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Short- and Long-run Competition of Retailer Pricing Strategies

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ABSTRACT

Retailers' pricing strategies are one of the most important determinants of the retail dynamics and the competitive structure of the retail market. Retailers use both short-term and long-term pricing strategies to optimize their market share. This study addresses several critical questions: (1) To what extent do retailers react to competitive price specials? (2) Do retailers alternate price specials of competing brands? and, (3) Can one identify stores or brands, that are price leaders or do retailers/brands set prices independently? We use cointegration analysis to estimate a model which allows us to study both the short- and the long-run dynamics of competitive prices within a single framework.

JEL Classifications: M31, D4

Keywords: price strategies; cointegration analysis

I. INTRODUCTION

It is well known that the location decision exerts a strong impact on the success or failure of a retailer. The location decision vis-a-vis the size and composition of the catchment area describes the maximum sales level that can be reached. Once the locational decision has been made, retailers have limited control over this decision variable. To increase store traffic, they necessarily have to rely on pricing, service and product variety. The pricing variable, in particular, constitutes an important tool for retailers.

Price is the dominant competitive tool in many local retail outlets (Coughlan and Mantrala 1994; Hamilton and Chernev 2013). The pricing decision is one of the most important and difficult decisions that a retailer makes. In the short run and long run, retailers need to consider competitive pricing strategies and anticipate competitor's reactions. These decisions consist of short-run tactical decisions, e.g., temporary price cuts, and longer-run strategic decisions determining price levels.

While a significant amount of research has examined the short-run dynamics of pricing strategies (Blattberg et al., 1995; Empen et al., 2015), long-run retailer pricing strategies have received less attention. The current paper is an empirical analysis of the short- and the long-run dynamics of competitive retailer pricing strategies.

In the long run, we study equilibrium relationships between prices while in the short-run the emphasis is on the competitive dynamics to temporary price change. That is, we will identify which brands compete with each other in the long-run and the short-run. Long-run pricing strategies are investigated by determining the existence of equilibrium relationships between competitive prices. Prices are in long-run equilibrium if there is no inherent tendency for any of the price series to change – while prices may be non-stationary and in short-run disequilibrium there are no persistent trends between prices in the long run. In equilibrium, retailers may be competing at different price levels. In the short run, we focus on how retailers respond to competitive pricing strategies. This study addresses several critical questions: (1) To what extent do retailers react to competitive price specials? (2) Do retailers alternate price specials of competing brands? and (3) Can one identify stores or brands, that are price leaders or do retailers/brands set prices independently?

We use cointegration analysis, a time-series method, to estimate a model which allows us to study both the short- and the long- run dynamics of competitive prices within a single framework. The paper is organized as follows. First, we willdiscuss the principles of cointegration analysis. This is followed by a description of the data. Next, the results of the analysis will be discussed. We will complete the paper by drawing some conclusions.

II. METHODOLOGY

The empirical approach used in this paper follows the framework by Powers et al. (1991). The first step is to test for non-stationarity of the data. If all price series are stationary, prices are in long-run equilibrium and simple linear regression can be used to analyze the short-run dynamics. When variables are non-stationary, simple regression analysis will lead to spurious correlations, biased results, and incorrect inferences for t- and F-statistics (Granger and Newbold 1974). It is possible to use first-differencing of the dependent variable, but this filters out the long-run relationships between variables. Cointegration analysis models non-stationary data while preserving the long-run trends in the data. Therefore, when data are non-stationary, we first test whether prices are in long-run equilibrium using cointegration analysis. When the data are cointegrated, a vector error-correction model (VECM) is estimated obtaining estimates for both the short- and the long-run relationships. If the data are non-stationary but not cointegrated, first-differencing is used to eliminate non-stationarity and a vector auto-regressive model (VAR) is estimated on the first-differences. This approach provides only the short-run estimates since first-differencing eliminates all long-run price trends. Hence, we start by testing for non-stationarity of sales and prices, followed by cointegration analysis of non-stationary prices.

A. Testing for Non-stationarity using the Unit Root Test

We begin by defining stationarity and later we introduce the notion of cointegration and error- correction models. The distinction between stationarity and evolution can be illustrated through a first-order auto-regressive model of the performance indicator in question:

$$y_t = a_0 + \rho y_{t-1} + e_t \qquad (1)$$

where, y_t is a univariate time series, a_0 is the intercept, ρ is the degree of persistence of y_{t-1}, and e_t is a random error with expected value 0 and a constant finite variance, $e_t \sim$IID $N(0,\sigma^2)$. Subtracting y_{t-1} from both sides and adding lagged terms for the dependent variables we obtain:

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=1}^{L} \beta_i \Delta y_{t+1} + e_t \qquad (2)$$

where, $\gamma = \rho - 1$, L=number of lagged terms.

When $\gamma = 0$ and a_0 is = 0 the time series are non-stationary, while for $\gamma \neq 0$ the time series is stationary or mean reverting. This is the basis of the unit-root test proposed by Dickey and Fuller (1979) and is called the Augmented Dickey-Fuller test (ADF).[1]

B. Cointegration Analysis

Cointegration is a time-series analysis, used to model the long-run relationship between variables when these variables are non-stationary (Engle and Granger 1987; Johansen and Juselius 1990). It tests whether there exists a steady-state relationship between variables that are evolving over time. When variables are non-stationary and in long-run equilibrium, the variables are cointegrated. More formally, non-stationary variables are cointegrated if there is a linear combination of integrated variables that is stationary. This is the definition of an equilibrium relationship used in this study. A major advantage of this approach is that it simultaneously measures the short- and the long-run effects of variables in a single framework. It measures the response and competitive interactions to short-run marketing inputs, as well as, the long-run equilibrium relationships between competing firms.

C. The Error-Correction Model

In this paper, we use the Johansen method (Johansen 1988; Johansen and Juselius 1990). This is a multivariate extension of the Engle and Granger (1987) model. The vector error-correction model (VECM) model is derived from the basic vector auto-regressive (VAR) model.

We start with specifying a VAR model in levels, with k lags.

$$P_t = A_o + A_1 P_{t-1} + A_2 P_{t-2} + \cdots + A_k P_{t-k} + \Psi X_t + u_t \quad (3)$$

where, P_t, $= [P_{1t}, P_{2t}, \ldots, P_{nt}]'$ a vector of prices, all may be endogenous; A_i = (n x n) matrix of parameters; X_t = a vector of exogenous variables; and $u_t \sim IN(0,\Sigma)$.

Next we reparameterize this model using a cointegrating transformation of the VAR model. Subtracting and adding P_{t-1},P_{t-2},and A_1 P_{t-2} to both sides of equation (3), we obtain:

$$\Delta P_t = A_o + \sum_{i=1}^{N} \Gamma_i \Delta P_{t-i} + \Pi P_{t-k} - \Psi X_t + u_t \quad (4)$$

where, $\Delta P_t = P_t - P_{t-1,}$ is the first difference of prices; $\Gamma = -(I - A_1 - \ldots\ldots - A_i)$, i = 1,2, ...k-1, and I is a unity matrix; $\Pi = -(I - A_1 - \ldots\ldots - A_k)$; and $u_t \sim IN(0,\zeta)$.

Equation (4) is a multivariate generalization of the error-correction model. It says, that price changes are a function of lagged changes in own and competitive prices (Γ_i's) and the previous period's equilibrium error, captured by the Π matrix which establishes the error-correction mechanism. The contemporaneous price effects are absorbed by the error term. The relationship between the long-run equilibrium and the error-correction term (Π) was shown above for the bivariate case. The error-correction matrix Π can be specified as $\alpha\beta'$ where α is the speed of adjustment, and β is the long-run parameter, and $\beta' P_{t-k,}$ are the error-correction terms (Engle and Granger 1987). Intuitively, this implies that when prices are cointegrated this matrix consists of a component which governs the long-run equilibrium relationship and a part which consists of the short-run deviations from the long-run equilibrium.

Johansen (1988) specified, when the rank of the Π matrix is positive (rank $0 < r < n$), then the Π matrix consists of the error-correction mechanisms, such that $\Pi = \alpha\beta'$. Where, β is an (nxr) matrix with the long-run price equilibrium coefficients (or the cointegrating vectors), and α is an (nxr) adjustment or feedback matrix. The r columns of the β matrix are the cointegrating vectors ($\beta_1, \beta_2, \ldots, \beta_r$) which contain information on the equilibrium relationships that dictate the long-run movement of the price series. The feedback matrix measures the speed at which the price series adjust to the disturbances in the equilibrium relationship (that is the current period's correction of the last period's deviation in order to maintain the long-run equilibrium relationship). The larger the alpha's the greater the response to previous period's deviations from the long-run equilibrium. When $a = 1$, price returns to equilibrium within the same time period. When $a = 0$, price does not respond.

D. Estimation and Testing for a Long-Run Equilibrium

Testing for the rank of the Π matrix is a test for cointegration of time-series (Johansen 1988). Since we have n price time-series, the dimension of the Π matrix is $n \times n$. When the rank of the Π matrix is n, then the vector of prices P_t is stationary (the variables are integrated of order zero). A rank of zero indicates that prices are non-stationary but not cointegrated. Hence, prices have no long-run link and can wander arbitrarily far away from each other. When the rank is $0 < r < n$, prices are cointegrated, and the rank of the matrix is the number of significant cointegrating vectors. Therefore, the test for the existence of a long-run price equilibrium (or cointegration) is: H_o = the rank of the Π matrix = $0 < r < n$.

Johansen (1988) developed a Maximum Likelihood Estimation procedure, based on reduced rank regression, to test for the rank of the Π matrix (the number of cointegrating vectors) and to estimate a and β. We use this method in this paper. We refer the reader to Johansen (1988), Johansen and Juselius (1990) or Hendry and Doornik (1996, chapter 11) for the details and derivations.

III. DATA AND ANALYSIS

The data used consists of weekly store-level data on sales and prices of toilet tissue and beer for a period of seven years. The data were supplied by Information Resources Inc., and was collected by supermarket scanners in a medium-sized test market in the USA. Sales are the weekly scanned sales for a particular brand. Price is a weighted average of the different varieties and different sizes (e.g. Budweiser and Bud Lite, etc.), and is adjusted for the rate of inflation. Basic pooling tests were conducted, which indicated that over 95% of sales of different varieties for a brand could be pooled (Bass and Wittink 1978).

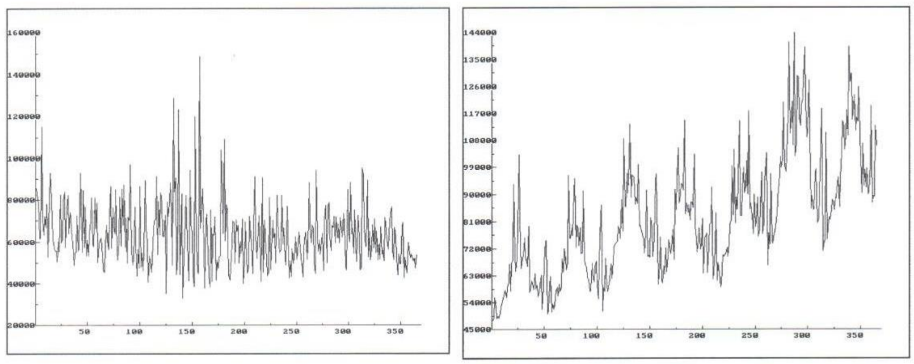
We include in our analysis the three major brands of toilet tissue (Soft & Gentle, Northern, and Charmin) and the five major brands of beer (Budweiser, Busch, Miller, Milwaukee’s Best, and Old Milwaukee). The three brands of tissue are national brands (Charmin is the most expensive brand and Soft & Gentle is the cheapest), which have a combined market share of over 80 percent of industry sales. The beer data includes four national brands (Budweiser and Miller are premium-priced beers; Busch and Old Milwaukee have a medium level price; Milwaukee’s Best is a cheaper regional beer), which have a combined share of over 60 percent. Private label and Generics sales consist of less than ten percent of industry sales for both product classes.

For the purpose of this study, we selected two different product categories, one with stationary industry sales and the other with increasing sales (see Figure 1). The tissue market has stationary sales and each brand's market share is stable over time, while the beer market is evolving, and several brands have non-stationary market shares. This allows us to study for potential differences in the short- and the long-run pricing strategies in stationary and non-stationary markets.

A. Results from Analysis

To study short and long-run price competition, we first perform non-stationarity tests on the individual price series. Next, for prices that are non-stationary, we use cointegration analysis to test for the existence of a long-run equilibrium relationship. Following this, we estimate the error-correction model and test for price leadership using Granger causality tests.

Figure 1
Total weekly industry sales volume for tissue and beer
Toilet Tissue Sales Beer Sales



B. Test for Non-Stationarity

The Augmented Dickey-Fuller test is used to test for the existence of a unit root. Table l, provides the results of these non-stationarity tests for the price series and sales series for the beer and tissue categories.[2] Results show that sales for all brands of tissue are stationary while three brands of beer have non-stationary sales. Furthermore, industry sales of tissue are stationary while beer sales areevolving. However, our focus is on price competition, hence we focus on the price series. We find that all time-series are non-stationary with the exception of Milwaukee's Best. Given that price series are evolving, we next use cointegration analysis to test for long-run equilibrium relationships between competitive prices for both beer and tissue.

Table 1
Results stationarity tests for sales and price series of beer and tissue [a]

Beer	Sales	Price
Budweiser	2.79/l (6)[b]	2.69 (8)
Busch	1.47 (7)	2.69 (6)
Miller	2.92 (4)	2.02 (6)
Milwaukee's Best	3.95** (7)	4.37** (4)
Old Milwaukee	4.08** (5)	2.04 (12)
Tissue	**Sales**	**Price**
Soft & Gentle	3.47** (7)	2.22 (8)
Northern	5.51** (6)	1.90 (6)
Charmin	4.92** (6)	1.73 (7)

[a] Test statistics for the Augmented Dickey-Fuller. [b] Number of lags included in parentheses.
** indicates sales or price series are stationary.

C. Results of Cointegration Analysis

Cointegration analyses are conducted to test for the existence of long-run price equilibria between competitive prices, to estimate the long and short-run parameters of the error-correction mechanism, and to conduct hypotheses tests concerning the parameter estimates. The following system of equations is estimated using Maximum Likelihood Estimation:

$$\begin{bmatrix}\Delta P_{1t}\\ \vdots \\ \Delta P_{nt}\end{bmatrix} = \Gamma_1 \begin{bmatrix}\Delta P_{1t-1}\\ \vdots \\ \Delta P_{nt-1}\end{bmatrix} + \cdots + \Gamma_{k-1}\begin{bmatrix}\Delta P_{1t-k+1}\\ \vdots \\ \Delta P_{nt-k+1}\end{bmatrix} + \begin{bmatrix}\pi_{11} & .. & \pi_{1n}\\ .. & .. & ..\\ \pi_{n1} & .. & \pi_{nn}\end{bmatrix}\begin{bmatrix}P_{1t-1}\\ \vdots \\ P_{nt-1}\end{bmatrix} + \Psi_1 \begin{bmatrix}X_{1t}\\ \vdots \\ X_{nt}\end{bmatrix} + \begin{bmatrix}u_{1t}\\ \vdots \\ u_{nt}\end{bmatrix} \quad (5)$$

First, we need to determine the number of lags to include in equation 5. We start with a VAR model using undifferenced data, including 8 lagged terms, and iteratively delete insignificant lags using the Bayesian Information Criteria (BIC). Once the number of lags is determined equation (5) is estimated using the Johansen and Juselius (1990) method. We determine the number of significant cointegrating vectors given by the cointegration rank, and the short- and the long-run parameters, α and β. Next we conduct hypotheses tests on the short- and the long-run parameters. The different tests conducted are summarized in Table 2.

Table 2
Summary of research hypotheses

Long-run reactions to permanent price changes	
H_0: Prices are in long-run equilibrium	Rank of $\Pi = 0 < r < n$
H_0: Brands or stores are not all competing at the same price tiers	H_0: $\beta_i = \beta_j$
Short-run reactions to permanent price changes	
H_0: Prices will take over one week to return to equilibrium	H_0: $0 < \alpha_i < 1$
H_0: A brand or store does not respond to a competitive price change	H_0: $\alpha_i \neq 0$
H_0: Short-run price adjustments are not symmetric	H_0: $\alpha_i \neq \alpha_j$
H_0: Prices are exogenous	H_0: $\alpha_{i1} = \cdots = \alpha_{in} = 0$
Price leadership	
H_0: A store or brand is a price leader	H_0: $\gamma_i = \alpha_i = 0$

D. Results of Long-Run Analysis

The results of the multivariate analysis using the Johansen method (Johansen, 1988; Johansen and Juselius, 1990) are provided in Table 3. First, we determine the number of significant cointegrating vectors (the rank of the Π matrix). Table 3, reports the Log-likelihood ratio test scores. The Likelihood ratio test or trace statistic is given as:

$$Q_r = -T\sum_{i=r+1}^{k}\log(1-\lambda_i) \quad (6)$$

where, r=0,1,..., k-1 is the number of significant eigen vectors, λ_i is the i-th largest eigenvalue of the matrix π, Q_r is the trace statistic and is the test of $H_1(r)$ against $H_1(k)$. The number of cointegrating relations r, is determined by sequentially testing this hypothesis from r=0 to r=k-1 until we fail to reject. The critical values are provided in Osterwald-Lenum (1992).

Table 3

Results of cointegration analysis showing number of significant cointegrating vectors (indicated by the likelihood ratio test)

Number of cointegrating vectors	1	2	3	4	5
		Beer			
Likelihood Ratio	76.2**	48.9**	21.1*	11.74*	1.4
Number of cointegrating vectors	1	2	3		
		Toilet Tissue			
Likelihood ratio	57.8**	32.2**	0.026		

** is statistically significant at 0.05; * is statistically significant at 0.10.

For the tissue data we find two significant cointegrating vectors, while for the beer two vectors are significant at the 0.05 level and two at the 0.10 level of significance. This raises the question whether to include two or four cointegrating vectors for the beer data. Due to the large number of parameters to be estimated these tests tend to have low statistical power, which may lead to failure to reject the null hypothesis. Therefore, we plot the cointegrating vectors over time and check the stationarity of the cointegrating vectors. Since the cointegrating vector consists of stable linear long-run relationship, this vector should be constant over time. A visual inspection shows that for the tissue data only the first two vectors are stationary, indicating that two cointegrating vectors govern the stable long-run trend between the three price series. For the beer data the first three vectors are stationary while the forth vector is almost stationary. Therefore, we will use the results with four cointegrating vectors.[3]

These results indicate that prices for tissue and beer are in long-run equilibrium. The next question pertains to the long-run relationship between prices. For example, certain brands may play agreater role in the preservation of a long-run equilibrium relationship. Specifica1ly, a brand may be more responsive to long-run price changes by certain competing brands than to other brands. Therefore, we look at the magnitude of the long-run relationships and test for the equality of long-runcoefficients. Table 4 provides the results of long-run coefficients for pair-wise tests forthe different price series. Though the results in Table 4 are based on bivariate cointegration analyses, all hypotheses tests were conducted using the multivariate model. For example, the long-run relationship between the prices of brand 1 and brand 2 of beer is, Price 1 = 1.39* Price 2. Next, we test for the existence of a one-to-one relationship between the long-run prices. The hypothesis of the equality of the long-run parameters, Ho: $\beta_i = \beta_j$, is tested using the Log likelihood Ratio Test. This test statistic has a X^2 distribution with r x (n-m) degrees of freedom, where r is the rank of the matrix with error-correction terms (Π), n is the dimension of Π, n-m is the number of restriction, $\widehat{\lambda_1^*}$ and $\widehat{\lambda_1}$ are the estimates of the eigenvalues of the restricted and unrestricted model. These resultsshow that for the beer data, Budweiser and Miller, and Busch and Old Milwaukee have a long-run one-to-one relationship. These results suggest that Budweiser and Miller are competing at the same price- tier while Busch and Old Milwaukee are competing at a lower price-tier. For the tissue data, Soft & Gentle and Northern are the closest competitors based on price, but this relationship is not as strong. It isimportant to note that though not all brands are competing at the same price tier, long-run prices tend to be in equilibrium.

Table 4
Results of long-run relationships between pair-wise prices using cointegration analysis

Beer prices	Long-runEquilibrium	Ho: $\beta_i = \beta_j^a$
1&2	Yes	1.39**
1&3	Yes	1.09
1&4	No	--
1&5	Yes	1.42**
2&3	Yes	0.78**
2&4	No	--
2&5	Yes	1.02
3&4	No	--
3&5	Yes	1.31**
4&5	No	--
Tissue prices	**Long-runEquilibrium**	**Ho: $\beta_i=\beta_j$**
1&2	Yes	0.87**
1&3	Yes	0.78**
2&3	Yes	0.89**

[a] β parameter from cointegration analysis (β_j is normalized to 1). ** indicates that β is statistically significantly different from β_j at the 95% level of confidence, based on a Chi-square test.

E. Results of the Short-nm Analysis

Having obtained the cointegrating vectors (and after including the restrictions), we obtain the VECM involving price of tissue as shown below:

$$\Delta P_{1,t} = -\,0.438\,\Delta P_{1,t-1} - 0.323\,\Delta P_{1,t-2} - 0.218\,\Delta P_{1,t-3} - 0.048\,\Delta P_{2,t-1} - 0.068\,\Delta P_{2,t-2} - 0.028\,\Delta P_{2,t-3}$$
(-6.54) (-5.10) (-4.16) (-0.77) (-1.19) (-0.62)

$$-\,0.062\,\Delta P_{3,t-1} - 0.044\,\Delta P_{3,t-2} - 0.001\,\Delta P_{3,t-3} - 0.007\,(P_{1,t-k} - 3.770\,P_{2,t-k} + 2.588\,P_{3,t-k})$$
(-1.36) (-1.08) (-0.01) (-0.47)

$$+\,0.118\,(-2.286\,P_{1,t-k} + P_{2,t-k} + 0.889\,P_{3,t-k}) + \varepsilon_{1,t}$$
(4.52)

$$\Delta P_{2,t} = -\,0.153\,\Delta P_{1,t-1} - 0.099\,\Delta P_{1,t-2} - 0.002\,\Delta P_{1,t-3} - 0.352\,\Delta P_{2,t-1} - 0.211\,\Delta P_{2,t-2} - 0.104\,\Delta P_{2,t-3}$$
(-1.87) (-1.29) (-0.32) (-4.60) (-3.03) (-1.88)

$$-\,0.217\,\Delta P_{3,t-1} - 0.107\,\Delta P_{3,t-2} - 0.042\,\Delta P_{3,t-3} + 0.093\,(P_{1,t-k} - 3.770\,P_{2,t-k} + 2.588\,P_{3,t-k})$$
(-3.91) (-2.14) (-1.03) (5.10)

$$-\,0.044\,(-2.286\,P_{1,t-k} + P_{2,t-k} + 0.889\,P_{3,t-k}) + \varepsilon_{1,t}$$
(-1.40)

$$\Delta P_{3,t} = -\,0.438\,\Delta P_{1,t-1} - 0.109\,\Delta P_{1,t-2} - 0.233\,\Delta P_{1,t-3} - 0.265\,\Delta P_{2,t-1} - 0.167\,\Delta P_{2,t-2} - 0.024\,\Delta P_{2,t-3}$$
(-0.50) (-1.10) (-2.83) (-2.70) (-1.87) (-0.35)

$$-\,0.357\,\Delta P_{3,t-1} - 0.292\,\Delta P_{3,t-2} - 0.147\,\Delta P_{3,t-3} - 0.133\,(P_{1,t-k} - 3.770\,P_{2,t-k} + 2.588\,P_{3,t-k})$$
(-5.03) (-4.54) (-2.84) (-5.66)

$$-\,0.111\,(-2.286\,P_{1,t-k} + P_{2,t-k} + 0.889\,P_{3,t-k}) + \varepsilon_{1,t} \qquad (7)$$
(-2.71)

where, 1=Soft & Gentle, 2=Northern, and 3=Charmin; t-values are given in parentheses.

In the above equation, there are three lagged price terms and two significant cointegrating vectors (as the rank of $\Pi = 2$, see Table 3) and we estimate six α and β parameters. The t-values are given in parentheses. The two cointegrating vectors constitute two long-run equilibrium relationships between the three price series. The results show that for all brands the changes in prices are negatively influenced by its ownlagged price changes. These results are indicative of frequent price changes, where temporary price cuts are followed by increases to the regular price level. Changes in price for Soft & Gentle are influenced by the brand's own lagged prices but not by competitors' prices. Northern's price is influenced by lagged changes in the price of Charmin, while Charmin's price changes are influenced by lagged changes in the price of Northern. The negative influence of lagged competitive prices indicates that retailers tend to alternate the price cuts of the different brands. The results for the beer analysis arereported in Table 5. One difference with the results for the tissue data is that not all prices are influenced by own lagged prices. Budweiser's short-run prices are mostly influenced by Milwaukee's Best and Old Milwaukee. In general most brands' short-run prices are influenced by Old Milwaukee's prices, which is the most frequently promoted brand. Furthermore, prices are negatively influenced by lagged competitive prices indicating that there is a lagged response to competitive price specials.

The short-run α parameters estimate the speed of adjustment, which is the time it takes for prices to move back to the long-run equilibrium relationship (e.g. after a price special). For example, $\alpha_{11} = -0.007$ reflects the speed of adjustment of the price of Soft and Gentle to its long-run equilibrium relationship with the prices of Northern and

Charmin. These results are used to test the hypotheses about the short-run pricing behavior, as indicated in Table 2. In the short run, prices are frequently in disequilibrium due to frequent price specials. The first question we address is how long does it take for prices to return to an equilibrium state? Therefore, the first hypothesis we look at is H_o: $\alpha_i = 0$. For tissue, four of the six α parameters are statistically significant (see equation 7), while 11 out of 20 for the beer data (see Table 5). In the first price equation for tissue, $\alpha_{11} = 0$, and $\alpha_{12} \neq 0$, hence only the second long-run equilibrium relationship has an effect on the price of Soft & Gentle. In all of the instances (for tissue and beer) we reject H_o: $\alpha_{11} = \ldots \alpha_{1n} = 0$, indicating that none of the prices are exogenous and all prices change to return to the equilibrium relationship. However, the degree of adjustment differs, depending on the magnitude of the beta parameter.

None of the α parameters were greater than one while most were significantly less than one suggesting that it will take more than one week for prices to return to equilibrium. The error-correction terms for tissue were smaller than for the beer data indicating a slower adjustment towards long-run equilibrium for tissue. In general, these results indicate that there is lagged response in competitive reactions. Finally, we tested for the equality of the α parameters, studying whether the speed of adjustment is symmetric (H_o: $\alpha_i = \alpha_j$). We could not reject the equality of the short-run parameters in most cases. This implies that the time it takes for prices to move back to the long-run equilibrium relationship e.g. after a price change is the same for most competitors.

F. Price Leadership

We use the Granger Causality test to study price leadership. The Granger Causality test is an F-test that determines whether laggedprices of brand 2 have an influence on the price of brand l in the presence of lagged prices for brand l.If lagged prices are significant, then the price of brand 2 Granger-causes price of brand 1. Given that prices are non-stationary, a problem with the Granger Causality test is that it requires differencing ofnonstationary data. This leads to a loss of any information about long-run causality. To overcome this problem, we use the vector error-correction model to test for causality, enabling us to distinguish between short- and long-run Granger causality. More specifically, we test for the significance of short-run Granger-causality (H_o: $\gamma_i = 0$), and for long-run Granger-causality (H_o: $\alpha_i = 0$). Note when two variables are cointegrated, at least one must Granger-cause the other (Granger 1986), however, this does not ensure price leadership as Granger causality can also be multidirectional.

The results of these tests are given in Table 6. Results show that in the short run, price of Soft & Gentle Granger-causes price of Charmin. However, price of Charmin does not influence price of Soft & Gentle. Therefore, Soft & Gentle is a price leader with respect to Charmin (but not to Northern). Yet, Northern and Charmin simultaneously influence each other's prices. These results tend to indicate that brands that compete in the long run do not necessarily compete in the short run. For example, the price of Soft & Gentle is influenced by the long-run prices of Northern and Charmin but not by their short-run price levels. For the beer data most of the short-run Granger-causality tests are insignificant. Old Milwaukee 'short-run' Granger-causes prices of Budweiser, Miller and Milwuakee’s Best.

Table 5
Results of VECM model for beer data

	Price l[a]	Price 2	Price 3	Price 4	Price 5
Price 1(-1)	.043 (.066)	-.177** (.051)	.093 (.063)	-.020 (.045)	-.077 (.063)
Price 1 (-2)	-.053 (.056)	-.099** (.043)	.012 (.053)	-.053 (.038)	-.015 (.053)
Price 2 (-1)	-.069 (.077)	-.189** (.059)	-.068 (.073)	-.059 (.053)	-.014 (.073)
Price 2 (-2)	-.001 (.086)	-.147** (.053)	.064 (.065)	.007 (.047)	.113 (.066)
Price 3 (-1)	-.050 (.066)	.001 (.051)	-.219** (.063)	-.032 (.046)	-.047 <.063)
Price 3 (-2)	.034 (.058)	-.021 (.045)	-.046 (.056)	-.056 <.040)	.017 (.056)
Price 4 (-1)	-.275** (.094)	.065 (.072)	-.069 (.090)	-.155** (.065)	-.315** (.090)
Price 4 (-2)	-.261** (.078)	-.076 (.060}	.063 (.074)	-.112** (.054)	-.125 (.075)
Price 5 (-1)	-.201** (.075)	-.072 (.058)	-.178** (.072)	-.133** (.052)	.095 (.071)
Price 5 (-2)	-.159** (.054)	-.038 (.042)	-.111** (.052)	-.111** (.037)	.079 (.052)
Coint Vector 1	-.600** (.007)	.132** (.055)	.050 (.069)	.081 (1.64)	.260** (.069)
Coint Vector 2	.001 (.007)	-.321** (.052)	.082 (.064)	.129** (.047)	.058 (.065)
Coint Vector 3	.168** (.057)	.048 (.044)	-.281** (.054)	.012 l.304)	.107** (.005)
Coint Vector 4	.454** (.102)	-.031 (.397)	.010 (.108)	-.511** <.070)	.546 (.097)

[a] Price 1=price of Budweiser, 2=Busch, 3=Miller, 4=Milwaukee's Best, 5=Old Milwaukee; ** is statistically significant at 0.05; * is statistically significant at 0.10.

Table 6
Results of price-leadership analysis for beer and tissue data

Beer[a]	Short-run[b]	Combined[c]	Beer	Short-run[b]	Combined[c]
Price 1→ 2	7.15**	49.31***	Price 3 →4	2.01	58.26***
Price 1→ 3	2.73	43.27***	Price 3 →5	1.15	235.71***
Price 1 →4	2.14	58.75***	Price 4 →1	13.02**	72.24***
Price 1 →5	1.75	231.45***	Price 4 →2	5.53	47.92***

Price 2 → 1	0.97	72.97***	Price 4 → 3	3.06	39.76***
Price 2 → 3	3.47	39.16***	Price 4 → 5	12.71**	123.67***
Price 2 → 4	1.87	60.55***	Price 5 → 1	9.74**	74.37***
Price 2 → 5	4.36	232.84***	Price 5 → 2	1.61	47.85***
Price 3 → 1	1.75	71.23***	Price 5 → 3	6.83**	38.09***
Price 3 → 2	0.44	48.44***	Price 5 → 4	9.75**	59.46***
Tissue[a]	Short-run[b]	Combined[c]	Tissue	Short-run[b]	Combined[c]
Price 1 → 2	4.13	24.87***	Price 3 → 1	2.63	39.39***
Price 2 → 1	3.47	36.75***	Price 2 → 3	8.69**	31.15***
Price 1 → 3	7.65**	37.48***	Price 3 → 2	16.64***	26.40***

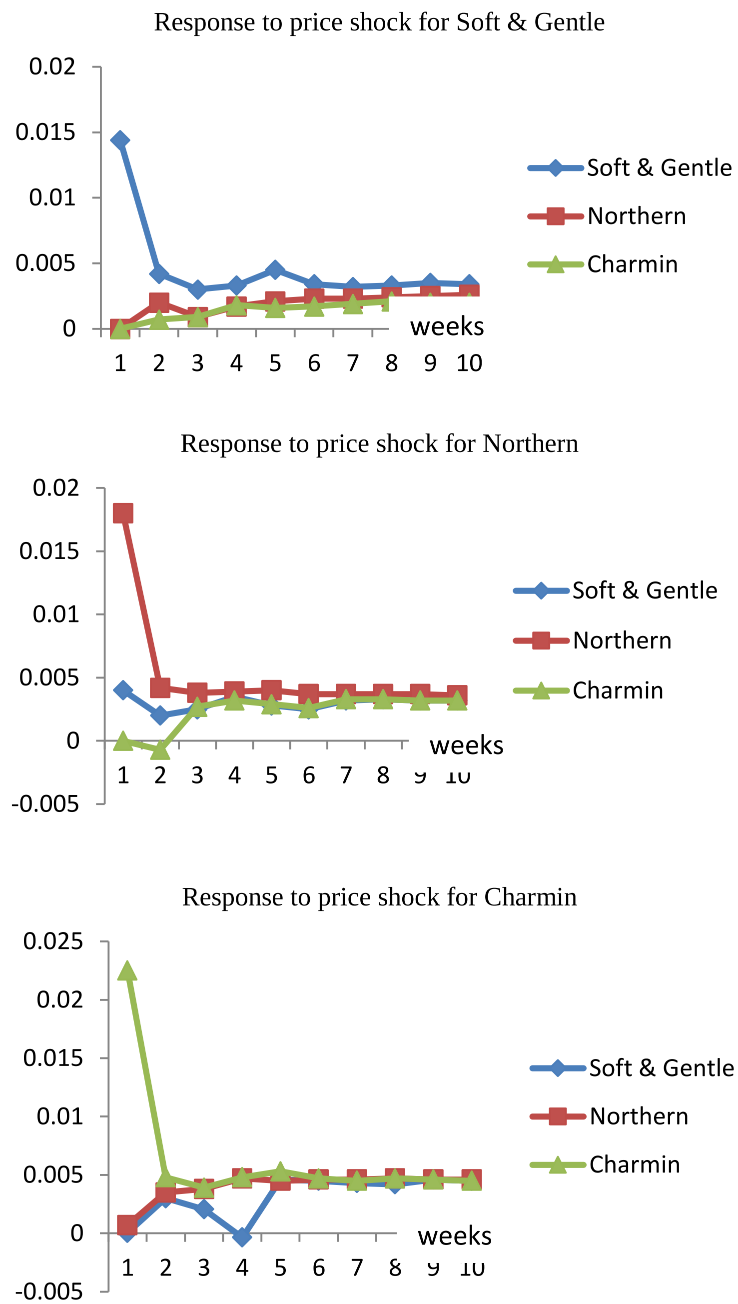
[a] Price beer: 1=price of Budweiser, 2=Busch, 3=Miller, 4=Milwaukee's Best, 5=Old Milwaukee
[a] Price toilet tissue: 1=price of Soft & Gentle, 2=Northem, 3=Charmin
[b] Value of F-test for hypothesis $\gamma_i = 0$
[c] Value of F-test for hypothesis $\alpha_i = 0$
*** is statistically significant at 0.01; ** is statistically significant at 0.05.

G. Impulse Response Function

Finally, to determine competitive reactions to temporary (unexpected) price changes we estimate the impulse response functions and the variance decomposition. The impulse response functions show the effect over time on price due to a significant shock in the system (for example, the effect of a significant price change or an unexpected event), as well as, the competitive response to this price shock. Consider the VECM in equation (5). A change in u_{1t} will immediately change the value of current price P_1. It will also change all future values of $P_1 \ldots P_n$ since lagged P, appears in all the equations. Thus a perturbation in one innovation in the VECM sets up a chain reaction over time in all the variables in the VAR. Impulse response functions calculate these chain reactions. Impulse response functions trace the effects of a shock to an endogenous variable on the variables in the VECM. By contrast, variance decomposition decomposes variation in an endogenous variable into component shocks to the endogenous variables in the VECM. The variance decomposition gives information about the relative importance of each random innovation to the variables in the VAR (for a discussion of these concepts see Hamilton, 1994).

The impulse response functions for the tissue data are plotted in Figure 2. The first graph displays the impact of a one standard deviation shock in the price of Soft & Gentle over time, and graphs 2 and 3 for Northern and Charmin. All graphs for beer display a similar trend as for the tissue data. There is a rapid decline after a price shock indicating little longer-lasting effect. In all instances we observe competitive responses which are quite similar. One interesting finding is that a short-run price change leads to a long-run shift in prices. These results imply that the usage of temporary price specials will lead to price wars and decreased prices.

Figure 2
Impulse response function for toilet tissue



Finally, we conduct a variance decomposition analysis shown in Table 7. The numbers in Table 7 are the variance explained in price due to a price shock. 75.7% of the variance in the price shock of Soft & Gentle after 10 weeks is explained by its own innovations, 14.2% by Northern and 10.1% by Charmin. Results are fairly similar for the different brands. Yet, one noticeable difference is that a significantly larger degree of variance due to a price shock to Charmin is explained by Northern rather than Soft & Gentle. For the beer data, we observe some differences across brands. In particular, Milwaukee's Best's price variance is mostly due to its own innovations, while Miller's price variance is to a larger extent due to competition. Also we observe asymmetry; the price of Budweiser is mostly influenced by the price of Miller. In general, we can conclude that Budweiser's price is relatively the most exogenous; its relative variance is mostly explained by its own innovations.

Table 7

Percentage of variance explained due to a change in price for beer and tissue

Beer price shock to:	Budweiser	Busch	Miller	Milwaukee's Best	Old Milwaukee
Budweiser	70.3[a]	4.1	13.7	8.9	3.0
Busch	6.9	79.3	7.1	3.9	2.7
Miller	6.2	12.0	67.3	8.8	5.7
Milwaukee's Best	1.4	4.9	6.3	85.8	1.5
Old Milwaukee	2.2	2.4	9.8	5.1	80.6

Tissue price shock to:	Soft & Gentle	Northern	Charmin
Soft & Gentle	75.7	14.2	10.1
Northern	9.0	77.5	13.5
Charmin	4.3	19.3	76.3

[a] Percentage of variance explained due to a change in price (for tissue after 10 weeks)

IV. CONCLUSION

Once stores are located, retailers have limited control over location as a means of retail competition. Retail dynamics and the competitive structure of the retail market under such circumstances typically depend on other strategy dimensions, pricing being the most important. To optimize their market share, retailers use both short-term and long-term pricing strategies. Short- term strategies reflect immediate responses to competitor's pricing decisions for specific products or brands while long-term strategies concern the positioning of the store in terms of prices. For regional science, this means that the analysis of the competitive structure and dynamics of any retail system necessarily requires an integrated analysis of the short- and long-term retail pricing strategies. The present paper offers an analysis, using cointegration analysis. Our study makes contributions to the literature on competitive response. We use cointegration analysis of the prices of different brands within a store chain over time and of prices of a single brand across store chains through time, in a study of the dynamics of competitive response. In contrast to previous research, we studied retailer competitive response by conducting our analysis at the store-chain level. Furthermore, most previous research has only studied short-run competitive responses (Leeflang and Wittink, 1992, 1996). Overall, results indicate that an important distinction must be made between the short- and long-run response to temporary and permanent changes in competitive prices.

We summarize our key findings as follows:

A. Long-run Price Competition:

- Most long-run price time-series are non-stationary (invalidating the usage of OLS estimation).
- Most prices are in long-run equilibrium, indicating that prices move together in the long run.
- All prices and relative prices were in long-run equilibrium for the stationary tissue market, but notso for the non-stationary beer market.
- We identify different price-tiers, where brands are competing more closely based on price. Though brands compete at different price-tiers, prices are in long-run equilibrium.

B. Short-run Price Competition:

- The short-run parameters (α's) are symmetric for most competing brands, indicating that the time it takes to return to the price equilibrium after a price change is symmetric.
- Our results show that changes in prices are negatively affected by a brand’s own lagged price changes, a result that is consistent with reactions to frequent price specials, where we observe an increase in sales followed by dip in sales after a price special.
- Half of the brands and store chains do not react to a price change in the short-run (e.g. do not match price specials).
- When a competitor reacts to a price change, on average it takes more than one week for prices to return to equilibrium ($\alpha < 1$).
- Competitors influence retailer pricing strategies; yet, responses tend to occur with a lag. None of the store chains or brands in this market is a price leader.
- Within in a store chain retailers tend to alternate promotions for different brands.

Our paper has important implications for managers. The results show which brands compete on price both in the short and long run. These competitive dynamics may be quite complex. For example, two brands competing based upon price in the long run may respond to competitive promotions from brands at different price tiers in the short-run. Our model can be used as a tool for retailers trying to anticipate competitive responses to a price change or anticipating price changes by competitors.

ENDNOTES

1. The aim of the ADF tests is to use the lagged changes in the dependent variable to capture the auto- correlated omitted variable which would otherwise appear in the error term (see Banerjee et al., 1993). A critical issue in the ADF test is the choice of the number of lags. The suggested strategy is to select the largest number of lags for which y is significant in Equation (5) (see Doomik and Hendry, 1996).
2. We included an intercept, an adjustment for seasonality, and dummy variables to adjust for outliers. The number of lags was set at 20, to ensure that residuals are well-behaved (it is better to set the number of lags too high, which leads to some loss in efficiency, than too low as remaining autocorrelation in the residuals will invalidate the tests). Non-stationarity tests were also conducted using different lag structures and results were similar.
3. We also estimated the results using the three cointegrating vectors and results were similar to the four-vector solution.

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