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A FACTOR ANALYSIS APPROACH TO MEASURE THE BIASED EFFECTS OF RETAIL FRUIT JUICE ADVERTISING

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Abstract

This study presents a structural factor analysis approach to measure the impact of advertising on consumer demand. It is assumed that advertising affects the latent perception of consumers, which in turn influences their purchasing behavior. This study investigates the relationship between consumer purchases and retail store advertising (i.e., newspaper advertising, in-store display, and point-of-purchase display) of three fruit juices using an extended Rotterdam model. The results show that the demand for orange juice and grapefruit juice was affected by their own advertising, while the demand for apple juice was only affected by advertising of competitive juices.

Key Words: advertising, fruit juices, factor, latent variable.

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Economists have devoted considerable attention to measuring the impact of advertising messages on sales. Recent studies have examined the effectiveness of advertising, using both single-equation (Ward and Dixon, 1989) and systems-of-demand-equations approaches (Duffy, 1991); the dynamic nature of advertising's effect on sales (e.g. Ward and Dixon, 1989), and the potential simultaneity of feedback relationships that may exist between advertising and sales (e.g. Schmalensee, 1972); and optimal advertising rules under various market arrangements (Nerlove and Arrow, 1962).

Chang and Kinnucan point out that it is important to find a proper measure of advertising effort because the impact of advertising on sales or market shares is in general unobservable, and an inaccurate measure would produce biased estimates of advertising impact. Recognizing that advertising variables are not readily quantified when attempting to measure the effectiveness of advertising, most past studies on food advertising employed advertising expenditures as proxies for advertising messages. However, the use of proxies or variables measured with error within the standard regression framework renders parameter estimates biased and inconsistent (Fuller, 1987). One of the approaches to correct for the measurement errors in variables is to use latent variable techniques (Bollen). Although models designed to handle latent variables have been widely used in some fields of the social sciences, they have not been commonly applied to economic data (Goldberger, 1972), especially in advertising studies.

Ray (1973) indicates that making choices among low-priced consumer goods with only trivial differences does not warrant careful consideration and attitude formation prior to action. He concludes that consumers buy on the basis of superficial top-of-mind awareness from either saturated advertising exposure or "on-the-spot" reminders. A 1987 study of more than 48,000 grocery shoppers by Nielsen Market Research Company found that about 70 percent of the fruit-juice buying decisions were made in-store instead of being specifically planned in advance (Nielsen, 1987). Therefore, in-store advertising and promotions are important for both manufacturers and retailers.

The purpose of this study is to demonstrate that using advertising expenditures as proxies for advertising effort in demand studies may lead to biased and inconsistent estimates and that the latent variable approach may provide an avenue to correct for measurement errors in advertising variables. The relationship between sales of three fruit juices (i.e., orange juice, grapefruit juice, and apple juice) and retailers' advertising activities (i.e., newspaper advertising, point-of-purchase display, and in-store displays) will be used as an example in this study.

In the present study, we examine how income, price, and retail advertising influence the demand for juice in the U.S. The model specification, i.e., an extended Rotterdam model with latent consumer-perception variables, is introduced in the next section and is followed by a description of the data and tests for data stationarity and cointegration. The test results for data stationarity and cointegration are used to justify the choice of Rotterdam demand functional form. The structural factor analysis model technique and empirical specification are discussed. Finally, we discuss the advantages of using the structural factor analysis modelling technique in analyzing the impact of advertising on demand.

Model Specification

The proper treatment of advertising in demand model specification remains a controversial issue. Some researchers (e.g., Theil 1976) argue that since advertising works by changing consumers' tastes and preferences (thus affecting the marginal utilities of the goods in question), advertising should enter directly into the utility function and, therefore, should be treated in demand specifications in the same manner as prices and income. Others (Nelson, 1974; Stigler and Becker, 1977; Kotowitz and Mathewson, 1979; Verma, 1980) suggest that advertising does not change tastes and preferences; rather, it influences demand by changing consumers' perceptions of the characteristics of the advertised good. They believe the hypothesis of "change-in-taste" implies "too much rationality" on the part of consumers. Consequently, advertising does not enter directly into the utility function, but enters into demand specifications through translating (perception of a basic need) or scaling (perception of quality) parameters. Recent research, however, shows that the differences between the two camps might not be as big as it appears. Brown and Lee (1992) show that the translating and scaling approaches to introduce advertising into demand specifications are nested in the Theil method.

In this research, it is assumed that advertising affects the advertising-induced consumer perception (AICP)[1] (real and/or fancied) of the advertised goods, which in turn influences consumer purchase behavior. AICP has both taste and informational interpretations in this specification. In contrast to the concept of "advertising goodwill stock" (Nerlove and Arrow, 1962), AICP measures advertising effect from an active consumer perspective rather than from a producer point of view (i.e., advertisers try to produce goodwill among potential customers). The commonality of both concepts is that both perception and goodwill are unobserved.

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[1] This perception is induced by advertising messages alone, so it can also be called "advertising effectiveness". We do not intend to contribute to the old discussion on the interrelationships among advertising, perception, and purchase.

Regardless of whether AICP is defined as a shifter of consumer preference or information on shadow price, AICP affects consumer demand together with prices and income.

The consumer demand functions in vector form are

(1) $q = q(p, m, \Xi)$,

where the q is a vector of commodities demanded, p is a vector of the corresponding commodity prices, m is consumer expenditure, and Ξ represents the AICP of the commodities. Totally differentiating equation (1) and multiplying the result by p_i/m, one obtains

(2) $$w_i \mathrm{dlog}\, q_i = \partial(p_i q_i/\partial m)\ \mathrm{dlog}\, m + \Sigma_{j=1}^{n}(p_i p_j/m)(\partial q_i/\partial p_j)\ \mathrm{dlog}\, p_j$$
$$+ \Sigma_{j=1}^{n}(p_i \Xi_j/m)(\partial q_i/\partial \Xi_j)\ \mathrm{dlog}\, \Xi_j,$$

where $w_i = p_i q_i/m$. Using the Slutsky decomposition, the above equation can be simplified as

(3) $$w_i \mathrm{dlog} q_i = \theta_i \mathrm{dlog} Q + \Sigma_j\ \pi_{ij} \mathrm{dlog} p_j + \Sigma_j\ \beta_{ij} \mathrm{dlog} \Xi_j, \quad \forall i$$

where $\theta_i = w_i(\partial \mathrm{log} q_i/\partial \mathrm{log} m) = p_i(\partial q_i/\partial m)$, is the marginal share; π_{ij} is the Slutsky coefficient; the homogeneity conditions imply that $\Sigma\theta_i = 1$, $\Sigma_j\pi_{ij} = 0$, and $\Sigma_j\beta_{ij} = 0$; the symmetry condition implies $\pi_{ij} = \pi_{ji}$, $\mathrm{dlog}Q = \mathrm{dlog}m - \Sigma_j w_j \mathrm{dlog}p_j = \Sigma_j\ w_j \mathrm{dlog}q_j$ is the Divisia volume index; and $\beta_{ij}=w_i\tau_{ij}$ and $\tau_{ij} = \partial \mathrm{log} q_i/\partial \mathrm{log}\Xi_j$ are AICP elasticities that can be further written as $-\Sigma_k\varepsilon^*_{ik}v_{kj}$ (Barten 1977). ε^*_{ik} is the compensated price elasticity and v_{kj} is the elasticity of the marginal utility of good k with respect to the AICP of good j. Theil (1976) assumes v_{kj} to be diagonal, while Selvanathan (1989) imposes no such restriction. Duffy (1991) indicates that Theil's specification, which requires price and advertising elasticities to be proportional to each other, is very restrictive. For this reason, Selvanathan's specification was used in this study.

Equation (3), after adding an error term, is an extended Rotterdam model when the finite change version is taken and the coefficients θ, π, and β are assumed constant. One of the addingup restrictions requires that $\Sigma_i\beta_{ij} = 0$, which means that the changes in AICP will not increase total expenditure; they can only change the budget shares of the commodities. Nichols (1985) indicates that a statistically significant $\beta_{ij} > 0$ implies that advertising is under-supplied because, as the profit is maximized, a marginal increase in AICP raises the characteristic productivity of the purchased goods more than the increases in market prices.

In addition to its theoretical advantages in incorporating advertising variables, the Rotterdam model is also chosen for its empirical convenience in reducing spurious regression errors. When dependent and independent variables in the demand system are not stationary, difference models such as the Rotterdam system render more reliable information than level version models (e.g., Almost Ideal Demand System, Translog, Linear Expenditure System, etc.). For consumer advertising analysis which identifies advertising effects by testing the significance of a strongly trended advertising proxy variable (e.g., advertising expenditure) in a demand model, the danger of a spurious regression should always be kept in mind. Spurious regression can be identified by testing the stationarity of variables in a level version demand system. This test is presented in the next section after a brief discussion of the data.

Data and Stationarity-Cointegration Test

U.S. per capita demand and retailers' advertising data for the three juices were provided by A. C. Nielsen Market Research Company. The data were collected from scanner check-out records of retail grocery stores with annual sales of more than four million dollars. These stores account for more than 80 percent of the total juice retail volume in the United States. The data are weekly observations for the period from November 14, 1987 through December 29, 1990 (a total of 160 observations) on consumer juice purchases, expenditures (from which average prices are derived), and the intensity of retail advertising activities. The conditional juice budget shares for the 160-week period were .76, .06, and .18 for orange juice, grapefruit juice, and apple juice, respectively. Population estimates reported by the U.S. Department of Commerce were used to derive the per capita demand.

The retail store advertising variables used in this study include in-store display (DSPL), newspaper advertising (NSP), and point-of-purchase display (POP). DSPL includes signs and displays at the supermarket windows and at the entrance; NSP includes newspaper advertisement with price features; and POP includes display and price comparisons at the ends-of-aisles and on the shelves.[2] The three types of advertising activities employed by retailers are measured by the percentage of market covered by the promotional activities. For example, if only store A had newspaper advertising for apple juice in the region and the store's total sales accounted for 25 per cent of the total retail sales in the regional market, then the percentage of market covered by the apple juice newspaper advertising for the market equals 25. The upper limit of market coverage is 100 (all stores advertised), and the lower limit is 0 (no store advertised). The presence of displays at a major store (with a dominant market share) means more shoppers would have been exposed to them.

Testing for model choice and spurious regression error were performed by evaluating the stationarity of variables in a level version demand system. A test on the dependent and independent variables (excluding advertising variables) using a level version Rotterdam (Barten,

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[2] The DSPL and the POP may also reflect some merchandising effects besides retailers' advertising. Since the goods considered in this paper are frequently consumed by most households, the retailers' incentive for "quick-sale merchandising" is small, and the distinction between advertising and merchandising is, therefore, not important.

1989) is presented in Table 1. The Z_α test developed by Phillips (1987) was used because its limiting distribution is robust to autocorrelated and heterogeneous innovation sequences. The test statistic is

$$(4) \qquad Z_\alpha = T(\hat{\alpha} - 1) - (1/2)(S_{Tl}^2 - S_u^2)/(T^{-2}\sum_1^T y_{t-1}^2)$$

where $S_{Tl}^2 = T^{-1}\sum_1^T u_t^2 + 2T^{-1}\sum_{\tau=1}^{l}\sum_{t=\tau+1}^{T} u_t u_{t-\tau}$ and $S_u^2 = T^{-1}\sum_1^T u_t^2$; y_t is a stochastic process generated in discrete time according to $y_t = y_{t-1} + u_t$. The Z_α test shows that these variables are difference stationary (contain single unit roots), and their first differences are stationary.

Two cases may now occur[3]. In the first case, the dependent and independent variables of the level version Rotterdam are cointegrated of the order (1,1), where the advertising effects are neutral. In this case, the OLS regression of the system yields excellent parameter estimates (Engle and Granger, 1987), but the difference model specification is misspecified in that it omits information about long-run equilibrium (Banerjee et al.). The estimation method described by Phillips (1991) is applicable, and the system should be estimated with difference exogenous variables as additional regressors.

In the second case, the dependent and independent variables are not cointegrated, and the residuals (which include the advertising effects) will be an integrated process. In this case, the

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[3] It should also be noted that there are other possible model choices involving differencing only some of the model variables (Bewley and Elliott, 1992).

use of difference models, such as the Rotterdam system, is appropriate.[4] The Johansen approach (1987) was used to test for cointegration. In the Johansen approach, a concentrated maximum likelihood estimator was obtained by first concentrating out weak exogenous variables and reducing the joint distribution to a conditional model (Banerjee et al., 1993).

The test results presented in Table 1 indicate that there were no unique cointegrating vectors. The hypothesis of two unit roots (hence no cointegrating vector) cannot be rejected at the 5 percent statistical level using both statistics. A similar conclusion can be derived at by using the test method of Bewley and Elliott (1992). Therefore, the extended Rotterdam model expressed in (3) was chosen for this study.

Factor Analysis Model and Empirical Specification

Three latent variables are used in the structural factor analysis model to measure the AICP for each juice. The individual effect as well as the interactions among the three latent variables are studied. Each latent variable has five indicators, three retail advertising/display variables (DSPL, NSP, POP), and two lagged newspaper advertising variables (NSP_{t-1}, NSP_{t-2}). The DSPL and the POP are "on-the-spot" reminders or stimulus-types of advertising; therefore, no lag effects are assumed. Two-period lags are chosen for newspaper advertising because newspaper

[4] Even without a formal test or with an ambiguous test result, practitioners may still be better advised to work with difference rather than level models because the consequences of differencing when not needed are much less serious than those of failing to difference when it is appropriate. Plosser and Schwert (1978) argue that in the first scenario, differencing produces a moving average error, while ignoring it still gives consistent (but inefficient) estimates; in the second scenario, the disturbance term will not be homoskedastic, making the least square properties and test inferences invalid.

advertising usually lasts a seven-day period over two consecutive weeks whereas discount and coupon sales are usually valid for less than three weeks.

The structural factor analysis model can be specified by two parts: latent equations and measurement equations (Bollen, 1989),

(5) $\eta = \Gamma x + \zeta$,

(6) $y = \Lambda_y \eta + \varepsilon$,

where η ($m\times1$) is the vector of latent variables; x ($n\times1$) and y ($p\times1$) are the vectors of observed variables; ζ($n\times1$) is a vector of disturbance terms; and Γ and Λ_y are coefficient matrices compatibly defined. The ε ($p\times1$) is a vector or measurement errors for y. The measurement errors are uncorrelated with the latent variables, η, and have an expected value of zero and variance Θ_ε. When Θ_ε are significant, indicator variables (y) are noisy and filtered to the latent variables (η) by the model.

The latent and indicator variable vectors in this problem are defined as

(7) $\eta=[w_1\Delta\log(q_1)\ w_2\Delta\log(q_2)\ w_3\Delta\log(q_3)\ \Delta\log(\Xi_1)\ \Delta\log(\Xi_2)\ \Delta\log(\Xi_3)]'$,

(8) $y=[w_1\Delta\log(q_1)\ w_2\Delta\log(q_2)\ w_3\Delta\log(q_3)\ ID'_{1:5,1}\ ID'_{1:5,2}\ ID'_{1:5,3}]'$,

(9) $x=[\Delta\log(p_1)\ \Delta\log(p_2)\ \Delta\log(p_3)\ \Delta\log Q)]'$,

where $ID_{1:5,j}$ (j=1, 2, 3) is a vector of the five indicators mentioned in the previous section for orange juice (j=1), grapefruit juice (j=2), and apple juice (j=3); therefore, y has the dimension of 18×1. Note that the first three variables in η are observed, i.e., they are their own indicators.

The full model is given below for clarity:

(10) $w_i\ \Delta\log q_i = \gamma_i\ \Delta\log Q + \Sigma_{j=1}^{3}\gamma_{ij}\ \Delta\log p_j + \Sigma_{j=1}^{3}\beta_{ij}\ \Delta\log\Xi_j + \zeta_i,\quad \forall i$

(11) $ID_{kj} = \lambda_{kj}\Delta\log\ \Xi_j + \varepsilon_{kj},\qquad \forall k,j.$

There are 15 explicit indicators: ID_{1j} represents DSPL for juices including orange juice (j=1), grapefruit juice (j=2), and apple juice (j=3); ID_{2j} are POPs; ID_{3j} are NSPs; ID_{4j} are newspaper advertising lagged one period (NSP_{t-1}); and ID_{5j} are newspaper advertising lagged two periods (NSP_{t-2}). To make the indicators compatible with the AICP form, all the indicators have undergone a log difference transformation. The residuals of the regular Rotterdam model (excluding advertising variables) can be also considered as implicit indicators of the latent AICP variables.

To make the model identifiable, some constraints are introduced to provide a scale for the latent variable which, in this case, is given the same scale as the first indicator, DSPL. This translates to Λ_{i1} being equal to one. The covariance of ζ, $\Psi^2 = \text{cov}(\zeta\zeta')$, is also constrained to be diagonal as part of the maintained hypotheses and the identification restrictions. The basic idea is that the latent variables account for the intercorrelations of the indicators. Once the effects of the latent variables are removed, there no longer remains any correlation among the indicators. This is part of the definition of being indicators (Jöreskog, pp. 297, 1993).

The structural factor analysis model defined by (10) and (11) was jointly estimated by a multivariate moment estimator which minimizes the difference between the sample covariances and the covariances predicted by the model (Bollen, 1989). S is defined as the sample covariance matrix of observed variables, cov(y,x); κ is a vector that contains the model parameters, Γ, Λ_y, Θ_ε, and Ψ; and $\Sigma(\kappa)$ is the implied structural covariance matrix written as a function of κ. That is

$$(12) \qquad \Sigma(\kappa) = \begin{vmatrix} \Sigma_{YY}(\kappa) & \Sigma_{YX}(\kappa) \\ \Sigma_{XY}(\kappa) & \Sigma_{XX}(\kappa) \end{vmatrix},$$

where $\Sigma_{yy}(\kappa) = E(yy')$

$$= E[(\Lambda_y \eta + \varepsilon)(\Lambda_y \eta + \varepsilon)']$$

$$= \Lambda_y E(\eta\eta')\Lambda'_y + \Theta^2_\varepsilon$$

$$= \Lambda_y(\Gamma S_{xx}\Gamma' + \Psi^2)\Lambda'_y + \Theta^2_\varepsilon,$$

where S_{xx} is defined as the covariance matrix for exogenous variable x, Θ^2_ε=cov($\varepsilon\varepsilon'$), and Ψ^2 = cov($\zeta\zeta'$). Other elements (Σ_{xx}, Σ_{xy}, and Σ_{yx}) of the implied covariance matrix can be defined accordingly. The implied covariance matrix for the structural factor analysis model is specified as:

$$(13) \qquad \Sigma(\kappa) = \begin{vmatrix} \Lambda_y(\Gamma S_{XX}\Gamma' + \Psi^2)\Lambda_Y + \Theta^2_\varepsilon & \Lambda_Y \Gamma S_{XX} \\ S_{XX}\Gamma'\Lambda'_Y & S_{XX} \end{vmatrix}$$

The sample covariance matrix of observed variables is defined as S. ML is used to estimate parameters ($\hat{\kappa}$) by minimizing the difference between S and $\Sigma(\hat{\kappa})$ (Anderson, 1989). The overall model fit can be measured by Jöreskog's (1993) goodness of fit index (GFI).

Results

Empirical application of the Rotterdam structural factor model to the fruit juice advertising data shows the significant potential of this framework. The overall fit measurement shows a good match of the data to the model. The GFI is 0.92, which ranks high in a range from 0 to 1. The parameter estimates are also largely consistent with the substantive theory and hypotheses.

All conditional marginal shares (θ_i) and own-price Slutsky coefficients (π_{ii}) are significantly different from zero at the one percent level (Table 2). Orange juice has the largest marginal share and grapefruit juice the smallest. All own-price Slutsky coefficients have negative signs; the latent roots of the Slutsky coefficients matrix are zero or negatives, which indicates that the matrix is negative-semidefinite. All cross-product Slutsky coefficients are positive, suggesting that these three juices are substitutes for each other.

Coefficients for AICP variables (β_{ij}) show that orange and grapefruit juice demands are significantly affected by their own AICP, while apple juice AICP is not significant in affecting its own demand.[5] The demand for orange juice is significantly affected by grapefruit juice AICP but not by apple juice AICP. The demand for apple juice is significantly affected by orange juice AICP only. Results also show that consumers' (favorable) perception of each juice has negative effects on the other two juice demands, which is consistent with the substitutive and competitive nature of the price effects. This may also be indicative of the nature of retail advertising; that is, the advertising may highlight a discount price for the product. The AICP variable in this case has more information characteristics. The significance of the latent AICP variables in these demand equations demonstrates that retail promotional activities affect consumer demand, and the effects are not uniform across commodities.

Results presented in Table 2 also show that all current indicator coefficients (Λ) are significant. Both newspaper advertising (NSP) and point-of-purchase (POP) display indices are important in improving AICPs of all three juices. The validity of the in-store display (DSPL) indicator cannot be judged, since it is normalized to unity. The coefficient estimates for lagged newspaper advertising (both NSP_{t-1} and NSP_{t-2}) are significant for grapefruit and apple juices.

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[5] Retail advertisements usually target certain brands. Switching purchases of non-advertised brands to advertised brands may help to explain the insignificant impacts of AICP on the demand for apple juices.

Although most demand studies on advertising use lagged values of advertising indicator variables (Lee and Brown, 1992b), the evidence in this study shows that the lagged effect of retail advertising was limited. This has to do with the nature of the retail advertising, because store displays are often used to provide consumers with "on-the-spot" stimuli or reminders to purchase the product. Even for retailers' newspaper advertising, price information expires within a week and coupons usually expire within three weeks. We conclude that, in contrast with other studies on brand or generic promotions, the lagged effect of retail advertising is a less important issue.

The significance of the variances ($\Theta_{\varepsilon i}$) in the indicator equations implies that these indicators are indeed imperfect. To use these variables directly in the demand system would introduce measurement error bias. To compare the results of the latent variable approach to the one which uses the proxies directly in place of Ξ in equation (3), the coefficient estimates of the latter are presented in Table 3. In this direct approach, nine advertising proxies - $DSPL_i$, POP_i, and NSP_i (i=1,2,3) - were included in each demand equation (the lagged advertising variables are not included because of a multicollinearity problem). Results show that the signs of the coefficient for these advertising proxies are not consistent with expectation, i.e., positive own-advertising effect and zero or negative cross-advertising effect. For example, the results shown in Table 3 indicate that in-store orange juice display had a negative impact on the demand for orange juice and apple juice newspaper advertising had a positive impact on the demand for grapefruit juice. These unexpected results thwart any meaningful interpretation of the influences of these nine proxy variables on juice demand.

Note that the structural factor analysis model uses fewer advertising variables (in this case three latent AICP variables) in the consumer demand equations than advertising proxies (in this case nine variables); thus, each advertising parameter estimated in the structural factor analysis model contains more information. The latent variable approach provides an avenue to study the causal relationship between demand and advertising. By using multiple indicators for each latent variable, the model extracts information from the multiple indicator variables, but avoids using them directly. It provides a clear interpretation of advertising effects and thus proves to be a better framework to model advertising effects. It also reduces the chance of having multicollinearity problems. The predictive power is improved tremendously since the sum of the squares of the one period ahead prediction errors in the latent variable approach (equals 2.25) is less than ten percent of that when using the same data and advertising indicators as proxies directly (equals 26.31).

Slutsky-compensated price elasticities, expenditure elasticities, and demand elasticities with respect to AICP were derived and presented in Table 4. The results show that the demand for grapefruit juice was price elastic and the demand for orange and apple juices was price inelastic. The conditional expenditure elasticity of orange juice is greater than those of grapefruit and apple juices. When the expenditure on the three juices increases, the conditional budget share of orange juice will increase at a faster rate than the increase in the budget shares of grapefruit and apple juice. The demand elasticities with respect to consumer perceptions of these juices are smaller in absolute magnitude than the price and expenditure elasticities. Chang and Kinnucan (1991) explains that this is an indication that price and income effects dominate over the advertising effects on the demand for the three juices.

Summary and Concluding Remarks

In this study, advertising effects were modelled in a consumer demand framework as latent variables. The approach assumes that retail-promotion advertising affects consumers' perceptions of advertised goods, and that consumer perceptions affect consumer purchase behavior. Physical measurements of advertising, such as advertising expenditure, gross rating points, and the three retail advertising coverage indices used in this study, are indicators of AICP. As such, the use of physical advertising measurements directly in demand analysis may introduce measurement errors in variable problem and results in biased parameter estimates. The structural factor analysis approach provides an avenue for the analysts to correct for the measurement errors using additional indicator equations. The indicator equation disturbance variances (Θ) are significant in this study, indicating that there are measurement errors in the indicators and that these indicators should not be used directly as proxies for advertising in demand analysis. The structural factor analysis approach used in this study provides a method to minimize the problem of measurement error in advertising variables. The result of this study shows that newspaper advertising and point-of-purchase advertising were important indicators of unobservable retail advertising effort and they had significant effects on consumers' perception and purchases of the three juices.

Results of this study indicate that retailers' advertising efforts had an important impact on consumers' demand for fruit juices. The demand for orange juice and grapefruit juice was positively affected by their own advertising and negatively by the advertising of their substitute, i.e., apple juice. The demand for apple juice was not affected by its own advertising. The point-of-purchase materials and retailers' newspaper advertising were found to have significant impacts on consumers' perceptions of advertised juices. The lagged effects of retailers' advertising on juice demand were insignificant.

The stationarity and cointegration test results presented in this study also demonstrate difficulties researchers may face in choosing appropriate models when time series data are involved. Since many time series data are not stationary, the choice of functional form is no longer a personal preference. When the demand system is not cointegrated, a level version demand model may entail serious spurious regression errors, which makes any inference on advertising effectiveness useless. This problem may have been severe in some of the previous time series advertising studies. Plosser and Schwert (1978) suggest that a difference model, such as the Rotterdam model, should be used when no data stationarity test is done beforehand for similar types of studies.

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Table 1. Tests for Non-stationarity and Cointegration in the level version Rotterdam system for fruit juice demands

Variable		**Non-Stationary Test (Z_α)[a]**		
Price of Orange Juice	$\log(p_1)$	-0.011		
Price of Grapefruit Juice	$\log(p_2)$	-0.033		
Price of Apple Juice	$\log(p_3)$	-0.019		
Orange Juice Share	w_1	-0.015		
Grapefruit Juice Share	w_2	-0.067		
Apple Juice Share	w_3	-0.034		
Stone Quantity Index	$\Sigma_j w_j \log q_j$	-0.041		
	Cointegration Test			
	Test Statistics		Critical Value	
Trace Test	H_0: $r = 0$	H_0: $r \leq 1$	H_0: $r = 0$	H_0: $r \leq 1$
	4.35	3.82	12.53	3.84
Maximum Eigenvalue Test	H_0: $r = 0$	H_0: $r = 1$	H_0: $r = 0$	H_0: $r = 1$
	4.44	3.96	11.44	3.84

[a]The critical value at five percent significance level for Z_α is -7.9 (Fuller, pp. 371, 1979). The truncation lag number is l=5.
[b]The critical values of five percent significance level are from Banerjee et al.

Table 2. Parameter estimates for latent variable structural model (symmetry and homogeneity imposed)

Variable	Parameter	Orange Juice (i = 1)		Grapefruit Juice (i = 2)		Apple Juice (i =3)	
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
		Conditional Slutsky Coefficient					
$\Delta\log(p_1)$	π_{11}	-0.0979	0.0185	0.0120	0.0300	0.0859	0.0318
$\Delta\log(p_2)$	π_{12}	0.0120	0.0300	-0.0927	0.0105	0.0807	0.0109
$\Delta\log(p_3)$	π_{13}	0.0859	0.0318	0.0807	0.0109	-0.1666	0.0255
		Conditional Marginal Share					
$\Sigma_i w_i \Delta\log(q_i)$	θ_i	0.7935	0.0093	0.0536	0.0032	0.1529	0.0079
		Conditional Perception Coefficients					
$\Delta\log(\Xi_1)$	β_{11}	0.0448	0.0079	-0.0221	0.0028	-0.0227	0.0063
$\Delta\log(\Xi_2)$	β_{12}	-0.0058	0.0016	0.0097	0.0021	-0.0039	0.0600
$\Delta\log(\Xi_3)$	β_{13}	-0.0116	0.0105	-0.0732	0.0036	0.0848	0.0631
		Demand Residual Standard Errors					
	Ψ	0.0043	0.0003	-0.0015	0.0001	0.0014	0.0001
		Indicator Coefficients					
DSPL	Λ_{i1}	1.0000		1.0000		1.0000	
POP	Λ_{i2}	2.7811	0.1864	4.1772	0.3510	4.1674	0.1861
NSP	Λ_{i3}	1.1394	0.2102	2.4912	0.3301	2.8205	0.2023
NSP_{t-1}	Λ_{i4}	0.5965	0.2215	1.1572	0.9653	0.9201	0.7601
NSP_{t-2}	Λ_{i5}	0.0021	0.0011	0.0732	0.2739	0.0542	0.6521
		Indicator Residual Variances					
	$\Theta_{\varepsilon 1}$	0.0549	0.0040	0.0762	0.0058	0.0549	0.0033
	$\Theta_{\varepsilon 2}$	0.1726	0.0098	0.3065	0.0195	0.1595	0.0088
	$\Theta_{\varepsilon 3}$	0.0741	0.0186	0.2290	0.0322	0.0000	0.0344
	$\Theta_{\varepsilon 4}$	0.1854	0.0103	0.3641	0.0205	0.2588	0.0143
	$\Theta_{\varepsilon 5}$	0.3421	0.1893	0.4527	0.5932	0.0482	0.3891

Table 3. Coefficient estimates for the proxy advertising variables

Parameter	Orange Juice (i = 1)		Grapefruit Juice (i = 2)		Apple Juice (i =3)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
$DSPL_1$	-0.0111	0.0075	0.0028	0.0024	0.0083	0.0065
$DSPL_2$	-0.0031	0.0045	0.0038	0.0015	-0.0007	0.0039
$DSPL_3$	-0.0288	0.0083	0.0044	0.0027	0.0244	0.0073
POP_1	0.0043	0.0029	-0.0016	0.0009	0.0027	0.0025
POP_2	-0.0009	0.0012	0.0005	0.0004	0.0004	0.0011
POP_3	-0.0038	0.0024	0.0005	0.0008	0.0033	0.0021
NSP_1	-0.0008	0.0031	-0.0013	0.0010	0.0021	0.0027
NSP_2	-0.0003	0.0016	0.0011	0.0005	-0.0008	0.0014
NSP_3	-0.0047	0.0030	0.0020	0.0010	0.0027	0.0027

Table 4. Demand elasticity estimates

	Orange Juice	Grapefruit Juice	Apple Juice
	Slutsky Compensated Price Elasticity Estimates		
Orange Juice	-0.1296	0.0159	0.1137
	(0.049)[a]	(0.003)	(0.0411)
Grapefruit Juice	0.1912	-1.4770	1.2858
	(0.087)	(0.103)	(0.301)
Apple Juice	0.4726	0.4440	-0.9166
	(0.103)	(0.182)	(0.391)
	Expenditure Elasticity Estimates		
	1.0503	0.8540	0.8413
	(0.291)	(0.281)	(0.381)
	Consumer Perception Elasticity Estimates		
Ξ_{oj}	0.0593	-0.3521	-0.1249
	(0.012)	(0.163)	(0.052)
Ξ_{gj}	-0.0077	0.1546	-0.0215
	(0.003)	(0.024)	(0.004)
Ξ_{aj}	-0.0700	-0.5099	0.4666
	(0.012)	(0.190)	(0.138)

[a]Numbers in parentheses are standard errors of elasticity estimates.