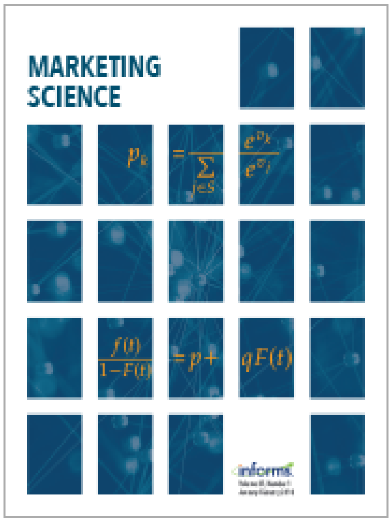

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Asymmetric and Neighborhood Cross-Price Effects: Some Empirical Generalizations

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Abstract

This paper provides some empirical generalizations regarding how the relative prices of competing brands affect the cross-price effects among them. Particular focus is on the asymmetric price effect and the neighborhood price effect. The asymmetric price effect states that a price promotion by a higher-priced brand affects the market share of a lower-priced brand more so than the reverse. The neighborhood price effect states that brands that are closer to each other in price have larger cross-price effects than brands that are priced farther apart. The main objective of this paper is to test if these two effects are generalizable across product categories, and to assess which of these two effects is stronger.

While the neighborhood price effect has not been rigorously tested in past research, the asymmetric price effect has been validated by several researchers. However, these tests of asymmetric price effect have predominantly used elasticity as the measure of cross-price effect. The cross-price elasticity measures the percentage change in market share (or sales) of a brand for 1% change in price of a competing brand. We show that asymmetries in cross-price elasticities tend to favor the higher-priced brand simply because of scaling effects due to considering percentage changes. Furthermore, several researchers have used logit models to infer asymmetric patterns. We also show that inferring asymmetries from conventional logit models is incorrect.

To account for potential scaling effects, we consider the absolute cross-price effect defined as the change in market share (percentage) points of a target brand when a competing brand's price changes by one percent of the product category price. The advantage of this measure is that it is dimensionless (hence comparable across categories) and it avoids scaling effects. We show that in the logit model with arbitrary heterogeneity in brand preferences and price sensitivities, the absolute cross-price effect is symmetric.

We develop an econometric model for simultaneously estimating the asymmetric and neighborhood price effects and assess their relative strengths. We also estimate two alternate models that address the following questions: (i) If I were managing the *i*th highest priced brand, which brand do I impact the most by discounting and which brand hurts me the most through price discounts? (ii) Who hurts whom in National Brand vs. Store Brand competition?

Based on a meta-analysis of 1,060 cross-price effects on 280 brands from 19 different grocery product categories, we provide the following empirical generalizations:

1. The asymmetric price effect holds with cross-price elasticities, but tends to disappear with absolute cross-price effects.
2. The neighborhood price effect holds with both cross-price elasticities and absolute cross-price effects, and is significantly stronger than the asymmetric price effect on both measures of cross-price effects.
3. A brand is affected the most by discounts of its immediately higher-priced brand, followed closely by discounts of its immediately lower-priced brand.
4. National brands impact store brands more so than the reverse when the cross-effect is measured in elasticities, but the asymmetric effect does not hold with absolute effects. Store brands hurt and are, in turn, hurt the most by the lower-priced national brands that are adjacent in price to the store brands.
5. Cross-price effects are greater when there are fewer competing brands in the product category, and among brands in nonfood household products than among brands in food products.

The implications of these findings are discussed.

(*Cross-Price Elasticities*; *Packaged Goods*; *Price Competition*; *Promotions*; *Private Labels*.)

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Introduction

In their comprehensive book on Sales Promotion, Blattberg and Neslin (1990, p. 373) observe that "the key issue that still needs to be addressed is the analysis of cross-elasticities to understand competitive effects of deals." Cross-price effects measure the effect of a brand's price promotion (temporary price reduction) on a competitive brand's market share. Studying patterns in cross-price effects enables researchers and managers to understand brand price competition and market structure, thereby guiding price promotion strategies.

The broad purpose of this paper is to provide some empirical generalizations that offer insights into how the relative prices of two competing brands affect the cross-price effects between them. As Bass (1995) notes, the building blocks of science are empirical generalizations, defined as patterns of regularity that repeat over different circumstances.

Empirical generalizations on promotion effects have been studied by Blattberg et al. (1995). They define an empirical generalization as one where the sign of the effect is consistent with the phenomenon in at least three different studies. With respect to cross-price promotion effects, they identify the following empirical generalization: Cross-promotion effects are asymmetric and promoting a higher-priced (higher quality) brand impacts a lower-priced (lower quality) brand more so than the reverse. This phenomenon, known as the asymmetric price effect, was documented by Blattberg and Wisniewski (1989) and has been extensively studied in the literature (e.g., Allenby and Rossi 1991; Bronnenberg and Wathieu 1996; Hardie et al. 1993; Sethuraman 1995; Sivakumar 1997; Sivakumar and Raj 1997). Our paper refines and enhances the repertoire of empirical generalizations in cross-price effects through a meta-analysis (Farley and Lehmann 1986) of 1,060 cross-price effects on 280 brands from 19 different grocery product categories. In particular, we develop empirical generalizations related to the following questions:

1. *Does the asymmetric price effect hold for both cross-price elasticities and absolute cross-price effects*? Cross-price effects are typically studied using cross-price elasticities which measure the percentage change in market share of the target brand for a one percent change in the price of a competing brand. We emphasize the need for analyzing both cross-price elasticity and absolute cross-price effect, where the latter is defined as the change in market share (percentage) points of a target brand when a competing brand's price changes by one percent of product category price. We find that the asymmetric price effect holds in the case of cross-price elasticities but with absolute cross-price effects it tends to disappear. This finding, as shown later, is to be theoretically expected for cross-price effects from logit models. However, we find the same result for cross-price effects from nonlogit (market share and sales) models as well.

2. *Is there a neighborhood cross-price effect?* While much of the discussion in the literature has focused on asymmetric price effect, the neighborhood price effect has received very little attention. The neighborhood price effect states that brands that are closer to each other in price have higher cross-price effects than brands whose prices are farther apart. We develop an econometric model for jointly estimating the asymmetric and neighborhood price effects and compare their relative magnitudes. We find that the neighborhood price effect is significant with both cross-price elasticities and absolute cross-price effects, and it is considerably stronger than the asymmetric price effect.

3. *What can the* ith *highest-priced brand expect in terms of cross-price effects*? From the standpoint of making price promotion decisions, managers are especially interested in the following question: If I were managing the *i*th highest priced brand, which brand do I impact the most by discounting and which brand hurts me the most through price discounts? To address these questions, we analyze the brands in terms of price ranks and develop a set of descriptive generalizations regarding what the *i*th highest priced brand can expect in terms of cross-price effects. We find that a brand is affected the most by discounts of its immediately higher-priced brand, followed closely by discounts of its immediately lower-priced brand.

4. *Who hurts whom in National Brand vs. Store Brand competition*? In general, national brands are the higher-priced, higher-quality brands. Retailers in the U.S. attempt to draw sales from the national brands by offering a store brand or a private label brand of acceptable quality at lower prices. Sales of these store brands have

grown considerably in the nineties (Hoch and Banerji 1993) and the price competition has intensified. For making price promotion decisions, the following questions are of interest: Do national brands hurt store brands more with discounting than vice versa? What type of national brands (high-priced or low-priced) hurt store brands with their discounts and what types of national brands are hurt by store brands when they discount? We find that national brands impact store brands more when the cross-effect is measured in elasticities, but the asymmetric effect does not hold with absolute effects. Store brands hurt and are, in turn, hurt the most by the lower-priced national brands that are adjacent in price to the store brands.

5. *What are some other factors which influence patterns in cross-price effects*? We investigate some covariates in our meta-analytic model and find that cross-price effects are greater when there are fewer brands competing in the category. We also find some evidence indicating that cross-effects are greater among brands in nonfood household product categories than among brands in food products.

The paper is divided as follows. First, we discuss some background literature related to asymmetric and neighborhood price effects. Second, we consider the systematic differences between cross-price elasticities and absolute cross-price effects. Third, we develop an econometric model for jointly estimating the asymmetric and neighborhood price effects. Fourth, we describe the data used for testing the empirical generalizations. Fifth, we estimate the models and present the results for both cross-price elasticities and absolute cross-price effects. Sixth, we address the question of what the *i*th highest-priced brand can expect in terms of cross-price effects. Seventh, we analyze the cross-price effects in the context of national brand vs. store brand competition. Finally, we discuss the implications and directions for future research.

Asymmetric and Neighborhood Price Effects

Blattberg and Wisniewski (1989) empirically demonstrated the *asymmetric price effect*. The phenomenon is that when a high-priced (high-quality) brand promotes, consumers of a low-priced (low-quality) brand will switch to the promoted high-quality brand. However, when the low-priced (low-quality) brand promotes, few consumers of the high-priced brand will switch to the promoted low-priced brand. Blattberg and Wisniewski offered an explanation of the phenomenon in terms of an U-shaped heterogeneity distribution in preferences for the higher-priced brand over the lower-priced brand. Alternative rationales for the asymmetric price effect have been provided by Allenby and Rossi (1991), Hardie et al. (1993), and Sivakumar (1997). Several empirical studies have validated the effect (e.g., Blattberg and Wisniewski 1989, Mulhern and Leone 1991).

In addition to the asymmetric price effect, we consider a neighborhood price effect which states that brands that are closer to each other in price have larger cross-price effects than brands that are priced farther apart. Empirical results from previous studies suggest the presence of the neighborhood price effect. Rao (1991) observed in three product categories that brands typically discounted just below the price of the brand with the next higher price, suggesting that a brand competes most with its neighboring (in terms of price) brands. Russell (1992) empirically showed that the extent of substitution between two brands could be related to price tiers—brands within the same price tier had higher substitution indices. In the context of competition between national brands and store brands, Sethuraman (1995) found that national brands that were priced closer to store brands had higher cross-price elasticities with store brands than national brands that were priced much higher than store brands. One possible explanation for the neighborhood price effect is due to Bronnenberg and Wathieu (1996). They show analytically that the impact of a price discount of a brand on the sales of another brand is inversely related to the difference in quality between the two brands, i.e., the lower the quality difference the higher is the cross-price effect. Because price is likely to be positively correlated with quality,[1] brands which are closer in price should have greater cross-price effect.

[1]Srinivasan and MacLaurin (1998) study the positioning of n competitive brands along a quality dimension and find that the equilibrium prices and qualities are strongly positively correlated.

Based on the above discussion, we formally state the hypotheses related to the two effects as follows:

ASYMMETRIC PRICE EFFECT. *The cross-price effect of a price change of a higher-priced brand on the market share (or sales) of a lower-priced brand will be greater than the cross-price effect of a price change of a lower-priced brand on the market share (or sales) of a higher-priced brand.*

NEIGHBORHOOD PRICE EFFECT. *The cross-price effect of a price change of brand i on the market share (or sales) of brand j will be higher the closer the price of brand i is to the price of brand j.*

Alternative Measures of Cross-Price Effects

We start with the commonly used measure of cross-price effect, namely the cross-price elasticity $\eta_{i \rightarrow j}$, i.e., the percentage change in the market share s_j of a target brand j for a one percent change in the price p_i of a competing brand i. Throughout, we use the symbol $i \rightarrow j$ to denote the effect of a price change by brand i on brand j's market share. Thus,

$$\eta_{i \rightarrow j} = (\partial s_j / \partial p_i)\ (p_i / s_j). \tag{1}$$

Cross-price elasticities have provided the language which links much of marketing theory to marketing models and practice, and serve as useful measures of competition (Cooper 1988).

A scaling effect with the elasticity measure can be illustrated in the context of the asymmetric price effect between a national brand and a store brand. Typically, the national brand is larger in price than the store brand. Consequently, a 1% change in the price of the national brand is larger in terms of dollars and cents than a 1% change in the price of store brand, and this itself can potentially lead to a larger effect for the national brand's price reduction. For instance, a 50 cents price promotion by a national brand priced at $2 may be more effective than a 25 cents price promotion by a store brand priced at $1, both being 25% price discounts. The greater impact for the national brand may, in part, be due to its larger price reduction. Stated differently, won't the store brand's price promotion be more effective if it were to give a 50 cents discount rather than a 25 cents discount?

A second scaling effect with the elasticity measure in the context of the asymmetric price effect arises due to market share differences. Often the (leading) national brands have larger shares than the store brands. Therefore, the same amount of change in market share (percentage) points becomes larger when expressed as a percentage of the smaller market share of the store brand compared to the larger market share of the national brand. For instance, a 2 percentage point share drop translates to a greater elasticity when a store brand with 5% share is affected, compared to a national brand with a 20% share. Although expressing the market share movement as a percentage of the base share may better capture the psychological pain experienced, there is no fundamental asymmetry in economic terms. (In any event, theories on the asymmetric price effect do not use the above scaling effect as the basis for explaining the phenomenon.) The two scaling effects inherently bias the results towards finding a larger cross-price elasticity for the national brand's price cut on the store brand compared to the reverse. (See also Sivakumar and Raj (1997, p. 82) for a discussion of why elasticity is not a good measure to evaluate asymmetric price effects.)

To avoid the above scaling effects, we consider an alternative measure of cross-price effect that expresses the change in market share (percentage) points of brand j for a $1 (or 1 cent) change in the price of brand $i = (\partial s_j / \partial p_i)$. A difficulty with this alternative measure is that it will change whether the price is measured, for instance, per pound or per ounce. This difficulty is particularly serious in the meta-analysis context with different product categories. We will be combining the cross-price effect from one study based on (say) cents per pound with the cross-price effect from another study based on (say) cents per gallon. To overcome this problem, we define the absolute cross-price effect $\gamma_{i \rightarrow j}$ as the change in market share (percentage) points of a target brand j when the price of the competing brand i changes by *one-percent of the product category price*. The product category price (p_c) is computed as the (market share) weighted average brand price in the category. By using 1% of product category price, we keep price change the same for both brands i and j. Thus,

$$\gamma_{i \rightarrow j} = (\partial s_j / \partial p_i)\ (0.01\ p_c). \tag{2}$$

We note that the absolute cross-price effect is a dimensionless measure, as is the cross-elasticity. From (1)–(2) it follows that

$$\eta_{i \to j} = \gamma_{i \to j} (p_i/s_j)/(0.01 \; p_c). \tag{3}$$

We now show that the interpretation of asymmetry from cross-elasticities can be particularly misleading in the case of results from Logit models.

Symmetry of Logit-Based Absolute Cross-Price Effects

Consider a Logit model where the probability θ_{ik} that consumer k would choose brand i is given by

$$\theta_{ik} = \exp(u_{ik} - b_k p_i)/\Sigma_j \exp(u_{jk} - b_k p_j), \tag{4}$$

where preferences (u_{ik}) and price sensitivities (b_k) are permitted to be heterogeneous across consumers. The individual-level cross-price elasticities for consumer k are given by the familiar expression (e.g., Ben-Akiva and Lerman 1985, p. 111):

$$\eta^k_{i \to j} = (\partial\theta_{jk}/\partial p_i)\, (p_i/\theta_{jk}) = b_k \; \theta_{ik} \; p_i. \tag{5}$$

The market share for brand j is given by $s_j = \Sigma_k\, (q_k\, \theta_{jk})/\Sigma_k\, q_k$, where q_k denotes the (exogenously specified) purchase quantity of consumer k. It then follows from (2) and (5) that the market-level absolute cross-price effect is given by

$$\gamma_{i \to j} = (0.01 \; p_c)\, \Sigma_k\, (q_k \; b_k \; \theta_{ik} \; \theta_{jk})/\Sigma_k \; q_k. \tag{6}$$

We note that $\gamma_{i \to j} = \gamma_{j \to i}$ *so that the absolute cross-price effects are symmetric under the Logit model.* (See Russell et al. (1993, p. 11) for a similar result.)[2] The above result states that even if consumers are heterogeneous in terms of brand preferences and price sensitivities, the absolute cross-price effect is symmetric, thereby raising doubts about the heterogeneity-based explanation of asymmetric price effect (Blattberg and Wisniewski 1989). However, several caveats are worth mentioning. First, the result has been shown only for the Logit model. Second, the symmetry result arising from Equation (6) is based on infinitesimal price changes, but large price changes may lead to asymmetry. Third, even in a logit type model, asymmetry can arise due to income effects from a price reduction (Allenby and Rossi 1991) and/or when price enters the utility function as a deviation from a reference price and there is loss aversion (Hardie et al. 1993, Bronnenberg and Wathieu 1996).

If absolute cross-price effect is symmetric, what does this imply for cross-price elasticity? The correlation between price and market share computed across brands in a grocery product category often tends to be positive; e.g., national brands have higher prices and higher market shares than store brands. The equilibrium price and market shares are strongly positively correlated in Srinivasan and MacLaurin's (1998) analysis of n competitive brands' positioning along a quality dimension. In our database, the average within-category Spearman rank order correlation between prices and market shares is 0.35.[3] Without loss of generality, let the brand indices be renumbered so that $p_1 > p_2 > p_3 \ldots$; (i.e., $p_i > p_{i+k}$ for $k = 1,2,\ldots$). By the positive correlation indicated above, $s_1 >' s_2 >' s_3 \ldots$ (or $s_i >' s_{i+k}$) where $>'$ means "tends to be greater than," though they may not be greater at all times. Because $\gamma_{i \to i+k} = \gamma_{i+k \to i}$ for the Logit model and $p_i > p_{i+k}$ and $s_{i+k} <' s_i$, it follows from (3) that

$$\begin{aligned} \eta_{i \to i+k} &= \gamma_{i \to i+k} \; (p_i/s_{i+k})/(0.01 \; p_c) \\ &>' \gamma_{i+k \to i} \; (p_{i+k}/s_i)/(0.01 \; p_c) \\ &= \eta_{i+k \to i}, \quad \text{so that } \eta_{i \to i+k} >' \eta_{i+k \to i}. \end{aligned}$$

In summary, if price and market share are positively correlated across brands, as is found to be the case in grocery products, we may observe asymmetric price effect in cross-price elasticities estimated from Logit models, even though there is symmetry in absolute cross-price effects.[4]

We illustrate the above point using Table 5 of Kamakura and Russell (1989). For the total sample of

[2]If price enters the utility function in logarithmic form, i.e., $b_k \, p_i$ and $b_k \, p_j$ in Equation (4) are replaced by $b_k \log p_i$ and $b_k \log p_j$, respectively, then $\gamma_{i \to j} \, p_i = \gamma_{j \to i} \, p_j$.

[3]We caution the reader that our data pertain to grocery product categories only. Whether such a positive correlation exists for consumer durable goods and/or industrial products is an empirical question.

[4]In fact, one would expect to observe asymmetry when $[p_i/s_{i+k}] >' [p_{i+k}/s_i]$. Given that $p_i > p_{i+k}$, the above condition holds even if price and market share are uncorrelated or mildly negatively correlated. The condition will not hold only when price and market share are strongly negatively correlated.

consumers, the leading national brand A has a cross-price elasticity over the store brand P, $\eta_{A\rightarrow P} = 1.20$, but $\eta_{P\rightarrow A} = 0.34$, an apparently large asymmetry ($\eta_{A\rightarrow P}/\eta_{P\rightarrow A} = 3.5$). The prices of the two brands are $p_A =$ \$4.29 and $p_P =$ \$3.09, respectively and the (market share) weighted average category price $p_c =$ \$3.70. The market share (percentage) points of the two brands are $s_A = 35.5$ and $s_P = 13.8$, respectively. Using Equation (3) we note that $\gamma_{A\rightarrow P} = \eta_{A\rightarrow P}$ $[s_p/p_A]$ $(0.01\ p_c) = 0.14$ which is the same as that of $\gamma_{P\rightarrow A} = \eta_{P\rightarrow A}$ $[s_A/p_P]$ $(0.01\ p_c) = 0.14$. In other words, a 3.7 cents change (1% of category price) in the price of either of the two brands affects the other brand's share by the same 0.14 percentage points. The large asymmetry in cross-price elasticity is solely due to the fact that the national brand's price is much larger than the store brand's price, and the store brand's market share is much smaller than that of the national brand.

In non-Logit models (e.g., Probit, aggregate sales and market share models), the γ's need not be symmetric, and hence such models are more appropriate for testing asymmetry. But even in these models, the scaling effect of $[p_i/s_{i+k}] >' [p_{i+k}/s_i]$ would tend to bias the cross-price elasticity towards asymmetry. Because of the potential bias in cross-price elasticity measure towards asymmetry in grocery product categories, we consider the tests based on absolute cross-price effects to be stronger tests of asymmetry. Because both the asymmetric price effect and neighborhood price effect theories are general, and not specific in terms of cross-elasticities (η) or absolute cross-effects (γ), we test our hypotheses with both η and γ.

Econometric Model

We use the more general term cross-price effect ($\text{CPE}_{i\rightarrow j}$) to refer to both cross-price elasticity (η) and absolute cross-price effect (γ) of the price change of brand i on the market share of brand j. We are interested in understanding patterns in cross-price effects. In particular, we want to test whether the cross-price effect depends on the price proximity of brands i and j. Hence, the independent variable we use is the relative price of brands i and $j = (p_i/p_j)$.[5] We build the econometric model by considering the relationship between relative price and cross-price effects separately for two cases, $p_i \leq p_j$ and $p_i > p_j$, and then combining them.

Case (i) $p_i \leq p_j$

Consider two brands i and j with the same price. The neighborhood price effect states that when the prices are closest, i.e., $p_i/p_j = 1$, the cross-price effect would be the largest. Let us denote that cross-price effect to be α, i.e., when $p_i/p_j = 1$, $\text{CPE}_{i\rightarrow j} = \text{CPE}_{j\rightarrow i} = \alpha$. Now consider the case $p_i < p_j$. For now, let us ignore the asymmetric price effect and consider only the neighborhood price effect. This effect states that as relative price (p_i/p_j) becomes progressively smaller than 1, the cross-price effect would also become progressively smaller. We assume a linear relationship so that

$$\text{CPE}_{i\rightarrow j} = \alpha - \beta_N\,(1 - p_i/p_j) \quad \text{for } p_i \leq p_j,\ \beta_N > 0. \tag{7}$$

In a later section, we relax the linearity assumption.

The use of p_i/p_j poses a problem in the interpretation of the effects. Consider two brands A and B with prices \$1 and \$2, respectively. When A is the discounting brand (i) and B is the brand whose sales is affected (j), $p_i/p_j = 0.5$, which is 0.5 unit to the left of the point $p_i/p_j = 1$. When B is the discounting brand (i) and A is the brand (j) whose sales is affected, $p_i/p_j = 2$, which is one unit to the right of the point $p_i/p_j = 1$. That is, we create an asymmetry simply because of the measure p_i/p_j. To overcome this problem, we use the price ratio p_L/p_H, where p_L is the price of the lower-priced brand L (between i and j) and p_H is the price of the higher-priced brand H. The range of p_L/p_H is always between 0 and 1.[6] Since we are currently considering the case $p_i \leq p_j$, $p_i/p_j = p_L/p_H$.

Thus Equation (7) can be written as:

[5] In the meta-analysis, we have data on multiple product categories with different units of measurement (e.g., rolls, pounds, quarts). Consequently, using the ratio p_i/p_j allows us to pool the data more effectively than the price differential $p_i - p_j$, which would be affected depending on, for example, whether price is measured per ounce or per pound.

[6] Using p_H/p_L would make the ratio unbounded. Consequently, we use the bounded measure p_L/p_H.

$$\text{CPE}_{i \to j} = \alpha - \beta_N (1 - p_L/p_H) \quad \text{for } p_i \leq p_j, \tag{8}$$

and is shown as the dotted line in Figure 1.

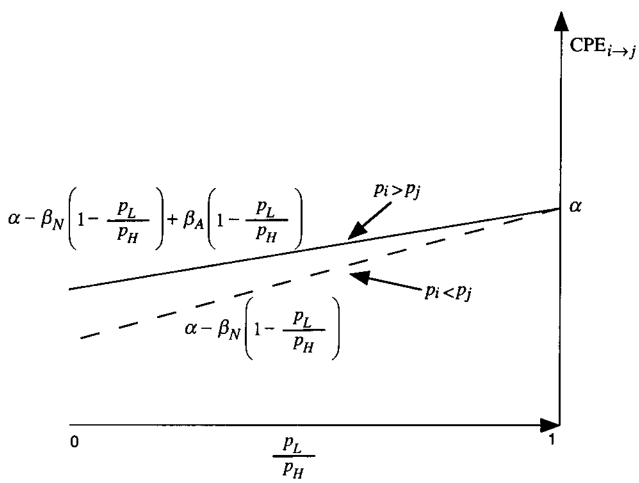
Case (ii) $p_i > p_j$

The asymmetric price effect states that the cross-price effect of the higher-priced brand's discount on the lower-priced brand's market share is greater than the reverse, i.e., $\text{CPE}_{H \to L} > \text{CPE}_{L \to H}$. In other words, keeping the ratio p_L/p_H fixed, $\text{CPE}_{i \to j}$ will be greater when $p_i > p_j$ than when $p_i < p_j$.[7] We assume that the asymmetric price effect $\text{CPE}_{H \to L} - \text{CPE}_{L \to H}$ becomes progressively larger as p_H becomes progressively larger than p_L. (The difference is obviously zero when $p_H = p_L$.) We assume a linear relationship so that

$$\text{CPE}_{H \to L} = \text{CPE}_{L \to H} + \beta_A (1 - p_L/p_H),\ \beta_A > 0. \tag{9}$$

[7]While the concept of asymmetric price effect is often framed in terms of price "tiers" (e.g., Blattberg and Wisniewski 1989), operationalization of the price tier construct becomes highly subjective. Furthermore, the theories proposed in support of the asymmetric price effect (e.g., Allenby and Rossi 1991; Bronnenberg and Wathieu 1996; Hardie, Johnson, and Fader 1993) apply to any two brands with differing price (quality) levels and not only to brands in different price tiers.

Figure 1 Asymmetric and Neighborhood Cross-Price Effects (CPE) as a Function of (p_L/p_H)[a]



Notation: $i \to j$: Effect of a price change of brand i on the market share of brand j; p_L is the lower of (p_i, p_j); p_H is the higher of (p_i, p_j).

[a]The solid line (slanted downward from right to left) illustrates the case of $\beta_N > \beta_A$. The solid line would be slanted upward from right to left if $\beta_A > \beta_N$.

In a later section, we relax the linearity assumption. Substituting for $\text{CPE}_{L \to H}$ from Equation (8) (recall that Equation (8) represents the effect of lower-priced brand on market share of a higher-priced brand), we obtain from Equation (9):

$$\text{CPE}_{i \to j} = \alpha - \beta_N (1 - p_L/p_H) + \beta_A (1 - p_L/p_H) \quad \text{for } p_i > p_j, \tag{10}$$

and is shown as the solid line in Figure 1.

Equation (8) for $p_i \leq p_j$ and Equation (10) for $p_i > p_j$ can be combined into a single equation by using a dummy variable as follows:

$$\text{CPE}_{i \to j} = \alpha - \beta_N (1 - p_L/p_H) + \beta_A (1 - p_L/p_H)\ \text{DUMHL} + \text{Covariates} + \epsilon_{i \to j}, \tag{11}$$

where DUMHL = Dummy variable representing the case when the price of discounting brand i is higher than the price of brand j whose sales is affected = 1 if $p_i > p_j$, and 0 otherwise.
Covariates = Other variables in the data set (e.g., type of product, number of brands in the category) that may influence the cross-price effect (to be discussed later).
$\epsilon_{i \to j}$ = Error.

The statistical hypotheses for testing (H1) asymmetric price effect and (H2) neighborhood price effect are the following one-tailed tests:

(H1) Asymmetric Price Effect:
H_{10}: $\beta_A \leq 0$; H_{1A}: $\beta_A > 0$.

(H2) Neighborhood Price Effect:
H_{20}: $\beta_N \leq 0$; H_{2A}: $\beta_N > 0$.

In addition, we are interested in determining which of these two effects is stronger. Because theory does not tell us which is stronger, we test the following two-tailed hypothesis:

(H3) H_{30}: $\beta_N - \beta_A = 0$; H_{3A}: $\beta_N - \beta_A \neq 0$.

The neighborhood price effect would be stronger if $\beta_N > \beta_A$ while the asymmetric price effect would be stronger if $\beta_A > \beta_N$.

Data

We performed a literature search of leading marketing, business and economic journals published between

1970 and 1996 and identified studies which (i) reported market level, unconstrained, short-term cross-price elasticity matrix for all brands analyzed,[8] and (ii) provided price and market share information. Fifteen studies met these criteria.[9] Several studies analyzed multiple products from multiple stores or chains. In particular, the 15 studies analyzed 19 different grocery product categories with a total of 280 brands, some from different chains/stores for a total of 72 data sets. If the same data set was used in different studies (e.g., Sethuraman 1995; 1996) but there was no duplication in cross-elasticities, we included both studies. Where the authors provided multiple estimates of elasticities using different functional forms, the estimate from the best functional form as identified by the authors was chosen. Where the authors did not identify the best functional form, we chose the best functional form based on model fit. Following this procedure, we obtained 1,060 cross-price elasticity estimates.

Approximately 95% of the cross-price elasticities are between -1 and 2—about 70% of the cross-price elasticities between 0 and 1, 15% between 1 and 2, and approximately 10% between -1 and 0. The mean cross-price elasticity is 0.52 (std. dev. = 0.86). In general, we expect a price cut (decrease in price) by a brand to decrease the sales of a competing brand, or the true cross-price elasticity to be nonnegative. However, what we obtain from the studies are estimated cross-price elasticities with associated measurement (estimation) errors. Because of these errors, estimates are negative in some cases. So, we consider these observations also as legitimate estimates (with measurement error) and include them in our analysis. Deleting these observations or truncating all negative values to zero would lead to potential biases in the estimated coefficients of the econometric model.

[8] We did not include matrices in which, for instance, some cross-elasticities were constrained to be equal.

[9] The studies are Allenby (1989); Allenby and Lenk (1994); Bemmaor and Mouscheau (1991); Blattberg and Wisniewski (1989); Bolton (1989); Bronnenberg and Wathieu (1996); Bucklin and Srinivasan (1991); Carpenter et al. (1988); Chintagunta (1993); Cooper (1988); Kamakura and Russell (1989); Kim et al. (1995); Russell and Bolton (1988); Sethuraman (1995, 1996). Two studies—Bolton (1989) and Sethuraman (1995)—did not report all the cross-price elasticities in their papers. These estimates were obtained from the authors.

Recall that the absolute cross-price effect $\gamma_{i\to j}$ was defined as the change in the market share (percentage) points of brand j when brand i's price changes by 1% of average category price. The average category price (p_c) is computed as a (market share) weighted average of the brand prices. Across the product categories considered in the study, the mean p_c is \$1.40 (std. dev. = \$0.83) so that, on average, 1% p_c is 1.4 cents. Approximately 97% of the absolute cross-price effects are between -0.25 and 0.5—about 78% of the absolute cross-price effects between 0 and 0.25, 9% between 0.25 and 0.5, and approximately 10% between -0.25 and 0. The mean absolute cross-price effect is 0.08 (std. dev. = 0.16).

Model Estimation and Results

The 15 studies in our database fall into three categories:

(i) *Market Share Models*: Three studies that estimate cross-elasticities with aggregate (store- or market-level) market share data using Attraction or double-log models.

(ii) *Sales Models*: Six studies that estimate cross-elasticities with aggregate sales data using linear, semi-log, or double-log models.

(iii) *Logit Models*: Six studies that estimate cross-price elasticities with consumer panel data using Logit choice models.

As discussed earlier, Logit models impose an inherent symmetric structure in the absolute cross-price effects and hence are not meaningful for testing asymmetry. The aggregate market share and sales models do not impose any constraints on the cross-effects, and hence are more appropriate for testing asymmetry. However, because one is a sales-based model and the other is share-based, there may be differences in the relevant effects estimated from these models. Following Lambin et al. (1975), it can be shown that (aggregate) sales cross-elasticity = share cross-elasticity + category expansion elasticity, where sales elasticity $[(\partial q_j/\partial p_i)(p_i/q_j)]$ is the percentage change in sales of brand j for 1% change in price of brand i, share elasticity $[(\partial s_j/\partial p_i)(p_i/s_j)]$ is the percentage change in market share of brand j for 1% change in price of brand i, and category expansion elasticity $[(\partial Q/\partial p_i)(p_i/Q)]$ is the percentage change in category sales for 1% change in price of brand *i*. Based on a study of thirteen grocery product categories, Bell et al. (1997) report that most of the price elasticity (86%) is due to brand choice. So, we expect the category expansion effects to be small relative to brand switching effect. Consequently, we expect the share and sales models to produce similar effects. We start by estimating Equation (11) separately for observations estimated from market share models and for observations from sales models. Then we combine these data sets, confirm that the regression equations can be pooled, and estimate the pooled effects.

Next, we estimate Equation (11) using observations from consumer panel-based Logit models. It would be useful to verify if the theoretically expected symmetry in absolute cross-price effects is actually observed in the data. Also the theory is based on infinitesimal price changes, whereas the empirical observations are based on discrete price changes. Furthermore, while Logit models are inherently biased when estimating asymmetric effects, they pose no problem for testing neighborhood price effects. Finally, for completeness, we estimate asymmetric and neighborhood price effects using all observations.

The covariates used in the model are number of brands in the product category, dummy variables to account for differences in functional form in the models that generated the cross-price effects (e.g., linear, semilog), dummy variables for capturing product category differences (e.g. fabric softener, orange juice), and dummy variables to capture chain/store differences in cases where the same product category was analyzed in multiple stores. We discuss the results for relevant covariates in a later section.

Inspection of condition indices did not reveal problems of multicollinearity in the regression models. The highest absolute correlation was 0.40 for the Logit data set, 0.43 for the sales data set, and 0.48 for the share data set. Heteroscedasticity was detected using the Breusch-Pagan/Godfrey test (Greene 1993, p. 395) and corrected using the weighted least squares approach (Kmenta 1986, pp. 269–283). Approximately 2–3% of the observations for which the magnitude of the residual was more than three times its standard error were identified as outliers, and excluded from the analysis.

Tests of equality of coefficients in model (11) for the market share and sales data sets: $\beta_{A|\text{share}} = \beta_{A|\text{sales}}$ and $\beta_{N|\text{share}} = \beta_{N|\text{sales}}$ failed to reject the null hypothesis with both cross-price elasticities ($F_{2,817} = 1.38, p > 0.10$) and absolute cross-price effects ($F_{2,811} = 1.48, p > 0.10$). Therefore, we pooled the observations from these models.

Regression Analysis of Cross-Price Elasticities

The regression results for the cross-elasticity models are presented in Table 1. The R^2 values range from 0.17

Table 1 Estimates of Asymmetric and Neighborhood Price Effects: Cross-Price Elasticities (η)

Data Set	# obsns.[a]	R^2 (adj. R^2)	β_N (s.e.)	β_A (s.e.)	$\beta_N - \beta_A$ (s.e.)
Market Share Models	263	0.38 (0.37)	1.22* (0.24)	0.40* (0.24)	0.82* (0.24)
Sales Models	591	0.17 (0.12)	1.43* (0.32)	0.66* (0.31)	0.78* (0.32)
Sales + Share Models (pooled)	854	0.20 (0.17)	1.40* (0.22)	0.52* (0.22)	0.88* (0.22)
Logit Models	184	0.40 (0.36)	0.90* (0.33)	0.68* (0.34)	0.22 (0.33)
All Observations (pooled)	1038	0.23 (0.20)	1.32* (0.19)	0.55* (0.20)	0.79* (0.19)

Table 2 Estimates of Asymmetric and Neighborhood Price Effects: Absolute Cross-Price Effects (γ)

Data Set	# obsns.[a]	R^2 (adj. R^2)	β_N (×100) (s.e.)	β_A (×100) (s.e.)	$(\beta_N-\beta_A)$ (×100) (s.e.)
Market Share Models	263	0.41 (0.40)	10.1* (3.82)	1.50 (3.82)	8.60* (3.80)
Sales Models	585	0.12 (0.07)	9.72* (4.71)	4.57 (4.70)	5.15 (4.72)
Sales + Share Models (pooled)	848	0.22 (0.18)	9.87* (3.20)	4.08 (3.22)	5.79 (3.21)
Logit Models	184	0.40 (0.37)	30.1* (7.74)	6.40 (7.73)	23.7* (7.74)
All observations (pooled)	1032	0.26 (0.23)	11.2* (3.10)	2.95 (3.12)	8.25* (3.10)

Notes for Tables 1 and 2

s.e. = standard error.

β_A = Asymmetric Price Effect; β_N = Neighborhood Price Effect.

[a]Excludes outliers.

*Significant at 5% level (one tailed test for β_A, β_N; two tailed for $\beta_N - \beta_A$).

to 0.40. This range of values is similar to $R^2 = 0.28$ obtained in prior meta-analysis of price elasticities (Tellis 1988). The null hypothesis H_{10}: $\beta_A \leq 0$ is rejected in all data sets indicating a strong and significant asymmetric price effect. The null hypothesis H_{20}: $\beta_N \leq 0$ is rejected in all data sets indicating a strong and significant neighborhood price effect. The null hypothesis H_{30}: $\beta_N - \beta_A = 0$ is also rejected in all except the Logit model. The magnitudes of the estimates indicate that the neighborhood price effect is considerably stronger than the asymmetric price effect.

Regression Analysis of Absolute Cross-Price Effects

The regression results for the absolute cross-effects models are presented in Table 2. The R^2 for the models range from 0.12 to 0.41. The null hypothesis H_{10}: $\beta_A \leq 0$ is not significant in observations from Logit models, as expected (see earlier discussion). It is also not significant at the .05 level in share and sales models suggesting that, in general, asymmetric price effect tends to disappear with absolute cross-effects. (The result is directionally consistent but not statistically significant.) The null hypothesis H_{20}: $\beta_N \leq 0$ is rejected in all data sets indicating a strong and significant neighborhood price effect. The null hypothesis H_{30}: $\beta_N - \beta_A = 0$ is also rejected in all except the Sales and (Sales + Share) models. The magnitudes of the estimates indicate that the neighborhood price effect is considerably stronger than the asymmetric price effect.

Tests of Robustness

We ran several alternative models to test the robustness of our main results, viz.: (i) The asymmetric price effect is strong and significant with cross-price elasticities but weaker and nonsignificant with absolute cross-price effects. (ii) The neighborhood price effect is strong and significant with both cross-price elasticities and absolute cross-price effects; it is also considerably stronger than the asymmetric price effect. Because Logit model observations have an inherent bias when measuring asymmetric effects, they are excluded and *the tests of robustness and all subsequent analysis are performed using pooled observations from market share and sales models only.*

Nonlinear Models. We assumed a linear relationship between price ratio (p_L/p_H) and cross-price effects. It is possible that the relationship is nonlinear. We included a quadratic term $(1 - p_L/p_H)^2$ in Equation (11) and estimated the following nonlinear model:

$$\begin{aligned}\text{CPE}_{i \to j} = \alpha &- \beta_N (1 - p_L/p_H) + \beta_A (1 - p_L/p_H)\,\text{DUMHL} - \beta'_N \\ &(1 - p_L/p_H)^2 + \beta'_A (1 - p_L/p_H)^2 \\ &\text{DUMHL} + \text{Covariates} + \text{Error}. \qquad (12)\end{aligned}$$

The increase in adjusted R^2 obtained by including the quadratic terms was very small (0.002 for elasticity model and 0.00 for absolute effects) and not statistically significant. We also studied power function models where the linear term $(1 - p_L/p_H)$ in Equation (11) was replaced by $(1 - p_L/p_H)^\delta$. Values of δ less than 1 represent a concave function while δ greater than 1 represents a convex function; $\delta = 1$ is the linear function (Equation (11)) estimated previously. We varied δ from 0 to 2 and compared the models based on fit (R^2). Again the difference in adjusted R^2 between the best-fit nonlinear model and the linear model was small (of the order of 0.004) and the basic results are unchanged. In summary, the linear models appear to fit the data almost as well as the best-fit nonlinear models and the results are robust.

Deleting Observations with $p_i = p_j$. Cross-price effects between brands which are equally priced ($p_i = p_j$) are quite informative about neighborhood price effect—these brands represent the closest possible neighbors and also enable the estimation of α (see Equation (11)). However, brand-pairs with $p_i = p_j$ do not provide information on asymmetric price effect. Hence, we tested whether the dominance of neighborhood price effect is observed even when observations with $p_i = p_j$ are deleted. As expected, the magnitude of the neighborhood price effect becomes slightly smaller. However, the main results did not change. The neighborhood price effect is strong and significantly larger than the asymmetric price effect for both η and γ.

Including Outlier Observations. We identified about 2–3% of total number of observations as outliers based on their large normalized residuals (greater than 3) and excluded them. To see the effect of these outliers, we estimated the price effects after including these observations. The neighborhood price effect is strong and significant with both elasticities and absolute effects. The asymmetric price effect is not statistically significant in either case probably because of the large standard errors that are obtained due to inclusion of extreme values.

Nonindependence of Observations. A common problem found with meta-analysis studies using regression procedures is the violation of the assumption of independence of observations. Farley and Lehmann (1986, p. 106) and Hunter and Schmidt (1990, p. 452) state that the bias due to nonindependence of observations may not be serious so long as the number of nonindependent observations is small relative to the total number of observations used in meta-analysis.

In our meta-analysis of cross-price effects, nonindependence of observations mainly arises due to the same brand in a data set appearing in multiple observations. For instance, consider four brands—i, j, k, l. These brands will lead to the following 12 cross-elasticities: $\eta_{i\to j}$, $\eta_{i\to k}$, $\eta_{i\to l}$, $\eta_{j\to i}$, $\eta_{j\to k}$, $\eta_{j\to l}$, $\eta_{k\to i}$, $\eta_{k\to j}$, $\eta_{k\to l}$, $\eta_{l\to i}$, $\eta_{l\to j}$, $\eta_{l\to k}$. Because brands i and j appear in both elasticities $\eta_{i\to j}$ and $\eta_{j\to i}$, these two observations are likely to be correlated. Similarly, because brand i appears in elasticities $\eta_{i\to j}$ and $\eta_{i\to k}$, the two observations may be correlated. The observations $\eta_{i\to j}$ and $\eta_{k\to l}$ can be deemed as independent because they represent elasticities for two different pairs of brands.

We account for the nonindependence of observations by modeling the error $\epsilon_{i\to j}$ in Equation (11) as

$$\epsilon_{i\to j} = u_{ij} + v_i + v_j \quad \text{or} \quad \epsilon_{i\to j} = u_{ij} + v_i - v_j,$$

where v_i, $v_j \sim \text{IID}(0, \sigma_v^2)$ are brand-specific error components, and $u_{ij} \sim \text{IID}(0, \sigma_u^2)$ is random error. We used a Generalized Least Squares (GLS) procedure to estimate Equation (11), and tested for the robustness of our results by examining one of the data sets, viz., the market share models data set.[10] There is only a small change in the GLS regression coefficients from the results reported in Tables 1 and 2 for cross-price elasticities and absolute cross-price effects. The standard errors of the estimates increased slightly in some cases, but there was no change in the results regarding statistical significance.[11]

[10]We could not undertake analysis of the sales model as the SAS PROC IML procedure we use on IBM 3090 with memory of 20 Meg, could only handle matrix operations on 420 observations. The sales model has over 580 observations.

Empirical Generalizations Based on Price Ordering

In the preceding sections, we developed a continuous-price econometric model for the specific purpose of testing asymmetric and neighborhood price effects and evaluating their relative magnitudes. From the standpoint of making price promotion decisions, managers are also interested in the following question: If I were managing (say) the highest priced brand or the fourth-highest priced brand, what can I expect in terms of cross-price effects? That is, which brand do I impact the most by discounting and which brand could hurt me the most through price changes? To address these questions, we analyze the data in terms of price ranks and develop a set of empirical generalizations regarding what the ith highest priced brand can expect in terms of cross-price effects. The analysis in this section can also be viewed as a further robustness check of our earlier empirical results in that we do not assume any specific functional form for linking relative prices of competing brands to cross-price effects.

Hypotheses

To obtain some insights into the pattern of cross-price effects by price rank, brands within each product category can be rearranged so that brand 1 ($i = 1$) denotes the highest-priced brand, $i = 2$ denotes the second highest priced brand, and so on. For the ith ranked (highest-priced) brand, $i - 1$ and $i + 1$ ranked brands are the closest price neighbors, $i - 2$ and $i + 2$ ranked brands are the second-closest neighbors. More generally, $i - k$ and $i + k$ ranked brands are the kth closest price neighbors. Based on our discussion in the earlier section titled, "Asymmetric and Neighborhood Price Effects," we state the neighborhood price effect hypothesis in terms of price ranks as follows:

HYPOTHESIS 4. *The ith highest-priced brand is most affected by discounts of its immediate price neighbors ($i - 1$th and $i + 1$th brand). The cross-price effect decreases when*

[11]The error variance-covariance matrix, the GLS procedure used for estimating their parameters, and the GLS results are available upon request.

the discounting brand (i − kth and i + kth brand) is more distant in price, i.e., as k increases.

The asymmetric price effect states that the higher-priced (lower price rank) brand's effect on the market share or sales of a lower priced brand ($i \rightarrow i + k$) is greater than the lower-priced brand's effect on the higher-priced brand ($i + k \rightarrow i$). We formally state the asymmetric price effect hypothesis in terms of price ranks as follows:

HYPOTHESIS 5. *The cross-price effect of a discount of the ith highest-priced brand on the market share or sales of a lower-priced (i + kth) brand is greater than the cross-price effect of a lower-priced brand on the market share or sales of a higher-priced brand, i.e.,* $\mathrm{CPE}_{i \rightarrow i+k} > \mathrm{CPE}_{i+k \rightarrow i}$.

Preliminary Analysis

Table 3 presents the mean cross-price elasticity between a brand and its *k*th closest-priced neighbor. (The values for $k > 6$ are not reported because of small sample sizes < 10.[12]) Consistent with the neighborhood price effect hypothesis, the *i*th highest-priced brand is affected most by its immediate (first) neighbors ($i -$ 1th and $i +$ 1th brand). The average cross-price elasticity is 0.696 (Column 5). The neighborhood price effect also suggests that the *i*th brand should be successively less affected by discounts of more distant brands, i.e., as we move to second neighbor ($k = 2$), third neighbor ($k = 3$), etc. In Table 3 (Column 5), as k increases, the average cross-price elasticity decreases except in the case when *k* increases from 2 to 3.

Similar results are found with patterns of absolute cross-price effects (Table 4). The *i*th highest-priced brand is affected most by its immediate neighbors ($k = 1$). As *k* increases, the average absolute cross-price effect decreases except when *k* goes from 2 to 3. The asymmetric effect would suggest that the difference (Column 3–Column 4) would be positive. This is found to be the case in five out of six cases with elasticities and four out of six cases with absolute cross-price effects.

[12]We also exclude observations for which $p_i = p_j$. Furthermore, a brand-pair (*i*, *j*) appears as two observations in Tables 1 and 2 but is counted as one observation in Tables 3 and 4.

Table 3 **Average Cross-Price Elasticity of a Brand on Its *k*th Closest-Priced Neighbor***

k	# Obsns.	Higher-Priced Brand's Effect on Lower-Priced Brand ($\eta_{i \rightarrow i+k}$)	Lower-Priced Brand's Effect on Higher-Priced Brand ($\eta_{i+k \rightarrow i}$)	$\frac{(\eta_{i \rightarrow i+k}) + (\eta_{i+k \rightarrow i})}{2}$	$(\eta_{i \rightarrow i+k}) - (\eta_{i+k \rightarrow i})$
1	181	0.754	0.638	0.696	0.116
2**	105	0.344	0.340	0.342	0.004
3	54	0.545	0.488	0.517	0.057
4	33	0.236	0.187	0.212	0.049
5	18	0.224	0.026	0.125	0.198
6	13	0.022	0.058	0.040	−0.036

*Data pertain only to market share and sales models (not logit models).

**On Average, the cross-price elasticity of a brand on its *second-closest lower-priced neighbor* is 0.344. The average cross-price elasticity of a brand on its *second-closest higher-priced neighbor is 0.340.*

Table 4 **Average Absolute Cross-Price Effect of a Brand on Its *k*th Closest-Priced Neighbor***

k	# Obsns.	Higher-Priced Brand's Effect on Lower-Priced Brand ($\gamma_{i \rightarrow i+k}$)	Lower-Priced Brand's Effect on Higher-Priced Brand ($\gamma_{i+k \rightarrow i}$)	$\frac{(\gamma_{i \rightarrow i+k}) + (\gamma_{i+k \rightarrow i})}{2}$	$(\gamma_{i \rightarrow i+k}) - (\gamma_{i+k \rightarrow i})$
1	181	0.086	0.093	0.090	−0.007
2	105	0.057	0.065	0.061	−0.008
3**	54	0.082	0.070	0.076	0.012
4	33	0.047	0.039	0.043	0.008
5	18	0.022	0.008	0.015	0.014
6	13	0.013	0.007	0.010	0.006

*The absolute cross-price effect reported here is the change in the market share (percentage) points of brand *j* when brand *i*'s price changes by 1% of average category price, p_c. Across the product categories considered in the study, the mean p_c is $1.40 so that, on average, 1% p_c is 1.4 cents. The data on cross-price effects pertain only to market share and sales models (not logit models).

**On average, the absolute cross-price effect of a brand on its *third-closest lower-priced neighbor* is 0.082. The average absolute cross-price effect of a brand on its *third-closest higher-priced neighbor* is 0.070.

Econometric Model

We present an econometric model for testing the asymmetric and neighborhood price main effects (H4 and H5). In addition, we examine whether there is an interaction between asymmetric and neighborhood price effects. That is, is the asymmetry greater when the brands are neighboring brands or when the brands are distant brands? Since asymmetry has been generally discussed in the literature in terms of high-price-tier brands and low-price-tier brands, the spirit of that discussion would suggest that the asymmetry would become more significant when they are nonneighboring brands (brands priced farther apart) than when they are neighboring closer-priced brands. On the other hand, Sivakumar (1997) shows that asymmetric price effect is smaller if the price differential is larger, i.e., if the brands are distant in price. So, the sign of the effect is ambiguous.

The following model is used for testing H4 and H5 and investigating if there is an interaction between neighborhood and asymmetric price effects:

$$\begin{aligned} \text{CPE}_{i\to j} = {} & \alpha + \beta_{N1}\ \text{NEIBOR1} + \beta_{N2}\ \text{NEIBOR2} \\ & + \beta_{N3}\ \text{NEIBOR3} + \beta_{N4}\ \text{NEIBOR4} \\ & + \beta_{A}\ \text{ASYM} + \beta_{A1}\ \text{ASYM*NEIBOR1} \\ & + \beta_{A2}\ \text{ASYM*NEIBOR2} \\ & + \beta_{A3}\ \text{ASYM*NEIBOR3} \\ & + \beta_{A4}\ \text{ASYM*NEIBOR4} + \text{Covariates} \\ & + \text{Error.} \end{aligned} \tag{13}$$

NEIBORK = Dummy variable for kth closest-priced neighbor ($k = 1$ to 4)
= 1 if $j = i + k$ or $j = i - k$ when brands are arranged in price ranks,
= 0, otherwise.

We combine all the observations with $k > 4$ into the baseline dummy variable and call them "distant" brands. Thirty observations with $k = 0$ ($p_i = p_j$) are excluded from this analysis.

ASYM = Dummy variable for high-priced brand's effect on low-priced brand
= 1 if rank of $i <$ rank of j, i.e., brand i is higher priced than brand j,
= 0, otherwise.

According to the neighborhood price effect (H4), β_{N1} to β_{N4} should be positive and $\beta_{N1} > \beta_{N2} > \beta_{N3} > \beta_{N4} > 0$. The asymmetric price effect (H5) states that $\beta_A > 0$, and the interaction effect can be tested with the null hypothesis, H_0: $\beta_{A1} = \beta_{A2} = \beta_{A3} = \beta_{A4} = 0$.

The covariates used in the model are number of brands in the category, product type (food or non-food), functional form used for the estimation (linear, semi-log, log-log, MCI Attraction) and dummy variables to indicate store differences.

Regression Analysis and Findings

The estimates from Model (13) for cross-price elasticity are reported in Table 5 (Column 2). Coefficients β_{N1} to β_{N4} are all positive with the first three coefficients being

Table 5 Regression Results—Price Rank Model (Equation 13)

	Cross-Price Elasticity (η)		Absolute Cross-Price Effect ($\gamma \times 100$)	
Variable (Coefficient)	With Interaction	Without Interaction	With Interaction	Without Interaction
Intercept (α)	0.68 (0.23)*	0.67 (0.23)*	21.60 (3.2)*	21.60 (3.09)*
NEIBOR1 (β_{N1})	0.40 (0.11)*	0.41 (0.09)*	3.92 (1.53)*	3.28 (1.18)*
NEIBOR2 (β_{N2})	0.19 (0.12)*	0.22 (0.09)*	1.34 (1.57)	1.82 (1.19)*
NEIBOR3 (β_{N3})	0.30 (0.13)*	0.30 (0.10)*	1.47 (1.78)	2.19 (1.29)*
NEIBOR4 (β_{N4})	0.11 (0.15)	0.09 (0.11)	1.00 (1.97)	1.45 (1.42)
DISTANT (base)	0	0	0	0
ASYM (β_A)	0.09 (0.13)	0.11 (0.05)*	−0.12 (1.71)	−0.16 (0.61)
ASYM*NEIBOR1 (β_{A1})	0.01 (0.15)	—	−1.27 (1.96)	—
ASYM*NEIBOR2 (β_{A2})	0.08 (0.16)	—	0.96 (2.10)	—
ASYM*NEIBOR3 (β_{A3})	0.00 (0.18)	—	1.42 (2.42)	—
ASYM*NEIBOR4 (β_{A4})	−0.04 (0.21)	—	0.89 (2.75)	—
# of brands	−0.06 (0.02)*	−0.06 (0.02)*	−1.88 (0.25)*	−1.87 (0.25)*
Non-Food	0.10 (0.05)*	0.10 (0.05)*	0.06 (0.64)	0.05 (0.64)
Food (base)	0	0	0	0
Sales (Linear)	−0.12 (0.15)	−0.13 (0.15)	−4.49 (2.03)*	−4.44 (2.03)*
Sales (Semi-log)	−0.32 (0.16)*	−0.32 (0.16)*	−6.31 (2.26)*	−6.26 (2.26)*
Sales (Log-log)	−0.13 (0.15)	−0.12 (0.15)	−3.77 (2.10)*	−3.69 (2.10)*
Share (base)	0	0	0	0
R^2 (adjusted R^2)	0.18 (0.15)	0.18 (0.15)	0.23 (0.20)	0.22 (0.20)

*Significant at the 0.05 level. Standard errors are in parentheses.

Data ($n = 854$) pertain only to market share and sales models (not logit models).

statistically significant. Immediate price neighbor (NEIBOR1) has the highest coefficient value (0.40). The values generally decrease when k increases except when k goes from 2 to 3. The equality of neighborhood effects, $\beta_{N1} = \beta_{N2} = \beta_{N3} = \beta_{N4} = 0$ is rejected: $F_{4,799} = 4.34$, $p < 0.05$. Thus we find evidence for neighborhood price effects.

Coefficient β_A is positive as predicted though not statistically significant. Test of $\beta_{A1} = \beta_{A2} = \beta_{A3} = \beta_{A4} = 0$ failed to reject the null hypothesis, $F_{4,799} = 0.17$, $p > 0.10$ suggesting that there is no significant interaction between asymmetric effect and price neighbors. When we deleted the variables representing the interaction effect, the main effect of asymmetry β_A becomes statistically significant (see Table 5—Column 3). One possible reason for the lack of significance of β_A in the model with interactions is the multicollinearity between the main effect variable ASYM and interaction variables ASYM*NEIBOR.

The estimates from Model (13) for absolute cross-price effects are also reported in Table 5 (Column 4). Coefficients β_{N1} to β_{N4} are all positive with the first coefficient being statistically significant. Their magnitudes are decreasing except when k goes from 2 to 3. The equality of neighborhood effects H_0. $\beta_{N1} = \beta_{N2} = \beta_{N3} = \beta_{N4} = 0$ is rejected: $F_{4,789} = 2.55$, $p < 0.05$.

Coefficient β_A is negative (reversed in sign) but not statistically significant. Test of H_0: $\beta_{A1} = \beta_{A2} = \beta_{A3} = \beta_{A4} = 0$ failed to reject the null hypothesis, $F_{4,789} = 0.82$, $p > 0.10$, suggesting that there is no significant interaction between asymmetric effect and price neighbors. When we deleted the variables representing the interaction effect, the main asymmetric effect β_A continued to be negative in sign and not statistically significant.

Overall, the results of Model (13) confirm those of Model (11).

Covariates. The coefficient corresponding to Number of Brands variable is negative and significant in all models. That is, the average cross-price effect is higher when there are fewer brands in the market. In other words, price competition between any two brands is more intense when there are fewer other brands in the market. In addition, nonfood products have significantly higher cross-price elasticity than food products.

National Brand vs. Store Brand Competition

Blattberg and Wisniewski's (1989) pioneering study and several studies following theirs (e.g., Kamakura and Russell 1989, Mulhern and Leone 1991, Sethuraman 1995) have suggested that patterns of cross-price effects can be related to price tiers. In particular, they focused on the competition between the high-price-tier national brands and low-price-tier store brands. There are at least two good reasons for this focus. In general, national brands are the higher-priced, higher-quality brands. Retailers in the U.S. attempt to draw sales from the national brands by offering a store brand or private label alternative of acceptable quality at lower prices. Thus, store brands represent a low-priced substitute for national brands and therefore the competition between national brands and private labels is an useful setting for understanding price competition between brands in different price tiers. Second, store brands have witnessed considerable growth in recent times. They now account for over 48 billion dollars of grocery product sales and the dollar share of store brands is expected to grow from the current 14% to about 20% by early in the next century (Hoch and Banerji 1993, Khermouch 1996).

The competition between national brands and store brands provides a natural setting for testing asymmetric price effects. (Our objective is not to separate out the price tier effect from the national vs. store brand effect, which is difficult to do because of collinearity.) In particular, we address the following questions:

1. *Is the cross-price elasticity of national brands' discount on store brand sales* $\eta_{\mathrm{NB}\to\mathrm{SB}}$ *greater than the cross-price elasticity of store brands' discount on national brand sales* $\eta_{\mathrm{SB}\to\mathrm{NB}}$?

2. *Does the asymmetric effect hold for absolute cross-price effects as well, i.e., is* $\gamma_{\mathrm{NB}\to\mathrm{SB}} > \gamma_{\mathrm{SB}\to\mathrm{NB}}$?

3. *What type of national brands (high-priced or low-priced) hurt store brands with their discounts and what types of national brands are hurt by store brands when they discount?*

Data and Analysis

Six of the nine studies that estimated cross-price effects using sales or share models analyzed and identified the store brands. From these studies, observations which represented cross-price effects between national brands and store brands were selected. There are 105 observations with cross-price effect of national brand discount on store brand sales ($CPE_{NB \rightarrow SB}$) and 105 observations with cross-price effect of store brand discount on national brand sales ($CPE_{SB \rightarrow NB}$). In all these cases, the prices of store brands were lower than the prices of national brands. Generic brands were not included in this analysis.

The mean cross-price elasticity of national brand's price cut on store brand market share (or sales), $\eta_{NB \rightarrow SB} = 0.48$. The mean cross-price elasticity of store brand's price cut on national brand market share (or sales), $\eta_{SB \rightarrow NB} = 0.34$. The difference ($\eta_{NB \rightarrow SB} - \eta_{SB \rightarrow NB} = 0.14$) is statistically significant ($t_{104} = 1.88$, $p < 0.05$).

The mean absolute cross-price effect of national brand's price cut on store brand sales, $\gamma_{NB \rightarrow SB} = 0.07$. The mean cross-price effect of store brand's price cut on national brand sales, $\gamma_{SB \rightarrow NB} = 0.072$. The difference ($-0.002$) is negative (reverses in sign) though not significant.

To see which national brands compete the most with store brands, we compute the mean cross-price effects for the kth closest priced neighbor. The results are given below.

National Brand	# Obsns.	Cross-Price Elasticity NB → SB	Cross-Price Elasticity SB → NB	Absolute Cross-Price Effect NB → SB	Absolute Cross-Price Effect SB → NB
Closest in Price to Store brand ($k = 1$)	24	.688	.638	.101	.130
2nd Closest ($k = 2$)	25	.638	.350	.091	.084
3rd Closest ($k = 3$)	24	.552	.321	.079	.055
4th Closest ($k = 4$)	13	.229	.222	.042	.067

Consistent with the neighborhood price effect, the average cross-price effect is the highest with the national brand that is closest in price to the store brand. Since a large number of categories in this data set had 4 or 5 brands, the closest-priced brand tends to be the moderately priced 3rd or 4th highest-priced national brands. The cross-price effects decrease as we move to more distant neighbors (as k increases).

To identify the national brands that compete the most with store brands after accounting for other variables, we ran a regression model similar to Equation (13) without the interaction effects (which were found to be nonsignificant).

$$\begin{aligned} CPE_{NB \leftrightarrow SB} = {} & \alpha + \beta_{N1} \text{ NEIBOR1} \\ & + \beta_{N2} \text{ NEIBOR2} + \beta_{N3} \\ & \text{NEIBOR3} + \beta_A \text{ ASYM} \\ & + \text{Covariates} + \text{Error}. \end{aligned} \tag{14}$$

NEIBORK = Dummy variable for kth closest-priced national brand ($k = 1$ to 3)
= 1 if the national brand is the kth closest neighbor of the store brand
= 0, otherwise.

ASYM = Dummy variable for measuring asymmetry between national brand and store brand
= 1 if discounting brand (i) is the national brand and j is the store brand
= 0, if discounting brand (i) is the store brand and j is the national brand.

The relevant estimates are as follows:

CPE	ASYM (s.e.)	NEIBOR1 (s.e.)	NEIBOR2 (s.e.)	NEIBOR3 (s.e.)
Elasticity (η)	0.14(.06)*	.34(.10)*	.18(10)*	.12(.10)
Absolute Effect ($\gamma \times 100$)	−.35(1.29)	3.95(2.02)*	.58(2.04)	.07(1.95)

* = Significant at 0.05 level.

The basic results hold in the context of national brand vs. store competition as well—asymmetric effect (ASYM) disappears with absolute cross-price effects; national brands which are closest in price to the store brands (NEIBOR1) compete the most with store brands.

Discussion of Results and Conclusion

Understanding inter-brand price competition is useful for gaining insights into market structure and competitive promotion strategies. Blattberg and Wisniewski (1989) introduced an interesting concept called the asymmetric price effect. This concept states that when high-priced/high-quality brands discount, they impact the low-priced/low-quality brands more so than the reverse. This concept has been extensively discussed in the literature.

The neighborhood price effect, which has received relatively less attention, states that brands that are closer to each other in price have greater cross-price effects than brands that are priced farther apart. This paper tests the empirical generalizability of these two effects as well as generates some additional empirical generalizations.

An important finding is that the asymmetric price effect holds in the case of cross-price elasticities (% change in market share or sales for 1% change in competitor price) but tends to disappear with absolute cross-price effects (change in market share (percentage) points of a target brand when a competing brand's price changes by 1% of category price). This finding holds for observations from both logit and non-logit (market share and sales) models. The following inferences can be made from these results:

1. The findings are consistent with the Logit choice model (with brand preferences and price sensitivities heterogeneous across consumers), for which theory predicts that there would be no asymmetry in absolute cross-price effects.

2. The conventional belief is that store brand consumers switch to national brands when national brands promote but national brand consumers do not switch to store brands when they promote. This is a statement regarding absolute cross-price effects that does not seem to hold in the aggregate.

3. The observed asymmetry in cross-price elasticities, as shown earlier, may simply be due to the (theoretically expected and empirically observed) positive correlation between price and market share across brands.

Our finding of symmetry in absolute cross-price effects runs somewhat counter to Kumar and Leone (1988, Table 1) who observe asymmetry in absolute effects in at least one of three brand-pairs.[13] However, our finding that the conventional asymmetric price effect is not generalizable is consistent with other recent studies that report null or opposing effects. For instance, Bronnenberg and Wathieu (1996) suggest that asymmetric price effect would depend on the relative price-quality positioning between the two brands. In particular, if the lower-priced brand has more favorable price-quality positioning, then the asymmetry would be reversed; in fact, the lower-priced, lower-quality brand may hurt the higher-priced brand more through discounting than vice versa. Lemon and Winer (1993) show that asymmetry is not observed in categories where there is extensive brand switching due to price promotions. Relatedly, Ailawadi, Gedenk, and Neslin (1998) find that deal-prone consumers switch among brands in general and not specifically from lower-priced store brands to higher-priced national brands. Heath et al. (1996) conducted several lab experiments and point out that asymmetry may not be observed under all conditions. In particular, they argue that one theoretical basis for asymmetry, viz., the income effect offered by Allenby and Rossi (1991), may be quite weak in grocery products where the average purchase price is not very high.

What appears to be a generalizable finding is that there is a strong neighborhood price effect. Brands that are priced closer to each other have greater cross-price effects than brands that are priced farther apart. In particular, a brand is most affected by discounts of a competing brand that is immediately higher in price, followed by discounts of a brand that is immediately lower in price.

The strong neighborhood price effect may itself be a possible reason for the weak asymmetric price effect. The reasoning can be linked to the concept of consideration sets. Consider a store brand priced at $1.00, a low-priced national brand priced at $1.20, and a high-priced national brand at $1.80. Theories supporting the conventional asymmetric price effect assume that the consumer who purchases the low-priced store brand

[13]We could not include their observations in our meta-analysis because their study did not provide brand price or market share information.

has the high-priced national brand in his/her consideration set. The strong neighborhood price effect suggests that it may not be necessarily be the case. The greatest cross-price effect for the store brand is with its immediate price neighbors ($1.20 national brand). The cross-price effects go down considerably when we go to distant higher-priced brands. That is, few consumers consider the high-priced ($1.80) national brand and switch when it is discounted. Therefore, the asymmetric price effect may be weak.

The above findings have important implications for brand managers. If the asymmetric price effect were the dominant effect, the store brand manager should be relatively more concerned about the price cuts of the higher-priced ($1.80) national brand. If the neighborhood price effect were dominant, which we find to be the case, the store brand manager should be more concerned about the discounts by the lower-priced ($1.20) national brand. More generally, our results indicate that brand managers should pay closer attention to discounts of its closely priced neighboring brands and take appropriate defensive actions.

The empirical analysis also yielded other interesting results. We find that cross-price effects are larger when there are fewer brands in the market. This finding is consistent with intuition. When there is a large number of brands on the market, the sales draw due to a brand's price cut is distributed across several brands, so any one brand may not be highly affected by discount of a competing brand. Whereas, if there are say just two brands on the market and if one brand discounts, it will likely draw a significant number of consumers from its only competitor. That the results holds across different models and across both measures of cross-price effects suggest this phenomenon is indeed an empirical generalization.

We also find that the cross-price elasticity is higher for brands in the nonfood products category than in food products. In our data set, the categories representing food products include coffee, ketchup, orange juice, peanut butter, tuna, waffles, and wine. The nonfood products include bathroom tissue, bleach, cleanser, fabric softener, lacquer, and litter. Typically, these non-food products are household cleaning related products (not health or beauty aid products). Our analysis suggests that the price competition (in terms of cross-elasticity) for these nonfood products are greater than that for food products. So, from a competitive price promotion standpoint, managers of nonfood household products should engage in more discounting than food products.

Limitations and Future Research Directions

We believe there are two main limitations with our empirical analysis which are typical of most meta-analytic studies with similar focus. First, like Assmus et al. (1984), Tellis (1988), Sethuraman and Tellis (1991), we meta-analyze point estimates and not their ranges of values. So, our findings are valid for small short-term changes in prices around the average price. Second, our database consists only of grocery products. Thus, our generalization results pertain mainly to grocery products. Whether the generalizations hold for other durable goods and for industrial products are issues for future research.

The existence of asymmetry in elasticities but not in absolute cross-price effects provides at least three avenues for future research. First, future research can identify the conditions when asymmetric (absolute) price effect holds and when it will not, along the lines of Bronnenberg and Wathieu (1996). Second, an interesting question is whether there are any asymmetries in absolute cross-price effects at all, not just based on price ordering. Unfortunately, most studies did not provide variances or covariances of the estimates, so we could not test the hypothesis in our meta-analysis data set. Third, the difference in finding between elasticity measure and absolute measure raises the question of which measure is more relevant. From a broad perspective, because one measure is a scaled version of the other, both are equally relevant. From a profitability standpoint, if a firm's objective is to increase (absolute) profits obtained from promotion, then perhaps the absolute cross-price effect is more proximal to such computations. As stated earlier, asymmetries in elasticities may arise simply due to the positive correlation between price and market share. Hence, from the standpoint of testing asymmetry, we believe analyzing absolute cross-price effects provides a stronger test.[14]

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