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ESTIMATES OF PROMOTIONAL IMPACTS ON ORANGE JUICE AND GRAPEFRUIT JUICE DEMAND BASED ON TIME SERIES AND CROSS-SECTIONAL DATA

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Estimates of Promotional Impacts on Orange Juice and Grapefruit Juice Demand Based on Time Series and Cross-Sectional Data

Retail demand for orange juice (OJ) and grapefruit juice (GJ) was studied based on ACNielsen data for grocery stores that do $2 million or greater business annually, by city, by week over about a three and a half year period. Data on four competitive products---OJ drinks, OJ blends, GJ cocktail, and GJ blends---were also included in the analysis. Fifty two cities[1] were included in the analysis and the time period was from week ending 9/17/05 through 3/14/09 resulting in a total of 9,568 observations (52 times 184).

Data richness and degrees of freedom were important factors for choice of model in this study. Individual demand equations by city were not estimated as there were not enough observations and variation in the data to obtain statistically significant results for many of the demand responses for many of the cities. Some demand responses may, however, be the same across cities, in which case, imposing restrictions on the responses across cities may yield better parameter estimates to the extent the restrictions are true. For each week, there are 52 city specific observations that can be used in estimating a common demand response across cities. For example, variation in a promotion variable across cities might help explain the level of city demand. In addition, for each city there is the variation in the promotion variable over time that can also be used to estimate the demand response. In this study, restrictions that require some of the demand responses to be the same across cities were imposed using a model based on combined data by city and week.

The fixed effects, cross-section and time series model was used in the analysis. It is assumed that the model's intercept varies across city and time, but the demand elasticities with respect to prices and the impacts of promotions are the same across cities as well as time. Formally, the demand by city by week for a juice or juice drink product is specified as

(1) $\log q_{ict} = \mu_{ic} + \beta_{ic} t + \gamma_{it} + \sum_j \varepsilon_{ij} \log p_{jct} + \sum_k \eta_{ik} s_{ikct} + \sum_{j \neq i} \delta_{ij} s_{jct}$,

where subscripts i, c and t stand for the product, city and week, respectively; q is gallons, p is price and s are promotional variables measured as the share of total dollar sales on promotion. The own-promotional variables (s_{ikct}) are for features (k=1), displays (k=2), features and displays (k=3) and temporary price discounts (k=4). The cross-promotional variables are for any promotion ($s_{jct} = \sum_k s_{jkct}$). The coefficient ε_{ij} is a price elasticity (i=j, own; and i≠j, cross). The coefficient η_{ik} or δ_{ij} indicates the percentage change in demand for a change in the promotional share. The coefficient μ_{ic} indicates a city specific effect. Cities have different populations, consumer income levels and perhaps preferences based on the demographic background of its population, all of which likely influence μ_{ic}. The coefficient β_{ic} is for city specific trends. The

[1] All major U.S. cities were included except New Orleans which was omitted due to its continued recovery from hurricane Katrina.

coefficient γ_{it} indicates a time specific effect: over time demand may change due to seasonality, generic and brand OJ advertising across all cities, changes in competitive product prices and advertising levels not included in the model, and other factors.

Since the time period analyzed is relatively short, population, income and preferences are treated as constant for a city. Based on this treatment, the coefficient μ_{ic} is assumed to be constant over the weeks studied. The data analyzed, however, are sales in grocery stores that do \$2 million or greater business annually, excluding sales in Wal-Mart outlets. The term $\beta_{ic}t$ is included in equation (1) to capture the negative effects that expanding Wal-Mart sales may have on the sales in the stores doing \$2 million or greater business. This variable may also capture other city specific factors such as the downturn in the economy and trends in consumer income and spending (μ_{ic} captures impacts of income variability across cities while $\beta_i t$ and γ_{it} capture impacts of income changes over time).

Dropping the product subscript i for convenience, equation (1) can be written as

(2) $\log q_{ct} = \mu_c + \beta_c t + \gamma_t + \sum_j \varepsilon_j \log p_{jct} + \sum_k \eta_k s_{kct} + \sum_{j \neq i} \delta_j s_{jct}$.

In equation (2), the city and time specific term, $\mu_c + \beta_c t + \gamma_t$, which we will refer to as α_{ct}, is modeled using dummy variables, i.e.,

(3) $\alpha_{ct} = \sum_n \mu_n D_{nct} + \sum_n \beta_n t\, D_{nct} + \sum_m \gamma_m Z_{mct}$

where $D_{nct} = 1$ if $n = c$ and $D_{nct} = 0$ if $n \neq c$; and $Z_{mct} = 1$ if $m = t$ and $Z_{mct} = 0$ if $m \neq t$. The subscript n runs from 1 to 52 for the cities analyzed, while the subscript m runs from 1 to 184 for the weeks analyzed.

The dummy variables follow two restrictions, i.e.,

(4) $\sum_n D_{nct} = 1$,

and

(5) $\sum_m Z_{mct} = 1$.

As a result of these restrictions, a singularity problem exists in estimating the model. This problem can be overcome by re-specifying the model.

Consider the second term on the right-hand side of equation (3), $\sum_n \beta_n t D_{nct}$. Adding and subtracting $\beta_1 t = (\sum_n D_{nct})\, \beta_1 t$ to this term results in

(6) $\beta_1 t + \sum_{n=2 \text{ to } 52} (\beta_n - \beta_1) t D_{nct}$.

The term $\beta_1 t$ in equation (6) can be written as $(\sum_m Z_{mct})\, \beta_1 t = (\sum_m Z_{mct}\, \beta_1 m)$, since $tZ_{mct} = m$ if $m = t$ and zero otherwise. Combining this term with the third term on the right-hand side of equation (3) yields

(7) $\sum_m (\gamma_m + \beta_1 m) Z_{mct}$

Thus, equation (3) can be written as

(8) $\alpha_{ct} = \sum_n \mu_n D_{nct} + \sum_{n=2 \text{ to } 52} (\beta_n - \beta_1) t D_{nct} + \sum_m (\gamma_m + \beta_1 m) Z_{mct}$

or, adding and subtracting $\mu_1 + \gamma_1 + \beta_1$,

(9) $\alpha_{ct} = \mu_1 + \gamma_1 + \beta_1 + \sum_{n=2 \text{ to } 52} (\mu_n - \mu_1) D_{nct} + \sum_{n=2 \text{ to } 52} (\beta_n - \beta_1) t D_{nct} + \sum_{m=2 \text{ to} 184} (\gamma_m - \gamma_1 + \beta_1 (m-1)) Z_{mct}$

or

(10) $\alpha_{ct} = \alpha^* + \sum_{n=2 \text{ to } 52} \mu^*_n D_{nct} + \sum_{n=2 \text{ to } 52} \beta^*_n t D_{nct} + \sum_{m=2 \text{ to } 184} \gamma^*_m Z_{mct}$

where $\alpha^* = \mu_1 + \gamma_1 + \beta_1$; $\mu^*_n = (\mu_n - \mu_1)$; $\beta^*_n = (\beta_n - \beta_1)$; $\gamma^*_m = (\gamma_m - \gamma_1 + \beta_1 (m-1))$.

Given specification (10) for the city and time specific effects, demand model (2) can be written as

(11) $\log q_{ct} = \alpha^* + \sum_{n=2 \text{ to } 52} \mu^*_n D_{nct} + \sum_{n=2 \text{ to } 52} \beta^*_n t D_{nct} + \sum_{m=2 \text{ to } 184} \gamma^*_m Z_{mct} + \sum_j \varepsilon_j \log p_{jct} + \sum_k \eta_k s_{kct} + \sum_{j \neq i} \delta_j s_{jct}$.

The summation subscripts for the city and time effects run 2 to 52 and 2 to 184, respectively, which removes the singularity problem. The specific effects for the first city (μ_1), the first time period (γ_1) and the first city, first week trend (β_1) are embedded in the intercept α^*. The first city trend effects for weeks 2 through 184 are embedded in the parameters γ^*_m's.

Model Estimates

Estimates of the OJ and GJ demand equations are shown in Tables 1 and 2, respectively. Two models were estimated for each juice---one model with and one without cross-promotional impacts. The tables show the price elasticities and promotional impacts. The estimates for the large number of dummy variables (μ^*_n, β^*_n and γ^*_m) are omitted to save space. Figures 1 and 2 show the time coefficients (γ^*_m's).

OJ model 1 and 2 each had a high R^2 of .997. Focusing on model 2 first, all of the 51 city effects (μ^*_n) were statistically different from zero at the $\alpha = .10$ level or higher, indicating that the specific effects for these cities differed from that for the base city which was Chicago. All except 11of the trend coefficients (β^*_n) were statistically significant, again indicating the city trend effects largely differed from that for Chicago. The time estimates, which are differences in week effects from the first week plus the trend effect for Chicago ($\gamma_m - \gamma_1 + \beta_1 (m-1)$), were largely statistically significant, exhibiting seasonality and a negative trend in the latter weeks studied due perhaps to the economic downturn (Figure 1).

The results for models 1and 2 were similar, except again model 1 did not include cross-promotional effects. Four out five of the cross-promotional effects were positive and statistically significant. Since the products studied were thought to be substitutes, we expected these cross-promotional effects would be negative. Model 1 was estimated to see if restricting these cross-promotional effects to zero made a difference in the other parameter estimates. The differences were relatively minor. Continuing to focus on model 2, the own-price elasticity for OJ was -1.05 and statistically significant. Four of the five cross-price elasticity estimates were either positive or not significantly different from zero indicating substitute or neutral relationships. The cross-price estimate for GJ blends was unexpectedly negative and significant indicating a complementary relationship (this may be a spurious result).

All the OJ promotional coefficients in model 2 were positive and statistically significant. The coefficients for OJ features and displays were each around .19 indicating that these promotions, each, by itself, increases OJ demand by about 19%. The combined effect of features and display is a 27% increase in demand. OJ price discounts had the smallest impact, about 3%. The promotional impacts for model 1 were similar.

Each of the two GJ models also had a high R^2 of .993 (Table 2). Again we focus on GJ model 2 but the differences between the two models are not great. All but one (Atlanta) of the 51 city effects (μ^*_n) were statistically different from zero; that is, except for Atlanta the city specific effects differed from that for Chicago. All except 8 of the trend coefficients (β^*_n) were statistically significant, indicating the city trend effects largely differed from that for Chicago as was the case for OJ. The time estimates (γ_m- γ_1+ β_1(m- 1) for GJ demand exhibit a similar but somewhat different seasonality pattern compared to that for OJ, and indicate an increasing trend over time for Chicago as opposed to the negative trend for OJ (Figure 1).

The cross-promotional effects for GJ demand were either negative or insignificant. The cross effect with respect to OJ and GJ blend promotions were both negative and significant. The own-price elasticity for GJ was -.85 and statically significant. The cross-price elasticity estimates were either positive and significant or not significantly different from zero, except for that for GJ blends. Again, the positive and insignificant estimates indicate substitute or neutral relationships. As in the case of the OJ demand estimates, the cross price estimate for GJ blends was unexpectedly negative and significant indicating a complementary relationship (again this may be a spurious result).

All the GJ promotional coefficients were positive and statistically significant with relatively high values (higher than the corresponding estimates for OJ). The estimates indicate that features, displays and features and displays together increase GJ demand by 30%, 67% and 88%, respectively. GJ price discounts increased demand by an estimated 13%. The relatively large promotional impacts for GJ may reflect the relatively small size of the GJ category and the relatively large potential gains in sales that may occur through substitution into this category from other larger product categories.

Conclusions

The cross-section and time series model used in this study yielded a number of important estimates for OJ and GJ demand. The own- and cross-price elasticities were, in general, similar to those found in past studies. The dummy variable estimates to control for city size, seasonality and other city specific trends appear reasonable, suggesting this modeling approach, and perhaps other variants, is useful for analyzing combined city data over time. The promotional estimates of the study support previous findings that featuring and displays significantly increase demand. Features and displays together have the largest impact. Price discounts have the smaller impacts but their magnitudes are larger than found in previous studies. Finally, although both the OJ and GJ promotional impacts were relatively large, those for GJ were larger than those for OJ.

Table 1. OJ demand estimates based on a 52 city cross section and time series from 9/17/05 through 3/14/09.

		Model 1[a]				Model 2[a]			
Dependent Variable		Coeff. Est.	Std. Error	t Value	Pr > |t|	Coeff. Est.	Std. Error	t Value	Pr > |t|
	Intercept	14.23221	0.03906	364.4	<.0001	14.14172	0.0433	326.63	<.0001
Promotion	OJ features	0.204	0.012	17.010	<.0001	0.193	0.013	15.310	<.0001
($ share)	OJ displays	0.193	0.041	4.750	<.0001	0.185	0.041	4.540	<.0001
	OJ feat.+disp.	0.281	0.025	11.150	<.0001	0.269	0.026	10.560	<.0001
	OJ price disc.	0.041	0.010	4.070	<.0001	0.028	0.011	2.470	0.013
	Prom. OJ DRK					0.006	0.005	1.120	0.264
	Prom. OJ BL					0.000	0.004	0.120	0.903
	Prom. GJ					0.022	0.006	3.540	0.000
	Prom. GJ CKL					0.014	0.005	3.010	0.003
	Prom. GJ BL					-0.001	0.003	-0.390	0.699
Price (log)	Price OJ	-1.048	0.015	-68.110	<.0001	-1.055	0.016	-67.890	<.0001
	Price OJ DRK	0.040	0.008	5.160	<.0001	0.042	0.008	5.220	<.0001
	Price OJ BL	-0.011	0.008	-1.360	0.175	-0.008	0.010	-0.790	0.428
	Price GJ	0.079	0.014	5.740	<.0001	0.110	0.016	6.900	<.0001
	Price GJ CKL	0.009	0.007	1.350	0.177	0.023	0.008	2.910	0.004
	Price GJ BL	-0.017	0.005	-3.730	0.000	-0.015	0.006	-2.300	0.022

[a] R^2 was .997 for each model.

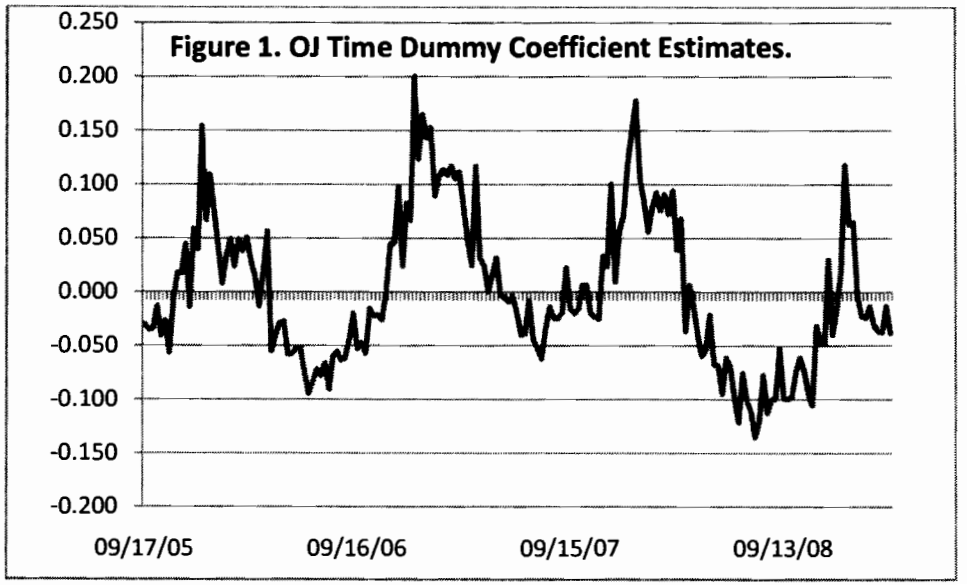
Figure 1. OJ Time Dummy Coefficient Estimates.
0.250
0.200
0.150
0.100
0.050
0.000
-0.050
-0.100
-0.150
-0.200
09/17/05
09/16/06
09/15/07
09/13/08

Table 2. GJ demand estimates based on a 52 city cross section and time series from 9/17/05 through 3/14/09.

Dependent Variable		Model 1[a] Coeff. Est.	Model 1[a] Std. Error	Model 1[a] t Value	Model 1[a] Pr > |t|	Model 2[a] Coeff. Est.	Model 2[a] Std. Error	Model 2[a] t Value	Model 2[a] Pr > |t|
	Intercept	10.469	0.059	178.630	<.0001	10.549	0.065	162.810	<.0001
Promotion	GJ features	0.291	0.014	20.710	<.0001	0.301	0.014	21.110	<.0001
($ share)	GJ displays	0.667	0.042	15.850	<.0001	0.674	0.042	15.990	<.0001
	GJ feat.+disp.	0.869	0.051	17.000	<.0001	0.884	0.051	17.260	<.0001
	GJ price disc.	0.114	0.010	11.790	<.0001	0.127	0.010	12.380	<.0001
	Prom. OJ					-0.054	0.015	-3.720	0.000
	Prom. OJ DRK					0.011	0.008	1.400	0.163
	Prom. OJ BL					0.005	0.006	0.920	0.355
	Prom GJ CKL					-0.004	0.007	-0.580	0.560
	Prom. GJ BL					-0.011	0.005	-2.220	0.027
Price (log)	Price OJ	0.096	0.021	4.570	<.0001	0.060	0.023	2.600	0.009
	Price OJ DRK	-0.011	0.012	-0.910	0.361	-0.006	0.012	-0.530	0.599
	Price OJ BL	-0.007	0.012	-0.600	0.550	0.002	0.015	0.150	0.881
	Price GJ	-0.850	0.024	-35.100	<.0001	-0.840	0.024	-34.340	<.0001
	Price GJ CKL	0.024	0.010	2.440	0.015	0.021	0.012	1.790	0.074
	Price GJ BL	-0.029	0.007	-4.170	<.0001	-0.046	0.010	-4.700	<.0001

[a] R^2 was .993 for each model.

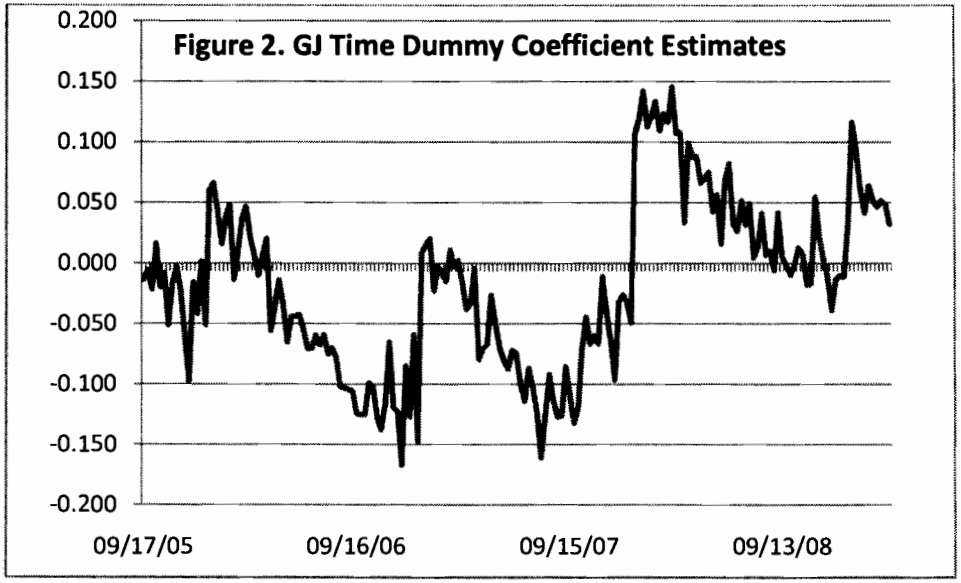
Figure 2. GJ Time Dummy Coefficient Estimates
0.200
0.150
0.100
0.050
0.000
-0.050
-0.100
-0.150
-0.200
09/17/05
09/16/06
09/15/07
09/13/08