

Consumers' Price Sensitivities Across Complementary Categories

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In this paper, we examine the pattern of correlation among consumer price sensitivities for customer purchase incidence decisions across complementary product categories. We use a hierarchical Bayesian multivariate probit model to uncover this pattern. We estimated this model using purchase incidence data for six categories involving three pairs of complementary products.

Our results show a new and interesting pattern of correlation among price parameters of complementary products. For example, we find that the correlation of own-price sensitivities of complementary products is negative. These results are consistent across the three complementary pairs of products. We also investigate the reason for this counterintuitive result.

Finally, we present some managerial implications of our model. We show how our model can be used for cross-category targeting decisions by retailers. We find that compared to nontargeted discounting, the average profitability gain from customized discounting across the three category pairs is only 1.29% when complementarity is ignored, but this gain improves to 8.26% when full complementarity is taken into account. We also investigate whether ignoring the complex pattern of correlation has implications for managerial actions regarding targeting and optimal discounting. We find that retailers can make misleading inferences about the impact of targeted discounts when they ignore cross-category effects in modeling.

Key words: cross-category analysis; price sensitivity; multivariate probit; hierarchical Bayesian analysis

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1. Introduction

Are consumers' price sensitivities across product categories correlated? This question is important from both a theoretical and managerial perspective. Theoretically, it is useful to understand if price sensitivity is a consumer-specific trait. In other words, are some consumers more price sensitive than others regardless of the product category they purchase? Managerially, a better understanding of these consumer traits can help both manufacturers and retailers. If some consumers are inherently more price sensitive than others in multiple categories, it has strong implications for their targeting and micromarketing decisions. It may also help firms in cross-selling. Firms may be able to use information about consumers' purchase behavior in one category to predict their behavior in other categories (Iyengar et al. 2003).

Because of its theoretical and practical importance, marketing researchers have examined consumers' cross-category purchase behavior for more than four

decades. For example, Blattberg et al. (1978) examined household characteristics that determine their deal proneness. Bell et al. (1999) analyzed several categories and decomposed price elasticities into category-, brand-, and consumer-specific factors. Ainslie and Rossi (1998) studied consumers' sensitivities to price and promotion in their brand choice behavior across five categories. Wedel and Zhang (2004) built a store-level sales model that incorporates cross-effects to study national and private label competition. Table 1 provides a summary of the subset of cross-category research that focuses on correlation in price sensitivities.

A common and potentially generalizable result from the studies reported in Table 1 is that consumers' price sensitivities are indeed strongly correlated across product categories. Further, this correlation is positive, suggesting that a consumer who is very price sensitive in category A is also likely to be very price sensitive in category B.

Table 1 Evidence from the Multicategory Literature

Authors	Categories	Model	Correlation in price effects
Brand choice models			
1. Ainslie and Rossi (AR) (1998)	Canned tuna, ketchup, margarine, peanut butter, toilet tissue	Independent multinomial probit variance components for marketing-mix effects	0.28
2. Seetharaman et al. (1999)	Same as AR (1998)	Same as AR (1998) with interpurchase time included	0.15
3. Kim et al. (1999)	Same as AR (1998)	Independent logit pairwise correlations	0.05 to 0.16
4. Erdem and Sun (2002)	Toothpaste, toothbrush	Multivariate multinomial probit	0.63
5. Iyengar et al. (2003)	Breakfast foods, table syrup	Independent multinomial probit; covarying marketing-mix effects	0.21
6. Singh et al. (2005)	Potato chips, tortilla chips, pretzels, cheese, mayonnaise	Multinomial logit with factor structure on marketing-mix effects	0.36 pretzels and potato chips 0.45 potato and tortilla chips
7. Song and Chintagunta (2006)	Detergent (powder and liquid), softener (dry and liquid)	Multivariate logit	0.50-0.94

Two things can be noted based on the previous literature on cross-category effects. First, most studies that examine the nature of correlation in price sensitivities have focused on consumers' brand choice behavior (e.g., Ainslie and Rossi 1998, Singh et al. 2005). Studies that incorporated purchase incidence and brand choice in an integrated framework (Erdem and Sun 2002, Song and Chintagunta 2006, Mehta 2006, Niraj et al. 2007, and Song and Chintagunta 2007) have not focused on the correlation in price sensitivities. Similarly, studies that have examined purchase incidence or category choice alone have primarily focused on error correlation rather than the correlation in price sensitivities (e.g., Manchanda et al. 1999, Russell and Petersen 2000, Chib et al. 2002). A priori, there is no reason to believe that price correlation does not remain strong for purchase incidence models also. In this paper, we empirically examine this issue.

Second, and more importantly, many papers that examined correlation in price sensitivities used unrelated product categories. For example, Ainslie and Rossi (1998) use ketchup, peanut butter, stick margarine, toilet tissue, and tuna fish categories and specifically exploit this independence of categories in their model specification. A priori, we would expect that if consumers' price sensitivities are positively correlated in unrelated categories, they will be even more strongly and positively related in complementary categories (e.g., spaghetti and sauce). In this paper, we show this intuition to be wrong. In fact, we find that in the purchase incidence models price sensitivities for complementary products are negatively correlated. We further show that if we use a commonly misspecified model, this correlation is strongly positive for the same data. We also examine the reasons for this change in the direction of correlation.

This paper is organized as follows. We first describe our model in §2. We then describe the data used (§3), the models we estimate (§4), and the results of our analysis (§5). Next, in §6, we provide theoretical and empirical support for the complex pattern of correlations we uncover. We then show, in §7, how managers can use the model for cross-category targeting of optimal discounts. In §8, we conclude with a summary of our findings and contributions.

2. Model

We use a multivariate probit model for consumers' purchase of multiple categories. Our modeling approach has three main characteristics. First, the utility errors across categories are correlated to permit coincidence (Manchanda et al. 1999). Second, the price sensitivity (and other marketing-mix) coefficients are correlated across categories. Third, the preference or intercept depends on household demographics. These intercepts are also correlated across categories.

Specifically, each household, $i = 1$ to I , makes purchases across a set of $j = 1$ to J categories on a given trip t to the store. The purchase incidence decisions can be represented by a vector $\mathbf{y}_{it} = \{y_{i1t}, y_{i2t}, \dots, y_{iJt}\}$ of binary variables. Consistent with random utility formulation, the observed purchase behavior is modeled in terms of latent utilities for the categories. Therefore, the underlying utilities for the J categories can be written as

$$\mathbf{u}_{it} = \boldsymbol{\alpha}_i + \mathbf{X}_{it}\boldsymbol{\beta}_i + \boldsymbol{\epsilon}_{it}, \quad (1)$$

where the vector $\boldsymbol{\alpha}_i = \{\alpha_{i1}, \alpha_{i2}, \dots, \alpha_{iJ}\}$ contains the individual-level category-specific intercepts that represent the strength of the individuals' preferences for a given category. The causal parameters in $\boldsymbol{\beta}_i = \{\boldsymbol{\beta}_{i1}, \boldsymbol{\beta}_{i2}, \dots, \boldsymbol{\beta}_{iJ}\}$ capture the effect of covariates (e.g., price) on the purchase incidence decisions.

The unobservable effects that influence purchasing behavior on a shopping trip are represented by the vector $\epsilon_{it} = \{\epsilon_{i1t}, \epsilon_{i2t}, \dots, \epsilon_{ijt}\}$. To capture the commonalities among these unobservable factors, we assume that $\epsilon_{it} \sim N(0, \Sigma_u)$. Given the binary nature of the observed responses, the scale of the utilities are not observable. Thus, for identification, Σ_u is restricted to be a $J \times J$ correlation matrix. This correlated error structure for the utilities captures co-occurrence. If $\text{corr}(\epsilon_{ijt}, \epsilon_{ij't}) > 0$, it implies that utility for category j shares contemporaneous unobserved factors with the utility for category j' . These unobserved factors may characterize underlying complementary consumption contexts that drive joint purchasing activities across categories.

To capture the heterogeneity across households, we further model the intercepts as follows:

$$\alpha_i \sim N(\mathbf{Z}_i \boldsymbol{\alpha}, \boldsymbol{\Sigma}_\alpha), \quad (2)$$

where \mathbf{Z}_i is a matrix containing the demographics for household i and $\boldsymbol{\Sigma}_\alpha$ captures the covariation in the intercepts. The demographics model the observed portion of the heterogeneity in consumers' purchase behavior.

Finally, we specify

$$\boldsymbol{\beta}_i \sim N(\boldsymbol{\mu}_\beta, \boldsymbol{\Sigma}_\beta), \quad (3)$$

where $\boldsymbol{\Sigma}_\beta$ captures the covariation in consumers' response sensitivities to the marketing-mix variables such as price. Given our primary interest in exploring the nature of price correlation across complementary categories, this matrix is of critical importance to us.

The relationship between the observed data and the latent utilities can then be written as

$$y_{ijt} = \begin{cases} 1 & \text{if } u_{ijt} > 0, \\ 0 & \text{otherwise.} \end{cases} \quad (4)$$

The above formulation of the error structure yields a multivariate probit model (Greene 1997, Chib and Greenberg 1998). This formulation is appropriate for our research because it allows the analysis of a "basket of goods" (purchase incidence in more than one category, simultaneously) for any given purchase trip. Thus, we can model both the size of the basket as well as its composition.

We use simulation-based Bayesian inference for obtaining parameter estimates. Markov Chain Monte Carlo (MCMC) methods utilizing data augmentation procedures (Tanner and Wong 1987, Albert and Chib 1993) and the Metropolis-Hastings algorithm were used to simulate parameter draws from the posterior distribution.

3. Data

We use scanner panel data, provided by ACNielsen, for three pairs of complementary categories: spaghetti

Table 2 Pairwise Purchase Incidence in Estimation Sample

Category	Spaghetti	Sauce	Detergent	Softener	Cake mix	Frosting
Spaghetti	301	437	154	135	88	53
Sauce	...	837	297	227	147	110
Detergent	734	440	108	89
Softener	414	92	70
Cake mix	243	334
Frosting	116

and sauce, detergent and fabric softener, and cake mix and cake frosting. The data span 124 weeks from January 1993 to May 1995 and come from households in a major metropolitan area in the midwestern region of the United States. Households that made at least one purchase in each of the six categories during the 124 weeks were first selected. This yielded a sample of 226 households. From these, a random sample of 126 households was drawn for estimation. The total number of store trips in the estimation sample is 16,032. At least one category was purchased on 1,656 trips.

The pairwise incidence across all six categories is given in Table 2. The diagonal elements in this table give the trips when there was a purchase only in that category. For example, spaghetti was bought by itself on 301 shopping trips. The off-diagonal elements indicate the joint incidence between categories. For example, spaghetti and sauce were bought 437 times on the same shopping trip. A simple χ^2 test revealed that all the numbers in the table show significant dependence. Further, a ϕ -test revealed that the associations for spaghetti-sauce, detergent-softener, and cake mix-frosting pairs are much higher than that for the other pairs. These pairs are labeled "pasta," "laundry," and "dessert" groups, respectively.

We use price, promotion, and inventory as explanatory variables. Consistent with previous cross-category research, the price variables are constructed as follows. When a household makes a purchase in a category, the price paid is tabulated. On the occasions when a household does not make a purchase in a given category, prices are constructed using a weighted average across the brands bought by the household during the history of the data set.¹ To allow for the differences in size of item purchased and to facilitate comparisons across categories, the price variable is computed as price per unit of measurement (e.g., ounce).

The category-level promotion variable is constructed using the feature and display information in the store files. When a brand is on display or feature, the promotion variable is one, otherwise it is zero.

¹ While a category-level price can be an imperfect measure of prices faced, our use of weighted averages over the consideration set mitigates this concern.

Table 3 Correlation in Price Data

	Spaghetti	Sauce	Detergent	Softener	Cake mix	Frosting
Spaghetti	1.00	0.20	0.12	0.001	0.13	0.16
Sauce	...	1.00	0.05	-0.04	0.06	0.07
Detergent	1.00	0.16	0.09	0.11
Softener	1.00	0.06	0.05
Cake mix	1.00	0.09
Frosting	1.00

Note. Correlations in bold indicate significance at 95% level.

As in the case of prices, the category-level promotion variable is the weighted average of promotion across brands bought by a household in each time period. This variable takes values between zero and one.

We use the approach suggested by Bucklin and Gupta (1992) to construct a category-level inventory variable for a household. Specifically, the inventory variable for household i in category j at time t , I_{ijt} , is defined as

$$I_{ijt} = I_{ij,t-1} + Q_{ij,t-1} - C_{ij} * W_{j,t-1}, \quad (5)$$

where $Q_{ij,t-1}$ is the quantity purchased (in ounces) by household i in category j at time $t-1$; $W_{j,t-1}$ is the time interval (in weeks) between trips at $t-1$ and t , and C_{ij} is the average weekly consumption of household i in category j . The average weekly consumption of a household in a category is computed as total quantity of a product (in ounces) purchased by the household in the estimation period divided by the total number of weeks. The inventory in the first time period for each household is set to zero. Finally, to make the size of the inventory variable compatible with prices and promotions, we divided I_{ijt} by 100.²

Table 3 shows the correlation in the observed prices for the six categories. In general, most categories show a modest positive correlation. This price correlation is slightly higher for the spaghetti and sauce pair as well as for the detergent and softener pair, reflecting the retailers' pricing policy.

4. Estimated Models

We estimate two models as described below:

Own-Effects Model. In this model, we only use explanatory variables for the product category in question. For example, the utility of detergent is influenced by the price, promotion, and inventory of only detergent.

Cross-Effects Model. The own-effects model is reasonable for unrelated categories as used by Ainslie

² This construction of the inventory variable is potentially endogenous to the purchase incidence decision. We estimated our model with lagged quantity in lieu of the inventory variable and our results did not change qualitatively. We thank an anonymous reviewer for this insight.

and Rossi (1998). For example, Ainslie and Rossi (1998, p. 94) justify the use of this modeling approach by stating that, "it is hard to imagine that shifts in prices of ketchup would materially affect the demand for canned tuna fish." However, when examining related or complementary categories, this model is misspecified. For example, Manchanda et al. (1999) show that price of a category (e.g., frosting) has a significant impact on the utility of a related category (e.g., cake mix). Therefore, for complementary products a cross-effects model is more appropriate. In a cross-effects model, the utility of a product, say detergent, is influenced by the price, promotion, and inventory of detergent (own-effect) as well as by the price, promotion, and inventory of fabric softener (cross-effect). While the inclusion of covariates of other unrelated categories in the utility equation is straightforward, in our application, not surprisingly, we found these effects to be nonsignificant. Therefore, our cross-effects model is restricted to inclusion of covariates from related categories only (e.g., covariates of sauce influence the utility of spaghetti and vice versa).

In both models, the errors across products are correlated to allow for co-incidence. Both models allow for consumer heterogeneity and are estimated simultaneously across all six products instead of on pairs of products at a time. This allows us to examine the correlation in consumers' price sensitivity across related as well as unrelated categories. The models are estimated using a Bayesian framework as indicated earlier. The MCMC sampler was run for 50,000 iterations and convergence was ensured by monitoring the properties of the time series of the draws. We chose a "burn-in" length of 12,500 iterations and the remaining 37,500 draws were used for summarizing the posterior distribution using the posterior means and their 95% posterior intervals.

5. Results

The MCMC draws allow us to compute the marginal likelihoods of the two models. The log-marginal likelihood value for the own-effects model is -14,920.90 and that for the cross-effects model is -14,487.90. This indicates that our data provides greater evidence for the cross-effects model. We also obtain estimates for the population means of the category intercepts (including the impact of demographics on the intercepts), error correlation or co-incidence across categories, and response sensitivities to price, promotion, and inventory for both models. As the estimates of the above quantities from the own-effects model are very similar to those from cross-effects model, we report the results only from the latter.³

³ Results for the own-effect model are available from the authors upon request.

Table 4 Cross-Effects Model: Population Means for Response Sensitivities

Category	Intercept (μ_a)			Response sensitivities (μ_β)					
	α_0	α_{Income}	α_{HSize}	OP	CP	OM	CM	OI	CI
Spaghetti	0.774	0.001	0.058	-0.287	-0.089	0.595	0.094	-1.139	0.114
Sauce	0.519	-0.022	0.109	-0.226	-0.063	0.746	0.207	-0.493	0.237
Detergent	1.203	-0.037	0.028	-0.229	-0.070	0.405	0.169	-0.400	0.179
Softener	0.510	0.028	-0.126	-0.261	-0.056	0.258	0.062	-0.876	0.062
Cake mix	0.568	-0.027	0.054	-0.220	-0.073	0.314	-0.020	-1.395	0.037
Frosting	0.299	-0.021	0.049	-0.167	-0.061	0.049	0.22	-1.837	-0.002

Note. HSize: household size; OP: own-price; CP: cross-price; OM: own-promotion; CM: cross-promotion; OI: own-inventory; CI: cross-inventory. Parameters in bold indicate significance at 95% level.

5.1. Cross-Effects Model

The parameter estimates for the cross-effects model are presented in Tables 4-7. The population means for the response sensitivities are reported in Table 4. The demographics, income and household size, capture observed sources of heterogeneity. Their effect appears to be significant only in a few categories. Focusing on the own-price, own-promotion, and own-inventory parameters, we find that they significantly impact utility and their signs are consistent with expectations.

For example, the own-price parameters are negative for all six categories, and own-promotion parameters are positive. In other words, a high price reduces and a promotion enhances the likelihood of a consumer buying a product category. Further, inventory has a negative and significant impact (Column OI in Table 4) suggesting that high inventory has a negative influence on the purchase probability of a category.⁴ Compared to other categories, inventory appears to have a stronger impact on cake mix and frosting. This is not surprising considering the nature of these products (e.g., perishability, "nonessential"). In summary, all parameters have the expected signs. It is interesting to note that the magnitude and the signs of these coefficients are also consistent with their counterparts in the own-effects model.

An examination of the cross-effect terms in Table 4 shows significant parameters with expected signs. For example, all cross-price (CP) parameters are negative, as expected for complementary products (e.g., a price increase for sauce has a negative impact on the purchase of spaghetti). Similarly, three of the six cross-promotion parameters are positive. Positive parameters for cross-inventory also highlight the complementary nature of the products. For example, a high inventory of sauce increases the probability

⁴ We also estimated a model in which the inventory variable was replaced by a lagged purchase quantity variable to alleviate potential endogeneity concerns. However, the results from this model are qualitatively similar.

Table 5 Error Correlation Matrix (Σ_u) from the Cross-Effects Model

	Spaghetti	Sauce	Detergent	Softener	Cake mix	Frosting
Spaghetti	1.00	0.62	0.17	0.22	0.16	0.09
Sauce	...	1.00	0.20	0.22	0.17	0.17
Detergent	1.00	0.58	0.11	0.13
Softener	1.00	0.15	0.13
Cake mix	1.00	0.88
Frosting	1.00

Note. Correlations in bold indicate significance at 95% level.

that a consumer buys spaghetti.⁵ Finally, as expected, all cross-effects parameters are smaller in magnitude than the own-effects parameters.

Table 5 shows the posterior means for the error correlation across utilities, i.e., the entries in Σ_u . The entries imply significant positive correlation in errors across categories, and is indicative of a strong evidence of coincidence (e.g., common shopping occasion). The estimates clearly illustrate the complementary nature of the three pairs of categories. For example, the error correlation for the utilities of spaghetti and sauce is 0.62, for softener and detergent is 0.58, and for cake mix and frosting is 0.88. These correlations are significantly higher than the correlations for other pairs of categories. This demonstrates that the utilities share unobserved influences for complementary products and ignoring this cross-category dependence is likely to yield misleading results.

The correlations in utility intercepts capture how the household-level intrinsic propensities to buy are related across categories. These exhibit a similar pattern to what we found for the utility errors, with the intercepts for complementary categories showing markedly higher correlations. Again, both the magnitude and the signs of the correlations in the intercepts and the utility errors are comparable across the two models.

⁵ It can be argued that cross-price and cross-promotion variables capture purchase complementarity while cross-inventory captures consumption complementarity of products. We thank a reviewer for the suggestion to include inventory as a covariate.

Table 6 Correlation in the Own-Price Sensitivities

	Spaghetti	Sauce	Detergent	Softener	Cake mix	Frosting
(a) Own-effects model						
Spaghetti	1.00	0.71	0.33	0.38	0.43	0.54
Sauce	...	1.00	0.43	0.37	0.34	0.45
Detergent	1.00	0.39	0.25	0.32
Softener	1.00	0.30	0.42
Cake mix	1.00	0.53
Frosting	1.00
(b) Cross-effects model						
Spaghetti	1.00	-0.22	-0.28	0.21	0.08	0.23
Sauce	...	1.00	0.25	0.09	0.13	0.08
Detergent	1.00	-0.13	-0.22	0.12
Softener	1.00	0.15	0.17
Cake mix	1.00	-0.32
Frosting	1.00

Note. Correlations in bold indicate significance at 95% level.

We also study the across household correlation in the promotion and inventory coefficients obtained from the two models. Most of the correlations in promotion and inventory sensitivities are positive for the cross-effect model, and their magnitude and direction is consistent with our results for the own-effects model. In general, we find a dampening of some correlations in the cross-effects model (e.g., the average inventory correlation in the own-effects model is smaller than the average inventory correlation in cross-effects model). This could be due to the addition of cross-inventory terms that are correlated.⁶

The most interesting and counterintuitive result comes from a comparison of the correlation of own-price sensitivities in the two models (see Table 6). We find that for the own-effects model, all correlations among the price sensitivities of related and unrelated categories are strongly positive (Table 6(a)). In contrast, results from the cross-effects models show very different results with several insignificant and many negative (and significant) correlations (Table 6(b)). A close examination of Table 6(b) shows some striking patterns across the products. First, only four out of the 12 correlations among unrelated categories (e.g., spaghetti and detergent) show significant correlations. This is in contrast to the own-effects model results where we find all 12 correlations positive and significant. Second, and more importantly, the own-price correlations among complementary products are negative and significant. This result is consistent across all three pairs of complementary products (spaghetti-sauce, detergent-softener, and cake mix-frosting).

Table 7 provides a richer picture of price sensitivity correlation for the three pairs of complementary products: spaghetti (P) and sauce (S); detergent (D)

Table 7 Correlation in the Own-Price and Cross-Price Sensitivities

	Spaghetti _{OP}	Sauce _{CP}	Spaghetti _{CP}	Sauce _{OP}
Pasta group				
Spaghetti _{OP}	1.00	-0.78	0.16	-0.22
Sauce _{CP}	...	1.00	-0.33	0.49
Spaghetti _{CP}	1.00	-0.81
Sauce _{OP}	1.00
Laundry group				
Detergent _{OP}	1.00	-0.64	0.32	-0.13
Softener _{CP}	...	1.00	-0.40	0.37
Detergent _{CP}	1.00	-0.78
Softener _{OP}	1.00
Dessert group				
CakeMix _{OP}	1.00	-0.64	0.42	-0.32
Frosting _{CP}	...	1.00	-0.22	0.37
CakeMix _{CP}	1.00	-0.74
Frosting _{OP}	1.00

Note. Correlations in bold indicate significance at 95% level.

and softener (T); and cake mix (C) and frosting (F). In this table, we report the correlation in the own-price as well as the cross-price sensitivities for the related products (all correlations are significant). Recall that in the cross-effects model, the utility of spaghetti is a function of the own-price of spaghetti and the cross-price of sauce. Similarly, the utility of sauce is a function of the own-price of sauce and the cross-price of spaghetti. In other words,

$$\begin{aligned} \text{utility for category 1} &= f(\text{own-price of category 1,} \\ &\quad \text{cross-price of category 2),} \\ \text{utility for category 2} &= f(\text{own-price of category 2,} \\ &\quad \text{cross-price of category 1).} \end{aligned}$$

Table 7 shows the correlation among these four parameters. This table shows a striking pattern that is consistent across all three pairs of products.⁷

(i) As reported in Table 6(b), the own-price parameters for complementary products are negatively correlated (-0.22 for P&S, -0.13 for D&T, and -0.32 for C&F).

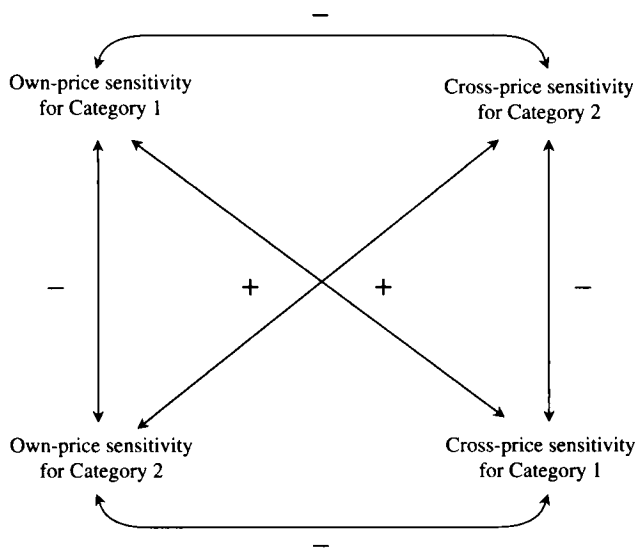
(ii) The correlation between cross-price sensitivities for related categories is also negative. Specifically, the correlation between cross-price parameters for P&S is -0.33 , that between D&T is -0.40 , and that between C&F is -0.22 .

(iii) The own-price parameter of a product has a negative correlation with the cross-price parameter of

⁷ We plotted household-level price parameters from the own-effects and cross-effects models for the three pairs of complementary categories. The plots were consistent with the results reported in Tables 6(b) and 7.

⁶ Detailed results are available from the authors upon request.

Figure 1 Pattern in Price Sensitivity for Related Categories



the complementary product. For example, the correlation between the own-price of spaghetti and the cross-price of sauce is -0.78 , and the correlation between the own-price of sauce and the cross-price of spaghetti is -0.81 .

(iv) Finally, the correlation between the own-price sensitivity of a category and the parameter for that same category's cross-price sensitivity in the utility of its complementary category is positive. For example, the correlation between the own-price of spaghetti (in its own utility equation) and the cross-price of spaghetti (in the utility equation for sauce) is positive (0.16). The same is true for the correlation between sauce parameters (0.49). This is true for the other two complementary pairs as well.

The relationships between the own-price and cross-price parameters are summarized in Figure 1. This pattern is consistent for all three pairs of complementary products, thereby providing some generalization of our results.

6. Understanding the Pattern of Correlations

Why do the own-price correlations flip from being positive in the own-effects model to negative in the cross-effects model? Further, why do we have the pattern of correlations as shown in Figure 1? In this section, we address these two important questions.⁸

To investigate the pattern of correlations, we use the household-level price sensitivities from both the own-effects and cross-effects models. For each variable included in the models, we get 126 household-level parameters based on a sample of MCMC draws.

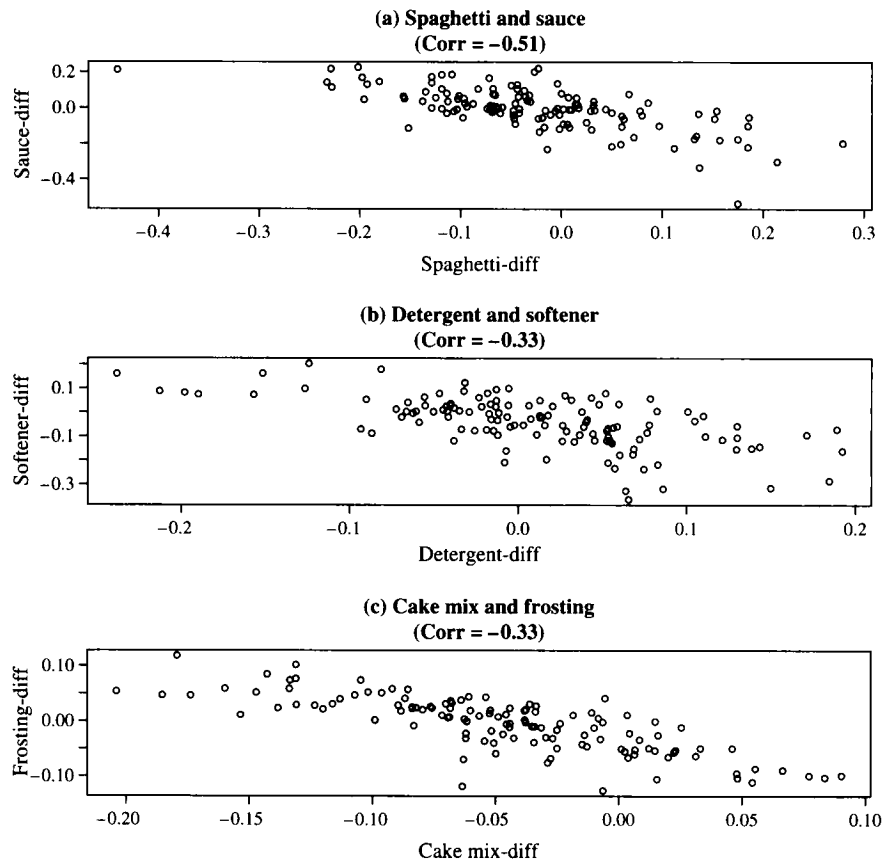
⁸ Note that we are focusing on the correlations in price parameters, not on the parameter values.

We use these household-level parameters for the discussion in this section.

6.1. Consumer Behavior Theory

To help us understand these correlations, we draw upon two main insights from consumer behavior—consumers categorize products (Barsalou 1983, 1991; Bettman and Sujan 1987; Ratneshwar et al. 1996) and consumers allocate budgets to separate accounts or categories (Heath and Soll 1996). The nature of our products and the categorization literature suggests that consumers pair together spaghetti and sauce (pasta group), detergent and fabric softener (laundry group), and cake mix and frosting (dessert group). Further, research by Heath and Soll (1996) and others suggests that consumers allocate budgets to product groups such that if they overconsume or overspend for one product in a group, they are likely to underconsume or reduce expenditure on other products in that group. In other words, if a consumer spends too much on spaghetti, his mental budgeting is likely to reduce his spending on sauce. This also implies that if consumers are less price sensitive for one product in a group (e.g., spaghetti), they are likely to be more price sensitive to another product in the same group (e.g., sauce). This is consistent with the negative correlation between own-price parameters of related products, as well as the negative correlation between the own-price and cross-price parameters within an equation. (See Table 7 and its discussion in §5.1, points (ii) and (iii), respectively.) The magnitude of these within equation correlations are higher than the magnitude of the other correlations because within an equation these coefficients influence the same decision.

In general, one product in the group is likely to become a focal product. This may depend on the consumption pattern, amount of money spent on the product, variations in prices in the market place, or the necessity of a product. The argument of focal category is also consistent with the suggestion that consumers are cognitive misers and may focus their effort on the purchase of one of the related products. If spaghetti is the focal product for some consumers in the pasta group, then its price will not only affect their decision to buy spaghetti (the own-price effect) but also affect their decision to buy sauce (cross-price effect). This would make the own-price and cross-price effects of spaghetti to be positively correlated (0.16), as shown in Figure 1. By the same token, if sauce is not the focal category, its price has limited impact on consumers' purchase decision of sauce (own-price effect) as well as on their purchase of spaghetti (cross-price effect), once again making the own-price and cross-price coefficients of the second product in the group to be positively correlated

Figure 2 Scatter Plots Containing the Difference in Own-Price Parameters from the Own-Effects and Cross-Effects Models for Pairs of Complementary Categories

Note. For example, Spaghetti-diff is the difference in the own-price coefficients from the own-effects and cross-effects models for the spaghetti category.

(0.49). Once we obtain these patterns, the remaining patterns in Figure 1 must follow for them to be logically consistent.

It is important to note that consumer heterogeneity plays a critical role for this result to hold. If *all* consumers have spaghetti as their focal category, then it would simply lead to a higher mean price coefficient for spaghetti and a lower mean price coefficient for sauce. In other words, this will affect the mean price parameters but not their correlation. The impact on price correlation will occur only if some people use one category (e.g., spaghetti) as their focal category and others use the complementary category (e.g., sauce) as their focal category.⁹

6.2. Empirical Evidence

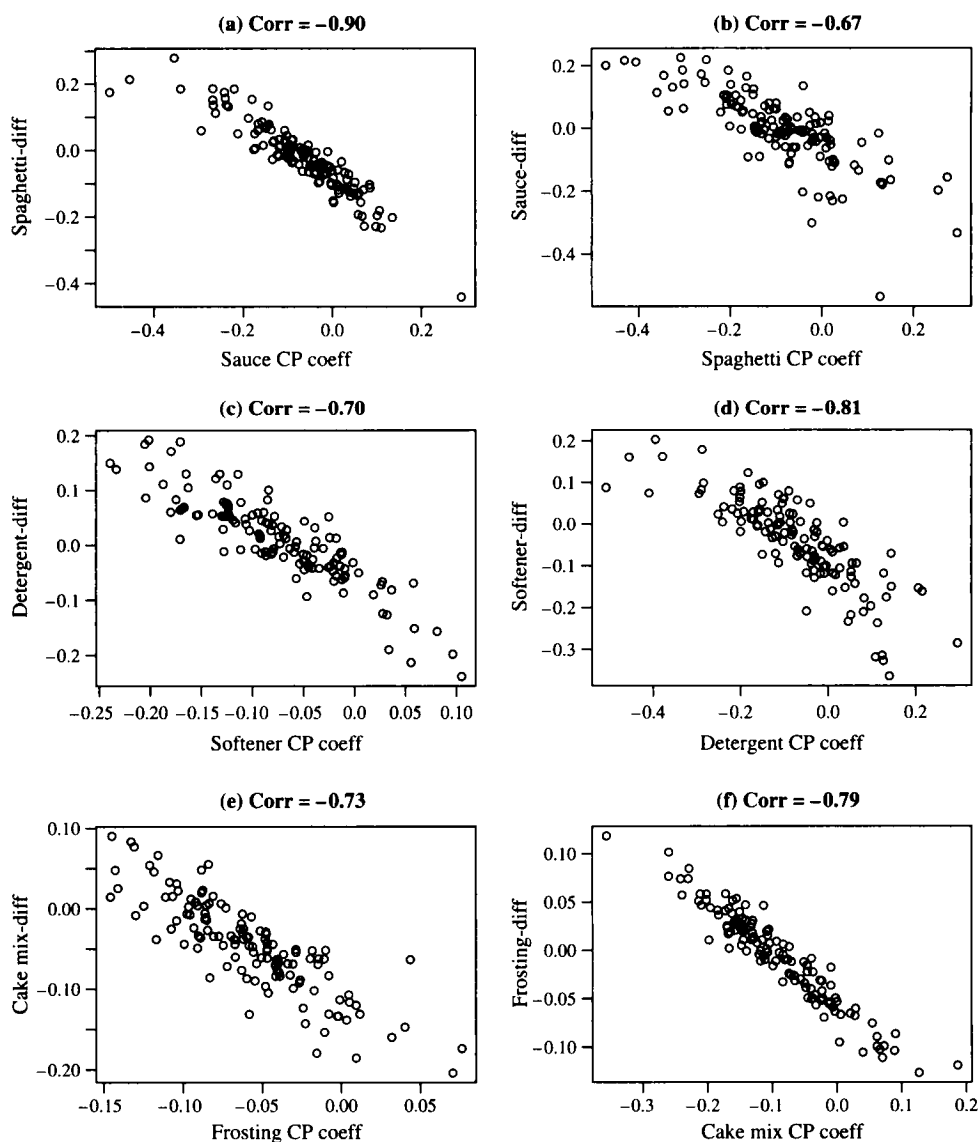
To confirm that our data are consistent with behavioral theory, we plot the difference in the own-price parameters between the cross-effects and the own-effects models for each complementary pair of products (Figure 2). For example, the own-price parameters from the own-effects model for household #74 for spaghetti

and sauce are -0.138 and -0.382 , respectively. However, in the cross-effects model, this household's price parameters for these categories change to -0.312 and -0.191 . The difference in the price parameters for this household between the two models is $-0.312 - (-0.138) = -0.174$ for spaghetti (Spaghetti-diff) and $-0.191 - (-0.382) = 0.191$ for sauce (Sauce-diff). In other words, compared to the own-effects model, the cross-effects model suggests that this household is more price sensitive for spaghetti and less price sensitive for sauce (note that because the price parameters are negative, a larger negative number indicates greater price sensitivity). In contrast, household #14 has spaghetti and sauce price parameters of -0.293 and -0.274 in the own-effects model, and -0.275 and -0.411 in the cross-effects model. The difference in price parameters for this household is 0.018 for spaghetti and -0.137 for sauce. In other words, while the own-effects model suggested that this household is more sensitive to spaghetti than sauce, the cross-effects model suggests the opposite.

Figure 2(a) plots these differences for all the 126 households in our data for spaghetti and sauce. This figure shows that most of the data points are

⁹ We thank a reviewer for this insight.

Figure 3 Scatter Plots for the Difference in the Own-Price Coefficients of a Category Between the Two Models (Ordinate) vs. the Cross-Price Coefficient of the Complementary Category (Abcissa)



either in the upper left quadrant (which denotes consumers who are more sensitive to spaghetti, just like household #74), or in the lower right quadrant (which denotes consumers who are more sensitive to sauce prices, just like household #14). In fact, there is a strong negative correlation across the plots in Figure 2. Put differently, our data suggests a strong heterogeneity where some consumers are more sensitive to one product (e.g., spaghetti) in the complementary pair, while others are more sensitive to the second category (e.g., sauce).

When cross-prices are included in the model, the own-price parameter for spaghetti goes up and the own-price parameter for sauce goes down for the "spaghetti consumers" (e.g., household #74). The reverse happens for the "sauce consumers" (e.g., household #14). This causes a reversal in the sign for

the correlation from positive to negative. Note that consumer heterogeneity is critical to this sign reversal.

To further corroborate this, Figure 3(a) plots the difference in the own-price parameter of spaghetti between the two models and the cross-price parameter of sauce. Recall two things: First, the cross-price parameter for complementary products (i.e., sauce) is negative. Second, a negative difference in the own-price parameter of spaghetti between the two models suggests a "spaghetti consumer" who is more sensitive to spaghetti prices. We expect that a spaghetti consumer is less sensitive to the cross-prices of sauce and vice versa. In other words, we expect a negative correlation between the cross-price parameter of sauce and difference in the own-price parameter of spaghetti. This is precisely what we get in Figure 3(a). In Figure 3(b), we also find that sauce consumers are

not sensitive to the cross-prices of spaghetti. A similar pattern is seen for the other two complementary categories (Figures 3(c)–3(f)).

This rich pattern of own and cross-price correlations is both interesting and new. Previous studies have either not examined related products or found a simple positive correlation between price parameters of unrelated products in the brand choice context. In contrast, we find that the own-price parameters of related products have negative, not positive, correlation. The contrast between the simple pattern of positive correlations obtained for the own-effects model and the complex pattern of correlations yielded by the cross-effects model indicates that ignoring the cross-effects can lead to misspecification. This misspecification can be potentially further compounded by positive correlations between the actual price correlations between complementary categories within the data.¹⁰ While in our case, these correlations are moderate (see Table 3), ignoring cross-effects does have an impact in making the coefficients positively correlated in the simpler model.

It is interesting to note that while the own-price parameters show a negative correlation for complementary products in the cross-effects model, the own-promotion and own-inventory parameters continue to have a strong positive correlation. This suggests that consumer categorization and choice of focal category is driven largely by price. This is consistent with Heath and Soll (1996), who suggest that consumers allocate budgets to product groups in such a way that if they overspend in one category they tend to underspend in the other.

6.3. Summary

We find a new and interesting pattern of price correlation. Our results are contingent on four aspects.

- *Complementary products:* Most previous studies examined independent or unrelated product categories. For these products, an own-effects model is quite reasonable because it is unlikely that the price of, say, detergent will affect the purchase of spaghetti. However, when complementary categories are considered, it is important to include cross-effects of complementary products. We have shown that inclusion of cross-effects significantly influences the correlation of price parameters among complementary products.

- *Purchase incidence model:* We have examined consumers' purchase of a category. In other words, our focus was on purchase incidence models. In these models, it is natural to consider prices (and other cross-effects) of related categories because the price of spaghetti may influence the purchase of sauce. Almost all previous studies that examined price parameter correlation focused on brand choice behav-

ior (Table 1). In brand choice models, the focus is typically on own and competing brand prices. It is possible that the results of this study change in the brand choice context. We leave it for future research.

- *Focal category:* Our discussion in §§6.1 and 6.2 suggests that the rich pattern of price correlation occurs because one product in a pair of complementary products becomes a focal product for consumers.

- *Consumer heterogeneity:* If all consumers have the same product as their focal category, it will change the mean parameter values but not the correlation in price parameters. For the correlations to be influenced, some consumers should have one product as their focal category, while others should have the complementary product as their focal category. This is exactly what we find in all three pairs. Whether this is true in general or true for certain types of products needs further investigation.

7. Managerial Implications

Until now we have focused on the rich pattern of correlation in price sensitivities across the categories. We now investigate whether ignoring this complex pattern has implications for managerial actions. For example, retailers can use our model in making cross-category decisions regarding optimal discounts. Two facets of our modeling approach can be exploited by retailers to improve profitability. First, as the model accounts for household differences, retailers can target households with customized discounts. Second, retailers can leverage the structure of preferences across categories to optimize targeted discounts across pairs of complementary categories. To assess whether ignoring the pattern of correlations has any implications for these decisions, we compare the impact of targeting on cross-category profits that is predicted from the cross-effects model with that from the own-effects model.

Here, we use each model's parameters and conduct a simulation to assess the gains attributable to the facets identified above. In running these simulations, we assume that the quantity is exogenous and set it equal to the average quantity bought by each consumer. We investigate for each pair of complementary categories the optimal discounts and the resulting profits that are indicated by the two models for three distinct decision scenarios.

Scenario 1: No Complementarity. In this scenario, we study a situation when retailers set an optimal discount for a single category to maximize the profit within that category. For example, a retailer might set the prices of spaghetti to optimize profits from spaghetti alone. Similarly, the retailer could set the prices of sauce to maximize profits for sauce alone. In this scenario, the retailer ignores the complementarity across the pair of categories in setting prices.

¹⁰ We thank an anonymous reviewer for this insight.

Scenario 2: Partial Complementarity. Here, we assume that the retailer sets a discount within a single category (e.g., for spaghetti or sauce, but not for both) so as to maximize the profits across the pair of complementary categories (e.g., spaghetti and sauce). In this scenario, the objective function incorporates both categories, but the decision variable (optimal discount) is set for only a single category.

Scenario 3: Full Complementarity. Here, the retailer calculates simultaneous optimal discounts for each category within the complementary pair (i.e., for both spaghetti and sauce simultaneously) to maximize the combined profits for the pair.

In each scenario, we computed optimal profits and optimal prices for both targeted and nontargeted decisions. In computing the optimal discounts, we searched over a grid of discounts ranging from 0% to 25% in steps of 5%. We also assumed a regular gross margin of 25% in each of the six categories to compute profits. For obtaining the targeted optimal discounts, we calculated a separate optimal discount for each household and the resulting profits were then aggregated across households. In contrast, for computing the optimal nontargeted discounts, each household was offered the same discount and aggregate profits were compared across the different discounts to ascertain the optimal value.

Table 8 reports the optimal targeted and nontargeted discounts and the corresponding profits for each pair of complementary categories in each of the three scenarios for the cross-effects model.¹¹ As expected, for each pair of categories, a targeted discount in comparison to a nontargeted one results in a greater profit within each of the three scenarios. For example, for the spaghetti-sauce pair of categories, we find that in Scenario 1, when spaghetti is discounted, the optimal nontargeted discount of 0% results in a profit of \$3,854 for the pair, whereas the optimal targeted discount of 1.66% within spaghetti (averaged across households) results in a larger optimal profit of \$3,905 for the pair.

We also find that on average, profits in Scenario 2 are higher than profits in Scenario 1, and similarly, profits in Scenario 3 are higher than profits in Scenario 2. For example, within the spaghetti-sauce pair, the targeted profit in Scenario 2 when spaghetti is discounted is \$4,174. This is higher than the corresponding profit of \$3,905 in Scenario 1. Similarly, within Scenario 3, the targeted profit of \$4,319 for the pair is higher than each of the two targeted profits (i.e., when spaghetti is discounted, \$4,174, or when sauce is discounted, \$4,001) in Scenario 2. A similar pattern is applicable for the other two categories.

¹¹ For the sake of brevity, we do not include the corresponding table for the own-effects model.

Table 8 Optimal Discounts and Profits for Category Pairs

Scenario	Nontargeted discount			Targeted discount		
	Spaghetti discount (%)	Sauce discount (%)	Pair profit (\$)	Spaghetti discount (%)	Sauce discount (%)	Pair profit (\$)
1	0	No	3,854.52	1.66	No	3,905.17
1	No	0	3,854.52	No	0.75	3,896.72
2	5	No	3,895.76	7.98	No	4,174.10
2	No	0	3,854.52	No	3.73	4,001.10
3	5	0	3,895.76	7.78	6.59	4,319.44

Scenario	Detergent discount (%)	Softener discount (%)	Pair profit (\$)	Detergent discount (%)	Softener discount (%)	Pair profit (\$)
	1	0	No	3,977.51	1.11	No
1	No	0	3,977.51	No	2.66	4,056.43
2	0	No	3,977.51	4.41	No	4,149.43
2	No	0	3,977.51	No	7.10	4,129.58
3	0	0	3,977.51	4.41	8.60	4,300.15

Scenario	Cake mix discount (%)	Frosting discount (%)	Pair profit (\$)	Cake mix discount (%)	Frosting discount (%)	Pair profit (\$)
	1	0	No	1,994.64	0.52	No
1	No	0	1,994.64	No	1.82	2,034.58
2	0	No	1,994.64	4.88	No	2,036.77
2	No	5	1,996.79	No	6.19	2,074.72
3	0	5	1,996.79	4.16	7.65	2,112.24

More interesting is the fact that the gains from targeting increase with the degree of complementarity that is captured by the scenario. The profitability gain from targeting is the percentage improvement in optimal profits that results when a retailer uses a targeted strategy instead of a nontargeted one. The percentage gains are averaged across the three category pairs to yield the average percentage gain for a scenario. The average profitability gain from targeting across the three category pairs is about 1.29% within Scenario 1. Within Scenario 2 this gain is 4.18%, and for Scenario 3 it is 8.26%. These results clearly show that firms can gain considerably by exploiting the complementarity of categories.

What can retailers conclude if instead of using the cross-effects model, they rely on the simpler own-effects model to infer gains from targeting? Using the own-effects model parameters, we find that the average profitability gain from targeting across the three category pairs is about 0.14% within Scenario 1. Within Scenario 2 this gain is also 0.14%, and for Scenario 3 it is 0.27%. This implies that not only does the own-effects model indicate much smaller profitability gains from targeting, but more interestingly, it also suggests that these gains do not increase very much with the extent of complementarity that

is captured by the scenario. Thus, in summary, retailers can make misleading inferences when the modeling effort ignores cross-effects. Accounting for the complex mosaic of pricing effects can better inform retailers about marketing actions that span across categories.

8. Conclusions

In this paper, our interest was in understanding how household-specific price sensitivities for purchase incidence decisions are correlated across categories. We focused on categories that are related through consumption complementarities and used a hierarchical Bayesian multivariate probit model to explore the nature of this covariation. We estimated the model using purchase incidence data from six product categories involving three pairs of complementary products. Our results reveal a very interesting and rich correlational pattern. Specifically, we find that for related pairs of categories, the own-price sensitivities and cross-price sensitivities of related products are negatively correlated. In addition, the correlation between the own-price parameter of one category and the cross-price parameter of its related category are also negative. Finally, the correlation between the own-price sensitivity of a category and the parameter for that same category's cross-price sensitivity in the utility of its related category are positive.

Our paper contributes substantively to the literature on the nature of price sensitivities in cross-category contexts by uncovering a complex mosaic of correlations. Our findings augment results from previous research on unrelated categories, where the correlation among price sensitivities was shown to be significantly positive. In contrast, we find that once complementary categories are included and consequently cross-effects are factored into the analysis, the correlation among the own-price effects could turn negative. We justify the observed correlational pattern by appealing to theories in consumer behavior about the presence of focal categories. We focused on purchase incidence. It would be interesting to investigate whether similar results arise in cross-category brand choice models involving complementary product categories.

A limitation of our work is that we have used a reduced form framework to model the indirect utility across a limited set of categories. When a large number of categories are modeled simultaneously, the nature of relationships among categories would be more nebulous and our reduced form approach of incorporating cross-price effects may result in a surfeit of parameters. In such situations, structural models for cross-category decisions that are based

on an explicit accounting of utility maximization behavior (Song and Chintagunta 2006, 2007; Mehta 2006; Gentzkow 2007) are more useful because economic structure typically induces greater parsimony. Such structural models account for cross-price effects via the budget constraint and via a specification of the direct utility across categories. It would be interesting to explore the nature of price correlations in such structural models. Such an approach will allow researchers to trace how different primitives of the economic utility maximization problem influence the manifest nature of price correlations in reduced form models that are based on these structural approaches.¹² We leave this interesting exploration to future researchers. Our research could also be extended to include other decision variables such as quantity. Finally, our results could be replicated on other sets of categories.

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¹² We thank the area editor for highlighting this issue.

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