Demand Elasticities for Fresh Fruit at the Retail Level

by

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Abstract

The obesity epidemic in the US and elsewhere has re-doubled efforts to understand determinants of the quality of consumers' diets. Part of the discussion has centered on the potential of "fat taxes" and/or the subsidization of the purchase of fresh fruits and vegetables to coax consumers to better diets. Whether this discussion has merit or not, fundamental to the debate are the demand elasticities of the commodities involved. This study employs weekly data from several retail stores on fruit prices and sales to estimate elasticities of individual fruits. Estimates show consumers are more responsive to price than has been found previously.

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The obesity epidemic in the US and elsewhere has re-doubled efforts to understand determinants of the quality of consumers' diets. Part of the discussion has centered on the potential of "fat taxes" and/or the subsidization of the purchase of fresh fruits and vegetables to coax consumers to better diets. Whether this discussion has merit or not, fundamental to the debate are the demand elasticities of the commodities involved. A search of the literature produced fifteen sources which included elasticities for fresh fruits in some form, not all of which are published. Of these, seven sources that contain estimates of elasticities for fresh fruit as an aggregate commodity, seven sources for individual fruit elasticities, and one that gives individual apple variety elasticities. The ranges of the elasticity estimates found are given in the following table.

Table 1. Ranges of Fruit Elasticity Estimates

Commodities		Fresh Fruit	Apples	Bananas	Oranges
Price Elasticities	Average	-0.51	-0.78	-0.56	-0.88
	Minimum	-1.32	-2.33	-0.74	-1.14
	Maximum	-0.21	-0.19	-0.24	-0.27
Expenditure Elasticities	Average	0.62	0.12	0.47	0.60
	Minimum	-0.13	-0.19	0.05	-0.89
	Maximum	1.60	1.11	1.21	1.76

The simple averages of estimates from previous studies suggest fruits are price and expenditure inelastic. From the ranges available in previous studies, it seems difficult to judge whether subsidization of fresh fruit consumption would have a significant effect on consumers' diets. Certainly, the less elastic ends of the estimates' ranges suggest that it would take large subsidies to induce a significant increase in fresh fruit consumption.

In this paper, we produce new fresh fruit elasticity estimates obtained from a unique store-level data set. Previous studies have been undertaken at an aggregate market or a household level, so this study adds useful information to applied studies of food demand. The data is gathered from two supermarkets in the Pacific Northwest. From each store weekly observations were gathered on both sales and prices of fruits, as well as the total display space devoted to each fruit. The fruits include: apples, pears, bananas, oranges, grapes, and other fruit. Individual varieties are aggregated into their fruit category and weighted average prices calculated. These data will be used to estimate demands for fruit from each store using a little over half the data (80 of 141 weeks). The final 61 weeks are reserved to evaluate each demand system's out-of-sample forecasting ability. The system with the best forecasting performance in a minimum root mean square error sense will then be used to estimate elasticities over the entire sample. Based on preliminary attempts, models will incorporate both seasonal effects and display space for each fruit group.

In the next section four demand systems are proposed for evaluation and each is briefly discussed. In the third section of the paper the details of the data and descriptive statistics are given. The fourth section presents results of forecast evaluation and elasticity estimates from the chosen model. The final section summarizes and concludes.

Some Demand Systems

The following demand systems will be evaluated: double-log, linear approximate almost ideal, almost ideal, and quadratic almost ideal systems. Experimentation with various types of dynamic models, such as Rotterdam, error correction, partial adjustment showed little or no improvement over static models for this problem.

The log-log demand system enjoys a long history in empirical work. Its coefficients are elasticities which are of primary interest here. However, there is little on theoretical grounds to justify this form (Deaton and Muellbauer). It is included because Kastens and Brester found that this form out performed theoretically consistent model when it came to forecasting, especially if theoretical restrictions were imposed. Therefore, the log-log system estimated will be:

$$\ln q_{it} = \beta_0 + \sum_{k=1}^{3} q_{ik} Q_{kt} + \sum_{l=1}^{6} d_{il} TD_{lt} + \sum_{j=1}^{n} e_{ij} \ln p_{jt} + e_i \ln x_t + \epsilon_{it}$$

$$s.t. \sum_{j=1}^{n} e_{ij} + e_i = 0 \ \forall \ i,$$

$$e_{ji} = \frac{\bar{w}_i}{\bar{w}_j} e_{ij} + \bar{w}_i (e_i - e_j) \ \forall \ j > i$$

In this (and the other models, as well) *Qs* represent seasonal dummies and *TDs* are the total display area for each fruit. The restrictions in the second line are those implied by homogeneity and those in third are implied by symmetry which is imposed at the sample means. The errors in all models are assumed multivariate normal with zero means and correlated across equations in the same time period, but not heteroskedastic in an equation or correlated across time periods. The log-log model does not add up, so all six equations are estimated. To make comparisons to other models, forecasts are exponentiated and then combined with the future prices and expenditure to generate forecasts of expenditure shares. These are then used to calculate root mean square errors (RMSE).

The AIDS model has expenditure shares, *w*, as dependent variables, as do the subsequent models. This is still one of the most used demand systems in empirical studies.

$$w_{it} = \alpha_i + \sum_{k=1}^{3} q_{ik} Q_{kt} + \sum_{l=1}^{6} d_{il} TD_{lt} + \sum_{j=1}^{n} \gamma_{ij} \ln p_{jt} + \beta_i (\ln x_t - \ln P_t) + \epsilon_{it}$$
$$where \;\; \ln P_t = \alpha_0 + \sum_j \alpha_j \ln p_{jt} + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \ln p_{it} \ln p_{jt}$$
$$s.t. \; \sum_{j=1}^{n} \gamma_{ij} = 0 \;\; \forall \; i,$$
$$\gamma_{ij} = \gamma_{ji} \;\; \forall \; i \neq j$$

The third line gives homogeneity restrictions and the fourth symmetry restrictions. The translog price index is estimated (in both the AIDS and QUAIDS models) assuming α_0 is zero.

The LA/AIDS model:

$$w_{it} = \alpha_i + \sum_{k=1}^{3} q_{ik} Q_{kt} + \sum_{l=1}^{6} d_{il} TD_{lt} + \sum_{j=1}^{n} \gamma_{ij} \ln p_{jt} + \beta_i (\ln x_t - \ln P_t^*) + \epsilon_{it}$$
$$where \;\; \ln P_t^* = \sum_j w_{jt} \ln \frac{p_{jt}}{\bar{p}_j}$$
$$s.t. \; \sum_{j=1}^{n} \gamma_{ij} = 0 \;\; \forall \; i,$$
$$\gamma_{ij} = \gamma_{ji} \;\; \forall \; i \neq j$$

There are a number of studies which look at what approximation to use for the price index, eg. Moschini, Asche and Wessells, and Buse, with some continuing disagreement, it seems, however, to make little practical difference.

The QUAIDS model:

$$w_{it} = \alpha_i + \sum_{k=1}^{3} q_{ik} Q_{kt} + \sum_{l=1}^{6} d_{il} TD_{lt} + \sum_{j=1}^{n} \gamma_{ij} \ln p_{jt} + \beta_i (\ln x_t - \ln P_t) + \frac{\lambda_i}{\prod_{j=1}^{n} \beta_j} (\ln x_t - \ln P_t)^2 + \epsilon_{it}$$

$$where \;\; \ln P_t = \alpha_0 + \sum_j \alpha_j \ln p_{jt} + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \ln p_{it} \ln p_{jt}$$

$$s.t. \; \sum_{j=1}^{n} \gamma_{ij} = 0 \;\; \forall \; i,$$

$$\gamma_{ij} = \gamma_{ji} \;\; \forall \; i \neq j$$

The QUAIDS model is a rank three system which allows for more flexible representation of expenditure effects, which could also effect the price elasticities, so it is included, as well.

The Data

The data used for this study included weekly dollar sales and quantities sold from two retail grocery stores within the same chain. The produce sections in each store had some differences in organization and methods for displaying produce and were located in different demographic areas in the Portland, Oregon metropolitan area. Weekly store visits entailed data collection on apples, bananas, pears, oranges, grapes and other hand fruit.[1] Information collected included display prices, advertisements in flyers and in store promotions, area of display, and point-of-purchase material size. The stores provided printouts of dollar sales and units sold.

The in-store promotion and display characteristics were examined in preliminary analysis: after price, the in-store characteristic that had the most critical impact on demand estimates was the display area given to each product. For this reason display area is included as part of the demand system, other variables, while influential at a disaggregate level, are less important after aggregation.

Display size varies by season, and is more variable in one store than the other. Increasingly one store has devoted a fixed level of space to apples within one set of displays with specials and expansions into secondary free-standing displays at some times. The same basics apply to pears though display of other fruits is more variable. In the second store there is more random display between varieties and fruits though expansions to secondary displays are also not uncommon. Because sales and specials are also associated with expansions, it is important to consider display area in models to evaluate price elasticity.

Forecasting Performance

Each model was estimated using the first 80 weeks of data. Those estimates were then combined with the actual values of the right-hand-side variables for weeks 81 through 141 to forecast the dependent variables for each model. The log-log models forecasts are exponentiated and used to calculate a forecast expenditure share for each fruit to make comparisons possible. Root mean square errors (RMSEs are multiplied by 100) are then calculated for each model for each fruit and then summed. Results are given in table 2 and 3.

Table 2. Out-of-Sample Forecast RMSEs*100 - Store 2

Fruit	log-log	AIDS	LAAIDS	QUAIDS
Apple	**3.33**	4.36	4.37	4.92
Pear	1.70	1.77	1.81	**1.62**
Banana	4.46	3.63	3.74	**3.18**
Orange	5.65	4.98	5.30	**4.72**
Grape	5.26	**5.20**	5.38	5.46
Other	**9.34**	9.46	9.43	9.44
Sum	29.75	29.41	30.03	29.33

Estimation sample: weeks 1-80; forecast sample: weeks 81-141. Bold indicates the entry is the smallest in that row.

Table 3. Out-of-Sample Forecast RMSEs*100 - Store 3

Fruit	log-log	AIDS	LAAIDS	QUAIDS
Apple	**4.21**	4.45	4.59	4.52
Pear	**2.17**	2.35	2.33	2.30
Banana	4.81	4.54	**4.52**	4.57
Orange	4.99	**3.60**	3.69	3.61
Grape	**4.14**	5.19	5.14	4.67
Other	9.42	9.12	8.87	**8.71**
Sum	29.75	29.25	29.14	28.37

Estimation sample: weeks 1-80; forecast sample: weeks 81-141. Bold indicates the entry is the smallest in that row.

No model dominates for all fruits at either store, but the QUAIDS model has the smallest RMSE in three of six case for store two, while the log-log model has the smallest RMSE in three of six cases for store three. The worst forecasts in both stores are for other fruit as should be expected. At the bottom of each column the sum of the RMSEs for each model are given. For both stores, the QUAIDS model produces the lowest sum. It will be used in the next section to produce elasticity estimates from the overall data sets for each store.

Fresh Fruit Elasticities

Elasticities for the QUAIDS model are calculated as follows (Banks, Blundell, and Lewbel). Differentiate the share equations with respect to the logarithms of expenditure and of prices:

$$\mu_i \equiv \frac{\partial w_i}{\partial \ln x} = \beta_i + \frac{2\lambda_i}{\prod_k p_k^{\beta_k}}(\ln x - \ln P)$$

$$\mu_{ij} \equiv \frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \mu_i(\alpha_j + \sum_k \gamma_{jk} \ln p_k) - \frac{\lambda_i \beta_j}{\prod_k p_k^{\beta_k}}(\ln x - \ln P)^2$$

then $e_i = \mu_i / w_i + 1$ and $e_{ij} = \mu_{ij} / w_i - \delta_{ij}$. Prior to estimation, all prices were normalized to have sample mean = 1. This simplifies the calculations of the elasticities somewhat as now the μs are:

$$\mu_i \equiv \frac{\partial w_i}{\partial \ln x} = \beta_i + 2\lambda_i(\ln x)$$

$$\mu_{ij} \equiv \frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \mu_i \alpha_j - \lambda_i \beta_j (\ln x)^2$$

and the sample average shares are used. Standard errors for the elasticities are calculated using the delta method and assuming the average shares are constants.

Table 4. Estimated Elasticities from Store 2.

	Apples	Pears	Bananas	Oranges	Grapes	Other	Expenditure
Apples	**-1.13**	0.04	0.03	0.08	**0.18**	0.11	**0.70**
Std Error	0.05	0.10	0.06	0.36	0.09	0.12	0.05
Pears	**0.18**	**-1.44**	0.10	0.07	**0.25**	0.07	**0.77**
Std Error	0.09	0.10	0.22	0.06	0.06	0.10	0.10
Bananas	0.02	0.01	**-0.98**	**0.08**	**0.11**	0.02	**0.74**
Std Error	0.04	0.02	0.04	0.03	0.02	0.14	0.05
Oranges	0.01	0.01	0.00	**-1.37**	0.25	**-0.30**	**1.40**
Std Error	0.06	0.05	0.08	0.08	0.43	0.09	0.09
Grapes	0.11	0.07	0.04	0.27	**-1.62**	0.01	**1.12**
Std Error	0.30	0.19	0.44	0.39	0.06	0.43	0.26
Other	-0.01	0.00	-0.10	-0.14	-0.07	**-0.99**	**1.30**
Std Error	0.18	0.09	0.31	0.58	0.10	0.21	0.08

Bolded entries are at least twice their standard errors. Standard errors are calculated by the delta method assuming mean shares are fixed.

Table 5. Estimated Elasticities from Store 3.

	Apples	Pears	Bananas	Oranges	Grapes	Other	Expenditure
Apples	**-1.19**	0.06	**0.07**	0.06	**0.16**	0.03	**0.82**
Std Error	0.04	0.11	0.03	0.28	0.03	0.05	0.05
Pears	**0.19**	**-1.68**	**0.13**	0.02	**0.25**	0.16	**0.93**
Std Error	0.08	0.11	0.06	0.05	0.06	0.32	0.11
Bananas	**0.10**	0.05	**-0.90**	0.02	**0.12**	-0.07	**0.68**
Std Error	0.05	0.04	0.07	0.08	0.03	0.12	0.06
Oranges	0.07	0.01	-0.02	**-1.30**	0.27	-0.08	**1.05**
Std Error	0.06	0.03	0.05	0.06	0.50	0.21	0.11
Grapes	0.12	0.08	0.02	0.15	**-1.67**	0.02	**1.28**
Std Error	0.43	0.45	0.50	0.62	0.05	0.93	0.29
Other	-0.07	0.03	-0.20	-0.06	0.02	**-0.99**	**1.29**
Std Error	0.19	0.28	0.18	0.83	0.28	0.42	0.12

Bolded entries are at least twice their standard errors. Standard errors are calculated by the delta method assuming mean shares are fixed.

All fruits are own-price elastic with the exception of bananas which are slightly inelastic, but not significantly so. Apples, pears, and bananas are expenditure inelastic while oranges, grapes and other fruits are expenditure elastic. The only significant complementary relationship (The fruit salad effect?) is between oranges and other fruits at store 2. All other significant cross-price elasticities show that fruits are substitutes at both stores. The agreement across stores is striking, as well.

Summary and Conclusions

Data from two grocery stores in the Pacific Northwest are used to judge between four different demand systems based on out-of-sample forecasting. The model with the lowest overall root mean square error was the quadratic almost ideal (QUAIDS) for both stores, although the forecasting ability of none of the four demand systems was probably significantly worse. The QUAIDS model was then re-estimated for both stores using the entire data set and elasticity estimates and their standard errors were calculated at the sample mean shares. These turned out to be more elastic with respect to own-price and expenditure than the averages of previous estimates and toward the more elastic of the previous estimates. Few of the cross-price elasticities were significant, but of those that were all but one showed a slight substitutability between the fruits.

Since our data come from two stores in the Pacific Northwest, it is heroic to generalize. However, the stores are located in a major metropolitan area and therefore are likely to be representative of other urban populations.

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