

Variety and Cost Pass-Through among Supermarket Retailers

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1 Introduction

Wholesale prices rose at unprecedented rates in 2008. The extent to which higher wholesale prices are reflected in higher retail prices is an issue of critical importance to both players in the food supply chain, and macroeconomic policymakers. Theoretical models of input-price pass-through show that competitive, single-product retailers will pass a rise in costs along to consumers on a one-to-one basis if they face perfectly elastic demand. Imperfectly competitive retailers, however, will absorb some of the change in costs depending upon the curvature of demand, the competitiveness of local markets (Nakamura and Zerom, 2010) and the structure of retailing costs (Hellerstein, 2008). Recently, Hamilton (2009) shows that over-shifting, or passing through costs on a more than one-to-one basis, can occur among imperfectly competitive, multi-product retailers. The reason is straightforward. Rising input costs cause retailers to reduce the number of products they sell, which softens price competition in the retail market and causes retail prices to rise. In this paper, we test this hypothesis using store-level data on breakfast cereal sales from a large sample of U.S. grocery retailers.

Much of the previous empirical research on pass-through has focused on why retail prices reflect only part of a rise in cost. Focusing on the related issue of exchange-rate pass-through, Nakamura and Zerom (2010), Hellerstein (2008) and a number of others document the effects of: (1) imperfect competition, (2) local costs, and (3) price rigidity.¹ Using a similar approach, Kim and Cotterill (2008) show that retailers absorb some of the change in wholesale cheese prices so pass-through is significantly below 1.0 as well. There is very little empirical research on the phenomenon of over-shifting, or the observation that pass-through can be greater than 100%. Over-shifting is of particular concern during periods of rising prices because it implies that consumers are asked to bear a disproportionate share of rising input costs.

Policymakers tend to focus on the pass-through of "commodity" or raw input prices all the way through to the retail level. However, estimating commodity-price pass-through rates requires the researcher to model both wholesale and retail pass-through (Hellerstein, 2008). Typically, wholesale prices are not available, so must be inferred from an assumed structure of the vertical pricing game played between retailers and wholesalers. If the assumed form of the game is not correct, however, the error in doing so is only compounded in estimating retail pass-through rates. Therefore, in this study we focus on the simpler problem of estimating retail pass-through only using wholesale prices similar to those used in Nakamura and Zerom (2010).

Our primary contribution lies in explaining the phenomenon of overshifting in response to changes in input prices. While understood to be a theoretical possibility with important practical and welfare implications, there are few tests of why overshifting may occur, or documented cases of overshifting in practice. Second, we contribute to the methodological literatures on pass-through in both the industrial organization and international literatures in pointing out the potential weaknesses of an increasingly popular approach to modeling pass-through. While we do not offer our model as the only option, empirical research on pass-through in multi-product environments must be able to accommodate the endogeneity of assortment depth, and its effect on pricing behavior. Third, on a substantive level we document the extent to which changes in commodity prices are passed through to consumer food prices. Previous research in the policy sphere (Leibtag et al., 2009) finds that very little commodity price inflation is passed through to consumers, but our findings raise some concerns that the opposite may be true. For consumer products sold through multi-product retailers, which the vast majority are, over-shifting may be an important and serious policy concern.

¹ Although there is a large empirical literature on pass-through asymmetry (Berck, et al., 2009) our focus in this paper is on explaining the extent and not the rate of pass-through.

2 Empirical Model of Variety Effects on Store Competition

We estimate a structural model of consumer demand, supermarket pricing, variety decisions as well as price- and variety-pass-through. Supermarket price and variety choices are made conditional on consumer demand. We assume retailers set variety levels as Nash oligopolists, conditional on retail prices, and then choose retail prices based on the realization of the variety game, again using Nash rules.

Our demand model considers how variation in price and variety affects consumers' choice of stores, and choice of products once in the store. Therefore, our demand model is hierarchical in nature. Specifically, consumer demand is represented by a random utility model in which consumers are assumed to make a discrete choice of one product (brand) from among those represented in our sample of retail data, or some other brand from another outlet, which is defined as the outside option. Because consumers can buy cereal from sources other than those captured by our scanner data, we model the hierarchical nature of a consumer's choice process: consumers first choose whether to buy from the traditional supermarkets described by our data, or another source, and then the specific brand. Consequently, we adopt a Generalized Extreme Value (GEV) model of consumer demand. With the GEV assumption, we allow for differing degrees of substitution among products within each group: supermarket purchases and others. Without further modification, the GEV model still exhibits the independence of irrelevant alternatives (IIA) property within each group (store) and the unrealistic pattern of substitution that this implies. Therefore, we allow the product-specific preference term, the marginal utility of income and the variety-effect to vary randomly over individuals. The resulting correlation between unobserved heterogeneity and attributes of each product generates demand curvature that, in turn, creates a general pattern of substitution among products.

The random-parameters GEV model is well-understood in the literature, so we provide only the essential elements of our application here. In terms of a formal utility model, the utility consumer h obtains from consuming product j in store i during month t (u_{hijt}) is a function of the product's price in each store (p_{ijt}), product- and store-specific preferences, δ_{hij} , a concave function of the number of products sold in the store ($f(N_{it})$) and a set of product attributes (x_{jkt}) such that:

$$u_{hijt} = \delta_{hij} + \alpha_h p_{ijt} + f(N_{it}) + \sum_{k=1}^K \beta_k x_{jkt} + \xi_{jt} + \tau_{hijt} + (1 - \sigma)\varepsilon_{hijt}, \quad \forall j \in J, i \in I, \quad (1)$$

for the set of products J and stores I where σ is the GEV scale parameter, ξ_{jt} is an iid error term that reflects attributes of the product that may be important to utility, but are unobserved by the econometrician such as location on the shelf, unmeasured advertising, perceived quality or package characteristics or of the store such as location, cleanliness or the number of services offered; ε_{hijt} is an iid error term that reflects unobserved consumer heterogeneity and is assumed to be extreme-value distributed, and τ_{hijt} is an error component that is distributed so that the entire error $\tau_{hijk} + (1 - \sigma)\varepsilon_{hijt}$ remains extreme-value distributed (Cardell, 1997). Utility associated with the choice of the outside good is $u_{h00t} = \varepsilon_{h00t}$. The parameter σ is interpreted as a measure of the degree of substitutability among groups (or its inverse, heterogeneity) such that if $\sigma = 1$ there is perfect substitution among stores and the model collapses to a simple-logit model among all products and stores. The product attributes included in the vector \mathbf{x}_{jt} are a binary discount variable (d_{ijt}) that assumes a value of 1 if the product is reduced in price by at least 10% from one month to the next and

then returned to its previous value in the following month, an interaction term between the discount and price ($d_{ijt}p_{ijt}$) and a set of store and brand binary variables.²

Implicit in our model is the assumption that consumers derive utility from variety. While this assumption is not without detractors (Kuksov and Villas-Boas, 2010) the notion that consumers derive more utility the greater the likelihood they will be able to find a product that meets their desired specifications is well established (Kim, Allenby and Rossi, 2002). We define $f(N_{it})$ as a simple quadratic function: $f(N_{it}) = \gamma_1 N_{it} + 1/2\gamma_2 N_{it}^2$ and expect that $\gamma_1 > 0$ and $\gamma_2 < 0$, although we leave this as a hypothesis to be tested.

Unobserved consumer heterogeneity is an important determinant of brand choice in empirical models of supermarket retailing (Draganska and Klapper, 2007). Therefore, we assume the marginal utility of income (price-response), product-specific preferences and the marginal utility of variety to each depend on a vector of consumer attributes (age and income) and a normally distributed error term. As a result, the final random coefficient logit model is estimated using simulated maximum likelihood (SML) algorithms (Train, 2003) using the control-function method introduced by Petrin and Train (2010) to account for the obvious endogeneity of prices in the mean utility specification. We describe this method in more detail below.

2.1 Price and Variety Choice

On the supply side, the structure of the game is as follows: (1) in the first stage, retailers make variety decisions conditional on the pricing decisions of all rivals and observed wholesale prices, (2) retailers compete in prices based on their prior assortment decisions, and (3) consumers choose among the six sample stores and the sample of cereals represented in our data. Typically, structural models of retail pass-through involve simultaneous estimation of demand and a retail margin equation and then simulating the impact of changes in cost in order to determine the rate of cost-pass-through (Kim and Cotterill, 2008). However, we derive pass-through rates analytically by totally differentiating the first order conditions for price and variety in wholesale prices. We then estimate both price- and variety-pass-through using a generalized method of moments (GMM) estimation method. In this way, we test our core hypotheses directly without relying on simulation methods and indirect tests.

Retailers maximize profit by choosing prices and assortment depth in their own store. The solution concept for the game played by all retailers in a market is, therefore, Nash in prices and assortment. We solve the problem by backward induction, beginning with the retailers' pricing problem and then deriving their assortment decision rules. The profit equation for retailer i is written as (dropping the time subscript for clarity):

$$\pi_i = M \sum_{j \in J} s_{ij}(p_{ij} - c_{ij} - w_{ij}) - g(N_i), \quad (2)$$

where w_{ij} is the wholesale price paid by retailer i for product j , M is the size of the aggregate market for all products, and $g(N_i)$ is a convex cost function that reflects the fact that costs rise in assortment in an increasing way (Draganska and Jain, 2005). Because we assume utility is concave in variety, an equilibrium is assured, and tractability maintained, by assuming a linear cost function: $g(N_i) = \lambda_0 + \lambda_1 N_i$. Retailing costs are assumed to be separable from wholesale purchases and constant in the volume sold, and linear functions of input prices. Therefore, the expression for retailing costs is:

$$c_{ij}(\mathbf{v}_r) = \sum_{i \in I} \sum_{j \in J} \eta_{ij0} + \sum_{l \in L} \eta_{wl} v_{rl} + \epsilon_{ijr}, \quad (3)$$

²Despite the results of Nevo (2001), nutritional attributes performed poorly in this model so were excluded from the attribute list.

where \mathbf{v}_r is a vector of L retailing prices, η_{ij0} are brand- and store-specific fixed-effects, and ϵ_{ijr} is an iid error term. Retailing costs are estimated after substituting equation (1) into the first-order conditions and pass-through equations derived next.

With these assumptions, the first order conditions in prices, conditional on optimal varieties already being chosen, are given by:

$$\frac{\partial \pi_i}{\partial p_{ij}} = Ms_{ij} + M \sum_{k \in J} (p_{ik} - c_{ik} - w_k) \frac{\partial s_{ik}}{\partial p_{ij}} = 0, \quad \forall i \in I, j \in J, \quad (4)$$

so each retailer is assumed to internalize all pricing externalities within the store, but does not take into account all the cross-price effects from products sold in other stores. In matrix notation, we stack these first-order conditions over all retailers and introduce an ownership matrix, Ω , with element $\omega_{ij} = 1$ if product j is sold by retailer i and zero if not and write:

$$\mathbf{p} = \mathbf{c} + \mathbf{w} - (\Omega \mathbf{S}_p)^{-1} \mathbf{s}, \quad (5)$$

where bold notation indicates a vector (or matrix), and \mathbf{S}_p is the matrix of share-derivatives with element $\partial s_{ij} / \partial p_{lk}$. The specific form of these derivatives for the random-coefficient nested logit model are provided in the technical appendix below. Retailers' variety choices must take into account not only the intra-marginal effect on retail prices, but also the inter-marginal effect on rival's prices. In this way, we capture the competitive effect of assortment decisions while minimizing the competitive effect of price changes.³ Therefore, the first-order conditions for the retailers' optimal choice of variety is given by:

$$\begin{aligned} \frac{\partial \pi_i}{\partial N_i} &= M \sum_{j \in J} s_{ij} \frac{\partial p_{ij}}{\partial N_i} + M \sum_{j \in J} (p_{ij} - c_{ij} - w_j) \frac{\partial s_{ij}}{\partial N_i} \\ &+ M \sum_{l \in I} \sum_{k \in J} (p_{lk} - c_{lk} - w_k) \frac{\partial s_{lk}}{\partial p_{lk}} \frac{\partial p_{lk}}{\partial N_i} - \frac{\partial g_i}{\partial N_i} = 0, \quad \forall i \in I. \end{aligned} \quad (6)$$

Optimal variety choices depend on the relative strength of: (1) a price-effect (first term in (6)), (2) a competitive, or business-stealing effect (second term in (6)), (3) a rival-effect on the prices charged by other stores (third term in (6)), and the cost of increasing variety (fourth term in (6)). We can solve this equation for the optimal variety for each retailer under the Nash-in-variety assumption in matrix notation to give:

$$\mathbf{N} = (1/\lambda_1)(\mathbf{M}\mathbf{s}'\mathbf{P}_N + \mathbf{M}(\mathbf{p} - \mathbf{c} - \mathbf{w})'\mathbf{S}_N + \mathbf{M}(\mathbf{p} - \mathbf{c} - \mathbf{w})'\mathbf{S}_p\mathbf{P}_N), \quad (7)$$

where \mathbf{P}_N is a vector of price-derivatives in variety, \mathbf{S}_N is a vector of share-derivatives in variety and the other variables are as defined above. At this point, we can estimate (6) and (7) simultaneously to recover the parameters of the retailing cost function and the cost-of-variety function using only information from the demand side and the assumed structure of the game. We can then simulate the solution for optimal price and variety choices under various assumptions regarding changes in the wholesale price to calculate empirical pass-through rates as in Kim and Cotterill (2008). However, there is a better, more direct alternative when data on observed wholesale prices are available, as in our case.

By totally differentiating the first-order conditions in (6) and (7) with respect to the wholesale price, we obtain analytical solutions for both the price- and variety-pass through rates. In this way, we derive a more direct test the primary hypothesis of the study, namely that wholesale prices are negatively related to retailers' variety choices, and, as a result, retail

³This is a reasonable assumption given the weight of the literature that shows inter-store effects of price changes for specific products is minimal, at best (Slade, 1995).

pass-through rates are higher when we explicitly consider the impact of variety competition on retail price competition than when we do not. The total differentials are straightforward, but tedious, and yield solutions that we write in estimable form as:

$$SP_{ij} = SPP_{ij}\phi + SN_{ij}\theta + \varepsilon_P, \quad (8)$$

and for the variety-pass-through model:

$$SN_{ij} = SPN_{ij}\phi + SNN_{ij}\theta + \varepsilon_N, \quad (9)$$

where SP_{ij} is the vector of share-derivatives in price, SPP_{ij} is the matrix of share-second-derivatives, SN_{ij} is the vector of share-derivatives in variety, SPN_{ij} is the matrix of share-derivatives, SNN_{ij} is the matrix of share-second-derivatives in variety, and ε_P and ε_N are iid error terms.

We estimate the entire empirical model in two stages: first estimating the demand model, and then using the implied share derivatives in price and variety to estimate equations (8) and (9) after substituting in the cost equation (3). As explained in more detail below, we estimate this entire "supply system" or the pricing and variety equations using generalized method of moments (GMM) to account for the obvious endogeneity of prices and share derivatives on the right-side of the model.

3 Data and Estimation Methods

3.1 Data

Our empirical application of this model considers the ready-to-eat breakfast cereal market. Our data describes 33 months (June 2007 - March 2010) of supermarket chain-level retail sales of ready-to-eat breakfast cereal in the Los Angeles retail market. The data are from IRI InfoScan for the top six supermarkets in Los Angeles: Albertsons, Food 4 Less, Ralphs, Safeway, Stater Brothers, Vons and Vons Pavilions and include all branded UPCs, including both private label brands and national brands. For this study, we focus on 19 top brands (by volume share) and include all other brands as part of the outside option. These brands were chosen based on their market share ranking among the six sample stores, constrained by the requirement that each brand is sold in all stores. We define the total market as the population of Los Angeles and, assuming Angelinos consume breakfast cereal at approximately the same rate as consumers in the U.S. as a whole, use per capita consumption data (USDA, ERS) to impute a total-market consumption level. The outside option is then calculated as the total market less the cereal sales captured in our data. In this way, the outside option captures not only the brands excluded from our sample, but cereal purchased through retailers that do not participate in the IRI InfoScan data syndication system (Wal*Mart, Sam's Club and Costco), or through foodservice, convenience and institutional outlets.

The wholesale price data are from the Price-Trak data product sold by Promodata, Inc. These data represent prices paid to grocery wholesalers by supermarket retailers and cover most major brands of cereal sold by major manufacturers (all brands included in our sample). Price-Trak includes data on the price charged by manufacturers before allowances are applied, markups charged by wholesalers to retailers, the effective date of new case prices, "deal allowances" or off-invoice items offered to retailers by the wholesaler, the type of promotion suggested by the wholesaler to the retailer, and the allowance date. Of these variables, we define the wholesale price as the price charged to the retailer net of any allowances. One limitation of this datasource is that it represents prices charged by wholesalers to only non self-distributing retailers. Although we recognize that the retailers in our sample do generally self-distribute, the wholesale price data we use is likely to be highly correlated with prices paid by all because restrictions under the Robinson-Patman Act require any

deals offered in a market to be offered to all. To the extent that the prices our retailers pay differ from the wholesale prices in the dataset, our wholesale price may be measured with error. Compared with existing methods of imputing wholesale prices (Villas-Boas and Zhao, 2005; Berto Villas-Boas, 2007), however, our error is likely to be minimal. All retailing input-price data are from the Bureau of Labor Statistics (BLS, 2010a) and include average weekly earnings by workers in the grocery retailing industry, an index of healthcare costs paid by retailers, and an index of utility prices paid by retailing businesses.

3.2 Estimation Methods and Identification

We estimate the structural model of demand and pass-through in two stages. We estimate the first-stage demand model using the control function method described by Petrin and Train (2010) and the second stage pricing model using Generalized Method of Moments (GMM). In aggregate, market-level scanner data, retail prices in the demand system are likely to be endogenous so we test for this possibility using a Hausman (1978) specification test. In other words, some of the unobserved factors that are now in the econometric error term of the estimated demand equation are likely to be highly correlated with observed prices: shelf-facing, display area, in-store promotions and a host of other factors. Without an estimator that takes this into account, all parameter estimates would be biased and inconsistent. Addressing endogeneity using the simulated generalized method of moments (SGMM) approach of BLP has become a workhorse in the empirical industrial organization and marketing literatures. As Petrin and Train (2010) explain, however, their method may not be available to some researchers either because their data is not consistent with the BLP approach or their models are inherently more complex, making the BLP approach infeasible. Further, Berry, Linton and Pakes (2004) show that the BLP contraction algorithm, which matches observed to predicted market shares in order to impute a vector of mean utilities, is highly sensitive to sampling error. In studies that use only a few regional markets or only select stores in each market, this will be significant. Consequently, we adopt the “control function” approach developed by Petrin and Train (2010).

With the control function approach, we control for the bias likely to arise from the endogeneity in prices using a two-stage estimation approach. In the first stage, we estimate an instrumental variables (IV) regression in which we regress the endogenous prices on a set of variables likely to serve as valid instruments. We then use the residuals from this regression as explanatory variables in the mixed-logit demand equation, which is estimated using simulated maximum likelihood (SML, Train, 2003). By introducing the IV residuals into the demand model, we account for unobservables in the endogenous price that may be correlated with errors in the demand equation. Because using the residuals as an explanatory variable introduces a source of error in the second-stage of the demand model, we bootstrap the standard errors in the mixed logit model in order to ensure correct inferences are drawn.

Our identification strategy is well-accepted in the literature. Namely, we require instruments that are correlated with endogenous prices, but not the unobservables in the demand equation. Unobservable factors that are likely to influence prices for the products in question include such things as targeted, market-specific advertising, chain-level merchandising efforts, or variations in local tastes that are not captured by the demographic variables included in the demand model. Following others in this literature (Berto Villas-Boas, 2007; Draganska and Klapper, 2007) we use a variety of instruments. First, we interact retail and production input prices with the set of binary brand-indicators. Product-specific variation in costs will be correlated with prices for the same product, but not likely to be correlated with unobservable factors in the same demand equation. Second, we include a set of lagged share values in order to pick up any state dependence in demand that may arise from habit, learning or inertia.

On the supply side, retail markups and assortments are also likely to be endogenous. Therefore, we estimate the price- and variety-pass-through equations using GMM. Our identification strategy is, again, well accepted in the literature. Just as variables that capture

independent variation in supply identify the demand-side parameters, instruments on the supply-side must reflect variation in demand that is independent of unobservables in the pricing equation. For this purpose, we capture brand-specific variation in demand by including demographic variables such as income, age, and average household size interacted with brand-specific dummy variables. Second, we include lagged margin values which are appropriate if pre-determined and correlated with current-period margins. As in the case of the demand model, the pricing instruments also include a set of product-specific binary variables to capture brand-specific preferences that are otherwise not accounted for in the continuous instruments.

4 Results and Discussion

In this section, we present and interpret the results obtained by estimating the structural model of price- and variety-pass-through rates. We first present the demand-side estimates and then the pass-through model. Compared to the reduced-form model presented above, this model controls for the curvature of demand in both prices and varieties, the feedback effects from choosing varieties endogenously and both retailing costs and the costs of additional assortment. When presenting the pass-through model results, we compare estimates from a model in which we do not control for the endogeneity of prices or variety (non-linear seemingly unrelated regressions) to those obtained from the GMM model. In this way, we compare the pass-through rate estimates between a more conventional model and one in which both variables are endogenous.

Our demand model differs from a simple logit model in three ways: (1) we allow for hierarchical choice among stores using a GEV specification, (2) we allow for unobserved consumer heterogeneity by allowing the constant term, marginal utility of income and both the linear and quadratic variety effects to be random functions of age and income, and (3) we estimate the demand model using the control function method of Petrin and Train (2010). Because a simpler model is always preferred unless more complexity is demanded by the data, we conduct specification tests to assess the appropriateness of each of these modeling elements. Space limitations prevent offering the details of these tests, but they do statistically confirm our choice of demand specification. Consequently, we use estimates from the random coefficients nested logit model as inputs to the second-stage pass-through model.

[table 1 in here]

The results obtained by estimating the pass-through system are shown in table 2. In this table, we present estimates from our preferred instrumental variables estimator (GMM) with one that does not control for the endogeneity of variety in order to show the differences in estimated pass-through rates that results. Although both the non-linear seemingly unrelated regressions (NLSUR) and GMM estimators provide acceptable fits to the data (based on the chi-square statistics comparing their explanatory abilities to a null alternative) a Hausman (1978) test for exogeneity yields a test statistic value of 78.453, so we reject the non-IV estimator out of hand on statistical grounds.⁴ However, it is interesting from an economic perspective to compare the pass-through estimates of the two models. In both of these models, we provide both a "direct pass-through" and a "total pass-through" estimate. The coefficient on the wholesale price is interpreted as a direct pass-through rate as it reflects only the direct effect of wholesale price variation on the retail price, while the total pass-through rate, ϕ , takes into account the optimizing behavior of the retailers, and how competing in variety and prices conditions their willingness to pass wholesale price increases on to consumers. Although there are two equations in the model, because of the cross-equation restrictions implied by the structural derivation, most parameters are shared

⁴The Hausman (1978) test statistic is chi-square distributed with degrees of freedom equal to the number of potentially endogenous variables (11), which implies a critical value of 19.675.

across the two equations. Therefore, we do not break out estimates for each equation in table 6. In terms of the specific parameter estimates, we find that assortment costs rise in the number of SKUs, as expected. Rising assortment costs and concave utility mean that there will be an equilibrium assortment level. Further, and consistent with our preliminary analysis, the variety pass-through rate (θ) is negative, which means that retailers reduce their assortment when wholesale prices are rising. Intuitively, if wholesale prices rise, *ceteris paribus*, retailers are left with lower margins to cover the fixed costs of adding to their assortment. Consequently, they reduce assortments if wholesale prices rise.

Most importantly, however, if we do not account for the endogeneity of variety decisions, the price pass-through rate is less than 1 (0.730). This partial pass-through outcome is consistent with previous research (Hellerstein, 2008; Nakamura and Zerom, 2010), but is clearly a biased estimate given the results of our exogeneity tests. When we properly account for the endogeneity of variety by using an appropriate IV estimator, the pass-through rate rises and, in this case, shows a moderate degree of overshifting, or price-pass through greater than 1. For a null hypothesis that $\phi = 1$, the t-ratio is 1.67 so overshifting exists, but only at a 10% level of significance with a two-tailed test. Although this result has been shown to be a theoretical possibility (Delipalla and Keen, 1992; Andersen, de Palma and Kreider, 2001; Hamilton, 2009) this is the first empirical evidence that overshifting can occur in practice. Because the reduction in variety caused by the rise in wholesale prices softens price competition, retailers increase prices in equilibrium. Although some increase would be expected due to the competitive need to cover higher wholesale costs, we find that the indirect, or strategic effect, of a wholesale price increase can lead to overshifting.

5 Conclusions and Implications

In this study, we investigate the wholesale price pass-through rates when joint price and variety competition are considered explicitly. While the literature contains many examples of research intended to explain incomplete pass-through, our aim is the opposite: to explain pass-through that is greater than 100%, or more than what we would expect from perfectly competitive firms with inelastic demand. Specifically, we test the theory developed by Hamilton (2009) who maintains that overshifting is possible if we consider the multi-product nature of retailing. Wholesale price increases cause retailers to reduce the number of products they offer (termed their variety or assortment), which softens price competition among oligopolistic retailers. The resulting rise in retail prices thus supports the direct pass-through effect and can possibly cause retail prices to rise proportionately more than the original wholesale price increase.

We test this theory using a structural model of the grocery retailing market for a specific consumer packaged good that has experienced rapid wholesale price increases (and subsequent reductions) in recent years: breakfast cereal. Our model consists of a random-coefficient nested logit model of demand at the brand-level for six retailers in the Los Angeles market. Structural equations for retail-price and retail-variety pass-through are derived from the first-order conditions to a general Nash-game of retail competition in price and variety. By using directly-observed wholesale prices, we are able to estimate direct and indirect pass-through rates that account for simultaneous price and variety competition. We find that wholesale price increases are associated with reductions in variety at the retail level, both in an econometric model that accounts for the endogeneity of price and variety and one that does not. In a non-instrumental variable model that does not account for the endogeneity of variety, however, we find wholesale-price pass-through rates significantly less than 100%. On the other hand, when we correct for endogeneity using an appropriate set of instruments in a GMM framework, the estimated pass-through rate is greater than one. This evidence lends support to the theoretical model of Hamilton (2009) who showed that such an occurrence is indeed a theoretical possibility.

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Table 1: Random Coefficient Nested Logit Demand Model: RTE Breakfast Cereals, Los Angeles, June 2007 - March 2010.

Variable	Non-Random Parameters		Variable	Random Parameters	
	Estimate	t-ratio.		Estimate	t-ratio.
Discount	0.219*	9.256	Means of Random Parameters		
Discount*Price	-0.853*	-7.226	Price	-2.800*	-11.110
Albertsons	-0.579*	-26.534	Variety	25.918*	17.022
Food 4 Less	0.691*	28.889	Variety2	-30.259*	-13.964
Ralphs	0.285*	20.099	Constant	-11.671*	-42.433
Stater Bros.	0.326*	27.908	Std. Deviations of Random Parameters		
Vons Pavilion	-1.377*	-112.989	Price	0.964*	39.047
Cheerios	0.131*	3.776	Variety	0.412*	32.245
Cinnamon Toast Crunch	0.223*	5.989	Variety2	0.592*	19.586
Lucky Charms	0.100*	2.408	Constant	0.050*	16.527
Corn Flakes	0.154*	3.208	Rand. Para. Functions: Age and Income		
Frosted Flakes	0.234*	5.119	Price(Age)	0.004*	2.264
Raisin Bran	0.195*	4.989	Price(Income)	0.043*	6.048
Special K	0.390*	8.660	Variety(Age)	-0.090*	-3.221
Frosted Mini Wheats	0.235*	4.955	Variety(Income)	-0.760*	-8.426
Rice Krispies	0.136*	3.056	Variety2(Age)	0.144*	3.524
Cap'n Crunch	0.128*	2.942	Variety2(Income)	1.095*	8.468
All-Bran	-0.128*	-3.987	Constant(Age)	0.013*	2.890
Honeycomb	-0.124*	-2.658	Constant(Income)	0.120*	7.794
Honey Bunches of Oats	-0.072	-1.696	Estimate of Std. Deviation		
Kashi	-0.119*	-3.211	Std. Dev.	0.170*	148.213
Kix	0.048	1.260			
Life	0.020	0.393			
Nature's Path	0.203*	4.440			
Oatmeal Squares	-0.056	-1.053			
Quarter 1	0.154*	29.775			
Quarter 2	-0.010*	-2.343			
Quarter 3	-0.028*	-5.302			
μ_1	0.608*	2.593			
η_1	0.000*	-2.793			
σ	0.768*	216.473			
LLF	1,181.03				
Chi-Square	2,362.06				

* Indicates significance at the 95% level. Model is estimated using simulated maximum likelihood.

Table 2: Price and Variety Pass-Through Model: NLSUR and GMM.

	NLSUR		GMM	
	Estimate	t-ratio	Estimate	t-ratio
Constant	0.737*	60.316	0.849*	3.834
Wages	-0.458*	-30.243	-0.574*	-2.458
Health Care	-0.952*	-30.146	-1.946*	-4.671
Utilities	-0.029	-0.541	1.855	1.759
Wholesale Price	1.968*	308.294	2.184*	25.639
ϕ	0.730*	664.310	1.010*	164.498
θ	-8.125*	-160.216	-9.655*	-53.922
δ_2	-0.016*	-51.638	-0.022*	-11.299
LLF	3567.663		265.368	
Chi-square				

* Indicates significance at the 5% level. ϕ is the indirect price-pass-through rate, and θ is the variety-pass-through rate.