

# NCCC-134

APPLIED COMMODITY PRICE ANALYSIS, FORECASTING AND MARKET RISK MANAGEMENT

## **Pass-Through and Consumer Search: An Empirical Analysis**

by

Timothy J. Richards, Miguel I Gómez and Jun Lee

Suggested citation format:

Richards. T. J., M. Gómez and J. Lee. 2012. "Pass-Through and Consumer Search: An Empirical Analysis." Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO. [<http://www.farmdoc.illinois.edu/nccc134>].

## **Pass-Through and Consumer Search: An Empirical Analysis**

**Timothy J. Richards, Miguel I Gómez and Jun Lee\***

*Paper presented at the NCCC-134 Conference on Applied Commodity Price Analysis,  
Forecasting, and Market Risk Management St. Louis, Missouri, April 16-17, 2012*

*Copyright 2012 by Timothy J. Richards, Miguel I. Gómez and Jun Lee. All rights reserved.  
Readers may make verbatim copies of this document for non-commercial purposes by any means,  
provided that this copyright notice appears on all such copies.*

---

\* Timothy J. Richards (trichards@asu.edu) is the Morrison Professor of Agribusiness in the Morrison School of Agribusiness and Resource Management at Arizona State University; Miguel I. Gómez (mig7@cornell.edu) is an assistant professor in the Charles H. Dyson School of Applied Economics and Management at Cornell University; and Jun Lee (jl653@cornell.edu) is a Ph.D. student in the Charles H. Dyson School of Applied Economics and Management at Cornell University.

## Pass-Through and Consumer Search: An Empirical Analysis

*Retail-price pass-through is one of the most important issues facing manufacturers of consumer-packaged goods. While retailers tend to pass wholesale prices through to consumers quickly and completely, they often do not pass trade promotions on. Currently, asymmetric pass-through is commonly thought to result from retailers' exercise of market power. Alternatively, it may be due to consumer search behavior, and retailers' competitive response. We test this theory using a panel threshold asymmetric error correction model (TAECM) applied to wholesale and retail scanner data for ready-to-eat cereal for a number of retailers in the Los Angeles metropolitan market. We find that consumer search behavior contributes significantly to imperfect pass-through. By allowing pass-through to depend on market power and consumer search costs, we find results that are contrary to the conventional wisdom. Namely, market power causes retail prices to fall quickly and rise slowly, while consumer search costs cause retail prices to rise quickly and fall slowly precisely the "rockets and feathers" phenomenon.*

**Keywords:** cereal; panel data; retail-price pass-through; threshold error correction models; price transmission asymmetry.

**JEL Code:** C32, Q17.

### Introduction

The importance of deal pass-through to manufacturers is well understood - the efficiency of trade promotion dollars is commonly cited as one of the most important issues facing suppliers (Gómez, Rao and McLaughlin 2007; Nijs et al. 2010). While manufacturers would prefer retailers to completely pass-through trade deals, somewhat paradoxically, they would rather retailers not pass through wholesale price increases (Boyle 2009). In the past, this issue was little more than a curiosity. With input prices rising rapidly for food manufacturers in 2008 and again in 2010, however, the problem became very real. Manufacturers were forced to increase wholesale prices to maintain margins and, at the same time, increase trade deals in order to maintain market share in a rising-price environment. Most of the empirical literature on trade promotion pass-through (Kim and Staelin 1999; Kumar, Rajiv and Jeuland 2001; Ailawadi and Harlam 2009; Nijs et al. 2010) considers only retailer responses to negative changes in wholesale prices - trade promotions - and not upward movements in wholesale prices as well. In this study, we offer a more comprehensive treatment of pass-through that is relevant to both wholesale price discounts and price increases.

Incomplete trade promotion pass-through can result from many potential causes: (1) demand curvature (Tyagi 2009); (2) information asymmetries (Kumar, Rajiv and Jeuland 2001; Busse, Silva-Russo and Zettelmeyer 2006); (3) market power (Moorthy 2005); or (4) inventory cost (Cui, Raju and Zhang 2008). While each of these is likely relevant, the notion that pass-through depends fundamentally on more primitive types of consumer behavior and not institutional rigidity or excessive use of market power is a compelling one. Indeed, formal tests of the role of market power in mediating pass-through rates invariably fail to find much influence (Frey and Manera 2007). Instead, recent theoretical research on the more general pass-through

issue maintains that incomplete pass-through by retailers is largely a function of consumers' rational search strategy, and retailers' rational response (Tappata 2009; Yuan and Han 2011).<sup>1</sup> Consequently, we offer a panel-data time-series based empirical test that controls for as many causal factors as possible, including a more accurate measure of market power than used in the extant literature, in testing the hypothesis that consumer search behavior is largely responsible for incomplete promotion pass-through, and the asymmetry of pass-through between trade promotions and wholesale price increases.

Empirical models of promotion pass-through estimate either reduced form (Besanko, Dube and Gupta 2005) or structural (Kumar, Rajiv and Jeuland 2001; Ailawadi and Harlam 2009) specifications of the pass-through mechanism between promotions at either the manufacturer or wholesaler level and retail prices. If wholesale and retail prices tend toward a long-run equilibrium, however, as is generally thought to be the case, then the price series are likely to be cointegrated so an error-correction model (ECM, Granger and Lee 1989) is more appropriate. Ignoring the fact that the series are cointegrated invites the likelihood of spurious regression, or finding a significant relationship when none exists in fact (Engel and Granger 1987). However, simple ECMs are misspecified when the underlying equilibrium relationship is not specifically linear, but rather non-linear due to threshold effects. When retail price adjustment occurs only after consumers perceive sufficient incentive to search, both when prices are rising and when they are falling, retail price pass-through likely occurs only after an adjustment-threshold is reached. Moreover, there is nothing that would lead us to believe that the price-relationship is symmetric between rising and falling prices. Consequently, our empirical model is a threshold asymmetric error correction model (TAECM) applied in the context of panel data. Our empirical model is not new as Tsay (1989) developed methods for testing for thresholds in autoregressive models, while Balke and Fomby (1997) introduced error-correction to the general threshold framework developed by Tsay (1989). The TAECM approach is not only appropriate for the problem at hand, but provides useful information for both researchers interested in the performance of the consumer-product supply chain and practitioners designing trade promotion programs and price adjustments in response to increased production costs. By formally testing a model of consumer search, we provide evidence that incomplete pass-through is not, in fact, a result of market power, but rather fully consistent with competitive behavior by retailers and wholesalers. For practitioners, understanding why pass-through is imperfect, and finding ways of dealing with the underlying causes of incomplete pass-through can help alleviate some of the inefficiencies inherent in the current system.

Our primary objective is to explain why the pass-through rate for trade promotions and increased wholesale prices tend to be generally less than complete, or instantaneous, and is far lower than the pass-through rate for wholesale price increases. While the literature contains other empirical explanations for this observation, ours is the first to test the typical explanations against others recently advanced in the theoretical literature, in particular, the influence of consumer search costs on pass-through. A secondary objective, therefore, is to apply a new approach to studying

---

<sup>1</sup> In the economics literature, pass-through refers to the rate at which production costs are passed-through to the retail price; the transmission of prices from wholesale to retail, or the rate at which exchange rate fluctuations are passed-along to consumers. In marketing, pass-through often refers to how much of every dollar in trade promotion is reflected in lower retail prices. In this study, we assume a general definition and investigate the reasons why retail prices change with respect to any variation in wholesale prices.

trade promotion behavior that may be useful in other categories, other markets, time periods or retail environments.

We find that both consumer search costs and market power are important in determining the rate of retail-price pass-through, but that consumer search costs explain the pattern of asymmetric adjustment most often observed in the data (i.e., the "rockets and feathers" phenomenon (Bacon 1991)). Specifically, market power causes retail prices to fall quickly and rise slowly - opposite to rockets and feathers - while consumer search costs cause retail prices to rise quickly and fall slowly. Deal pass-through, therefore, can be expected to be higher among more powerful retailers, and those that offer a low search-cost environment.

Empirically modeling pass-through is difficult due to the fact that wholesale price data are generally not available. Recent studies make significant and important contributions to the empirical literature by using unique, yet proprietary datasets (Ailawadi and Harlam 2009; Nijs et al. 2010) that include retail and wholesale prices for a matched-set of products. Nakamura and Zerom (2010) match retail coffee sales data with wholesale price data obtained from PromoData, Inc. for a broad sample of retailers in the Los Angeles metropolitan area. In this study, we merge IRI Infoscan data on brand-level breakfast cereal prices with wholesale price and trade-promotion data from PromoData matched at the UPC-level. By doing so, we are able to rest the relevance of publicly-available wholesale price data for estimating pass-through, and ensure that our wholesale prices are as close as possible to those actually paid for our sample of brands.

This paper contributes to the literature on retail-price pass-through in three ways. First, we offer an empirical test of a recent theoretical explanations for incomplete pass-through, namely variation in the intensity of consumer search between regimes of rising and falling prices. Here, we also test for the influence of retailer market power on pass-through. Second, our empirical model extends existing models of pass-through as we explain incomplete pass-through both when wholesale prices are rising and when they are falling. Third, we introduce a new model of retail-price pass-through in the context of panel data that explicitly takes into account the underlying time-series properties of retail and wholesale prices, and the relationship between them. By introducing an econometric approach that is new to pass-through analysis, we hope to provide insights that previous empirical models were unable to find.

In the next section, we develop an empirical model of trade promotion pass-through, beginning with theoretical insights and empirical tests of the theory, and leading to a new model of promotion pass-through that accounts for recent developments in the consumer search literature. In Section 3, we explain our empirical model, including the panel integration and cointegration tests, the estimation of thresholds, and the identification of consumer search and market power in the econometric model. Section 4 consists of a description of our empirical data, and some stylized facts gained through a preliminary investigation of our wholesale and retail price data. Estimation results and a discussion of their implications for consumer search theory are provided in section 5, while section 6 offers some conclusions, more general implications, and suggestions for future research that may address some of the weaknesses of our study or some of the new questions we raise.

## **Modeling Pass-Through**

### *Background Literature on Pass-Through*

Perhaps because of its importance to manufacturers, there are many explanations in the literature for why trade promotion money is either not passed through to consumers completely, or passed through more than 100%. Bulow and Pfleiderer (1983) and Tyagi (1999) explain variation in pass-through rates simply as a function of the curvature of demand. If demand is concave, then a single-product monopolist retailer will pass-through trade deals at a rate less than 100%, but some convex demand environments imply equilibrium pass-through rates greater than 100%. Retailers are generally not monopolists, however, so others seek to explain incomplete pass-through in a competitive environment. Kim and Staelin (1999), for example, construct a theoretical model with which they seek to explain the observation that retailers are receiving more and more side-payments from manufacturers, but do not seem to profit from doing so. If manufacturers set side-payments as Stackelberg leaders, and then retailers compete in prices, the authors show that it is still optimal for manufacturers to offer promotional allowances even though pass-through is not complete. Similarly, Moorthy (2005) also uses the nature of competition in the industry to explain incomplete deal pass-through. Specifically, his theoretical model of retail pass-through assumes that retailers practice category management (optimize profit over categories of related products) and compete with other retailers. A category-wide focus highlights the role of cross-brand pass-through, which he shows can be either positive or negative depending on the structure of demand for products in the same category. Namely, brand-substitution effects lead to negative cross-brand pass-through as lower wholesale prices for one good lead to higher prices for others due to brand-switching. On the other hand, trade promotion with strategic complementarity leads to lower prices for brands that compete with the promoted brand because promotion creates a general profit opportunity due to the larger overall category size. Retail competition also adds another layer of complementarity as promotion can raise the sales of all firms.

Competitive considerations are only part of the story. Kumar, Rajiv and Jeuland (2001) explain the "partial pass-through" problem as arising out of a fundamental information asymmetry between consumers and retailers, and investigate ways in which manufacturers may ameliorate the problem. While retailers most certainly know when manufacturer prices have fallen, consumers do not. Retailers have an incentive to retain as much of the promotion as possible, but if they never pass on a promotion, and consumers know the distribution of trade promotions, they will lose customers to the outside option. Retailers resolve the essential tension between profitability and volume by offering periodic promotions that match the trade promotion offered, signaling to consumers that they do, on occasion, pass-through the discounts. Manufacturers can ease pass-through by paring trade promotions with advertising directed at consumers, or combining a push and pull strategies.

Observing that larger, chain retailers are amenable to trade promotions, but independent retailers are generally not, Cui, Raju and Zhang (2008) develop a model of promotion pass-through in which trade deals allow manufacturers to price discriminate between retailers with low inventory cost and high inventory cost. Only retailers with relatively low inventory costs will forward-buy, while the others will prefer to not be offered trade promotions. Their model explains why manufacturers continue to offer trade deals despite their evident inefficiency, and also why some retailers like trade promotions, while others do not. While they explain many of the apparent

paradoxes in trade promotion, they do not explain why pass-through rates vary once the money is taken.

Among empirical studies, Dreze and Bell (2003) consider scan-back trade deals, which are essentially ex-post promotions in which the retailer is rewarded for passing-through trade promotions. Manufacturers often lose money on trade promotions due to retailer forward-buying, or purchasing future requirements only when the deal is on, diverting or imperfect pass-through. Point-of-sale scanners allowed the emergence of scan-back deals, which fundamentally change the profitability of trade promotions for manufacturers. Through both a theoretical model and empirical testing, Dreze and Bell (2003) explain manufacturers' preference for scan-back deals and show that they can be designed to leave retailers weakly better off and manufacturers strictly better off. Moreover, they show that, for the beverage category, scan-back deals do not lead to excess ordering and increase retail sales through lower retail prices. Besanko, Dube and Gupta (2005) study pass-through rates for 78 products over 11 categories for a single supermarket retailer. Estimating a reduced-form model, they find pass-through rates generally greater than 60%, and higher own-pass-through rates for products with either a larger market share, or higher contribution margin. Small brands are also disadvantaged with respect to cross-brand pass-through as promoting larger brands is less likely to induce a similar response in smaller brands (positive pass-through), while promoting smaller brands is more likely to cause a discount-response in larger brands. Based on their results, cross-brand pass-through cannot be ignored, the criticism of McAlister (2009) notwithstanding.<sup>2</sup> Pauwels (2007) estimates an impulse-response function in 75 brands across 25 categories to determine the relative effects of own- and competitor promotion pass-through. Pauwels (2007) reports a pass-through rate of 65% from wholesale to retail prices, but also finds that competitors match 15% of the wholesale price reduction, reducing the promotion elasticity from 1.78 by 10%. However, this response rate is an average over all categories and varies widely by brand and category, with large-share categories having higher pass-through rates than smaller categories. Smaller brands are particularly disadvantaged with respect to promotions: they have lower retail pass-through, have lower retail support, benefit less from competitive promotions, but provide greater benefit to competitors through their own promotions.

Others find that trade promotion pass-through rates can indeed be greater than 100%. Ailawadi and Harlam (2009) conduct an empirical analysis of retailer promotion pass-through using a unique dataset covering all manufacturer promotion and allowance activity for a two-year period from a single retailer. They find that the retailer passes-through more than 100% of manufacturer allowances in aggregate, but the median is far less for any single manufacturer. Moreover, some manufacturers are promoted even without funding .private label and high-share manufacturers in high-lift and high-margin categories in particular. They find that the most important determinants of pass-through are whether the manufacturer sells private labels and its market share, both in focal and other categories. In general, however, pass-through is higher in categories with high share, high lift, low concentration and, surprisingly, low margin categories. These findings are important as they cast some doubt on whether incomplete pass-through is even an empirical

---

<sup>2</sup> McAlister (2007) argues that the multiple-zone pricing data used by Besanko, Dube and Gupta (2005) does not reflect truly independent pricing decisions among zones. Controlling for this fact, the authors do not find evidence of cross-brand pass-through in the data used by Besanko, Dube and Gupta (2005).

reality. Taking an entirely different approach, Nijs et al. (2010) estimate pass-through rates for a single product category using data from over 1,000 retailers in 30 states. Their goal is to model pass-through in the context of the entire supply chain for the category, because pass-through necessarily involves dynamic considerations that must change over time, and vary across categories. Variation in pass-through occurs not only due to changes in the economic environment, but also due to measurement discrepancies as the authors show that accounting measures bias estimates of promotion effectiveness because the average cost measures misstate the actual cost of the promotion. Using correct, economic measures of cost they find mean pass-through percentages of 71.0%, 59.0%, and 41.0% for retailers, wholesalers and the entire supply chain, respectively. Contrary to Ailawadi, they find pass-through rates still significantly below 1 and that product and market attributes (competitiveness) have very little influence on their magnitude - modeling the entire supply chain still does not induce over-shifting among consumers.

In the economics literature, the question of pass-through typically concerns how changes in manufacturing input cost or exchange-rate fluctuations are passed through to consumers in the form of retail prices. Nakamura and Zerom (2010) consider a number of alternative explanations for less-than-complete exchange rate pass-through, including demand curvature, local cost conditions and strategic pricing behavior on the part of intermediaries. Benabou and Gertner (1993) offer an alternative explanation grounded not in structural attributes of the industry at hand, but rather in the uncertainty generated by price inflation. Specifically, Benabou and Gertner (1993) recognize that the information content in changing prices is endogenous to the agent's incentive to search. Their model shows that inflation actually leads to more competitive outcomes as it provides a greater incentive to search. Under relatively high search costs, however, the opposite occurs as their model predicts that market power rises in the general level of inflation because the informational content of prices is diminished. More recent theoretical studies follow Benabou and Gertner (1993) by focusing on consumers' incentives to search, and the information content of prices. In the auto industry, Busse, Silva-Risso and Zettelmeyer (2006) investigate the "pass-through invariance hypothesis," namely that the incidence of a promotion offered by a third-party to the auto purchase transaction (the manufacturer) should be the same whether it is offered to either the buyer (customer) or reseller (dealer). Contrary to the hypothesis, they find that end-consumers receive 70% - 90% of a promotion directed at customers, but only 30% - 40% of a promotion targeted to dealers. While customer promotions are well-publicized, dealer promotions are not. Particularly in an environment where the end price results from direct negotiations between the buyer and the dealer, information asymmetries are the primary cause of incomplete promotion pass-through. Although supermarket prices are not negotiated, shoppers' expectations can nonetheless be similarly conditioned by communication directly from the manufacturer.

Offering coupons is one way in which manufacturers can address the incomplete pass-through problem. Gerstner and Hess (1991) show that coupons are less expensive than promotional allowances for manufacturers because coupons are less costly than trying to induce retailers to lower their price to consumers' reservation price. A combination of push and pull strategies allows retailers to price discriminate, but they also show that it is in manufacturers interest to offer rebates (coupons) even when all consumers use them and retailers do not price discriminate. Ultimately, they argue that the primary function of a push strategy is to induce pass-through, or



to provide incentives for the retailer to participate. For purposes of this study, however, we do not have information on whether pull strategies are used in conjunction with trade promotions so we implicitly assume that coupon use is randomly distributed among the brands in our sample, and that consumers redeem them across brands with equal probability.

Empirically, the notion that cost increases are passed quickly and completely through to consumers, but decreases in cost tend to lead to retail prices that fall more like feathers (Bacon 1991), is well-documented. Several empirical studies attribute asymmetrical pass-through to market power on the part of retailers, whether in gasoline (Borenstein, Cameron and Gilbert 1997; Deltas 2008; Verlinda 2008), beef (Goodwin and Piggott 2001) or fresh produce (Ward 1982). Peltzman (2000), however, finds no support for the market power hypothesis in a comprehensive study of pass-through covering hundreds of product categories. Although it is tempting to conjecture that asymmetric price adjustment is due to market power, the pervasiveness of this observation in otherwise seemingly competitive markets - like retail gasoline sales in a saturated market - suggests that there must be an alternative explanation.

Reflecting a broad skepticism that market power could explain such a pervasive phenomenon, Yang and Ye (2008), Tappata (2009) and Yuan and Han (2011) explore theoretical explanations that assume pass-through is determined as an equilibrium between competitive firms and rational consumers. Tappata (2009) extends the explanation for equilibrium price dispersion developed in Varian (1980) to endogenize consumer search behavior. He shows that rational consumers will search more when prices are rising relative to when they are falling, so prices are more rapid to adjust in an upward direction. Said differently, the dispersion of prices shrinks when firms' costs are high relative to when they are low, because active search constrains firms' price-setting powers. Similarly, Yuan and Han (2011) also show that retail prices rise quickly when costs increase because consumers search more intensively, but fall more slowly when costs fall again as sellers reduce prices only enough to cause consumers to not search for new prices. Although these models are each developed to explain pass-through of wholesale costs rather than trade deals, the emphasis on information asymmetries and search suggests a valuable line of reasoning that may explain some of the anomalies observed in promotion pass-through. Moreover, our empirical model of promotion pass-through is able to identify unique features of the consumer search model, so we are able to test whether imperfect pass-through results from search or the more usual explanation, market power. Unlike in the cost pass-through case, studying promotion pass-through provides a unique opportunity to test the information asymmetry hypothesis as manufacturers have the ability to resolve some of this asymmetry through pull strategies such as couponing and advertising. We exploit this opportunity in the empirical model below.

#### *Implications of a Model of Consumer Search and Pass-Through*

In this section, we outline a theoretical model of consumer search and show how rational consumer behavior, and firm response, leads naturally to a threshold asymmetric error-correction model of retail-price pass-through. Lewis (2008), however, notes that the existent search models in the literature all apply to the homogeneous product case. While this assumption is relatively benign in the retail gasoline industry, it most certainly does not describe the retail food market. Consequently, we extend the search model of Tappata (2009) to allow for differentiated products and derive a set of comparative statics that allow us to test our underlying hypothesis, namely that imperfect pass-through of trade promotion deals is not due to the exercise of market power

on the part of retailers, but is rather an artifact of consumer search, and consumer heterogeneity. As demonstrated by Chandra and Tappata (2010), the non-sequential search model of Tappata (2009) is sufficiently simple to generate comparative static results that are testable with the appropriate data.

Tappata (2009) extends Varian (1980) in a relatively simple way by endogenizing consumer search behavior. Only a fraction of consumers choose to search, and search behavior is endogenous to the perceived benefits of searching, and the cost of doing so. Firms are rational, so set less disperse prices when wholesale prices are high relative to when they are low, because their ability to set prices is limited by a fixed reservation price. Consumers are rational, so anticipate such behavior on the part of retailers and search less when wholesale prices are high. Price expectations are formed adaptively so non-*iid* wholesale price shocks have an important effect on search behavior.

If consumer search is at least in part responsible for incomplete pass-through, then variables that influence the cost of search are useful in empirically identifying the effect of search on pass-through. Comparative statics of the Tappata (2009) consumer search model show the following results. First, price dispersion rises with the number of firms, and shifts toward monopoly prices, because the probability of offering the lowest price in the market declines at an exponential rate. However, when endogenous search is included, a higher number of firms in the market induces more consumers to search, thus forcing prices down. Consequently, the net effect of an increase in the number of firms, or products, is ambiguous in a consumer search model and cannot be used to identify the search effect (contrary to Lewis (2008)). Second, when search is endogenous, higher wholesale prices cause search intensity to fall, and retail prices to rise, but become less disperse. Because the opposite occurs when wholesale prices fall, such as during a promotion, prices become more disperse when trade promotions reduce wholesale prices. Intuitively, demand becomes more elastic when prices rise, and less elastic when they fall, so retail prices adjust faster upward than downward. This effect, however, is indistinguishable from what we would expect if the retailer exercises monopoly pricing power (Moorthy 2005). A third effect is unique to the consumer search model as it applies to a multi-product retail context. Higher consumer search costs lead to lower search intensity and, hence, higher retail prices.<sup>3</sup> Consumer search costs, in turn, can be thought of in terms of the number of products offered by the retailer. Therefore, we use the number of products sold during a given period as a proxy for search costs to identify whether consumer search is a determinant of pass-through asymmetry.

### **An Empirical Model of Pass-Through**

Our empirical model consists of three stages, following the general panel threshold error-correction methodology introduced by Hansen (1999). In the first stage, we test each of our panel data series - retail prices and wholesale prices - for stationarity and, after establishing the nature of the time-series properties of our data series, we then estimate the panel cointegration relationships between the retail and wholesale price series, which include trade promotions. In the second stage, we use Hansen's (1999) approach to estimate retail-price adjustment thresholds

---

<sup>3</sup> This paradox is not unique to the Tappata (2009) model as Diamond (1971) shows that, in a market with homogeneous goods, the unique Nash equilibrium as the number of firms rises converges on the monopoly price.

in panel data. From the theory described above, two thresholds are necessary to capture the apparent inability of retail prices to adjust completely, in either an upward or downward direction, in response to wholesale price changes. In the third stage, we use these estimated thresholds to define three price-adjustment regimes. We estimate the asymmetric error-correction model in each regime, and test for the effect of market power and consumer search costs on the speed of retail price adjustment.

#### *Testing for Integration and Cointegration in Panel Data*

In this section, we describe how we test for integration in retail and wholesale prices and for cointegration between retail and wholesale cereal prices in a panel data set. Typically, augmented Dickey-Fuller (ADF) or Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are commonly used for this purpose in time series for a single cross-sectional unit of observation. However, heterogeneities between individuals in panel data require another type of unit root test that takes into account the information provided by cross-sectional variation at each point in time. A number of approaches have been developed to increase the power of panel cointegration tests by exploiting the information provided by cross-sectional price variation. There are two broad types of test: (1) an ADF-type test that assumes a null hypothesis of nonstationarity, and (2) a KPSS-type that assumes a null hypothesis of stationarity.

Examples of ADF-type tests include Levin, Lin and Chu (LLC 2002) and Im, Pesaran and Shin (IPS 2003). LLC and IPS propose panel unit root tests on the basis of the standard ADF test in individual series. However, a critical assumption underlying these tests is that the cross sectional observations are independent. Because the LLC and IPS tests are biased in the presence of cross-sectional dependence, and that is precisely the case with the panel dataset considered here, we use a test developed by Hadri (2000).

While LLC (2002) and IPS (2003) approaches are based on ADF type unit root test where the null hypothesis is that all individual series are stationary, Hadri (2000) proposes a residual-based Lagrange Multiplier test which is an extension of stationarity test for time series of Kwiatkowski et al. (1992). The advantage of using Hadri's test is that it is unbiased in the case of cross-section dependency in the panel data. More specifically, Hadri considers the following representation in panel context with fixed effects and individual trends for a given price series  $p_{it}^r$ :

$$p_{it}^r = \rho^r t + \gamma_{it}^r + \varepsilon_{it}^r, \quad (1)$$

where  $i$ ,  $r$  and  $t$  denote the cross-section and time-series component, respectively;  $\gamma_{it}^r = \gamma_{it}^r + u_{it}^r$  implies that  $p_{it}^r$  follows a random walk. Here  $\varepsilon_{it}^r$  and  $u_{it}^r$  are assumed to be mutually independent and *iid* over cross-section  $r$  and time-series  $t$ . Therefore, equation (1) can be written as:

$$p_{it}^r = \rho^r t + \gamma_0^r + \sum_{t=1}^T u_{it}^r + \varepsilon_{it}^r = \rho^r t + \gamma_0^r + e_{it}^r, \quad (2)$$

where  $e_{it}^r = \sum_{t=1}^T u_{it}^r + \varepsilon_{it}^r$  and  $\gamma_0^r$  represents the initial values, assumed to be fixed and unknown.

The null hypothesis for trend-stationarity is established by testing whether the variance of the random walk  $\sigma_u^2$  equals zero. If  $\sigma_u^2 = 0$ , then  $e_{it}^r$  is reduced to  $\varepsilon_{it}^r$ , which implies that the random walk  $\gamma_{it}^r$  converges to a constant (i.e.,  $\gamma_{it}^r \rightarrow \gamma_0^r$ ). On the contrary, when  $\sigma_u^2 \neq 0$ , then  $e_{it}^r$  is non

stationary, given that  $\gamma_{it}^r$  is still a random walk. For testing purposes, Hadri (2000) proposes the following one-side LM statistic:

$$LM_{Hadri} = \frac{\frac{1}{RT^2} \sum_{r=1}^R \sum_{t=1}^T (S_{it}^r)^2}{\hat{\sigma}_\varepsilon^2}, \quad (3)$$

where  $\hat{\sigma}_\varepsilon^2$  is a consistent estimator of  $\sigma_\varepsilon^2$  under the null hypothesis that all panels are stationary and  $(S_{it}^r)^2 = \sum_{j=1}^T \hat{\varepsilon}_{rj}$  is the partial sum of the residuals from the regression in equation (2).

Two price series in a supply chain are often cointegrated and ignoring these long-run co-movements between two series may lead to spurious parameter estimates in any model of pass-through. The test developed by Johansen (1988) is commonly used in a pure time-series context. However, in panel data, the Johansen test can be biased because of heterogeneous cross-sectional properties. Therefore, we use a battery of tests developed by Pedroni (1999) that are more appropriate for panel data. Specifically, Pedroni (1999) develops two classes of panel cointegration tests for panels with heterogeneous cointegration vectors, employing a residual-based approach, that include both "within dimension" and "between dimension" components. Consider the long-run relationship between prices charged by retailer  $r$  ( $p_{it}^r$ ) for brand  $i$  and wholesale prices paid by the same retailer ( $w_{it}^r$ ), including individual effects ( $\lambda_{it}^r$ ) and a time trend ( $t$ ), written as follows:

$$p_{it}^r = \lambda_{it}^r + \theta^r t + \beta^r w_{it}^r + \varepsilon_{it}^r. \quad (4)$$

In this model, the estimated residuals from the regression in (4) are:  $\hat{\varepsilon}_{it}^r = p_{it}^r - \lambda_{it}^r - \theta^r t - \beta^r w_{it}^r$ , where  $\hat{\varepsilon}_{it}^r$  represents deviations from the long-run equilibrium between the two price series. The residual-based approach to test for co-integration examines whether the residuals contain a unit-root under the null hypothesis of no cointegration using the following general augmented Dickey-Fuller (ADF)-type test:

$$\hat{\varepsilon}_{it}^r = \phi \hat{\varepsilon}_{it-1}^r + \sum_{j=1}^J \eta_j \Delta \hat{\varepsilon}_{it-j}^r + u_{it}^r, \quad (5)$$

where  $u_{it}^r$  is an *iid* error term.

To accommodate heterogeneous cross-sectional vector, Pedroni (1999) extends equation (4) by allowing  $\eta_j$  and  $J$  to vary across individual according to:

$$\hat{\varepsilon}_t^r = \phi \hat{\varepsilon}_{t-1}^r + \sum_{j=1}^{J^r} \eta_j^r \Delta \hat{\varepsilon}_{t-j}^r + u_t^r, \quad (6)$$

where the other terms are as defined previously.

We apply the two different classes of cointegration test statistics developed by Pedroni (1999): *Panel* statistics and *Group Mean* statistics. Panel statistics, often referred to as the "within" dimension test, are analogous to panel unit-root statistics against homogeneous alternatives. The *Panel* statistics are based on pooling the residuals of the regression in (4) along the "within" dimension of the panel. *Panel* statistics test the null hypothesis of no cointegration ( $\phi_r = 0$ ) for

all cross-section individuals ( $r$ ), against the alternative hypothesis of  $\phi_r = \phi$ ,  $-2 < \phi < 0$  for all  $r$ . There are four *Panel* test statistics: panel- $\nu$ , panel- $\rho$ , panel-*PP* and panel-*ADF*. These are analogous to the variance ratio test statistic, the panel version of the Phillips and Perron  $\rho$ - and  $t$ -statistics, and the augmented DF test statistic, respectively, where  $\phi_r$  is the autoregressive coefficient of the residuals in the  $r$ -th individual in equation (6).

The *Group Mean* statistics are commonly known as "between" dimension tests and they are similar to a panel unit root statistic against heterogeneous alternatives. The *Group Mean* statistics allow for heterogeneous coefficients under the alternative hypothesis:  $H_A : \phi_r = \phi$ ,  $-2 < \phi < 0$  for all  $r$ . We apply three "within" dimension tests: a panel  $\rho$ -statistic, a panel *PP*-statistic and a panel *ADF*-statistic. These statistics are obtained by averaging the autoregressive coefficients from the unit root tests of the residuals for each individual in the panel. All seven cointegration tests are asymptotically standard normal-distributed. The panel  $\nu$ -statistic is a one-sided test, whereas the other six statistics are two-sided tests. As we explain in more detail below, we reject the null hypothesis of no co-integration relationship in each case. We find a single cointegration vector for each relationship, so proceed to estimate the panel error correction model described in the next section.

#### *A Panel Threshold Asymmetric Error Correction Model*

Given our finding that retail and wholesale cereal prices are indeed co-integrated, estimating pass-through rates consistently requires a panel error-correction approach. Based on observations by others who have estimated pass-through rates in retail food markets (Goodwin and Piggott 2001), however, our model should also accommodate asymmetrical pass-through to upward and downward wholesale price changes as well as threshold-effects. Asymmetric pass-through is likely in the cereal industry because of the nature of competition among food retailers in many markets or consumer search costs, to name the two explanations that are the focus of our study. Further, pass-through is also likely to be non-linear, or involve significant threshold effects, due to the relatively high fixed costs .menu costs .associated with retail price adjustment (Levy et al. 1997). Therefore, we follow Hansen (1999) and include both non-linearity and asymmetry in the retail-price pass-through model for breakfast cereal. Our empirical approach involves two stages: (1) in the first stage we estimate the threshold parameters (or parameters in a multi-regime model) following Hansen (1999), and (2) in the second stage, we estimate asymmetric and long-run price adjustment terms conditional on the prior threshold parameters. We explain each stage more formally next.

Consider the co-integration relationship between wholesale price paid by retailer  $r$  for brand  $i$  ( $w_{it}^r$ ) and retail price ( $p_{it}^r$ ) charged by retailer  $r$  for brand  $i$  at time  $t$  as follows:

$$ECT_{it}^r = \varepsilon_{it}^r = p_{it}^r - \lambda^r - w_{it}^r, \quad (7)$$

where  $r = 1, \dots, R$  indexes retailers and  $t = 1, \dots, T$  time periods. The error term  $\varepsilon_{it}^r$ , which is also referred to as the error correction term ( $ECT_{it}^r$ ) measures the deviation from the long-run equilibrium between the price series. In a standard error correction model, these error terms are linear and identical regardless of the magnitude of deviations. However, the adjustment costs referred to above are likely to generate thresholds that trigger adjustments toward the long-run

equilibrium in response to exogenous shocks.<sup>4</sup> A threshold model is a natural way to test the consumer search hypothesis because search only occurs, and retailers will only adjust prices in response, once the gains from search exceed consumers' marginal cost of searching for potentially lower prices. Empirically, however, identifying price-thresholds is problematic because they are unobserved in the data, so must be inferred from observed price behavior. To test for these potential nonlinearities we follow Hansen (1999) and employ the following autoregressive (AR) representation with a two-regime threshold for the error term  $\varepsilon_{it}^r$  in a balanced panel:

$$\Delta\varepsilon_{it}^r = \begin{cases} \mu_i^r + \beta^{(1)} \cdot ECT_{it-1}^r + \sum_{p=1} \delta_p \Delta\varepsilon_{it-1}^r + e_{it}^r, & ECT_{it-d}^r \leq \gamma_1 \\ \mu_i^r + \beta^{(2)} \cdot ECT_{it-1}^r + \sum_{p=1} \delta_p \Delta\varepsilon_{it-1}^r + e_{it}^r, & \gamma_1 < ECT_{it-d}^r \end{cases} \quad (8)$$

where  $\gamma_1$  is the threshold parameter, and  $d$  measures the duration of the delay. Price adjustment in this specification is asymmetric in the sense that the coefficients  $\beta^{(1)}$  and  $\beta^{(2)}$  may differ based on whether the magnitude of the error-correction term ( $ECT_{it-1}^r$ ) is smaller or larger than the threshold value  $\gamma_1$ . Hansen(1999) proposes a two-step approach based on ordinary least squares to estimate the value of  $\gamma_1$ . First, the individual effect  $\mu_i^r$  in equation (8) is eliminated by removing individual specific means. Let the vector of independent variables, dependent variable and residuals with individual-specific means removed be written as  $X^*$ ,  $\varepsilon^*$  and  $e^*$ , respectively. Using this notation, equation (8) is rewritten as:  $\varepsilon^* = X^*(\gamma_1)\beta + e^*$  so the coefficients  $\beta^{(1)}$  and  $\beta^{(2)}$  are estimated by OLS, conditional on the value of  $\gamma_1$ , using the estimator:

$$\hat{\beta}(\gamma_1) = (X^*(\gamma_1)'X^*(\gamma_1))^{-1}X^*(\gamma_1)\varepsilon^*, \quad (9)$$

and the regression residuals are calculated as:  $\hat{\varepsilon}^*(\gamma_1) = \varepsilon^* - X^*(\gamma_1)\hat{\beta}(\gamma_1)$ . The threshold value is subsequently estimated by minimizing the sum of squared errors as follows (Chan 1993; Hansen 1999):

$$\hat{\gamma}_1 = \arg \min S_1(\gamma_1) = \hat{\varepsilon}^*(\gamma_1)'\hat{\varepsilon}^*(\gamma_1). \quad (10)$$

Although this method provides point estimates of the threshold parameter, it remains to draw inferences regarding  $\hat{\gamma}_1$ . Therefore, the next step is to test the statistical significance of the estimated threshold value, under the null hypothesis of  $\beta^{(1)} = \beta^{(2)}$ . A likelihood ratio (LR) test is used for this purpose. The LR test statistic is calculated as:  $F_1 = (S_0 - S_1(\hat{\gamma}_1))/\hat{\sigma}_1^2$ , where  $\hat{\sigma}_1^2 = S_1^*(\hat{\gamma}_1^*)/n(T - 1)$  and  $S_0$  is obtained from the model without thresholds as follows:

$$\Delta\varepsilon_{it}^r = \mu_i^r + \beta \cdot ECT_{it-1}^r + \sum_{p=1} \delta_p \Delta\varepsilon_{it-p}^r + e_{it}^r, \quad (11)$$

---

<sup>4</sup> This fixed cost can be either explicit as in Levy et al. (1997), or implicit as in Blinder et al. (1998). An example of an implicit adjustment cost would be losing a consumer to a competitor who did not raise his retail price. Indeed, the existence of thresholds in retail price adjustment reflects the concept of retail price fixity that is widely studied by macro and microeconomists alike (Blinder et al. 1998). Delayed-response in retail price adjustment can be due to menu costs (Levy et al. 1998), a failure to coordinate price changes (Ball and Romer 1991), inventory adjustment costs (Slade 1999) or the perception of perhaps a kinked-demand curve whereby competitors respond to a price increase, but not a price reduction (Blinder et al. 1998).

This LR test is somewhat problematic, however, in that the asymptotic distribution of  $F_1$  is non-standard. Consequently, Hansen (1999) offers a bootstrapped procedure to obtain the  $p$ -value from the first-order asymptotic distribution.

While the model described above is more realistic than the basic model that assumes smooth price adjustment, there may be more than one threshold in the error correction process in which case it is necessary to test for additional thresholds. For example, if we consider a two-threshold case (i.e., three regimes), equation (8) is modified as follows:

$$\Delta \varepsilon_{it}^r = \begin{cases} \mu_i^r + \beta^{(1)} \cdot ECT_{it-1}^r + \sum_{p=1} \delta_p \Delta \varepsilon_{it-1}^r + e_{it}^r, & ECT_{it-d}^r \leq \gamma_1 \\ \mu_i^r + \beta^{(2)} \cdot ECT_{it-1}^r + \sum_{p=1} \delta_p \Delta \varepsilon_{it-1}^r + e_{it}^r, & \gamma_1 < ECT_{it-d}^r \leq \gamma_2, \\ \mu_i^r + \beta^{(3)} \cdot ECT_{it-1}^r + \sum_{p=1} \delta_p \Delta \varepsilon_{it-1}^r + e_{it}^r, & \gamma_2 < ECT_{it-d}^r \end{cases} \quad (12)$$

where  $\gamma_2$  is assumed to be unique from  $\gamma_1$ . We again use the Hansen (1999) estimator for multiple-break-points.<sup>5</sup> Let  $S_1(\hat{\gamma}_1)$  be the sum of squared errors estimated from the single threshold model above. If the estimated  $\hat{\gamma}_1$  from equation (9) is smaller than  $\gamma_2$ , conditional on the fixed value  $\hat{\gamma}_1$ , the second threshold  $\gamma_2$  is estimated and can be obtained by finding the value that minimizes the conditional sum of squares given by:

$$\hat{\gamma}_2 = \arg \min S_2(\gamma_2) = \hat{S}(\hat{\gamma}_1, \gamma_2). \quad (13)$$

If the  $F_1$  test rejects the null hypothesis of no threshold in favor of the existence of a single threshold, it is also necessary to test the null hypothesis of the existence of one threshold against the alternative hypothesis of the existence of two thresholds, or more. The LR test statistic for this purpose is  $F_2 = (S_1(\hat{\gamma}_1) - S_2^*(\hat{\gamma}_2^*)) / \hat{\sigma}^2$ , where the estimated variance is  $\hat{\sigma}^2 = S_2^*(\hat{\gamma}_2^*) / n(T - 1)$ . As in the single threshold model, statistical significance is tested through a bootstrap procedure. If  $F_2$  is sufficiently large, the null hypothesis of one-threshold model can be rejected, in favor of a two-threshold model specification. The same procedure is repeated to test for the existence of more than two thresholds.

Once the threshold value is estimated, we then estimate a panel threshold error correction model (ECM) that allows for both asymmetric and nonlinear long-run pass-through. The panel ECM is written in terms of observed brand-level retail and wholesale prices as:

$$\Delta p_{it}^r = \begin{cases} \alpha_{0i} + \theta^{(1)} \cdot ECT_{it-1}^r + \alpha_1 \Delta p_{it-1}^r + \alpha_2 \Delta w_{it}^r + \alpha_3 \Delta w_{it-1}^r + e_{it}^r, & ECT_{it-1}^r \leq \gamma_1 \\ \alpha_{0i} + \theta^{(2)} \cdot ECT_{it-1}^r + \alpha_1 \Delta p_{it-1}^r + \alpha_2 \Delta w_{it}^r + \alpha_3 \Delta w_{it-1}^r + e_{it}^r, & \gamma_1 < ECT_{it-1}^r \leq \gamma_2 \\ \alpha_{0i} + \theta^{(3)} \cdot ECT_{it-1}^r + \alpha_1 \Delta p_{it-1}^r + \alpha_2 \Delta w_{it}^r + \alpha_3 \Delta w_{it-1}^r + e_{it}^r, & ECT_{it-1}^r > \gamma_2 \end{cases} \quad (14)$$

<sup>5</sup> Hansen (1999) uses results from Chong (1995) and Bai (1997) to show that a sequential estimator estimates multiple-break-points consistently.

where  $p_{it}^r$  and  $w_{it-1}^r$  are the brand-level analogs of the retail and wholesale price vectors introduced above. Because our focus is on pass-through, it is important to be very clear as to how marginal changes in wholesale prices effect retail prices in this model. Fortunately, the TAECM provides a very direct measure of pass-through. Recall that the  $ECT_{it}^r$  variable measures the extent to which retail and wholesale prices deviate from their long-run equilibrium. Therefore, the pass-through rate is measured as the extent to which retail prices move back toward the long-run equilibrium, or the  $\theta^{(k)}$  parameters in (14). These parameters also allow us to test whether market power or consumer search costs influence pass-through rates.

Conventional wisdom in much of the earlier literature held that rapid upward retail price adjustment and relatively sluggish downward adjustment ("rockets and feathers") is due to retailers' exercise of market power. More recently, however, Tappata (2009) and Yang and Ye (2008) explain this phenomenon as fully consistent with rational consumer search behavior. Using the TAECM framework, we propose a simple method of testing market power and consumer search as empirical determinants of retail pass-through. Introducing variables designed to measure retail market power and consumer search allows us to examine the source of any pricing asymmetries that may exist in the data. In this regard, our empirical approach goes beyond measuring pass-through asymmetries to explain why pass-through rates may differ between rising and falling wholesale price regimes. Indeed, one weakness of the TAECM approach is that it is agnostic as to the source of variation in adjustment rates over time, whereas the theoretical literature is very explicit in this regard. Therefore, we allow the adjustment parameters  $\theta^{(k)}$  to depend on measures of market power and consumer search. In the latter case, we assume search costs vary directly with the number of products over which consumers search, or the number of products in a retail store,  $N_t^r$ . Whereas Peltzman (2000) uses weak proxies for market power to test whether pricing power was responsible for pricing asymmetries, we develop a reduced-form approach more akin to a "new empirical industrial organization" (NEIO) approach. Nakamura and Zerom (2010) show that pass-through depends not only the curvature of demand, but on competitive responses by competing brands in the same market. We follow the approach taken by Richards, Hamilton and Allender (2011) and allow the adjustment parameters to depend on retailer and time-varying estimates of the absolute value of the demand elasticity,  $\eta_{it}^r$ .<sup>6</sup> When the variation in demand is driven by factors specific to the brand in question, this method can identify changes in market power over time (Bresnahan 1989) and can test for the impact of market power on the pass-through rate in a more powerful way than Peltzman (2000).

Extending the TAECM developed above to include variety and market power leads to estimated version of the panel threshold ECM written as:

---

<sup>6</sup> By defining this variable in terms of the absolute value of the price-elasticity of demand, higher values imply less market power. The demand elasticity is estimated using standard discrete-choice methods. Specifically, we use a mixed logit model estimated with the simulated maximum likelihood /control function approach of Train (2003) and Petrin and Train (2010). Details are available from the authors.



$$\Delta p_{it}^r = \begin{cases} \alpha_{0i} + \theta^{(1)}(N_t^r, \eta_{it}^r) \cdot ECT_{it-1}^r + \alpha_1 \Delta p_{it-1}^r + \alpha_2 \Delta w_{it}^r + \alpha_3 \Delta w_{it-1}^r + e_{it}^r, \\ ECT_{it-1}^r \leq \gamma_1 \\ \alpha_{0i} + \theta^{(2)}(N_t^r, \eta_{it}^r) \cdot ECT_{it-1}^r + \alpha_1 \Delta p_{it-1}^r + \alpha_2 \Delta w_{it}^r + \alpha_3 \Delta w_{it-1}^r + e_{it}^r, \\ \gamma_1 < ECT_{it-1}^r \leq \gamma_2 \\ \alpha_{0i} + \theta^{(3)}(N_t^r, \eta_{it}^r) \cdot ECT_{it-1}^r + \alpha_1 \Delta p_{it-1}^r + \alpha_2 \Delta w_{it}^r + \alpha_3 \Delta w_{it-1}^r + e_{it}^r, \\ ECT_{it-1}^r > \gamma_2 \end{cases} \quad (15)$$

where the adjustment parameters are allowed to vary with variety and pricing power, by brand, retailer and by week. Our primary hypotheses, therefore, concern the  $\theta^{(k)}$  parameters in equation (15), which are assumed to be linear functions of consumer search costs and market power:

$$\theta^{(1)} = \phi_{11} N_t^r + \phi_{12} \eta_{it}^r, \theta^{(2)} = \phi_{21} N_t^r + \phi_{22} \eta_{it}^r, \theta^{(3)} = \phi_{31} N_t^r + \phi_{32} \eta_{it}^r, \quad (16)$$

where  $N_t^r$  is measured as the number of stock-keeping units (SKUs) of ready-to-eat breakfast cereal each week  $t$  for each retailer  $r$ , and the elasticity,  $\eta_{it}^r$ , is the absolute value of the own-price elasticity of demand that varies by week, brand and retailer. To form testable hypotheses regarding the values of each of the  $\phi_{ij}$  parameters, it is important to differentiate between the nature of the disequilibrium in each regime. First, when  $ECT_{it-1}^r \leq \gamma_1$ , retail and wholesale prices are relatively close, so retail prices are expected to rise. Second, when  $\gamma_1 < ECT_{it-1}^r \leq \gamma_2$ , the gap between retail and wholesale prices is of a more normal value and no expectations as to retail price movements are formed. Third, when  $ECT_{it-1}^r > \gamma_2$ , retail prices are relatively high and are expected to fall to restore the long-run equilibrium. Next, recall that lower value of the own-price elasticity represents greater pricing power for the brand in question. Therefore, conventional theory maintains  $\phi_{12} > 0$  as market power allows retailers to pass along more of a wholesale price shock than would otherwise be the case, while  $\phi_{32} < 0$  as retailers with market power need not pass-along immediately the full value of any reduction in wholesale prices. Said differently, retailers with market power are less concerned with competitive responses to higher retail prices so raise them quickly when retail prices are expected to rise (i.e., when wholesale prices rise), and lower them slowly when retail prices are expected to fall (i.e., when wholesale prices fall). The theory is silent on how market power influences adjustment in the middle regime. With respect to consumer search costs, recall that  $N_t^r$  serves as a proxy for search costs faced by consumers. Greater variety implies higher search costs because consumers must evaluate a greater number of alternatives before finding the one that they prefer. Therefore, greater variety is expected to lead to less-complete adjustment in the lower regime ( $\phi_{11} < 0$ ) as the gains to search are relatively low when retail and wholesale prices are close. Pass-through rates are expected to rise in variety in the upper regime ( $\phi_{31} > 0$ ) because retail prices are relatively high so the expected gains from search are high. If  $\phi_{11} < 0$ , then the rate of upward retail-price adjustment slows in variety as the returns to searching are lower, fewer consumers are searching, and firms have less of an incentive to raise prices. Our hypothesis is that the cost of search rises in the number of variants offered by the store, so the pass-through rate should fall accordingly. Further, because retailers with more market power need not pass the trade deal on, we expect the downward adjustment rate in retail prices to fall with market power (directly with the elasticity of demand). This is the "rockets and feathers" phenomenon.

Finally, we also test whether there are short-run asymmetries by disaggregating wholesale price changes into rising and falling regimes, and replacing the wholesale price terms in (15) with the following notation:

$$\dots \alpha_2^+ \Delta^+ w_{it}^r + \alpha_2^- \Delta^- w_{it}^r + \alpha_3^+ \Delta^+ w_{it-1}^r + \alpha_3^- \Delta^- w_{it-1}^r, \quad (16)$$

where  $\Delta^+ w_{it}^r = \Delta w_{it}^r$  if  $\Delta w_{it}^r > 0$  and is zero otherwise, and  $\Delta^- w_{it}^r = \Delta w_{it}^r$  if  $\Delta w_{it}^r < 0$ , and is zero otherwise. Short run asymmetry implies  $\alpha_2^+ \neq \alpha_2^-$  and  $\alpha_3^+ \neq \alpha_3^-$ . With this, most general, specification, we study pass-through behavior in both rising and falling wholesale price regimes, and below and above the adjustment thresholds.

## Data and Estimation Methods

### Data

In this study, we focus on pass-through in a frequently-purchased consumer packaged good category: ready-to-eat breakfast cereal. Breakfast cereal represents an ideal context in which to study promotional pass-through behavior. First, breakfast cereal is perhaps one of the most scrutinized categories in the empirical industrial organization and marketing literatures (Schmalensee 1978; Cotterill and Haller 1997; Nevo 2001; Nevo and Wolfram 2002; Shum 2004). Second, breakfast cereal is widely purchased by consumers across all income strata so the distribution of preferences should clearly identify the parameters of interest. Third, the market is dominated by two major manufacturers so price and non-price competition at the manufacturer level is strong. Fourth, supermarket retailers offer very similar breakfast cereal assortments, so demand shocks in one market that are not manifest in other are likely due to market-specific factors and will help identify the demand parameters. Finally, cereal is derived directly from commodity inputs - albeit through a complicated production process - so the extreme volatility exhibited by commodity markets between 2007 - 2010 should also help identify not only variations in demand, but pricing behavior also. In fact, the prominence of the two major cereal manufacturers (Kelloggs and General Mills) and the popularity of cereals mean that retail price increases are often headline news (Wall Street Journal 2010).

Our data describes 156 weeks (March 2007 - March 2010) of supermarket chain-level retail sales of ready-to-eat breakfast cereal for five retailers in the Los Angeles market. In this market, we focus on cereal sales from the largest retail chains that participate in the IRI InfoScan data syndication program. The data include all branded UPCs, including both private label brands and national brands,<sup>7</sup> but we focus on 10 top high-volume brands across all stores.<sup>8</sup> The brands include Frosted Mini Wheats (18 oz), Raisin Bran (20 oz), Frosted Flakes (17 oz), Corn Flakes (12 oz), Rice Krispies (12 oz), Special K (12 oz), Cap'n Crunch (16 oz), Honey Bunches of Oats (13 oz), Go Lean Crunch (15 oz), and Life Cinnamon (21 oz). We chose these brands based on sales volume (they each had to be major brands with at least 1% category share) and price

<sup>7</sup> We include Vons and Vons Pavilions as separate chains because Pavilions stores are managed independent of Vons, and maintain a fundamentally different variety/pricing strategy. According to a company spokesman, Pavilions sells a greater variety of organic foods, wine, produce and specialty items.

<sup>8</sup> For the demand model, we include all other brands in the outside option, as well as cereals from other outlets. Details are available from the authors.

variability at both wholesale and retail, subject to the requirement that each brand is sold in all stores.

The absence of data from mass merchandisers is an important limitation of any empirical study using syndicated scanner data. However, our data does not suffer from this "Wal\*Mart gap." In our sample market - Los Angeles - Wal\*Mart has only a small presence so our store-level scanner data covers the retail market for breakfast cereal more completely than would be the case in other markets.<sup>9</sup>

Identifying the price dynamics we describe, and the relationship to assortment depth, requires sufficient variability in both prices and variety. To investigate whether this is the case, we construct summary statistics of each at the store level. Table 1 documents the extent of both price and assortment variation among our sample stores. Clearly, the stores in our sample differ considerably in their overall price level, assortment depth and promotion frequency. While Albertsons sells breakfast cereals for nearly exactly the sample average (\$0.226/oz), it stocks an average of some 27.6% more brands than the sample mean, and promotes 9.4% more frequently. On the other hand, prices in Food 4 Less are 7.4% less than average, and it stocks 27% fewer brands than the average store. Although five stores is a small sample to draw inferences regarding the relationship between price and assortment depth, the correlation among our sample stores is 47.3%, suggesting that stores with more variety are able to charge higher prices. High-price stores also promote more frequently, as the correlation between price and promotion frequency is fully 79.6%. Averaging prices across brands within each store, however, obscures differences in the composition of sales between supermarkets. Table 2 shows sample average retail and wholesale price for each cereal. Although we would expect prices for similar brands to be highly correlated among stores, the relative variability of price and market share depends on the brand. Taking two brands as examples, the coefficient of variation in the price of Frosted Mini Wheats among stores is only 3.8%, while the coefficient of variation in share is over 30.0%. Meanwhile, the coefficient of variation in the price of Life Cinnamon among stores is 11.4% and the same measure for market share is 26.7%. Therefore, we are confident that there is sufficient variation in the sample data to identify the relationships that we investigate.

[Tables 1 and 2 in here]

Table 2 also summarizes the wholesale price of each brand over the sample period. 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 data source is that it represents prices charged by wholesalers to only non self-distributing

---

<sup>9</sup> Prior to July 2001, Wal\*Mart did not participate in data syndication programs so was not represented in any Nielsen or IRI aggregate-level data products. It is represented in Nielsen's HomeScan product, but this is a household-level data set.

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.

Estimating the demand model requires instruments for the endogenous retail prices. We interact manufacturing input prices with brand-level dummies for this purpose (Berto Villas-Boas 2007). Brand-level input prices represent valid instruments because they are highly correlated with retail prices, yet mean independent of the demand errors. All input-price data are from the Bureau of Labor Statistics (BLS 2010a) and include average weekly earnings by workers in the food manufacturing industry, an index of healthcare costs paid by firms, and an index of utility prices paid by manufacturing businesses. BLS gathers primary data on wages for a large number of industries (400) and occupations (800) using the Current Employment Statistics (CES) survey. The CES "...surveys about 140,000 businesses and government agencies, representing approximately 410,000 individual worksites, in order to provide detailed industry data on employment, hours, and earnings of workers on nonfarm payrolls..." (BLS 2010b). Utility prices are from the BLS Consumer Price Index program (BLS 2010a) and, for current purposes, are market-specific indices. The mean and standard deviation for each socio-economic and demographic variable (age, household size and income), which are also used in the demand model, for the Los Angeles market are from the Bureau of Census (BoC 2010).

## Results and Discussion

In this section, we present and discuss the results obtained by estimating the panel asymmetric threshold error-correction model. Because selecting the final form of the model (i.e., symmetric or asymmetric adjustment, single or double threshold, etc.) does not depend entirely upon theory, we present the results from estimating a number of successively-more-comprehensive models and conduct a series of hypothesis tests to determine the one that provides the best fit to the data. First, however, we present the results from testing each of the data series for stationarity, and then examine each for the existence of cointegration relationships. Both sets of tests recognize the panel nature of our data.

Table 3 shows the results from conducting panel unit root tests on the retail and wholesale prices, both in levels and in first-difference form. We use the Hadri tests described above for this purpose. According to the Hadri tests, for the variables in levels the null hypothesis that all panels are stationary is strongly rejected at 5% significant level, implying that some panels contain unit roots; whereas for the first difference variable the null of stationarity is strongly accepted indicating all panels follow an  $I(0)$  process. Based on these results, we proceed to test for co-integration between wholesale and retail cereal prices.

[Table 3 in here]

The null hypotheses in all seven Pedroni tests are that there are no co-integration relationships between variables. The test statistics for each of these hypotheses are given in Table 4. In each case, we reject the null hypothesis so conclude that there is indeed a long-run, or cointegration relationship between retail and wholesale prices for each brand and retailer. Given this evidence, we then estimate the panel ECM in symmetric and asymmetric form, present the threshold value estimates as well as their statistical significance, and then the panel TECM, again in symmetric and asymmetric form.

[Table 4 in here]

The base ECM assumes that retail prices adjust to any change in wholesale prices, no matter how small, whether upward (wholesale price increase) or downward (trade promotion). We first test whether the preferred specification maintains symmetric or asymmetric pass-through. We do so in two ways: (1) a likelihood ratio (LR) test with parameters on the partitioned-adjustment terms restricted to zero in the more simple model, and vice versa, and (2)  $t$ -tests of the significance of the individual short-run adjustment parameters in each case. Based on the results in Table 5, the LR statistic is 1.713 (critical  $\chi^2_{2,0.05} = 5.991$ ) so we reject the asymmetric model in favor of symmetric adjustment. However, examining each of the short-run adjustment terms ( $\Delta w_{it-1}^r$ ), we see that  $p$ -values for the contemporaneous and lagged terms in the symmetric model are 0.275 and 0.265, respectively, while the  $p$ -values for the response in retail prices for discounts (negative changes in wholesale prices) are 0.084 and 0.070, respectively, for the contemporaneous and lagged terms in the asymmetric model. While not significant at more usual levels (0.05), these results do suggest that wholesale price reductions (i.e., promotions) are passed-through to consumers at a higher rate (2.3% and 2.4% for current and lagged terms) than are price increases. Consequently, although the LR test favors symmetric adjustment, we nonetheless regard the information in the asymmetric pass-through model as useful. We next consider long-run pass-through, or the effect of adding  $ECT_{it-1}^r$  to the model. In terms of the symmetric model, the results in Table 5 show that retail prices adjust 64.1% toward their equilibrium values each week in response to a deviation, or a shock to wholesale prices. The parameter estimate is less-than-zero because a large deviation implies that retail prices move in the opposite direction (fall when retail prices are too high, or rise when they are too low) in order to restore the long-run equilibrium. Search costs do not have a statistically significant effect on pass-through, but market power does. Recall that higher values of the elasticity imply less market power. Therefore, a positive parameter estimate means that when retailers are more competitive (have less market power), pass-through falls as retail prices adjust less completely. By corollary, more market power implies higher pass-through. Because the mean elasticity value is positive, when calculated at the mean elasticity the net pass-through rate is 56.7%. In the asymmetric pass-through model, the response to deviations from the long-run equilibrium are nearly the same: more market power lower raises the pass-through rate. Again, net pass-through is just over 56.7%. Finding that market power causes pass-through to occur more completely is counter to much of the existing empirical evidence as current orthodoxy holds that retailers have an incentive to adjust retail prices slowly in response to changes in wholesale prices, absorbing additional profit in the transition periods. It is, however, consistent with the "rockets and feathers" phenomenon when wholesale prices are rising (retail prices are expected to rise) because retailers with market power pass wholesale price increases along more completely if

they have some market power. However, this result is predicated on the assumption that retailers behave the same way in response to both small and large changes in wholesale prices.

[Table 5 in here]

We test for the existence of 1, 2 or 3 thresholds using the LR tests developed by Hansen (1999). These results are reported in Table 6. Applying the testing procedure described in Hansen (1999), we find two significant threshold values:  $\gamma_1 = 0.0237$  and  $\gamma_2 = 0.1028$ . Although both thresholds are greater than zero, the bulk of the mass of the lower threshold is below zero (66.5% of observations), so we interpret this regime as representing periods in which the retail price was relatively low, and must adjust upward. On the other hand, observations above  $\gamma_2$  represent periods in which the retail price is relatively high and should adjust downward to re-establish the long-run equilibrium.

[Table 6 in here]

The results in Table 7 present a more realistic description of retailer behavior by allowing for non-linear pass-through. Table 7 defines asymmetry in terms of regimes of relatively high or low retail prices compared to the long-run equilibrium: retail prices are relatively high when  $ECT_{it-1}^r > \gamma_2$  and are relatively low when  $ECT_{it-1}^r < \gamma_1$ . In the first two columns of Table 7, we allow for only this long-run definition of asymmetry while we include both long-run and short-run adjustment asymmetry in the last two columns. Recall that the pass-through rate in each regime is assumed to be a linear function of variables measuring market power and the depth of assortment. In the first regime,  $ECT_{it-1}^r < \gamma_1$ , we find a strong direct effect that, in fact, moves retail prices away from equilibrium (a positive coefficient indicates adjustment away from equilibrium), whereas search-cost effect moves retail prices closer to equilibrium, and market power further away, for a net pass-through rate of 83.76% toward equilibrium each week (again calculated at the mean market power and search cost values). In this regime, the negative search cost effect suggests that higher search costs raise the pass-through rate. Retail prices are relatively low so are expected to rise. Expecting greater returns to search, consumers begin to do so and retailers respond by more completely adjusting retail prices. Said differently, if search costs are higher, consumers will search less, and retail prices rise. A negative market power effect means that higher values of the price elasticity (less market power) are associated with higher pass-through rates. This finding is consistent with simple theoretical pass-through models as the pass-through rate is theoretically higher in competition than it is in monopoly (Tyagi 1999). Trade promotions during this regime will be passed along more completely by retailers with deeper assortments, but less completely by retailers with market power. Note that in this regime, each component of the long-run adjustment term is statistically significant which, in turn, supports our theoretical contention that pass-through rates depend both on consumer search costs and market power.

[Table 7 in here]

In the upper regime, where  $ECT_{it-1}^r > \gamma_2$ , we find that search costs and market power have the opposite effect compared to the lower regime. These results are also shown in Table 7. This is the case that is most relevant to our context: if a wholesaler reduces prices to promote a brand,

the error correction term is likely to be high (and positive) until the retailer decides how much of this promotion to pass on to consumer. In this case, retail prices are relatively high so must adjust downward if the long run equilibrium between retail and wholesale prices is to be reestablished. Including all three effects (constant pass-through rate, consumer search and market power), the net pass-through rate is similar to the first regime: 83.75% toward equilibrium each week (or 83.75 cents of each \$1.00 in trade promotions is passed along to consumers). However, in this regime the search cost effect implies lower pass-through rates, while more market power (lower price elasticity) is associated with higher rates of retail price pass-through. When retail prices are high, consumers expect them to fall. Therefore, higher costs of search driven by greater variety cause consumers to search less and retail prices to fall less quickly than they would otherwise. In other words, the pass-through rate falls as retail prices adjust more slowly. This is the "rockets and feathers" phenomenon as retail prices adjust completely upward when assortment changes, but fall slowly back down. This effect, however, is only statistically significant at an 8.75% level. Greater market power, on the other hand, is associated with retail prices adjusting more completely to the long-run equilibrium than would otherwise be the case. If retail prices are relatively high, and wholesalers offer a promotion, a monopoly retailer will find it optimal to pass the promotion along almost completely in order to re-establish his optimal margin. In more competitive markets, however, retailers fear that passing along a discount will be met with a destructive response from a rival so are less willing to start a price war. Such counter-cyclical pricing behavior is predicted by other models of retail price behavior (Rotemberg and Saloner 1986) that are constructed under different assumptions than ours here. Consequently, we find that partial pass-through of trade deals is more likely due to consumer search, and retailers' rational response to search, than it is to market power.

Allowing for asymmetry in short-run retail price adjustment does not improve goodness-of-fit ( $\chi^2 = 0.18$ ) so we again prefer symmetric short-run adjustment over asymmetric. However, it is interesting to note that short-run adjustment rates when wholesale prices are rising are nearly double the rate when wholesale prices are falling. Although the magnitude of the short-run rates is dominated by the stronger incentive to return to the long-run equilibrium documented above, this effect supports the underlying "rockets and feathers" phenomenon cited earlier: retail prices rise quickly when retailers face an incentive to raise them, but fall slowly when retailers should reduce prices.

In summary, whereas the existing literature explains the "rockets and feathers" phenomenon as an apparent result of retailers exercising market power, we find the opposite. Rather, when retail price should rise, they do so more slowly if retailers have market power, while they fall more quickly. Trade promotions are passed through more completely by retailers with market power while wholesale price increases, which have become more common in recent years due to rising manufacturing costs, are moderated by powerful retailers. The "rockets and feathers" observation, moreover, is better explained by consumer search and retailers response to it. When the returns to search are high, consumers will search more actively and retail prices respond quickly. Trade promotion pass-through, therefore, is reduced by consumer search behavior, and retailers' optimal response, as the returns to search are lower when consumers expect retail prices to fall.

## **Conclusions and Implications**

In this study, we investigate why retail-price pass-through is incomplete in consumer packaged goods, and why retail price adjustment upward appears to be faster than downward adjustment. Much of the previous literature explains this asymmetry, or "rockets and feathers" observation as resulting from retailers' exercise of market power, while recent theoretical work argues that asymmetric pass-through may instead be due to consumer search behavior, and retailers rational response. Essentially, if search costs rise, search intensity falls and retail prices rise. When retail prices are expected to rise, this phenomenon appears as a higher pass-through rate, but when they are expected to fall it manifests as a decline in the pass-through rate. We devise a test for the "consumer search" and "market power" and apply our test to retail and wholesale breakfast cereal price data for five retailers in the Los Angeles market over a 156 week period.

Our econometric model takes into account the time-series properties of retail and wholesale price data. If retail and wholesale prices are cointegrated, as logic would suggest they are, then conventional pass-through models are likely to produce biased results unless the non-stationarity of the underlying time series is not appropriately addressed. We employ a panel error-correction model (ECM) to account for cointegration, but extend the basic ECM model in three ways. First, we allow for asymmetric adjustment of retail prices to wholesale prices by segmenting the wholesale price series into positive and negative adjustment regimes. Such short-term asymmetry, however, does not take more extended periods of asymmetry into account. Second, therefore, we allow for non-linear retail price pass-through by disaggregating the ECM into three regimes based on whether the error-correction term is greater than an upper threshold, lower than a bottom threshold or between the two. Because previous research shows that there are significant costs, both implicit and explicit, to changing retail prices, modeling retail pass-through with this asymmetric threshold error correction model (TAECM) framework is appropriate. Third, we test the market power and consumer search hypotheses by allowing the long-run pass-through parameters in the TAECM to vary with the elasticity of demand, and number of SKUs stocked during each week. These variables proxy market power and consumer search costs, respectively, in ways that are more theoretically-consistent than previous attempts to estimate models of retail pass-through.

By allowing pass-through to depend on market power and consumer search costs, we find results that are contrary to the conventional wisdom. Namely, market power causes retail prices to fall quickly and rise slowly, while consumer search costs cause retail prices to rise quickly and fall slowly - precisely the "rockets and feathers" phenomenon. Deal pass-through, therefore, can be expected to be higher among more powerful retailers, and those that offer a low search-cost environment. Limited selection, low price dispersion, heavy price advertisement, or frequent emails / Facebook updates / Twitter feeds are all means of minimizing consumer search costs. The implications of our research are potentially important for both retailers and manufacturers in a number of different ways. Because our model is couched in terms of more general pass-through issues than trade promotions .rising wholesale prices, higher labor costs, lower technology costs, and many others - our research explains a wide range of retail price pass-through observations that have previously been attributed to retailers' exercise of market power. Second, manufacturers and wholesalers interested in improving pass-through performance would be well served to consider ways in which they can reduce consumer search costs, perhaps by directly communicating trade promotions to consumers. Others have shown that these strategies



are effective in increasing deal pass-through rates. Third, we provide a theoretical and empirical basis for arguments that defend retailers from accusations that the retail consolidation trend has concentrated retailing into too few hands. Rather than welfare-reducing, the price patterns due solely to market power effects appear to be welfare-enhancing. Fourth, costly consumer search for complex service products such as insurance, retirement plans or even basic banking services may be at least partly to blame for high margins, and economic inefficiency, in many of these markets.

## References

- Ailawadi, K.L., and B.A. Harlam. 2009. "Retailer Promotion Pass-Through: A Measure, Its Magnitude, and Its Determinants," *Marketing Science* 28: 782-791.
- Bacon, R.W. 1991. "Rockets and Feathers: the Asymmetric Speed of Adjustment of UK Retail Gasoline Prices to Cost Changes," *Energy Economics* 13: 211-218.
- Bai, J. 1997. "Estimating Multiple Breaks at One Time," *Econometric Theory* 13: 315-352.
- Balke, N.S., and T.B. Fomby. 1997. "Threshold Cointegration," *International Economic Review* 38: 627-645.
- Ball, L., and D. Romer. 1991. "Sticky Prices as a Coordination Failure," *American Economic Review* 81: 539-552.
- Benabou, R., and R. Gertner. 1993. "Search with Learning from Prices: Does Increased Inflationary Uncertainty Lead to Higher Markups?" *Review of Economic Studies* 60: 69-94.
- Besanko, D., J.P. Dube, and S. Gupta. 2005. "Own-Brand and Cross-Brand Retail Pass-Through," *Marketing Science* 24: 123-137.
- Berto Villas-Boas, S. 2007. "Vertical Relationships Between Manufacturers and Retailers: Inference with Limited Data," *Review of Economic Studies* 74: 625-652.
- Blinder, A., E. Canetti, D. Lebow, and J. Rudd. 1998. *Asking About Prices: A New Approach to Understanding Price Stickiness*, New York, NY: Russell Sage Foundation.
- Boyle, M. 2009. *Grocery Stores Fight Back Against Food Prices*, Business Week January 29, 2009.
- Borenstein, S., A.C. Cameron, and R. Gilbert. 1997. "Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes?" *Quarterly Journal of Economics* 112: 305-339.
- Bresnahan, T. 1989. "Empirical Studies of Industries with Market Power," in *The Handbook of Industrial Organization: Volume II* eds. R. Schmalensee and R. Willig. Amsterdam: North-Holland.
- Bulow, J.I., and P.P. Pfleiderer. 1983. "A Note on the Effects of Cost Changes on Prices," *Journal of Political Economy* 91: 181-185.
- Busse, M., J. Silva-Russo, and F. Zettelmeyer. 2006. "\$1000 Cash Back: The Pass-Through of Auto Manufacturer Promotions," *American Economic Review* 96: 1253-1270.
- Chan, K.S. 1993. "Consistency and Limiting Distribution of the Least Squares Estimator of a Threshold Autoregressive Model," *The Annals of Statistics* 21: 520-533.

- Chandra, A., and M. Tappata. 2010. "Consumer Search and Dynamic Price Dispersion: An Application to Gasoline Markets," Working paper, Sauder School of Business, University of British Columbia, Vancouver, B.C.
- Chong, T.T.L. 1995. "Partial Parameter Consistency in a Misspecified Structural Change Model," *Economic Letters* 49: 351-357.
- Cotterill, R., and L. Haller. 1997. "An Econometric Analysis of the Demand for RTE Cereal: Product Market Definition and Unilateral Market Power Effects," University of Connecticut Food Marketing Policy Center, Research Report No. 35.
- Cui, T.H., J.S. Raju, and Z.J. Zhang. 2008. "A Price Discrimination Model of Trade Promotion," *Marketing Science* 27: 779-795.
- Deltas, G. 2008. "Retail Gasoline Price Dynamics and Local Market Power," *Journal of Industrial Economics* 56: 613-628.
- Diamond, P.A. 1971. "A Model of Price Adjustment," *Journal of Economic Theory* 3: 156-168.
- Drèze, X., and D.R. Bell. 2003. "Creating Win-Win Trade Promotions: Theory and Empirical Analysis of Scan-Back Trade Deals," *Marketing Science* 22: 16-39.
- Engle, R.F., and C.W.J. Granger. 1987. "Cointegration and Error Correction: Representation, Estimation, and Testing," *Econometrica* 55: 251-276.
- Frey, G., and M. Manera. 2007. "Econometric Models of Asymmetric Price Transmission," *Journal of Economic Surveys* 21: 349-415.
- Gerstner, E., and J. Hess. 1991. "A Theory of Channel Price Promotions," *American Economic Review* 81: 827-886.
- Gómez, M.I., V.R. Rao and E. McLaughlin. 2009. "Empirical Analysis of Budget and Allocation of Trade Promotions in the U.S. Supermarket Industry," *Journal of Marketing Research* 44: 410-424.
- Goodwin, B.K. and N.E. Piggott. 2001. "Spatial Market Integration in the Presence of Threshold Effects," *American Journal of Agricultural Economics* 83: 302-317.
- Granger, C.W.J., and T.H. Lee. 1989. "Investigation of Production, Sales and Inventory Relationships using Multicointegration and Non-Symmetric Error Correction Models," *Journal of Applied Econometrics* 4: S145-S159.
- Hansen, B.E. 1999. "Threshold Effects in Non-Dynamic Panels: Estimation, Testing and Inference," *Journal of Econometrics* 93: 345-368.

- Hadri, K 2000. "Testing for Stationarity in Heterogeneous Panel Data," *Econometrics Journal* 3: 148-161.
- Im, K., H. Pesaran, and Y. Shin. 1997. "Testing for Unit Roots in Heterogeneous Panels," *Journal of Econometrics* 115: 53-74.
- Johansen, S. 1988. "Statistical Analysis of Cointegration Vectors," *Journal of Economic Dynamics and Control* 12: 231-254.
- Kim, S.Y., and R. Staelin. 1999. "Manufacture Allowances and Retailer Pass-Through Rates in a Competitive Environment," *Marketing Science* 18: 59-76.
- Kumar, N., S. Rajiv, and A. Jeuland. 2001. "Effectiveness of Trade Promotions: Analyzing the Determinants of Retail Pass Through," *Marketing Science* 20: 382-404.
- Kwiatowski, D., P.C.B. Phillips, P. Schmidt, and Y. Shin. 1992. "Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root: How Sure are we that Economic Time Series have a Unit Root?" *Journal of Econometrics* 54: 159-178.
- Levin, A., C.F. Lin and C.S.J. Chu. 2002. "Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties," *Journal of Econometrics* 108: 1-24.
- Levy, D., M. Bergen, S. Dutta, and R. Venable. 1997. "The Magnitude of Menu Costs: Direct Evidence from Large U.S. Supermarket Chains," *Quarterly Journal of Economics* 112: 791-825.
- Lewis, M. 2008. "Price Dispersion and Competition with Differentiated Sellers," *Journal of Industrial Economics* 56: 654-678.
- McAlister, L. 2007. "Cross-Brand Pass-Through: Fact or Artifact?" *Marketing Science* 26: 876-898.
- Moorthy, S. 2005. "A General Theory of Pass-Through in Channels with Category Management and Retail Competition," *Marketing Science* 24: 110-122.
- Nakamura, E., and D. Zerom. 2010. "Accounting for Incomplete Pass-Through," *Review of Economic Studies* 77: 1192-1230.
- Nevo, A. 2001. "Measuring Market Power in the Ready-to-Eat Cereal Industry," *Econometrica* 69: 307-342.
- Nevo, A., and C. Wolfram. 2002. "Why do Manufacturers Issue Coupons? An Empirical Analysis of Breakfast Cereals," *RAND Journal of Economics* 33: 319-339.
- Nijs, V., K. Misra, E.T. Anderson, and L. Krishnamurthi. 2010. "Channel Pass-Through of Trade Promotions," *Marketing Science* 29: 250-267.

- Osterwald-Lenum, M. 1992. "A Note with Fractals in Asymptotic Distribution of the Maximum Likelihood Cointegration Rank Test Statistics: Four Cases," *Oxford Bulletin of Economics and Statistics* 54: 461-472.
- Pauwels, K. 2007. "How Retailer and Competitor Decisions Drive the Long-Term Effectiveness of Manufacturer Promotions for Fast Moving Consumer Goods," *Journal of Retailing* 83: 297-308.
- Pedroni, P. 1999. "Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors," *Oxford Bulletin of Economics and Statistics* 61: 653-670.
- Peltzman, S. 2000. "Prices Rise Faster Than They Fall," *Journal of Political Economy* 108: 466-502.
- Petrin, A., and K. Train. 2010. "A Control Function Approach to Endogeneity in Consumer Choice Models," *Journal of Marketing Research* 47: 3-13.
- Phillips, P.C.B., and P. Perron. 1988. "Testing for a Unit Root in Time Series Regression," *Biometrika* 75: 335-346.
- Richards, T.J., S.F. Hamilton, and W.J. Allender. 2011. "Retail Price Pass-Through with Vertical Strategic Interaction: the Case of Commodity Price Inflation," forthcoming at *International Journal of Industrial Organization*.
- Rotemberg, J.J., and G. Saloner. 1986. "A Supergame - Theoretical Model of Price Wars during Booms," *American Economic Review* 76: 390-407.
- Schmalensee, R. 1978. "Enter Deterrence in the Ready-to-Eat Cereal Industry," *Bell Journal of Economics* 9: 305-327.
- Shum, M. 2004. "Does Advertising Overcome Brand Loyalty? Evidence from the Breakfast-Cereals Market," *Journal of Economics and Management Strategy* 13: 241-272.
- Slade, M.E. 1999. "Sticky Prices in a Dynamic Oligopoly: An Investigation of (s, S) Thresholds," *International Journal of Industrial Organization* 17: 477-511.
- Tappata, M. 2009. "Rockets and Feathers: Understanding Asymmetric Pricing," *RAND Journal of Economics* 40: 673-687.
- Train, K. 2003. *Discrete Choice Methods with Simulation*, Cambridge University Press.
- Tsay, R.S. 1989. "Testing and Modeling Threshold Autoregressive Processes," *Journal of the American Statistical Association* 84: 231-240.
- Tyagi, R.K. 2009. "A Characterization of Retailer Response to Manufacturer Trade Deals," *Journal of Marketing Research* 36: 510-516.

- U.S. Bureau of Census. Current Population Survey. (<http://www.census.gov/cps>, March 22, 2010).
- U.S. Bureau of Labor Statistics. Consumer Price Index. (<http://www.bls.gov/CPI/>, March 22, 2010a).
- U.S. Bureau of Labor Statistics. Employment, Hours and Earnings from the Current Employment Statistics Survey. (<http://www.bls.gov/data/>, March 22, 2010b).
- USDA. Economic Research Service. .Food Availability (Per Capita) Data System.. (<http://www.ers.usda.gov/Data/FoodConsumption/FoodAvailSpreadsheets.htm>, March 21, 2010).
- Varian, H.R. 1980. "A Model of Sales," *American Economic Review* 70: 651-659.
- Verlinda, J.A. 2008. "Do Rockets Rise Faster and Feathers Fall Slower in an Atmosphere of Local Market Power? Evidence from the Retail Gasoline Market," *Journal of Industrial Economics* 56: 581-612.
- Villas-Boas, J.M., and Y. Zhao. 2005. "Retailer, Manufacturers and Individual Consumers: Modeling the Supply Side in the Ketchup Marketplace," *Journal of Marketing Research* 42: 83-95.
- Wall Street Journal. 2010. "Report: Price of Breakfast Cereal Going Up," (<http://abclocal.go.com/wls/story?section=news/consumer&id=7738495>, Oct. 10, 2010).
- Ward, R.W. 1982. "Asymmetry in Retail, Wholesale, and Shipping Point Pricing for Fresh Vegetables," *American Journal of Agricultural Economics* 64: 205-212.
- Yang, H., and L. Ye. 2008. "Search with Learning: Understanding Asymmetric Price Adjustments," *The RAND Journal of Economics* 39: 547-564.
- Yuan, H., and S. Han. 2011. "The Effects of Consumers' Price Expectations on Sellers' Dynamics Pricing Strategies," *Journal of Marketing Research* 48: 62-71.

Table 1. Summary of Retail Prices, Discounts and SKUs

Store	Measure	Units	Means	Std. Dev.	Min	Max	N
1. Albertsons	$p_t^r$	\$/oz	0.226	0.085	0.070	0.518	156
	$N_t^r$	#	420.424	34.475	367.0	464.0	156
	<i>Disc</i>	%	0.276	0.447	0.000	1.000	156
2. Food 4 Less	$p_t^r$	\$/oz	0.210	0.057	0.080	0.350	156
	$N_t^r$	#	243.879	17.700	221.0	279.0	156
	<i>Disc</i>	%	0.209	0.407	0.000	1.000	156
3. Ralphp	$p_t^r$	\$/oz	0.234	0.066	0.080	0.434	156
	$N_t^r$	#	372.273	27.098	333.0	420.0	156
	<i>Disc</i>	%	0.279	0.449	0.000	1.000	156
4. Vons Pavilion	$p_t^r$	\$/oz	0.228	0.055	0.130	0.412	156
	$N_t^r$	#	306.061	17.845	285.0	356.0	156
	<i>Disc</i>	%	0.249	0.433	0.000	1.000	156
5. Vons	$p_t^r$	\$/oz	0.222	0.056	0.121	0.384	156
	$N_t^r$	#	325.242	18.595	304.0	374.0	156
	<i>Disc</i>	%	0.242	0.429	0.000	1.000	156

Table 2. Summary of Retail and Wholesale Price Data

Store	Brand	N	Retail Price (\$/oz)				Wholesale Price (\$/oz)			
			Min	Max	Mean	Std	Min	Max	Mean	Std
Albertsons	Frosted Mini-Wheats	156	0.093	0.276	0.193	0.050	0.044	0.177	0.168	0.022
	Raisin Bran	156	0.081	0.234	0.169	0.045	0.025	0.155	0.133	0.040
	Frosted Flakes	156	0.110	0.323	0.218	0.063	0.024	0.208	0.173	0.059
	Corn Flakes	156	0.087	0.321	0.240	0.062	0.039	0.213	0.199	0.028
	Rice Krispies	156	0.144	0.438	0.294	0.095	0.042	0.265	0.224	0.073
	Special K	156	0.178	0.380	0.300	0.057	0.050	0.262	0.224	0.077
	Cap'n Crunch	156	0.104	0.299	0.212	0.067	0.035	0.206	0.173	0.062
	Honey Bunches of Oats	156	0.113	0.368	0.290	0.079	0.026	0.238	0.171	0.095
	Go Lean Crunch	156	0.167	0.326	0.264	0.046	0.018	0.199	0.155	0.067
Food 4 Less	Life Cinnamon	156	0.119	0.247	0.207	0.041	0.022	0.179	0.154	0.048
	Frosted Mini-Wheats	156	0.111	0.237	0.201	0.028	0.044	0.177	0.168	0.022
	Raisin Bran	156	0.100	0.203	0.160	0.030	0.025	0.155	0.133	0.040
	Frosted Flakes	156	0.116	0.259	0.194	0.044	0.024	0.208	0.173	0.059
	Corn Flakes	156	0.145	0.281	0.245	0.034	0.039	0.213	0.199	0.028
	Rice Krispies	156	0.164	0.345	0.298	0.042	0.042	0.265	0.224	0.073
	Special K	156	0.166	0.358	0.289	0.054	0.050	0.262	0.224	0.077
	Cap'n Crunch	156	0.094	0.263	0.160	0.035	0.035	0.206	0.173	0.062
	Honey Bunches of Oats	156	0.119	0.331	0.278	0.046	0.026	0.238	0.171	0.095
Ralphs	Go Lean Crunch	156	0.190	0.265	0.228	0.020	0.018	0.199	0.155	0.067
	Life Cinnamon	156	0.094	0.210	0.153	0.026	0.022	0.179	0.154	0.048
	Frosted Mini-Wheats	156	0.111	0.255	0.210	0.037	0.044	0.177	0.168	0.022
	Raisin Bran	156	0.079	0.234	0.191	0.042	0.025	0.155	0.133	0.040
	Frosted Flakes	156	0.117	0.293	0.216	0.052	0.024	0.208	0.173	0.059
	Corn Flakes	156	0.096	0.441	0.277	0.057	0.039	0.213	0.199	0.028
	Rice Krispies	156	0.167	0.374	0.308	0.062	0.042	0.265	0.224	0.073
	Special K	156	0.133	0.391	0.327	0.066	0.050	0.262	0.224	0.077
	Cap'n Crunch	156	0.105	0.306	0.228	0.064	0.035	0.206	0.173	0.062
Vons Pavillion	Honey Bunches of Oats	156	0.127	0.384	0.285	0.069	0.026	0.238	0.171	0.095
	Go Lean Crunch	156	0.168	0.333	0.249	0.046	0.018	0.199	0.155	0.067
	Life Cinnamon	156	0.119	0.238	0.223	0.029	0.022	0.179	0.154	0.048
	Frosted Mini-Wheats	156	0.110	0.255	0.183	0.038	0.044	0.177	0.168	0.022
	Raisin Bran	156	0.095	0.230	0.162	0.039	0.025	0.155	0.133	0.040
	Frosted Flakes	156	0.146	0.303	0.232	0.044	0.024	0.208	0.173	0.059
	Corn Flakes	156	0.117	0.324	0.283	0.043	0.039	0.213	0.199	0.028
	Rice Krispies	156	0.169	0.401	0.274	0.068	0.042	0.265	0.224	0.073
	Special K	156	0.209	0.393	0.289	0.044	0.050	0.262	0.224	0.077
Vons	Cap'n Crunch	156	0.120	0.330	0.229	0.066	0.035	0.206	0.173	0.062
	Honey Bunches of Oats	156	0.153	0.380	0.294	0.059	0.026	0.238	0.171	0.095
	Go Lean Crunch	156	0.168	0.322	0.256	0.045	0.018	0.199	0.155	0.067
	Life Cinnamon	156	0.103	0.265	0.211	0.041	0.022	0.179	0.154	0.048
	Frosted Mini-Wheats	156	0.112	0.254	0.182	0.038	0.044	0.177	0.168	0.022
	Raisin Bran	156	0.091	0.231	0.160	0.040	0.025	0.155	0.133	0.040
	Frosted Flakes	156	0.147	0.304	0.231	0.045	0.024	0.208	0.173	0.059
	Corn Flakes	156	0.109	0.321	0.278	0.040	0.039	0.213	0.199	0.028
	Rice Krispies	156	0.159	0.400	0.271	0.069	0.042	0.265	0.224	0.073
Special K	156	0.208	0.389	0.288	0.044	0.050	0.262	0.224	0.077	
Cap'n Crunch	156	0.115	0.328	0.226	0.067	0.035	0.206	0.173	0.062	
Honey Bunches of Oats	156	0.153	0.366	0.287	0.055	0.026	0.238	0.171	0.095	
Go Lean Crunch	156	0.167	0.318	0.253	0.044	0.018	0.199	0.155	0.067	
Life Cinnamon	156	0.098	0.261	0.209	0.043	0.022	0.179	0.154	0.048	



Table 3. Panel Unit Root Tests

Variable	Hadri Tests <sup>b</sup>
$w_t^r$	32.27** <sup>a</sup>
$\Delta w_t^r$	-7.23
$p_t^r$	42.45**
$\Delta p_t^r$	-7.30

a. \*\* indicates significance at 5%.

b.  $H_0$ : All panels are stationary;  $H_A$ : Some panels contain unit roots.

Table 4. Panel Cointegration Tests

Within Dimension		Between Dimension	
Panel $\nu$ -statistics	29.58** <sup>a,b</sup>	Group $\rho$ -statistics	-52.77**
Panel $\rho$ -statistics	-59.37**	Group $PP$ -statistics	-39.47**
Panel $PP$ -statistics	-37.54**	Group $ADF$ -statistics	-40.10**
Panel $ADF$ -statistics	-36.40**		

a.  $H_0$ : No cointegration

b. \*\* indicates significance at 5%.

Table 5. Symmetric and Asymmetric ECM Estimates

	ECM		AECM	
	Estimates	Std. Err.	Estimates	Std. Err.
$ECT_{t-1}$	-0.6413*** <sup>a</sup>	0.0518	-0.6414**	0.0518
$\Delta p_{t-1}^r$	0.2261**	0.0113	0.2260**	0.0113
$\Delta w_t^r / \Delta^+ w_t^r$	0.0099	0.0091	-0.0032	0.0133
$\Delta^- w_t^r$	N.A.	N.A.	0.0232**	0.0134
$\Delta w_{t-1}^r / \Delta^+ w_{t-1}^r$	0.0101	0.0091	-0.0039	0.0133
$\Delta^- w_{t-1}^r$	N.A.	N.A.	0.0242**	0.0134
$N_t^r \cdot ECT_{t-1}$	-0.1299	0.1698	-0.1285	0.1698
$\eta_t^r \cdot ECT_{t-1}$	0.0622**	0.0172	0.0659**	0.0172
$d\Delta p_{t-1}^r / dECT_{t-1}$ <sup>b</sup>	-0.5673		-0.5675	
$LLF$	13,480.43		13,482.15	
$R^2$	0.27		0.27	

a. \*\* indicates significance at 5% level.

b. The marginal effect of  $ECT_{t-1}$  including market power and variety effects.

Table 6. Threshold Estimates and Hypothesis Tests

Number of Thresholds	Estimated Thresholds	LR Statistics	Bootstrap $p$ -value <sup>a</sup>	Confidence Interval (95%)
1	0.1028	23.39	0.023	[0.1012, 0.1028]
2	0.0237	23.40	0.047	[-0.0442, 0.0316]
	0.1028			[0.1012, 0.1028]
3	0.0237	4.59	0.767	[-0.0442, 0.0316]
	0.0354			[0.1012, 0.1028]
	0.1028			

a. 300 bootstrap replications were used to obtain the  $p$ -value.

Table 7. Symmetric and Asymmetric Threshold ECM Estimates

	TECM <sup>a</sup>		TAECM	
	Estimates	Std. Err.	Estimates	Std. Err.
$ECT_{t-1}^{(1)}$	1.3112** <sup>b</sup>	0.0523	1.3113**	0.0524
$ECT_{t-1}^{(2)}$	-3.4576**	0.0745	-3.4586**	0.0746
$ECT_{t-1}^{(3)}$	-3.4087**	0.2683	-3.4079**	0.2683
$\Delta p_{t-1}^r$	0.1148**	0.0081	-3.4079**	0.2683
$\Delta w_t^r / \Delta^+ w_t^r$	0.0220**	0.0063	0.1148**	0.0080
$\Delta^- w_t^r$	N.A.	N.A.	0.0258**	0.0092
$\Delta w_{t-1}^r / \Delta^+ w_{t-1}^r$	0.0098	0.0063	0.0181**	0.0093
$\Delta^- w_{t-1}^r$	N.A.	N.A.	0.0114	0.0092
$N_t^r \cdot ECT_{t-1}^{(1)}$	-1.3145**	0.1815	0.0081	0.0092
$N_t^r \cdot ECT_{t-1}^{(2)}$	0.7244**	0.2448	-1.3132**	0.1815
$N_t^r \cdot ECT_{t-1}^{(3)}$	1.7040	0.9978	0.7230**	0.2448
$\eta_t^r \cdot ECT_{t-1}^{(1)}$	-1.1344**	0.0184	-1.1345**	0.0184
$\eta_t^r \cdot ECT_{t-1}^{(2)}$	1.4851**	0.0222	1.4856**	0.0222
$\eta_t^r \cdot ECT_{t-1}^{(3)}$	1.1031**	0.0416	1.1033**	0.0416
$d\Delta p_{t-1}^r / dECT_{t-1}^{(1)}$	-0.8376		-0.8375	
$d\Delta p_{t-1}^r / dECT_{t-1}^{(2)}$	-0.8923		-0.8927	
$d\Delta p_{t-1}^r / dECT_{t-1}^{(3)}$	-0.9131		-0.9130	
<i>LLF</i>	16,336.89		16,337.07	
$R^2$	0.65		0.65	

a. Estimate threshold values are  $\gamma_1 = 0.0236$  and  $\gamma_2 = 0.1028$ .

b. \*\* indicates significance at 5% level.