ADVERTISING AND THE RETAIL DEMAND FOR ORANGE JUICE

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ABSTRACT
This report analyzes the impact of both FDOC and branded advertising on the demand for orange juice at the retail level of the marketing chain, defined as supermarkets and supercenters with sales in excess of $2 million per year. Data for the analysis are from AC Nielsen and Competitive Media Reporting for January 1989 to September 2002. Both econometric (structural) models and vector autoregression (time-series) models are used in the analysis. The results suggest FDOC advertising over the period increased total orange juice consumption by 3.31% to 7.67% on average resulting in nearly 2.2 million to 5.2 million more gallons of orange juice sales each month. In contrast, branded advertising was not found to be a statistically significant determinant of orange juice demand.

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ADVERTISING AND THE RETAIL DEMAND FOR ORANGE JUICE

EXECUTIVE SUMMARY

The Florida Department of Citrus (FDOC) is an executive agency of Florida State government operating under a state marketing order since 1935. Facilitating the marketing process, and more specifically, the generic promotion of citrus, are primary functions of the agency. The FDOC is funded through a per-box tax levied on citrus growers in accordance with the stipulations set forth in the State of Florida citrus code, Chapter 601, F.S. Proceeds from the taxes total nearly $65 million annually and are used to fund the general operations of the FDOC, including both domestic and foreign advertising and promotion of citrus juices and fresh citrus. Since 1989, approximately $22 million on average has been allocated annually by the FDOC to the advertising of Florida orange juice via print, television, and radio media.

This report describes the impact of both FDOC and branded advertising expenditures on the demand for orange juice at the retail level of the marketing chain, defined as supermarkets and supercenters with sales in excess of $2 million per year. The primary reasons for concentrating only on the retail level are the following: (1) consumers are the recipients of the advertising messages and it is necessary to understand how their behavior changes in response to those messages; (2) despite the fact the analysis deals with supermarkets and supercenters, this segment of the marketing chain accounts for nearly 63% of product disappearance; (3) data are plentiful and relatively free of major structural changes so as to allow a rigorous analysis of the demand for orange juice; and (4) this analysis yields a current picture of the impacts of FDOC advertising efforts and brand advertising efforts on the demand for orange juice.

Data to estimate the demand for all orange juice and its components (frozen concentrate; refrigerated not from concentrate; refrigerated reconstituted; and shelf stable orange juice) are from AC Nielsen and from Competitive Media Reporting (CMR) over the period of January 1989 to September 2002. The Nielsen data pertain to sales (dollars), volumes (gallons), and prices (dollars/gallon) for all orange juice and orange juice products. The CMR data provide information on: (1) FDOC advertising expenditures on orange juice; (2) branded advertising expenditures on orange juice; and (3) advertising expenditures on fruit juices and drinks, excluding orange juice.

Both econometric (structural) models and vector autoregression (time-series) models are used in the analysis. The use of these different model formulations allows a check on the robustness of the empirical results. This check is especially important given that measuring the effects of advertising on demand depends heavily on the ability to capture carryover effects. The respective models of the demand for orange juice express monthly per capita consumption as a function of: (1) the monthly real (inflation-adjusted) price of orange juice; (2) the monthly real price of grapefruit juice; (3) monthly real disposable personal income per person; (4) real monthly advertising expenditures on orange juice made by the FDOC; (5) real monthly branded advertising expenditures on orange juice made predominantly by Tropicana, Minute Maid, and

Florida's Natural; (6) real monthly advertising expenditures on fruit juices and drinks, excluding orange juice; and (7) seasonality.

The analysis clearly demonstrates that FDOC advertising efforts expand the demand for orange juice. The advertising elasticity associated with FDOC advertising expenditures is estimated to be 0.011 from the econometric model and to be between 0.015 and 0.019 from the vector autoregression models. The similarity of these estimates from two different methodological approaches adds credibility to the analysis. Without question, this finding speaks to the issue of robustness.

The analytical results suggest that total orange juice consumption increases with FDOC advertising campaigns by 3.31% to 7.67% on average. More specifically, because of FDOC advertising efforts, nearly 2.2 million to 5.2 million more gallons of orange juice were sold each month at retail supermarkets and supercenters from January 1989 to September 2002 or roughly 26 million to 62 million more gallons per year. Put another way, each inflation-adjusted dollar spent by the FDOC on advertising orange juice translates into an additional 1.88 gallons to 4.36 gallons of orange juice sold at the retail level of the marketing channel over this same time frame. For every dollar of FDOC advertising expenditure, retail revenue increased by $5.75 to $13.32 on average over the sample period. Importantly, both methodological approaches support the conclusion that branded advertising on orange juice is not a statistically significant determinant of orange juice demand. These results also are in agreement with previous studies investigating the impacts of FDOC and branded advertising on the demand for orange juice.

In addition, besides real FDOC advertising expenditures on orange juice, both the econometric (structural) model and the vector autoregression models suggest that other key drivers of orange juice consumption are the real price of orange juice and seasonality. Further, both methodological approaches reveal that monthly real per capita income does not affect monthly per capita orange juice consumption. From the structural model, there exists evidence to indicate that real grapefruit juice price and real advertising expenditures on fruit juices and drinks, excluding orange juice, significantly affect orange juice demand. The evidence from the vector autoregression models, however, does not support this contention.

The analysis also considered the economic effects of drastically-reduced FDOC advertising expenditures for orange juice over the last several months of 2001. Based on calculations from the econometric model and the vector autoregression models, the cumulative loss in consumption of orange juice from September 2001 to September 2002 was between 9.4 million to 13.1 million gallons and the cumulative loss in sales of orange juice was in the range of $41.2 million to $57.6 million dollars. In both the econometric model and the vector autoregression models, we considered the possibility that this response pattern was due to the tragic events of September 11, 2001. In all models, the influence of a post September 11th effect was negligible. The bottom line is that severe decreases in funding of FDOC advertising efforts on orange juice translated into sizeable declines in orange juice consumption and sales. With the relatively large injections of FDOC advertising expenditures on orange juice in calendar year 2002, consumption and sales rebounded eventually. However, this rebound did not occur until approximately nine months after the initial severe decline in FDOC advertising effort in September 2001. Consequently, if decreases in FDOC advertising expenditures occur relative to the typical FDOC advertising expenditure pattern, the analysis suggests that there will be notable losses in consumption and sales of orange juice. Once again, this finding speaks to the importance of FDOC advertising efforts in stimulating the demand for orange juice. Simply put, the analysis confirms that the FDOC advertising campaign in recent years has effectively shifted out the U.S. demand for orange juice.

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The Florida Department of Citrus (FDOC) is an executive agency of Florida State government operating under a state marketing order since 1935. Facilitating the marketing process and, more specifically, the generic promotion of citrus, are primary functions of the agency. The FDOC is funded through a per-box tax levied on citrus growers in accordance with the stipulations set forth in the State of Florida citrus code, Chapter 601, F.S. Proceeds from the taxes total nearly $65 million annually and are used to fund the general operations of the FDOC, including both domestic and foreign advertising and promotion of citrus juices and fresh citrus.

This report analyzes the impact of both FDOC and branded advertising expenditures on the demand for orange juice at the retail level of the marketing chain, defined as supermarkets and mass merchandisers with sales in excess of $2 million per year. Since 1989, approximately $22 million has been allocated annually by the FDOC to the advertising of Florida orange juice via print, television, and radio media. The primary reasons for concentrating on the retail level in this analysis are the following: (1) consumers are the recipients of the advertising messages and it is necessary to understand how their behavior changes in response to those messages; (2) despite the fact that the analysis deals with supermarkets and mass merchandisers, this segment of the marketing channel accounts for nearly 63% of product disappearance; (3) data are plentiful and relatively homogeneous (an absence of major structural changes) so as to allow a rigorous analysis of the demand for orange juice; and (4) this analysis yields a current picture of the impacts of FDOC and brand advertising efforts on the demand for orange juice.

In the ensuing analysis, data available from AC Nielsen over the period January 1989 to September 2002 are used to estimate the demand for all orange juice and its components - frozen concentrate (FCOJ); refrigerated not from concentrate (NFC OJ); refrigerated reconstituted (RECON OJ); and shelf stable (SS OJ). The Nielsen data pertain to sales (dollars), volumes (gallons); and prices (dollars/gallon) for all orange juice as well as for FCOJ, NFC OJ, RECON OJ, and shelf stable SS OJ. In addition, data associated with advertising expenditures available from Competitive Media Reporting (CMR) over the period January 1989 to September 2002 are used in the estimation of the various demand functions for orange juice at the retail level. These data provide information on: (1) FDOC advertising expenditures on orange juice; (2) branded advertising expenditures on orange juice; and (3) advertising expenditures on fruit juices and drinks, excluding orange juice.

This report is organized as follows. First, the theoretical framework underlying the analysis is discussed. Using this framework, the use of econometric (structural) and time-series models are justified so as to meet academic standards. Then, to insure the replicability of the empirical work, the data used to estimate the various models are discussed in three sub-sections: (1) data on dollars, prices, and quantities of orange juice; (2) data on dollars, prices, and quantities of grapefruit juice; and (3) data on advertising expenditures of orange juice made by the FDOC, branded advertising expenditures of orange juice; and advertising expenditures made on fruit juices and drinks, excluding orange juice. In the next section of the report, the results associated with the estimation of the econometric and time-series models are presented. Attention centers on measuring the impacts of the advertising efforts on the demand for orange juice – specifically FDOC advertising expenditures on orange juice; the branded advertising expenditures on orange juice; and the advertising expenditures on competing fruit juices and drinks. Subsequently, an analysis of the repercussions of FDOC advertising expenditures nearing zero ("nearly going dark") from September 2001 to November 2001 is presented. Then, the static benefit-cost ratios, with no discounting, associated with FDOC advertising efforts at the retail level of the marketing channel are calculated and discussed. Finally, the analytical results from this report are compared to those of previous studies which also focus on the impacts of advertising on the demand for orange juice. The report ends with some concluding comments.

Theoretical Framework

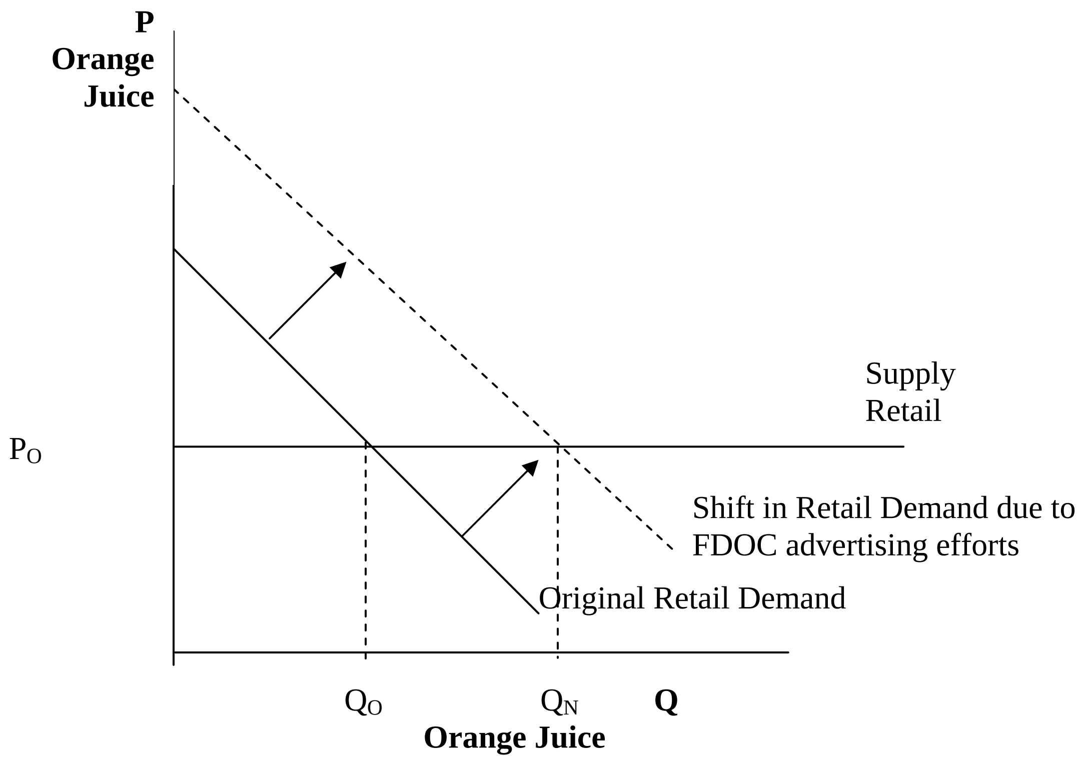
The key element of analysis of this report is the estimation of the demand for orange juice. From economic theory, potential drivers of orange juice demand include: (1) the real (inflation-adjusted) price of orange juice; (2) the real prices of possible substitutes and/or complements; (3) real disposable personal income; (4) real advertising expenditures, including FDOC advertising expenditures on orange juice; branded advertising expenditures on orange juice; and advertising expenditures on competing fruit juices and drinks; and (5) given the use of intra-year data in the analysis, seasonality. While the primary focus is on total orange juice demand, models of the demand for FCOJ, NFC OJ, RECON OJ, and SS OJ are also estimated. The analysis implicitly assumes that advertising is a component of the utility function for a representative consumer. After maximizing utility subject to a budget constraint, the demand function contains advertising as one of the exogenous variables.

Both econometric (structural) models and vector autoregression (time-series) models are developed in the analysis. The use of these different model formulations allows a check on the robustness of the empirical results. This check is especially important given that measuring advertising impacts depends heavily on the ability to monitor carryover effects. That is, both contemporaneous (current) and lagged (past) advertising expenditures must be accounted for in the analysis of the demand for orange juice.

Figure 1 demonstrates a change (shift) in the demand for orange juice attributed to the advertising efforts of the FDOC or of brand manufacturers. To measure the extent of the shift and to avoid confounding of effects, all possible drivers of orange juice demand must be controlled for and the effect of FDOC or brand advertising on the demand for orange juice isolated. If advertising impacts demand, the demand function must shift to the right, all other factors held constant. Given that the data for this analysis correspond to observations from retail supermarkets or supercenters, the supply curve is assumed to be perfectly elastic. That is, patrons from these establishments may purchase all they desire at any given price.

Grapefruit juice is hypothesized to be a substitute product for orange juice. Information pertaining to grapefruit juice is available from the AC Nielsen data. The prices of other juices are accounted for through the use of the Consumer Price Index for Nonalcoholic Beverages

Figure 1: Illustration of the Shift in Demand Due to FDOC Advertising and/or Branded Advertising



GOALS:

(a) Measure the change in demand for orange juice due to the advertising effects of the FDOC – movement from Q_O to Q_N

(b) Measure the role of brand advertising on the demand for orange juice

KEY ELEMENT: Construction of the demand curve for orange juice incorporating (FDOC) and brand advertising expenditures

Assumption:
Supply curve is perfectly elastic.

(CPINAB). Consequently, the structural specification for the demand function for orange juice may be expressed as:

(1) q_{it} = f [p_{it}, p_{st}, y_t, $FDOCOJADV_t$, $BRANDOJADV_t$, $FJDADV_t$, Seasonality], where

q_{it} = gallons (per capita) of orange juice (either all orange juice, FCOJ, NFC OJ, RECON OJ, or SS OJ) consumed in time period t; and the per capita consumption in time period t is the total consumption divided by the US population in time period t.

p_{it} = the real price of orange juice in period t (nominal price of orange juice in period t deflated by CPINAB in period t).

p_{st} = the real price of grapefruit juice (the nominal price of grapefruit juice deflated by CPINAB in period t). If q_{it} corresponds to components of orange juice, p_{st} corresponds to the real price vector of remaining components. The deflator of these nominal prices also is the CPINAB in time period t.

y_t = real disposable personal income per capita in time period t (national disposable personal income divided by the US population in time period t and then divided by the Consumer Price Index (CPI) for all items).

$FDOCOJADV_t$ = real advertising expenditures of orange juice made by the FDOC in time period t (nominal expenditures deflated by the CPI in time period t).

$BRANDOJADV_t$ = real branded advertising expenditures of orange juice in time period t (nominal expenditures deflated by the CPI in time period t).

$FJDADV_t$ = real advertising expenditures on fruit juices and drinks, excluding orange juice, in time period t (nominal expenditures deflated by the CPI in time period t).

Seasonality is accounted for through the use of a set of indictor (0-1) variables.

This specification is unique in the fact that three different measures of advertising effort are included in the demand specification. The variables $FDOCOJADV_t$ and $BRANDOJADV_t$ measure real FDOC and branded advertising expenditures of orange juice. In addition, the potential influence of advertising expenditures on other fruit juices and drinks ($FJDADV_t$) is included which is not commonly done in studies of advertising impacts on demand.

The functional form adopted for the single-equation econometric specifications is the double logarithmic form (i.e., the use of logarithmic transformation of all variables except the set of indictor variables). With this functional form, the estimated coefficients associated with the drivers of demand for orange juice are elasticities. The use of natural logarithmic transformations with advertising expenditures is common so as to make explicit diminishing marginal returns associated with advertising efforts.

Incorporating Branded and Generic Advertising Expenditures into Econometric (Structural) Models

Single-equation econometric (structural) demand specifications for orange juice and its components suffice in the analysis advertising effects on demand the supply curve at the retail level of the marketing channel is assumed to be perfectly elastic. Hypotheses include: (1) own-price effects are negative; (2) cross-price effects are positive, indicative of gross substitutability among the products in question; (3) income effects are positive; (4) the effects of FDOC and branded advertising expenditures are positive; (5) the effects of advertising expenditures on fruit juices and drinks, excluding orange juice, are negative, and (6) there are seasonal effects in the consumption of orange juice.

The key in this analysis is the focus on the distributed lag structure for advertising in order to capture carryover effects (Lee, Brown, Fairchild (1989); Ward and Meyers (1979); Kinnucan and Forker (1986); Forker and Ward (1993)). In this spirit, let:

(2) $$h(Y_t) = \alpha_0 + \alpha_1 g(X_t) + \phi BGW_t + \psi GGW_t + \varepsilon_t ,$$

where Y_t is product disappearance at time period t, t=1, 2, …, T; X_t is a dimensional vector of predetermined variables other than advertising; and BGW_t and GGW_t are the goodwill (GW) stocks of brand and generic advertising expenditures. The two advertising goodwill variables are constructed as:

(3) $$BGW_t = \sum_{j=0}^{m1} w_j \, f_1\left[BADV_{t-j}\right]$$

(4) $$GGW_t = \sum_{j=0}^{m2} w_j \, f_2\left[GADV_{t-j}\right]$$

where $BADV_{t-j}$ and $GADV_{t-j}$ refer to current and lagged brand and generic advertising expenditures, respectively, for j=0, 1, …, m_1 or m_2 and f_1 and f_2 typically correspond to natural logarithmic transformations or square root transformations.

The generic and branded advertising elasticities from (2), (3), and (4) are given by:

(5) $$\frac{\partial Y_t}{\partial GGW_t}\frac{GGW_t}{Y_t} = \frac{\psi}{h'(Y_t)}\frac{GGW_t}{Y_t}$$

(6) $$\frac{\partial Y_t}{\partial BGW_t}\frac{BGW_t}{Y_t} = \frac{\phi}{h'(Y_t)}\frac{BGW_t}{Y_t} .$$

In general, if AGW_t is a measure of the goodwill stock of any type of advertising (branded or generic) in time period t, then:

(7) $$AGW_t = \sum_{i=0}^{m} w_i \, f\left[ADV_{t-i}\right]$$

where ADV_{t-i} refers to current and lagged advertising expenditures for i = 0, 1, …, m and f again generally corresponds to either natural logarithmic or square root transformations. The advertising goodwill variable structure in (7) allows for carryover effects of advertising on demand.

The key issue is the nature of the lag structure in equation (7). Possible lag structures include: (1) the quadratic exponential distributed lag structure (EDL); (2) the polynomial inverse lag structure (PIL); (3) the polynomial distributed lag structure (PDL); and (4) the geometric lag structure (GL) among others. The various lag structures mitigate the impact of collinearity among the lagged advertising variables. In addition, the lag structures reveal the nature of the effect of advertising on product disappearance.

Under the exponential distributed lag (EDL) structure, the lag weights are constructed as:

(8) $$w_i = \exp(\lambda_0 + \lambda_1 i + \lambda_2 i^2)\text{, i = 0, 1, …, m.}$$

Then algebraic substitution of equation (8) into equation (7) gives:

(9) $$\begin{aligned} AGW_t &= \exp(\lambda_0) f[ADV_t] + \exp(\lambda_0 + \lambda_1 + \lambda_2) f[ADV_{t-1}] + \\ &\exp(\lambda_0 + 2\lambda_1 + 4\lambda_2) f[ADV_{t-2}] + ... + \exp(\lambda_0 + m\lambda_1 + m^2\lambda_2) f[ADV_{t-m}] \end{aligned}$$

As Cox (1992) points out, the quadratic EDL specification is flexible enough to represent either geometric decay or a hump-shaped carryover effect.

The polynomial inverse lag (PIL) structure is given by:

(10) $$w_i = \sum_{j=2}^{k} \frac{c_j}{(i+1)^j}\text{, j=2, …, k (the degree of the polynomial)}$$

If the degree of polynomial is 2, then:

(11) $$w_i = \frac{c_2}{(i+1)^2}$$

If the degree of polynomial is 3, then:

(12) $$w_i = \frac{c_2}{(i+1)^2} + \frac{c_3}{(i+1)^3}$$

If the degree of polynomial is k (k>3), then:

(13) $$w_i = \frac{c_2}{(i+1)^2} + \frac{c_3}{(i+1)^3} + ... + \frac{c_k}{(i+1)^k}$$

If the degree of the polynomial be 2 in equation (11), then:

$$(14) \qquad AGW_t = c_2\left[f[ADV_t] + \frac{f[ADV_{t-1}]}{2^2} + \frac{f[ADV_{t-2}]}{3^2} + ... + \frac{f[ADV_{t-m}]}{(m+1)^2}\right]$$

The polynomial distributed lag (PDL) structure is given by:

$$(15) \qquad w_i = c_0 + c_1 i + c_2 i^2 + c_3 i^3 + ... + c_r i^r$$

where r is the degree of the polynomial. In most cases, the degree of polynomial chosen is either 2 or 3. One may also incorporate head and/or tail restrictions.

In the case of a second degree polynomial, the PDL lag structure becomes:

$$(16) \qquad w_i = c_0 + c_1 i + c_2 i^2 .$$

Then, $w_0 = c_0$; $w_1 = c_0 + c_1 + c_2$; $w_2 = c_0 + 2c_1 + 4c_2$; and in general $w_m = c_0 + c_1 m + c_2 m^2$.

Substituting equation (16) into equation (7) and rearranging terms gives:

$$(17) \qquad \begin{aligned} AGW_t &= c_0\{ f[ADV_t] + f[ADV_{t-1}] + f[ADV_{t-2}] + ... + f[ADV_{t-m}]\} \\ &+ c_1\{ f[ADV_{t-1}] + 2f[ADV_{t-2}] + ... + mf[ADV_{t-m}]\} \\ &+ c_2\{ f[ADV_{t-1}] + 4f[ADV_{t-2}] + ... + m^2 f[ADV_{t-m}]\}. \end{aligned}$$

Assuming a head restriction, then $c_0 - c_1 + c_2 = 0$ or $c_0 + c_2 = c_1$. Assuming a tail restriction, then $c_0 + c_1 (m+1) + c_2 (m+1)^2 = 0$. If both head and tail restrictions are assumed, only 1 or 2 parameters need to be estimated rather than the set of three parameters, c_0, c_1, and c_2. Similar representations hold for other polynomial degrees.

The geometric lag (GL) structure is given by

$$(18) \quad w_i = w_0 \lambda^i , \quad 0 < \lambda < 1.$$

Because $0<\lambda<1$, the distribution of w_i follows a geometric decay pattern. Then, algebraic substitution of equation (18) into (7) gives:

$$(19) \qquad AGW_t = w_0 f[ADV_t] + w_0 \lambda f[ADV_{t-1}] + ... + w_0 \lambda^m f[ADV_{t-m}].$$

$$(20) \qquad AGW_t = w_0\{ f[ADV_t] + \lambda f[ADV_{t-1}] + ... + \lambda^m f[ADV_{t-m}]\}$$

Importantly, from equation (7), one may calculate contemporaneous, interim, and long-run effects of advertising. Contemporaneous impacts are given by ϕw_0 or ψw_0. Interim impacts are cumulative sums of the effects of advertising. The long-run effect of advertising is given by

$\phi\sum_{i=0}^{m} w_i$ or $\psi\sum_{i=0}^{m} w_i$. Moreover, one may calculate the mean lag associated with the advertising response. The mean lag corresponds to the average length of time for the advertising expenditure to transfer into a change in product disappearance. The mean lag is given by:

(21) $$\frac{\sum_{i=0}^{m} iw_i}{\sum_{i=0}^{m} w_i}.$$

With the polynomial inverse lag specification, the polynomial distributed lag specification, and the geometric lag specification, $\psi = \phi = 1$ from equation (2) without loss of information. The formal structure given in equation (2) to equation (21) allows a consideration of the impact of branded and FDOC advertising expenditures on: (1) total orange juice (OJ); (2) FCOJ; (3) NFC OJ; (4) RECON OJ; (5) SS OJ; or (6) the aggregate of refrigerated NFC and RECON OJ.

Specification of Time-Series Models

Alternatives exist to the previously discussed econometric (structural) representations of the demand function for orange juice. According to Sims (1980), one may consider equation (1) as multiple economic time series, where lags (to be determined from the data and *a priori* knowledge) of each variable in (1-1) are allowed (in the most general case) to affect the current position of each series. A general statement of the resulting model is given as a vector autoregressive representation (VAR):

(22) $$x_t = \sum_{k=1}^{K} \alpha(k) x_{t-k} + \delta_t$$

where $\alpha(k)$ is an autoregressive matrix of dimension (nxn) at lag k which connects x_t and x_{t-k} and δ_t is a vector residual term of dimension (nx1). In terms of the equations of the VAR, many, indeed most, of the autoregressive parameters $\alpha(k)$ are equal to zero and K is the maximum lag, found through loss function search procedures. Moving all terms involving x_t and x_{t-k} to the left-hand-side of the VAR and writing lags in terms of the lag operator (B), we get the autoregressive representation as:

(23) $$(1 - \alpha(B))x_t = \delta_t$$

Merely inverting the autoregressive representation gives us the standard moving average representation:

(24) $$x_t = (1 - \alpha(B))^{-1}\delta_t.$$

Written in more discernable terms as an infinite sum gives:

(25) $$x_t = \delta_t + \pi(1)\, \delta_{t-1} + \pi(2)\, \delta_{t-2} + \pi(3)\, \delta_{t-3} + \pi(4)\, \delta_{t-4} + \ldots$$

In equation (25), the $\pi(i)$ are moving average parameter matrices of dimension (nxn) derived from the VAR equation and δ_{t-i} are vectors of historical shocks of dimension (nx1). The structure of the VAR equation allows us to decompose the x vector at t into its historical components. For any particular element of x_t, say element i, we can write it as:

$$x_{it} = \delta_{it} + \sum_{j=1}^{n} \pi_{ij}(1)\,\delta_{jt-1} + \sum_{j=1}^{n} \pi_{ij}(2)\,\delta_{jt-2} + . . . \tag{26}$$

where δ_{jt-k} is the shock in series j in period t-k and $\pi_{ij}(k)$ is the i,j element of the π matrix of the moving average parameter matrix, which gives the response of series i to the shock in period t-k in series x_j. At any time t we can accumulate that portion of the series which is "due to" past shocks in any of the particular series (j) of the vector time-series.

Historical decompositions of time-series models are not independent of the ordering of contemporaneous correlation. In this analysis, the "causal flows" in contemporaneous time will be investigated following the directed graph procedures of Spirtes, Glymour, and Scheines (1993) and Swanson and Granger (1997). Such methods allow the use of a nonrecursive ordering of contemporaneous correlation, which avoids much of the criticism leveled on VAR work with the standard Choleski factorization (Cooley and LeRoy (1985)). In particular, the historical decompositions will allow an examination of the movement in consumption of orange juice due to historical shocks in real FDOC advertising expenditures on orange juice; real branded advertising expenditures on orange juice; real advertising expenditures on fruit juices and drinks, excluding orange juice; the real price of orange juice; the real price of grapefruit juice; and real per capita income.

Data

Three general sets of data used in the analysis of the effects of advertising on orange juice demand are discussed in this section of the report: (1) orange juice and orange juice products data, (2) grapefruit juice data, (3) advertising expenditure data.

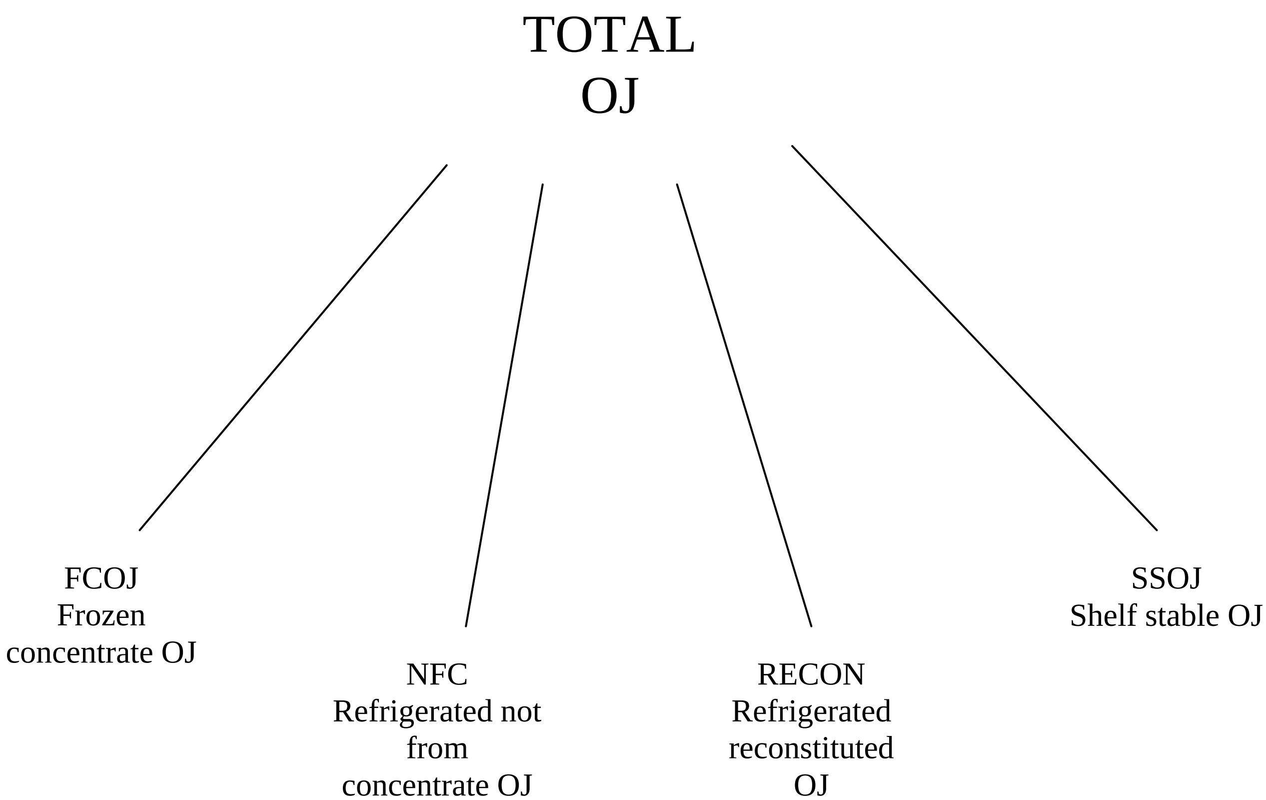
Orange Juice and Orange Juice Product Data

Weekly data were available from AC Nielsen from January 9, 1988 to September 28, 2002 for sales (in dollars), quantities (volumes in gallons), and prices (dollars per gallon) of: (1) total orange juice; (2) frozen concentrated orange juice; (3) refrigerated NFC orange juice; (4) refrigerated RECON orange juice; and (5) shelf stable orange juice. The breakdown of total orange juice into components is exhibited in Figure 2.

The weekly data, however, do not match the monthly periodicity of real disposable income, population, the Consumer Price Index, the Consumer Price Index for Nonalcoholic Beverages, or any of the measures of advertising expenditures. To match the periodicity of these variables, adjustments of the weekly AC Nielsen scanner data were made to arrive at monthly figures. The traditional Nielsen scanner data pertain to retail supermarkets with sales exceeding $2 million per year.

Additional data from supercenters plus WalMart were available from AC Nielsen as well. The data on supercenters were in four-week period intervals. The first four-week interval of the available data ended October 5, 1996 and the last four-week interval ended November 24, 2001.

Figure 2: Schematic Diagram of Total Orange Juice (OJ) and Orange Juice Products



These data, however, understated NFC OJ gallons and dollars from October 5, 1996 to October 2, 1999 and overstated RECON OJ gallons and dollars over the same period. The data were problem-free for total orange juice, FCOJ, SS OJ, and the combined refrigerated category of NFC OJ and RECON OJ. In addition, these data were discontinued after the four-week period ending November 24, 2001. From the four-week period ending October 30, 1999 to November 24, 2001 the data were free of problems over the period. The data from supercenters provided on average an additional 5.36% gallons of total orange juice; 4.72% more dollars of total orange juice; 6.08% more gallons of FCOJ; 5.18% more dollars of FCOJ; 5.83% more gallons of NFC OJ; 4.10% more dollars of NFC OJ; 7.24% more gallons of RECON OJ; 7.50% more dollars of RECON OJ; 4.31% more gallons of SS OJ; and 3.83% more dollars of SS OJ.

The AC Nielsen group combined data from WalMart plus supercenters in four-week periods ending April 15, 2000 to September 28, 2002. There were no issues with these data, unlike the additional data on supercenters. The WalMart plus supercenters data provide on average an additional 7.84% more gallons of total orange juice; 6.65% more dollars of total orange juice; 8.60% more gallons of FCOJ; 7.18% more dollars of FCOJ; 5.40% more gallons of NFC OJ; 4.75% more dollars of NFC OJ; 9.86% more gallons of RECON OJ; 8.94% more dollars of RECON OJ; 4.77% more gallons of SS OJ; and 4.47% more dollars of SS OJ.

The four-week period data from WalMart and the four-week period data from supercenters overlapped from April 15, 2000 to November 24, 2001. The correlations of these overlapping data for gallons and value of all types of orange juice ranged from .9940 to .9979, except for SS OJ where the correlations for gallons and value were .9302 and .9406, respectively.

Due to the importance of mass merchandisers such as supercenters and WalMart in the food marketing chain, data from these purveyors are included in the analysis. For total orange juice, data from supercenters over the four-week period ending October 5, 1996 to the four-week period ending March 18, 2000 were used. In addition, for total orange juice, the WalMart data over the four-week period ending April 15, 2000 to the four-week period ending September 28, 2002 were used. For FCOJ, NFC OJ, RECON OJ, and SS OJ, to avoid problems with data inconsistency for NFC OJ and RECON OJ, the information from supercenters over the four-week period ending October 30, 1999 to the four-week period ending March 18, 2000 were used. For these orange juice products, the WalMart data over the four-week period ending April 15, 2000 to the four-week period ending September 28, 2002 were used.

The data from supercenters and WalMart, however, are in terms of four-week periods. Therefore, to match the monthly frequency of the previously described data from retail supermarkets with sales in excess of $2 millions, adjustments of the data from four-week periods into monthly periods were made. Subsequently, the monthly data from supercenters and WalMart were added to the monthly data from retail supermarkets. The combined data pertaining to total orange juice run from September 1996 to September 2002, while the combined data pertaining to FCOJ, NFC OJ, RECON OJ, and SS OJ run from October 1999 to September 2002. The monthly data from supercenters and WalMart provide on average an additional 5.84% gallons of total orange juice; 5.11% more dollars of total orange juice; 7.95% more gallons of FCOJ; 6.49% more dollars of FCOJ; 5.33% more gallons of NFC OJ; 4.50% more dollars of NFC OJ; 9.05% more gallons of RECON OJ; 8.25% more dollars of RECON OJ; 4.31% more gallons of SS OJ; and 4.07% more dollars of SS OJ.

In summary, all data from AC Nielsen dealing with value, gallons, and prices of orange juice are of a monthly periodicity. These monthly data run from January 1988 to September 2002. From January 1988 to August 1996, the data for total orange juice only pertain to retail supermarket purveyors with annual sales in excess of $2 million. From September 1996 to September 2002, the data for total orange juice include supercenters and WalMart as well along with retail supermarkets. From January 1988 to September 1999, the data for FCOJ, NFC OJ, RECON OJ, and SS OJ only deal with retail food stores with sales in excess of $2 million per year. From October 1999 to September 2002, the data for the orange juice products include supercenters and WalMart as well.

Table 1 provides a comparison of the annual per capita consumption figures of orange juice taken from the AC Nielsen data with the annual figures provided by the U.S. Department of Agriculture (USDA). Over the period 1988 to 2001, the AC Nielsen data account for 52.0% to 74.4% of the USDA disappearance data. On average then, the data from the supermarkets and mass merchandisers provide information for nearly 63% of total per capita consumption of orange juice.

Descriptive statistics associated with nominal and real prices ($/gallon) and quantities (gallons as well as gallons per person) from the monthly AC Nielsen data from January 1988 to September 2002 are exhibited in Tables 2 to 4 and in Figures 3 to 11. The following highlights some key points from this set of descriptive statistics.

Over the period January 1988 to September 2002, as exhibited in Table 2, monthly dollar expenditures on orange juice from retail supermarkets and mass merchandisers were roughly $258 million on average. The range of these expenditures went from $210 million to $346 million. This figure translates into nearly 67 million gallons per month or slightly more than 0.25 gallons per person per month on average. Over this 177-month period, consumption of orange juice ranged from 51.5 million gallons per month to 80.3 million gallons per month. On a per capita basis, consumption of orange juice varied from 0.206 gallons to 0.292 gallons. Nominal prices over this time frame averaged $3.86 per gallon, with a range of $3.23 per gallon to $4.60 per gallon. On average, FCOJ prices were the lowest at $3.07 per gallon, followed by RECON OJ prices at $3.64 per gallon. SS OJ prices were the highest among the orange juice components at $5.15 per gallon on average, followed by NFC OJ prices at $5.04 per gallon. A December 1989 freeze resulted in notable increases in prices of all forms of orange juice in 1990 (Binkley et al. (2001)).

As exhibited in Table 3, over the period January 1988 to September 2002, RECON OJ represented roughly 40.4% of expenditures made on orange juice; NFC OJ represented 33.7% of the total orange juice expenditures; the share of expenditures attributed to FCOJ was about 24%; and the remaining share of expenditures on orange juice attributed to SS OJ, was 1.9 %. However, these figures change noticeably if only the period January 2002 to September 2002 is considered. Under current market conditions, NFC OJ occupies the highest share of orange juice expenditures at 51.2%; the second highest share is held by RECON OJ at 38.0%. So, refrigerated orange juice currently accounts for almost 90% of all expenditures made on orange juice, at least from retail supermarkets and mass merchandisers. Notice that the expenditure share for FCOJ dropped dramatically to about 9.4% for the first nine months of 2002, compared to its expenditure share of 24% over the entire 177-month period. The expenditure share for SS OJ for the period January 2002 to September 2002 was 1.3%, less than the 1.9% share over the period January 1988 to September 2002.

Table 1: A Comparison of Per Capita Consumption Numbers on Orange Juice Based on AC Nielsen Data and on USDA Disappearance Data

Table 2: Descriptive Statistics of Expenditure, Consumption, and Prices of Orange Juice, January 1988 to September 2002

	Expenditure (Mil $)	Consumption (Gallons)	Consumption (Gal/person)	Nominal Price ($/gallon)	Inflation-Adjusted (Real) Price
All Orange Juice					
Average	258	66,716,171	0.250763	3.86	3.11
Standard Deviation	34	5,737,425	0.016746	0.37	0.32
Minimum	210	51,514,424	0.206195	3.23	2.51
Maximum	346	80,301,880	0.292521	4.60	4.08
Stationary in Levels	No	Yes	Yes	No	No
Stationary in First Differences	Yes	NA	NA	Yes	Yes
Frozen Concentrated Orange Juice					
Average	59	19,170,268	0.073370	3.07	2.49
Standard Deviation	20	6,181,575	0.026742	0.29	0.36
Minimum	27	8,180,998	0.028477	2.56	1.97
Maximum	98	31,311, 288	0.128183	4.04	3.59
Stationary in Levels	No	No	No	No	No
Stationary in First Differences	Yes	Yes	Yes	Yes	Yes
NFC Orange Juice					
Average	88	17,536,179	0.064773	5.04	4.07
Standard Deviation	37	7,076,792	0.023258	0.32	0.45
Minimum	26	5,415,541	0.022176	4.49	3.43
Maximum	164	31,361,826	0.109249	6.07	5.43
Stationary in Levels	No	No	No	No	No
Stationary in First Differences	Yes	Yes	Yes	Yes	Yes
RECON Orange Juice					
Average	103	28,419,145	0.106675	3.64	2.94
Standard Deviation	13	3,140,716	0.008607	0.34	0.40
Minimum	82	21,452,084	0.085695	2.98	2.34
Maximum	143	37,034,548	0.130951	4.56	4.05
Stationary in Levels	No	No	No	No	No
Stationary in First Differences	Yes	Yes	Yes	Yes	Yes
Refrigerated Orange Juice					
Average	192	45,955,324	0.171448	4.15	3.35
Standard Deviation	49	9,705,866	0.028185	0.35	0.36
Minimum	117	29,933,826	0.119815	3.53	2.74
Maximum	303	66,730,406	0.234692	4.95	4.42
Stationary in Levels	No	No	No	No	No
Stationary in First Differences	Yes	Yes	Yes	Yes	Yes
Shelf Stable Orange Juice					
Average	4.7	912,668	0.003510	5.15	4.16
Standard Deviation	0.9	179,716	0.000835	0.25	0.41
Minimum	3.1	572,205	0.002016	4.61	3.50
Maximum	6.7	1,273,187	0.005218	5.75	5.02
Stationary in Levels	No	No	No	No	No
Stationary in First Differences	Yes	Yes	Yes	Yes	Yes

Table 3: Product Share of Orange Juice Expenditures and Consumption[a]

Product	Average Share of Orange Juice Expenditures (%)	Share of Orange Juice Expenditure (%) for the Year 2002
FCOJ	23.96	9.42
NFC OJ	33.69	51.25
RECON OJ	40.45	38.02
Shelf Stable OJ	1.89	1.31
	Average Share of Orange Juice Consumption (%)	Share of Orange Juice Consumption (%) for the Year 2002
FCOJ	29.50	12.72
NFC OJ	26.13	42.91
RECON OJ	42.97	43.30
Shelf Stable OJ	1.40	1.07

[a]Based on monthly data from January 1988 to September 2002

Table 4: Monthly Per Capita Orange Juice Consumption

	All OJ	FCOJ	NFC OJ	RECON OJ	SS OJ
January	1.12	1.14	1.07	1.12	1.06
February	0.97	0.99	0.96	0.97	0.95
March	1.06	1.09	1.05	1.05	1.06
April	0.97	0.96	0.98	0.97	0.97
May	0.97	0.95	1.00	0.97	1.01
June	0.92	0.89	0.96	0.92	0.93
July	0.94	0.90	0.96	0.95	0.94
August	0.97	0.94	0.99	0.97	0.97
September	0.97	0.98	0.97	0.96	1.02
October	1.02	1.03	0.99	1.03	1.08
November	1.00	1.01	1.00	1.00	1.00
December	1.08	1.11	1.06	1.07	1.02

Figure 3: Total Per Capita Orange Juice Consumption, January 1988 to September 2002

Figure 4: Per Capita Frozen Concentrate Orange Juice (FCOJ) Consumption, January 1988 to September 2002

Figure 5: Per Capita Refrigerated Not From Concentrate Orange Juice (NFC OJ) Consumption, January 1988 to September 2002

Figure 6: Per Capita Refrigerated Reconstituted Orange Juice (RECON OJ) Consumption, January 1988 to September 2002

Figure 7: Per Capita Shelf Stable Orange Juice (SS OJ) Consumption, January 1988 to September 2002

Figure 8: FCOJ Share of Per Capita Orange Juice Consumption, January 1988 to September 2002

Figure 9: NFC OJ Share of Per Capita Orange Juice Consumption, January 1988 to September 2002

Figure 10: RECON OJ Share of Per Capita Orange Juice Consumption, January 1988 to September 2002

Figure 11: SS OJ Share of Per Capita Orange Juice Consumption, January 1988 to September 2002

The same pattern is evident in looking at the share of orange juice consumption. As shown in Table 3, over the period January 1988 to September 2002, the share of consumption was nearly 43.0% for RECON OJ; 29.5% for FCOJ; 26.1% for NFC OJ; and 1.40% for SS OJ. But for the current period January 2002 to September 2002, the share of consumption was 43.3% for RECON OJ; 42.9% for NFC OJ; 12.7% for FCOJ; and 1.1% for SS OJ. In essence, consumption of NFC OJ is displacing consumption of FCOJ and SS OJ. Convenience may be the primary reason for this displacement. In examining the demand for orange juice using these data, it is important to account for the convenience factor due to the rise in share of consumption of NFC OJ (Binkley et al. (2001)).

Table 4 provides the seasonal factors of orange juice consumption on a per person or per capita basis. These calculations are based on the use of the X12 procedure developed by the Bureau of the Census. The highest three months of per capita consumption of total orange juice, FCOJ, NFC OJ, and RECON OJ occur in January, December, and March in that order. The lowest two months of per capita consumption of these products are June and July in that order. The seasonal factors for SS OJ are similar, except the highest three months correspond to October, January, and March, and the lowest two months correspond to June and July. Simply put, in considering the demand for orange juice using monthly data, it is important to account for seasonality.

Grapefruit Juice Data

The same procedure outlined for orange juice data was used in developing monthly time-series observations for grapefruit juice which is hypothesized to be a substitute for orange juice. Table 5 demonstrates that over the period of January 1988 to September 2002, monthly dollar expenditures for grapefruit juice ranged from $15.0 million to $23.6 million, averaging $18.7 million per month, only 7% as much as was spent monthly on orange juice over the same period. Monthly consumption for grapefruit juice varied from 3.2 million to 5.7 million gallons, about 4.2 million gallons on average. On a per person basis, monthly grapefruit juice consumption averaged .016 gallons/person, with a range of 0.011/person to 0.023 gallons/person. The respective monthly consumption figures represent about 6% of the monthly consumption of orange juice.

Nominal prices for grapefruit juice were $4.44 per gallon on average, ranging from $3.86 to $5.16 per gallon. Nominal prices of grapefruit juice from retail supermarkets and mass merchandisers were higher on average than nominal prices of orange juice from the same retail establishments over the period January 1988 to September 2002.

The seasonal patterns in per capita grapefruit juice consumption are evident in Table 6. The highest months of per capita consumption are January and March and the lowest are November and December. The seasonal pattern of per capita grapefruit juice and orange juice consumption, differ considerably.

Figure 12 depicts the monthly per capita consumption of grapefruit juice between January 1988 and September 2002. In examining the demand function for orange juice, the real price of grapefruit juice may play a key role.

Table 5: Descriptive Statistice of Expenditure, Consumption, and Prices of Grapefruit Juice, January 1988 to September 2002

	Expenditure (MIL$)	Consumption (Gallons)	Consumption (Gal/person)	Nominal Price ($/gallon)	Inflation-Adjusted (Real) Price
Average	18,708,480	4,231,687	0.015996	4.44	3.57
Standard Deviation	1,884,125	512,508	0.002435	0.33	0.23
Minimum	15,035,815	3,210,860	0.011148	3.86	3.09
Maximum	23,641,702	5,699,580	0.023354	5.16	4.07
Stationary in Levels	No	No	No	No	No
Stationary in First Differences	Yes	Yes	Yes	Yes	Yes

Table 6: Monthly Per Capita Grapefruit Juice Consumption

January	1.08
February	0.96
March	1.06
April	1.01
May	1.03
June	0.99
July	1.01
August	1.00
September	0.98
October	1.00
November	0.93
December	0.93

Figure 12: Per Capita Grapefruit Juice Consumption, January 1988 to September 2002

Advertising Expenditure Data

In the analysis of the effects of advertising on orange juice demand, advertising effort is measured by the dollar amount spent on advertising. Three types of advertising expenditures are used in the analysis: (1) FDOC OJ advertising expenditures; (2) brand orange juice product advertising expenditures; and (3) advertising expenditures for other fruit juices and drinks.

The advertising expenditure data came principally from Competitive Media Reporting (CMR) through the Richards Group. For 1987 and 1988, the CMR data are quarterly observations. For 1989 and beyond, however, the CMR data are monthly observations. The advertising expenditures available from CMR are for: (1) magazines; (2) Sunday magazines; (3) newspaper; (4) outdoor; (5) network television; (6) spot television; (7) syndicated television; (8) cable TV networks; (9) network radio; and (10) national spot radio. Despite the disaggregation of the data into various media outlets, the aggregate advertising expenditures are used in the analysis. An example of this information for May 2002 and June 2002 is exhibited in Table 7.

To match the monthly data from AC Nielsen pertaining to sales, quantities, and prices of orange juice and grapefruit juice, the demand analysis uses monthly time-series observations from January 1989 to September 2002. A schematic diagram of components of advertising expenditures for fruit juices and drinks based on the data available from CMR is presented in Figure 13. Attention is focused on FDOC advertising expenditures for orange juice, branded advertising expenditures for orange juice, and advertising expenditures on other fruit juices and drinks.

Descriptive statistics on nominal and real advertising expenditures associated with the monthly CMR data from January 1989 to September 2002 are exhibited in Table 8. On average, the nominal monthly advertising expenditure on orange juice made by the FDOC was roughly $1.8 million. Over that period, monthly FDOC advertising expenditures for orange juice varied from as low as $2,300 to as high as $7.0 million. To put these figures in perspective, the average nominal monthly advertising expenditure on grapefruit juice made by the FDOC was close to $300,000 while the average nominal monthly advertising expenditure on other citrus juices was about $22,000. In short, the share of FDOC advertising expenditures for citrus juices attributed to orange juice was nearly 85% whereas the share attributed to grapefruit juice and other citrus juices was 14.0% and 1.0%, respectively. Table 9 demonstrates the seasonality of FDOC expenditures for orange juice advertising indicting that the expenditures are highest in January, March, October, and December and lowest in May, July, August, and September. This seasonal pattern is similar to the seasonal pattern in orange juice consumption.

Looking back at Table 8, the average nominal monthly branded advertising expenditure on orange juice was slightly more than $4.7 million over the period January 1989 to September 2002, about 2.6 times the average monthly FDOC expenditure on orange juice advertising. The range of monthly branded advertising expenditures on orange juice ranged from a low of $191,000 to a high of $14.4 million. A list of the various brands and the accompanying parent companies is presented in Table 10. The top three brands accounting for about 88% of all branded advertising expenditures for orange juice over the 165-month period of January 1989 to September 2002 were: (1) Tropicana, $2.05 million per month on average (46.2% share);

Table 7: Illustration of Competitive Media Reporting Data on Advertising Expenditures for Fruit Juices and Drinks, May 2002 and June 2002

Table 7 continued

Table 7 continued

Figure 13: Schematic Diagram of Components of Advertising Expenditures for Fruit Juices and Drinks, Data from Competitive Media Reporting

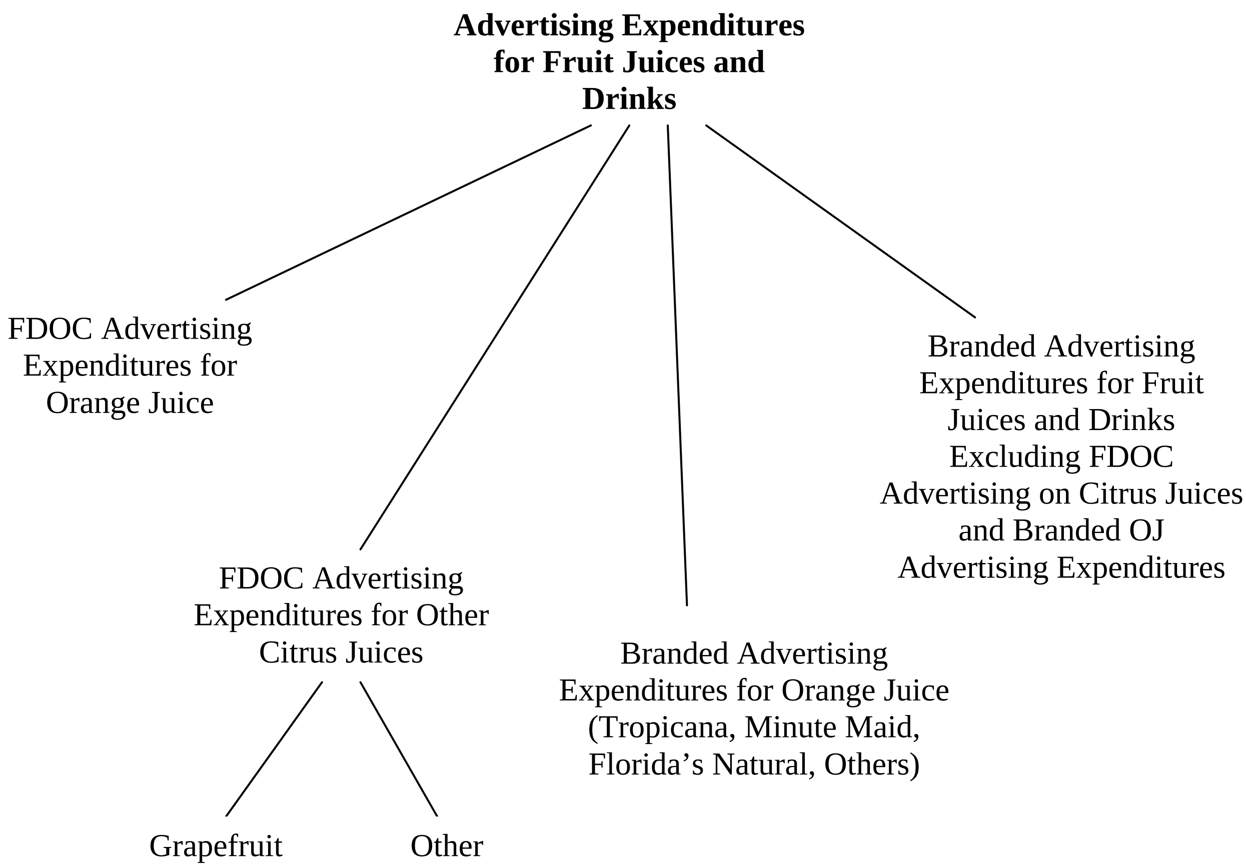


Table 8: Descriptive Statistics on Nominal and Real Advertising Expenditures, Monthly Data from January 1989 to September 2002

	FDOC OJ		Branded OJ		FDOC Grapefruit Juice		Fruit Juices & Drinks Excluding OJ	
	Nominal (000$)	Real (000$)	Nominal (000$)	Real (000$)	Nominal (000$)	Real (000$)	Nominal (000$)	Real (000$)
Average	1,811.3	1,190.0	4,736.3	3,058.3	299.7	203.7	16,894.0	11,037.5
Std Dev	1,219.5	774.6	2,695.0	1,635.4	509.6	333.3	6,228.4	4,011.7
Minimum	2.3	1.3	190.7	130.3	0.0	0.0	4,586.4	3,493.6
Maximum	7,012.2	3,948.3	14,391.4	8,883.6	4,426.5	2,798.0	37,026.0	24,343.2
Stationary in Levels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Monthly Real Advertising Expenditures for Orange Juice and Other Fruit Drinks

	Real FDOC Advertising Expenditures on Orange Juice	Real Branded Advertising Expenditures on Orange Juice	Real Advertising Expenditures on Fruit Juices and Drinks, Excluding Orange Juice
January	1.68	0.85	0.71
February	0.88	1.39	0.83
March	1.26	1.03	1.02
April	0.99	1.21	1.29
May	0.69	1.43	1.45
June	0.88	0.97	1.33
July	0.51	0.96	1.25
August	0.65	0.86	1.08
September	0.75	0.92	0.94
October	1.41	0.98	0.83
November	0.89	0.82	0.79
December	1.38	0.56	0.47

Table 10: Orange Juice Brands Advertised Associated Parent Companies

PARENT COMPANY	BRAND
Anderson Erickson Dairy	Anderson Erickson Ready-to-Serve Orange Juice
Coca-Cola	Minute Maid
Lykes Bros Inc. Lykes Pasco Packaging Corp	Florida Gold
McCain Foods Ltd.	McCain's Frozen Orange Juice
Procter & Gamble Co./Cargill Inc.	Citrus Hill
Seagram Co. Ltd/Pepsico Inc.	Tropicana
Sunkist Growers Inc	Sunkist Orange Juice
(Company Unknown)	Just Pik't Frozen Orange Juice
(Company Unknown)	Farm Fresh R-T-S OJ
Citrus World Inc	Donald Duck
Oakhurst Dairy Co	Oakhurst Dairy Ready-to-Serve OJ
Citrus World Inc	Fresh N Natural
Lykes Pasco Packaging Corp	Old South
Trauth Louis Dairy Inc	Louis Trauth Dairy Ready-to-Serve OJ
Roberts Dairy Co	Roberts Dairy Ready-to-Serve OJ
Turner Dairies Inc of Memphis	Turner Dairy OJ
United Dairy Farmers	United Dairy OJ
(Company Unknown)	Locust Farm OJ
Crystal Cream & Butter Co	Crystal Cream OJ
(Company Unknown)	Westlynn Creamery OJ
Colemans Dairy of Arkansas	Coleman Dairy
Dean Foods Co	Mayfield Dairy
Unilever NV	Sunkist
Pine State Creamery Co	Pine State Creamery
DiGiorgio Corp	Awake
Philip Morris Companies Inc	Knudsen
Hiland Quality Checked Dairy	Hiland Quality Checked
Golden Guernsey Dairy Coop	Golden Guernsey
Home Juice	Tree Fresh
Fairmont-Roberts Zarda/Mid-AM Dairy Co	Fairmont-Zarda
Citrus World Inc	Florida's Natural
Dairymen Inc	Dairymen's Dairy
Cirtus World Inc	Texsun
Penn Traffic Co	Sani Dairy
Southern Belle Dairy Co	Southern Belle Dairy
(Company Unknown)	Florida Sunshine RTS
(Company Unknown)	Tampico
Cascadian Farms	Cascadian Farms
Very Fine PDTS Inc	Very Fine
Lykes Bros Inc	Sunkist
Sunkist Growers Inc	Sunkist Premium
Upstate Milk Co-operatives, Inc	Upstate Milk Co-op
Shurfine-Central Corp	Shurfine
Parmalat SPA	Parmalat
Coca-Cola Co	Simply Orange
Aztar Corp	Tropicana Cow Acid
Olympic Foods, Inc	Sunkist Pure
Pepsico	Dole

(2) Minute Maid, $1.52 million per month on average (24.8% share); and (3) Florida's Natural, $0.72 million per month on average (16.7% share). However, over the more recent period of January to September 2002, the share accounted for by the top three brands dropped to 78.6%, with both Tropicana and Minute Maid experiencing some drop in share (42.0% and 8.1%, respectively) and Florida's Natural experiencing an increase (28.5%). Obviously, smaller firms have increased their share of branded advertising on orange juice in the more recent period.

Considering only advertising expenditures on orange juice over the January 1989 to September 2002 time period, branded advertising accounted for 70.2% of total advertising expenditures compared to 29.8% by the FDOC. In 2002, FDOC increased advertising expenditures on orange juice, accounting for 37.1% of total orange juice advertising expenditures compared to the 62.9% share accounted for by branded advertising.

As Table 9 demonstrates branded advertising on orange juice also exhibits a seasonal pattern but one which differs substantially from that of the FDOC advertising. Branded advertising expenditures are highest in February, April, and May and lowest in January, August, November, and December.

Over the period January 1989 to September 2002, monthly advertising expenditures on all fruit juices and drinks averaged $23.44 million while those on fruit juices other than orange juice averaged $16.89 million per month. All fruit juice advertising expenditures ranged from $4.59 million to $37.03 million per month. During that period, orange juice accounted nearly 28% of all fruit juice advertising with FDOC orange juice advertising accounting for 7.7% and branded orange juice advertising accounting for 20.2%.

Other products, including apple juice, grape juice, cranberry juice, grapefruit juice, and other citrus juice products, account for the remaining 72% of advertising expenditures on fruit juice and drink advertising. To provide a comparison, the annual advertising and promotion expenditures for other selected products are presented in Table 11.

Plots and descriptive statistics of real advertising expenditures on orange juice made by the FDOC, real branded advertising expenditures on orange juice, and advertising expenditures on fruit juices and drinks, excluding orange juice are given in Figures 14 through 16. Advertising expenditures on fruit juices and drinks, excluding orange juice also exhibit a seasonal pattern. Table 9 shows that these advertising expenditures are highest in April, May, June, and July and lowest in January, February, October, November, and December.

Empirical Results

This section reports the empirical results from the estimating both the econometric and time-series (vector autoregression) models. As discussed in the previous section of the report, monthly data from January 1989 to September 2002 are used in model estimation. Emphasis is placed on measuring the impacts of advertising efforts by various parties on the demand for orange juice. The empirical results from the structural models are presented first followed by the results from the vector auto-regression models.

Table 11: Annual Advertising and Promotion Expenditures for Selected Products

	FDOC Expenditures for Orange Juice ($)	FDOC Expenditures for Grapefruit Juice ($)	FDOC Expenditures for Other Citrus Juices ($)	Branded Expenditures for Orange Juice ($)	Total Fruit Juices and Drinks ($)
1987	13,062,200	2,042,900	211,900	56,557,350	232,098,000
1988	12,274,900	3,516,000	40,500	61,676,800	215,418,500
1989	17,665,300	5,670,400	0	63,451,200	248,095,800
1990	22,497,000	4,185,700	93,000	50,143,900	262,459,500
1991	21,544,900	5,884,500	100,600	29,127,000	224,437,500
1992	21,531,900	4,206,500	153,700	38,414,000	217,434,500
1993	20,629,000	4,445,900	625,000	31,904,200	226,217,500
1994	20,495,000	1,750,600	406,300	32,242,200	271,192,300
1995	20,777,750	978,750	1,620,800	37,637,700	261,832,300
1996	21,954,500	7,848,200	469,900	49,971,500	293,415,100
1997	25,464,950	3,917,850	45,700	79,306,000	306,226,200
1998	22,285,400	1,738,700	25,400	74,194,500	327,340,600
1999	18,971,600	2,399,700	3,000	80,771,400	333,075,000
2000	26,021,200	3,510,500	71,500	78,072,500	343,321,100
2001	9,674,600	2,838,500	0	90,543,300	283,868,300
2002 (thru Sept)	29,346,900	69,600	35,600	45,604,100	268,942,310

Figure 14: Real (Inflated-Adjusted) FDOC Advertising Expenditures for Orange Juice, January 1989 to September 2002

Figure 15: Real (Inflated-Adjusted) Branded Advertising Expenditures for Orange Juice, January 1989 to September 2002

Figure 16: Real (Inflated-Adjusted) Advertising Expenditures for Fruit Juices and Drinks, Excluding Orange Juice, January 1989 to September 2002

Empirical Results from the Structural Models

Following the previous discussion on the theoretical framework, the dependent variable in the structural models of the demand for orange juice are the per capita consumption of total orange juice; FCOJ; NFC OJ; RECON OJ; or SS OJ. Independent variables include: (1) the monthly real price of orange juice or monthly real prices of orange juice components; (2) the monthly real price of grapefruit juice; (3) monthly real disposable personal income per person; (4) real monthly advertising expenditures on orange juice made by the FDOC; (5) real monthly branded advertising expenditures on orange juice; (6) real monthly branded advertising expenditures on fruit juices and drinks excluding orange juice; and (7) seasonality.

We augment the model specifications by accounting for potential structural changes over the January 1989 to September 2002 period. We account for the fact that from January 1989 to August 1996, the data for total orange juice only pertain to retail supermarket purveyors. Thereafter, the data for total orange juice include mass merchandisers as well as retail supermarkets. This structural change in the data is represented by the indicator variable SC0996 which equals 1 for all observations beyond August 1996 and 0 otherwise. From January 1988 to September 1999, the data for FCOJ, NFC OJ, RECON OJ, and SS OJ only deal with retail food stores with sales in excess of $2 million per year. From October 1999 to September 2002, the data for the respective orange juice products include supercenters and WalMart as well. This structural change in the data is captured by the indicator variable SC1099 which equals 1 for all observations beyond September 1999 and 0 otherwise.

In addition, we attempt to account for the structural change in product form. Generally speaking, over the 165-month period of January 1989 through September 2002, NFC OJ sales have displaced FCOJ sales. We represent this displacement through the variable CONVENIENCE, given as the ratio of NFC OJ sales to total orange juice sales.

The use of market-level commercial scanner databases such as the AC Nielsen data is appropriate to examine the demand for orange juice. As noted by Cotterill (1994): “The availability of these new commercial scanner data sources now allows significant advances in our understanding of food marketing because one can now estimate firm and brand level as well as market or commodity demand models” (p. 126). Also, the use of regional or national data, rather than local data, allows more comprehensive analysis of marketing questions.

Empirical findings from previous studies support the hypothesis that advertising has carryover or lagged effects (e.g., Nerlove and Waugh (1961); Waugh (1959); Ward and Lambert (1993); Ward and Dixon (1984); Wohlgenant and Clary (1992)). However, theory provides relatively little guidance as to the structure and length of these dynamic processes. Conventionally, researchers allow the data to choose the optimal number of lags to include in the specification of a particular advertising stock variable through the use of statistical criteria like the Akaike Information Criterion (AIC) or the Schwarz Loss statistic (SL). The coefficients associated with the contemporaneous and lagged advertising expenditures also are commonly assumed to be a free-form lag or to follow some type of distribution, e.g., a geometric decay or a polynomial (or Almon) distributed lag. To illustrate, Piggott et al. (1996) consider the advertising process to follow a free-form lag of four quarters. Cox (1992), as well as Brester and Schroeder (1995), use a second-order exponential lag distribution while Baye, Jansen, and Lee (1992) employ a geometric lag.

The structural models estimated in this study employ a second-degree polynomial (or Almon) distributed lag with head and tail restrictions to characterize the carryover effects of FDOC advertising expenditures on orange juice, branded advertising expenditures on orange juice, and advertising expenditures on fruit juices and drinks, excluding orange juice. With the head and tail restrictions, and use of the second-degree polynomial lag, only a single coefficient associated with each of the three advertising expenditure variables need to be estimated. The estimation process allowed for a minimum of two lags and a maximum of twelve lags in the carryover advertising responses. The maximum of twelve lags was suggested by industry experts. This maximum lag length also is supported by the extant literature on the estimation of demand models with advertising effects. Clarke concluded that 90% of the cumulative effects of advertising for frequently purchased products, such as orange juice, are captured within three to nine months. Given the presence of the three types of advertising expenditures, to find the optimal lag lengths of advertising effort, it was necessary to estimate 11^3 or 1,331 structural models associated with each product form, accounting for each possible permutation of lags. Given the interest in not only total orange juice but also FCOJ, NFC OJ, RECON OJ, and SS OJ, in total, it was necessary to estimate 6,655 different structural models. The final structural specification chosen then was based on the minimization of the SL statistic.

Quantifying the impacts of direct and competing commodity advertising is important for producer associations considering the use of checkoff funds for promotion activities and firms considering brand advertising. This study, as is the case with most studies that have investigated the impact of advertising (either generic or branded) on sales of products, relies on a single-equation modeling approach.

The single-equation econometric specifications use the double logarithmic functional form. Consequently, the estimated coefficients associated with the drivers of demand for orange juice (total, FCOJ, NFC OJ, RECON OJ, or SS OJ) are elasticities. Also, the use of natural logarithmic transformations with advertising expenditures is common so as to make the diminishing marginal returns associated with advertising efforts explicit.

Empirical Results for the Demand for All Orange Juice

The estimated coefficients and their associated p-values in the demand model for all orange juice are exhibited in Table 12. The model explains about 96% of the variability in per capita consumption of orange juice. The method of estimation was generalized least squares where the residuals follow an autoregressive process of order 3.

Significant drivers of the demand for all orange juice are: (1) the real price of orange juice, where the own-price elasticity of demand is –0.684; (2) the real price of grapefruit juice, where the cross-price elasticity of demand is 0.388; (3) real advertising expenditures of the FDOC on orange juice; (4) real advertising expenditures on fruit juices and drinks, excluding orange juice; (5) seasonality; and (6) the structural change factor SC0996.

The demand for all orange juice at the retail demand level (retail supermarkets and mass merchandisers) is inelastic. A 10% change in real orange juice price leads to a 6.8% change in per capita consumption of orange juice in the opposite direction. Grapefruit juice and orange juice are gross substitutes. A 10% change in real grapefruit juice price leads to a 3.9% change in per capita consumption of orange juice in the same direction.

Importantly, advertising expenditures made by the FDOC on orange juice significantly shift the demand curve for orange juice outward as hypothesized in Figure 1. The optimal lag length associated with FDOC advertising efforts is 4 months, given the monthly periodicity of the data. The cumulative advertising elasticity is 0.01102, literally meaning that a 10% change in FDOC advertising expenditures on orange juice yields a 0.11% change in per capita consumption.

Graphically, the relationship between per capita consumption of all orange juice and real FDOC advertising expenditures on orange juice is presented in Figure 17. This depiction illustrates that per capita consumption of orange juice increases but at a decreasing rate with increases in real FDOC advertising efforts. This illustration is consistent with the diminishing marginal returns concept often discussed in the literature on advertising. The slope of this curve, or the marginal effect of advertising, yields the change in per capita consumption of orange juice due to a $1 change in real FDOC advertising expenditures on orange juice. Importantly, while the advertising elasticities in our analysis are constant, the marginal effects vary from month to month. The marginal effects are equal to the advertising elasticity times the ratio of consumption level (gallons) to advertising level (dollars).

In contrast, the statistical evidence in Table 12 reveals that branded advertising expenditures on orange juice have no statistically significant impact on per capita consumption of orange juice. The optimal lag length for branded advertising expenditures on orange juice is 12 months; while this effect is positive as expected, the cumulative advertising elasticity is 0.00066, roughly one-sixteenth the cumulative advertising elasticity associated with the FDOC efforts. Thus, the demand curve for orange juice indeed shifts outward due to branded advertising efforts but negligibly. Consequently, branded advertising expenditures for orange juice do not materially increase overall orange juice consumption. Branded advertising expenditures on orange juice therefore are targeted for affecting market share.

Advertising expenditures on fruit juices and drinks, excluding orange juice, negatively affect the per capita consumption of orange juice as expected. The cumulative cross-advertising elasticity is –0.05048, roughly 4.5 times the cumulative advertising elasticity associated with the FDOC efforts. A 10% increase in advertising expenditures on fruit juices and drinks, not counting orange juice, translates into a decline in orange juice consumption by 0.5048%. The optimal lag length for advertising expenditures on fruit juices and drinks, excluding orange juice, is 9 months.

Accounting for all other factors, seasonality is evident in per capita orange juice consumption. The reference or base month in the econometric analysis is December. Per capita consumption is 4.33% higher in January compared to December. In all other months, per capita consumption is lower relative to December. The difference ranges from 0.23% lower in March to 13.22% lower in June. Consistent with the descriptive statistics, the top three months for orange juice

Table 12: Empirical Results from the Econometric (Structural) Model for Total Orange Juice

Table 12 continued

Figure 17: Relationship Between Per Capita Consumption of Total Orange Juice and Real FDOC Advertising Expenditures

consumption are January, December, and March. The bottom three months are June, July, and February (see Table 4 for comparison purposes).

The addition of supercenters and WalMart to the monthly data yields a 5.57% increase in per capita consumption of orange juice, all other factors invariant. Again, this result is consistent with the data description presented earlier. Monthly real per capita rises but not monotonically over the period January 1984 to September 2002. The ratio of NFC OJ sales to all orange juice sales, a measure of "convenience", rose from 12% to 52% over this time frame. Nevertheless, neither income nor the share of NFC OJ dollars to total orange juice dollars (CONVENIENCE) statistically affects per capita consumption of orange juice. The income effect is negative but not statistically different from zero. The "convenience" effect is positive, but as well, not statistically different from zero.

Empirical Results for the Demand for Orange Juice Products

The structural models for the several orange juice products are similar to that for all orange juice. Considering a number of closely related products expands the number of possible substitute products. Although the empirical results from single-equation models are presented here, the possibility of treating the respective demand relationships as a group through the use of a seemingly unrelated regression (SUR) model was considered. However, the estimation results from the SUR model were similar to the estimation results from the single-equation models (very little gains in estimation from the use of the SUR procedure).

The estimation results associated with the structural demand models for FCOJ, NFC OJ, RECON OJ, and SS OJ are given in Tables 13 through 16. The goodness-of-fit ($\overline{R}^2$) statistics range from 0.9631 (RECON OJ) to 0.9973 (FCOJ), indicating that these models account for almost all the variability in per capita consumption of orange juice products.

The own- and cross-price elasticities of demand for orange juice products are summarized in Table 17. All of the own-price elasticities are negative, as expected. Each is greater in absolute value than the own-price elasticity estimated for all orange juice (-0.683) given in Table 12 which is consistent with the behavior of elasticities in general. Own-price elasticities for the disaggregate products (FCOJ, NFC OJ, RECON OJ, and SS OJ) are greater in magnitude than for the aggregate product (all orange juice). In particular, the demands for FCOJ and NFC OJ are price elastic, quite sensitive to own-price changes. In contrast, the demands for RECON OJ and SS OJ are price inelastic. Of the 16 cross-price elasticities, all but two are positive, indicating that the orange juice products are gross substitutes for each other and that the orange juice products and grapefruit juice are gross substitutes. However, only six of these cross-price elasticities are significantly different from zero. Grapefruit juice is a gross substitute for NFC OJ and RECON OJ. The cross-price elasticities are 0.3096 and 0.2177, respectively. The consumption patterns of NFC OJ, FCOJ, and RECON OJ on a per capita basis are sensitive to changes in the real prices of SS OJ. The cross-price elasticities range from 0.1950 for NFC OJ to 0.3745 for FCOJ.

The addition of monthly data from supercenters and WalMart to the monthly data from retail supermarkets yields a 9.46% increase in FCOJ per capita consumption and a 13.61% increase in

Table 13: Empirical Results from the Econometric (Structural) Model for FCOJ

Table 13 continued

Table 14: Empirical Results from the Econometric (Structural) Model for NFC OJ

Table 14 continued

Table 15: Empirical Results from the Econometric (Structural) Model for RECON OJ

Table 15 continued

Table 16: Empirical Results from the Econometric (Structural) Model for SS OJ

Table 16 continued

Table 17: Own- and Cross-Price Elasticities of Demand for Orange Juice Products

Price / Consumption	FCOJ	NFC OJ	RECON OJ	SS OJ	Grapefruit Juice
FCOJ	-1.1894*	0.1179	0.4115*	0.3746*	0.0098
NFC OJ	-0.0389	-1.0903*	0.1908	0.1950*	0.3096*
RECON OJ	0.0075	0.0647	-0.9222*	0.2430*	0.2177*
SS OJ	-0.1228	0.0999	0.3059	-0.8393*	0.0909

* statistically significant at the .05 level

RECON OJ per capita consumption. No statistically significant changes in NFC OJ or SS OJ per capita consumption are evident due to the addition of information from mass merchandisers.

Income and convenience (the ratio of NFC sales to total orange juice sales) are negatively related to FCOJ and RECON OJ per capita consumption. As expected, convenience is positively related to NFC OJ per capita consumption. Income is not a statistically significant determinant of NFC OJ consumption. Finally, neither income nor convenience is a key determinant of SS OJ demand.

Empirical Results from the Vector Autoregression Models

This section focuses on the effects of the advertising of orange juice by the FDOC through the use of time-series econometric methods and directed acyclic graphs. These methods differ from structural econometric methods, as time series methods do not seek to identify and ultimately estimate the parameters of underlying demand and supply relations. Rather, the methods employed here focus attention on the data themselves and the regularities found therein. Readers who desire a discussion of the reasons for undertaking such an "atheoretic" analytic approach are referred to Sims (1980) for a detailed discussions of the issues.

The cumulative advertising elasticities and their associated lag lengths for the orange juice products are exhibited in Table 18. FDOC advertising efforts positively and significantly affect the per person consumption of FCOJ, NFC OJ, and RECON OJ. The advertising elasticities vary from 0.00617 for NFC OJ to .01094 for RECON OJ. On the other hand, FDOC advertising efforts negatively and significantly affect the per capita consumption of SS OJ. The cumulative advertising elasticity for SS OJ is -0.04974. Branded advertising expenditures on orange juice show no significant impact on consumption of orange juice products except for FCOJ. The cumulative branded advertising elasticity in this case is -0.04900. Finally, advertising expenditures on fruit juices and drinks, excluding orange juice, are negatively related to the consumption patterns of the various orange juice products, particularly so for FCOJ and NFC OJ. By and large, the product-specific results dealing with FDOC advertising expenditures on orange juice, branded advertising elasticities on orange juice, and advertising expenditures on fruit juices and drinks, excluding orange juice, support the results gleaned from the analysis of all orange juice.

Table 18: Cumulative Advertising Elasticities of Demand for Orange Juice Products

Consumption \ Advertising	FDOC advertising expenditures on orange juice	Branded advertising expenditures on orange juice	Advertising expenditures on fruit juices and drinks, excluding orange juice
FCOJ	.00921*	-.04900*	-.09459*
Lag length	5	8	12
NFC OJ	.00617*	-.01283	-.08735*
Lag length	3	6	12
RECON OJ	.01094*	.01762	-.05675
Lag length	4	9	12
SS OJ	-.04974*	.06022	-.13814
Lag length	12	11	12

* statistically significant at the .05 level

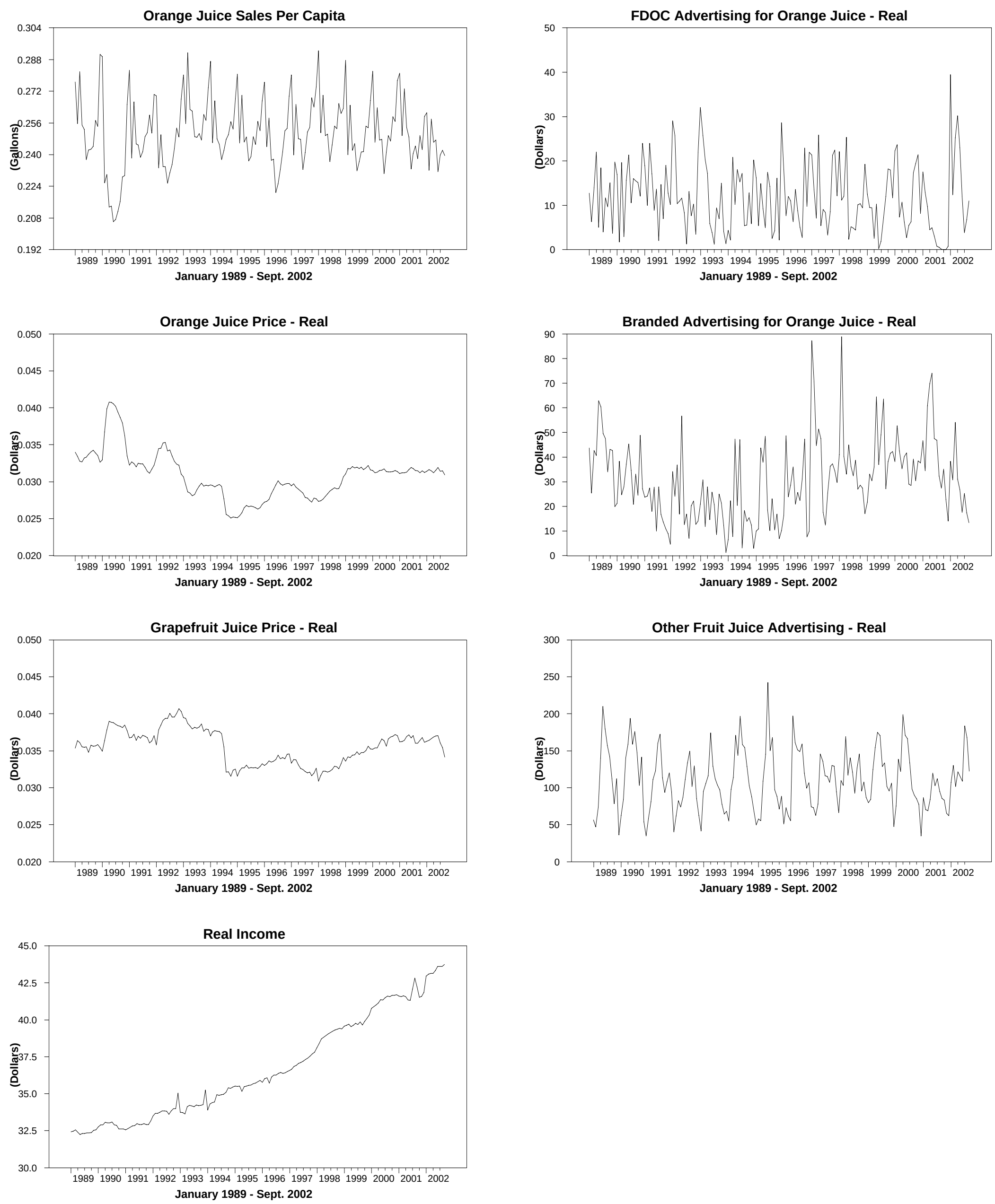
The seasonal patterns of FCOJ, NFC OJ, and RECON OJ consumption are similar to that of total orange juice consumption. Consumption is highest in January, December, and March but lowest in June and July. The seasonal pattern for SS OJ consumption, however, is different than that for the other product forms. Shelf stable orange juice consumption is highest in October, March, January, and September and lowest in June, February, July, and August. The SS OJ seasonal pattern in consumption as well as the NFC OJ, RECON OJ, and FCOJ seasonal patterns in consumption are consistent with those reported in Table 4 for all orange juice.

Graphical Presentation of Seven Study Variables

The focus here is on orange juice sales per capita, real orange juice price, real per capita U.S. income, real grapefruit juice price, real FDOC advertising expenditures on orange juice, real private label (branded) advertising for orange juice, and real other fruit juice advertising. Each variable is measured over the period January 1989 to September 2002. Figure 18 plots each variable against time. The motivation for beginning with plots of the data is to provide a sense of how each series moves through time and the patterns that may help in modeling their joint movement.

Note that orange juice sales per capita appear to vibrate around a monthly mean of approximately ¼ of a gallon per person (the actual mean is .2508 gallons per person per month). A seasonal pattern is evident from the plot and should be investigated further. Note, there is no strong persistent upward or downward trend in the per capita sales series.

Figure 18: Plots of Seven Variables Relevant to Monthly Orange Juice Sales, January 1989 to September 2002



The real orange juice price (orange juice price divided by the CPI for beverages) is above its historical mean (0.031) in 1989 and the early 1990s, falls below 0.030 in the mid-1990s, and increases to a rather stable price, just above its historical mean, in the late 1990s and early 2000s. This series appears to wander away from its historical mean (0.031) for several years at a time, suggesting (perhaps) a random walk-like behavior. More will be said later on this possibility for all series.

The real grapefruit juice price (grapefruit juice price divided by the CPI for beverages) is above its historical mean (0.035) from 1989 through early 1994, then falls rather drastically to less than 0.030 in the mid-1990s after which it increases steadily to values above its historical mean from late the 1990s through early 2002. The grapefruit price series also appears to wander away from its historical mean (.035) for several years at a time, suggesting again a random walk-like behavior.

Real income per capita (U.S. GDP per capita divided by the CPI) increases constantly over the 1989 – 2002 study period, crossing its mean of 36.68 in late 1995. Because it is below its mean in the early years and above its mean in later years, real per capita income is clearly non-stationary.

Monthly real FDOC orange juice advertising (FDOC advertising expenditures on orange juice per month divided by CPI) appears to vibrate around its historical mean of 11.90. While in any particular period it may be at values twice its mean or within the same year one-half its mean, the series appears to return to its historical mean within a few periods. Unlike the real per capita income series, the historical mean of the real FDOC orange juice advertising series appears to be informative with respect to values of the series in both early and late periods of the study. Unlike the real price of grapefruit and orange juice, the FDOC orange juice advertising series does not wander away from its historical mean for several years at a time.

Real branded advertising of orange juice appears to show a non-trivial seasonal pattern. In addition, there appears to be a slight decrease in trend advertising from 1989 through 1994 and then a slight trend increase in branded advertising from 1995 through 2002. The overall mean of branded advertising (30.58) appears to be informative over the early years of 1989 through 1990 and in the late years of 1997 through 2002. Yet, even in the mid-1990s, branded advertising crosses its historical mean in 1994, 1995, and 1996. A more formal test of non-stationarity (given below) should improve on the visual impressions for this series.

The final series analyzed here is advertising for other fruit juices which includes advertising for grapefruit juice financed by the FDOC. The obvious feature one notices from the plot of this series is the regular seasonal pattern and the informative nature of the historical mean (110.70) over early, mid- and late data points. While the series moves away from its historical mean, it returns to it (crosses its mean) within a few months. The mean appears to be informative at sub-periods, early in the sample (1989-1992), late the sample (2001-2002), and points between.

Stationarity of Individual Series

The plots analyzed above provide a sense that the time-series properties of the seven series may not be same. Clearly real income shows a time-series pattern that appears much different from that of orange juice sales per capita. The former appears to grow without bound, while the latter vibrates around an apparently stable mean. Statistical tests of how each series relate to other series may have invalid properties if we attempt to explain a series that is mean reverting with a series that is non-mean reverting (Granger and Newbold (1974)). To allow for possible non-stationary in levels of these series, the analysis follows the usual practice of considering the logarithms of the data in the results offered here. In addition, the possibility that some of the series need to be studied in first differences rather than their levels (undifferenced data) is considered.

Table 19 provides Dickey-Fuller and Augmented Dickey-Fuller tests that the series are individually non-stationary. That is, the tests in Table 19 consider the hypothesis that each series, say X_t, evolves according to the process, $X_t = X_{t-1} + e_t$. If such behavior characterizes any of the series, some adjustment in the data analysis must be made (e.g., study first differences, $W_t = X_t – X_{t-1}$, rather than levels). Table 20 offers similar tests on seasonal differences. The tests in Table 20 consider whether the series are non-stationary in their seasonal frequencies. If the latter is the case, a similar adjustment (seasonal differencing) would be recommended before analysis of the relationships between and among series.

In Table 19, the null hypothesis on each Dickey-Fuller test (DF) and each augmented Dickey-Fuller test (ADF) is that the series listed in the far left-hand column is non-stationary. One rejects the null hypothesis for calculated values of DF or ADF tests less than –2.89.

The term k in parentheses indicates the numbers of lags of the dependent variable in the ADF regression, as determined by the Schwarz loss statistic. The tests indicate that three series (real orange juice price, real grapefruit price and real income) are nonstationary while the other series (orange juice sales per capita, real FDOC advertising for orange juice, real branded advertising for orange juice and real other fruit juice advertising) are stationary.

Table 20 gives a similar set of tests on seasonal non-stationary behavior on each series. Here all factorizations of the seasonal difference ($X_t - X_{t-12}$) to accommodate the possibility that year-to-year monthly observations change in a non-stationary manner are considered. The tests consider the possibility that say, changes from January 1989 to January 1990 to January 1991, follow a non-stationary pattern. If such behavior is observed to characterize any of the series, that series would be modeled as a transformed series by taking seasonal differences. The tests follow the work of Beaulieu and Miron (1993). There is no evidence of seasonal non-stationary behavior in any of the series, however.

Given the results in Tables 19 and 20, orange juice sales per capita, real FDOC advertising for orange juice, real branded advertising for orange juice, and real advertising for other fruit juices are modeled in levels (non-differenced series). The real price of orange juice, the real price of grapefruit juice, and real income per capita are modeled in first differences ($W_t = X_t – X_{t-1}$) .

Table 19: Tests of the Null Hypothesis of Unit Roots at Zero Seasonal Frequency for Seven Monthly Variables Relevant to Orange Juice Sales, January 1989-September 2002

Series	DF	ADF(k)	Decision
OJ Sales (per capita)	-7.08	-4.89(12)	Reject
OJ Price (real)	-1.32	-2.43 (1)	Fail to Reject
GF Price (real)	-1.53	-1.53 (0)	Fail to Reject
Income (real)	.49	.87 (1)	Fail to Reject
FDOC OJ Adv. (real)	-6.37	-6.37 (0)	Reject
OJ Brd. Adv (real)	-7.68	-5.26 (1)	Reject
Other Juice Adv (real)	-6.05	-8.50 (4)	Reject

Table 20: Tests of Unit Roots at Seasonal Frequencies for Seven Monthly Variables Relevant to Orange Juice Sales, January 1989-September 2002

	Seasonal Frequencies				
	$\pi/2$	$2\pi/3$	$\pi/3$	$5\pi/6$	$\pi/6$
Series	$F_{3,4}$	$F_{5,6}$	$F_{7,8}$	$F_{9,10}$	$F_{11,12}$
OJ Sales (per capita)	23.89	20.66	24.71	18.68	26.72
OJ Price (real)	27.93	26.06	26.73	17.81	32.81
GF Price (real)	22.74	19.23	23.33	10.81	23.11
Income (real)	16.95	15.22	7.32	8.36	17.22
FDOC OJ Adv. (real)	13.52	8.71	15.21	8.61	7.83
OJ Brd. Adv (real)	8.50	15.60	7.94	11.28	5.21
Other Juice Adv (real)	8.00	20.60	6.38	18.88	4.81

Vector Autoregressions

A vector autoregression (VAR) specifies the current value of each series (stationary transformed series) as a function of lags of itself and all other series. So, for example, current period sales per capita of orange juice are modeled as a function of lags of orange juice sales per capita as well as lags of each of the other six series. The number of lags to include in the specification is, of course, unknown and must be determined from the data. Geweke and Meese (1981) offer Monte Carlo evidence on selection criteria applied here. In this analysis, the Schwarz Loss statistic is used to determine the number of lags. Again, the null hypothesis on each test DF and ADF is that the series listed in the far left-hand column is non-stationary. The null hypothesis is rejected for calculated values of DF or ADF tests less than –2.89. The term k in parentheses indicates the numbers of lags of the dependent variable in the ADF regression, as determined by the Schwarz Loss statistic. The rows under the heading "DF" refer to the Dickey-Fuller test on the null hypothesis that the data from the series listed in the far left-hand column are non-stationary in levels (non-differenced data). The test for each series of data is based on an ordinary least squares regression of the first differences of data from series on a constant and one lag of the levels of the series (un-differenced data). The statistic reported in the column in the DF column (t-statistic) is associated with the estimated coefficient on the lagged levels variable from this regression. Under the null hypothesis, the statistic is distributed in a non-standard t. Critical values are given in Fuller (1976). The 5% critical value is –2.89 so that observed t values less than this critical value are rejected.

The column listed under the heading "ADF" refer to the Augmented Dickey Fuller test associated with the null hypothesis that the data on a particular series (far left-hand column) is non-stationary in levels (same null as above). Here the test is of the same form as that described above, except that k lags of the dependent variable are added to the right-hand side of the DF regression. Here the value for k is determined by minimizing the Schwarz loss metric on values of k ranging from 1 to 12. The ADF regression was run with lags of the dependent variable ranging from one lag to twelve lags. The Schwarz loss metric was minimized at the value given in the column headed by the label "k". Again the critical value of the t-statistic is –2.89 and values of the calculated statistic less than this critical value are rejected.

A constant and eleven seasonal dummy variables are included in the test of unit roots on each series. Further, each series is transformed by the logarithmic operation. Critical values on F-tests at 95% confidence are 6.26. These critical values are obtained from Table A.1 of Beaulieu and Miron (1993). For seasonal unit roots, the test must fail to reject the null hypotheses for each series at all frequencies: $\pi/2$, $2\pi/3$, $\pi/3$, $5\pi/6$ and $\pi/6$. The justification for considering this test is to rule out or in the necessity of applying a seasonal difference, $(1-B^{12})X_t = w_t$, to any of the seven series where the original series is denoted as X_t and B is the lag operator ($B^{12} = X_{t-12}$). The time series analysis would then be done on w_t as it would be stationary. The results reported here indicate that no seasonal differencing is required.

The Schwarz Loss statistic (SL) and the Akaike Information Criteria (AIC) are used to determine the lags t-k, for k = 0, 1, 2, …, 6. Here the SL is calculated as:

(27) $$SL_k = \log(|\Sigma_k|) + (m\times k)\times\log(T)/T,$$

where $|\Sigma_k|$ is the determinant of the estimated residual covariance matrix fit as a VAR of lag length k, m=7 is the number of series studied, and T is the number of observations used to fit the models.

The AIC is of similar form except that the degrees of freedom adjustment (the second additive term) does not penalize for additional variables as drastically as does the SL statistic:

(28) $$AIC_k = \log(|\Sigma_k|) + (m\times k)/T.$$

The model for which the SL or the AIC is a minimum is selected. For large samples, the SL is preferred to the AIC, as the latter tends to overfit (i.e., to select too large a model) while the SL is consistent (does not overfit). However, in finite samples both metrics are usually consulted.

In addition to lag length, the two loss functions (SL and AIC) are used to help determine whether seasonal dummy variables should be included in the model. Table 21 gives calculated values for the SL and the AIC for four possible specifications: (1) no seasonal dummy variables and no lags, (2) lags 1 – 6 and no seasonal dummy variables, (3) no lags and seasonal dummy variables, and (4) lags 1-6 and seasonal dummy variables. As indicated in Table 21, both metrics agree that the best model is a vector autoregression with one period lag and seasonal dummy variables. Equation (29) is a general statement of the model suggested as optimal by the SL and the AIC:

$$(29) \qquad X_i(t) = \mu_i + \sum_{j=1}^{11} \delta_{ij} D_j + \sum_{k=1}^{7} \beta_{ik} X_k(t-1) + e_i(t) \quad ; \ i=1,2, ..., 7$$

That is, each series (X_i) in period t depends on a constant (μ_i); eleven monthly dummy (indicator) variables D_j, j=1,2, … , 11; and one lag of each of the seven variables (including itself); and a current period error (innovation) term ($e_i(t)$).

To account for the possibility that the search on lags presented in Table 21 is overly conservative on lag selection and to give the reader a bit more confidence on the lag one results, the results on two-lag and three-lag VARs are also considered. That is, the results on models similar to equation (29) are considered except with two-period and three-period lags of each variable as in equations (30) and (31), respectively:

$$(30) \quad X_i(t) = \mu_i + \sum_{j=1}^{11} \delta_{ij} D_j + \sum_{k=1}^{7} \beta_{ik} X_k(t-1) + \sum_{k=1}^{7} \beta_{ik} X_k(t-2) + e_i(t) \quad ; \ i=1,2, ..., 7.$$

$$(1\text{-}31) \quad X_i(t) = \mu_i + \sum_{j=1}^{11} \delta_{ij} D_j + \sum_{k=1}^{7} \beta_{ik} X_k(t-1) + \sum_{k=1}^{7} \beta_{ik} X_k(t-2) + \sum_{k=1}^{7} \beta_{ik} X_k(t-3) + e_i(t); \ i=1,2, ..., 7.$$

Each of the above three equations, (29) through (31), is itself a system of seven equations. Each set of equations has the same set of right-hand-side variables. Accordingly, ordinary least squares regression can be utilized to estimate the parameters (the β_{ik}'s) of each equation.

Table 22 gives the marginal significance levels on tests of the hypothesis that the coefficient associated with lags of each variable in the orange juice sales per capita equation is equal to zero. At one lag (estimates for equation 1-29) lagged sales, lagged real orange juice price, lagged real income and lagged real FDOC advertising for orange juice have significant coefficient estimates at the 5% or lower significance level. At two lags the results are similar to those at one lag; with a possible exception that at two lags the real price grapefruit juice shows a modest influence on orange juice sales per capita in terms of significance level (.06). At three lags the results again agree with the results at one lag, the marginal significance level on lagged FDOC orange juice advertising is .03, again suggesting that FDOC advertising for orange juice is significant at usual levels of testing.

Table 21: Statistical Loss Functions for Selection of the Seasonal Deterministic Variables and Lag Length of Unrestricted VAR, Orange Juice Market Variables, January 1989 to September 2002

Model	Schwarz Loss	AIC
1. No Seasonals; No Lags	-34.272	-34.502
2. Seasonals; No Lags	-34.303	-36.064
3. Seasonals; Lags t-k		
k=1	-36.241*	-39.614*
k=2	-35.195	-39.179
k=3	-34.051	-38.645
k=4	-32.743	-38.949
k=5	-31.602	-38.419
k=6	-30.566	-38.994
4. No Seasonals; Lags t-k		
k=1	-35.252	-37.093
k=2	-34.498	-36.951
k=3	-33.409	-36.472
k=4	-32.306	-36.981
k=5	-31.064	-36.349
k=6	-29.986	-36.882

[a] An asterisk (*) indicates a minimum. The SL statistic and the AIC are calculated as given in equations (27) and (28).

Table 22: F-tests and Marginal Significance in Coefficients of Lagged Variables in the Dynamic Regression (VAR) Equations on Orange Juice Per Capita Sales

	VAR Model Lags					
Variable	Lag 1		Lag 2		Lag 3	
	F-test	signifi-cance	F-test	signifi-cance	F-test	signif-cance
OJ Sales	440.3	0.00	221.05	0.00	129.54	0.00
OJ Price	7.09	0.01	9.21	0.00	6.59	0.00
GF Price	1.53	0.22	2.85	0.06	2.29	0.08
Income	3.92	0.05	3.45	0.04	2.19	0.09
OJ FDOC Adv.	5.49	0.02	4.89	0.01	2.99	0.03
OJ Brand Adv.	0.23	0.63	0.47	0.62	0.33	0.80
Other Juice Adv.	0.06	0.80	0.06	0.94	0.03	0.99

The F-tests and marginal significance levels reported in Table 22 correspond to the estimates of the coefficients associated with the variables listed in the far left-hand column in the orange juice sales per capita equation of the VAR. Results are reported for the VAR of lag length one, two and three (as listed in the alternative columns of Table 22). Diagnostic Q-statistics on residuals from each VAR equation are not suggestive of non-white residuals. For the orange juice sales per capita equation, the Q-statistics associated with the hypothesis that errors are not auotcorrelated have p-values of .10 for the one lag VAR, .95 for the two lag VAR, and .99 for the three lag VAR. Accordingly, at a 5% significance level, the analysis fails to reject the null hypothesis of "white noise errors (innovations) for all three regressions.

Table 23 presents results on tests for autocorrelation in residuals (surprises or innovations) in each equation of the VAR. Results are given for the one-lag, two-lag and three-lag VARs. Results indicate that residuals (surprises or innovations) in the quantity of orange juice sales per capita equation are not correlated through time, at normal levels of significance. The results on branded advertising for orange juice suggest that the three-lag VAR is probably better behaved in terms of residual correlation, as the Q-statistics on the one-lag and two-lag VARs for branded advertising show evidence of innovation correlation problems. Q-statistics are associated with the null hypothesis that the residuals (innovations) from the VAR equation in the far left-hand column are white-noise (not auto-correlated). The statistic is calculated from the weighted sum of the square of the correlations on residuals separated by j lags, ρ_j for j=1 to 36.

$$(32) \quad Q = T(T+2) \sum_{j=1}^{36} (1/T\text{-}j)\, \rho_j^2$$

where T is the number of observations (165) and we study the sum of 36 correlations. Under the null hypothesis of well-behaved residuals (innovations) the statistic is distributed chi-squared with 36 degrees of freedom.

Directed Graph in Contemporaneous Time

Innovations (errors) from fitting a three-lag VAR in the seven variables (orange juice sales per capita, real price of orange juice, real price of grapefruit juice, real income, real advertising expenditures for orange juice by the FDOC, real advertising expenditures for orange juice by branded labels, and real advertising expenditures for other fruit juice) have the lower triangular correlation matrix depicted in Figure 19. The matrix gives the contemporaneous correlation between surprises (errors or innovations) in each variable and those in other variables in the seven-variable system.

Each column is labeled with the variable name associated with innovations in each equation. Row labels are the same as column labels.

Based on the correlations in Table 19 and partial correlations derivable from this matrix (see Whittaker (1990)), an algorithm from artificial intelligence was used to help sort-out "causal" relations among these seven variables in contemporaneous time. Following the algorithm (PC algorithm) and search techniques given in Spirtes, et. al (2000) and Haigh and Bessler (2003),

Table 23: Q-statistics and Marginal Significance in Coefficients of Lagged Variables in the Dynamic Regression (VAR) Equations on Orange Juice Per Capita Sales

	VAR Model Lags					
Variable	Lag 1		Lag 2		Lag 3	
	Q-test	signifi-cance	Q-test	signifi-cance	Q-test	signif-cance
OJ Sales	47.19	0.10	23.18	0.95	16.80	0.99
OJ Price	36.24	0.46	39.37	0.32	38.15	0.37
GF Price	28.73	0.80	27.99	0.82	28.34	0.81
Income	44.65	0.15	38.93	0.34	41.95	0.23
OJ FDOC Adv.	25.68	0.90	34.57	0.53	53.08	0.04
OJ Brand Adv.	118.86	0.00	58.85	0.01	46.67	0.11
Other Juice Adv.	56.47	0.02	58.62	0.01	51.85	0.05

Figure 19: Lower Triangular Correlation Matrix on Innovations in Contemporaneous Time from the Seven-variable VAR with Lags of Three Periods

QOJ_t	POJ_t	PGJ_t	INC_t	$FDOCAOJ_t$	$BAOJ_t$	$OAFJ_t$
1.0000						
-0.3750	1.0000					
-0.0940	0.6030	1.0000				
-0.0460	-0.0130	-0.0310	1.0000			
0.0220	-0.0740	-0.0580	0.1470	1.0000		
-0.0410	0.1090	0.0710	-0.0070	-0.0870	1.0000	
-0.0580	0.0680	-0.0360	-0.0210	0.1260	-0.1090	1.0000

[a] QOJ=per capita sales of orange juice; POJ=real price of orange juice; PGFJ=real price of grapefruit juice; INC=real per capita income; FDOCAOJ=real advertising expenditures for orange juice; BAOJ=real advertising for orange juice by private firms; and OAFJ=real advertising expenditures on other fruit juices.

the “causal structure” behind these innovations is given in Figure 20. PC algorithm resulted in identifying the “causal inverted fork” QOJ → POJ ← PGJ and the undirected path INC – FDOCAOJ – OAFJ.

The direction of “causal flow” between QOJ, POJ and PGJ is determined using the sepset conditions programmed in PC algorithm, as described in Spirtes et. al (2000) and applied in Akleman, Bessler and Burton (1999). *The rule to note is that a common cause screens off association between its effects while a common effect does not screen off association between its possible causes.*

PC algorithm was not able to direct the path INC – FDOCAOJ – OAFJ. Consequently, the search routine introduced in Haigh and Bessler (2003) was followed to "score" each alternative possible directed path. Each of the four patterns in Figure 20 is scored with the SL and AIC such that the model that minimizes SL or AIC is choosen. Here the loss metrics result in the same model in Figure 20: QOJ → POJ ← PGJ and INC → FDOCAOJ← OAFJ.

As an alternative support for the causal graph in contemporaneous time, a test offered by Sims (1980) was considered. This procedure is a likelihood ratio test on over-identifying restrictions on the causal path connecting innovations. Under the null hypothesis that the causal path is consistent with the data, the test statistic is distributed chi-squared with degrees of freedom equal to the number of zero restrictions placed on the innovation paths. A just-identified causal pattern between innovations would have 21 non-zero restrictions in this seven-variable study. The above causal graph puts 17 of these equal to zero (as there are four nonzero parameters to estimate - one for each arrow in the above pattern). This pattern (QOJ → POJ ← PGJ and INC → FDOCAOJ← OAFJ) generates a likelihood ratio statistic of 12.5. For 17 degrees of freedom, the zero restrictions (the causal pattern) are not rejected using any reasonable significance level (.01, .05, .10, or .20).

For completeness, the likelihood support for a similar causal pattern as that above was considered except that a causal edge from FDOCAOJ → QOJ was added. That is, the following directed graph in contemporaneous time was considered:

(33)

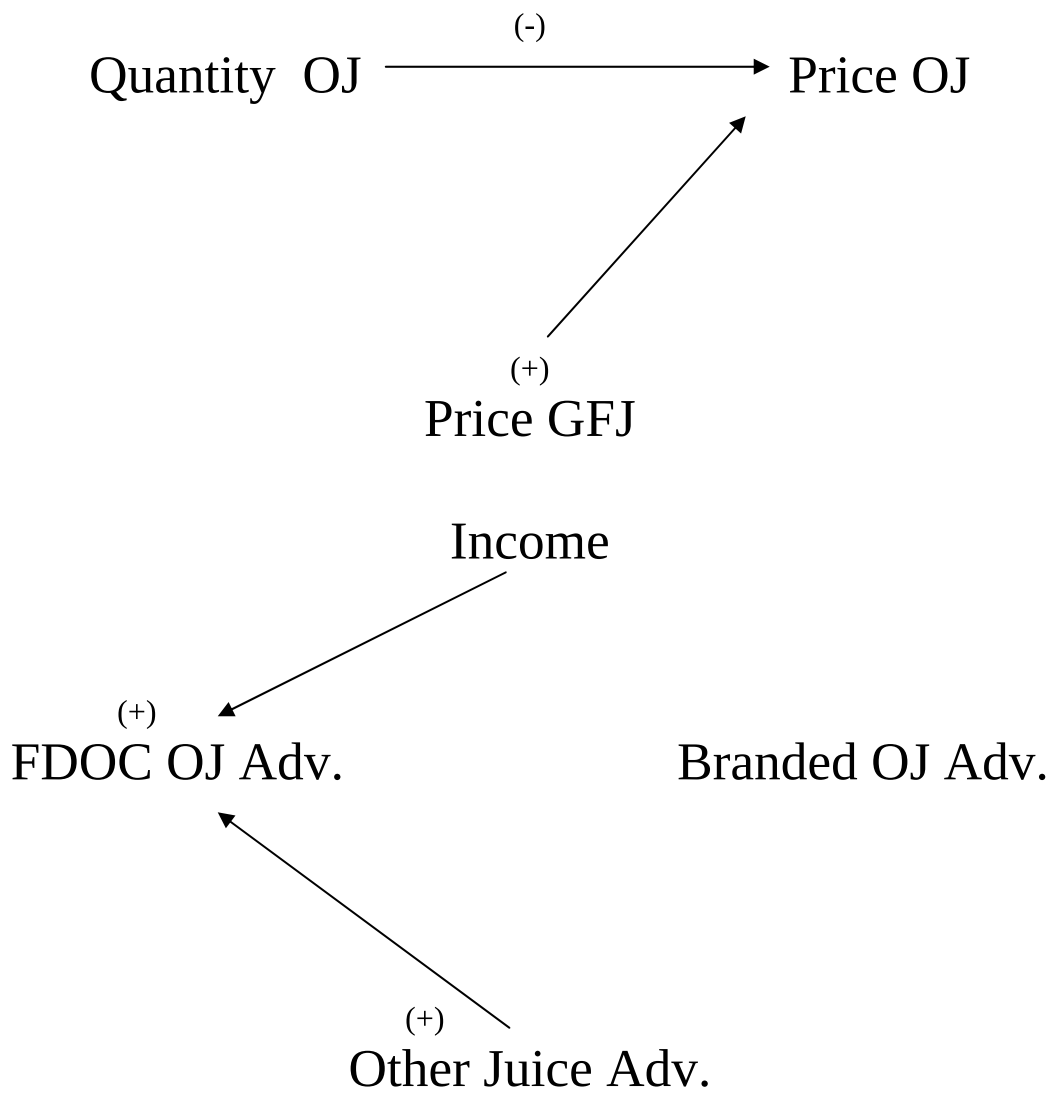
QOJ → POJ ← PGJ
↖
INC → FDOCAOJ← OAFJ

The likelihood ratio test statistic on this last causal graph is 304.40 which is rejected at any reasonable level of significance. The degrees of freedom on this test are 16, one less than that above because this path has one less zero restriction because the edge FDOCAOJ → QOJ was added. The test statistic associated with this last graph suggests that FDOC advertising expenditures do not show up in retail sales in current time, but take at least one period (one month) to show-up in terms of changes in retail sales of orange juice.

Relative Importance of Each Series on Orange Juice Sales

Given the causal structure summarized in Figure 20 and the estimated vector autoregression, both current and lagged influences among the seven variable set can be summarized from standard innovation accounting techniques. The description on these techniques is given in Sims (1980). Forecast error decompositions and impulse response functions are presented here. The decompositions summarize the relative importance of each variable on itself and all other variables in the model. The impulse responses summarize the dynamic pattern of movement of each variable to a shock (surprise) in a particular variable.

Figure 20: Search on Alternative Directed Acyclic Graphs on Innovations (Surprises) from a VAR on Seven Variables Related to Orange Juice Sales



[a] The same graph is found when three- and one-lag VARs are studied.

Table 24 gives these partitions at current time (step 0) and steps 1, 2, 6, 12 and 24 months ahead. These numbers show the relative importance of each variable in the seven-variable system on itself and the other six variables, at various forecast horizons. The summation of numbers in any row under the seven variables will be 100 (up to rounding error). Partitions for only for orange juice sales per capita are listed, as that is the variable of interest. A large percentage in the column under a given variable indicates that the column variable is an important influence on orange juice sales per capita. Table 24 presents results for the 1-lag, 2-lag and 3-lag VARs. In general, the results agree across the three different VARs.

Decompositions at each step are given for a "Bernanke" factorization of contemporaneous innovation covariance which treats innovations in all innovations as exogenous in contemporaneous time except that innovations on OJ Sales, OJ Price and GF Price are related as follows: OJ Sales → OJ Price ← GF Price and INC→ FDOC ADV← OTH JU ADV. Justification for such an ordering is based on a directed graph on observed innovations from the error correction model of lag length two. The decompositions sum to one hundred in any row (within rounding error limits). Thus, each row gives the percentage decomposition of the standard error measure (column 2) due to each series listed in rows three through ten. For example, under the 3-lag VAR panel at a twelve-month horizon, the uncertainty in OJ Sales has a standard error of 0.04 which is decomposed as follows: 71.62% of this variation is explained by historical variation in OJ Sales, 19.70% by variation in OJ price, 0.30 % by variation in Grapefruit Juice Price, 1.12% by variations in Real Income Per Capita, 5.16% by variation in FDOC Advertising on OJ, 0.27% due to variation in Branded OJ Advertising, and 1.83% due to variation in Other Juice Advertising.

At current time (horizon 0), orange juice sales per capita are exogenous, i.e., determined by variables outside the seven-variable system. At horizons of 1 and 2 months, both real orange juice price and FDOC advertising for orange juice begin to have an influence on orange juice sales. This influence is persistent up through the two-year horizon. These results are robust across the three different lag length structures. Interesting, real income variation appears to have, at best, a modest influence on orange juice sales per capita. Its influence is generally less than FDOC advertising expenditures. Both branded advertising and advertising for other fruit juices show very weak influences on orange juice sales per capita.

Impulse Response Functions

Figures 21, 22, and 23 give the impulse response of each series to a one-time-only shock in every variable. The responses are normalized by dividing each response by the historical standard deviation of its VAR error (innovation) term. This normalization allows each response to be plotted on the same relative scale (-1, +1). The responses in each sub-graph are for 36 periods (three years) following an initial one-time only shock in the variable given at the column heading which is listed across the top of each figure as the heading "Innovation to". Each row in each of the three figures gives the associated response of a variable to each shock. Perhaps the best way to examine each figure is to first look at the general picture rather than to try and capture explicit numbers in any sub-graph. Where are responses strong? Where are responses weak? Since the responses are normalized, the sub-graphs can be legitimately compared without regard to units of measurement. The caution against trying to read off specific numbers on any sub-graph ordinate

Table 24: Forecast Error Decomposition on Orange Juice Sales Per Capita from 1-, 2-, and 3-lag Vector Autoregressions, January 1989 to September 2002

Horizon	Std. Err.	OJ Sales	OJ Price	GF price	Inc.	FDOC OJ Adv.	Brand OJ Adv.	Other Juice Adv.
				Lag 1 VAR				
0	.016	100.00	.00	.00	.00	.00	.00	.00
1	.024	95.32	2.24	.09	1.21	1.14	.00	.01
2	.026	91.61	4.43	.20	1.29	2.47	.00	.00
6	.037	84.40	7.73	.39	1.39	5.94	.07	.08
12	.038	83.03	8.09	.41	1.38	6.81	.11	.16
24	.038	83.00	8.10	.41	1.38	6.84	.11	.16
				Lag 2 VAR				
0	.016	100.00	.00	.00	.00	.00	.00	.00
1	.022	86.55	9.08	.91	2.16	1.28	.01	.00
2	.028	82.79	11.31	.62	2.79	2.41	.07	.01
6	.038	74.61	15.37	.48	2.50	6.01	.06	.20
12	.040	71.81	16.26	.47	2.48	8.41	.06	.51
24	.040	71.67	16.30	.48	2.47	8.47	.06	.55
				Lag 3 VAR				
0	.014	100.00	.00	.00	.00	.00	.00	.00
1	.021	87.24	8.84	.58	1.85	1.48	.00	.00
2	.026	83.25	11.91	.39	2.14	2.23	.06	.02
6	.037	75.36	17.39	.27	1.27	4.88	.14	.69
12	.040	71.62	19.70	.30	1.12	5.16	.27	1.83
24	.040	71.37	19.70	.32	1.13	5.23	.37	1.88

Figure 21: Response of VAR System with One Period Lag to One Time Only Shock in Each Variable

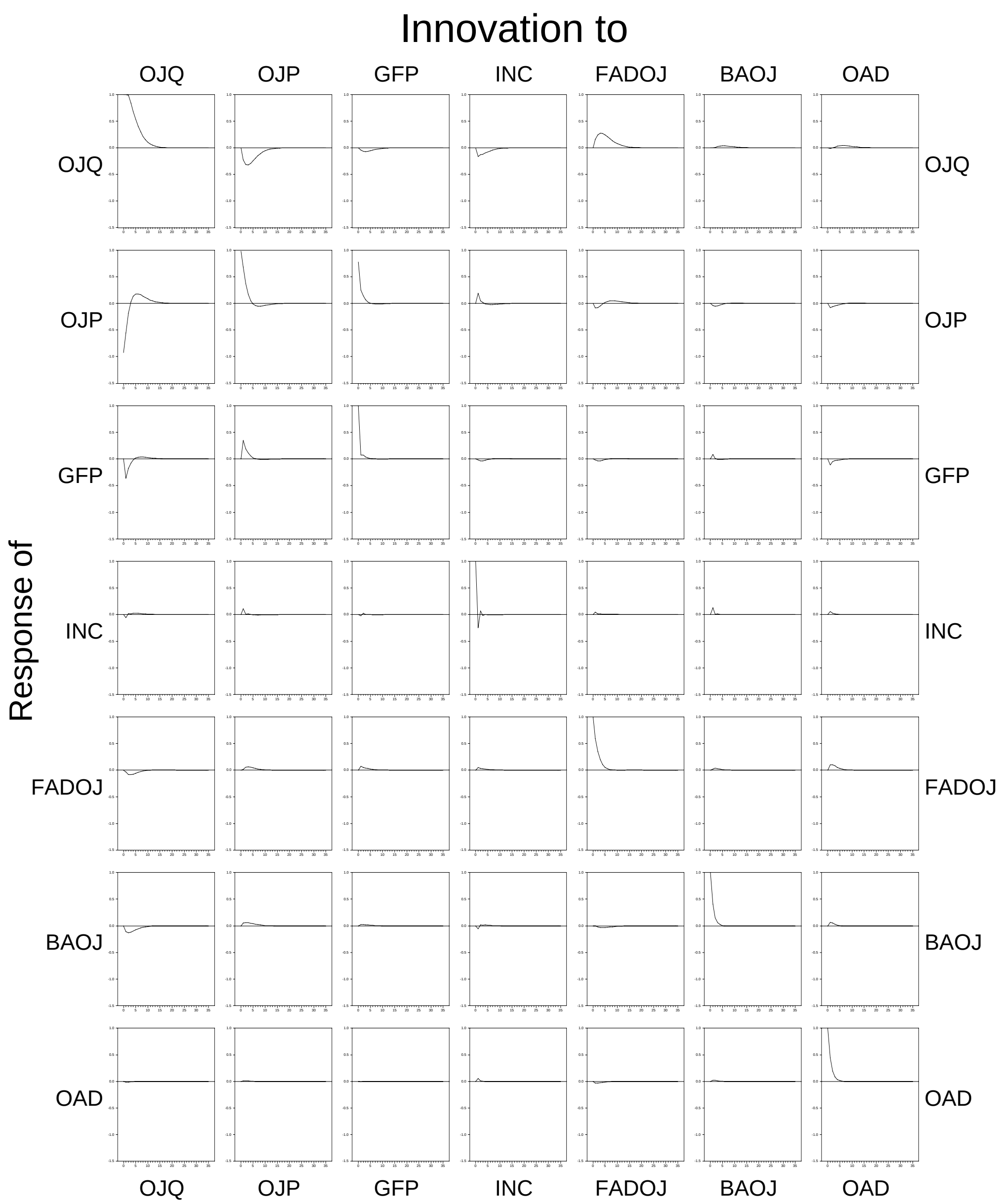


Figure 22: Response of VAR System with Two Period Lags to One Time Only Shock in Each Variable

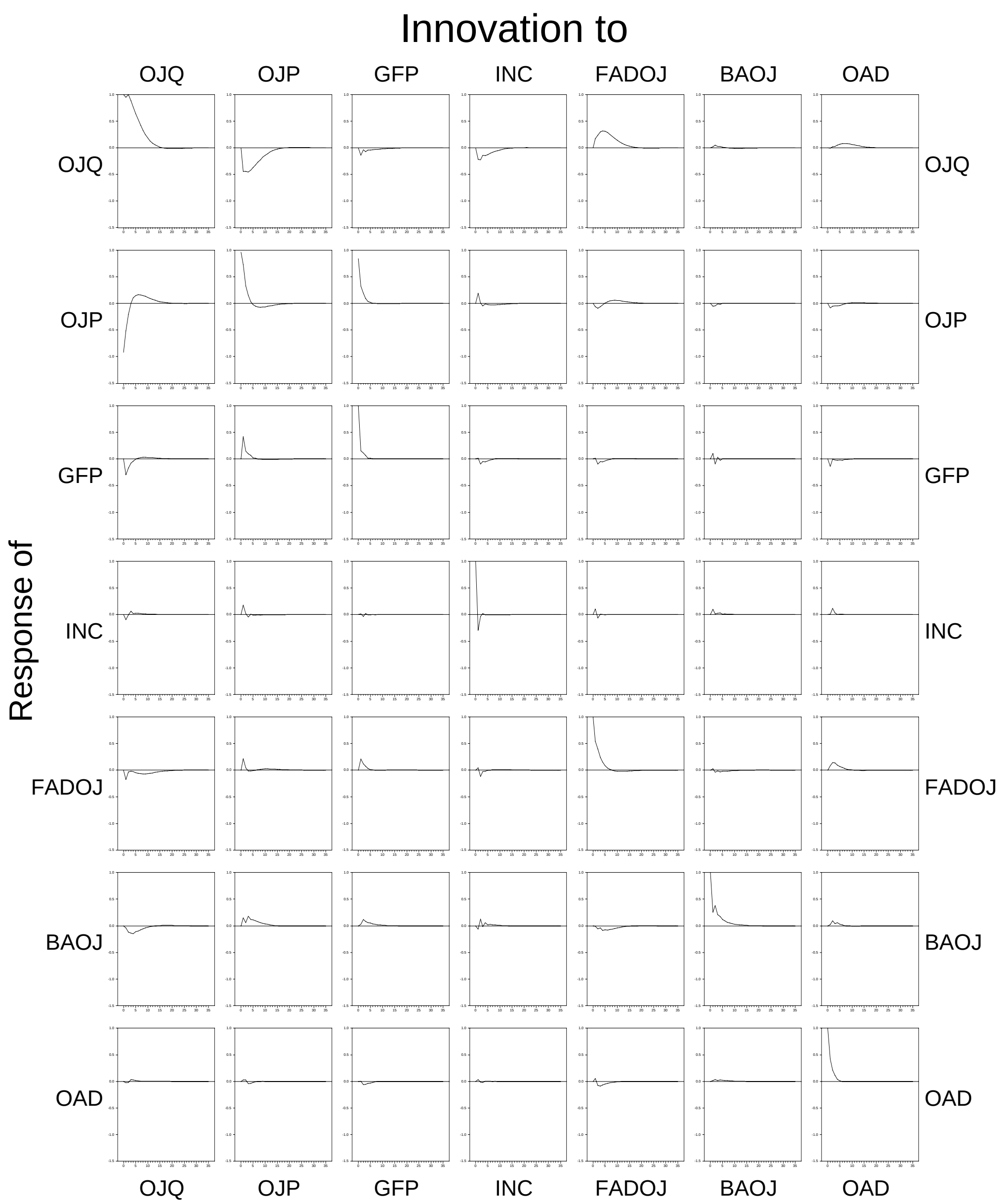
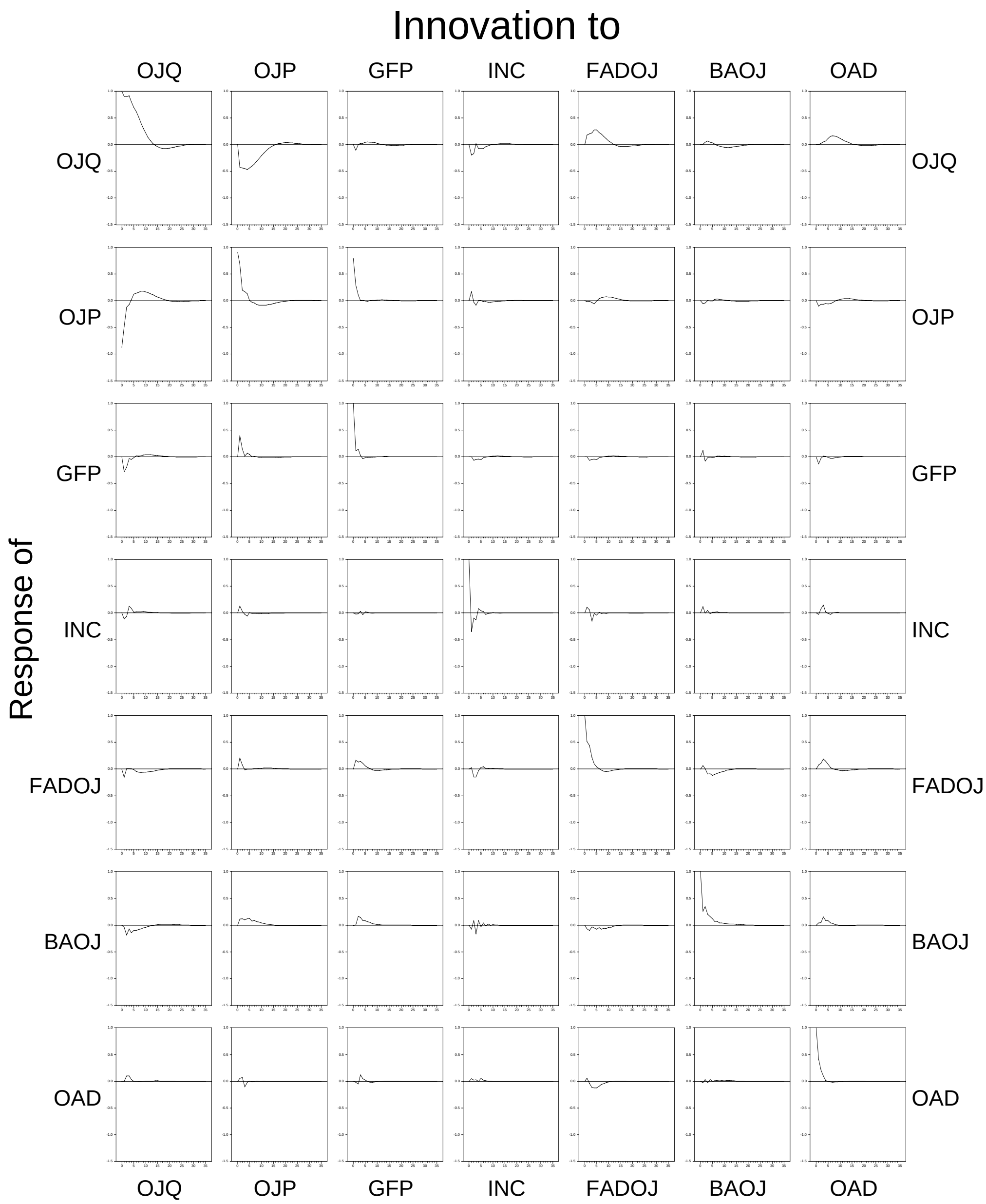


Figure 23: Response of VAR System with Three Period Lags to a One Time Only Shock in Each Variable



is to save the reader's eyes. The maximum y-ordinate on all sub-graphs is 1.0 and the minimum is -.5. Presenting all sub-graphs in a single figure has the benefit of allowing the reader to quickly grasp the dynamic structure in a relative sense. The cost of presenting all sub-graphs together is difficulty in reading the axes. Figures 21, 22, and 23 compare the relative response magnitude at different periods following a shock or surprise in each variable. The exact numbers (without normalizations) at any particular horizon 0 – 36 periods are provided in the Appendix.

The impulse responses are robust across the three different lag lengths considered. The noticeable dynamics are as follows. First, note that all dynamics are essentially "worked-out" within a twelve-month period so that year-to-year carryover effects are not a major component of the data. Second, the most important variable in the orange juice quantity row (sales of orange juice per capita) is a shock in orange juice sales per capita itself. The shock is positive and equal to one historical standard deviation on innovation (error) from the VAR (an innovation of 1000 total gallons per month). The second-most important variable in the dynamic behavior of orange juice sales is the shock in orange juice price. This response (how orange juice sales responds to a shock in orange juice price) is negative. Across all three lag structures (Figures 21, 22, and 23), the peak of the negative response in orange juice sales to a one-time-only shock in orange juice price is five months following the shock. Thereafter the response in sales continues to decline but dampens to zero by twelve moths following the shock. The third most important dynamic influence on orange juice sales is FDOC advertising of orange juice. Here the response is positive (orange juice sales responds to a one-time-only shock in advertising expenditures) for the first six months following the shock with responses thereafter damping to near zero. The peak response is over months 3 through 6 following the positive increase in advertising expenditures. The response of orange juice sales to shocks in branded advertising appears to be negligible in all three-lag structures over all periods studied.

The dynamic responses reveal other interesting characterizations of the seven-variable system. First, the response of orange juice sales is not strong and, in fact, shows up as a small negative response at the first six months following a shock in real income per capita. While certainly not large, the negative response does indicate that reliance on growth in real incomes is not an appropriate strategy for future returns. The dynamic responses to shocks in other fruit juice sales is actually positive for several periods following a one-time-only shock in other fruit juice advertising expenditures. The response is robust across all three-lag specifications and may reflect message garbling or confusion in the message signals by consumers.

An approximation of the elasticity ($\eta_{QOJ,FAD}$) of orange juice sales with respect to FDOC advertising for orange juice is given in Table 25 (i.e., the response of orange juice sales to a one-time-only shock in FDOC advertising expenditures).

Of course, an elasticity is generally a static number, reflecting the total change after all dynamics have worked themselves out. In this study, the analysis is arbitrarily cut off after a finite number of periods. Figures 21, 22, and 23 clearly indicate that all interesting dynamics are played out by twelve periods following the shock. Since the data are measured in logarithms, the ratio of the change in the log of orange juice sales due to a one time only change in the logarithm of FDOC orange juice advertising is used as an approximation for the elasticity of orange juice sales due to FDOC advertising ($\eta_{QOJ,FAD}$). Table 25 gives these approximations for the one-, two-, and three-

Table 25: Impulse Response of Quantity of Orange Juice Sales (QOJ) and FDOC Advertising of Orange Juice (FDOC ADV) to a One Time Only Shock (Innovation) in FDOC ADV: Summary of Responses and Approximate Elasticity for 1, 2 and 3 Lag VARs

	One lag VAR		Two lag VAR		Three lag VAR	
Steps Ahead	QOJ	FDOC ADV	QOJ	FDOC ADV	QOJ	FDOC ADV
0	.000	.837	.000	.802	.000	.787
1	.003	.475	.003	.422	.003	.396
2	.004	.274	.004	.308	.003	.343
3	.004	.154	.004	.180	.003	.164
4	.004	.083	.005	.111	.004	.067
5	.004	.043	.004	.055	.004	.016
6	.003	.021	.004	.021	.003	-.009
7	.002	.010	.003	.000	.003	-.031
8	.002	.005	.003	-.012	.002	-.048
9	.001	.002	.002	-.018	.001	-.049
10	.001	.001	.002	-.021	.001	-.042
11	.001	.001	.002	-.020	.000	-.033
12	.001	.001	.001	-.019	-.000	-.023
summation	.030	1.907	.037	1.808	.026	1.537
elasticity	.030/1.907 ≅ .015		.037/1.808 ≅ .019		.026/1.537 ≅ .017	

lag vector autoregressions which are all positive: $\eta_{QOJ,FAD,VAR1} \cong 0.015$; $\eta_{QOJ,FAD,VAR2} \cong .019$; and $\eta_{QOJ,FAD,VAR3} \cong .017$. The different elasticities are indicated by adding a third subscript (VAR1, VAR2 or VAR3) to indicate that the elasticity is based on the one-, two- or three-lag VAR.

In Table 25, the response of both Orange Juice Sales and FDOC advertising expenditures are represented as a dynamic process in three alternative vector autoregressions (one-, two-, and three-lag VARs). The approximate elasticities are calculated as the ratio of the summation of the responses of quantity of orange juice sales to advertising expenditures over the current and 12-step-ahead response.

Repercussions of Nearly Going Dark in 2001

In the latter part of 2001, FDOC advertising expenditures on orange juice were close to zero. Specifically, nominal advertising expenditures in September, October, and November of 2001 were $13,000, $2,300, and $5,200, well below the monthly average of $1.8 million over the January 1989 to September 2002 sample period. Beginning in January 2002 and continuing through September 2002, nominal FDOC advertising expenditures went from $698,200 (July

2002) to $7,012,200 (January 2002). In this section, the repercussions of nearly going dark from September 2001 to November 2001 are explored.

To accomplish this task, the demand for orange juice from January 1989 to August 2001 is first estimated. The per capita consumption of orange juice from September 2001 to September 2002 is the forecasted. The difference between actual and forecasted per capita orange juice consumption is calculated which is then translated into foregone orange juice consumption and total orange juice sales.

The parameter estimates and associated standard errors of the structural model for the demand for orange juice, based on monthly data from January 1989 to August 2001 are exhibited in Table 26. The optimal lag structure for the respective advertising expenditure variables is different than the lag structure associated with the model using the full range of data. In this case, the lag length is three months for FDOC advertising efforts on orange juice, twelve months for branded advertising on orange juice, and eleven months for advertising expenditures on fruit juices and drinks, excluding orange juice. The out-of-sample forecast accuracy associated with this model, based on comparing forecasted values of per capita consumption of orange juice with actual values over the holdout period from September 2001 to September 2002, is exceptional. As exhibited in Table 27, the mean absolute error is 0.004463 (gallons per person) and the mean absolute percent error is 1.80%.

The difference between actual and forecasted total orange juice consumption (in thousand gallons) and total orange juice sales (in thousand dollars) from this analysis is given in Table 28. As a consequence of nearly going dark in the September 2001 to November 2001 period, orange juice consumption and sales were lower from September 2001 to April 2002 than what would have been expected had regular FDOC advertising efforts been maintained. Eventually, the consumption and sales of orange juice rebounded from July 2002 to September 2002 as a result of FDOC efforts in calendar year 2002. Thus, the total cumulative loss in consumption and sales of orange juice over the 13-month period from September 2001 to September 2002 was 11.18 million gallons, equivalent to slightly more than $49 million in nominal sales and roughly $27.7 million in 1982-84 dollars.

The vector autoregression can be used to isolate the effects of the reduced FDOC advertising for orange juice sales in late 2001 and early 2002. Given equation (29), (30), or (31), or more precisely, their estimated forms, the vector *X* can now be written in terms of orthogonalized innovations as:

(34) $$X_t = \sum_{i=0}^{\infty} \Theta_i v_{t-i}$$

Table 26: Empirical Results Associated with the Econometric (Structural) Model in the Investigation of FDOC Advertising Expenditures Nearly Going Dark

Table 26 continued

Table 27: Out-of-Sample Forecast Ability of the Econometric (Structural) Model from September 2001 to September 2002

Table 28: Calculations Associated with the Repercussions of Nearly Going Dark Based on the Econometric Analysis

where the vector X is written as an infinite series of orthogonalized innovations, v_{t-i}. The matrix Θ_0 is not diagonal, but summarizes the causal pattern in contemporaneous time between innovations in each market.

From equation (34), an historical partition of the vector X at any date T+k can be calculated into information available at time t = T and information which is revealed at period t = T+1, T+2, … , T+k. Specifically, the vector X at period T+k can be written as:

$$(35) \qquad X_{T+k} = \sum_{s=0}^{k-1} \Theta_s v_{T+k-s} + [\sum_{s=k}^{\infty} \Theta_s v_{T+k-s}].$$

The position of the vector X that is due to information known up to period T is given by the term in brackets. Information that is revealed from T to T+k is given by the first summation expression on the right-hand side of the equation. Each of these terms ($\Theta_s v_{T+k-s}$) is the product of a matrix (Θ_s) and the vector of innovations at period T+k-s (v_{T+k-s}). For example, for k = 2, the moving average representation for orange juice sales can be written out using the notation of the lower case theta ($\theta_{QOJ,FAD}(0)$) denoting the element of the Θ matrix corresponding to the row associated with quantity of orange juice sales and the column associated with FDOC advertising expenditures at lag zero. The same pattern holds for other variables and lags. Thus, the value of the index in quantity of orange juice sales at period T+2 is expressed as a linear combination of historical innovations from each variable in the VAR as listed in brackets of equation (36):

$$
\begin{aligned}
(36)\quad X_{QOJ,T+2} = {} & \theta_{QOJ,QOJ}(0)v_{QOJ,T+2} + \theta_{QOJ,QOJ}(1)v_{QOJ,T+1} && \text{[due to Quantity of OJ Sales]}\\
& + \theta_{QOJ,POJ}(0)v_{POJ,T+2} + \theta_{QOJ,POJ}(1)v_{POJ,T+1} && \text{[due to Price of Orange Juice]}\\
& + \theta_{QOJ,PGF}(0)v_{PGF,T+2} + \theta_{QOJ,PGF}(1)v_{PGF,T+1} && \text{[due to Price of Grapefruit Juice]}\\
& + \theta_{QOJ,IN}(0)v_{IN,T+2} + \theta_{QOJ,IN}(1)v_{IN,T+1} && \text{[due to Real Income]}\\
& + \theta_{QOJ,FAD}(0)v_{FAD,T+2} + \theta_{QOJ,FAD}(1)v_{FAD,T+1} && \text{[due to FDOC OJ Adv.]}\\
& + \theta_{QOJ,BAD}(0)v_{BAD,T+2} + \theta_{QOJ,BAD}(1)v_{BAD,T+1} && \text{[due to Branded OJ Adv.]}\\
& + \theta_{QOJ,OAD}(0)v_{OAD,T+2} + \theta_{QOJ,OAD}(1)v_{OAD,T+1} && \text{[due to Other Juice Adv.]}\\
& + \text{base}_{QOJ,T}.
\end{aligned}
$$

Such a partition will allows an analysis of the behavior of each series in the neighborhood of important historical event (the late 2001 – 2002 reduction in FDOC advertising expenditures) and an inference as to which innovations were most important in moving the vector X at a particular time. In particular, we can graphically illustrate the value of $X_{QOJ,T+2}$ as the base forecast at period T (base $_{QOJ,T}$) plus the sum of innovations from series, which were observed in periods T+1 and T+2. These innovations are the new information from each series, which goes into the level (actual value) of X_{QOJ} observed at period T+2.

Figure 24 gives the historical decomposition of orange juice sales based on information through August 2001 and based on the three-lag VAR. Results on the one-lag and two-lag VAR are similar, as can be seen for FDOC advertising expenditures in Figure 25. Based on information known at August 2001 we forecasted ahead each month through September 2002. At each of these forecasted dates, the difference between actual orange juice sales and the forecasts of

Figure 24: Plots of Historical Decomposition of Logarithms of OJ Sales Per Capita from September 2001 through September 2002

Figure 25: Dollar Effect on Retail Revenue of FDOC Advertising of Orange Juice, September 2001 to September 2002, Bases on 1, 2, and 3 Lag Vector Autoregressions

orange juice sales can be expressed as arising from each of the seven variables studied in the VAR. Each panel of Figure 25 gives the error made in forecasting orange juice sales based on information through August 2001 that is due to the actual realization of that particular series over the subsequent months of September 2001, October 2001, November 2001 ,…, September 2002.

The upper most left-hand sub-plot in Figure 24 gives the logarithm of orange juice sales over the period September 2001 through September 2002. Note that the center of this upper left-hand-most sub-graph is approximately 5.50 and the exp(5.50) = 244.69 gallons per 1000 people or 0.245 gallons per person. This actual sales series differs from the forecasted series based on information known at August 2001 due to surprises (shocks) that actually occurred at each date in each of the seven series. These surprises (relative to what the series was thought to have been based on information through August 2001) in each of the seven series contribute to the actual series as given in equation (36) by the amount plotted in each of the sub-graphs.

The "effect" of the reduced advertising expenditures by FDOC is plotted in the sub-graph of Figure 24 labeled "Due to Shocks in Log FDOC OJ ADV. – Real" which are seen as negative contributions which reach their minimum trough in January 2002. The effects of the reduced FDOC advertising show weaker negative contributions after the January 2002 low. The surprises (shocks in the actual FDOC) actually bring the OJ sales back such that in June 2002, sales exceed the previously predicted level based on information through August 2001. This subplot shows the lags associated with advertising expenditures and subsequent response in sales and illustrates the "opportunity cost" of the reduced advertising regime. As discussed previously, the FDOC made rather large advertising expenditures in early 2002 (January, February, March, April, May and June). These large expenditures indeed had positive effects on orange juice sales. However, sales did not recover to above the level that would have occurred had FDOC expenditures remained at their historical levels throughout the last half of 2001 until June 2002.

Figure 25 gives the calculated revenue change over the September 2001 through September 2002 due to the surprises (shocks) in FDOC advertising expenditures. The estimated effects are given for the one-lag, two-lag, and three-lag VARs. Note first that the effects are similar across all three-lag specifications. The low point of the revenue effect is January 2002 at approximately \$15 million. Our estimate of the accumulated effects of the reduced advertising expenditures on retail sales revenues is between \$60 million (three-lag VAR) and \$75 million (1 and 2-lag VARs) in lost revenues.

Table 29 shows that the losses in orange juice consumption from the VAR models range from 9.384 to 13.145 million gallons and that the losses in orange juice sales range from \$41.2 to \$57.6 million in nominal sales and \$23.3 to \$32.5 million in 1982-84 dollars.

The bottom line is that severe decreases in funding FDOC advertising efforts on orange juice translate to relatively sizeable declines in orange juice consumption and sales. With the relatively large injections of FDOC advertising expenditures on orange juice in calendar year 2002, consumption and sales rebounded eventually. However, the rebound did not occur until approximately eight to twelve months after the initial severe decline in FDOC advertising effort in September 2001. Consequently, if declines in FDOC advertising expenditures occur relative

Table 29: The Repercussions of Nearly Going Dark: Comparison of Structural Model and Vector Autoregression Models

Table 29 continued

to the typical FDOC advertising expenditure pattern, this analysis suggests there will be notable losses in consumption and sales of orange juice. Once again, this analysis speaks to the importance of FDOC advertising efforts in stimulating the demand for orange juice.

Repercussions of September 11, 2001

The tragic events of September 11, 2001 have changed behavioral patterns of many Americans. Patterns of orange juice consumption and the responsiveness of sales to advertising expenditures also may have changed after that date. To consider this possibility, a dummy variable was added to the econometric and VAR models previously described which takes on the value of 1 for the months of September 2001 through September 2002 and 0 for all previous months (January 1989 to August 2001). Table 30 gives the estimated coefficients, associated standard errors and associated t-statistics corresponding to that dummy variable from the orange juice consumption equations from the one-, two-, and three-lag vector autoregressions and from the econometric model. For the respective vector autoregressions, in all three cases, the estimated coefficient is not significantly different from zero. In the three-lag case, the coefficient is actually positive although not statistically different from zero. In the case of the econometric model, the estimated coefficient associated with September 11, 2001 also is not significantly different from zero. Some may have expected the estimated coefficient for this variable to negative and significantly less than zero to reflect reduced consumption related to the terror attack events in New York, Washington, and Pennsylvania. No evidence of significant negative effects, however, is exhibited in the data analysis. As shown in Table 30, while certainly a tragedy beyond comprehension, September 11, 2001 had a negligible effect on orange juice consumption in the United States.

Effects of FDOC Advertising Expenditures on Orange Juice Consumption and Expenditures at the Retail Level of the Marketing Chain

This section presents the *static* benefit-cost ratios (BCRs), with no discounting, associated with FDOC advertising efforts at the retail level of the marketing channel. Using the econometric and vector autoregression models previously discussed, the benefits in terms of incremental consumption and sales associated with the presence of FDOC advertising versus no FDOC advertising altogether at the retail level of the marketing chain are calculated and presented. The calculation of the corresponding BCRs assumes no supply response.

This counterfactual analysis differs from the results reported earlier concerning the measurement of the impacts of nearly going dark. In that analysis, attention centered on three months in the latter part of 2001 that corresponded to near zero levels of FDOC advertising expenditures. In the analysis presented in this section, the benefits at the retail level from the existence of the FDOC advertising and promotion program are calculated.

The actual “experiment” that the FDOC conducted in the last several months of 2001 is invaluable for assessing the real world effects of advertising and promotion. In further assessing

Table 30: Estimated Effect of the September 11, 2001 Terrorist Event on Orange Juice Consumption

	One-lag VAR	Two-lag VAR	Three-lag VAR	Econometric Model
Estimated Coefficient	-.0037	-.0009	.0009	-.0127
Standard Error	.0066	.0068	.0074	.0129
t-statistic	-0.57	-0.13	+0.12	-0.98

of FDOC advertising effectiveness, a counterfactual experiment is conducted by setting FDOC advertising expenditures equal to zero over the period January 1990 through September 2002.

In calculating the benefits of FDOC advertising versus no FDOC altogether at the retail market level, per capita orange juice consumption with and without FDOC efforts are first compared. Then, the incremental gallons of orange juice sold due to FDOC advertising efforts as well as the incremental real (inflation-adjusted) value of orange juice sales are calculated. The BCR of the FDOC advertising and promotion program at the retail level is then calculated as the ratio of the cumulative real sales to the cumulative real advertising expenditures.

Table 31 presents the empirical results of this exercise from the econometric model. Recall that monthly data from January 1989 to September 2002 are used. Due to the lags in advertising indigenous to the structural (econometric) model, the model predictions of per capita orange juice consumption with and without FDOC advertising expenditures begin in April 1990 and end in September 2002. Table 31 summarizes the results by year.

The cumulative BCR (no discounting) over the April 1990 to September 2002 period is 13.32. However, this BCR assumes no supply response and only considers responses at the retail supermarket and supercenter level. Because of FDOC advertising, the quantity of orange juice sold increases by 7.67% on average. This figure translates into roughly 5.2 million more gallons of orange juice sold each month, or about 62 million more gallons of orange juice sold each year. For every $1 of advertising expenditure on an inflation-adjusted basis, an additional 4.36 gallons of orange juice are sold. Clearly, retailers benefit from the FDOC advertising and promotion program and, given the benefit-cost ratio of 13.32, the FDOC program is clearly economically feasible.

The counterfactual results are similar based on the analysis from the vector autoregression (VAR) model. The estimated additional gallons of orange juice sold per person per month and the estimated additional orange juice sales revenues due to FDOC advertising for orange juice between January 1990 and September 2002 from the VAR model are shown in Figures 26 and 27. The cumulative BCR (no discounting) is 5.75 which is somewhat smaller than the cumulative BCR from the econometric model. The quantity of orange juice sold increases by 3.31% on average which translates into 2.2 million more gallons of orange juice sold each month or about 27 million more gallons each year. That is, for every $1 of advertising expenditure on an inflation-adjusted basis, an additional 1.88 gallons of orange juice are sold.

Table 31: Static Benefit-Cost Ratios (BCRs) of FDOC Advertising Calculated from the Use of the Econometric Model, 1990 to 2002

Year	Incremental Gallons of OJ Sold Due to FDOC Advertising Expenditures		Incremental Real Sales of OJ Sold Due to FDOC Advertising Expenditures	Real FDOC OJ Advertising Expenditures	Static BCR
	Gallons	% Increase	Dollars	Dollars	$/$ spent
1990[a]	58,483,533	(11.72%)	$226,161,025	$13,331,020	16.97
1991	89,446,319	(11.62%	$287,077,378	$15,841,740	18.12
1992	73,120,793	(9.74%)	$245,765,184	$15,386,490	15.97
1993	62,704,690	(7.68%)	$183,102,554	$14,343,890	12.77
1994	48,357,496	(6.03%)	$133,416,610	$13,819,540	9.65
1995	33,480,835	(4.14%)	$88,131,479	$13,629,250	6.47
1996	37,504,128	(4.72%)	$108,710,684	$13,983,570	7.77
1997	47,170,385	(5.64%)	$133,897,126	$15,860,160	8.44
1998	66,948,033	(7,85%)	$192,066,923	$13,679,150	14.04
1999	80,031,319	(9,53%)	$254,537,611	$11,364,420	22.40
2000	79,265,205	(9.20%)	$249,108,900	$15,122,520	16.47
2001	58,083,035	(6.74%)	$182,572,199	$5,490,040	33.26
2002[b]	100,322,188	(6.72%)	$315,575,650	$16,400,080	19.24
CUMULATIVE	776,834,924	(7.67%)	$2,374,881,354	$178,252,000	13.32

[a] Includes only the months April to December
[b] Includes only the months January to September

Figure 26: Estimated Additional Gallons of Orange Juice Sold Per Person Per Month Due to FDOC Advertising for Orange Juice, January 1990 to September 2002

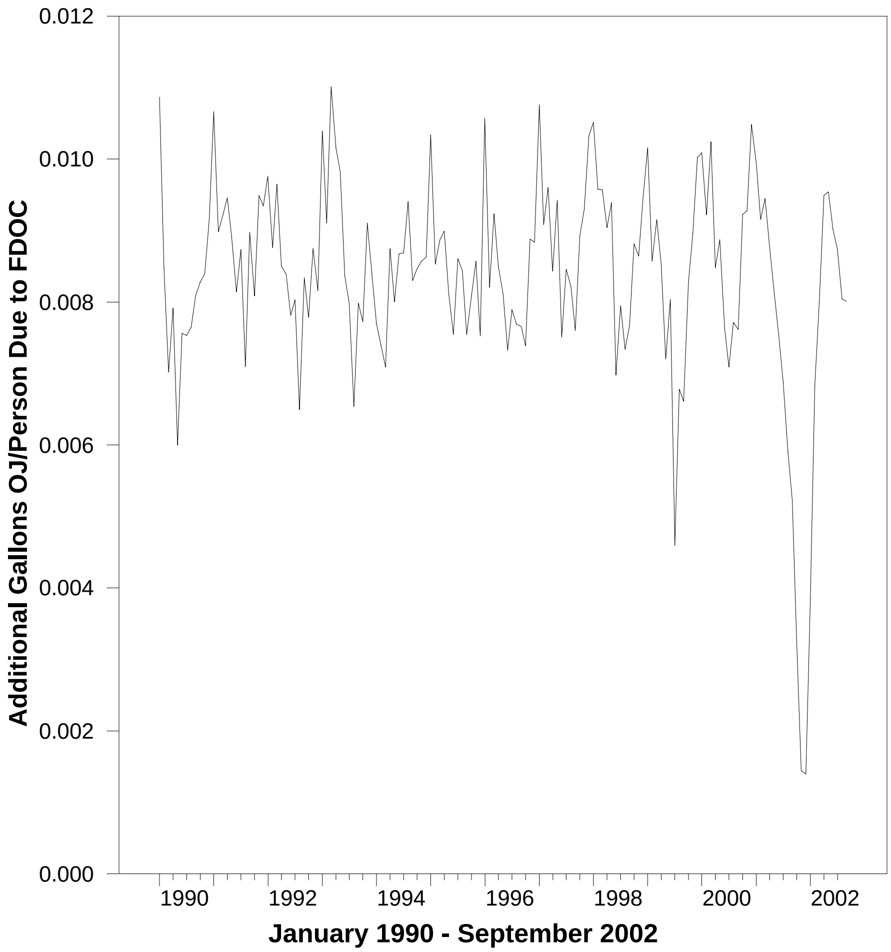
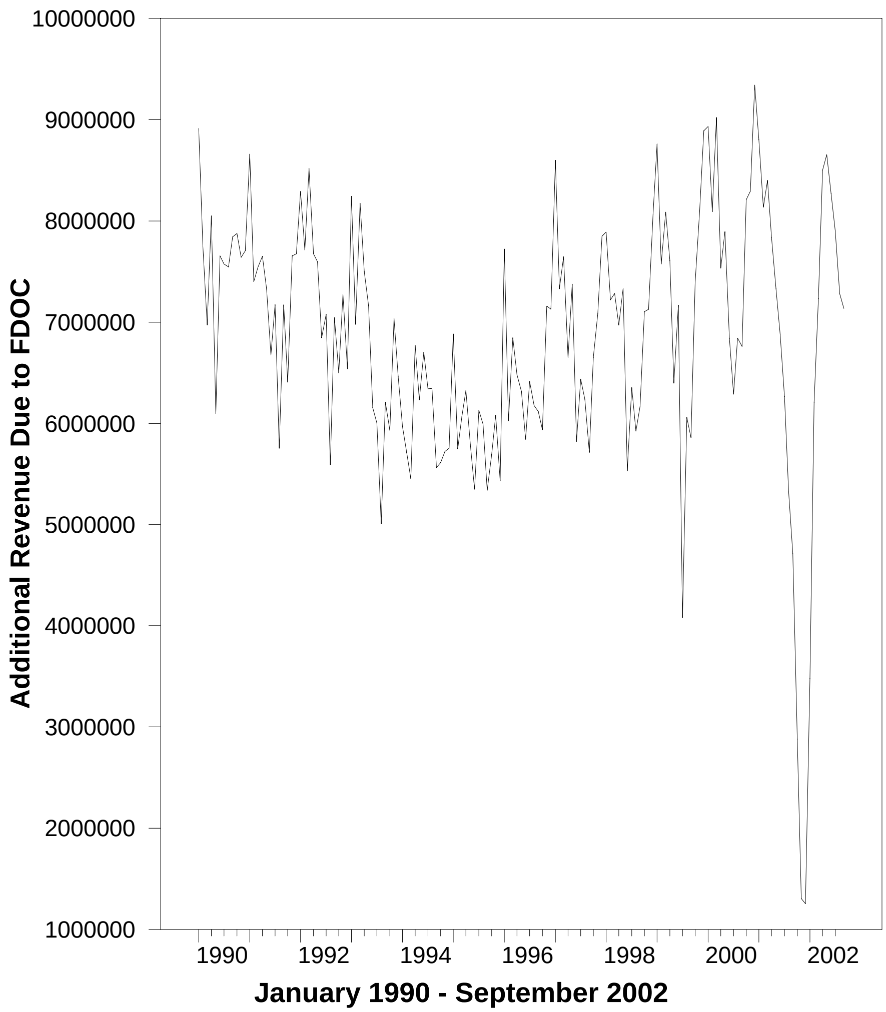


Figure 27: Estimated Additional Revenue Per Month Due to FDOC Advertising of Orange Juice, January 1990 to September 2002



The seven-equation VAR model produces more conservative estimates of the impacts of the FDOC program on retail consumption and sales largely due to feedback inherent in the dynamic processes associated with the VAR model. Recall too that the AC Nielsen scanner data correspond to roughly 60% of total orange juice consumption on average. Consequently, the impacts on consumption and sales due to the existence of the FDOC program are lower bounds.

Comparison of the Empirical Results with the Previous Studies

The empirical results of this study are summarized in Table 32. To put those results in perspective, the results of previous studies focusing on the impacts of advertising on the demand for orange juice are presented in Table 33 and reviewed in this section. Brown and Lee (1997) incorporated generic and brand advertising effects into a Rotterdam demand system, consisting of five orange juice brands (unidentified due to confidentiality) and a sixth category for all other juices and juice drinks. This demand model was applied to AC Nielsen and Leading-National Advertising (LNA) data on orange juice and other juice beverages. Nielsen gallon sales were transformed to per capita gallons using U.S. Department of Commerce data on U.S. population. The monthly advertising data were combined with the weekly Nielsen data by <u>repeating</u> the monthly advertising for each week in a given month. The data for this analysis covered the period of the week ending December 12, 1992 through the week ending March 30, 1996 (121 weekly observations). Also, the data were 52nd differenced to account for seasonality. The advertising expenditure data were not deflated. They estimated the own-price elasticity for orange juice to be –1.54 and the generic (FDOC) advertising elasticity for orange juice to be 0.0331 (Table 33). Brand advertising elasticities for orange juice were estimated to vary from 0.00008 to 0.0102 while the advertising elasticity for other juices and juice beverages was estimated to be –0.0004. Although they conclude that brand advertising elasticities were statistically significantly different from zero, brand advertising on orange juice had practically little effect on the overall demand for orange juice. The advertising efforts made by the FDOC, on the other hand, expanded overall demand for orange juice by roughly 3%.

Brown and Lee (1999) analyzed the impacts of FDOC triple-crown generic orange juice advertising on the retail demand for orange juice in 50 AC Nielsen metropolitan regions. The campaign was referred to as the “triple crown” because it was based on the endorsements of the American Cancer Society, the American Heart Association, and the March of Dimes. Their analysis was based on estimated weekly regional demand equations relating retail orange juice gallon sales to FDOC orange juice advertising and the price of orange juice. Branded advertising for orange juice also was included in the demand model but was found to be statistically nonsignificant and subsequently omitted from the analysis. Orange juice prices were derived by dividing dollar sales by gallon sales and were deflated through the use of the consumer price index (CPI). The data extended over the period for the week ending August 5, 1995 to the week ending October 25, 1997 (117 weekly observations).

In this 1999 study, Brown and Lee used the Nielsen generic orange juice TV gross ratings points (GRPs) to represent advertising. The GRP data were monthly and were combined with the Nielsen weekly sales data by equally allocating monthly GRPs across weeks. To account for seasonality, 52nd differences were used as in the 1997 study. Data on other demand factors such

Table 32: Summary of Empirical Findings on the Demand on Orange Juice

Time Frame and Scope	FDOC and Brand Advertising Data Used	Model Specification	Estimated Elasticities		
			Own-Price	FDOC Advertising	Brand Advertising
Time Frame: Weekly data aggregated to 165 monthly observations from 1/89 to 9/02	Inflation-adjusted dollar expenditures	Single-equation	-0.684 all OJ	0.011 all OJ	0.00066* all OJ
			-1.189 FCOJ	0.009 FCOJ	-0.049 FCOJ
			-1.090 NFC OJ	0.006 NFC OJ	-0.013* NFC OJ
Scope: US			-0.922 RECON OJ	0.011 RECON OJ	0.018* RECON OJ
			-0.839 SS OJ	-0.050 SS OJ	0.060* SS OJ

* Associated coefficient not statistically significant

Table 33: Empirical Findings on the Demand for Orange Juice in Recent Previous Studies

Researcher(s) and Date	Time Frame and Scope	FDOC and Brand Advertising Data Used	Model Specification	Estimated Elasticities		
				Own-Price	FDOC Advertising	Brand Advertising
Brown and Lee (1997)	Time Frame: Weekly AC Nielsen data 12/1292 to 3/30/96 - 121 weekly observations Scope: US	Leading National Advertiser (LNA) data	Rotterdam demand system	-1.54	0.033	Range from 0.00008 to 0.0102
Brown and Lee (1999)	Time Frame: Weekly AC Nielsen data 8/5/95 to 10/2597 - 117 weekly observations Scope: 50 AC Nielsen metro regions	Gross Ratings Points (GRPs)	Single-equation	Range from –0.710 (Miami) to –1.739 (Milwaukee)	Range from 0.001 (Kansas City) to 0.044 (Phoenix)	Not statistically different from zero
Brown (2002)	Time Frame: Weekly AC Nielsen data 9/13/97 to 11/24/2001 - 220 weekly observations Scope:US grocery store chains with >$2 million in annual sales + supercenters	Gross Ratings Points (GRPs)	Rotterdam demand system, single-equation	-0.22	0.050 (single-equation) 0.037 (Rotterdam model)	Not statistically different from zero
Brown and Lee (2002)	Time Frame: Weekly AC Nielsen data 9/13/97 to 11/24/2001 - 220 weekly observations Scope:US grocery store chains with >$2 million in annual sales + supercenters	Gross Ratings Points (GRPs)	Rotterdam demand system	-0.353 for major brands -0.525 for other orange juice	0.063 for major brands 0.046 for other orange juice	0.026 for major brands -0.033 for other orange juice

as income, population, and various individual product prices were not available by Nielsen region and for the weeks studied. Consequently, these demand factors were excluded from the analysis. They used a double logarithmic model to allow for diminishing returns to advertising. The generic advertising elasticities for the 50 metropolitan regions ranged from 0.001 for Kansas City to 0.044 for Phoenix (Table 33). The own-price elasticities varied from –0.710 for Miami) to –1.739 for Milwaukee. The impacts of advertising were estimated by first setting generic advertising levels to zero and then to sample values, yielding sales volume estimates with and without advertising. While the effectiveness varied from region to region, on average, generic advertising was estimated to increase orange juice demand by about 6.9%.

Brown (2002) used both a single-equation model and a Rotterdam demand system to estimate the impacts of FDOC and branded orange juice and grapefruit juice advertising on the demand for orange juice. Advertising effort was again measured by gross ratings points (GRPs) for TV advertising. Weekly AC Nielsen data for grocery store chains doing at least $2 million annual business plus supercenters were used in this analysis. The data included weekly dollar and gallon sales for various orange juice and grapefruit juice categories. Prices were derived by dividing dollar sales by gallon sales. U.S. Department of Commerce data in the U.S. population, disposable income, and the CPI also were used to transform gallon sales to per capita levels, deflate prices, transform disposable income to a per capita level, and deflate per capita income. The GRP data were quarterly and were combined with the weekly AC Nielsen data by repeating the quarterly GRP levels for each week in a given quarter. The period from the week ending September 13, 1997 to the week ending November 24, 2001 was examined (220 weekly observations).

In the single-equation version of the Brown (2202) model, orange juice gallon sales per capita were related to FDOC and brand advertising on orange juice, grapefruit juice advertising, the price of orange juice, income, seasonality, and a dummy variable for September 11 to capture possible effects resulting from changes in U.S. economy and consumer confidence after that point in time. The model focused on the impacts of FDOC and branded advertising GRPs for orange juice on the overall demand for orange juice. With the Rotterdam demand system model, attention was centered on individual brand demands for orange juice.

In this single-equation approach, Brown (2002) originally included income, a time trend, and the price of grapefruit juice in the model specifications. However, these variables were found to be highly correlated. To circumvent the collinearity problem, income was kept in the model as the measure of the information captured by the three correlated variables. Consequently, the impact of income on orange juice demand may reflect the joint effects of income, time, and the price of grapefruit juice.

The own-price elasticity of demand for orange juice was estimated to be –0.22. The income elasticity of demand for orange juice was estimated to be 0.43. Additionally, the advertising elasticity associated with efforts of the FDOC to promote orange juice was estimated to be 0.050 (single-equation model) and 0.037 (Rotterdam model). Importantly, brand advertising on orange juice and advertising on grapefruit juice were not statistically significant determinants of the demand for orange juice. The results for both the single-equation model and the Rotterdam demand system suggested a relatively strong relationship between FDOC TV GRPs and the demand for orange juice. FDOC advertising efforts on orange juice were estimated to increase the demand for orange juice by roughly 4-5% over the September 1997 to November 2001 period.

Using the same data used by Brown (2002), Brown and Lee (2002) estimated the impacts of FDOC advertising and branded advertising on orange juice on the demand for two categories of orange juice – major brands and other orange juice. The differential demand system or Rotterdam model (Theil 1971, 1975, 1976, 1980a,b) was used to specify the demand functions for the respective categories. The own-price elasticity estimates indicated that the demand for major brands of orange juice and the demand for other juice were price inelastic (-0.353 for major brands and –0.525 for other orange juice). The cross-price elasticities indicated that the two categories of orange juice were substitutes. The advertising elasticities they estimated indicate that band advertising increased the demand for the major brands in aggregate by 2.6% while decreasing the demand for other orange juice by 3.3%. The FDOC advertising elasticities they estimated indicate that generic advertising had relatively strong impacts, increasing the demands for the major brands and other orange juice by 6.3% and 4.6%, respectively. For the orange juice group in total, the advertising elasticity estimated by Brown and Lee (2202) suggest that FDOC and brand advertising increased overall orange juice demand by 5.5% and 0.1%, respectively. However, the brand estimate was not significantly different from zero.

Across all the studies, including this one, the empirical results suggest that (1) FDOC orange juice advertising has expanded the demand for orange juice and (2) branded advertising efforts on orange juice, while positive, have not had a statistically significant effect on total orange juice demand. Brand switching apparently has limited the brand advertising impact on the orange juice category.

While the approach, data used, and results among this and previous studies are similar, at least three things distinguish this study from earlier studies. First, this study used weekly data extended from the week ending January 9, 1988 through September 28, 2002. The time periods analyzed in earlier studies were much shorter (only 2 to 4 years), covering primarily the late 1990s (see Table 33).

A second major difference of this study from previous analyses is in the procedure of matching the *monthly* FDOC and branded advertising data on orange juice to the *weekly* AC Nielsen data. In the earlier studies reviewed, the monthly advertising data were combined with the weekly Nielsen data by repeating the monthly advertising for each week in a given month. In our study, the weekly dollars and gallons information are aggregated to form a monthly observations on orange juice purchases which match the time frequency of the FDOC and brand advertising expenditures on orange juice. This procedure matches orange juice consumption with advertising effort more precisely. In studies reviewed, each week of consumption was matched with advertising effort corresponding to the entire month. This matching would seem to overstate the amount of advertising effort in any given week.

Third, this study uses inflation-adjusted advertising expenditures while the other studies reviewed employed non-deflated LNA data or GRP data. Further, to account for seasonality, monthly indictor variables are employed in contrast to the previous studies which used 52nd differencing.

Fourth, single-equation model specifications are used in this study to estimate the demands for all orange juice; FCOJ; NFC OJ; RECON OJ; and SS OJ. Although the previous studies also employed single-equation models, the focus was on all orange juice demand. Some of the studies also used Rotterdam demand system models but the focus of demand system analysis in those studies, in general, was on the specific brand demands for orange juice.

Finally, to capture the advertising carryover effects, a second degree polynomial distributed lag is used. In earlier studies reviewed, demand is viewed as a function of a psychological stock of past and present advertising, subject to a decay effect. In all cases, evidence substantiates the effectiveness of FDOC advertising efforts on the demand for orange juice. The FDOC advertising elasticities from those earlier studies in which the scope is the entire United States ranged from 0.033 to 0.063. The FDOC advertising elasticity for all orange juice was estimated to be smaller in this study at 0.011. The brand advertising elasticities generally were not statistically different from zero in either this or the earlier studies. Even in the studies reporting statistically significant brand elasticities, those elasticities were typically small in magnitude.

Concluding Comments

In summary, the results of this study are in general agreement with earlier investigating the impacts of FDOC and branded advertising on orange juice demand using AC Nielsen data. Unequivocally, there exists a positive relationship between FDOC advertising and the demand for orange juice. FDOC advertising efforts expand overall orange juice demand while brand advertising efforts seem to have little effect on overall demand. This result is consistent with the fact that brand and generic advertising differ in nature. Brand advertising attempts to increase the demand for the brand in question, often at the expense of reduced demand for competing brands. FDOC advertising efforts increase the overall demand for the category.

In this study, the FDOC advertising elasticity of orange juice demand was estimated to be 0.011 based on the econometric (structural) model and to be between 0.015 and 0.019 based on the vector autoregression models. The similarity of the estimates of this advertising elasticity from two different methodological approaches adds additional credibility to the analysis. Without question, this finding speaks to the robustness of the results.

At the same time, both the econometric (structural) models and the time-series (VAR) models suggest that the primary drivers of orange juice demand are the real price of orange juice, seasonality, and real FDOC advertising expenditures on orange juice. Additionally, both methodological approaches reveal that real per capita income and real branded advertising expenditures on orange juice are not statistically significant determinants of orange juice demand. From the econometric (structural) models, there exists evidence to indicate that real grapefruit juice price and real advertising expenditures on fruit juices and drinks, excluding orange juice, are key elements affecting orange juice demand. The evidence from the VAR models does not support this conclusion.

The results imply that total orange juice consumption increases with the existence of the FDOC program by 3.31% to 7.67% on average. This figure translates into roughly 2.2 million to 5.2 million more gallons of orange juice sold each month or about 26 million to 62 million more gallons of orange juice sold each year. For every $1 of advertising expenditures (inflation-adjusted) made by the FDOC, an additional 1.88 gallons to 4.36 gallons of orange juice are sold. For every $1 of FDOC advertising expenditure, retail revenue increases by $5.75 to $13.32.

Importantly, the analysis in this report has focused only at the retail level of the marketing channel. To measure the rate-of-return to the citrus growers who pay the assessment, supply and demand conditions at the farm level must be integrated with the retail level of the marketing channel, including consideration of international markets. Thus, to measure the effect of advertising from the retail level down through the complex web of marketing channels and relationships to the grower, the analysis must take into account the production of oranges in Florida, California, Arizona, and Texas, exports of oranges, fresh and processing orange markets, orange juice production, inventories, domestic demand, import demand, exports from Brazil and elsewhere, and much more. Simply put, the finding in this study that FDOC advertising efforts on orange juice expand the orange juice demand at the retail level of the marketing channel is a necessary but not a sufficient condition to guarantee a positive rate-of-return to citrus growers. This rate-of-return calculation is the primary objective of a separate report by the authors ("Florida Orange Grower Returns from Orange Juice Advertising," TAMRC Consumer and Product Research Report No. CP-01-04, February 2004).

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APPENDIX
IMPULSE RESPONSES FOR ORANGE JUICE COMPONENTS

Figure A1. Response of VAR System with Frozen Concentrate to a One Time Only Shock in Each Variable

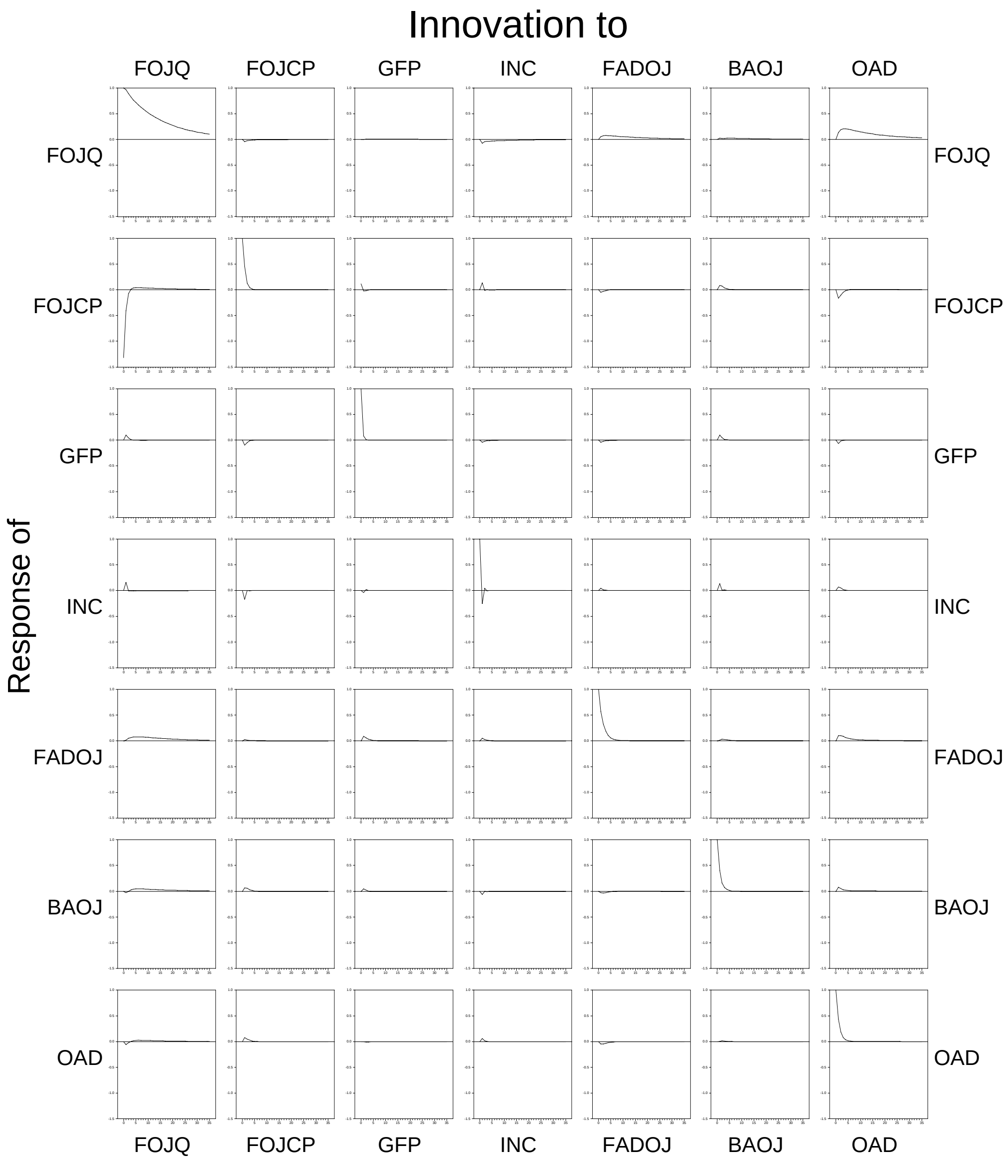

Figure A2. Response of VAR System with Non-Frozen Concentrate to a One Time Only Shock in Each Variable

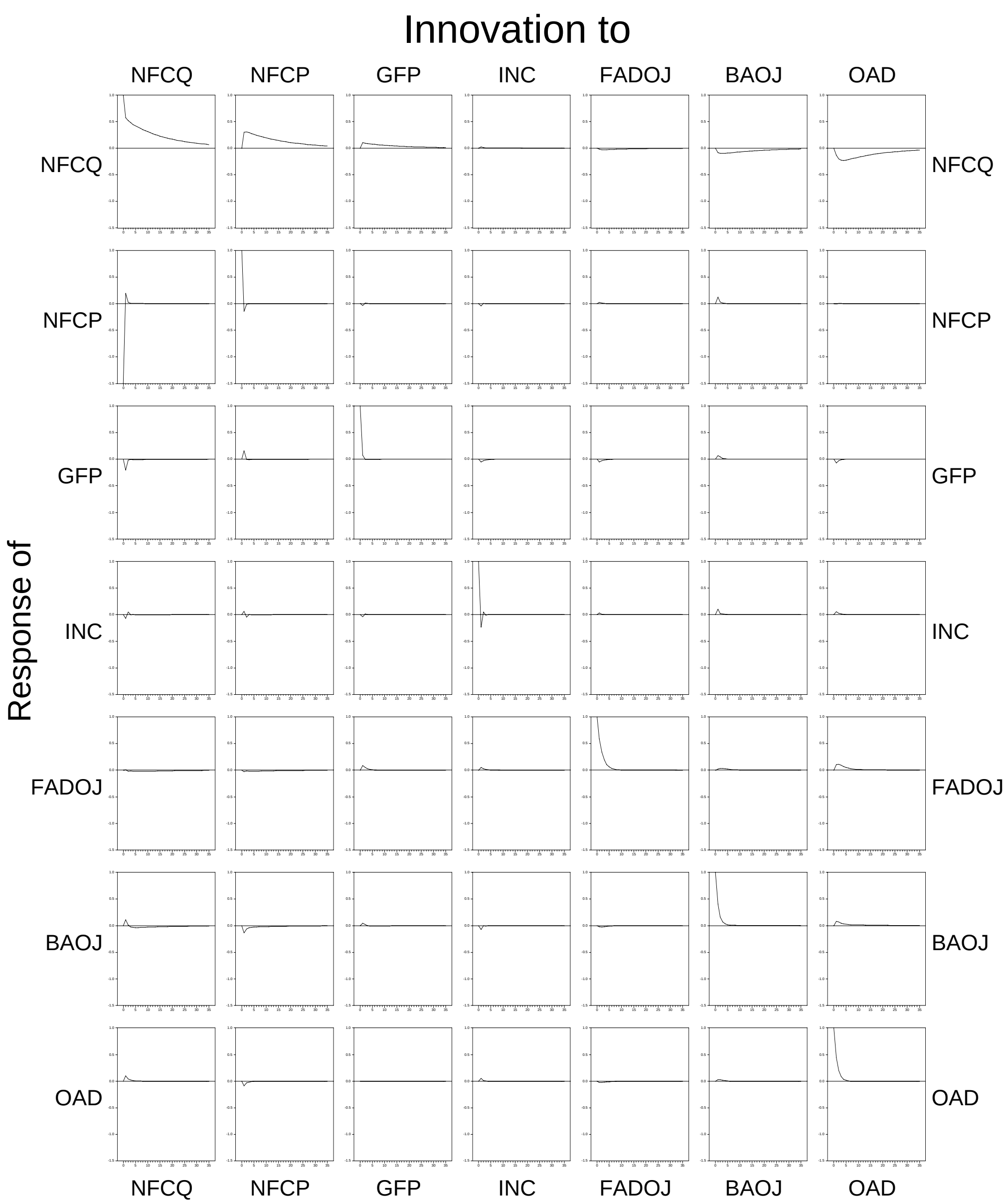

Figure A.3. Response of VAR System with Reconstituted Orange Juice to a One Time Only Shock in Each Variable

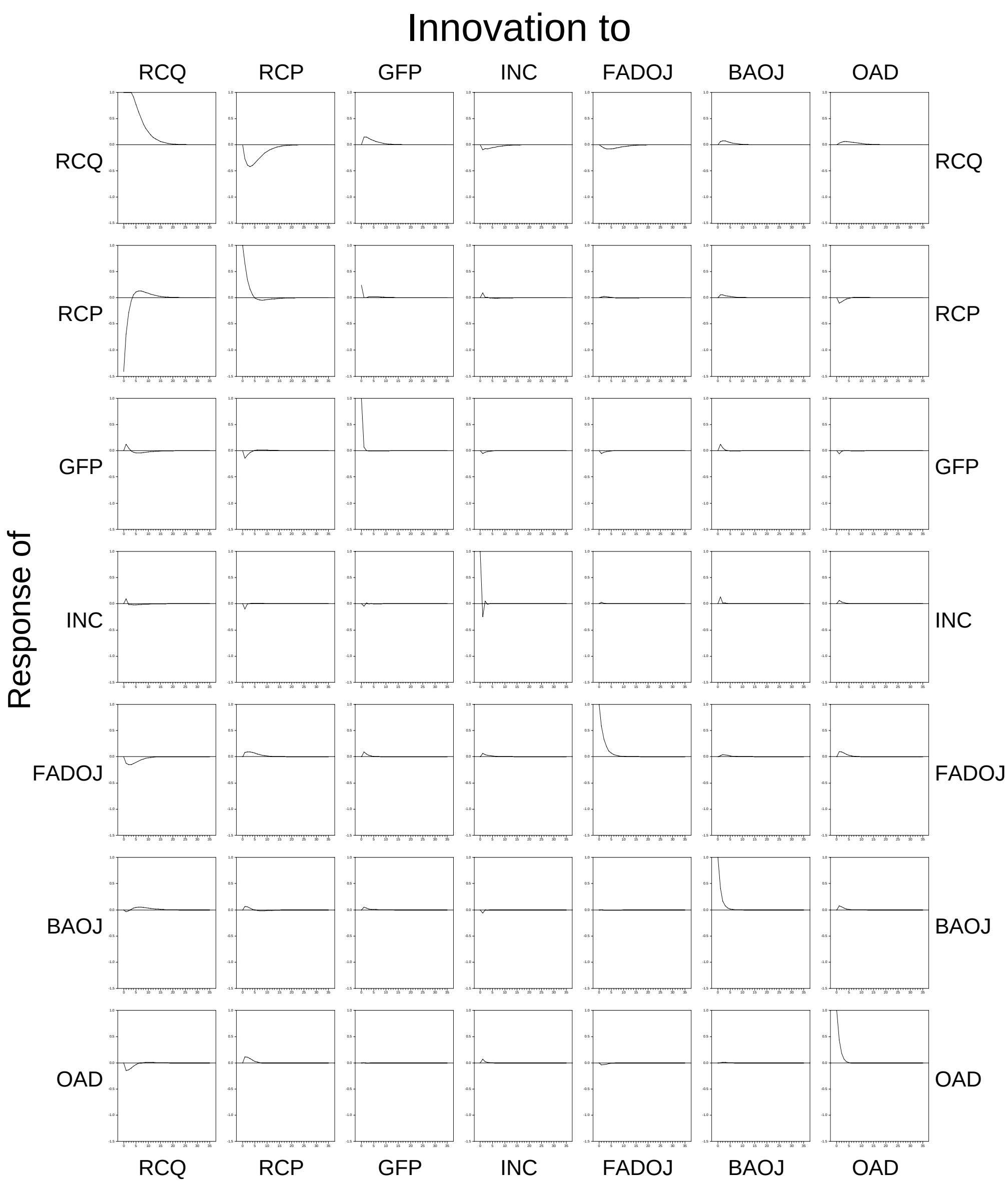

Figure A.4. Response of VAR System with Shelf Stable Orange Juice to a One Time Only Shock in Each Variable