of the important studies using scanner data for food demand analysis in the U.S. include Capps (1989) for meat products; Capps and Nayga (1991) and Brooker, Eastwood, and Gray (1994) for beef products; Capps, Seo, and Nichols (1997) for spaghetti Sauces; Maynard and Liu (1999), Stockton (2004), Chidmi, Lopez, and Cotterill (2005), and Torrisi, Stefani, and Seghieri (2006) for dairy products; and Chidmi and Lopez (2007) for breakfast cereals. Cotterill, Putsis and Dhar (2000) performed intra-category demand analyses using scanner data on six individual categories (milk, bread, butter, pasta, margarine, and instant coffee), as well as a pooled analysis on a sample of 125 categories and 59 geographic markets. Using scanner data Bergtold, Akobundu, and Peterson (2004) estimated unconditional own-price and expenditure elasticities across time for 49 processed food categories, which include beverages, dairy products, milled grains and pasta, fruits and vegetables, baking goods, condiments, and desserts.

While utilization of scanner data for food demand analyses has become increasingly popular, particularly in the U.S., very few seafood demand studies have utilized scanner data (*e.g.*, Capps and Lambregts 1991; Wessells and Wallstrom 1999), and Teisl, Roe, and Hicks (2002). Capps and Lambregts (1991) studied demand for disaggregated finfish and shellfish products using scanner data from a retail firm in Houston, TX (USA). They employed a multiproduct retail demand function. Wessells and Wallstrom (1999) utilized panel data consisting of scanner data to test stability of canned salmon demand using a random coefficient model across 34 U.S. cities from 1988 through 1992. Teisl, Roe, and Hicks (2002) used scanner data to test whether dolphin-safe labels altered consumer purchases of canned tuna.

The present study focuses on demand for unbreaded frozen seafood products in the U.S. by using A.C. Nielsen Inc., weekly national store-level scanner data.[1] The main product categories in the dataset include breaded-frozen, unbreaded-frozen, canned, entrée, anchovies and anchovy paste, and shelf-stable tuna. Of these, unbreaded frozen seafood products occupied the second highest market share (36% of total seafood excluding random weight fresh seafood products in supermarkets) after shelf-stable tuna (37%) in 2009–10.

During the last two decades, consumer demand analysis has moved toward system-wide approaches. The Almost Ideal Demand System (AIDS) (Deaton and Muellbauer 1980) is the major breakthrough in demand-system generation, and appears to be the most popular (Alston and Chalfant 1993; Buse 1994). Deaton and Muellbauer (1980) applied AIDS to annual British data from 1954 to 1974 and found plausible structural parameter estimates and reasonable price and income elasticity estimates. However, homogeneity and symmetry restrictions were rejected. Based on these and other results, Deaton and Muellbauer (1980) concluded that influences other than current prices and current total expenditures must be explicitly incorporated into the model to explain consumer behavior in a theoretically coherent and empirically robust way. They suggest generalizing their static model by adding dynamic elements and including other factors to improve their original framework. The AIDS, which incorporates habits and allows for autocorrelation, is a more viable demand system to use in modeling consumer behavior (Blanciforti and Green 1983).

The presence of habits or persistence in consumer consumption behavior patterns enables them to purchase the same product week after week. If consumers have consumption habits for diverse fish types, consumers purchasing a particular seafood product one week would not likely purchase the same in the next week. If in fact consumers' purchasing habits have inter-week relationships, this could have important policy implications for the seafood industry. Consumers' weekly behavior also hints at very short-term substitutability of products. There could be cases in which consumers preferring a particular product(s) would not prefer other particular product(s).

[1] A.C. Nielsen Inc., collects weekly store-level scanner data at the market level (52 markets in the U.S.) and national level. However, national-level data is not an aggregate of the data from the 52 individual markets and includes few more markets than those for which individual market-level data are provided.

Food consumption patterns changes with season, place, and time; hence, the responsiveness of demand to changes in the factors affecting them also changes. This is mainly due to changes in relative prices of products and income levels of consumers, distinct consumer tastes and preferences, and seasonal festivals and other celebrations across seasons (Dostie, Haggblade, and Randriamamonjy 2000). Empirical evidence suggests that seasonal variation in food prices largely influences the effective incomes and consumption potential of households (*e.g.*, Chambers 1981; Sahn 1989; Paxon 1993).

Using an extended AIDS for 14 unbreaded frozen seafood products, this article has analyzed: *i)* effects of own price, cross price, and scale on demand; *ii)* seasonality in demand for unbreaded frozen seafood products; and *iii)* the influence of lagged seafood purchases on current seafood purchases. It is expected that the results can be useful to U.S. seafood retailers, as they can better address consumer demand and improve their marketing strategies. The study is also potentially useful to the U.S. fisheries/aquaculture industries and policy makers to better plan production and design supports that could improve their competitiveness.

Data and Empirical Model

We used the national store-level weekly scanner data acquired from A.C. Nielsen Inc., for the period June 16, 2007 to June 12, 2010. A.C. Nielsen Inc., collects weekly store-level scanner data from food/grocery, drug, and mass channels[2] across the U.S. for frozen seafood, excluding random weight fresh products. The food channels include most of the major chains (more than 130 channels) in the U.S., and, therefore, account for the majority of food for at-home consumption sales in the U.S. A.C. Nielsen Inc., provides data at two levels: the market level (52 markets in the U.S.) and the national level. National level data is not an aggregate of the data from the 52 individual markets and includes a few more markets than those for which individual market-level data are provided.

This article used food/grocery channels data and termed the food/grocery channels as supermarkets. The unbreaded frozen seafood products considered in the study are: shrimp, salmon, crab, catfish, tilapia, flounder, cod, whiting, perch, tuna, pollock, lobster, scallops, and clams.[3] Catfish includes both basa/tra and channel catfish.

Equation 1 is the standard form of AIDS:

$$w_i = \propto_i + \sum_{j=1}^{n} \gamma_{ij} lnp_j + \beta_i (lnX_t - lnP_t), \tag{1}$$

where $w_i (= \frac{p_i q_i}{\sum_{i=1}^{n} p_i q_i})$ is the expenditure share of seafood product i, p_i is the retail price of commodity i, q_j is the purchase quantity of seafood product j including i, *ln* denotes natural logarithmic values of variables, $X_t (= \sum_{i=1}^{n} p_i q_i)$ is the total expenditure, *lnP* is the price index defined in equation 2, and $\propto_i$, γ_{ij}, and β_i are the parameters of the model.

[2] A.C. Nielsen Inc., defines: *i)* grocery channels as independent grocers or food stores having less than four stores with stores selling over \$2 million; *ii)* drug channels as independent drug stores as having less than four stores with stores selling over \$1 million; and *iii)* mass channels as stores having at least 10,000 square feet of selling space, at least three mass merchandise lines, no one line accounting for 80% of selling area (50% in the case of food) and high volume, fast turnover, and an image of selling merchandise for less than conventional prices.

[3] We considered crawfish and squid, too. Due to the multicollinearity problem and presence of a unit root in prices, we dropped these species.

$$lnP = \propto_0 + \sum_{j \neq i}^{n} \propto_j \, lnp_j + 0.5 \sum_{i=1}^{n} \sum_{j \neq i} \gamma_{ij}^{*} \, lnp_i lnp_j. \tag{2}$$

Due to the nonlinearity of *lnP* (equation 2), the Stone's price index is being used to develop a linear approximate AIDS. Some authors have argued to use some other indices (Pashardes 1993; Buse 1994; Moschini 1995). Eales and Unnevehr (1988) suggested using lagged shares instead of the current share in the Stone's price index in linear approximate AIDS to overcome the problem of simultaneity. We used the log linear version of the Paasche's index (Moschini 1995) with lagged shares. Equation 3 gives the dynamic version of the AIDS model:

$$w_{i,t} = \propto_{i,t} + \sum_{j=1}^{n} \gamma_{ij} lnp_{j,t} + \beta_i \left[lnX_t - \sum_{j=1}^{n} (w_{j,t-1} ln \frac{p_{j,t}}{p_{j,0}}) \right]. \tag{3}$$

Equation 3 does not control for seasonal effects and other demand shifters. We have modified $\propto_i$ (intercept) in equation 3 to account for effects of some of the demand shifters as follows:

$$\propto_{i,t} = \propto_{i,t}{}^{**} + \varphi_{i1} DS1 + \varphi_{i2} DS2 + \varphi_{i3} DS3 + \psi_{ij} \sum_{j=1}^{n} lnq_{j,t-1} + \mu_{i,t}\,, \tag{4}$$

where DS denotes dummy for season to analyze seasonality of demand (DS1 takes a value of '1' for the third quarter of the year, otherwise '0'; DS2 takes a value of '1' for the fourth quarter of the year, otherwise '0'; DS3 takes a value of '1' for first quarter of the year, otherwise '0'). The control season is the second quarter. The expression $q_{j,t\text{-}1}$ is a one-week lag quantity purchased of seafood j. We have incorporated the lagged quantities to examine how past week purchases of seafood j affects its own and its substitute's current weekly purchase. The expression $\mu_{i,t}$ is the error term, which accounts for random variation in the dependent variable.

Equation 5 presents the dynamic version of AIDS used in the present study:

$$w_{i,t} = \propto_{i,t}{}^{**} + \sum_{j=1}^{16} \gamma_{ij} lnp_{j,t} + \beta_i \left[lnX_t - \sum_{j=1}^{16} (w_{j,t-1} ln \frac{p_{j,t}}{p_{j,0}}) \right] + \varphi_{i1} DS1 + \varphi_{i2} DS2 + \varphi_{i3} DS3$$
$$+ \psi_{ij} \sum_{j=1}^{16} lnq_{j,t-1} + \mu_{t,i}\,. \tag{5}$$

Model Estimation

Estimation of the system of equations given in equation 5 as a complete system using theoretical restrictions will have a singularity problem. This is because the sum of the left-hand side (LHS) variables $(\sum_{j=1}^{n} w_i)$ is equal to the sum of the right-hand side (RHS) of the system of equations (due to adding-up restrictions). The most commonly used approach in the literature to overcome this problem is the Barten (1969) method; *i.e.*, estimating the system of equations by dropping one of the equations. We dropped the 'clam' equation because it had the lowest expenditure share. We estimated the model given in equation 5 using the iterated seemingly unrelated regression (ISUR) procedure in STATA12 software (STATACORP LP, Texas, U.S.). The following restrictions were tested:

$$\sum_{j=1}^{n} \gamma_{ij} = 0 \text{ (homogeneity)};\ \gamma_{ij} = \gamma_{ji}\,, i \neq j \text{ (symmetry)}. \tag{6}$$

Using adding-up restrictions (equation 7), we obtained the parameters of the dropped equation:

$$\sum_{i=1}^{n} \propto_{i,t}^{**} = 1\,; \sum_{i=1}^{n} \beta_i = 0, \sum_{i=1}^{n} \varphi_{i1} = 0, \sum_{i=1}^{n} \varphi_{i2} = 0, \sum_{i=1}^{n} \varphi_{i3} = 0, \text{and} \sum_{i=1}^{n} \psi_{ij} = 0. \tag{7}$$

We computed uncompensated price elasticities (ξ_{ij}), expenditure elasticities (η_i), and compensated price elasticities (ζ_{ij}) as follows (Chalfant 1987):

$$\xi_{ij} = -\delta + \frac{\gamma_{ij}}{w_i} - \beta_i \times \frac{w_j}{w_i};\ \eta_i = \frac{\beta_i}{w_i} + 1; \text{and } \zeta_{ij} = \xi_{ij} + w_j \times \eta_i. \tag{8}$$

where δ is the Kronecker delta, which is equal to one for own-price elasticities (i=j) and zero for cross price elasticities (i≠j).

Model Specification Tests

The study uses weekly time series data. We performed an augmented Dickey-Fuller test to test the null hypothesis (H_0): the time series contains a unit root, against the alternative hypothesis (H_1): the time series is generated by a stationary process. The test was conducted under two assumptions: *i)* the variable follows a random walk process with drift, and *ii)* the variable follows a random walk process without drift. We tested all expenditure share variables ($w_{i,t}'s$), all price variables ($lnp_{j,t}'s$), price index $(lnX_t - w_{j,t-1} ln\frac{p_{j,t}}{p_{j,0}})$, and $lnq_{j,t-1}$. Under both assumptions, the test statistic {z(T)} was found to be higher than critical test values (in absolute terms) up to the 0.10 level of significance for all time series except salmon prices. Thus, we reject H_0 for all variables except for the salmon price series.

In order to capture any possible multicollinearity problems associated with high correlation, we checked all variance-inflation factors (VIFs). Generally, individual VIFs greater than 10 and an average VIF greater than 6 is seen as indicative of severe multicollinearity. However, values of the VIF of 10, 20, or even higher do not, by themselves, discount the results of regression analyses (O'brien 2007). The maximum VIF of our data (RHS of equation 5) is 15.85 (salmon price variable), and the mean VIF is 5.70, suggesting some problem of multicollinearity.

Detecting autoregressive conditional heteroscedasticity (ARCH) effects is important from both theoretical and practical points of view (Hong and Lee 2001). Using Engle's LM test (Engle 1982) we tested ARCH effects in regression residual series. The test failed to reject the H_0; no ARCH effects for all share equations except for salmon, where ARCH effects were significant.

The study uses Breusch-Godfrey LM test for testing higher-order serial correlation in the disturbance term. The test failed to reject H_0 of no serial autocorrelation in the errors in the demand system except for the salmon equation, where significant positive serial correlation was found. Rejection of H_0 of no serial autocorrelation in the salmon equation may be due to the significant ARCH effects.

The model specification tests showed presence of a unit root in the salmon price variable, positively significant serial correlation, and significant ARCH effects in the salmon equation. Because none of the series other than the salmon price series on the RHS of equation 5 has unit root, chances of spurious regression due to non-stationarity of salmon price series are negligible, if any. Positively significant serial correlation and significant ARCH effects in salmon would reduce the levels of significance of parameters due to escalated standard errors; however, coefficients values remain unaffected. We estimated the system of equations (equation 5) without the salmon share equation and found that the estimated coefficients do not change substantially. Salmon is the third most important product after shrimp and tilapia, having a 5% share of total expenditures on the products considered. Thus, we retained the salmon equation and will discuss only the cross-price elasticities of other species with salmon price. Given the econometric problems with the salmon share equation as discussed above, we will not discuss the results of the salmon share equation and the associated elasticities.

We used the Hausman test to examine the exogeneity of the variables on the RHS of equation 5. Let ϑ be a consistent and asymptotic efficient estimator. ω is a consistent, but inefficient, estimator under that null hypothesis. The Hausman statistic can then be written as:

$$m = (\omega - \vartheta)' [var(\omega) - var(\vartheta)]^{-1} (\omega - \vartheta). \tag{9}$$

It has a chi-square distribution with degrees of freedom equal to the number of unknown parameters in ϑ. If m is larger than the critical value, then the null hypothesis is rejected. To test for exogeneity, ϑ is the SUR estimator, and ω is the 3 stage least squares (3SLS) estimator. Thus, under the assumption of exogenous RHS variables in the demand system, the SUR estimators are consistent and asymptotically efficient. If any of the RHS variables are endogenous, the SUR estimators are neither consistent nor efficient, whereas the 3SLS estimators are inefficient but consistent. The calculated test statistics (m) is 22.02 with 325 degree of freedom (df), which is highly non-significant. Hence, we did not find any evidence against the null hypothesis of exogeneity.

Using a log-likelihood ratio (LR) test, we tested the significance of theoretical restrictions. We compared the unrestricted model with the restricted models under three cases: *i)* model with homogeneity restrictions, *ii)* model with symmetry restrictions, and *iii)* model with homogeneity and symmetry restrictions. The calculated LR χ^2 statistics are 77.96 with 13 df, 168.842 with 78 df, and 202.94 with 91 df in cases *i)*, *ii)*, and *iii)*, respectively. These values are highly significant (<0.01 level of significance). Hence, the test shows significance of imposing restrictions, which suggests that the empirical results are at least theoretically consistent and valid for this functional specification.

Econometric Results and Discussion

Model Estimates

Tables 1 and 2 present model estimates. The model estimates follow the demand properties of homogeneity, symmetry, and adding-up. The fitted model explains 49 to 89% variation (100R-square) in the share equations (table 1). In most of the equations, the majority of the coefficients are significant up to the 0.10 level of significance (tables 1 and 2). Given the multicollinearity and positive serial correlation problems, we expect higher standard errors and low levels of significance of the coefficients.

Effects of Season and Lagged Demand

All unbreaded frozen seafood products, except flounder and lobster, exhibited seasonality in their demand, as the coefficients of one or more seasonal dummy variables are significantly different from zero (table 2). The demand for shrimp in the first quarter is about 2%; *i.e.*, $\{e^{\varphi\, i1\, =\, -0.018} - 1) * 100\}$ lower than that in the remainder of the year. Tuna demand is marginally higher during the second quarter. The demand for tilapia, whiting, scallops, and perch is higher in the first quarter, as compared to other quarters. In the fourth quarter, crab demand is lowest and catfish demand is highest. The demand for cod is highest in the first quarter and lowest in the third quarter.

Table 3 summarizes the effects of last week seafood consumption on current week consumption of different seafood products. We derived table 3 from table 2. The coefficients of own lagged quantities (ψ_{ii}) are positive and significant for shrimp, salmon, tilapia, cod, whiting, and tuna (table 2). This indicates that the consumer prefers to consume these species every week. In the case of scallops, the coefficient of own lagged quantity is significantly negative, which shows that consumers do not prefer to consume scallops every week.

Positive effects of own lagged quantities on current week purchase of a product and negative effects of its lagged quantities on current week purchases of most of the products indicates habit formation. For example, shrimp has positive effects of its lagged purchases on current purchases and negative effects on current purchases of salmon, catfish, tilapia, cod, whiting, perch, pollock, and scallops (table 3). Using a single equation dynamic demand model, Yanagida and Tyson (1984) revealed strong habit formation in shrimp consumption.

Contrary to it, negative effects of own lagged quantities on current week purchase and positive effects of its lagged quantities on current week purchases of other products indicate diverse consumption habits. We observed this phenomenon in scallop consumers who purchased scallops in the previous week and chose to purchase tuna in current week (table 3). Positive cross-lagged quantity effects in the case of substituting products (*e.g.*, lobster and shrimp, catfish, and whiting) indicate that seafood consumers who consumed a product in the previous week would prefer to consume its substitute product in current week (table 3).

Own-Price, Cross-Price, and Expenditure Elasticities

Table 4 gives estimated uncompensated own-price, compensated cross-price and expenditure elasticities. Compensated cross-price elasticities provide a better measure of substitutability because they take into account the substitution effect but not the income effect. The own-price elasticities are negative, showing that the underlying Slutsky matrix is negative semi-definite (*i.e.*, the demand function satisfies Walras's law, homogeneity of degree zero, and the Weak Axiom) (table 4).

Table 1
ISURE Estimates of the Share Equation for Price and Expenditure Variables, Unbreaded Frozen Seafood Products, U.S.

Equation→	Shrimp		Salmon		Crab		Catfish		Tilapia		Flounder		Cod	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
*ln*p_Shrimp	0.122^{***}	0.028	-0.030^{***}	0.006	-0.006^{ns}	0.008	-0.011^{***}	0.004	-0.050^{***}	0.014	0.000^{ns}	0.004	-0.005^{**}	0.002
*ln*p_Salmon	-0.030^{***}	0.006	0.034^{***}	0.002	-0.003^{ns}	0.002	-0.001^{ns}	0.001	0.005^{ns}	0.003	-0.003^{**}	0.001	0.005^{***}	0.001
*ln*p_Crab	-0.006^{ns}	0.008	-0.003^{ns}	0.002	0.027^{***}	0.005	0.001^{ns}	0.002	0.000^{ns}	0.005	-0.007^{***}	0.003	-0.002^{**}	0.001
*ln*p_Catfish	-0.011^{***}	0.004	-0.001^{ns}	0.001	0.001^{ns}	0.002	0.004^{ns}	0.003	0.003^{ns}	0.003	-0.002^{ns}	0.002	0.000^{ns}	0.001
*ln*p_Tilapia	-0.050^{***}	0.014	0.005^{ns}	0.003	0.000^{ns}	0.005	0.003^{ns}	0.003	0.012^{ns}	0.010	0.005^{ns}	0.004	0.000^{ns}	0.002
*ln*p_Flounder	0.000^{ns}	0.004	-0.003^{**}	0.001	-0.007^{***}	0.003	-0.002^{ns}	0.002	0.005^{ns}	0.004	0.010^{***}	0.003	0.000^{ns}	0.001
*ln*p_Cod	-0.005^{**}	0.002	0.005^{***}	0.001	-0.002^{**}	0.001	0.000^{ns}	0.001	0.000^{ns}	0.002	0.000^{ns}	0.001	-0.001^{**}	0.001
*ln*p_Whiting	-0.007^{ns}	0.006	-0.006^{***}	0.002	-0.004^{ns}	0.003	0.010^{***}	0.003	0.009^{*}	0.005	-0.007^{**}	0.003	0.001^{ns}	0.001
*ln*p_Perch	0.000^{ns}	0.002	0.000^{ns}	0.001	-0.002^{***}	0.001	-0.002^{*}	0.001	0.001^{ns}	0.001	0.002^{**}	0.001	0.000^{ns}	0.000
*ln*p_Tuna	-0.002^{*}	0.001	-0.001^{ns}	0.000	0.000^{ns}	0.001	-0.002^{**}	0.001	0.002^{ns}	0.001	0.000^{ns}	0.001	0.000^{ns}	0.000
*ln*p_Pollock	-0.002^{***}	0.001	-0.001^{*}	0.000	0.000^{ns}	0.001	0.000^{ns}	0.001	-0.001^{ns}	0.001	-0.001^{*}	0.001	0.000^{ns}	0.000
*ln*p_Lobster	-0.002^{ns}	0.003	0.000^{ns}	0.001	0.001^{ns}	0.002	-0.002^{*}	0.001	-0.001^{ns}	0.002	0.002^{ns}	0.001	0.000^{ns}	0.001
lnp_Scallop	-0.005^{ns}	0.005	0.000^{ns}	0.002	-0.002^{ns}	0.003	0.004^{*}	0.002	0.014^{***}	0.004	0.000^{ns}	0.002	0.002^{**}	0.001
*ln*p_Clam	-0.001^{ns}	0.001	0.000^{ns}	0.000	0.000^{ns}	0.000	-0.001^{***}	0.000	0.001^{ns}	0.001	0.000^{ns}	0.000	0.000^{ns}	0.000
ln(X/P)	0.106^{***}	0.016	-0.028^{***}	0.004	-0.001^{ns}	0.003	-0.003^{*}	0.002	-0.035^{***}	0.008	-0.010^{***}	0.002	-0.008^{***}	0.001
R-square	0.733		0.893		0.493		0.687		0.699		0.606		0.790	

***, **, and * denote significance of coefficients at the 0.01, 0.05, and 0.10 levels of significance, respectively. ^{ns} denotes non-significant coefficients up to 0.10 level of significance. S.E. means standard error. *ln* is natural logarithmic.

Table 1 (continued)

ISURE Estimates of the Share Equation for Price and Expenditure Variables, Unbreaded Frozen Seafood Products, U.S.

Equation→	Whiting		Perch		Tuna		Pollock		Lobster		Scallops		Clams		
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	
*ln*p_Shrimp	–0.007^{ns}	0.006	0.000^{ns}	0.002	–0.002*	0.001	–0.002***	0.001	–0.002^{ns}	0.003	–0.005^{ns}	0.005	–0.001	ne	ne
*ln*p_Salmon	–0.006***	0.002	0.000^{ns}	0.001	–0.001^{ns}	0.000	–0.001*	0.000	0.000^{ns}	0.001	0.000^{ns}	0.002	0.000	ne	ne
*ln*p_Crab	–0.004^{ns}	0.003	–0.002***	0.001	0.000^{ns}	0.001	0.000^{ns}	0.001	0.001^{ns}	0.002	–0.002^{ns}	0.003	0.000	ne	ne
*ln*p_Catfish	0.010***	0.003	–0.002*	0.001	–0.002**	0.001	0.000^{ns}	0.001	–0.002*	0.001	0.004*	0.002	–0.001	ne	ne
*ln*p_Tilapia	0.009*	0.005	0.001^{ns}	0.001	0.002^{ns}	0.001	–0.001^{ns}	0.001	–0.001^{ns}	0.002	0.014***	0.004	0.001	ne	ne
*ln*p_Flounder	–0.007**	0.003	0.002**	0.001	0.000^{ns}	0.001	–0.001*	0.001	0.002^{ns}	0.001	0.000^{ns}	0.002	0.000	ne	ne
*ln*p_Cod	0.001^{ns}	0.001	0.000^{ns}	0.000	0.000^{ns}	0.000	0.000^{ns}	0.000	0.000^{ns}	0.001	0.002**	0.001	0.000	ne	ne
*ln*p_Whiting	–0.017***	0.006	0.007***	0.001	0.002^{ns}	0.001	0.008***	0.001	–0.002^{ns}	0.002	0.006**	0.003	0.001	ne	ne
*ln*p_Perch	0.007***	0.001	–0.004***	0.001	0.000^{ns}	0.000	0.000^{ns}	0.000	–0.001***	0.000	–0.001^{ns}	0.001	0.000	ne	ne
*ln*p_Tuna	0.002^{ns}	0.001	0.000^{ns}	0.000	0.0001^{ns}	0.001	0.001*	0.000	0.000^{ns}	0.000	0.000^{ns}	0.001	0.000	ne	ne
*ln*p_Pollock	0.008***	0.001	0.000^{ns}	0.000	0.001*	0.000	–0.006***	0.001	0.001***	0.000	0.002***	0.001	0.001	ne	ne
*ln*p_Lobster	–0.002^{ns}	0.002	–0.001***	0.000	0.000^{ns}	0.000	0.001***	0.000	0.001^{ns}	0.001	0.003**	0.002	0.000	ne	ne
*ln*p_Scallop	0.006**	0.003	–0.001^{ns}	0.001	0.000^{ns}	0.001	0.002***	0.001	0.003**	0.002	–0.024***	0.004	0.000	ne	ne
*ln*p_Clam	0.001^{ns}	0.001	0.000^{ns}	0.000	0.000*	0.000	0.001**	0.000	0.000^{ns}	0.000	0.000^{ns}	0.000	0.002	ne	ne
ln(X/P)	–0.012***	0.003	–0.002***	0.001	–0.004***	0.000	–0.003***	0.000	0.006***	0.001	–0.006***	0.002	0.000	ne	ne
R-square	0.441		0.693		0.789		0.723		0.595		0.521		ne		

***, **, and * denote significance of coefficients at the 0.01, 0.05, and 0.10 levels of significance, respectively. ^{ns} denotes non-significant coefficients up to 0.10 level of significance. S.E. means standard error. *ln* is natural logarithmic. ne means not estimated (coefficients of the clam equation are derived from the adding-up restriction).

Table 2
ISURE Estimates of the Share Equations for Demand Shifters, Unbreaded Frozen Seafood Products, U.S.

Equation→	Shrimp		Salmon		Crab		Catfish		Tilapia		Flounder		Cod	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
*ln*q(t–1)_Shrimp	0.094***	0.023	–0.012**	0.005	–0.008*	0.004	–0.007***	0.003	–0.044***	0.011	–0.003^{ns}	0.003	–0.004**	0.002
*ln*q(t–1)_Salmon	–0.066**	0.026	0.022***	0.006	0.002^{ns}	0.005	0.005*	0.003	0.026**	0.013	0.003^{ns}	0.003	0.003^{ns}	0.002
*ln*q(t–1)_Crab	–0.022^{ns}	0.018	0.000^{ns}	0.004	0.005^{ns}	0.003	0.003^{ns}	0.002	0.004^{ns}	0.009	0.004*	0.002	0.001^{ns}	0.001
*ln*q(t–1)_Catfish	0.010^{ns}	0.017	–0.003^{ns}	0.004	–0.005^{ns}	0.003	0.002^{ns}	0.002	0.001^{ns}	0.008	–0.005**	0.002	–0.003**	0.001
*ln*q(t–1)_Tilapia	–0.045***	0.016	0.004^{ns}	0.004	0.007*	0.004	0.004*	0.002	0.022***	0.008	0.002^{ns}	0.002	0.005***	0.001
*ln*q(t–1)_Flounder	0.020^{ns}	0.013	–0.006*	0.003	–0.002^{ns}	0.002	–0.001^{ns}	0.002	–0.010^{ns}	0.006	–0.001^{ns}	0.001	0.000^{ns}	0.001
*ln*q(t–1)_ Cod	–0.024**	0.011	0.010***	0.003	–0.001^{ns}	0.002	0.000^{ns}	0.001	0.007^{ns}	0.005	0.002^{ns}	0.001	0.003***	0.001
*ln*q (t–1)_Whiting	0.021^{ns}	0.018	–0.005^{ns}	0.004	0.004^{ns}	0.003	–0.006***	0.002	–0.012^{ns}	0.009	–0.004**	0.002	0.000^{ns}	0.001
*ln*q(t–1)_ Perch	0.003^{ns}	0.011	–0.005*	0.003	0.002^{ns}	0.002	0.002^{ns}	0.001	–0.001^{ns}	0.005	0.001^{ns}	0.001	–0.001^{ns}	0.001
*ln*q(t–1)_Tuna	0.000^{ns}	0.015	0.003^{ns}	0.004	–0.005*	0.003	0.003*	0.002	0.002^{ns}	0.007	0.002^{ns}	0.002	–0.001^{ns}	0.001
*ln*q(t–1)_ Pollock	0.020^{ns}	0.016	–0.004^{ns}	0.004	–0.009***	0.003	–0.004**	0.002	–0.002^{ns}	0.008	0.001^{ns}	0.002	–0.001^{ns}	0.001
*ln*q(t–1)_ Lobster	–0.026***	0.008	0.004**	0.002	0.000^{ns}	0.001	0.001^{ns}	0.001	0.012***	0.004	0.002**	0.001	0.001^{ns}	0.001
*ln*q(t–1)_ Scallop	–0.007^{ns}	0.012	0.000^{ns}	0.003	0.000^{ns}	0.002	0.001^{ns}	0.001	0.004^{ns}	0.006	0.000^{ns}	0.001	0.001^{ns}	0.001
*ln*q(t–1)_ Clam	–0.012^{ns}	0.011	0.004^{ns}	0.003	0.000^{ns}	0.002	0.001^{ns}	0.001	0.006^{ns}	0.005	0.001^{ns}	0.001	0.000^{ns}	0.001
DS1 (III qtr)	0.008^{ns}	0.007	–0.004**	0.002	–0.001^{ns}	0.001	0.000^{ns}	0.001	–0.001^{ns}	0.004	–0.001^{ns}	0.001	–0.002***	0.001
DS2 (IV qtr)	0.014^{ns}	0.010	–0.006**	0.002	–0.003*	0.002	0.002*	0.001	–0.003^{ns}	0.005	0.001^{ns}	0.001	–0.002**	0.001
DS3 (I qtr)	–0.018**	0.008	0.000^{ns}	0.002	0.000^{ns}	0.002	0.001^{ns}	0.001	0.009**	0.004	0.000^{ns}	0.001	0.001**	0.001
Constant	–1.062**	0.425	0.415***	0.102	0.152*	0.082	0.072^{ns}	0.050	0.671***	0.208	0.146***	0.050	0.100***	0.031

***, **, and * denote significance of coefficients at the 0.01, 0.05, and 0.10 levels of significance, respectively. ^{ns} denotes non-significant coefficients up to the 0.10 level of significance. S.E. means standard error. *ln* is natural logarithmic.

Table 2 (continued)
ISURE Estimates of the Share Equations for Demand Shifters, Unbreaded Frozen Seafood Products, U.S.

Equation→	Whiting		Perch		Tuna		Pollock		Lobster		Scallops		Clams		
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	
*ln*q(t–1)_Shrimp	–0.007*	0.004	–0.004***	0.001	–0.001^{ns}	0.001	–0.002***	0.001	0.004*	0.002	–0.006**	0.003	–0.001	ne	ne
*ln*q(t–1)_Salmon	0.001^{ns}	0.004	0.000^{ns}	0.001	–0.001^{ns}	0.001	0.001**	0.001	–0.001^{ns}	0.002	0.005^{ns}	0.003	0.000	ne	ne
*ln*q(t–1)_Crab	0.000^{ns}	0.003	0.001^{ns}	0.001	–0.001*	0.001	0.001^{ns}	0.000	0.000^{ns}	0.002	0.003^{ns}	0.002	0.000	ne	ne
*ln*q(t–1)_Catfish	–0.003^{ns}	0.003	0.000^{ns}	0.001	–0.001^{ns}	0.001	–0.001^{ns}	0.000	0.004***	0.002	0.001^{ns}	0.002	0.000	ne	ne
*ln*q(t–1)_Tilapia	0.004^{ns}	0.003	0.002*	0.001	0.001**	0.001	0.001***	0.000	–0.002^{ns}	0.002	–0.005*	0.003	0.000	ne	ne
*ln*q(t–1)_Flounder	–0.001^{ns}	0.002	0.001^{ns}	0.001	0.000^{ns}	0.000	0.000^{ns}	0.000	0.000^{ns}	0.001	0.002^{ns}	0.002	0.000	ne	ne
*ln*q(t–1)_ Cod	0.000^{ns}	0.002	0.000^{ns}	0.000	0.001**	0.000	0.001*	0.000	0.000^{ns}	0.001	0.001^{ns}	0.002	0.000	ne	ne
*ln*q (t–1)_Whiting	0.005*	0.003	–0.001^{ns}	0.001	0.000^{ns}	0.001	0.000^{ns}	0.000	–0.001^{ns}	0.002	–0.002^{ns}	0.002	0.000	ne	ne
*ln*q(t–1)_ Perch	0.002^{ns}	0.002	0.001^{ns}	0.001	0.000^{ns}	0.000	0.000^{ns}	0.000	–0.002^{ns}	0.001	–0.002^{ns}	0.002	0.000	ne	ne
*ln*q(t–1)__Tuna	–0.002^{ns}	0.002	0.000^{ns}	0.001	0.001*	0.000	0.000^{ns}	0.000	–0.005***	0.001	0.001^{ns}	0.002	0.000	ne	ne
*ln*q(t–1)_ Pollock	–0.002^{ns}	0.003	0.000^{ns}	0.001	0.000^{ns}	0.000	0.000^{ns}	0.000	0.000^{ns}	0.001	0.001^{ns}	0.002	0.001	ne	ne
*ln*q(t–1)_ Lobster	0.001^{ns}	0.001	0.001^{ns}	0.000	0.000**	0.000	0.000**	0.000	0.000^{ns}	0.001	0.003**	0.001	0.000	ne	ne
*ln*q(t–1)_ Scallop	0.001^{ns}	0.002	0.001^{ns}	0.001	0.001***	0.000	0.001^{ns}	0.000	0.000^{ns}	0.001	–0.004**	0.002	0.000	ne	ne
*ln*q(t–1)_ Clam	0.000^{ns}	0.002	0.000^{ns}	0.000	0.000^{ns}	0.000	0.000^{ns}	0.000	0.000^{ns}	0.001	0.000^{ns}	0.001	0.000	ne	ne
DS1 (III qtr)	0.000^{ns}	0.001	0.000^{ns}	0.000	–0.001***	0.000	0.000**	0.000	0.000^{ns}	0.001	0.001^{ns}	0.001	0.000	ne	ne
DS2 (IV qtr)	0.000^{ns}	0.002	0.000^{ns}	0.000	–0.001***	0.000	0.000^{ns}	0.000	–0.001^{ns}	0.001	0.000^{ns}	0.001	0.000	ne	ne
DS3 (I qtr)	0.002*	0.001	0.001**	0.000	–0.001***	0.000	0.001***	0.000	0.001^{ns}	0.001	0.003**	0.001	0.000	ne	ne
Constant	0.243***	0.068	0.067***	0.019	0.058***	0.012	0.044***	0.011	–0.096**	0.039	0.188***	0.059	0.003	ne	ne

***, **, and * denote significance of coefficients at the 0.01, 0.05, and 0.10 levels of significance, respectively. ^{ns} denotes non-significant coefficients up to the 0.10 level of significance. S.E. means standard error. *ln* is natural logarithmic. ne means not estimated (coefficients of the clam equation are derived from the adding-up restriction).

Table 3
Effects of Last Week Consumption on Current Week Consumption

Seafood	Own-lagged Quantity Coefficient	Cross-lagged Quantity Coefficient: Positive and Significant	Cross-lagged Quantity Coefficient: Negative and Significant
Shrimp	Positive		Tilapia, cod, lobster
Salmon	Positive	Lobster	Shrimp, flounder, perch
Crab	Non-significant	Tilapia	Tuna, pollock
Catfish	Non-significant	Salmon, tilapia, tuna	Shrimp, whiting, pollock
Tilapia	Positive	Salmon, lobster	Shrimp
Flounder	Non-significant	Crab, lobster	Catfish, whiting
Cod	Positive	Tilapia	Shrimp, catfish
Whiting	Positive		Shrimp
Perch	Non-significant	Tilapia	Shrimp
Tuna	Positive	Tilapia, cod, lobster, scallops	Crab
Pollock	Non-significant	Salmon, tilapia, cod, lobster	Shrimp
Lobster	Non-significant	Shrimp, catfish	Tuna
Scallop	Negative	Lobster	Shrimp, tilapia

The demand for shrimp and lobsters in short-run is almost unitary own-price elastic and expenditure elastic, indicating the luxurious nature of these products in the U.S. The findings for shrimp are reasonable and consistent with the estimates of Doll (1972), Cheng and Capps (1988), and Singh, Dey, and Thapa (2011). Given that lobsters have a very high value (average price = USD 22 per pound, table 4), own-price and expenditure elasticity estimates seem reasonable.

The demand for crabs is own-price inelastic. Given the fact that crabs are specialty seafood, it is plausible that crab-loving segments of the U.S. population have inelastic demand for crabs. The results are in accordance with the findings of Cheng and Capps (1988) and Singh, Dey, and Thapa (2011).

The demand for unbreaded frozen catfish, tilapia, and flounder is own-price and expenditure inelastic. Whereas cod, whiting, perch, pollock, and scallop are relatively own-price elastic and expenditure inelastic.

Using double-log, Norman-López and Asche (2008) estimated the own-price and income elasticities of frozen fillets of U.S. catfish at –0.773 and 0.540 levels, respectively, in the U.S. market. The own-price elasticity of demand for fresh fillets of U.S. catfish is –1.029. Kinnucan and Miao (1999) and Kouka (1995) estimated own-price elasticity of catfish fillet as –0.706 and –1.17, respectively. Duc (2010) found the domestic demand for U.S. farm-raised catfish fillets as price elastic and Vietnam catfish fillets in the U.S. market as price inelastic. Data used in our study do not distinguish between U.S. farm-raised catfish and imports or between whole and fillets. Therefore, our own-price elasticity (–0.78) and expenditure elasticity (0.81) estimates for catfish seem rational.

Using a ‘Source Differentiated Almost Ideal Demand System’ (SDAIDS) model, Ligeon *et al*. (2007) conducted an import demand study for tilapia and tilapia products in the U.S. They estimated the own price elasticity of frozen fillets from Jamaica, Thailand, Indonesia, and China at –0.23, –0.14, –0.18, and –0.96 levels, respectively. Findings of Ligeon *et al*. (2007) indicated that fresh tilapia fillets, frozen tilapia fillets, and whole tilapia are all normal goods in the U.S. market. Norman-López and Asche (2008) found the own-price elasticities of fresh and frozen tilapia fillets to be –0.711 and –0.689, respectively. The income elasticities of demand for fresh and frozen imported tilapia fillets obtained are 0.157, and 0.564, respectively. The own-price elasticity (0.83) and expenditure elasticity (0.61) estimates for tilapia in our study are consistent with the findings of Norman-Lopez and Asche (2008) and Ligeon *et al*. (2007).

Table 4
Estimates of Own-price, Cross-price, and Expenditure Elasticities,
Unbreaded Frozen Seafood Products, U.S.

Equation		Shrimp	Salmon	Crab	Catfish	Tilapia	Flounder	Cod
Price elasticities	Shrimp	**–0.93**	0.09	0.50	0.08	0.14	0.70	0.37
	Salmon	0.01	**–0.28**	–0.04	0.00	0.11	–0.15	0.41
	Crab	0.02	–0.03	**–0.19**	0.07	0.03	–0.47	–0.14
	Catfish	0.00	0.00	0.03	**–0.78**	0.05	–0.13	0.02
	Tilapia	0.02	0.19	0.08	0.25	**–0.83**	0.45	0.09
	Flounder	0.01	–0.04	–0.20	–0.11	0.07	**–0.28**	0.05
	Cod	0.01	0.12	–0.06	0.01	0.01	0.04	**–1.10**
	Whiting	0.02	–0.10	–0.10	0.59	0.13	–0.44	0.09
	Perch	0.01	0.01	–0.06	–0.08	0.02	0.16	–0.02
	Tuna	0.00	0.00	0.00	–0.10	0.02	0.02	0.01
	Pollock	0.00	–0.01	0.00	0.00	–0.01	–0.08	0.00
	Lobster	0.01	0.00	0.04	–0.09	0.00	0.12	0.04
	Scallop	0.02	0.02	–0.02	0.23	0.19	0.00	0.19
	Clam	0.00	0.00	–0.01	–0.08	0.01	0.03	–0.01
Expenditure elasticity		1.15	0.44	0.96	0.81	0.61	0.32	0.40
Average share (%)		70.1	4.9	3.3	1.7	8.9	1.4	1.4
Average price ($/lb.)		6.51	5.24	5.21	3.32	3.68	3.90	6.30

Equation		Whiting	Perch	Tuna	Pollock	Lobster	Scallops	Clams
Price elasticities	Shrimp	0.41	0.72	0.31	0.27	0.47	0.52	0.11
	Salmon	–0.19	0.05	–0.04	–0.07	–0.01	0.04	0.10
	Crab	–0.13	–0.27	–0.01	0.00	0.16	–0.02	–0.10
	Catfish	0.40	–0.19	–0.31	0.01	–0.21	0.14	–0.83
	Tilapia	0.46	0.26	0.39	–0.10	–0.02	0.60	0.38
	Flounder	–0.25	0.30	0.06	–0.20	0.22	0.00	0.26
	Cod	0.05	–0.04	0.04	–0.01	0.07	0.09	–0.07
	Whiting	**–1.67**	0.90	0.40	1.43	–0.21	0.25	0.32
	Perch	0.27	**–1.52**	–0.05	0.04	–0.17	–0.01	0.04
	Tuna	0.09	–0.04	**–0.98**	0.14	0.05	0.01	–0.22
	Pollock	0.31	0.03	0.14	**–2.08**	0.10	0.07	0.31
	Lobster	–0.06	–0.17	0.07	0.14	**–0.91**	0.13	–0.17
	Scallop	0.27	–0.04	0.05	0.34	0.47	**–1.83**	–0.07
	Clam	0.02	0.01	–0.07	0.10	–0.04	0.00	**–0.06**
Expenditure elasticity		0.52	0.72	0.33	0.48	1.77	0.79	1.00
Average share (%)		2.6	0.8	0.6	0.6	0.8	2.8	0.2
Average price ($/lb.)		2.56	5.27	9.77	2.87	21.90	6.88	5.82

Note: **Bolded** figures are uncompensated own-price elasticities. Cross-price elasticities are compensated.

Imports of tilapia into the U.S. increased about 36% by volume in 2009 over 2005, and 22% by volume during April–June 2010 over the April–June 2009 period. This suggests that consumers may be substituting tilapia for other products. Harvey (2002) and Josupeit (2005) suggested tilapia has increased its market share by filling the gap left as a result of declining Vietnamese *basa* imports.

The estimated cross-price elasticities of demand for different species for tilapia indicate substitutability of tilapia for shrimp, salmon, flounder, whiting, tuna, and scallops (table 4). The cross-price elasticity estimates between tilapia and catfish are too low to establish a significant relationship between them (table 4). These results are consistent with the findings of Norman-Lopez and Asche (2008), who found that demand for fresh and frozen imported tilapia was independent of the demand for fresh and frozen domestic catfish. However, Muhammad *et al.* (2010) found tilapia as a substitute for domestic catfish in the U.S. Industry commentators have suggested that tilapia is competing with domestically produced catfish in the U.S. market (Harvey 2002; Josupeit 2005).

Catfish is the largest aquaculture industry in the U.S. In a highly competitive seafood market, domestic market growth is very important for the U.S. catfish industry. Domestically produced catfish accounts for more than 78% of total catfish sales in the U.S. Data used in this study does not differentiate between imported catfish, including *Pangas* and U.S. farm-raised channel catfish. Given nationwide presence of tilapia in the U.S. and uneven distribution of catfish (particularly domestically produced), studying the relationship between catfish and tilapia in the markets where they are having significant market shares (*e.g.*, southern region of the U.S.) can produce different results.

The cross-price elasticities of demand for catfish and whiting with respect to each other's prices are positive. This suggests catfish and whiting as substitute products; however, whiting is a stronger substitute for catfish as compared to catfish for whiting. Other weak substitutes for catfish are shrimp and scallops. Duc (2010) found that the prices of imported salmon had no significant effect on the prices of the U.S. and Vietnamese catfish fillets in the U.S. market. Our results regarding the effects of salmon prices on catfish demand in the U.S. support these findings.

Shrimp substitutes for salmon, catfish, tilapia, cod, tuna, pollock, crab, flounder, and lobster. Shrimp, tilapia, and cod are weak substitutes for unbreaded frozen salmon; whereas salmon substitutes for shrimp, tilapia, and cod. Flounder and whiting are complements to each other. Scallops and shrimp are substitutes for lobster. Scallops are also substitutes for shrimp.

Concluding Remarks

We used national store-level scanner data acquired from A.C. Nielsen Inc., to analyze the demand for 14 unbreaded frozen seafood products in the U.S. The scanner data is revealed preference data that represent actual market choices. We used a log-linear version of the Paasche's index with lagged shares as the price index in an AIDS model and modified the intercept of the standard AIDS model to account for effects of season and lagged demand. Results show that own-price, cross-price, and expenditure elasticities vary across species considerably, which highlights the importance of studying consumer demand behavior at disaggregated levels of seafood.

Given the weekly purchase behavior of the majority of U.S. seafood consumers, the study highlights the importance of studying the effects of the previous week purchases on current week purchases of seafood products. Such types of analyses provide information about habit formation, diversity in consumer preferences, weekly substitutability among products, and contrary preferences.

Contrary to industry commentators' expectations and in line with the findings of some recent studies, we did not find a significant relationship between tilapia and catfish at the national level. Our study did not distinguish between imported and domestically produced channel catfish and basa/tra. Also the distribution of tilapia and catfish is not similar across markets in the U.S. Studying substitutability between tilapia and catfish in markets where catfish has significant market shares (*e.g.*, south and midwest regions of the U.S.) can produce different results. Therefore, future research on more detailed regional analysis of seafood demand in the U.S. is warranted.

We have included season as an indicator variable that shifts the intercept. However, intercept shifts alone may not alter demand elasticities; or if they do, the elasticity changes may occur in restricted and functionally dependent ways. There is a need for future research to model season effects in demand using indicator variables to shift the intercept as well as each slope coefficient for each time period within the year.

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