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Retail-Price Drivers and Retailer Profits

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What are the drivers of retailer pricing tactics over time? Based on multivariate time-series analysis of two rich data sets, we quantify the relative importance of competitive retailer prices, pricing history, brand demand, wholesale prices, and retailer category-management considerations as drivers of retail prices. Interestingly, competitive retailer prices account for less than 10% of the over-time variation in retail prices. Instead, pricing history, wholesale price, and brand demand are the main drivers of retail-price variation over time. Moreover, the influence of these price drivers on retailer pricing tactics is linked to retailer category margin. We find that demand-based pricing and category-management considerations are associated with higher retailer margins. In contrast, dependence on pricing history and pricing based on store traffic considerations imply lower retailer margins.

Key words: retail-price drivers; retailer profits; time-series models; generalized forecast error variance decomposition

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1. Introduction

In today's competitive environment, retailers face the complicated task of setting prices for many items. A typical grocery store in the United States carries around 31,000 items in approximately 600 product categories (Kahn and McAlister 1997). A recent article underscores the complexity of the pricing problem: "While most companies are savvy about cutting costs, few have figured out how much money they are giving up by using 'lunk-headed' pricing due to a lack of detailed information about market demand" (*Business Week* 2000). Also, the trade press suggests that retailers lack good tools for making pricing decisions (AMR Research 2000), as they have been slow to adopt sophisticated pricing models (*Stores* 2002). Therefore, the actual retail prices observed over time may differ greatly from model-recommended courses of action.

As a result, uncovering the drivers of retail prices is of great importance to marketing executives and academics. Surprisingly, there has been little empirical research in this area. Two notable exceptions are Chintagunta (2002) and Shankar and Bolton (2004). The former investigates category pricing behavior by decomposing retail prices into wholesale price, markup, additional promotional payments, retailer store brand objectives, and interretail competition

for a single category in a single retail chain. Our study extends Chintagunta's (2002) work by using time-series models to develop empirical generalizations on the impact dynamics of cost-, customer-, company-, competitor-, market-, and category-drivers of retail prices over time and across brands, categories, and stores/chains. Shankar and Bolton (2004) use a cross-sectional design to study pricing strategies, focusing on price consistency, price-promotion intensity, price-promotion coordination, and relative brand price level. In contrast, we study *dynamic pricing tactics* with a focus on uncovering the drivers of retail prices over time.

From a modeling perspective, our study shares the basic VARX approach with Srinivasan et al. (2004). However, our research offers contributions in substantive, data, and methodological areas. First, Srinivasan et al. (2004) consider whether manufacturers or retailers benefit more from price promotions, while we focus on the drivers of retail prices across brands and categories over time. Second, they study which brand, category, and market conditions influence price-promotion elasticities and the allocation of their benefits across manufacturers and retailers. In contrast, we link the influence of price drivers on *retailer pricing tactics to retailer category margin* while controlling for brand and category characteristics. Our study

also offers several methodological contributions that are discussed in §3.

Our research contributes to the existing literature on retail-price drivers by answering three unresolved questions: What are the drivers of retailer pricing tactics over time? To what extent do these drivers account for the variation in retail prices over time? And, finally, how does the relative influence of these different drivers affect retailer margins? We address these questions in three empirical steps. First, we estimate the dynamic interactions between retail prices and their drivers using time-series models. Next, we use generalized forecast error variance decomposition (GFEVD) to quantify the relative influence of these drivers on retailer pricing. Finally, we analyze the association between retailer profits (category gross margin) and the influence of the price drivers on pricing as identified in Step 2.

The paper is structured as follows: Section 2 describes the drivers of retailer pricing; §3 introduces the methodology; §4 presents the data; results in §5 show the relative prominence of price drivers; and §6 examines the link between the influence of these price drivers on retailer pricing tactics and retailer category margin. We conclude with managerial implications and suggestions for future research in §7.

2. Retail-Price Drivers

Previous marketing literature suggests that retail prices for a focal brand are affected by competitive retailer pricing and store traffic (e.g., Chintagunta 2002), pricing history of the focal brand (e.g., Krishna et al. 2001), demand for the focal brand (e.g., Pesendorfer 2001), wholesale prices of the focal brand (e.g., Krishna et al. 2001), and category-management considerations (e.g., Zenor 1994).

Competitive Retailer Activity

Competitive retailer activity is expected to influence retailer prices and performance. For instance, price promotions by competing retailers may reduce store traffic, inducing the retailer to lower prices (Chintagunta 2002, Hall et al. 1997). However, empirical evidence on the link between retail prices and store traffic/store switching is mixed. Chintagunta (2002) concludes retail prices have a weak impact on store traffic for the five brands under consideration in his study. Likewise, research by Walters and colleagues (e.g., Walters and MacKenzie 1988) indicates that the link is weak at best.

Pricing History

Empirical studies on price rigidity show that a large proportion of the variation in prices, often in excess of 90%, is driven by pricing history (Dutta et al. 2002). For example, past pricing actions—such as temporary price reductions—can boost sales, inducing

the retailer to promote in subsequent periods even when it lowers retailer profits (Einhorn and Hogarth 1986, Srinivasan et al. 2004). Additional reasons for the dependency on pricing history include satisficing behavior due to limited information processing capacity (March and Simon 1958), formal budgeting rules that promote the status quo (Hulbert 1981), loss aversion (Tversky and Kahneman 1991), and decision anchoring (Plous 1993).

Recent experiments by Krishna et al. (2001) demonstrate that decision anchoring applies to retail pricing in the form of “a powerful tendency to rely on past prices in determining future prices” (Krishna et al. 2001, p. 1). When given a price history, the experiments’ subjects set future prices too low, mostly because they give more weight to extreme observations (i.e., price deals) than to regular prices. This phenomenon reflects a perceptual averaging of past prices (Alba et al. 1999). Moreover, after a price promotion, retail prices take a longer time to revert back to their mean than do sales (Srinivasan et al. 2004). Finally, Kopalle et al. (1999), Dekimpe and Hanssens (1999), and Van Heerde et al. (2000) report that price promotions often lead to subsequent price promotions.

Given the convergent evidence from theory, experiments, and empirical analyses, we expect that retail prices for a focal brand will depend strongly on its past retail prices.

Brand Demand

Both marketing theory and practice suggest that a brand’s level of demand is an important input into its pricing decisions. Indeed, a UK survey (Hall et al. 1997) reveals that retailers rate demand considerations as the most important price driver, ahead of wholesale prices and interretailer competition. In particular, low demand is often a motivation for remedial action, and (temporary) price reductions offer a quick fix to boost sales and meet performance quotas (Neslin 2002). Retailers understand the important relationship between price and demand and use that knowledge when setting retail prices (i.e., a brand’s demand history affects its current and future prices).

Wholesale Prices

Both retailer surveys (Hall et al. 1997) and experimental studies (Krishna et al. 2001) confirm that costs are an important consideration for managers in setting retail prices. Almost half the marketing budget of consumer packaged goods manufacturers is allocated to trade deals (Cox Direct 1998). The extensive use of trade deals leads to frequent changes in wholesale prices and is an important determinant of retailer profitability (*Economist* 1992). Retail prices are not only affected by current but also by past wholesale prices, as retailers forward buy and anticipate trade deal patterns (Hall et al. 2002).

Table 1 Overview of Analysis Steps

Methodology	Econometrics literature	Marketing literature	Research questions
1(a). Unit root tests Augmented Dickey-Fuller	Enders (2004)	Srinivasan et al. (2000) Pauwels et al. (2002)	Are performance and marketing variables (mean/trend) stationary or evolving (unit root)?
Structural break test	Perron (1989) Perron (1990) Zivot and Andrews (1992)	Deleersnyder et al. (2002)	Is there a structural break in the time-series of the performance and price variables?
1(b). VARX model Vector autoregressive model with exogenous variables (VARX)	Lütkepohl (1993)	Dekimpe and Hanssens (1995) Nijs et al. (2001) Srinivasan et al. (2004)	How do performance and price variables interact, accounting for exogenous factors?
2. Variance decomposition Forecast error variance decomposition	Enders (2004)	Hanssens (1998) Pauwels et al. (2004)	What are the drivers of retail price...?
Generalized forecast error variance decomposition (GFEVD)	Pesaran and Shin (1998)	This paper	... Without imposing a causal ordering on the variables?
3. Regression Regression analysis linking the results of Steps 2 and 3	Greene (1997) Murphy and Topel (1985) Bradley and Tibshirani (1993)	Nijs et al. (2001) Srinivasan et al. (2004)	Is the influence of the price drivers on retailer pricing associated with retailer profits?

Category Management

The move towards category management (*Progressive Grocer* 2001) implies that retailers increasingly consider the demand, costs, and prices of competing brands in a joint decision-making process when setting prices for a focal brand (Zenor 1994). Retailers set prices for different brands to maximize total category profits (see, e.g., Raju et al. 1995), and prefer to promote only one brand at a time in a given category (Leeftang and Wittink 1992, Tellis and Zufryden 1995). Manufacturers' wholesale prices will affect the selection of the brand (Hall et al. 2002) and may in turn influence the retail prices of all brands in a specific category (Besanko et al. 2005).

3. Methodology

Our empirical analysis proceeds in three steps. First, we estimate the dynamic interactions between retail prices and their drivers using vector-autoregressive models with exogenous variables (VARX). Second, GFEVD is used to quantify the relative influence of these drivers on retailer pricing. Finally, the influence of these price drivers on retailer pricing tactics, identified in Step 2, is linked to retailer profitability. Table 1 provides references for further details.

Step 1. Vector-Autoregressive Model Specification. VARX models are well suited to measure retail-pricing dynamics.¹ First, the endogenous treatment

of marketing actions implies that they are explained by both past marketing actions and past performance variables. Second, VARX models are able to capture complex feedback loops that may impact retail prices over time. For instance, a price promotion in a given week may generate a high demand response, inducing the retailer to offer additional price promotions in subsequent weeks. Competing retailers may respond with price promotions to maintain store traffic. By capturing such feedback loops, VARX estimation yields a comprehensive picture of observable retail-price drivers (Pauwels 2004).

In our empirical analysis, we use two different data sources: The first contains store-level data from the Denver area and the second contains store-level data from the Dominick's retail chain in the Chicago area. The Denver database provides information on competitive retail prices but not wholesale prices, while the Dominick's database contains information on wholesale prices and store traffic but not competitive retailer prices (see §4 for further details).

For the Denver database, we estimate a seven-equation VARX model per product category per store, where the endogenous variables are the sales volume for the top two brands (S_i , $i = 1, 2$), an other-brands composite (S_3), and the retail prices and competitive retail prices for the two major brands (RP_i and CP_i , $i = 1, 2$). In addition to the intercept (α), we add five sets of exogenous control variables: (i) a deterministic-trend t to capture the impact of omitted, gradually changing variables, (ii) a set of dummy variables (HD) that equal one in the shopping periods around major holidays (Chevalier et al. 2003), (iii) four-weekly dummy variables (SD) to account

¹ Our analysis focuses on cases where prices are either mean- or trend-stationary. Previous authors have shown that 96% of price series for the Dominick's data are stationary (e.g., Srinivasan et al. 2004). While the rare instances where there is evolution in prices may be interesting to analyze from a marketing standpoint, estimating (G)FEVD is infeasible since the variance for evolving variables is (theoretically) infinite.

for seasonal fluctuations in sales or prices, (iv) a step dummy variable for the impact of new-product introductions (NP), and (v) feature (F) and display (D) variables for each brand (see Pauwels et al. 2002, and Srinivasan et al. 2004 for a similar specification). To avoid overparameterization, we include feature and display as exogenous variables (Pesaran and Smith 1998). Recent research has shown little is gained by allowing for more intricate feature and display dynamics (Nijs et al. 2001, Van Heerde et al. 2000). The VARX is described in Equation (1):

$$\begin{bmatrix} S_{1,t} \\ S_{2,t} \\ S_{3,t} \\ RP_{1,t} \\ RP_{2,t} \\ CP_{1,t} \\ CP_{2,t} \end{bmatrix} = \begin{bmatrix} \alpha_{S_1} + \delta_{S_1}t + \sum_{h=1}^H \theta_{S_1}^h HD_{ht} + \sum_{s=2}^S \lambda_{S_1}^s SD_{st} + \eta_{S_1} NP \\ \alpha_{S_2} + \delta_{S_2}t + \sum_{h=1}^H \theta_{S_2}^h HD_{ht} + \sum_{s=2}^S \lambda_{S_2}^s SD_{st} + \eta_{S_2} NP \\ \alpha_{S_3} + \delta_{S_3}t + \sum_{h=1}^H \theta_{S_3}^h HD_{ht} + \sum_{s=2}^S \lambda_{S_3}^s SD_{st} + \eta_{S_3} NP \\ \alpha_{RP_1} + \delta_{RP_1}t + \sum_{h=1}^H \theta_{RP_1}^h HD_{ht} + \sum_{s=2}^S \lambda_{RP_1}^s SD_{st} + \eta_{RP_1} NP \\ \alpha_{RP_2} + \delta_{RP_2}t + \sum_{h=1}^H \theta_{RP_2}^h HD_{ht} + \sum_{s=2}^S \lambda_{RP_2}^s SD_{st} + \eta_{RP_2} NP \\ \alpha_{CP_1} + \delta_{CP_1}t + \sum_{h=1}^H \theta_{CP_1}^h HD_{ht} + \sum_{s=2}^S \lambda_{CP_1}^s SD_{st} + \eta_{CP_1} NP \\ \alpha_{CP_2} + \delta_{CP_2}t + \sum_{h=1}^H \theta_{CP_2}^h HD_{ht} + \sum_{s=2}^S \lambda_{CP_2}^s SD_{st} + \eta_{CP_2} NP \end{bmatrix} + \sum_{k=1}^K \begin{bmatrix} \beta_{1,1}^k & \cdots & \beta_{1,7}^k \\ \beta_{2,1}^k & \cdots & \beta_{2,7}^k \\ \beta_{3,1}^k & \cdots & \beta_{3,7}^k \\ \beta_{4,1}^k & \cdots & \beta_{4,7}^k \\ \beta_{5,1}^k & \cdots & \beta_{5,7}^k \\ \beta_{6,1}^k & \cdots & \beta_{6,7}^k \\ \beta_{7,1}^k & \cdots & \beta_{7,7}^k \end{bmatrix} \begin{bmatrix} S_{1,t-k} \\ S_{2,t-k} \\ S_{3,t-k} \\ RP_{1,t-k} \\ RP_{2,t-k} \\ CP_{1,t-k} \\ CP_{2,t-k} \end{bmatrix} + \sum_{l=0}^1 \begin{bmatrix} \gamma_{1,1}^l & \cdots & \gamma_{1,4}^l \\ \gamma_{2,1}^l & \cdots & \gamma_{2,4}^l \\ \gamma_{3,1}^l & \cdots & \gamma_{3,4}^l \\ \gamma_{4,1}^l & \cdots & \gamma_{4,4}^l \\ \gamma_{5,1}^l & \cdots & \gamma_{5,4}^l \\ \gamma_{6,1}^l & \cdots & \gamma_{6,4}^l \\ \gamma_{7,1}^l & \cdots & \gamma_{7,4}^l \end{bmatrix} \begin{bmatrix} F_{1,t-l} \\ F_{2,t-l} \\ D_{1,t-l} \\ D_{2,t-l} \end{bmatrix} + \begin{bmatrix} \varepsilon_{S_{1,t}} \\ \varepsilon_{S_{2,t}} \\ \varepsilon_{S_{3,t}} \\ \varepsilon_{RP_{1,t}} \\ \varepsilon_{RP_{2,t}} \\ \varepsilon_{CP_{1,t}} \\ \varepsilon_{CP_{2,t}} \end{bmatrix}, \quad (1)$$

where Σ is the covariance matrix of the residuals $[\varepsilon_{S_{1,t}}, \varepsilon_{S_{2,t}}, \varepsilon_{S_{3,t}}, \varepsilon_{RP_{1,t}}, \varepsilon_{RP_{2,t}}, \varepsilon_{CP_{1,t}}, \varepsilon_{CP_{2,t}}]'$. We use a stepwise procedure to determine the appropriate lag-length K

and to eliminate redundant parameters (details are provided in Appendix A.1).²

For the Dominick's database we estimate an eleven-equation VARX model per category per store, with sales volume of the top three brands (S_i , $i = 1, 2, 3$), an other-brands composite (S_4), wholesale and retail prices of the top three brands (WP_i and RP_i , $i = 1, 2, 3$), and store traffic (ST), a proxy for interretailer competition (Chintagunta 2002).³ The exogenous variables are the same as those in Equation (1).⁴

Our use of VARX models warrants further discussion in light of recent attention to the implications of the Lucas critique for marketing research (e.g., Bronnenberg et al. 2005, Franses 2005, Van Heerde et al. 2005). In contrast to structural models, our reduced-form models do not allow us to interpret individual coefficients or draw normative implications. Instead, a reduced-form VARX model is appropriate for "innovation accounting" (Enders 2004, p. 280), i.e., providing descriptive insights on the patterns observed in the data using variance decomposition and/or impulse response analysis. The purpose of this paper is to assess which factors drive retail prices over time. Hence, we do not impose structural restrictions on the dynamic relations between variables (see Sims 1980, Sudhir 2001). Rather, we focus on developing a rich and flexible empirical model of retail pricing (see also Besanko et al. 2005 for a recent discussion of the merits of reduced-form models). An important assumption of our approach is that innovations or "shocks" do not alter the nature of the underlying data-generating process (Darnell and Evans 1990, p. 121). Since we are interested in tactical "day-to-day" pricing rather than strategic regime changes, the use of a reduced-form VARX model is appropriate (Van Heerde et al. 2005). Moreover, the proposed

² An alternative method to resolve parameterization concerns is to pool across stores. In our study this would, however, reduce the number of estimates available for studying the link between the influence of the drivers on pricing and retailer performance, introducing a potential "degrees of freedom problem" in Step 3 of our analysis. We aim to achieve a balance between accuracy and statistical adequacy through the adopted VARX specification.

³ It is possible that the retailer sets prices interdependently across categories. An empirical analysis of correlations among price residuals across categories indicates, however, that such dependencies are small to negligible. To the extent that they do exist, these effects can be captured by the store traffic variable (Chintagunta 2002). As such, we leave the issue of cross-category price and demand dependencies for future research.

⁴ Feature and display indicators are called "price specials" and "bonus buys" in the Dominick's data description (<http://gsbwww.uchicago.edu/research/mkt/Databases/DFF/W.html>). Following Chintagunta et al. (2003), we refer to these marketing activities using the more common labels "feature" and "display." We operationalize the variables as the percentage of SKUs of the brands that are promoted in a given week.

VARX model explicitly accounts for endogeneity, an important threat to consistency (Franses 2005, p. 12).

Step 2. Price Drivers: Generalized Forecast Error Variance Decomposition. We use GFEVD (Pesaran and Shin 1998) to quantify the dynamic influence of competitive retail prices, brand demand, wholesale price and competitive wholesale price, and category-management considerations on a brand's retail price. In essence, GFEVD provides a measure of the relative impact over time of shocks initiated by each of the individual endogenous variables in a VARX model (see Hanssens 1998 for a marketing application of FEVD).⁵ Analogous to a "dynamic R^2 ," it calculates the percentage of variation in retailer pricing for a brand that can be attributed to both contemporaneous and past changes in each of the endogenous variables in Equation (1) (including retailer pricing for the brand itself, i.e., pricing history). An important issue in standard FEVD is the need to impose a causal ordering for model identification purposes. In practical applications of FEVD, available theory is often insufficient to justify the selection of one ordering over another. Indeed, since we seek to identify and quantify drivers of retail prices, any imposed ordering appears troublesome. Therefore, we minimize the impact of variable ordering by estimating GFEVD (Pesaran and Shin 1998) using Equation (2):

$$\theta_{ij}^g(t) = \frac{\sum_{l=0}^t \psi_{ij}^g(l)^2}{\sum_{l=0}^t \sum_{j=1}^m \psi_{ij}^g(l)^2}, \quad i, j = 1, \dots, m, \quad (2)$$

where $\psi_{ij}^g(l)$ is the value of a generalized impulse response function (GIRF) following a one standard-error shock to variable j on variable i at time l . In the GFEVD approach, an initial shock is allowed to—but need not depending on the size of the corresponding residual correlation—affect all other endogenous variables instantaneously. Generalized IRFs, which rely on an equivalent assumption, have recently been applied in a marketing setting by Dekimpe and Hanssens (1999), Nijs et al. (2001), Pauwels et al. (2002), Srinivasan et al. (2004), and Steenkamp et al. (2005). For details on the calculation of GIRFs, see for example Dekimpe and Hanssens (1999) and Nijs et al. (2001).⁶ Moreover, our GFEVD metric is an extension

of the one introduced by Pesaran and Shin (1998), since it will always sum to 100%.

The relative importance of the drivers is derived from the GFEVD values at 26 weeks, which reduces sensitivity to short-term fluctuations.⁷ To evaluate the accuracy of our GFEVD estimates, we obtain standard errors using Monte Carlo simulations (see Benkwitz et al. 2001, Horváth 2003 for an equivalent procedure to estimate the standard errors for IRFs).

Step 3. The Influence of Retail-Price Drivers and Retailer Profits. In the final step of our analysis, we investigate the link between the influence of the price drivers on retailer pricing tactics identified in Step 2 and retailer category margin. We are mainly interested in how the influence of these retail-price drivers on retailer pricing tactics is related to retailer margins; however, we do control for a series of covariates based on prior research (Bell et al. 1999, Blattberg et al. 1995, Narasimhan et al. 1996, Nijs et al. 2001, Srinivasan et al. 2004). Specifically, we estimate the following regression equation:

$$\begin{aligned} \text{MARGIN}_{jk} = & (\alpha_0 + \alpha_1 \text{ST}_{ijk}^I + \alpha_2 \text{PH}_{ijk}^I + \alpha_3 \text{BD}_{ijk}^I \\ & + \alpha_4 \text{WP}_{ijk}^I + \alpha_5 \text{CMP}_{ijk}^I + \alpha_6 \text{CMC}_{ijk}^I \\ & + \beta_1 \text{NB}_{ijk} + \beta_2 \text{PROM_FRQ}_{jk} \\ & + \beta_3 \text{PROM_DPT}_{jk} + \beta_4 \text{CAT_CONC}_{jk} \\ & + \beta_5 \text{NRBR}_{jk} + \beta_6 \text{STOCK}_k \\ & + \beta_7 \text{IMPULSE}_k) + \varepsilon_{jk}, \quad (3) \end{aligned}$$

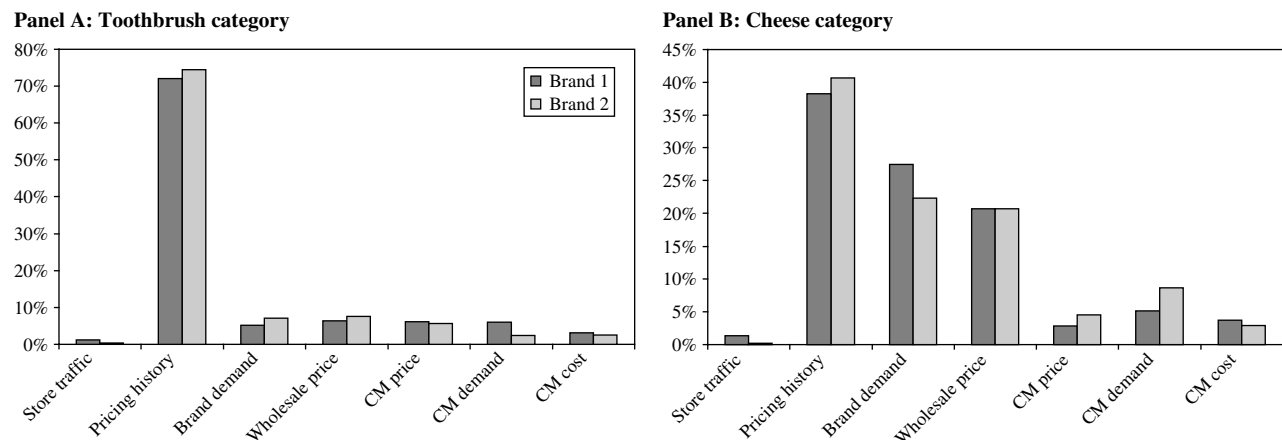
where MARGIN_{jk} is the margin in category k in store j and ε_{jk} is the error term. We denote the price-driver influence metrics for brand i by ST^I (store traffic), PH^I (pricing history), BD^I (brand demand), WP^I (wholesale price), CMP^I (category management—price), and CMC^I (category management—cost).⁸ The covariates are NB (national brand versus private label), PROM_FRQ (price-promotional frequency), PROM_DPT (price-promotional depth), CAT_CONC (category concentration), NRBR (number of brands in the category), STOCK (ability to stockpile), and IMPULSE (Is the product an impulse good?). In addition, we allow for store-fixed effects. Measurement details are provided in Appendix B.

⁵ The proposed VARX model does not assume that if week k contains a shock, week $k + 1$ does not. If, for example, a price promotion in the data always lasts three weeks, this is accounted for in the model. These subsequent shocks are not considered as separate shocks to the system but as an initial shock and its subsequent effects.

⁶ The use of impulse response functions to calculate the forecast error variance decomposition is equivalent to using forecast errors. See Lütkepohl (1993, §2.3.3) and Pesaran and Shin (1998) for a similar approach. A comparison of the GFEVD metric proposed by Pesaran and Shin (1998) and the metric calculated using Equation (2) above can be found at <http://mktsci.pubs.informs.org>.

⁷ Previous studies have shown that a period of 26 weeks (two quarters) is sufficient for stationary series in consumer-packaged goods to capture dynamic effects (Pauwels and Srinivasan 2004, Srinivasan et al. 2004).

⁸ Because our estimates of the price drivers sum to one, we must exclude one of them from Equation (3) to avoid perfect multicollinearity. Since category management considerations are measured by three metrics, we exclude one metric, namely, category demand.

Figure 1 Retail-Price Drivers for Two Leading Brands in Two Categories—Dominick's Data

Note. From GFEVD, we obtain the estimates in Figure 1 and Tables 2, 3, and 4 as follows:

For the Denver data, price drivers are measured as follows:

- *Competitive retail activity* is measured as the sum of the following two drivers:
 - *Competitive retail price same brand* (CRPS) is the percentage of variability in retail prices accounted for by the prices of the same brand charged by competing retailers.⁹
 - *Competitive retail price competing brand* (CRPC) is the percentage of variability in retail prices accounted for by the price of the competing brand charged by competing retailers.
- *Pricing history* (PH) is the percentage of variability in retail prices accounted for by past prices.
- *Brand demand* (BD) is the percentage of variability in retail prices accounted for by a brand's sales volume.
- *Category management* is measured as the sum of the following two drivers:
 - *Category management price* (CMP) is the percentage of variability in retail prices accounted for by the price of the competing brand in the category.
 - *Category management demand* (CMD) is the percentage of variability in retail prices accounted for by the sales volume of the competing brand in the category.

For the Dominick's data, price drivers are measured as follows:

- *Competitive retail activity*:
 - *Store traffic* (ST) is the percentage of variability in retail prices accounted for by store traffic.
- *Pricing history* (PH) is the percentage of variability in retail prices accounted for by past prices.
- *Brand demand* (BD) is the percentage of variability in retail prices accounted for by a brand's sales volume.
- *Wholesale price* (WP) is the percentage of variability in retail prices accounted for by the wholesale price of the brand.
- *Category management*, in Table 2, is measured as the sum of the following three drivers:
 - *Category management price* (CMP) is the percentage of variability in retail prices accounted for by the price of the two competing brands in the category.
 - *Category management demand* (CMD) is the percentage of variability in retail prices accounted for by the demand for the two competing brands in the category.
 - *Category management cost* (CMC) is the percentage of variability in retail prices accounted for by the cost of the two competing brands in the category (i.e., the sum of variance explained by the cost of each competing brand).

Estimation of Equation (3) by OLS (θ^{OLS}) will provide consistent parameter estimates (see Murphy and Topel 1985). However, the standard errors of these parameters may be biased since the price drivers are estimated with error. We use the bootstrap method outlined in Appendix A.2 to obtain corrected standard errors.

In addition to the substantive differences to Srinivasan et al. (2004) outlined in the introduction, our paper offers important contributions in terms of methodology and richness of data. First, we analyze an additional data set to Srinivasan et al. (2004): The Denver data, for which competing retailer prices are available. Second, while they study 25 categories within a single retail chain, our study is based on an analysis of 10,850 brand-store combinations in multiple chains in two retail markets. As such, the extensive data allow us to draw meaningful empir-

ical generalizations. Third, while they use impulse response functions, we apply *generalized forecast error variance decomposition* (GFEVD) for the first time in marketing. Our estimates are obtained from a rich VARX model to which we apply an innovative specification algorithm that ensures well-behaved residuals and model parsimony. This allows us to accurately quantify the influence on a brand's retail price of its own past price, competitive retail prices, brand demand, wholesale price and competitive wholesale price, and category-management considerations. Finally, we develop a bootstrap algorithm to correct the standard error bias introduced when using OLS to estimate Equation (3).

To review and illustrate our approach, Panel A in Figure 1 shows output of the GFEVD for two brands in a Dominick's store in the toothbrush category. Panel B in Figure 1 shows the GFEVD for two

brands in the cheese category in the same Dominick's store.

Past price dependence is the dominant driver for the two brands in the toothbrush category, explaining respectively (72%, 74%) of the variation in prices. Brand demand accounts for only (5%, 7%) of the variation. The influence of the other price drivers—category-management considerations (demand, price, and costs of competing brands), wholesale prices, and store traffic—is (23%, 19%) respectively. In sharp contrast to the toothbrush category, past price dependence explains (39%, 41%) of the variation in retail prices for the two brands in the cheese category. Brand demand accounts for (27%, 22%) and wholesale prices account for (21%, 21%) of the variation; category-management considerations and store traffic account for the remainder of the variation in retail prices (13%, 16%).

The average weekly retailer gross margin in a category is \$510 per store. For the toothbrush category (Panel A, Figure 1), the weekly retail profit is no more than \$39, i.e., 92% below the \$510 average cross-category profit. In contrast, the weekly retail profit is \$2,018 for the cheese category (Panel B, Figure 1), i.e., a striking 295% above average. In the former case, a higher emphasis on pricing history in setting retail prices is associated with lower retailer margins. In contrast, in the latter case, a higher emphasis on brand demand in setting retail prices is associated with higher retailer margins. Evidently, besides price drivers, these categories may also show differences in the characteristics included as covariates in Equation (3). The relevant question then becomes whether these examples are representative of a more general pattern. We investigate this issue in §§5 and 6.

4. Data Description

We use data from two sources: store-level scanner data from multiple retail chains in the Denver market and from the Dominick's retail chain in Chicago. We describe the databases below.

4.1. Denver Data

Data from the Denver market, provided by ACNielsen, consists of weekly store-level data for the

Table 2 Drivers of Retail Prices Based on GFEVD—Summary Across Categories

Retail-price drivers	Denver data Median ($n = 3,460$) (%)	Dominick's data Median ($n = 5,190$) (%)
Competitive retail activity		
Competitive retail price	5.5	
Store traffic		0.7
Pricing history	62.3	49.6
Brand demand	15.9	11.4
Wholesale price		26.4
Category management	9.6	7.9

period January 1993 through May 1995 (123 weeks).¹⁰ For each of 55 supermarkets, the data contain the weekly sales, prices, newspaper feature ads, and in-aisle display activity for each of the products carried in 43 categories. We focus on the top two brands in each category in each store: a total of 4,730 brand-store combinations. This data set offers the opportunity to evaluate the impact of competitive retailer activity on pricing; however, it does not have information on wholesale prices charged by manufacturers.

4.2. Dominick's Data

The second database contains scanner records for 24 product categories in 85 Dominick's stores, one of the two largest retail chains in the Chicago area. Data are available from September 1989 to May 1997, a total of 399 weeks. Variables include sales, retail and wholesale prices, feature and display, and store traffic. We focus on the top three brands in each category in each store, a total of 6,120 brand-store combinations. This data set allows us to investigate the link between the influence of the price drivers and retailer category margin; however, it does not contain information on prices in competing retail stores.

5. Results: Retail-Price Drivers

Based on our GFEVD analysis we derive empirical generalizations on the drivers of retail prices (summarized in Table 2). Detailed findings per category are reported for the Denver data in Table 3 and for the Dominick's data in Table 4.

⁹For private label brands, CRPS is the price of the private label product in the same category in competing retail stores. We argue that this is the relevant comparison because private labels are likely to be in similar price tiers, and are used to compete with other retailers. For instance, in the ongoing Dutch retailing price war, several of the price-cutting rounds involved the private label of the initiating retailer, to which the competing retailers responded by cutting prices on their own private labels (Van Aalst et al. 2005).

¹⁰Recent economic research (Ball and Mankiw 1994, Wynne 1995) argues that weekly store-level price data of small representative staple retail items are the most appropriate for studying the drivers of retail prices, since the retailer actually sets final goods prices, typically on a weekly level. Moreover, previous research finds that supermarket chains similar to Dominick's change prices of as many as 15% of the products they carry every week, in spite of the fact that their cost of changing prices compromises over 35% of their net margin (Levy et al. 1997).

Competitive Retail Activity

For the Denver data, competitive retailer prices account for 5.5% (3.1% + 2.4%) of the fluctuations in retail prices across the 43 categories. This finding is consistent with previous research which suggests that, even though retailers track each others' prices, interretailer competition accounts for only a small proportion of the variation in retail prices (e.g., Urbany et al. 2000, Chintagunta 2002). Indeed, Rao et al. (1995) demonstrate that retail-price promotions are essentially independent across competitors. Their theoretical explanation is that retail-price promotions are competitive mixed strategies. Since each firm is uncertain about its competitors' strategies, its promotion (re)actions must be independent of its competitors' actions. Hence, competitive retailer promotions should also be independent, a claim validated by our empirical results. For the Dominick's data, we use store traffic as a proxy for interretailer competition. We find that lower store traffic triggers only a minimal dynamic price response in subsequent weeks. This result is generalized across all categories and consistent with previous reports of weak links between price promotions and store traffic (see, for example, Walters and Rinne 1986, Walters and Mackenzie 1988). Our findings are also in line with those of Shankar and Bolton (2004) who study strategic pricing issues (a comparison of findings is available at <http://mktsci.pubs.informs.org>).

Pricing History

A brand's past prices are the dominant driver of retail prices in each category studied, accounting for 62.3% of the dynamic variation in retail prices for the Denver data and 49.6% for the Dominick's data. This confirms the "powerful tendency to rely on past prices in determining future prices" (Krishna et al. 2001). We investigate the performance implications of this behavior in §6.

Brand Demand

Brand demand accounts for approximately 15.9% of the variation in retail prices for the Denver data and 11.4% of the variation in retail prices for the Dominick's data. These results indicate that retailers acknowledge the essential relationship between prices and sales and incorporate demand considerations into retail pricing decisions (Hall et al. 1997).¹¹

¹¹ As mentioned in §2, retailers may form expectations on trade deal patterns. Such expectations are captured in the VARX model estimates since expectations are formed based on past realizations of the data-generating process. Future research could attempt to explicitly capture such expectations, perhaps by incorporating leads of wholesale prices, as in Van Heerde et al. (2000).

Wholesale Price

Wholesale prices are an important driver of retail prices across categories and account for 26.4% of the variance in retail price in the Dominick's data set, second only to pricing history. Retailers clearly take wholesale prices into consideration when setting retail prices. Information on wholesale prices is not available for the Denver data.

Category Management

Category-management considerations account for 9.6% (3.0% + 6.6%) of the variation in retail prices in the Denver data, and for 7.9% (2.5% + 2.8% + 2.6%) of the variation in retail prices for the Dominick's data.¹² Consistent with reported practice (Hall et al. 2002), category-management considerations are less important in driving retail prices compared to pricing history and brand demand.

A notable exception to this empirical generalization is the highly competitive soft drink category, where competing brands' demand, costs, and prices account for over 26.1% of variation in prices (Dominick's). Prior evidence of alternating retail-price promotions by major competitors Coca-Cola and Pepsi (see, e.g., Lal 1990) offers a plausible explanation for this result. Furthermore, for Coca-Cola and Pepsi in the Dominick's stores, the brand's price accounts for approximately 47% of the variation while competitive price accounts for 17%, close to a 3:1 ratio for the two components (see Krishna 1994).

In sum, across 10,850 brand-store combinations in 67 categories in two different retail areas, we find the following order of importance among retail-price drivers for the Denver and Dominick's data sets: pricing history (62.3%, 49.6%), wholesale price (26.4%, Dominick's only), brand demand (15.9%, 11.4%), category management (9.6%, 7.9%), and retail competition (5.5% Denver data only)/store traffic (0.7% Dominick's data only). Our results from Step 2 show considerable variability in the relative importance of price drivers across categories, which we explore next.

6. Results: The Influence of Retail-Price Drivers and Retailer Profits

In the third and final step of our empirical analysis, we examine the link between retailer gross category margin and the influence of each driver on retail

¹² Since the Denver data lack wholesale price information, results may be overstated due to the fact that wholesale price changes could cause correlation between a brand's price and the prices/demand of other brands in the category. This correlation can arise because retailers—attempting to entice category consumers to buy a certain brand—may adjust brand prices in response to a reduction in wholesale prices of competing brands in the product category (Besanko et al. 2005).

Table 3 Drivers of Retail Prices Based on GFEVD—Denver Data

	CRP same (CRPS) (%)			CRP comp. (CRPC) (%)			Pricing history (PH) (%)			Brand demand (BD) (%)			CM price (CMP) (%)			CM demand (CMD) (%)		
	25th	Median	75th	25th	Median	75th	25th	Median	75th	25th	Median	75th	25th	Median	75th	25th	Median	75th
Apple juice	0.9	1.8	4.7	0.9	2.0	3.6	61.8	69.1	76.8	12.1	17.5	21.0	1.1	2.3	5.0	2.7	4.4	7.9
Artificial sweeteners	0.9	2.2	4.2	1.2	2.1	4.7	61.0	74.1	82.7	4.1	5.6	16.1	1.2	2.7	6.6	3.6	5.0	8.8
Beer	3.4	9.0	17.2	1.9	4.3	7.5	30.8	52.3	67.5	6.9	11.8	15.7	1.5	4.8	22.3	4.4	9.3	15.1
Cake mix	2.0	3.6	11.0	0.7	1.5	2.6	52.6	61.3	68.8	11.8	16.7	23.8	1.0	1.7	4.0	6.1	8.2	11.4
Cereal	1.4	2.8	5.2	1.2	2.3	4.5	49.0	57.6	64.3	18.6	23.8	29.8	1.2	3.0	6.9	2.5	6.0	11.1
Cigarettes	6.3	10.3	26.6	2.6	4.9	9.1	38.8	45.5	60.8	5.1	9.4	12.1	3.3	8.6	10.9	4.7	6.0	9.9
Coffee (ground)	7.8	24.8	31.9	7.9	16.8	27.7	20.0	30.3	40.4	5.0	8.2	12.1	2.6	5.9	15.3	3.2	5.4	8.2
Coffee (soluble)	8.3	16.9	45.4	15.0	19.9	24.1	24.4	28.1	40.8	3.8	5.2	6.7	3.7	5.5	9.3	2.5	5.0	9.6
Conditioners	1.8	4.6	8.2	0.8	3.3	6.2	49.4	58.3	72.5	9.3	16.6	25.8	1.2	2.6	5.6	3.6	6.4	12.3
Cookies	1.1	3.0	4.6	0.8	1.8	4.7	59.5	63.4	73.5	11.2	19.4	26.8	1.2	2.4	4.3	3.0	4.3	7.7
Detergent (liquid, heavy duty)	2.5	5.2	11.6	1.9	3.7	5.1	59.5	66.9	75.2	2.2	4.7	7.5	2.4	4.8	9.3	3.4	6.2	11.7
Detergent (liquid, light duty)	1.2	2.4	3.9	0.8	2.4	5.9	58.8	62.7	68.5	18.9	23.2	27.9	0.5	1.4	3.7	2.7	4.6	7.7
Detergent (powder)	0.9	2.4	4.9	1.6	2.7	6.1	54.5	62.8	72.1	12.7	17.2	27.1	1.0	2.3	5.4	3.2	5.7	9.0
Diapers	2.6	4.4	11.3	1.7	3.6	6.7	51.0	60.7	69.2	7.1	10.2	14.3	1.8	3.7	7.7	7.0	10.0	13.3
Dishwasher detergent	0.7	2.3	5.9	1.3	2.5	5.2	61.7	70.2	78.4	6.5	11.5	19.5	1.0	1.8	3.7	3.5	5.8	9.6
Fabric softener (dry)	0.6	2.1	4.4	0.8	2.3	5.2	59.9	65.9	74.6	9.8	14.4	20.5	1.4	2.9	5.0	2.7	5.4	10.1
Fabric softener (liquid)	1.1	2.0	4.6	1.0	2.2	3.9	67.8	76.3	82.9	6.0	10.4	13.6	0.7	1.8	4.4	3.4	5.0	8.3
Flavored snacks	1.6	6.2	12.3	1.3	3.3	7.4	51.0	63.3	71.4	6.8	11.1	15.8	0.8	1.7	5.2	3.0	7.6	11.0
Frosting	3.0	7.1	11.8	1.4	3.4	5.3	52.9	60.0	70.6	6.0	10.5	15.0	1.8	4.5	7.2	5.8	9.3	13.8
Grape juice	1.3	3.7	6.9	0.5	0.9	2.6	74.9	80.0	86.9	4.8	7.0	8.1	0.5	1.4	2.8	2.8	4.7	7.2
Jams	0.6	1.9	5.3	1.1	2.8	5.0	55.3	59.5	67.0	13.7	21.5	24.7	1.7	3.7	6.5	3.2	7.0	10.6
Jelly	1.2	2.5	4.6	1.0	1.9	4.2	54.3	61.3	68.5	14.4	19.2	24.1	2.2	4.1	6.7	4.1	6.7	10.4
Light beer	6.4	7.5	13.2	4.8	6.7	8.6	40.8	48.4	53.2	7.3	11.4	18.8	7.1	10.1	13.7	7.4	10.8	15.5
Macaroni	0.5	1.3	2.6	0.8	1.3	2.9	51.7	63.3	69.5	15.1	21.1	27.7	1.2	2.9	5.2	4.3	8.3	11.5
Margarine	0.8	2.2	4.5	0.7	1.8	3.2	48.2	54.0	60.0	19.9	24.8	27.6	2.5	4.9	10.0	4.8	7.9	12.6
Orange juice (canned)	1.1	2.2	5.7	2.1	3.8	8.3	66.1	69.9	76.1	3.7	7.6	15.6	1.8	4.8	8.3	4.6	6.5	10.4
Orange juice (frozen)	1.4	2.3	4.2	0.4	1.2	2.9	54.5	63.1	72.4	12.3	18.7	25.2	1.6	4.2	7.3	3.1	5.2	9.9
Orange juice (other)	1.1	2.1	4.4	0.9	1.7	3.8	54.0	60.9	67.7	15.4	21.9	27.6	1.2	2.1	4.2	4.2	6.7	9.1
Peanut butter	1.7	4.3	8.0	1.4	2.8	5.3	56.3	66.4	74.8	8.0	12.7	17.2	1.3	2.4	5.1	3.5	5.4	9.1
Shampoo	2.1	3.8	6.2	1.0	2.9	6.2	48.5	62.3	71.9	8.1	13.4	22.8	1.3	3.1	5.8	5.0	7.7	13.8
Soda	2.1	4.1	9.2	1.0	2.7	4.7	51.2	60.6	71.9	7.4	15.0	19.4	1.1	3.0	5.7	5.0	10.0	15.1
Soft drinks (diet)	2.3	4.9	8.4	2.9	5.6	10.6	45.5	56.5	67.2	6.9	10.8	15.4	4.6	6.9	9.8	5.8	9.8	16.0
Soft drinks (regular)	2.5	4.8	10.5	1.5	3.5	6.3	47.0	57.0	73.7	7.5	11.4	17.2	2.1	3.2	7.4	7.5	11.3	18.7
Soup (canned)	2.7	3.7	5.4	0.9	1.9	4.1	54.0	58.7	62.5	23.1	26.6	30.1	0.7	1.6	3.0	2.5	4.8	7.4
Soup mix	1.4	2.4	4.8	0.7	2.0	2.4	64.9	69.1	82.8	8.3	14.1	18.8	1.5	1.8	5.0	3.3	4.8	6.9
Spaghetti	0.6	1.1	2.5	1.1	2.0	4.0	52.0	56.8	63.0	16.5	23.6	28.1	1.0	3.0	5.7	5.5	11.2	15.2
Spaghetti (mix)	0.3	2.0	6.5	0.5	1.2	5.2	61.3	77.4	84.6	1.3	3.7	7.7	0.7	1.8	4.4	2.7	5.3	9.1
Spaghetti (sauce)	1.2	2.6	5.7	1.0	2.4	5.0	57.8	65.9	73.9	6.5	16.9	24.2	1.6	2.7	5.7	2.5	4.5	9.9
Sprayed butter	1.0	4.2	11.0	1.2	2.5	4.8	47.7	67.6	77.1	8.2	12.4	17.1	2.2	4.6	8.0	3.0	5.8	11.6
Syrup	1.7	4.2	7.2	1.2	4.0	7.6	49.6	58.5	69.6	10.7	18.2	22.4	1.1	3.0	5.4	4.5	7.5	11.2
Tea (liquid)	1.9	7.1	12.7	1.5	2.5	5.1	54.5	61.7	68.0	7.7	11.6	17.2	2.6	5.2	7.7	4.7	6.5	11.6
Tea bags	1.0	2.3	4.2	1.1	2.2	3.6	59.0	67.8	75.8	9.3	14.2	21.2	1.1	1.8	4.4	4.5	7.2	9.3
Tomato juice	1.2	2.4	4.1	1.5	1.9	3.4	53.7	58.4	60.6	15.1	24.2	26.5	2.2	3.0	5.2	6.8	10.9	14.2
Total	1.2	3.1	6.4	1.0	2.4	5.3	52.9	62.3	72.1	8.6	15.9	23.4	1.3	3.0	6.3	3.7	6.6	11.3

Notes. See footnote to Figure 1 for a description of the price drivers. We report the median estimates by category (two brands per category in 55 stores). Total observations: 3,460.

pricing (see Table 5). We conduct this step only for the Dominick's data set since retailer category margins are not available for the Denver data. We tested for endogeneity by conducting the Hausman-Wu test for each potentially endogenous variable in Equation (3) (Davidson and MacKinnon 1993, Gielens and Dekimpe 2001). None of the tests revealed a violation of the exogeneity assumption ($p > 0.05$).

Competitive Retailer Activity

Our findings indicate that when store traffic considerations feature more prominently in retailer pricing,

retailer margins are *lower*. This may occur if the added revenues from incremental demand are not large enough to compensate for the margin loss on subsidized sales (Drèze 1995). As expected, pricing a category as a loss leader can diminish category profits.

Pricing History

The rationale for past price dependence is a debated issue in the marketing and economics literature. Past price dependence may be caused by the inability of managers to deal with multiple objectives in the face of limited information (Nagle and Holden 1995)

Table 4 Drivers of Retail Prices Based on GFEVD—Dominick's Data

	Store traffic (ST) (%)			Pricing history (PH) (%)			Brand demand (BD) (%)			Wholesale price (WP) (%)			CM price (CMP) (%)			CM demand (CMD)			CM cost (CMC) (%)		
	25th	Median	75th	25th	Median	75th	25th	Median	75th	25th	Median	75th	25th	Median	75th	25th	Median	75th	25th	Median	75th
Analgesics	0.2	0.5	0.8	47.1	48.7	50.7	7.6	10.7	12.8	32.5	35.1	36.5	0.9	1.4	2.2	1.1	1.7	2.9	1.0	1.4	2.3
Beer	0.6	1.3	2.1	48.2	52.2	57.9	11.3	13.8	17.4	8.8	12.9	18.2	3.6	5.6	9.9	2.4	3.9	6.6	2.5	4.5	6.8
Bottled juice	0.4	0.8	2.1	45.7	51.4	57.5	7.7	16.2	19.9	17.0	20.0	22.9	1.3	2.0	3.8	2.1	4.1	6.2	1.6	2.8	7.0
Canned soup	0.3	0.6	1.1	43.3	49.5	53.2	10.0	16.9	20.8	16.9	27.7	31.6	1.7	3.1	5.1	1.4	2.1	3.4	1.6	2.6	3.8
Cereal	0.3	0.5	0.9	44.3	48.0	53.3	16.6	19.9	22.5	22.8	25.0	27.4	0.8	1.5	2.4	1.5	2.1	2.8	1.1	1.7	2.3
Cheese	0.3	0.6	1.5	40.6	45.2	49.9	11.0	17.0	20.3	24.2	26.3	30.1	2.0	3.6	4.6	2.1	3.4	4.6	1.6	2.9	4.1
Cookies	0.3	0.7	1.2	40.8	42.7	47.4	7.2	21.5	24.8	27.8	29.1	33.0	1.3	1.6	2.2	1.9	2.7	3.5	1.1	1.5	2.0
Crackers	0.7	1.1	2.4	40.3	45.8	55.0	8.1	13.5	16.9	22.2	28.6	30.7	2.2	3.0	3.9	2.7	3.6	5.0	2.3	3.5	5.0
Dish detergent	0.4	0.8	1.4	54.7	59.7	64.3	2.2	5.6	10.4	18.6	22.1	26.0	2.0	3.4	5.1	1.8	2.7	4.0	1.5	2.5	3.9
Fabric softeners	0.3	0.8	1.6	51.7	54.5	57.6	5.2	7.7	11.1	12.8	24.7	29.8	2.0	3.6	6.5	1.9	3.2	4.6	1.4	3.2	7.0
Front-end candy	0.4	0.8	1.6	43.1	51.7	56.9	2.4	5.6	9.7	18.7	24.9	37.4	1.9	3.8	6.9	2.0	3.6	7.3	1.7	2.9	5.4
Frozen juice	0.4	0.8	1.5	50.6	55.2	58.8	10.4	13.9	17.9	11.5	19.3	25.9	2.0	3.0	5.2	2.2	3.3	4.6	1.9	3.0	4.9
Laundry detergent	0.4	0.8	1.6	44.9	48.5	51.4	6.6	8.8	13.1	25.3	31.0	35.5	1.2	2.2	3.7	1.7	2.9	4.6	1.7	3.3	6.3
Oatmeal	0.3	0.7	1.4	40.9	45.8	48.8	6.5	9.6	18.7	27.6	31.4	35.8	1.1	2.1	3.8	2.2	3.7	6.7	1.2	1.9	3.7
Paper towels	0.3	0.7	1.7	38.4	41.6	52.3	11.4	15.7	19.6	12.8	30.3	33.8	1.5	2.1	3.9	2.3	3.7	5.1	2.0	3.1	5.2
Refrigerated juice	0.3	0.5	1.0	43.9	49.2	54.5	15.2	18.5	21.0	14.8	18.2	21.6	2.1	3.1	4.5	3.2	4.4	5.7	3.0	4.9	7.2
Shampoos	0.5	1.5	2.8	46.1	52.5	60.1	1.7	3.7	5.8	11.5	29.3	34.8	1.6	3.1	5.5	2.9	4.6	10.5	1.6	3.5	7.1
Snack crackers	0.4	0.8	1.2	46.5	51.5	59.3	9.2	11.8	14.7	20.6	27.8	34.5	0.9	1.4	2.5	1.3	2.1	3.0	1.1	1.9	3.6
Soap	0.2	0.5	1.1	44.2	48.9	52.0	2.3	4.2	9.8	29.0	34.3	38.6	1.2	2.1	4.8	1.4	2.5	3.9	1.4	2.6	5.6
Soft drinks	0.3	0.7	1.4	45.6	47.2	49.0	2.7	5.4	24.3	17.8	19.1	20.3	2.7	16.8	19.0	1.4	2.1	2.9	2.7	7.2	8.8
Toilet tissue	0.1	0.3	0.7	39.4	43.8	53.1	12.3	19.0	22.2	17.1	30.3	34.9	1.6	2.3	3.5	1.6	2.4	3.5	1.9	2.7	4.4
Toothbrushes	0.4	1.0	1.8	54.2	56.7	59.7	2.7	4.3	6.7	22.7	26.3	30.5	1.9	3.7	5.9	1.5	2.5	4.0	1.6	2.6	3.8
Toothpaste	0.3	0.8	1.5	49.9	52.7	59.0	2.5	9.1	13.6	13.8	25.2	29.1	1.2	2.7	5.4	2.2	3.0	4.8	1.6	2.8	5.7
Tuna	0.1	0.3	0.7	40.7	43.7	46.4	9.4	12.4	15.5	34.8	36.5	37.8	1.6	2.2	2.9	1.5	2.4	3.3	1.5	2.2	2.9
Total	0.3	0.7	1.4	44.4	49.6	55.7	6.1	11.4	17.3	19.1	26.4	32.4	1.4	2.5	4.4	1.8	2.8	4.3	1.5	2.6	4.8

Notes. See footnote to Figure 1 for a description of the price drivers. We report the median estimates by category (three brands per category in 85 stores). Total observations: 5,190.

and complicated demand dynamics (Kopalle et al. 1999), or may result from profit optimization behavior (Maskin and Tirole 1988). As the influence of past price dependence in retail pricing is associated with lower retailer margins, our results are consistent with the former view and confirm both anecdotal (*Business Week* 2000) and experimental evidence (Krishna et al. 2001) of limited managerial sophistication in pricing.

Brand Demand

Being customer-oriented requires a detailed understanding of the dynamic price-demand response of consumers (e.g., Hall et al. 1997). For instance, unsatisfactory performance may lead managers to take corrective marketing and pricing actions to improve results in subsequent periods. Such demand understanding should increase the profit impact for the retailer (Hall et al. 2002). Our results suggest that demand-based considerations in retail pricing are indeed associated with *higher* retailer profitability.

Wholesale Price

In contrast, the influence of wholesale prices in retailer price setting does not significantly impact retailer margins. This does not imply that retailers should ignore costs. However, it suggests that rigid adherence to a cost-plus pricing approach does not

hurt or benefit retail category margins. Since manufacturers may have different goals and payoffs from promotions (e.g., Villas-Boas and Lal 1998), it is not always in the best interest of the retailer to simply pass through manufacturer price changes (Besanko et al. 2005). Instead, pass-through rates should depend on retailer profit considerations, such as category management and the price sensitivity of consumer demand (Moorthy 2005, Tyagi 1999).

Category Management

We find that the category management price driver is associated with *higher* retailer margin. This finding lends support to the promise of increased retailer profitability from the adoption of category-management pricing practices (e.g., Zenor 1994, *Progressive Grocer* 2001). Most notably, it is consistent with Hall et al.'s (2002) demonstration that a retailer would benefit from moving from single brand profit optimization to category profit optimization.

7. Implications and Conclusions

Based on our analysis of 10,850 brand-store combinations in 67 categories in two retail areas, we conclude that retail prices are driven by, in order of importance, (1) pricing history, (2) wholesale prices, (3) brand demand, (4) category management, and

Table 5 The Influence of Retail-Price Drivers and Retailer Profits—Dominick's Data

	Estimate	Standard error
<i>Price driver influence</i>		
Influence of store traffic	−29.75*	9.44
Influence of pricing history	−3.41*	0.91
Influence of brand demand	19.79*	2.17
Influence of wholesale price	−0.73	1.07
Influence of category management—price	17.39*	3.99
Influence of category management—cost	−3.85	4.45
<i>Covariates</i>		
National brand/private label	−327.86*	22.25
Category promotional frequency	35.17*	2.20
Category promotional depth	69.54	72.07
Category concentration	667.77*	42.19
Number of brands	37.68*	1.51
Storability	−279.00*	15.20
Impulse	−58.02*	20.26

Notes. Significant at the 1% level (*). Dependent variable: Retailer category margin. $n = 5,190$. $R^2 = 33.2\%$. Store specific intercepts are not shown due to space considerations.

(5) store traffic/interretailer price competition. Our study offers several actionable implications for marketing researchers, manufacturers, and retailers.

Implications for Marketing Researchers

Our approach offers several improvements over extant methodology. First, our VARX model specification algorithm enhances efficiency and parsimony. It ensures that the model residuals are well behaved (i.e., no autocorrelation) while limiting the level of parameterization. This is especially important given the size of the VARX needed to study price drivers and the high degree of autocorrelation found in both databases used in this research. Second, we apply GFEVD for the first time in marketing. Finally, we develop a bootstrap procedure to correct the standard error bias introduced when using OLS to estimate an econometric model where some of the independent variables are estimated quantities.

Implications for Manufacturers

First, our extensive analysis of price drivers provides insights into interbrand competition by quantifying the extent to which prices and demand of competing brands determine retail prices. Second, our findings indicate which manufacturers/brands need to be most concerned about competitive brands. This is reflected in the relative importance of competitive brands' prices and brand demand as drivers of the focal brand's retail price. Third, our study helps manufacturers get a better understanding of retail pricing and the extent to which price fluctuations are driven by the wholesale prices charged to individual retail chains. These insights cannot be obtained just by

observing retail prices due to the confounding effects of other retail-price drivers.

Implications for Retailers

First, from a retailer's perspective, the striking differences in price-driver importance across brands and categories should give pause. Are these differences intentional? Did they result from a routine based on principles that were once valid but are now obsolete? While only retailers themselves can truly answer these questions, our findings can help them pose the right questions. Second, retailers are interested in the extent of interretail competition in their markets: Strong competitive pricing reaction could greatly affect the outcome of their own actions. Our findings on interretail competition help retailers put such competitive concerns into perspective. Finally, our results demonstrate the importance of understanding which retail-price drivers improve profit performance. Specifically, customer-oriented, or demand-based, pricing combined with the move towards ECR and category management has positive bottom-line profit implications, while rigid adherence to cost-plus pricing by the retailer does not help (or hurt) margins. Moreover, our research shows that pricing a category as a loss leader will hurt category profitability while inertia in retail-price setting is also decidedly unprofitable.

Overall, our findings raise several important questions for future research. Why is pricing history such a dominant driver of retail-price setting? Interviews with retailers may reveal motivations such as pricing complexity, preference for the status quo, fear of competitive reaction, etc. Although our current research has assessed the link between (1) the influence of price drivers on retailer pricing and (2) retailer category margins, future studies should seek explanations for the observed differences in the influence of price drivers across categories. Indeed, the antecedents of price drivers could be related to specific brand, market structure, and product-category characteristics.

Our study has several limitations that are at the same time opportunities for future research. First, the Dominick's database provides information on wholesale prices and margins but lacks data on manufacturer promotional expenses such as slotting allowances, buy-back charges, and failure fees. Second, our data do not allow us to account for certain potential retail-price drivers such as manufacturer advertising and other brand building activities. Third, due to data limitations we are not able to specify models that incorporate both wholesale prices and retailer competition simultaneously. Fourth, we include the top two brands in the model for the Denver data and the top three brands in the model for the Dominick's data. Ideally, we would include data on all brands but this

would significantly increase the level of parameterization in our model and severely limit our ability to provide detailed estimates of pricing dynamics. Fifth, we analyze each product category separately. Further research is needed to investigate possible dependencies in pricing across categories. Finally, although our study uncovers associations between the influence of price drivers on pricing and performance, it cannot prove the existence of causal relationships.

We conclude by suggesting that retailers need to find opportunities to price products in a manner that will enhance profitability in an industry where margins are under ever-increasing pressure. We identify the price drivers that generate these opportunities. Moreover, our research sheds light on the trade-offs that retailers face when focusing on the different drivers of retail prices. Understanding and formalizing these trade-offs remains a fascinating area for marketing researchers and practitioners.

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Appendix A

A.1. VARX Specification

To accurately estimate (G)FEVD, it is important to include all relevant, endogenous variables in the VARX model used to derive them. Our setting requires a large VARX model (seven equations for the Denver data, eleven equations for the Dominick's data). Models of this size quickly run into parameterization problems. For example, adding one lag to an eleven-equation VARX would require the estimation of 121 additional parameters. A commonly used approach is to estimate the model with differing lags and select the specification that minimizes some criterion variable (e.g., BIC or AIC). Given the size of our VARX models, this approach is likely to either (1) select a lag-length that is too short for some of the endogenous variables, causing autocorrelated residuals, or (2) lead to overparameterization. To ensure that residuals are well behaved (i.e., no autocorrelation) and the model is not overparameterized, we use a five-step procedure to specify a subset VARX model. This procedure is outlined below and builds on work by Lütkepohl (1993), Bruggeman and Lütkepohl (2001), and Lütkepohl and Krätzig (2004).

1. For each individual equation in the VARX, determine the lag-length that minimizes the BIC criterion. The equation will include the same number of lags of all endogenous variables.

Table A.1 VARX Fit Statistics

	Number observations	Parameter observations	R^2 (%)	AC cases (%)
Denver	124	1:5.65	61	26.9
Dominick's	399	1:10.4	53	15.2

Note. R^2 is a median value across categories.

2. Determine if the residuals for each VARX equation are free of autocorrelation using the Breusch-Godfrey LM test (Lütkepohl 1993). If the null of no autocorrelation is rejected, add lags until the autocorrelation is successfully removed or a maximum number of lags has been included. For the Denver data set, we use a maximum of six lags; for the Dominick's data, the maximum is set to eight. If autocorrelation problems persist after the maximum number of lags has been reached, additional lags may be added for only the endogenous variable for the equation under investigation. Up to six or eight additional lags are allowed for the Denver and Dominick's data sets, respectively. Residual autocorrelation tests are conducted after each equation revision.

3. Once the basic lag structure has been determined for each equation, the individual parameter estimates are evaluated to determine if the level of parameterization can be reduced. In each equation, the parameter with the smallest t -statistic, in absolute value, is removed. Parameters are then reestimated and evaluated on their t -statistic. This procedure is repeated until all remaining parameters have a t -statistic larger than one in absolute value (Bruggeman and Lütkepohl 2001). It has been shown that utilizing the t -statistic in this manner is equivalent to using either the BIC or AIC criterion, depending on the threshold value for parameter elimination (Lütkepohl and Krätzig 2004).

4. Autocorrelation tests are again conducted for each equation. If any of the tests show evidence of autocorrelation, the results of the model are dropped from further analysis.

5. The parameters of the subset VARX model are estimated by FGLS (Hamilton 1994).

The model specification procedure outlined above allows us to estimate large VARX models that are not significantly overparameterized and yet still ensure that the residuals are well behaved. The average parameter to observation ratio is 1:5.65 for the Denver data set and 1:10.4 for the Dominick's data set. Note that despite the flexibility of our VARX specification approach, 26.9% (Denver) and 15.2% (Dominick's) of models show evidence of residual autocorrelation (AC cases). This result emphasizes the need to correct for marketing dynamics when conducting empirical research on scanner data. See Table A.1 below for additional measures of VARX model fit.

A.2. Bootstrap Algorithm to Correct the Standard Error Bias from OLS-Estimation

Phase 1. Select a sample, with replacement, of size n from the data set constructed for the third step in our analysis, where n is equal to the number of observations in that data set.

Phase 2. Add measurement error to each estimate of price driver influence. The errors are obtained from the Monte Carlo simulations conducted to determine the standard errors of the price driver estimates and contain information on the covariances amongst those driver estimates. This phase is repeated 250 times, each time creating a variation of the data set obtained in Phase 1.

Phase 3. Calculate parameter estimates θ^* for Equation (3) for each of the 250 augmented data sets created in Phase 2.

We repeat Phases 1 through 3 1,000 times. The standard deviation across the 250,000 parameter vectors ($\theta^{*1}, \theta^{*2}, \dots, \theta^{*250,000}$) is our estimate of the standard error of θ^{OLS} (see Bradley and Tibshirani 1993 for details).

Appendix B

B.1. Variable Operationalization

Retailer profitability. For the retailer, we compute the retailer's total category margins (defined in dollars) as $RM_t = \sum_{i=1}^I S_{i,t} \times (P_{i,t} - WP_{i,t})$, where i denotes the brand and I is the total number of brands in the category.

Store traffic. Store traffic is defined as the total number of customers visiting the store that buy at least one item in a given week.

Holiday dummy variables. Following Chevalier et al. (2003), we specify dummy variables that equal one in the shopping periods around the following holidays: Lent, Easter, Memorial Day, July 4th, Labor Day, Halloween, Thanksgiving, the week following Thanksgiving, Christmas, and the Super Bowl. Since front-end candy (one of the categories we analyze) is less likely to be bought immediately after Halloween, we add an additional dummy variable for the week following the holiday. For consistency, these 11 holiday dummy variables are incorporated in all categories analyzed.

B.2. Retail Competition

In the absence of information on the location of stores in the Denver database, we empirically identify stores that are considered by consumers as close competitors. Specifically, competitive retail prices for the top two brands were determined using information on shopping behavior from a consumer panel. For a store, the average competitive price charged for a brand at time t is a weighted average of the prices charged for that brand in all other stores. The weights are determined by counting the number of people in the panel that shop in both the focal and the competing store. To illustrate the computation, suppose we have one brand (X), three stores (A, B, and C), and 100 consumers. If 50 consumers shop at stores A and B and ten consumers shop at stores A and C, this suggests that stores A and B are closer competitors than stores A and C. The competitive retail price for brand X included in a time-series model for store A would be calculated as $(50 \times \text{price X in store B} + 10 \times \text{price X in store C})/60$.

B.3. Covariates

We operationalize the covariates used in Step 3 of our analysis as follows:

National brand vs. private label (NB). A dummy variable indicates whether the promoting brand is a national brand (=1) or a private label (=0).

Promotional frequency (PROM_FRQ). We define promotional frequency as the number of weeks in which negative price-promotion shocks are at least 5% of the brand's regular price. The regular price, in turn, is defined as the maximum price of the brand, following Raju (1992) and Foekens et al. (1999). The category-level measure is calculated as the market-share weighted average of the promotional frequency of the brands in the category.

Promotional depth (PROM_DPT). A brand's price-promotion depth is defined as the difference (%) between a promotional price (as defined for the frequency count) and the brand's regular price. The category-level measure is calculated as the market-share weighted average of the promotional depth of the brands in the category.

Category concentration (CAT_CONC). We measure the category concentration as the cumulative market share of the top three brands.

Number of brands (NRBR). The number of brands in the category is included to capture the extent of brand proliferation (Narasimhan et al. 1996).

Impulse buying (IMPULSE) and storability (STOCK). We use storability and impulse-buying scales defined by Narasimhan et al. (1996) to construct dummy variables indicating whether the product category is considered perishable or storable (=1), and whether it is an impulse good (=1) or not.¹³

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