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THE RELATIONSHIP BETWEEN MARKET CHARACTERISTICS AND PROMOTIONAL PRICE ELASTICITIES

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Many empirical studies in marketing and economics have estimated brand price elasticities for specific products in markets. Their results indicate that price elasticities seem to differ across brands, product categories, retail outlets, and regions. However, there has been very little research which examines the factors associated with these observed differences. This paper focuses on the promotional price elasticities of established, major brands in stable categories. It identifies some characteristics of markets which may be associated with differences in price elasticities for frequently purchased nondurables. A cross-sectional model of the effect of these market characteristics on price elasticities is developed and estimated utilizing own price elasticity estimates for brands at twelve stores. The results indicate market characteristics such as brand market share, couponing activity, display activity and feature activity explain a substantial amount of the variation in promotional price elasticities.
(Price Elasticities; Market Structure; Meta Analysis)

Introduction

Managers and researchers are frequently interested in assessing buyers' sensitivity to price as an input to strategic and tactical decisions about price, market segmentation, competitive market structure, and marketing effort. For these reasons, many empirical studies in marketing and economics have estimated price elasticities for products in specific markets. However, only a few studies have provided evidence of systematic relationships between market characteristics and the magnitudes of elasticities (e.g., Assmus, Farley and Lehmann 1984; Ghosh, Neslin and Shoemaker 1983; Lambin 1976). For example, Hagerty, Carman and Russell (1987) found that price elasticities estimated from the PIMS data base are larger in absolute value for low search products. This lack of research is rather surprising because an understanding of how marketing mix elasticities vary with market conditions is important to the development of successful marketing strategies. For example, by anticipating the magnitudes of price elasticities under different market conditions, managers can assess the value of alternative pricing policies.

The purpose of this paper is to investigate the market characteristics associated with differences in brand price elasticities for frequently purchased nondurables. Unlike earlier research concerning cross-sectional differences in elasticities, this study focuses on *promotional* price elasticities, rather than "regular" price elasticities. It examines the pro-

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motional price elasticities of established, major brands in stable categories to address questions such as the following: Are the sales of certain types of brands, such as high market share brands, characterized by price inelasticity? Are promotional activities by retailers, such as displays or newspaper advertising, systematically related to price elasticities?

This study investigates differences in brand price elasticities across markets, rather than differences in a single brand's price elasticity over time. Research in this area has taken two approaches. One approach considers the relationship between own price elasticities and one explanatory variable in a single product category. For example, Neslin and Shoemaker (1983) determined that own price elasticities of pre-sweetened cereals were relatively high compared to the cereal category as a whole. Since analyses of this type examine only a single category, it is difficult to generalize their findings to other product categories.

The second approach considers the relationship between own price elasticities and one explanatory variable across multiple product categories. For example, Lambin (1976) studied country-wide sales of heavily advertised brands in Western Europe, and found that the absolute values of short-run, own price elasticities were (weakly) inversely related to advertising intensity in a sample of 22 brands. Since analyses of this type do not control for differences in price elasticities due to other market characteristics (e.g., price levels, quality, distribution etc.), these findings are difficult to interpret.

In contrast, this study considers the relationship between price elasticities and multiple explanatory variables for several product categories. We estimate promotional price elasticities for national brands of frozen waffles, liquid bleach, bathroom tissue, and ketchup at twelve stores. A multivariate model is estimated which relates differences in the magnitudes of the price elasticities to market characteristics, such as brand market shares, advertising levels, and coupon magnitude. Since the scope of this study is substantially larger than other studies to date, it should yield more generalizable findings about the relationship between market characteristics and price elasticities. However, this study cannot examine an exhaustive list of market characteristics which may affect price elasticities. Rather, it focuses on those characteristics which vary across the brands, categories and stores in the data base. Hence, the effects of certain market characteristics, such as stage in the brand life cycle (Simon 1979; Shoemaker 1986) and the concentration level for the industry, are not considered.

The paper is organized in the following way. The next section discusses the relationship between selected market characteristics and own price elasticities. The following sections describe the data base and research methodology used to investigate this relationship. The methodology entails deriving estimates of promotional price elasticities from brand sales equations estimated with optical scanner data, and then subsequently combining these estimates with measures of market characteristics to estimate a model of the effects of market characteristics on price elasticities. The last three sections present the results of the study and discuss its implications.

Market Characteristics

This section identifies market characteristics that may be related to promotional price elasticities for the brands in this study. It considers how market characteristics may affect aggregate consumer price elasticity. However, it also considers whether certain market characteristics have arisen in response to the inherent price sensitivity of consumers, rather than the reverse. For example, advertising could cause price inelasticity, or price inelasticity could cause manufacturers to advertise more. Unfortunately, the direction of causality between market characteristics and price elasticities cannot be established in this study because it examines correlational evidence.

Brand Price

Price elasticity is a measure of the sensitivity of consumer demand to price changes. Expressed in continuous form,

$$\eta_{ij} = \frac{\partial S_i}{\partial P_j} \cdot \frac{P_j}{S_i} \tag{1}$$

where:

η_{ij} = the elasticity of sales of product i with respect to a change in price of product j;
S_i = the sales volume for product i; and
P_j = the price of brand j.

It is generally accepted that own price elasticities are negative. As shown in equation (1), price elasticities are a function or price level and sales level, so that cross-sectional differences in own price elasticities may be negatively related to price levels and positively related to sales levels (ceteris paribus).

Category Price Activity

Category price activity refers to the variability in brand prices over some representative period of time, averaged across all brands in the product category. Such brand price increases or decreases may be announced (e.g., price cuts featured in the media) or unannounced (e.g., simply a new shelf or item tag). Farley (1964) argued that price activity leads to changes in the rank order of brands from most expensive to least expensive within a product category, which causes the average consumer to switch in favor of the new lower priced brands. His analysis of 16 household and grocery products found a weak positive correlation ($p < 0.10$) between the amount of price activity in the product class and the percentage of consumers in a panel that switched brands. Another explanation for this finding is that, in the absence of substantial switching costs, the expected price savings from search will be higher for categories characterized by price activity. Hence, category price activity should be associated with more price elastic brand sales.

Brand Market Share

For the categories of grocery products examined in this study, the brands with high market shares tend to be well-known brands operating on the flat portion of their sales response functions, where the "flatness" seems to reflect consumers' preferences. These high share brands can be characterized as having "market power." Hence, the sales of brands with large market shares should tend to be own price inelastic. This prediction is supported by Ghosh, Neslin and Shoemaker's (1983) study of the market share price elasticities of cereal brands which found that the natural logarithm of market share was significantly ($p < 0.05$) related to short-term own price elasticities. Brands with higher market shares had smaller (i.e., inelastic) own price elasticities, where the absolute magnitude of the elasticities decreased at a decreasing rate.

Manufacturer Advertising

This paper distinguishes between manufacturer advertising and retailer advertising because manufacturer advertising of supermarket products tends to focus on nonprice information whereas retailer advertising tends to focus on price information. From the standpoint of the traditional economic model, manufacturer advertising of nonprice information can be considered to affect consumer tastes, change perceptions of product attributes, and differentiate the product from competitive offerings (e.g., Bain 1956). Consequently, it creates market power or brand loyalty, and brand sales are observed to be price inelastic (e.g., Comanor and Wilson 1974). An alternative economic approach postulates that advertising does not affect consumer tastes, but simply increases the amount of information available about competing products (Nelson 1970, 1974). Consequently, manufacturer advertising may increase awareness among consumers with different tastes so that the market includes a "choosier" segment that tends to be price elastic; or it may affect current buyers' perceptions about the availability of substitutes so that brand sales tend to become more price elastic (Eskin and Baron 1977).

The findings derived from longitudinal studies of the relationship between advertising and brand price elasticity are somewhat contradictory due to differences in the information content, copy, and media of the advertising, and to differences in the study contexts (e.g., Krishnamurthi and Raj 1985). However, two cross-sectional studies examined the relationship between price elasticities and manufacturer advertising expenditures (without controlling for other factors) and reported similar findings. Lambin (1976) studied country-wide sales of heavily advertised brands in Western Europe, and noted that the absolute values of short-run, own price elasticities were inversely related to advertising intensity in a sample of (roughly) 22 brands. Ghosh, Neslin and Shoemaker (1983) found that the sales of heavily advertised cereal brands tended to be more own price inelastic than those of less heavily advertised brands. These results could be explained by the notion that advertising differentiates brands and creates market power, or by the notion that firms rely on advertising when customers are price insensitive. If these findings extend to manufacturer advertising by well-established brands of supermarket products, the sales of brands characterized by higher levels of manufacturer advertising expenditures should be more own price inelastic.

Coupon Magnitude

Narasimhan (1984) developed an economic model of the consumer's purchase decision which predicted that, if there exists a segment of consumers with lower costs of usage for coupons, this segment will exhibit a higher frequency of coupon usage and greater sensitivity to price. In a panel of 1,000 consumers purchasing 20 household nondurables, the coupon users' product class demand function was significantly more price elastic than the coupon nonusers' function for 19 product categories. The results of his study suggest that the sales of brands in product *categories* characterized by more coupon activity may be more price elastic. In addition, since a *brand's* couponing activity may attract a segment of consumers which has lower costs of coupon usage and greater frequency of coupon usage, the sales of brands characterized by more coupon activity may be more own price elastic.

Display Activity

There are no cross-sectional studies of the relationship between display activity and own price elasticities. One way to think about the role of display activity is as follows. The relative frequency of displays (expanded shelf space, free-standing platforms/bins or end-of-aisle shelves) may influence consumer beliefs about the popularity and quality of market offerings. If display activity leads consumers to apply choice rules which do not rely on search for price information, brand sales may be price inelastic. Alternatively, if display activity encourages price comparisons, brands characterized by a high frequency of display activity should tend to be own price elastic. This reasoning suggests that *category* display activity and *brand* display activity may be systematically related to own price elasticities.

Retailer Advertising

Retailer advertising or "features" typically convey information about prices at the retail outlet. Feature activity for a brand or product class is defined to be the frequency of retailer advertising in newspapers or flyers. Studies of the role of reference prices and semantic price cues suggest that feature activity affects consumers' price perceptions, their evaluations of brands and their purchase decisions (e.g., Berkowitz and Walton

1980; Blair and Landon 1981; Winer 1986). Also, feature activity is likely to make current customers more aware of brand prices, as well as attracting a new segment of price sensitive shoppers to the market (e.g., Eskin and Baron 1977; Moriarity 1985). There are no cross-sectional studies of the relationship between feature activity and own price elasticities. However, the studies cited above suggest that *categories* with a high frequency of feature activity should have more price elastic brand sales than categories with a low frequency of feature activity. Also, if *brand* feature activity encourages price awareness and attracts price sensitive consumers to a particular brand, the sales of brands characterized by a high frequency of feature activity should also tend to be own price elastic.

Summary

The model of the effect of market characteristics on own price elasticities can be summarized by the following general form:

$$\eta_{ii} = f\left\{\begin{array}{l} ACTIVITY,\ SHARE_i,\ SHARE**2_i,\ B\text{-}MADVTG_i, \\ C\text{-}COUPON,\ B\text{-}COUPON_i,\ C\text{-}DISPLAY,\ B\text{-}DISPLAY_i, \\ C\text{-}FEATURE,\ B\text{-}FEATURE_i,\ PRICE_i,\ \mathbf{CATEGORY},\ LINEAR \end{array}\right\} \tag{2}$$

where:

η_{ii} = the elasticity of sales of brand i with respect to a change in price of brand i.

A subscript denoting the market (i.e., denoting the category and the geographic region in which the brand is sold) has been omitted from all variables in the equation for notational simplicity.[1] The variables in equation (2) include the market characteristics discussed in the preceding paragraphs. As shown in Table 1, the brand characteristics are defined as relative measures. For example, *B-COUPON*, *B-DISPLAY* and *B-FEATURE* are defined relative to the average value for all brands in the category. *SHARE* * * 2 is a quadratic term to capture the effects of diminishing marginal returns from increases in market share.

Equation (2) also includes the variables **CATEGORY** and *LINEAR*. **CATEGORY** is a vector of dummy variables (one for each product category) to capture the impact of systematic differences in consumer tastes for different product categories. Since the product categories have certain unique features (e.g., industries have different concentration ratios or waffles is the only frozen food), these dummy variables will also capture the effects of category-specific features. (They will capture main effects, but not interaction effects.) *LINEAR* is a dummy variable which takes on the value one when the elasticity is derived from a linear sales equation and zero when the elasticity is derived from a multiplicative sales equation. It is utilized to capture the impact of differences in functional form of the underlying sales equations from which the price elasticities are derived (as discussed in the following section).

Methodology

This section provides an overview of the methodology used to estimate the model of the relationship between market characteristics and price elasticities. The specification of the model is outlined, alternative methodological approaches are described, and estimation issues associated with equation (2) are discussed.

[1] Note that the model does not postulate systematic effects associated with brands or stores. After controlling for the effects of market characteristics, the null hypothesis that the coefficients of brand dummies were jointly equal to zero was not rejected. The same result was found for coefficients of store dummies. One reason for these results may be that the brands in this study were all major, nationally distributed brands.

TABLE 1
Definitions

Market Characteristic**	Measures
Brand Price (*PRICE*)	Average brand price (cents per 10 ounces or cents per roll) over time, divided by the weighted* average for all brands.
Category Price Activity (*ACTIVITY*)	Weighted average* of the coefficients of variation for brand prices at the store over the time period.
Brand Market Share (*SHARE*)	Average market share of the brand at the store over the time period.
Relative Brand Manufacturer Advertising (*B-MADVTG*)	LNA's estimate of manufacturer advertising expenditures for the brand divided by total manufacturer advertising for the category.
Category Coupon Magnitude (*C-COUPON*)	Average* coupon value redeemed in the product category during the time period.
Brand Coupon Magnitude (*B-COUPON*)	Average coupon value redeemed for the brand during the time period, divided by the weighted* average for all brands.
Category Display Activity (*C-DISPLAY*)	Percentage of weeks that the product category was on display in the store during the time period.
Relative Brand Display Activity (*B-DISPLAY*)	Percentage of weeks that the brand was on display during the time period, divided by the weighted* average for all brands.
Category Feature Activity (*C-FEATURE*)	Percentage of weeks that the product category was featured by the store during the time period.
Relative Brand Feature Activity (*B-FEATURE*)	Percentage of weeks that the brand was featured during the time period, divided by the weighted* average for all brands.

* Weights are market shares.
** The names in parentheses are the names of the variables used in the price elasticity model.

Model Specification

The general form of the model described in equation (2) can be summarized as follows. Re-writing equation (2),

$$\eta_{iim} = n(\mathbf{Z}_{im}) \tag{3}$$

where:

$\eta_{iim} \equiv$ the price elasticity of the sales of brand i with respect to the price of brand i at market m;

$n(\ ) \equiv$ a function with parameters that reflect consumer characteristics and tastes; and

$\mathbf{Z}_{im} \equiv$ a vector of variables describing characteristics of brands or the category, in market m, which remain stable over the T weeks for which sales are observed.

The subscript m denotes the market (i.e., category and store/geographic region), in which the brand is sold. The independent variables are market characteristics which remain stable during the observation period. This definition emphasizes the need for a reasonably short observation period, during which market conditions can be expected to remain unchanged.

Price elasticities measure consumer response to brand prices in a particular market which are derived from a sales response function. Hence, a model of the effects of market characteristics on price elasticities must have a second component: equations which describe brand sales in a particular market over time. Algebraically,

$$S_{imt} = s_{im}(\mathbf{X}_{imt}) + u_{imt} \tag{4}$$

where:

$S_{imt} \equiv$ sales of brand i in market m at time t;

$s_{im}(\ ) \equiv$ a function with parameters that depend on characteristics of the market ($\mathbf{Z}_{im}$) and consumer tastes;

$\mathbf{X}_{imt}$ = a vector of variables describing the market m at time t, including price, advertising, promotion, seasonal and economic factors in the market; and,

u_{imt} = a disturbance term reflecting model specification and measurement error.

The parameters of the sales response function $s_{im}(\ )$ will reflect market characteristics. For example, in a multiplicative model of sales, the parameters of the sales response function can be directly interpreted as elasticities, which we have postulated will depend on market characteristics.

Alternative Methodological Approaches

There are two methodological approaches estimating the effect of market characteristics on price elasticities: a simultaneous approach and a sequential approach. The simultaneous approach begins by recognizing that equation (4) can be re-written to describe an expanded model of consumer demand structure. That is,

$$S_{imt} = s^{*}(\mathbf{X}_{imt}, \mathbf{Z}_{im}) + u_{imt} \tag{5}$$

where:

$s^{*}(\ )$ ≡ a function with parameters that depend on consumer tastes.

Note that equation (5) incorporates both time series variables ($\mathbf{X}_{imt}$), and cross-sectional variables ($\mathbf{Z}_{im}$). Given a suitable functional form, equation (5) completely describes a system of equations for the sales of different brands in different categories at different retail locations. It can be estimated by a system estimation procedure, where the effects of market characteristics on price elasticities (i.e., the cross-sectional effects) are estimated by imposing restrictions across equations (e.g., Parsons 1975; Allenby 1986).

The simultaneous approach becomes complicated when there are a large number of brands, regions and/or independent variables (as in this study). Usually, it will be necessary to impose additional restrictions on the functional forms of the sales equations in order to make the estimation procedure tractable. (For example, the same functional form might be imposed on all sales equations.) Also, it will become computationally burdensome to test all the alternative restrictions on the functional form of the equations.

A second approach is to estimate equations (4) and (3) in sequential order. First, the sales equations are estimated. The same functional form is not imposed on all equations because this could lead to specification bias. Then estimates of own price elasticities are derived from these equations, and equation (3) is estimated using the unconstrained price elasticity estimates as the dependent variables. This approach is less efficient than the simultaneous approach, but the estimates of the effect of market characteristics on price elasticities (i.e., the cross-sectional effects) should still be consistent. In addition, this approach makes it possible to *test* whether market characteristics are associated with the magnitudes of price elasticities, rather than imposing an elasticity structure as part of the functional forms of the sales response equations. This feature is desirable because otherwise the results of the analysis may be due to the particular set of functional forms which were utilized (Assmus, Farley and Lehmann 1984).

The methodology used in this study utilizes the second approach. A general form for the sales equations is postulated, but the same functional form is not imposed on all sales equations. After statistical tests have determined the appropriate functional form, each brand sales equation is estimated and elasticity estimates are derived. Then a model based on equation (2) is estimated for own price elasticities.

Estimation Issues

The econometric issues associated with estimation of the price elasticity model are typical of those that arise in meta-analyses (Farley and Lehmann 1986). One issue that arises is that the dependent variable is an *estimate* of price elasticity, which suggests that there will be heteroscedasticity in the disturbance term. In particular, the variance of the disturbance term in the price elasticity model should be proportional to the variance of the elasticity estimate. As a result, ordinary least squares (OLS) estimation of the price elasticity model will produce consistent estimates of model coefficients, but estimates of the coefficient *standard errors* will be biased. Weighted least squares (WLS) estimation of the price elasticity model will yield efficient estimates of model coefficients, and unbiased estimates of coefficient standard errors (c.f., Maddala 1977).

The Data Base

This section explains how price elasticities were derived from the brand sales equations, and describes the measures of the market characteristics. Then the estimation of the price elasticity model is outlined.

Derivation of the Price Elasticity Estimates

Aggregate sales and marketing mix data were used to estimate own price elasticities for national brands of frozen waffles, liquid bleach, bathroom tissue and ketchup at the retail level. As in many other studies at the retail level, we estimated short-run or promotional price elasticities because the data almost entirely reflected temporary price changes (i.e., associated with promotional activities) rather than permanent price changes (i.e., that may occur due to major structural changes in the market environment). Generally promotional elasticities are more elastic than long-run elasticities due to the role of consumer expectations, stockpiling behavior, and competitive reactions.

Details concerning the estimation of the sales equations and the derivation of the price elasticities can be briefly summarized as follows. The data base consisted of store level, optical scanner data supplemented by field survey data, provided by Information Resources, Inc. It described weekly sales and marketing activity for brands at 12 different stores (belonging to several different chains in two cities) over a period of 75 weeks. The scanner data base included four product categories, each represented by three brands, at 12 stores. Statistical tests indicated that the data could not be pooled across stores. Thus, there were 144 ($4 \times 3 \times 12$) total possible brand sales equations. Thirty brand sales equations could not be estimated because some brands were not stocked in all stores, yielding 114 brand sales equations.

Brand sales were postulated to be a function of the brand's own current price, advertising, couponing activity, and display activity. They were also postulated to be a function of the current prices, advertising, couponing activity and display activity of each major competitor. In addition, sales were allowed to vary with respect to seasonality and the amount of store traffic. Statistical tests indicated that models which incorporated separate terms to reflect regular and promoted price (e.g., Guadagni and Little 1983) or lagged price terms were not appropriate.

After extensive analyses, a linear or multiplicative functional form was chosen for each equation using the Box-Cox transformation procedure (Box and Cox 1964; Box and Tidewell 1962).[2] For 49 (43%) of the equations, a likelihood ratio test could not reject the null hypothesis that the equation was multiplicative. For about 25 (22%) of

[2] The specification of the sales equations is a critical step in obtaining unbiased estimates of price elasticities. The functional forms initially considered include a linear model, a linear model with a quadratic price term, a multiplicative model, an exponential model, a model which incorporated price terms proposed by Guadagni and Little (1983), and a model which incorporated lagged terms. On the basis of statistical tests and goodness of fit criteria, a linear or multiplicative model (without lagged terms, regular/deal price terms, quadratic price terms or interaction terms) always dominated. A simple linear model was chosen for further testing, rather than a linear model with interactions, because analyses indicated that the incidence of statistically significant interaction terms (between price and promotion or advertising variables) in the linear model was approximately at a chance level. When the simple linear model was compared with the multiplicative model, the multiplicative model tended to perform better (as described in the text), probably because it is a parsimonious model which allows for interactions among all explanatory variables.

the equations, a likelihood ratio test could not reject the null hypothesis that the equation was linear. For the remaining 40 equations, these tests failed to distinguish among functional forms (because the likelihood function was very flat) and the functional form was selected on the basis of the correlation between the observed and predicted sales values. The fit tended to be very similar for both functional forms, but the linear functional form was a slightly better fit for 31 of the 40 equations. In the end, this classification procedure identified 56 linear sales equations and 58 multiplicative sales equations. OLS was used to estimate both linear and multiplicative sales equations. (OLS can be applied to the multiplicative models after they are linearized through a logarithmic transformation.) The average correlation (for all 114 sales equations) between observed and predicted sales values was about 77%.

For the multiplicative functional form, the price coefficients of these models can be directly interpreted as estimates of the price elasticities of the brands. For the linear functional form, own price elasticities of brand sales can be evaluated at the mean price and sales levels to provide an approximation of the elasticity for the neighborhood from which the estimates are derived. Computing the elasticity at the mean values of the independent variables makes it possible to compare elasticities that vary from point to point along the demand surface with constant elasticities (e.g., Farley and Lehmann 1986, p. 19).

The above procedure yielded 114 observations: 56 elasticities from linear sales equations and 58 elasticities from multiplicative sales equations. Since the sales equations contained marketing mix, store, and seasonal variables, these derived elasticity estimates represent the net effects of price after controlling for other sales influences. Descriptive statistics concerning the price elasticity estimates are displayed in Table 2. The average own elasticity varies by product class, with the least elastic being waffles and the most elastic being tissue.

18 of the 114 elasticity estimates derived from these equations did not have the negative sign that economic theory and prior research lead us to expect. These estimates typically had large standard errors due to the presence of multicollinearity in the data. Multicollinearity typically arises in optical scanner data bases due to the coordination of in-store displays and advertising features with promotional price changes, the highly seasonal nature of displays and features for grocery products, and the coordination of displays and features for products across brands and stores.

Measures of Market Characteristics

The measures of market characteristics are summarized in Table 1. Relative brand price is measured as average price (cents per 10 ounces of cents per roll) in the store over the relevant time period, divided by average price for all brands in the category. Product class price activity is measured as the weighted average of the coefficients of variation (i.e., standard deviation divided by the mean) for the prices of the major brands in the category, where the weights are equal to the brand market shares. Market share is measured as the market share of the brand in the store over the relevant time period.

A measure of manufacturer advertising was estimated from Leading National Advertisers Multi-Media Report (LNA) which describes manufacturers' nation-wide advertising expenditures (in millions of dollars) in five media: magazines and newspaper supplements, network television, network radio, spot television and spot radio. Manufacturer advertising for the brand is measured as LNA's estimate of expenditures for the time period, divided by total manufacturer advertising for the product category. Thus, it is implicitly assumed that the relative levels of national advertising for brands in a particular category are reasonably accurate reflections of the relative levels of advertising for these brands in the markets producing the data. Manufacturer advertising is the only measure which does not vary across stores.

TABLE 2
Descriptive Statistics

	Category			
Market Characteristic	Waffles	Bleach	Tissue	Ketchup
Own Price Elasticity	−1.74	−2.41	−3.12	−2.55
	2.07	2.70	3.80	2.76
Brand Price (cents per 10 oz. or per roll)	113.76	11.01	25.94	51.88
	11.80	1.61	2.57	2.65
Category Price Activity (coefficient of variation)	0.05	0.01	0.04	0.04
	0.01	0.01	0.01	0.02
Brand Market Share	0.25	0.42	0.13	0.30
	0.12	0.28	0.09	0.19
Manufacturer Advertising Expenditures for a Brand ($*M*)	1.13	10.56	7.68	6.66
	0.73	8.17	6.07	7.09
Category Coupon Magnitude (cents)	3.15	24.17	174.71	59.60
	6.43	29.48	196.83	71.07
Brand Coupon Magnitude (cents)	0.00	14.51	21.20	19.34
	0.00	24.53	36.37	25.78
Category Display Activity (% weeks)	0.00	0.08	0.18	0.22
	0.00	0.08	0.09	0.06
Brand Display Activity (% weeks)	0.00	0.08	0.06	0.17
	0.00	0.09	0.08	0.12
Category Feature Activity (% weeks)	0.13	0.11	0.29	0.23
	0.07	0.07	0.07	0.08
Brand Feature Activity (% weeks)	0.07	0.10	0.07	0.16
	0.04	0.06	0.06	0.11

[a] Means are reported in the first row, with standard deviations below. The number of observations for this table is 114 (representing 114 brand/store combinations of own price elasticities). All variables vary across stores, as well as brands, except for manufacturer advertising. Brand characteristics are measured as absolute, not relative values, in this table.

Coupon activity for a product class is measured as the average coupon value redeemed by customers in a given week, averaged over the 75-week time period. Coupon activity for a brand is measured in a similar fashion, and expressed relative to the weighted average value for all brands in the category. Display activity for a product class is measured as the percentage of weeks in the time period that the category was displayed by the retailer. Display activity for a brand is measured in a similar fashion, and expressed relative to the weighted average for all brands in the category. Feature activity for a category and brand are measured analogously.

The means and standard deviations of some characteristics of the brands and categories are displayed in Table 2. In this table, characteristics of the brands are described by their absolute, rather than their relative values. Brand advertising expenditures during the time period, estimated by Leading National Advertisers, ranged from about one to nine million dollars. Some manufacturers advertised nationally, but the majority of manufacturers (8/12) did not spend significant amounts. However, most brands were displayed in the stores, featured in newspapers or flyers, and promoted with coupons during this time period, which suggests that there is a substantial amount of cooperative advertising at the retail level. The frequency of brand displays ranged from zero to one out of every six weeks (i.e., 16%) for the average brand in each category. The average frequency of brand advertising features ranged from 7% to 15%.

A correlation matrix of the variables in the price elasticity model is displayed in Table

TABLE 3

Correlation Matrix of Market Characteristics

	ACTIVITY	*SHARE*	*B-MADVTG*	*C-COUPON*	*B-COUPON*	*C-DISPLAY*
ACTIVITY	1.00					
SHARE	−0.19	1.00				
B-MADVTG	−0.18	0.76	1.00			
C-COUPON	0.06	−0.24	−0.19	1.00		
B-COUPON	−0.27	0.12	0.17	0.31	1.00	
C-DISPLAY	−0.05	−0.17	−0.14	0.38	0.18	1.00
B-DISPLAY	−0.26	0.53	0.20	−0.08	0.13	0.16
C-FEATURE	0.14	−0.45	−0.29	0.34	0.06	0.69
B-FEATURE	−0.21	0.71	0.38	−0.24	0.17	−0.12
PRICE	−0.09	0.48	0.67	−0.20	0.27	−0.17

	B-DISPLAY	*C-FEATURE*	*B-FEATURE*	*PRICE*
ACTIVITY	−0.26	0.14	−0.21	−0.09
SHARE	0.52	−0.45	0.71	0.48
B-MADVTG	0.20	−0.29	0.38	0.67
C-COUPON	−0.07	0.34	−0.24	−0.20
B-COUPON	0.13	0.06	0.17	0.27
C-DISPLAY	0.16	0.69	−0.12	−0.17
B-DISPLAY	1.00			
C-FEATURE	−0.13	1.00		
B-FEATURE	0.74	−0.44	1.00	
PRICE	0.21	−0.20	0.36	1.00

3. (Due to space constraints, *BLEACH*, *TISSUE*, *KETCHUP*, *LINEAR* and *SHARE***2 are omitted.) Manufacturer advertising and market share are highly correlated. Also, the frequency of in-store displays and advertising features tend to be positively correlated across brands and stores. Analyses indicated that these measures were stable over the observation period.

Estimation of the Price Elasticity Models

The price elasticity model described by equation (2) was estimated with WLS. In the WLS procedure, the data are transformed by dividing the dependent and independent variables by the standard error of the elasticity estimate (derived from the multiplicative or linear sales equations), and then OLS is applied to the transformed data. For multiplicative equations, the standard errors of the elasticity estimates are the standard errors of the price coefficients. For linear equations, the standard errors of the elasticity estimates are the standard errors of the price coefficients multiplied by the ratio of average price divided by average sales (Kendall and Stuart 1977, pp. 246–247).

Results

26% of the variance in own price elasticities was explained by the model.[3] The hypothesis that this vector of model coefficients is equal to zero was rejected (at $p < 0.05$). These

[3] This R^2 is the squared correlation of the observed and predicted elasticities, not the R^2 of the transformed regression equation (which is higher). In addition, a split halves cross-validation was conducted. The data base was randomly split into two subsets of 57 observations. The own price elasticity model was estimated for each data subset, and used to predict the values of the elasticities in the other data subset. The correlations of the observed and predicted elasticities were 0.47 and 0.32. The signs of the coefficients estimated from the two data subsets were the same as the signs of the coefficients shown in Table 4 except for the following instance. In one data subset, the signs of the coefficients of category coupon activity and relative brand feature activity were the opposite of those in Table 4.

results are displayed in Table 4. The relationships between price elasticities and market characteristics are described in the following paragraphs.

Relative brand price. Relative brand prices are not strongly related to the magnitudes of own price elasticities ($p > 0.15$). This finding is probably due to the fact that this study focuses on major, national brands, which do not differ substantially on price within each category.

Category price activity. The coefficient of price activity is negative (as suggested in earlier discussion), but not statistically different from zero ($p > 0.15$). Hence, the extent of price activity in the category is not related to the magnitudes of own price elasticities. Note that this result holds after controlling for the effects of category display and feature activity, which are typically associated with price activity in this data base.

Brand market share. Brand sales are more own price inelastic with respect to the prices of brands with high market shares ($p < 0.05$). In addition, there is a pattern of diminishing marginal returns from higher levels of market share ($p < 0.10$). These results are consistent with the popular notion that large share brands are less responsive to own price changes. The magnitude of the impact of market share can be illustrated in the following way. Compare a brand which has an average market share (i.e., 0.24) with a brand which has a market share that is one standard deviation above average (i.e., 0.40). The model indicates that price elasticity of the brand with the higher market share will be about 0.52 smaller in absolute magnitude (ceteris paribus). For example, if the brand with the average market share had an own price elasticity of −2.0, we would expect that the brand with the higher market share would have an elasticity of about −1.5.

TABLE 4

WLS Results for the Own Price Elasticity Model

Independent Variables	Coefficient	Standard Error
Relative Brand Price	−2.38	2.63
Category Price Activity	−16.54	16.72
Brand Market Share	9.02***	4.38
Brand Market Share Squared	−9.61**	4.90
Relative Manufacturer Advertising	1.13	1.26
Category Coupon Magnitude	0.00*	0.00
Relative Brand Coupon Magnitude	0.07	0.45
Category Display Activity	8.01**	4.21
Relative Brand Display Activity	0.45*	0.29
Category Feature Activity	−8.02***	3.53
Relative Brand Feature Activity	−0.28	0.40
Bleach	−2.20***	0.93
Tissue	−1.22	0.91
Ketchup	−2.31***	0.97
Linear	0.76**	0.42
Intercept	0.24	2.59
Equation Statistics		
R-Square	0.26	
Adjusted R-Square	0.15	
F Statistic (15, 98)	2.30***	
Number of Observations	114	

* $p < 0.15$.
** $p < 0.10$.
*** $p < 0.05$.

Manufacturer advertising. Previous research has suggested that higher levels of manufacturer advertising should be associated with own price elasticities which are smaller in absolute magnitude, but this study does not find this relationship ($p > 0.15$). One possible reason for the discrepancy with previous research is that this study controls for the effects of other market characteristics (such as share) which are correlated with manufacturer advertising. Another reason is that the content, media vehicles and so forth of manufacturer advertising may vary substantially across brands and categories.

Coupon magnitude. The effects of category and brand coupon activity are very small, but the effect of category coupon activity is weakly statistically significant ($p < 0.15$). Higher coupon magnitudes are associated with price inelastic brand sales. This result is contradictory to earlier predictions. One interpretation of this result is that coupons do not attract a more price sensitive segment of consumers. Perhaps higher coupon magnitudes do not attract many new buyers because the penetration rates for bathroom tissue, bleach, and ketchup are already very high; or they may be insulating existing buyers from competitors' price changes rather than inducing switching; or they may lead customers' to expect large price cuts, so that a particular price cut has little effect. Another interpretation is that managers use higher coupon values in markets where they anticipate that customers are relatively insensitive to price.

Display activity. Brand sales are more inelastic with respect to their prices for categories ($p < 0.10$) or brands ($p < 0.15$) that are frequently displayed in the store. The effect of category display activity can be illustrated by comparing a category which has an average level of display frequency (12% or one out of every six weeks) with a category for which the level of display frequency is one standard deviation above average (i.e., 33%). The own price elasticities of brands in the category with the higher level of display frequency will be about 1.7 smaller in absolute magnitude than average. For example, if own price elasticities are −2.4 in a category with average display activity, they would average about −0.7 in a category with high display activity (ceteris paribus). The effect of brand display activity is much smaller in magnitude. For example, the own price elasticities of a brand with a relative brand display activity index which is one standard deviation above average will be 0.5 smaller in absolute magnitude that the price elasticities of a brand with an average relative brand display activity index.

Feature activity. It was suggested that brand sales should be more price elastic for categories and brands that are frequently featured in flyers or newspapers. This notion is supported by negative coefficients in the price elasticity model. The effect of category feature activity is statistically significant ($p < 0.05$), but the effect of brand feature activity is not. The effect of category feature activity can be illustrated by comparing a category which has an average frequency of features (19% or one out of every five weeks) with a category which is one standard deviation above average (i.e., 29%). The own price elasticities of the category with the higher level of feature frequency will be about 0.8 larger in absolute magnitude than average. One interpretation of these findings is that existing buyers have become more price sensitive, or that new, price sensitive buyers have entered the market in response to feature activity. Alternatively, managers may utilize features when they anticipate that customers are price sensitive.

Category effects. The category dummy variables explain ten percent of the variance in the promotional price elasticity estimates. There are systematic differences in the magnitudes of the own price elasticities across categories, *after accounting for the effects of market characteristics*. Sales of brands of bleach and ketchup are more own price elastic than sales of brands of waffles or bathroom tissue ($p < 0.05$). These differences may be due to the effects of category characteristics (e.g., price and advertising), as well as the effects of customer tastes.

There are at least four explanations for the differences in promotional price elasticities across categories. The first two explanations concern customers' tastes, or customers' value for the attributes or benefits offered by the product category. Firstly, customers may perceive substantial differences in the attributes of brands of waffles and tissue.[4] In contrast, brands of bleach and ketchup may be perceived as much more homogeneous. Secondly, frozen waffles appeal to a much smaller target market than bleach or ketchup, and these customers may be relatively insensitive to price relative to other attributes. Hence, customers seem to be less sensitive to price because nonprice attributes are important in the product category.

The third explanation concerns costs associated with the purchases decision, such as search costs. Frozen waffles are stored in freezer cases, so that price comparisons require more effort and inventorying is more costly. In contrast, bleach and ketchup are stored on shelves, so that price information will be much more conspicuous and inventorying is less costly. Hence, customers may be less sensitive to price when search and inventory costs are high.

Lastly, frozen waffles tend to have higher package prices and lower manufacturer advertising levels than bathroom tissue, bleach or ketchup. We might expect these category characteristics to be associated with more price elastic brand sales. However, these effects seemed to be swamped by the effects of customer tastes and nonprice costs associated with the purchase decision.

Functional form. The price elasticities derived from linear sales equations are higher (more positive) than the price elasticities derived from multiplicative sales equations ($p < 0.10$).[5] It is interesting to compare this result with a study by Assmus, Farley and Lehmann (1984), which reported that advertising elasticity estimates from additive models were higher than estimates from multiplicative models in their meta analysis of advertising sales study results. Note that "higher" elasticities derived from linear sales equations imply brand sales which are *less* elastic with respect to price and more elastic with respect to advertising. Perhaps linear models tend to omit a price-advertising interaction term which has a negative effect on sales, so that estimates of price and advertising elasticities from the linear models are biased in this way.

Discussion

The promotional price elasticities examined in this study were measured at the store level. For this reason, the effects of store level activities—particularly display and feature activity—tended to have the largest impact on price elasticities. For example, higher levels of feature activity within the category were associated with more price elastic brand sales, whereas higher levels of display activity within the category were associated with more price inelastic brand sales.

The effects of *category* display and feature activity were much larger than the effects of *brand* prices, display and feature activity. One possible explanation for this result is that the relative levels of prices, display activity and feature activity tend to be similar for the national brands considered in this study—so that their effects are difficult to

[4] Frozen waffles differ in size, shape, flavor, consistency and taste. Although the physical differences in brands of bathroom tissue may not seem to be substantial (primarily color and ply), customers may *perceive* substantial differences due to manufacturer advertising which emphasizes attributes such as softness and absorbency.

[5] Based on the corrected SSE from WLS, it was possible to conduct an F-test to determine whether elasticities derived from multiplicative and linear models could be pooled. The test indicated that interaction effects between *LINEAR* and the other variables in the model were not necessary ($p > 0.15$), although the inclusion of *LINEAR* (to capture the main effect of functional form) was necessary. Thus, separate models for elasticities derived from multiplicative and linear functional forms were not necessary.

detect. Their effects might be more noticeable if national and local brands were compared, or name brands and private label brands were compared.

Manufacturer characteristics also had an impact on promotional price elasticities. High share brands seem to have "market power" in the sense that they are own price inelastic. Since a brand's market share and a brand's relative expenditures on advertising are strongly related in this data base, the effect of manufacturer advertising, if any, may be masked by the effect of market share.

Overall, these results indicate that market characteristics are systematically related to promotional price elasticities, and that the resultant differences in price elasticities are large enough to be of managerial importance. Since the marketing literature has typically attributed differences in price elasticities across markets to differences in customer tastes (e.g., "clientele effects") or to model specification and data characteristics (e.g., Tellis 1988), it is rather surprising to discover that these differences are partially due to differences in the nature and intensity of marketing effort in the markets. Furthermore, it is surprising to discover these systematic differences seem to be consistent across categories, as well as across brands and stores. Although the findings described in this paper are not generalizable to all categories of products because this study analyzed only a sample of major brands for four categories of frequently purchased nondurables, it seems reasonable to believe that they may hold for similar products, such as paper products, soaps and convenience foods (for which linear or multiplicative sales equations are appropriate).

After controlling for the effects of market characteristics, there are still substantial differences in promotional price elasticities across categories. Hence, although market characteristics are associated with differences in price elasticities, customer tastes (i.e., customers' value for the particular attributes or benefits offered by the category) seem to be important in explaining differences in promotional price elasticities across categories.

Concluding Remarks

This study has found that the magnitudes of promotional price elasticities are systematically related to the nature and intensity of marketing activities in different markets. Hence, certain promotional pricing strategies may be more useful in some markets than others. For example, these results indicate that a category characterized by frequent display activity is quite different from one characterized by frequent newspaper advertising, so that price competition is likely to be more important in the latter category. They also indicate that a promotional pricing program may be much more effective in markets where the brand has a low share than in markets where the brand has a high share. Results of this type should be particularly interesting to managers of mature brands in established categories. Marketing programs should be flexibly applied to take into account these kinds of differences across regions.

Consequently, managers and researchers should be very cautious about basing their decisions on assessments of consumer price sensitivity drawn from their experiences in a particular market. This observation leads to two practical recommendations for managers. First, it is important to conduct a test or study of a new marketing program in a test region which is representative of the target market in order to obtain generalizable results. Second, since regions are unlikely to be homogeneous, it is important to replicate the test under alternative market conditions.

Many manufacturers and retailers sell products in multiple markets (e.g., geographic areas) with differing characteristics. For these companies, numerous replications of marketing studies are very costly. However, if differences in markets have a systematic relationship to differences in promotional price elasticities, numerous replications may not be required. It may be possible to anticipate the magnitude of the promotional price elasticity of an existing brand in a new (or different) market on the basis of the market's particular characteristics. In order to make these kinds of extrapolations, manufacturers and retailers should assemble a body of historical or experimental data that describes regional differences, as well as utilize their past experience.

Since this study examines only short-run price elasticities, it is not possible to make inferences about long-run optimal policies for manufacturers or retailers. In addition, the results of this study do not necessarily imply that manufacturer and retailer marketing efforts affect price elasticities. A correlational study cannot demonstrate causality. Marketing characteristics (such as display activity) may have arisen in response to the inherent price sensitivity of consumers, rather than the reverse. Perhaps this study will stimulate theoretical work which considers the underlying processes that link market characteristics and price elasticities.

Future research could also examine a larger number of categories and a wider variety of brands in each category. With more categories and brands, it would be possible to investigate a broader array product/market characteristics, such as the degree of heterogeneity of brands in the product category, the relative amounts of advertising expenditures in different media, the product category's penetration of the household market, the brand and product life cycles and the industry concentration ratio.[6]

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