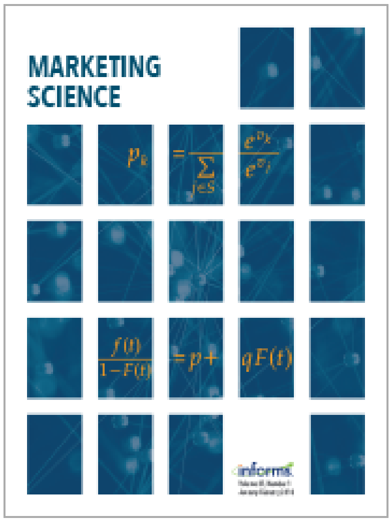

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Jean-Pierre Dubé, Sachin Gupta,

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Cross-Brand Pass-Through in Supermarket Pricing

Jean-Pierre Dubé
Graduate School of Business, University of Chicago, Chicago, Illinois 60637, jdube@chicagogsb.edu

Sachin Gupta
Johnson Graduate School of Management, Cornell University, Sage Hall, Ithaca, New York 14850, sg248@cornell.edu

We investigate the sensitivity of cross-brand pass-through estimates to two types of pooling: across stores, and across regular price and promotional price weeks. Using the category data from Besanko, Dubé, and Gupta (2005), hereafter BDG, we find consistent support across all 11 categories for the predictive power of the wholesale prices of substitute products for retail shelf prices. A Bayesian procedure is used to address the small sample issues that arise in the absence of pooling. Even though the unpooled results render our inferences for specific cross-brand pass-through magnitudes reported in BDG as imprecise, consistent with McAlister (2007), we *do* find significant empirical support for cross-brand pass-through.

We next assess the sensitivity of cross-brand pass-through estimates to pooling. This requires us to construct a much longer time series of 224 weeks for the refrigerated orange juice category, in contrast with the 52-week samples used in BDG and McAlister (2007). We find strong empirical support for the predictive power of wholesale prices of substitute products for retail shelf prices. In addition, we find evidence of nonzero own- and cross-brand pass-through elasticities for which our inferences are much more precise. These findings are robust to the separation of regular and promotional price weeks. However, the magnitudes of own-brand and cross-brand pass-through are quite different during promotional and regular price weeks. Our results clearly show that with longer data series and more robust models that can handle small sample sizes, there is evidence of cross-brand pass-through, substantiating the findings in BDG. Finally, we comment on why our results are entirely consistent with both the theoretical and empirical literatures on category pricing and retailer behavior.

Key words: pricing; promotion; retailing; channels of distribution; econometric models
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1. Introduction

Besanko, Dubé, and Gupta (BDG 2005) describe the pass-through behavior of Dominick's Finer Foods (DFF), a major supermarket chain, using retail and wholesale prices for 78 products across 11 categories. The data come from stores located in 15 retail price zones for a 52-week period. They find evidence of statistically significant own-brand and cross-brand pass-through rates. McAlister (2007) questions the finding of statistically significant cross-brand pass-through rates. She argues that because retail price zones do not react independently to wholesale prices, Besanko et al. analysis overstates the number of independent observations by a factor of 15. Upon correcting for this overstatement, she finds that the number of statistically significant cross-brand pass-through rates is smaller than the number that would be expected by chance. The insignificant parameter estimates are taken as support for the view that cross-brand pass-through is zero in the supermarket pricing context.

McAlister's argument is based on her description of DFF's pricing practice, as identified in the literature, and its implications for econometric identification of pass-through elasticities from the pricing data. She notes that DFF maintained different "regular" retail prices across stores based on *price zones*. These differences were intended to exploit heterogeneity in shoppers' price sensitivities across stores as well as differences in local competition. Furthermore, in a week when DFF executed a temporary price promotion, promoted retail prices were identical across price zones. In other words, a single promotional retail price was chosen and implemented throughout the chain.

The crux of McAlister's econometric critique of BDG (2005) is as follows:

1. When BDG pooled data across 15 price zones to estimate own- and cross-brand pass-through elasticities, in effect they (incorrectly) replicated observations of identical promotional retail prices 15 times. As a consequence, they overstated the sample size and hence the statistical significance of their tests.
2. BDG's pooled data contained variation in regular retail prices between stores which should not be attributed to differences in wholesale prices, because

those are attributable to time-invariant differences in shopper price sensitivities.

3. The wholesale prices reported by DFF do not necessarily correspond to the economic marginal cost of selling a unit of a good, i.e., the replacement cost of a good sold out of inventory. DFF instead uses the average acquisition cost, AAC.

We agree with the concerns raised about the wholesale prices (point 3 above)—this point has been made previously (e.g., Peltzman 2000 and BDG 2005). While there is little we can do about the manner in which wholesale prices were collected, we argue that the AACs might not be entirely inappropriate for the measurement of pass-through because they do reflect how DFF perceived its costs when setting its prices. We also agree with the description of DFF's pricing practices, in particular the setting of regular and promotional retail prices. However, we believe that the implied consequences of these practices for the econometric identification of pass-through elasticities need to be examined with appropriately specified models before reaching any conclusions about the validity of our original empirical findings. This is the main goal of this paper.

The first component of our analysis consists of re-examining the 11 categories used in BDG (2005). Therein, a short time series of 52 weeks was used to avoid concerns about the assumed time-invariance of pass-through in the empirical model. The use of only 52 weeks of data in BDG (2005) necessitated some data pooling across stores. For instance, a category with 5 products involves the estimation of 25 own- and cross-brand pass-through rates. Therefore, we do not find it surprising that in the absence of any pooling, McAlister (2007) reports highly imprecise estimates of slope parameters. However, we argue that insignificant slope parameters do not imply a lack of empirical support for cross-brand pass-through and, in this regard, we respectfully disagree with the main conclusion of McAlister. Subsequently in this paper, we use a much larger sample to carry out this test in a setting where it has more power.

To assess the power of the wholesale prices of substitute products in predicting retail shelf prices we proceed as follows. Because the current analysis does not use any data pooling across stores, a Bayesian procedure is used to obtain correct small-sample inferences. Testing for the incidence of cross-brand pass-through in a category is recast as a model selection problem. Namely, we test the posterior probability associated with an unrestricted model (i.e., with cross-brand pass-through) versus a restricted model with all the coefficients on substitute products' wholesale prices set to zero (i.e., without cross-brand pass-through).[1] Even though our inferences on individual cross-brand pass-through elasticities are found to be imprecise, we nevertheless find higher posterior probability associated with the unrestricted model in the vast majority of cases in each of the 11 categories. We consider this strong evidence in support of cross-brand pass-through. Therefore, we respectfully disagree with McAlister's main conclusion that the data provide no empirical support for cross-brand pass-through.

To address McAlister's concerns about the pooling of promotional and regular price weeks, we need more data. Therefore, we use additional weekly DFF data for the refrigerated orange juice category for a four-year period, a much longer time series than the 52-week data series used in BDG (2005). This longer time series also enables us to verify whether our pass-through estimates (incidence and magnitude) are sensitive to pooling the data across stores versus estimating separately by store and relying only on within-store price variation. Detailed model specifications are shown in §3.

The key conclusion based on our analysis of the additional refrigerated orange juice data is that the findings of statistically significant own- and cross-brand pass-through elasticities reported in BDG (2005) are maintained. However, we do find interesting differences between pass-through elasticities based on regular retail prices versus promotional prices. This finding suggests that the magnitude of pass-through depends on the promotional conditions, a detail not addressed by BDG (2005). Furthermore, the incidence of nonzero cross-brand pass-through elasticities is smaller than previously reported. Finally, in the vast majority of cases, we find higher posterior probability for an unrestricted model (i.e. with cross-brand pass-through) versus a restricted model with all the cross-brand pass-through elasticities set to zero. This finding is robust to estimating only with promotional or only with regular price weeks.

The rest of this paper is organized as follows. In §2, we summarize our model and our Bayesian inference procedure and apply it to the 11 categories used in BDG (2005). In §3, we describe the 224-week sample of refrigerated orange juice data. In §4, we present the four models that we estimate on the refrigerated orange juice data and describe our results. We conclude in §5 by discussing why our results are theoretically reasonable and consistent with a large literature.

[1] This test is analogous to the asymptotic *F*-test that the cross-brand pass-through parameters are jointly zero. Herein, we prefer the Bayesian model selection approach as it is valid even in our small sample with only 52 weeks (i.e., with no pooling of data across stores).

2. Cross-Brand Pass-Through in the 11 Categories Used in Besanko et al. (2005)

In this section, we use the 11 product categories studied in BDG (2005). To make sure our results are comparable, we use the same zone-level aggregation of the data. Thus, a unit of observation is the retail price of a given product during one of the 52 weeks in one of the 15 retail price zones. We refer the reader to BDG (2005) for a discussion of the DFF data and the details associated with the construction of this sample.

Methodology. In our analysis, we index the products by $i = 1, \ldots, I$, the zones by $s = 1, \ldots, S$, and the weeks by $t = 1, \ldots, T$. We specify the following zone-level model with zone specific coefficients:

$$\ln(P_{ist}) = \alpha_{is} + \beta_{is} \ln(C_{ist}) + \sum_{j \neq i} \beta_{ijs} \ln(C_{jst}) + \varepsilon_{ist}, \quad i = 1, 2, \ldots, I, \tag{1}$$

where P_{ist} is the retail price of product i in zone s during week t, C_{ist} is the wholesale price of product i in store s during week t, and ε_{ist} is a mean-zero error. The parameter β_{is} is the own-brand pass-through elasticity of product i in zone s, and β_{ijs} is the cross-brand pass-through elasticity of product i with respect to the wholesale price of product j in zone s. We refer the reader to BDG (2005) for the motivation of this specification for measuring pass-through and its interpretation as a reduced form of a category profit-optimization problem.

For each product, the inference problem amounts to 15 regressions, one for each zone. Roughly speaking, this was the approach used in BDG, although they restricted the cross-brand pass-through parameters, β_{ij}, to be the same across zones (i.e., no zone subscript). In the absence of any pooling, a concern with the 52-week sample is that the data might be insufficient to identify each of the own-brand and cross-brand pass-through elasticities for a given product, or to identify an asymptotic test. Hence, instead of using OLS, we estimate (1) using a Bayesian Markov Chain Monte Carlo (MCMC) approach. Because this methodology is now quite well known in the literature, we report the model details in the appendix, and we refer the interested reader to Rossi et al. (2007) for technical details.[2] An advantage of using Bayesian inference is that the posterior draws enable us to examine the exact small-sample properties of our pass-through estimates.

Our main goal herein is not per se to revisit the specific magnitudes of own-brand and cross-brand pass-through. Rather, our goal is to test whether the data provide empirical support for the incidence of cross-brand pass-through. We construct this test as a model selection problem between a null model without cross-brand pass-through, M_0, and an alternative model with cross-brand pass-through, M_1.

$$\Theta'_{is} = (\alpha_{is}, \beta_{is}, \{\beta_{ijs}\}_{j \neq i}), \quad i = 1, \ldots, I, \; s = 1, \ldots, S;$$
$$M_0\colon \beta_{ijs} = 0, \quad \forall\, j \neq i;$$
$$M_1\colon \textit{unrestricted}.$$

Our goal is to select the model, M_0 versus M_1, with the higher posterior probability. Given the data in a zone s, y_s, each of our models, M_0 and M_1, has the following posterior probability:

$$p(M_i \mid y_s) = \frac{p(y_s \mid M_i) p(M_i)}{p(y_s)}, \quad i = 0, 1,$$

where $p(M_i)$ is the prior model probability. To assess relative posterior fit, we simply compare the posterior probability of the data conditional on each model, or the log marginal density,

$$p(y_s \mid M_i) = \int p(y_s \mid \beta, M_i) p(\beta \mid M_i)\, d\beta, \tag{2}$$

which integrates the density (in logs) over the parameters. Note that even though the unrestricted model, M_1, nests the restricted model, M_0, our model selection test is robust to overfitting because it implicitly penalizes a model for the number of parameters.[3] We can further assess the degree of empirical support for the unrestricted model, M_1, versus the restricted model, M_0, by using (2) to compute the Bayes factor. We use the posterior draws from the chain to compute the log marginal density using the Newton and Raftery approach. For details, we refer the interested reader to Rossi et al. (2006).

Results. In Table 1, we report our MCMC results on own- and cross-brand pass-through for the 11 categories. One must be careful in comparing these findings with those reported in BDG (2005). Whereas BDG reported pass-through *rates*, which are transformations of the estimated coefficients of wholesale prices, herein we report the coefficients directly. The coefficients are interpretable as own- and cross-brand pass-through *elasticities*. We do so because our goal is not to reevaluate the magnitudes estimated in BDG but mainly to assess the predictive power of cross-brand pass-through.

The first column, Model Selection, contains our most important results on model predictive fit based

[2] For the estimation herein, we construct a chain with 10,000 draws, using the first 1,000 as a burn-in period.

[3] We refer the interested reader to Rossi et al. (2006) for a discussion about the approximate relationship between the log marginal density and its asymptotic limit, or *Bayesian information criterion*, which imposes a penalty on a model based on the number of parameters.

Table 1 Bayesian Inference on Pass-Through for the 11 Categories Used in Besanko et al. (2005)

	Model selection	Own-brand pass-through elasticities				Cross-brand pass-through elasticities		
Category	Percentage of cases where $\hat{p}(y \mid M_{CPT}) > \hat{p}(y \mid M_{noCPT})$	Number estimated	Number of negative estimates	PT $\neq 0$ (95% posterior credibility)	PT > 1 (95% posterior credibility)	Number estimated	CPT > 0 (95% posterior credibility)	CPT < 0 (95% posterior credibility)
Bath tissue	56	90	15	60	0	450	45	16
Beer	50	105	0	45	0	630	30	15
Crackers	18	105	0	105	0	630	60	23
Dish detergent	84	165	15	105	0	1,650	180	120
Frozen OJ	83	75	0	60	0	300	60	19
Laundry detergent	71	180	15	150	0	1,980	270	133
Oat cereal	64	45	15	30	0	90	0	30
Paper towels	86	90	15	59	0	450	105	30
Refrigerated OJ	79	105	15	105	0	630	116	90
Toothpaste	97	150	30	45	0	1,350	109	76
Tuna (canned)	42	60	0	45	0	180	16	0
Total	69	1,170	120	809	0	8,340	991	552

on differences in log marginal density, (2). Here we summarize for each category the percentage of cases where the unrestricted model generates a higher posterior log marginal density, $p(M_1 \mid y_s)$, than the restricted model (i.e., with no cross-brand pass-through), $p(M_0 \mid y_s)$. Each case represents a specific product in a specific zone. In 9 of the 11 categories, the unrestricted model provides a superior fit to the restricted model in at least 50% of the cases. In 4 of the 11 categories, the unrestricted model provides a superior fit to the restricted model in over 80% of the cases. Because the log marginal density penalizes a model with more parameters, as discussed above, it is unlikely this finding is merely due to randomness. Furthermore, we can use the Bayes factor of the unrestricted model to measure its degree of empirical support. Pooling across all the categories and products, we find that the unrestricted model has a Bayes factor larger than 6 in more than 50% of the cases. Therefore, despite the small sample, our findings indicate consistent support across categories for the predictive power of cross-brand pass-through.

In Table 1, we also report summary statistics on the precision and sign of our estimates for the own- and cross-brand pass-through elasticities. Not surprisingly, our inferences for cross-brand pass-through are very imprecise, and in many instances we are unable to distinguish our posterior means from zero with 95% credibility. This aspect of the findings is consistent with McAlister's finding of many statistically insignificant cross-brand pass-through coefficients using t-tests. However, it is important to note that imprecision of specific parameters does not, per se, imply a lack of predictive power for the joint set of cross effects.

The findings in this section confirm the conclusions in BDG (2005) regarding the predictive power of the wholesale prices of substitute products for retail shelf prices. However, the current results are still not robust to McAlister's concerns regarding promotional pricing. Nor does the current analysis, which no longer pools across zones, provide precise inferences on the magnitudes of cross-brand pass-through.

3. A 224-Week Sample of Refrigerated Orange Juice Data

In this section, we construct a sample with a longer time series to evaluate the pooling concerns raised by McAlister (2007) more thoroughly. We use a weekly time series of 224 weeks of DFF data for 83 stores for the refrigerated orange juice (RFJ) category. We do not aggregate the data to the zone level as in BDG (2005) so that we can assess more carefully the implications of pooling across stores. Thus, in Equation (1), we now interpret s as indexing the 83 stores rather than the 15 zones as in BDG (2005). Our data include the top 10 brand sizes in the category, as defined in Montgomery (1997). Each brand size is an aggregation of stock keeping units (SKUs) that have similar pricing in each week. For estimation, we retain all store weeks for which all 10 brands' prices are observed, generating a sample with 17,968 store weeks. In Table 2 we show descriptive statistics of the data. Tropicana Premium 32 ounces has the highest average retail and wholesale prices per ounce, while the 64-ounce pack of the Dominick's private label has the lowest average wholesale and retail prices. The data include a promotion indicator variable that identifies in-store displays. We use this variable as a proxy for temporary price promotion weeks. Thus, for a given product, a week is considered a promotional price week if the promotion indicator for that product is one. A potential limitation of this promotion indicator is that there might be additional weeks during which a price was discounted for promotional purposes without any merchandizing support.

Table 2 Descriptive Statistics of Refrigerated Orange Juice Data

	Retail price				Wholesale price			
Product	Mean	SD	Min	Max	Mean	SD	Min	Max
Tropicana Premium 64 oz	0.043	0.008	0.015	0.060	0.030	0.004	0.008	0.042
Tropicana Premium 96 oz	0.047	0.006	0.030	0.061	0.034	0.003	0.023	0.043
Floridas Natural 64 oz	0.043	0.005	0.019	0.052	0.028	0.003	0.010	0.038
Tropicana 64 oz	0.035	0.006	0.014	0.048	0.024	0.003	0.008	0.032
Minute Maid 64 oz	0.034	0.006	0.014	0.050	0.025	0.003	0.003	0.032
Minute Maid 96 oz	0.040	0.006	0.026	0.053	0.029	0.003	0.024	0.036
Tree Fresh 64 oz	0.032	0.007	0.010	0.043	0.021	0.005	0.007	0.030
Dominicks 64 oz	0.026	0.006	0.008	0.042	0.017	0.003	0.006	0.025
Dominicks 128 oz	0.028	0.005	0.011	0.039	0.019	0.003	0.012	0.025
Tropicana Premium 32 oz	0.053	0.005	0.031	0.064	0.039	0.002	0.024	0.044

Notes. ($N = 17{,}963$ store weeks).

4. Models and Estimation Results

Before specifying models to estimate pass-through, we examine the sources of variation in retail prices. Given DFF's pricing practice as described previously, for each product we divide the 17,968 store weeks into regular price and promotional price weeks and conduct separate analyses of variance (ANOVA) on each subset. In Table 3 we show the results of the two ANOVAs. Table 3 also reports the number of store weeks for which each product runs a promotion (versus not). For instance, Tropicana Premium 64 ounces is promoted in nearly half of the observed store weeks (i.e., promoted during 9,051 store weeks and not promoted during 9,201 store weeks). In contrast, Tropicana Premium 32 ounces is promoted during only 13% of the store weeks. In general, we have many observations of regular and promotion weeks for each product.

We note that while there is a reasonable amount of cross-store price variation in regular price weeks, consistent with DFF's pricing practices there is little variation in promotional prices across stores (with the exception of Tropicana Premium 32 oz.). This difference suggests that it is useful to consider separate models for regular versus promotional prices. Furthermore, there is an opportunity to compare the results of pass-through analyses based on data pooled across stores, which is similar to the analyses in BDG (2005), with the results of separate estimation by store.

As in the previous section, we use the following model, where we now use $s = 1, \ldots, S$ to denote each store rather than zone:

$$\ln(P_{ist}) = \alpha_{is} + \beta_{is}\ln(C_{ist}) + \sum_{j\neq i}\beta_{ijs}\ln(C_{jst}) + \varepsilon_{ist}, \quad i = 1, 2, \ldots, I. \tag{3}$$

We estimate the model in four different ways to assess the impact of pooling data across stores and to assess the impact of separating regular price from promotional price variation:

- Model A: Data are pooled across the 83 stores and all 224 weeks, without distinguishing between regular and promotional price weeks.
- Model B: The model is estimated separately for each of the 83 stores, without distinguishing between regular and promotional price weeks.
- Model C: The model is estimated separately for each of the 83 stores, using regular price weeks only.
- Model D: The model is estimated separately for each of the 83 stores, using promotional price weeks only.

As in §2, for a given product i, each of the models, A to D, is estimated as a linear regression. In the current formulation, Model A pools the data across the 83 stores, but it does not impose any cross-store restrictions on the parameters. Hence, instead of using OLS (as in BDG 2005), we set up Model A as a hierarchical linear regression that we estimate using MCMC methods. Models B, C, and D are estimated using

Table 3 ANOVA: Variation in Regular Prices vs. Promotional Prices in Refrigerated Orange Juice Data

	Tropicana Premium 64 oz	Tropicana Premium 96 oz	Florida's Natural 64 oz	Tropicana 64 oz	Minute Maid 64 oz	Minute Maid 96 oz	Tree Fresh 64 oz	Dominick's 64 oz	Dominick's 128 oz	Tropicana Premium 32 oz
					Regular prices					
No. of observations (store weeks)	9,201	13,744	11,684	10,468	8,760	10,663	10,568	9,783	13,474	16,123
R-squared (store)	0.18	0.27	0.16	0.16	0.17	0.21	0.16	0.06	0.11	0.48
R-squared (store, own cost)	0.52	0.7	0.28	0.44	0.51	0.56	0.29	0.19	0.36	0.73
R-squared (store, own cost, cross cost)	0.59	0.75	0.4	0.49	0.62	0.66	0.34	0.3	0.59	0.73
					Promotional prices					
No. of observations (store weeks)	9,051	4,508	6,568	7,784	9,492	7,589	7,684	8,469	4,778	2,129
R-squared (store)	0.02	0.08	0.03	0.02	0.02	0.12	0.02	0.01	0.02	0.35
R-squared (store, own cost)	0.37	0.26	0.33	0.19	0.18	0.55	0.43	0.23	0.39	0.52
R-squared (store, own cost, cross cost)	0.47	0.38	0.4	0.28	0.23	0.64	0.51	0.29	0.55	0.55

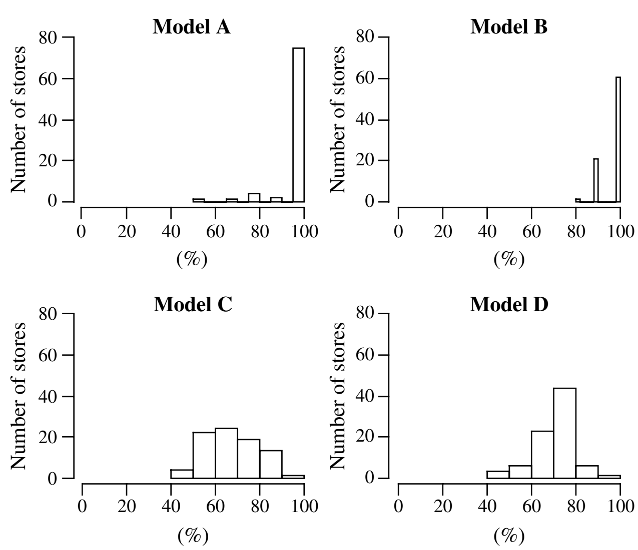
standard Bayesian regression techniques analogous to the specifications estimated in §2.

Using Models A through D, for each of the 83 stores, we estimate 10 own-brand pass-through elasticities and 90 cross-brand pass-through elasticities. To assess the predictive power of the various wholesale prices, we compute the percentage of estimated distributions in which zero falls outside the 95% posterior credibility region. We organize our results to address the following questions: First, is there evidence of nonzero own- and cross-brand pass-through elasticities, and do the results depend upon the pooling scheme (i.e., do they vary across the four models)? Second, what is the magnitude of own- and cross-brand pass-through elasticities, and do the results depend upon the pooling scheme? Answers to these two questions are presented next.

Are Own-Brand Pass-Through Elasticities Different from Zero?

For each of the 83 stores we compute the percentage of own-brand pass-through elasticities that is statistically different from zero. In Figure 1 we show the distribution of this percent. The distribution is similar for Models A and B, indicating that pooling data across stores (versus not) does not make a big difference to the number of own-brand pass-through estimates that are found to be nonzero. This lends support to the findings reported using only pooled data in BDG (2005) in the sense that pooling does not seem to over-inflate the perceived precision of the own-brand pass-through estimate. Comparing the results for Models A and B, which are based on all weeks, with the results for Models C and D, we note that identification of own-brand pass-through benefits from pooling data across regular and promotional price weeks. Finally, comparing results for Models C and D, we find that the distribution of nonzero own-brand pass-through elasticities is shifted to the left for regular price weeks, suggesting less posterior credibility on nonzero pass-through based on regular prices alone. These results are suggestive of an important distinction between pass-through measures based on regular versus promotional prices. Below, we discuss a more formal test for this difference.

Figure 1 Percent of Own-Brand Pass-Through Elasticities for Which Zero Lies Outside the 95% Posterior Credibility Region



Are Cross-Brand Pass-Through Elasticities Different from Zero?

Before looking at inferences on the posterior means of various cross-brand pass-through elasticities, we first look at the analogous model selection problem to the one we considered in §2. Namely, we compare the posterior probability of an unrestricted model M_1 (i.e., with cross-brand pass-through) to a restricted model M_0 with all cross-brand pass-through parameters set to zero. We summarize the results from the model selection problem in Table 4. For each of the 10 products, we report the total number of cases across the 83 stores where the unrestricted model generates a higher posterior log marginal density than the restricted model (i.e., with no cross-brand pass-through). In columns 1 and 2 we find that, overall, we select the unrestricted model in more than 67% of the cases. To assess the degree of empirical support for the unrestricted model with cross-brand pass-through, we compute the Bayes factor. Across all the stores and products, we find that the unrestricted model has a Bayes factor greater than 12.8 in more than 50% of the cases. In columns 3 and 4, we look at the results based only on weeks with regular prices and find that we select the unrestricted model in over 85% of the cases. At regular prices, the unrestricted model has a Bayes factor greater than 2,300 in more than 50% of the cases.[4] In columns 5 and 6, we focus on the results based only on promotional price weeks, selecting the unrestricted model in more than 52% of the cases. At promotional prices, the unrestricted model has a Bayes factor greater than 1.2 in more than 50% of the cases. Thus, the empirical support for cross-brand pass-through is weaker during a promotional price week. Nevertheless, these findings provide unambiguous support for the predictive power of the wholesale prices of substitute products for retail

[4] We performed diagnostic checks to validate the very large Bayes factors. Plots of the posterior draws on the likelihoods of the restricted and unrestricted models show that the large factors are not driven by outliers. We also performed classical F-tests of the restriction that cross-brand pass-through is zero for regular price weeks. The restriction was rejected in 97% of the 830 cases (83 stores times 10 products), and the mean F-statistic was bigger than 8.

Table 4 Model Selection in the 224-Week Refrigerated Orange Juice Sample, by Product Across the 83 Stores

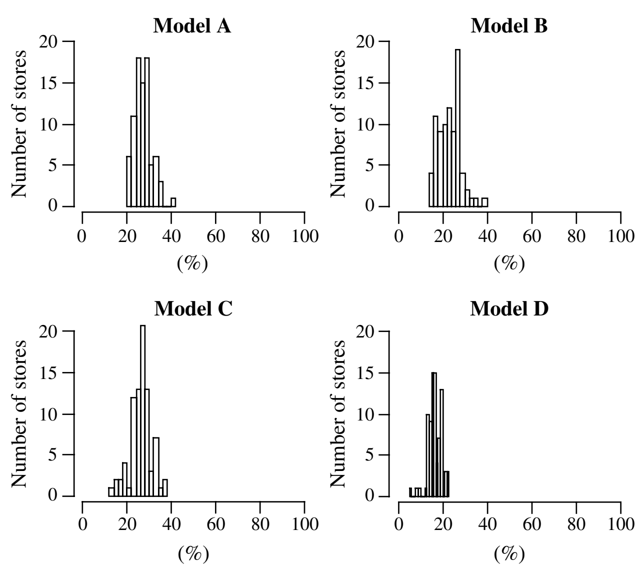
	Cases in which $\hat{p}(y \mid M_{CPT}) > \hat{p}(y \mid M_{noCPT})$						Cases in which model with interactions dominates (all weeks)	
	All weeks		Regular price weeks		Promotional price weeks			
Product	Count	Percent	Count	Percent	Count	Percent	Count	Percent
Tropicana Premium 64 oz	30*	36.1	72	86.7	68	81.9	83	100.0
Tropicana Premium 96 oz	52	62.7	82	98.8	25	30.1	80	96.4
Floridas Natural 64 oz	74	89.2	82	98.8	24	28.9	83	100.0
Tropicana 64 oz	26	31.3	51	61.4	28	33.7	83	100.0
Minute Maid 64 oz	24	28.9	77	92.8	7	8.4	83	100.0
Minute Maid 96 oz	82	98.8	82	98.8	83	100.0	73	88.0
Tree Fresh 64 oz	51	61.4	39	47.0	46	55.4	83	100.0
Dominicks 64 oz	72	86.7	67	80.7	22	26.5	83	100.0
Dominicks 128 oz	82	98.8	83	100.0	71	85.5	74	89.2
Tropicana Premium 32 oz	69	83.1	72	86.7	60	72.3	53	63.9
Overall	562	67.7	707	85.2	434	52.3	778	93.7

* *To be read as*: In 30 of 83 (or 36.1% of) stores the unrestricted model (with cross-brand pass-through) generated higher log marginal density than the restricted model (without cross-brand pass-through) in the sample that pooled regular price with promotional price weeks.

shelf prices, although the extent of this finding is mitigated by the consideration of a regular versus a promotional price week.

For each of the 83 stores, we also compute the percentage of cross-brand pass-through elasticities that is statistically different from zero, and we show the distribution of this percent in Figure 2. Again, the distributions for Models A and B are qualitatively similar, indicating that results do not depend critically on pooling data across stores and hence supporting our findings in BDG (2005). Comparing results for Models C and D, we find that the distribution of nonzero cross-brand pass-through elasticities is shifted to the right for regular price weeks (Model C), further confirming the usefulness of separating regular from promotional prices. This result is also consistent with the finding of very large Bayes factors for the unrestricted model specification for regular price weeks.

Figure 2 Percent of Cross-Brand Pass-Through Elasticities (Out of 90) for Which Zero Lies Outside the 95% Posterior Credibility Region



In the last two columns of Table 4, we also provide results from a formal test for differences in promotional versus regular price pass-through. We compare the log marginal density of model B, M_0, to an augmented version of model B with interaction terms between a promotion dummy variable and each of the own- and cross-brand pass-through elasticities, M_1. That is, we effectively combine Models C and D into a single model that is fit to all the data and includes a full set of interaction terms. For each product, we find that the model with interactions has better posterior fit than one without in more than 93% of the stores. This finding confirms the importance of separating promotional and regular weeks in the measurement of pass-through.

What Is the Magnitude of Own-Brand and Cross-Brand Pass-Through Elasticities?

In Table 5 we report the average posterior means of the own-brand and cross-brand pass-through elasticities across the 83 stores for each of the 10 products, for Models A through D. Comparison of Models A and B indicates small differences in the average elasticities, supporting our earlier conclusion that pooling across stores does not change results substantively. On the other hand, comparison of Models C and D indicates large differences in elasticities between regular price and promotional price weeks. In particular, 7 of the 10 mean own-brand pass-through elasticities are larger in magnitude for promotional price weeks. On the other hand, no clear pattern is evident for the cross-brand pass-through elasticities.

To sum up, McAlister (2007, p. 887) claims: "When we step back and think about it, it is unlikely that a grocery retailer would or could consistently execute a policy of positive and/or negative cross-brand pass-through." Our empirical results suggest otherwise. We find from the analysis of the refrigerated orange juice data that pooling across stores does not have a large effect on the number of nonzero estimates of own- and cross-brand pass-through elasticities. However, we do find that it is meaningful to separate the analysis by regular and promotional price weeks. Most importantly, after accounting for the critique of McAlister (2007), we continue to find statistical evidence of nonzero cross-brand pass-through coefficients as reported in BDG (2005), although the incidence is smaller in our current analysis (about 19% as against 63% earlier). This latter result is not surprising, given that we have reduced considerably the

Table 5a **Cross-Store Average of the Posterior Mean Own and Cross-Brand Pass-Through Elasticities for Model A (Read as Cross-Brand Pass-Through Elasticity for Brand in Row with Respect to Brand in Column)**

	Model A									
Product	Tropicana Prem 64	Tropicana Prem 96	Florida's Natural 64	Tropicana 64	Min Maid 64	Min Maid 96	Tree Fresh 64	Domin 64	Domin 128	Tropicana Prem 32
Tropicana Premium 64 oz	0.71	0.10	−0.11	−0.09	−0.12	−0.21	0.10	0.01	0.14	0.43
Tropicana Premium 96 oz	0.05	0.57	0.04	−0.02	0.02	−0.03	0.01	0.04	0.08	0.10
Florida's Natural 64 oz	−0.21	0.16	0.32	0.08	−0.14	0.20	0.04	−0.07	0.15	0.24
Tropicana 64 oz	0.20	0.38	0.00	0.57	−0.05	0.00	0.01	−0.24	0.14	−0.59
Minute Maid 64 oz	−0.01	0.26	−0.04	−0.05	0.48	0.13	0.03	0.05	−0.03	0.07
Minute Maid 96 oz	0.02	0.29	0.08	0.19	0.01	0.39	0.10	−0.05	−0.04	−0.03
Tree Fresh 64 oz	−0.11	0.66	0.19	0.18	−0.01	0.14	0.52	−0.09	−0.17	−0.85
Dominicks 64 oz	0.06	0.21	−0.38	−0.03	0.26	−0.47	0.01	0.92	−0.37	0.55
Dominicks 128 oz	0.18	0.25	−0.12	−0.07	−0.09	0.15	0.00	−0.15	0.27	1.50
Tropicana Premium 32 oz	0.06	−0.03	0.02	−0.02	−0.02	0.06	0.00	−0.03	0.04	0.84

Table 5b **Cross-Store Average of the Posterior Mean Own and Cross-Brand Pass-Through Elasticities for Model B (Read as Cross-Brand Pass-Through Elasticity for Brand in Row with Respect to Brand in Column)**

	Model B									
Product	Tropicana Prem 64	Tropicana Prem 96	Florida's Natural 64	Tropicana 64	Min Maid 64	Min Maid 96	Tree Fresh 64	Domin 64	Domin 128	Tropicana Prem 32
Tropicana Premium 64 oz	0.73	0.11	−0.11	−0.08	−0.12	−0.21	0.10	0.01	0.14	0.46
Tropicana Premium 96 oz	0.05	0.48	0.04	−0.02	0.02	−0.03	0.02	0.04	0.08	0.10
Florida's Natural 64 oz	−0.21	0.16	0.28	0.09	−0.14	0.20	0.04	−0.08	0.14	0.27
Tropicana 64 oz	0.19	0.34	0.02	0.61	−0.05	0.01	0.01	−0.24	0.14	−0.42
Minute Maid 64 oz	−0.01	0.25	−0.04	−0.05	0.47	0.13	0.03	0.06	−0.02	0.08
Minute Maid 96 oz	0.02	0.28	0.07	0.19	0.01	0.24	0.10	−0.05	−0.02	−0.07
Tree Fresh 64 oz	−0.13	0.62	0.20	0.19	−0.01	0.14	0.53	−0.10	−0.18	−0.66
Dominicks 64 oz	0.06	0.22	−0.38	−0.03	0.26	−0.45	0.00	0.94	−0.36	0.56
Dominicks 128 oz	0.21	0.27	−0.13	−0.08	−0.09	0.13	0.01	−0.15	0.30	1.30
Tropicana Premium 32 oz	0.06	−0.02	0.01	−0.02	−0.02	0.05	0.00	−0.03	0.04	0.50

Table 5c **Cross-Store Average of the Posterior Mean Own and Cross-Brand Pass-Through Elasticities for Model C (Read as Cross-Brand Pass-Through Elasticity for Brand in Row with Respect to Brand in Column)**

	Model C									
Product	Tropicana Prem 64	Tropicana Prem 96	Florida's Natural 64	Tropicana 64	Min Maid 64	Min Maid 96	Tree Fresh 64	Domin 64	Domin 128	Tropicana Prem 32
Tropicana Premium 64 oz	0.32	0.29	0.04	−0.03	−0.06	−0.10	0.06	0.06	0.16	0.25
Tropicana Premium 96 oz	0.05	0.33	0.11	0.00	0.01	−0.03	0.07	0.06	0.05	0.17
Florida's Natural 64 oz	−0.24	0.20	0.12	0.10	−0.04	0.10	−0.01	0.02	0.08	0.47
Tropicana 64 oz	0.17	0.27	0.13	0.44	0.00	0.05	0.00	−0.05	−0.13	−0.14
Minute Maid 64 oz	0.09	0.33	0.09	0.07	0.20	0.08	0.06	0.15	−0.14	0.02
Minute Maid 96 oz	−0.03	0.37	0.09	0.15	0.09	0.03	0.08	0.05	−0.02	0.02
Tree Fresh 64 oz	−0.05	0.10	0.15	0.11	−0.02	0.35	0.28	−0.09	−0.32	0.26
Dominicks 64 oz	0.06	0.05	−0.43	0.14	0.11	−0.26	0.03	0.77	−0.49	0.84
Dominicks 128 oz	0.22	0.23	−0.17	−0.10	−0.01	−0.04	0.03	−0.13	0.26	1.39
Tropicana Premium 32 oz	0.06	−0.02	0.01	−0.02	−0.02	0.07	0.00	−0.02	0.06	0.46

Table 5d Cross-Store Average of the Posterior Mean Own and Cross-Brand Pass-Through Elasticities for Model D (Read as Cross-Brand Pass-Through Elasticity for Brand in Row With Respect to Brand in Column)

	Model D									
Product	Tropicana Prem 64	Tropicana Prem 96	Florida's Natural 64	Tropicana 64	Min Maid 64	Min Maid 96	Tree Fresh 64	Domin 64	Domin 128	Tropicana Prem 32
Tropicana Premium 64 oz	0.92	0.18	−0.11	0.00	−0.22	−0.46	0.25	−0.15	0.29	0.32
Tropicana Premium 96 oz	0.27	0.22	0.00	−0.06	−0.07	−0.02	−0.05	0.06	0.13	0.25
Florida's Natural 64 oz	−0.05	0.32	0.21	0.01	−0.15	0.44	0.07	−0.15	0.04	−0.18
Tropicana 64 oz	0.16	0.44	0.17	0.73	−0.11	−0.26	0.00	0.22	−0.27	−0.77
Minute Maid 64 oz	−0.12	0.13	0.08	−0.20	0.36	0.27	−0.09	−0.09	0.34	0.08
Minute Maid 96 oz	0.05	0.14	0.05	0.22	−0.15	0.50	0.14	−0.21	0.03	−0.03
Tree Fresh 64 oz	−0.04	1.06	0.13	0.20	−0.06	−0.31	0.57	−0.19	0.32	−0.99
Dominicks 64 oz	−0.27	−0.07	−0.27	−0.34	0.19	−0.12	−0.02	1.04	−0.11	1.22
Dominicks 128 oz	0.33	0.08	−0.09	−0.03	−0.04	0.77	−0.03	−0.04	−0.10	0.26
Tropicana Premium 32 oz	−0.02	0.16	0.05	0.07	0.01	−0.11	0.02	−0.07	0.11	0.44

amount of pooling in the estimation exercise. In particular, we now estimate each of the cross-brand pass-through elasticities separately for a store rather than pooling them across stores within a zone.

5. Discussion and Conclusions

In this paper we present analyses of retailer pass-through behavior using model specifications that are robust to the pooling and sample size critiques of McAlister (2007). In the original sample of 11 categories from BDG (2005), we find empirical support for the predictive power of cross-brand pass-through even without pooling across zones. In a new sample with a longer time series for the refrigerated orange juice category, we continue to find a substantial number of nonzero cross-brand pass-through elasticities, evidence that is consistent with the results reported in BDG (2005). We expect these results will be replicated in other categories.

McAlister (2007, p. 876) challenges the discussion of cross-brand pass-through as inconsistent with the extant empirical literature: "Most empirical studies assume that cross-brand pass-through is rarely practiced in the grocery industry." We respectfully disagree with this statement and point out that cross-brand pass-through has been a standard element of the literature, either explicitly or implicitly. The theoretical literature on category-profit-maximizing retailers focuses explicitly on the role of cross-price elasticities of demand between brands for optimal pricing, which naturally implies cross-brand pass-through behavior (e.g., Choi 1991, Lee and Staelin 1997, Shugan and Desiraju 2001, Moorthy 2005). Analogous multiproduct pricing models that imply cross-brand pass-through are also used routinely in the empirical literature on retail pricing behavior (e.g., Besanko et al. 1998, Villas-Boas and Zhao 2005, Meza and Sudhir 2006, Villas-Boas 2007). In fact, Sudhir (2001) formally tests several competing forms of pricing conduct in a supermarket retail channel. He finds that Stackelberg equilibrium pricing conduct fits the supermarket data better than vertical Nash equilibrium pricing. Because Stackelberg pricing leads to nonzero cross-brand pass-through in equilibrium, whereas vertical Nash pricing leads to zero cross-brand pass-through, Sudhir (2001)'s findings embody a test of nonzero cross-brand pass-through. Therefore, the account for cross-brand pass-through in our empirical model is entirely consistent with this large body of literature.

McAlister also argues that manufacturers closely monitor the execution of promotional deals with retailers and would react adversely if cross-brand pass-through were practiced. This argument assumes that manufacturers have a degree of control over retailers' pass-through behavior that is belied by manufacturers' claims that only half of trade promotion dollars are passed through to consumers (Cannondale Associates 2001).

McAlister (2007) further argues that pass-through measures based on DFF's wholesale prices are inaccurate due to the manner in which DFF computes its margins. Note that while these measures might not correspond well to the microeconomic definition of marginal cost, they are nevertheless the measures that DFF used in setting its own prices. Furthermore, to date, the DFF database is the most comprehensive collection of retail and wholesale prices available for academic use. Ultimately, the scientific approach to resolving the debate over cross-brand pass-through would be to encourage the collection of better measures of wholesale prices and to supplement these measures with trade deal information. We view this as an important direction for future research.

Appendix. The Hierearchical Linear Model (Model A)

Recall that our pass-through model for prices of a product i in store s during week t is as follows:

$$\ln(P_{ist}) = \alpha_{is} + \beta_{is}\ln(C_{ist}) + \sum_{j\neq i}\beta_{ijs}\ln(C_{jst}) + \varepsilon_{ist}, \quad i = 1, 2, \ldots, I. \tag{4}$$

The last term, ε_{ist}, is assumed to be an independent draw from a normal distribution with mean zero and variance σ_s^2 (i.e. $\varepsilon_{ist} \sim N(0, \sigma_s^2)$).

To pool the data, as we do in Model A, we still need to allow for heterogeneity across stores. We introduce heterogeneity by assuming that each store has its own idiosyncratic vector of own- and cross-brand pass-through elasticities associated with a product i, $\beta_{is} = (\beta_{i1s}, \ldots, \beta_{iIs})'$. The pooling of the data across all the stores arises from the assumption that all the pass-through vectors, $\{\beta_{is}\}$, have a common prior distribution:

$$\beta_{is} = \bar{\beta}_i + \nu_{is}, \quad \nu_{is} \sim i.i.d.N(0, V_\beta). \tag{5}$$

Equation (2) implies that the store-specific parameters have a normal prior distribution with mean $\bar{\beta}_i$ and variance V_β. In contrast, Models B, C, and D assume there is no commonality across the store parameters (i.e., independent priors).

To complete the model, we also need a prior distribution on the regression error variances, σ_{is}^2. To keep things simple, we follow the convention in the literature and assume that each of the error variances is independent:

$$\sigma_{is}^2 \sim \frac{\eta s_{0,is}^2}{\chi_\eta^2}. \tag{6}$$

We also need a final stage of priors on the parameters $\bar{\beta}_i$ and V_β:

$$\begin{gathered} V_\beta \sim IW(\upsilon, V), \\ \bar{\beta}_i \mid V_\beta \sim N(\bar{\bar{\beta}}, V_\beta \otimes A^{-1}), \end{gathered} \tag{7}$$

which are the natural conjugate priors of the multivariate regression model described in (1).

The technical details of the Gibbs sampler used to construct our estimates can be found in any standard textbook (e.g., Rossi et al. 2006). Our estimates of Model A are based on a Markov chain with 10,000 draws, where the first 1,000 draws are used as a burn-in period. We use the following prior settings:

$$\eta = 3, \quad \upsilon = 15, \quad V = \begin{pmatrix} \upsilon & & 0 \\ & \ddots & \\ 0 & & \upsilon \end{pmatrix}, \quad A = 0.01, \quad \bar{\bar{\beta}} = 0,$$

$$s_{0,is}^2 = \mathrm{var}(\ln(P_{is})).$$

We use these diffuse prior settings to let the data themselves drive the "shape" of the distribution of taste heterogeneity. We use the analogous settings for the standard Bayesian regression models without random coefficients, used in §2 and Models B, C, and D in §3.

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