Competitive Pricing Analysis in Mature Evolving Markets A Time Series Approach

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A Time Series Approach

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ABSTRACT

Competitive behavior between players in a mature market can have a different structure than those in growing markets. Pricing component of the marketing mix is less relied upon to expand market share in growing markets, while there is a greater reliance upon product differentiation and building stronger brand equity. On the other hand, in mature markets, there is usually very little scope for product differentiation, so there is a greater reliance on pricing for competitive gains. Since market share expansion in a mature market comes directly from competitive sales declines, pricing strategy changes in one brand leads to a fairly instantaneous reaction from other brands in the category and retail prices in general reflect the equilibrium condition of consumption.

This paper applies methods from Time Series Econometrics to identify nonstationary behavior and long-run equilibrium of retail prices of brands in mature and evolving markets. The results indicate that long-run equilibrium in prices may be an outcome of the maturity of markets, as the persistence of the shocks in the prices do not result in the persistence in shocks to sales. The cointegrating condition created by the intense price competition imposes a stationarity restriction on sales, hence eliminating the possibility of any long term pricing strategy and pricing becomes tactical.

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1. Introduction

In young markets or products, market expansion leads to sales evolution; however in mature or equilibrium markets, sales are typically stable.[2]

Competitive price responses and sales evolution or disequilibrium are a direct result of Brand competition. Since pricing decisions have a direct impact on profits and prices themselves are a function of supply-side factors like input-costs, commodity prices, a change in long-term pricing strategy is not something that Brand managers would like to do often.

Therefore, when the category itself is growing and evolving, Brand Managers may resort to other options like increasing consumer awareness and product differentiation through different advertising and positioning strategies. But when the markets are mature, there is not too much innovation and differentiation possible in the product, and consumer awareness and distribution hover around the maximum. Therefore there is a greater tendency for Brand Managers to rely on pricing and promotional strategies to improve market share.

Since market share expansion in a mature market comes directly from competitive sales declines, competitive reaction to any new marketing initiative is fierce and retail prices in general reflect the equilibrium condition of consumption.

Recent research in brand competition have leveraged Time Series techniques like Unit Root, Cointegration Tests and Equilibrium-correction models to analyze and model Brand evolution and market equilibrium. They have established that some categories, brand and control factors are stable while others are in various stages of evolution or equilibrium (for e.g. Dekimpe and Hanssens, 1995).
Dekimpe, Hanssens and Silva-Risso (1999) have enumerated the following four scenarios of market evolution:

1. Stable brand sales occurring in a stable category implying that all gains and losses are temporary and brand marketing is tactical in nature.
2. Stable brand sales in an evolving category implies a lack of long-run marketing effectiveness as the brand is unable to establish permanent gains, in spite of operating in an evolving category.
3. Evolving brand sales in a stable category implies that the brand is locked in a strategic battle for long-run position.
4. Evolving Brand sales in an evolving category, implying that firms may be able to improve not only their absolute long-run performance but also their relative position.

A Brand that is reflective of #2 above may not survive for long as the other evolving Brands within the category will most likely annihilate its market share

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[2] In this study we use the concepts of stability and evolution synonymously with stationarity and nonstationarity respectively. We also treat nonstationarity and unit root processes synonymously.

#3 can be considered a direct result of the different performance regimes Brands may go through. Pauwels and Hanssens (2004) have suggested that brand performance is subject to two opposing influences: mean reversion and change and that neither lasts for a long time in mature markets. Therefore it is possible that in a stable category we could have brands that could be going through a regime of evolution.

Therefore both #2 & #3 can be considered as exceptions.

In general if an oligopolistic category such as the one analyzed here, if the category is evolving most likely the brands are too and if the category is stable, so are the brands that comprise it.

For the purposes of this study we can simplify this classification into:
1. Brands with stable sales in a stable category.
2. Brands with evolving sales in an evolving category.

The competitive dynamics in both cases can be captured through the sales response function, by specifying Brand sales as a function of Brand marketing and pricing as well as competitive and environmental factors, using regression-based estimation. This is generally referred to as a ‘marketing-mix’ model (Joseph, 2004). A wide variety of lagged, non-linear and seasonal effects can be controlled for in this method.

Since the sales-response model for #2 would involve regression between nonstationary variables, standard regression estimation and inference become invalid (Granger & Newbold, 1974; Phillips, 1986). In this case, depending on the existence or absence of equilibrium relationships evidenced by cointegration, either an Error/Equilibrium Correction Model, or a model in first differences could be specified (Engle, R. F. & Granger, C. W. J., 1987).

In #1, if both sales and the explanatory variables are stationary, we can estimate the sales response function using the levels of the series. An interesting situation arises if the sales series is stationary, but some of the control variables are nonstationary. The common econometric practice is to difference the nonstationary variables, since there is no Error Correction Representation possible.

According to Joseph, 2004, if the nonstationary explanatory variables are cointegrated, it may possible to include the nonstationary explanatory variables in their levels, since the cointegrating relationship causes their linear combination to be stationary. This is especially possible in mature categories, because of the intense competition between Brands, competing factors like retail prices or promotions neutralize stochastic trends in each other which might otherwise have led to nonstationary sales for one Brand.

For instance, consider the sales of Brand as the function of its own and its competitor’s retail price; if one Brand is a price leader and another a price follower and both price series are nonstationary, they will have a common stochastic trend and in the sales equation these trends will cancel each other out since the own price and the cross-price coefficients/elasticity will have opposite signs.[3]

This gives us an important insight into the dynamics of mature markets; the sales-price relationship for Brands in mature markets, reflect the equilibrium condition of consumption. Competitive price responses in an effort to defend market share, creates a cointegrating condition between Brands' prices, which results in mean-reversion in sales despite nonstationarity of prices; the stochastic shocks in prices do not translate to persistent effects on sales. Sales return to equilibrium levels after temporary periods of disequilibrium. Therefore Sales become a function of not only current period Price changes but also of the lagged disequilibrium response, which causes equilibrium correction in both the Price series and the Sales series. The error correction term therefore belongs in both the difference Price Equation, which would be the Error Correction representation in the sense of Engle and Granger, 1987, but also of the levels Sales equation.

The rest of the paper is organized as follows;
Section 2 reviews the data and also undertakes a preliminary analysis of the competitive environment as a precursor to a more structured Time Series Analysis of the variables, which follows in Section 3. Section 4 develops the functional model for the sales response function for the three brands and Section 4 reviews the empirical model results. Lastly Section 5 discusses the findings and develops conclusions and some directions for further research.

2. Data & Preliminary Competitive Analysis

a. Data:

The empirical data for this study has been collected from Syndicated Point-of-Sales information for a Beverage category. The data represents weekly sales, average retail price, price discounts, distribution, merchandising and Television advertising for three competing brands in four different geographic markets.

Due to client confidentiality and non-disclosure reasons we will refer to the three Brands as Brand A, Brand B and Brand C, and the four markets as Market I, Market II, Market III and Market IV.

The following is a list of variables that were originally tested for inclusion in each of the model estimated:

1. Log-transformed Market-level Sales for Brands A, B and C.

[3] There might be instances where a brand exhibits nonstationarity in one of its marketing activities, whereas its competitor doesn't show a similar nonstationary effect. In this case it might be conjectured that the sales of that brand is not impacted by the absolute levels of the nonstationary variable, only by its increments. For example if a brand exhibits nonstationarity in its price discount variable over time and there is no corresponding cointegrating effect in its competitor's price discounts, it is possible that sales are driven not by the level of price discounting but by the change in price discounting one period to the next (Joseph, 2004).

2. Log-transformed Market-level Average retail price for Brands A, B and C, calculated as the log of the ratio of Total Dollar Sales to Total Equivalized Unit Sales.
3. Price Discounts calculated as the percent difference between non-promoted price and promoted price.
4. Market-level Distribution for Brands A, B and C. This is a syndicated measure and is generally calculated as the average percent of All Commodity Volume (ACV) in a market that had sales for a specific item or brand during a specific time period.
5. Market-level Merchandising represented by the percent of a market's ACV which sold a particular product with any type of trade support- Feature, Display, Feature and Display, temporary Price Reduction (TPR).
6. Commodity price (Average Daily Close aggregated to Weekly frequency using simple averaging) obtained from the New York Board of Trade website for the underlying commodity that is an input for the finished product that makes the category.
7. Seasonality variable created using a 52-week seasonal index of total base sales for all three Brands.[4]
8. Television advertising for Brands A and B, represented by planned Gross Ratings Points collected from the media scheduling plans. Brand C executed very little Television advertising which was not available. The GRP data was transformed assuming a lagged log decay of the effect of TV Advertising on consumers.[5]

All of the above data is for weekly frequency and where they were not, they have been converted to a weekly frequency.

b. Preliminary Competitive Analysis:

We undertook a preliminary competitive analysis of the three brands to determine the competitive landscape. Below is a summary of market-shares[6] and year-over-year market share and average price changes, for the three Brands in each of the four markets:

[4] Base sales as provided through Syndicated data sources excludes promotional volume, hence the seasonal index calculated this way is not influenced by seasonal trade promotions. We added the three Brands base sales as a proxy for total category sales.
[5] Broadbent (1979) introduced the concept of Adstock, which assumes advertising has a delayed effect extending several periods beyond the original exposure. The transformation we use assumes an average decay of about 20% per week for a 5 week period in a distributed lag model.
[6] Market-shares have been calculated assuming these three Brands comprise the category, which is approximately correct since the remaining players have comparatively negligible sales.

1. Market I:

Fig.1 Historical Market Shares

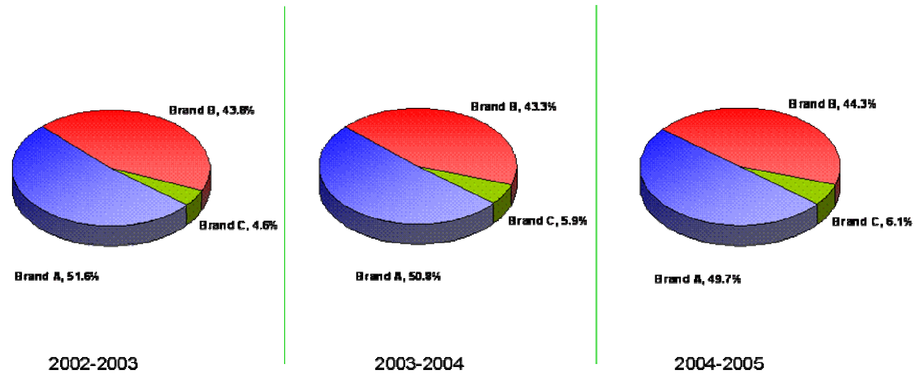
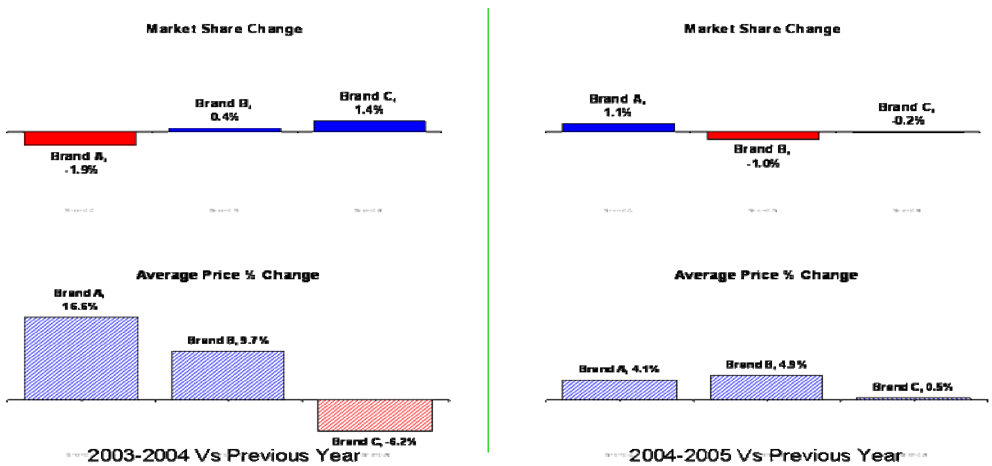


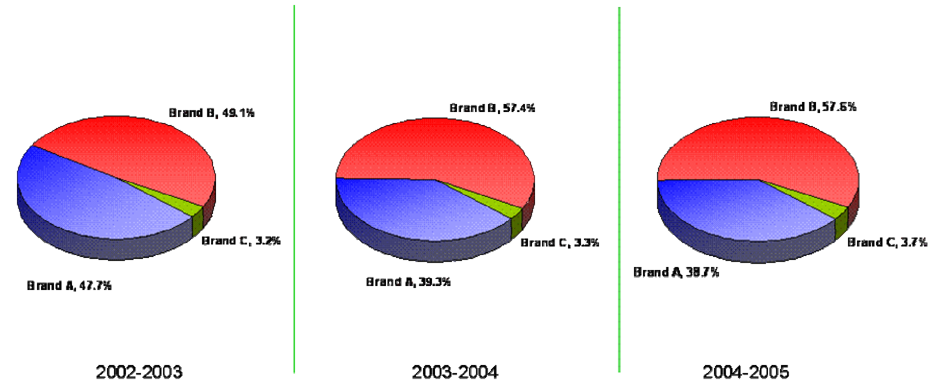
Fig.2 Historical Market Share & Average Price % Change



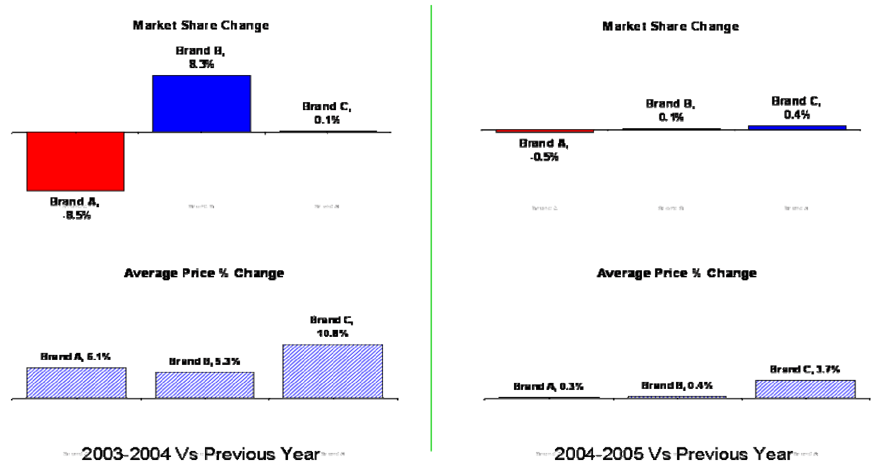
For Market I, the market-shares reveal that Brand A is the dominant player closely followed by Brand B, and Brand C is a relatively small player in the category. Average price changes for Brands A and B are similar. Market share changes seem to be negligible with each Brand more or less maintaining its position in the market.

2. Market II:

<u>Fig.3 Historical Market Shares</u>



<u>Fig.4 Historical Market Share & Average Price % Change</u>



For Market II, Brand B seems to have slightly bettered its position overall by gaining share against Brand A, but in the present year Brand A seems to have stabilized. The Increase in Brand B's market-share doesn't seem to have resulted from a pricing change since it actually increased its price in the same period.

3. Market III:

<u>Fig.5 Historical Market Shares</u>

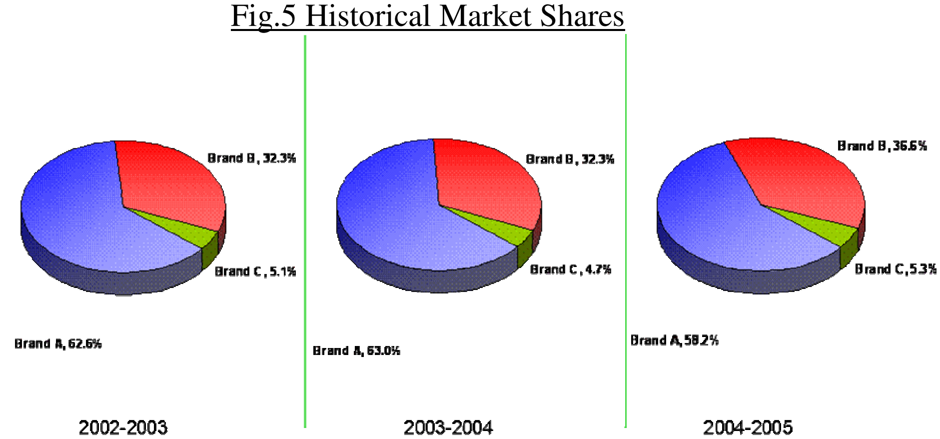
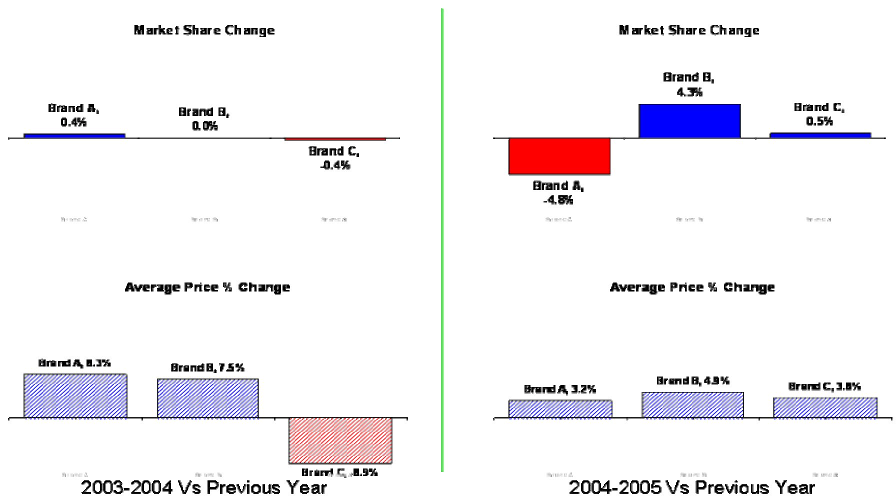


Fig.6 Historical Market Share & Average Price % Change



For Market III, until the present year all Brands seem to have maintained their relative positions. In the present year, Brand B again seems to have made competitive incursions on Brand A, once more not apparently resulting from change in its pricing since Brand B price has increased during the same period.

4. Market IV:

Fig.7 Historical Market Shares

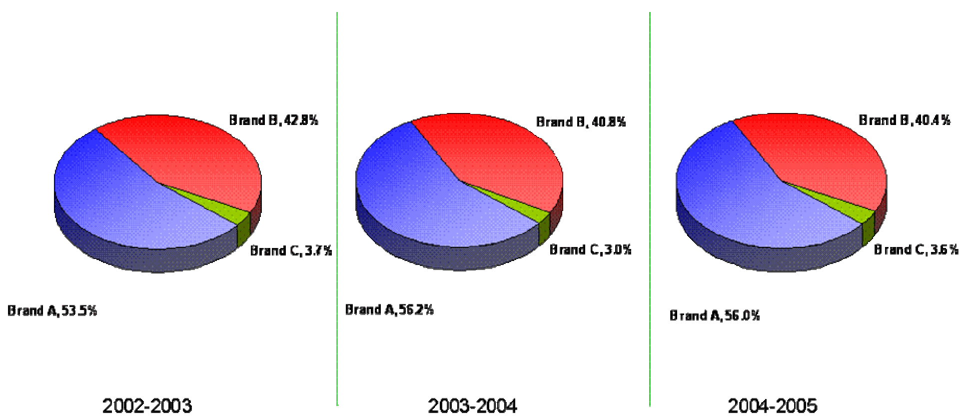
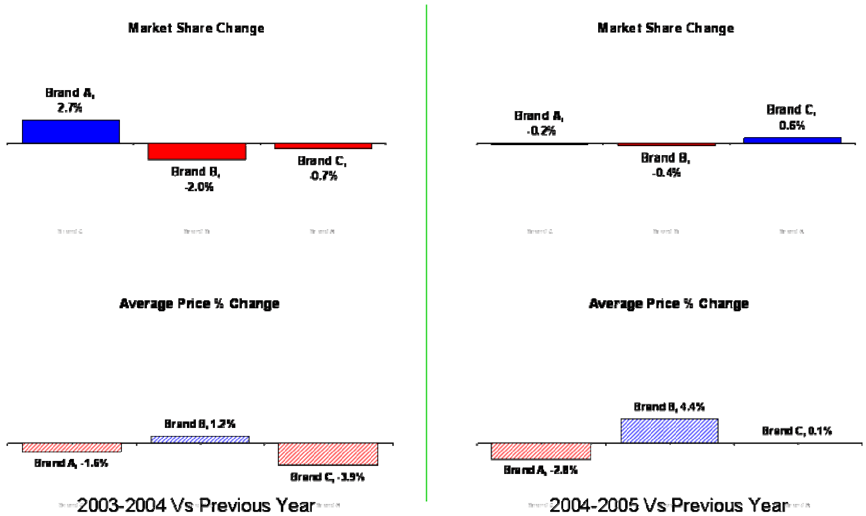


Fig.8 Historical Market Share & Average Price % Change



For Market IV, in spite of average Price fluctuations, all Brands seem to be more or less maintaining relative positions.

Overall, from a preliminary analysis of the market shares and average Price changes in the four markets, we can see that significant Price fluctuations do not correspond to significant long-run market-share changes (This doesn't necessarily imply a low demand elasticity of price, since at the weekly levels, there might be significant short-run impact, which will only be revealed in a response model.

3. Unit Root & Cointegration Testing

a. Unit Root Testing:

We used the Augmented Dickey-Fuller (ADF) Unit Root Test to determine if stochastic trends were present in each of the analyzed series and control variables. We followed a methodology for unit root pre-testing for unknown DGP similar to the one outlined in Enders, 2003, pg. 213-214:

1. Start with the least restrictive of the plausible models (which will generally include a trend and a drift, and test the null hypothesis of nonstationarity. If the null hypothesis is rejected, there is no need to proceed any further. Conclude that the series doesn't contain a unit root.
2. If null is not rejected, test for the significance of the trend. If the trend is not significant we can proceed to the next step. If the trend is significant, conclude there is a unit root.
3. Estimate the model without the trend and test for the presence of a unit root using the $\tau\mu$ (Tau) statistic. If the null is rejected, we can conclude there is no unit root, if the null is not rejected, test for the significance of the mean. If the drift is not significant proceed to the next step. If the drift is significant, conclude there is a unit root.

4. Estimate the model without the trend or drift and use the τ statistic to test for the presence of a unit root. If the null is rejected, conclude that the series has no unit root; otherwise conclude the series has a unit root.

The results of the ADF tests revealed unit roots in the data series for the Average Price for all three Brands in all four markets and also in Commodity Price series. (Please see Appendix I for results of the ADF tests).

b. Cointegration Testing

The detection of stochastic trends in each of the average price series prompts the testing for long run equilibrium or cointegration between the average price series in each market.[7]

Linear combinations of nonstationary variables are also nonstationary, but there may exist some nonstationary variables whose linear combination may be stationary. Such variables are said to be cointegrated (Engle and Granger, 1987).

Engle and Granger, 1987, recommend a Two-stage method for testing for cointegration, but this procedure is ideal for a bivariate cointegration situation as it tests for a single cointegrating relationship. A multivariate model is best served by the Johansen multivariate procedure (Johansen, 1988, and, Johansen and Juselius 1990) as there may be more than one cointegrating relation and this method tests for r cointegrating relations.

We first test all four nonstationary variables in each market (three Brand prices and the Commodity Price) for cointegration. Comparing the calculated value of the *Trace* statistic against critical values provided by the *VARMAX Procedure* in SAS® indicates that in each market the cointegration system has a rank of 2, indicating the presence of two distinct cointegration vectors. Recursively excluding one series each from the test indicates that the Commodity Price is not cointegrated with the Average Price series. This confirms that only the three Average Price series are cointegrated.

4. Empirical Model

The cointegration between the Average Prices for the three Brands in consideration with the fact that the Sales series themselves are stationary gives rise to the logical conclusion that the stationarity of Sales is an outcome of the cointegration between the Price series, which is in turn an obvious corollary to the competition between the Brands.

[7] It is also possible that there might be inter-market effects of price competition, in addition to the within market effects, for e.g. the equilibrium competitive pricing condition between two brands in one market may be determined also by their respective prices in other markets. But we have limited the scope of this paper to 'intra-market' pricing behavior.

If the three Price Series did not cointegrate, their stochastic trends would not cancel out hence the Sales which is a linear combination of the Price series and other explanatory variables, would also have been nonstationary.

Consider a Brand with Sales, S_A and price, P_A.
Then, a simple Sales Response function can then be written as;

$$S_A = \beta_A P_A + \beta_B P_B + e \qquad \text{.........}(1)$$

Where P_B represents the Price of a competitor, β_A and β_B represent the response parameters and e represents the disturbance term.

Now given that $P_A, P_B \sim CI\ (1, 1)$, we have the following long-run model for the two prices:

$$P_A = \acute{\alpha} P_B + \mu \qquad \text{.........}(2)$$

With $\acute{\alpha}$ as the long run coefficient and the disturbance term $\mu \sim I\ (0)$.

(2) can be multiplied with any scalar to derive equivalent cointegrating relationships.

Since in (1) we are fitting an I (0) dependent variable to nonstationary variables that are $CI\ (1, 1)$, we are in effect estimating values of β_A and β_B that result in a linear combination of P_A and P_B that is $I\ (0)$ and therefore, we have a stable regression, with $I\ (0)$ residuals.

When we extend this to the three Brands case as we are analyzing in this study, the presence of the two distinct cointegration relationships makes it a little more complex. The two cointegration equations should be considered distinct from the sales response function while the Sales series are themselves a function of only the changes or differences of the Price Series as long as equilibrium is maintained.

Disequilibrium in one period may be caused by the shock to one of the Price series in the two cointegration equations, which is reflected in both the $I\ (1)$ Price series and $I\ (0)$ Sales series of the corresponding Brand. This disequilibrium is corrected in the next few periods, which is incorporated through the lagged disturbance term from the cointegration equations in the Sales Response function itself. Therefore we assume that the disequilibrium might cause a temporary change in the relative market position of a Brand through a change in sales, but this temporary shift will mean-revert in the next few periods.

With this theory we can proceed to develop the long run model for their Prices and the functional form of sales response for each of the three Brands.

Let S_a, S_b and S_c be the sales for the three Brands *A, B* and *C,* and P_a, P_b and P_c be their respective Prices. For simplicity sake we will leave out for now the intercept terms and the stationary variables like merchandising, discounting and Television advertising.

Therefore the two long run equilibrium models for Prices normalized on P_a are as follows:

$P_a = \beta_1 P_b + \mu_{ab}$ $\mu_{ab} \sim (0, \sigma^2)$ ....(3)

$P_a = \beta_2 P_c + \mu_{ac}$ $\mu_{ac} \sim (0, \sigma^2)$ ....(4)

Where β_1 and β_2 are the long run coefficients and the modified sales response function is as follows:

$S_a = \lambda_1 \Delta P_a + \lambda_2 \Delta P_b + \lambda_3 \Delta P_c + \alpha_1\mu_{ab,\ t-1} + \alpha_2\mu_{ac,\ t-1} + e_1 \quad e_1 \sim (0, \sigma^2)$...........(5)

$S_b = \lambda_4 \Delta P_a + \lambda_5 \Delta P_b + \lambda_6 \Delta P_c + \alpha_1\mu_{ab,\ t-1} + \alpha_2\mu_{ac,\ t-1} + e_2 \quad e_2 \sim (0, \sigma^2)$...........(6)

$S_c = \lambda_7 \Delta P_a + \lambda_8 \Delta P_b + \lambda_9 \Delta P_c + \alpha_1\mu_{ab,\ t-1} + \alpha_2\mu_{ac,\ t-1} + e_3 \quad e_3 \sim (0, \sigma^2)$...........(7)

Where λi can be interpreted as short-term price elasticity (since we are working with logs of both sales and prices), with λ_1, λ_5 and λ_9 as the own price short-term elasticities, and the remaining λi as the short-term cross-elasticities in the respective sales response equations.

Since α_i is the adjustment coefficient for the price disequilibrium which has a negative relation with sales for most goods, typically expected sign for α_i should be the opposite of the expected sign for the adjustment coefficient in the error correction model for Price, i.e., it should be positive.[8] This makes economic sense, since the previous period Price disequilibrium will cause sales to move in the opposite direction and hence the current period sales will offset the price disequilibrium by moving in the same direction as the price disequilibrium. [9]

All the regressors in the Sales Response model are *I (0),* hence standard regression inference is valid. Also since current period sales do not enter current period Price equation there are no simultaneity issues and *OLS* should yield unbiased and consistent estimates. Since we are not differencing the Sales series, we do not lose the low frequency long-run cycles within sales, but the downside is that we might have residual autocorrelation as we don't difference the Sales series, which even though stationary will most likely be positively autocorrelated.

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[8] On the other hand if the error correction term were based on a positively correlated variable like Advertising, the adjustment coefficient would be negative since a positive error in the previous period would lead to a negative correction in Sales this period.

[9] $\mu_{ab,\ t-1}$ and $\mu_{ac,\ t-1}$ are referred to as *ec1*and *ec2* respectively in the results tables.

5. Empirical Results

We have tabulated the empirical results for the three Brands in each of the four markets in Appendix IV.

Markets I & II exhibit significant first order residual correlation. This confirms our expectation that the lack of differencing of the dependent variable might lead to low estimates of the DW statistic. For the worst offender, Brand C in Market II, we used *Proc Autoreg* in SAS® to remove residual correlation. [10]

The equilibrium correction (*ec)* term did not stay in all the models. Out of the 10 Markets in which the *ec* term stayed in 5 came in with a positive coefficient and 4 came in insignificant for $\alpha = 0.1$. Interestingly in 3 markets, the equilibrium adjustment term stayed in with a very significant negative coefficient.

In the markets where the differenced price variables stayed, they have expected signs, although in 4 out of 12 markets they were not significant for $\alpha = 0.1$.

The short-term price elasticities (PE) are in almost all Brands and Markets reasonable and of correct sign. The stationary variables have been included only where they were significant ($\alpha = 0.1$) and of the right sign. R-squares range from 0.44 to 0.74.

Own elasticities range from (2.3259) to (0.1419), with Brand C coming in with generally low elasticities, which makes sense due to its niche market position.

In Market I, Brand A own PE is (0.7781) and there are no short-run Cross-elasticities, but the adjustment elasticity for the long-run relation between Brand A and Brand B is significant (0.5348), indicating that there is no short-run pricing impact between Brand A and Brand B, but they do have a long-run cross-elasticity.

Another interesting example is the model for Brand B sales in Market I, where it has a high and significant own PE (1.0263) and Brand A is complementary to Brand B and the long-run equilibrium is between Brand B and C, therefore the short-term cross-elasticity for Brand C has the expected sign.

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[10] *Proc Autoreg* in SAS® estimates the following equation for the AR error process:

$$\nu t = -\varphi 1\nu t\text{-}1 + \ldots\ldots\ -\varphi i\nu t\text{-}n + \varepsilon t$$

Therefore in the output for Proc Autoreg, AR 'ν' term coefficient signs are reversed, for positively correlated νt, the estimated coefficient will be negative and for negatively correlated νt, the estimated coefficient will be positive. We have reversed the sign of the AR coefficient to convey a more intuitive sense of the underlying correlation structure in the error term.

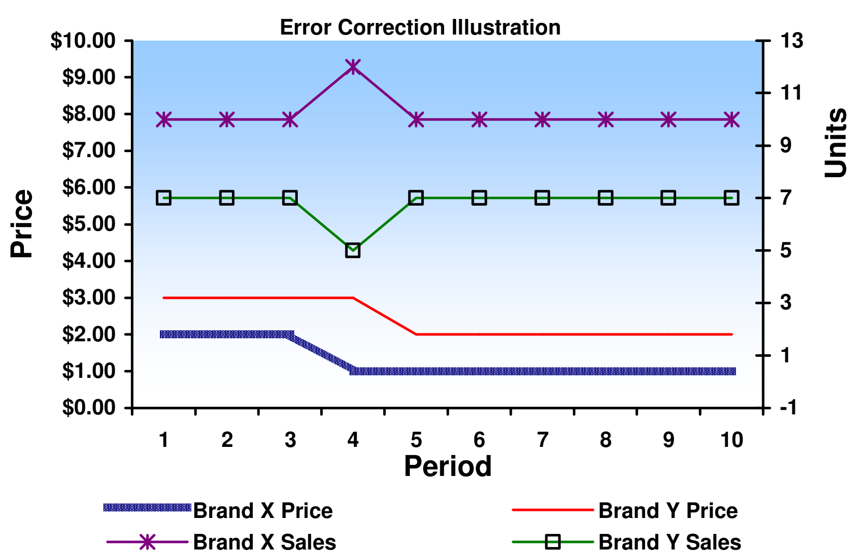
6. Discussion and Conclusions

Although the empirical results from the market models for the three Brands leave a little more to be desired in terms of standard regression diagnostics, and significance of the adjustment coefficients which is in less than 50% of the analyzed models, the preliminary results in this study confirm at least in some cases that there is a very distinct correction mechanism between the nonstationary price variables and the stationary sales series.

The adjustment coefficients may not have an interpretation as speeds of adjustment, but they have an interpretation as elasticities of correction. Since they represent disequilibrium between prices for competing Brands, the coefficient itself is the elasticity of the equilibrium correction. For instance a coefficient of 0.3 would indicate that for every percent price disequilibrium or shock in a given period, the between the two Brands, the following period sales would change by 0.3%. In simple terms it would mean that given the other Brand's price constant a 0.3% of sales gained would be lost for every 1% equilibrium error caused by the Brand cutting its price.

The chart below is a simple illustration of equilibrium correction between the prices and sales in two competing Brands X and Y.

Fig.9 Error Correction Illustration



In period 3, Brand X cuts its price by $1, causing its sales to increase by 2 units at the cost of Brand Y's sales, which dips by 2 units. In the following period, Brand Y cuts its price by $1, restoring its lost sales, and sales return to equilibrium levels, although the price series, which are nonstationary with persistent shocks, do not revert to their previous levels.

In a real market, the structure of competition is much more complex, with possibly several Brands vying for market-share. In such a complex scenario, the actions of one player reverberate through several other Brands in the category before equilibrium is restored. Also a small niche player might be insulated from the shocks in the prices of the larger players in the category although it might cointegrate with their prices due to common input costs, which is why we did not see the adjustment term staying in all models. The negative adjustment coefficients are harder to explain as it does not make sense that the previous period's disequilibrium would lead to further disequilibrium, unless the sales were nonstationary too, in which case it should have been differenced and an Error Correction Model in the traditional sense would become applicable. In the case of stationary sales, negative price adjustment coefficients might be indicative of an incorrect rejection of the null of unit root.

The above results provide a potential method to incorporate a hybrid approach of levels regression and Error Correction Modeling to better represent the dynamics of competitive pricing in mature markets.

Appendix I- Unit Root Tests

Augmented Dickey-Fuller Unit Root Tests								
Market	**Series**	**Type**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Market I	Brand A Average Price	Zero Mean	-0.0477	0.6709	-0.08	0.6549		
Market I	Brand A Average Price	Single Mean	-14.5128	0.0407	-2.36	0.1549	2.8	0.357
Market I	Brand A Average Price	Trend	-27.8027	0.0102	-3.39	0.056	6.03	0.0665
Market I	Brand A Sales	Zero Mean	-0.0384	0.673	-0.12	0.6401		
Market I	Brand A Sales	Single Mean	-98.1445	0.0012	-6.06	<.0001	18.34	0.001
Market I	Brand A Sales	Trend	-115.961	0.0001	-6.54	<.0001	21.55	0.001
Market I	Brand B Average Price	Zero Mean	0.1377	0.7138	0.3	0.7718		
Market I	Brand B Average Price	Single Mean	-18.486	0.0143	-2.64	0.0871	3.63	0.1467
Market I	Brand B Average Price	Trend	-40.7763	0.0005	-3.69	0.0259	6.83	0.0364
Market I	Brand B Sales	Zero Mean	-0.0572	0.6687	-0.17	0.6226		
Market I	Brand B Sales	Single Mean	-156.054	0.0001	-7.09	<.0001	25.12	0.001
Market I	Brand B Sales	Trend	-157.817	0.0001	-7.1	<.0001	25.25	0.001
Market I	Brand C Average Price	Zero Mean	-0.0675	0.6663	-0.18	0.6214		
Market I	Brand C Average Price	Single Mean	-29.8981	0.0012	-3.33	0.0153	5.55	0.0227
Market I	Brand C Average Price	Trend	-35.4858	0.0015	-3.41	0.0541	5.96	0.0703
Market I	Brand C Sales	Zero Mean	-0.0318	0.6745	-0.13	0.6393		
Market I	Brand C Sales	Single Mean	-83.476	0.0012	-5.67	<.0001	16.05	0.001
Market I	Brand C Sales	Trend	-84.1819	0.0005	-5.65	<.0001	15.98	0.001
Market II	Brand A Average Price	Zero Mean	0.0684	0.6975	0.29	0.7698		
Market II	Brand A Average Price	Single Mean	-16.5449	0.0239	-2.51	0.1141	3.24	0.244
Market II	Brand A Average Price	Trend	-20.4496	0.0549	-2.8	0.199	3.97	0.3847
Market II	Brand A Sales	Zero Mean	-0.0955	0.66	-0.29	0.5802		
Market II	Brand A Sales	Single Mean	-106.419	0.0001	-6.09	<.0001	18.53	0.001
Market II	Brand A Sales	Trend	-134.387	0.0001	-6.7	<.0001	22.51	0.001
Market II	Brand B Average Price	Zero Mean	0.1496	0.7167	0.57	0.8392		
Market II	Brand B Average Price	Single Mean	-18.5646	0.014	-2.54	0.1077	3.48	0.1853
Market II	Brand B Average Price	Trend	-22.5696	0.0343	-2.81	0.196	4	0.3777
Market II	Brand B Sales	Zero Mean	-0.0915	0.6609	-0.33	0.566		
Market II	Brand B Sales	Single Mean	-58.6576	0.0012	-4.89	0.0001	11.98	0.001
Market II	Brand B Sales	Trend	-62.1938	0.0005	-4.99	0.0004	12.45	0.001
Market II	Brand C Average Price	Zero Mean	0.0576	0.695	0.17	0.7356		
Market II	Brand C Average Price	Single Mean	-23.9901	0.0034	-3.03	0.0348	4.65	0.0495
Market II	Brand C Average Price	Trend	-57.5115	0.0005	-4.18	0.0061	8.74	0.001
Market II	Brand C Sales	Zero Mean	-0.1442	0.649	-0.44	0.5216		
Market II	Brand C Sales	Single Mean	-48.0374	0.0012	-4.39	0.0005	9.67	0.001
Market II	Brand C Sales	Trend	-49.8973	0.0005	-4.47	0.0023	10.01	0.001
Market III	Brand A Average Price	Zero Mean	0.1608	0.7194	0.58	0.8407		
Market III	Brand A Average Price	Single Mean	-10.1252	0.1248	-1.66	0.4514	1.6	0.6638
Market III	Brand A Average Price	Trend	-19.0469	0.0744	-2.49	0.334	3.53	0.4721
Market III	Brand A Sales	Zero Mean	-0.0919	0.6608	-0.22	0.6047		
Market III	Brand A Sales	Single Mean	-204.292	0.0001	-7.69	<.0001	29.53	0.001
Market III	Brand A Sales	Trend	-205.739	0.0001	-7.71	<.0001	29.9	0.001
Market III	Brand B Average Price	Zero Mean	0.1705	0.7217	0.8	0.8847		
Market III	Brand B Average Price	Single Mean	-7.6001	0.2327	-1.53	0.5172	1.55	0.6748
Market III	Brand B Average Price	Trend	-24.0231	0.0247	-2.85	0.1804	4.25	0.3275
Market III	Brand B Sales	Zero Mean	-0.1341	0.6513	-0.42	0.5293		
Market III	Brand B Sales	Single Mean	-129.596	0.0001	-6.78	<.0001	23.01	0.001
Market III	Brand B Sales	Trend	-135.636	0.0001	-6.88	<.0001	23.68	0.001
Market III	Brand C Average Price	Zero Mean	0.0688	0.6976	0.13	0.7231		
Market III	Brand C Average Price	Single Mean	-34.2877	0.0012	-3.27	0.0184	5.4	0.0264
Market III	Brand C Average Price	Trend	-38.7239	0.0007	-3.28	0.0731	5.55	0.0917
Market III	Brand C Sales	Zero Mean	-0.1154	0.6555	-0.33	0.5654		
Market III	Brand C Sales	Single Mean	-249.341	0.0001	-8.14	<.0001	33.17	0.001
Market III	Brand C Sales	Trend	-269.615	0.0001	-8.3	<.0001	34.44	0.001
Market IV	Brand A Average Price	Zero Mean	0.0354	0.6898	0.13	0.7232		
Market IV	Brand A Average Price	Single Mean	-20.6792	0.008	-2.66	0.0842	3.56	0.1629
Market IV	Brand A Average Price	Trend	-20.7311	0.0516	-2.49	0.3342	3.51	0.4765
Market IV	Brand A Sales	Zero Mean	-0.0295	0.675	-0.11	0.6461		
Market IV	Brand A Sales	Single Mean	-160.867	0.0001	-7.2	<.0001	25.91	0.001
Market IV	Brand A Sales	Trend	-169.446	0.0001	-7.23	<.0001	26.26	0.001
Market IV	Brand B Average Price	Zero Mean	0.1506	0.7169	0.57	0.8383		
Market IV	Brand B Average Price	Single Mean	-18.1747	0.0155	-1.95	0.3102	2.1	0.5349
Market IV	Brand B Average Price	Trend	-30.7527	0.005	-2.72	0.2286	4.47	0.2833
Market IV	Brand B Sales	Zero Mean	-0.0683	0.6662	-0.26	0.591		
Market IV	Brand B Sales	Single Mean	-151.949	0.0001	-7.02	<.0001	24.68	0.001
Market IV	Brand B Sales	Trend	-152.289	0.0001	-7.01	<.0001	24.56	0.001
Market IV	Brand C Average Price	Zero Mean	-0.0189	0.6774	-0.07	0.6599		
Market IV	Brand C Average Price	Single Mean	-42.7607	0.0012	-3.79	0.0038	7.18	0.001
Market IV	Brand C Average Price	Trend	-42.6	0.0005	-3.76	0.0212	7.13	0.0283
Market IV	Brand C Sales	Zero Mean	-0.051	0.6701	-0.16	0.6271		
Market IV	Brand C Sales	Single Mean	-149.239	0.0001	-6.99	<.0001	24.4	0.001
Market IV	Brand C Sales	Trend	-150.65	0.0001	-6.97	<.0001	24.32	0.001
All Markets	Commodity Price	Zero Mean	0.8925	0.8925	1.88	0.9855		
All Markets	Commodity Price	Single Mean	1.0854	0.9898	0.49	0.9858	1.75	0.6237
All Markets	Commodity Price	Trend	-4.7298	0.8364	-1.09	0.9268	1.45	0.8889

Appendix II- Johansen Cointegration Rank Tests

Average Price Series & Commodity Price

Market I						
Cointegration Rank Test						
H_0: Rank=r	**H_1: Rank>r**	**Eigenvalue**	**Trace**	**Critical Value**	**DriftInECM**	**DriftInProcess**
0	0	0.2376	94.37	47.21	Constant	Linear
1	1	0.1827	52.59	29.38		
2	2	0.1296	21.52	15.34		
3	3	0.0009	0.13	3.84		
Market II						
Cointegration Rank Test						
H_0: Rank=r	**H_1: Rank>r**	**Eigenvalue**	**Trace**	**Critical Value**	**DriftInECM**	**DriftInProcess**
0	0	0.3646	123.05	47.21	Constant	Linear
1	1	0.1861	53.21	29.38		
2	2	0.1302	21.5	15.34		
3	3	0.0001	0.02	3.84		
Market III						
Cointegration Rank Test						
H_0: Rank=r	**H_1: Rank>r**	**Eigenvalue**	**Trace**	**Critical Value**	**DriftInECM**	**DriftInProcess**
0	0	0.3303	147.71	47.21	Constant	Linear
1	1	0.2572	85.97	29.38		
2	2	0.2291	40.17	15.34		
3	3	0.0006	0.09	3.84		
Market IV						
Cointegration Rank Test						
H_0: Rank=r	**H_1: Rank>r**	**Eigenvalue**	**Trace**	**Critical Value**	**DriftInECM**	**DriftInProcess**
0	0	0.3669	137.75	47.21	Constant	Linear
1	1	0.2361	67.34	29.38		
2	2	0.1544	25.88	15.34		
3	3	0.0003	0.05	3.84		

Results for the Johansen Cointegration Rank Tests Excluding Commodity Price

Market I						
Cointegration Rank Test						
H_0: Rank=r	**H_1: Rank>r**	**Eigenvalue**	**Trace**	**Critical Value**	**DriftInECM**	**DriftInProcess**
0	0	0.2262	77.04	29.38	Constant	Linear
1	1	0.1479	37.55	15.34		
2	2	0.0804	12.91	3.84		
Market II						
Cointegration Rank Test						
H_0: Rank=r	**H_1: Rank>r**	**Eigenvalue**	**Trace**	**Critical Value**	**DriftInECM**	**DriftInProcess**
0	0	0.2262	77.1	34.8	Constant	Constant
1	1	0.1479	37.6	19.99		
2	2	0.0807	12.96	9.13		
Market III						
Cointegration Rank Test						
H_0: Rank=r	**H_1: Rank>r**	**Eigenvalue**	**Trace**	**Critical Value**	**DriftInECM**	**DriftInProcess**
0	0	0.3593	108.46	29.38	Constant	Linear
1	1	0.1656	39.9	15.34		
2	2	0.075	12.01	3.84		
Market IV						
Cointegration Rank Test						
H_0: Rank=r	**H_1: Rank>r**	**Eigenvalue**	**Trace**	**Critical Value**	**DriftInECM**	**DriftInProcess**
0	0	0.3593	108.66	34.8	Constant	Constant
1	1	0.1657	40.1	19.99		
2	2	0.0762	12.21	9.13		

Appendix III- Empirical Results (Unadjusted for Autoregressive Error)

Market I- Brand A

Ordinary Least Squares Estimates					
SSE	13.0900024	DFE	148		
MSE	0.08845	Root MSE	0.2974		
SBC	92.0805861	AIC	70.7766103		
Regress R-Square	0.5294	Total R-Square	0.5294		
Durbin-Watson	1.4035	Pr < DW	<.0001		
Pr > DW	1				
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-2.856	4.8561	-0.59	0.5573
ΔPa	1	-0.7781	0.1383	-5.62	<.0001
ACV_Distribution_Brand A	1	0.1109	0.0487	2.28	0.0242
ACV on Any Promotion_Brand A	1	0.011	0.001166	9.45	<.0001
ACV on Any Promotion_Brand B	1	-0.005226	0.001404	-3.72	0.0003
Seasonal Index	1	0.0104	0.002999	3.45	0.0007
ec1	1	0.5348	0.221	2.42	0.0167

Market I- Brand B

Ordinary Least Squares Estimates					
SSE	13.6998246	DFE	147		
MSE	0.0932	Root MSE	0.30528		
SBC	104.181823	AIC	79.8344223		
Regress R-Square	0.4471	Total R-Square	0.4471		
Durbin-Watson	1.5904	Pr < DW	0.0036		
Pr > DW	0.9964				
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	8.1956	0.3229	25.38	<.0001
ΔPb	1	-1.0263	0.1586	-6.47	<.0001
ΔPa	1	-0.3146	0.1428	-2.2	0.0292
ΔPc	1	0.6114	0.277	2.21	0.0289
ACV on Any Promotion_Brand B	1	0.007648	0.001446	5.29	<.0001
RFG_DC2	1	0.0414	0.013	3.19	0.0017
Seasonal Index	1	0.009056	0.00323	2.8	0.0057
ec2	1	0.5417	0.1829	2.96	0.0036

Market I- Brand C

Ordinary Least Squares Estimates					
SSE	4.28611202	DFE	148		
MSE	0.02896	Root MSE	0.17018		
SBC	-80.972067	AIC	-102.27604		
Regress R-Square	0.5625	Total R-Square	0.5625		
Durbin-Watson	1.3396	Pr < DW	<.0001		
Pr > DW	1				
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	5.6196	0.4562	12.32	<.0001
ΔPc	1	-0.8906	0.1557	-5.72	<.0001
ACV_Distribution_Brand C	1	0.0205	0.004939	4.14	<.0001
Price_Discount_Brand C	1	0.006985	0.001176	5.94	<.0001
ACV on Any Promotion_Brand A	1	-0.002839	0.000654	-4.34	<.0001
ACV on Any Promotion_Brand B	1	-0.002076	0.000807	-2.57	0.011
ec1	1	-0.3147	0.1178	-2.67	0.0084

Market II- Brand A

Ordinary Least Squares Estimates					
SSE	12.1974302	DFE	145		
MSE	0.08412	Root MSE	0.29003		
SBC	96.2642235	AIC	65.8299723		
Regress R-Square	0.5075	Total R-Square	0.5075		
Durbin-Watson	1.4736	Pr < DW	0.0001		
Pr > DW	0.9999				
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.4762	3.3899	0.14	0.8885
ΔPa	1	-0.6013	0.2403	-2.5	0.0134
ACV_Distribution_Brand A	1	0.0791	0.0342	2.31	0.0221
ACV on Any Promotion_Brand A	1	0.008106	0.001225	6.62	<.0001
Price Discount_Brand A	1	0.0107	0.002591	4.13	<.0001
ACV on Any Promotion_Brand B	1	-0.002302	0.001106	-2.08	0.0391
Price Discount_Brand B	1	-0.005617	0.00244	-2.3	0.0227
ACV on Any Promotion_Brand B	1	-0.004169	0.001534	-2.72	0.0074
Seasonal Index	1	0.009597	0.00312	3.08	0.0025
ec2	1	-0.3262	0.2383	-1.37	0.1732

Market II- Brand B

Ordinary Least Squares Estimates					
SSE	8.22565854	DFE	147		
MSE	0.05596	Root MSE	0.23655		
SBC	21.1188229	AIC	-0.1398453		
Regress R-Square	0.6645	Total R-Square	0.6645		
Durbin-Watson	1.3287	Pr < DW	<.0001		
Pr > DW	1				
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	8.6851	0.1859	46.71	<.0001
ΔPb	1	-0.9668	0.2386	-4.05	<.0001
ACV on Any Promotion_Brand B	1	0.006336	0.000879	7.21	<.0001
Price Discount_Brand B	1	0.0171	0.002158	7.94	<.0001
Seasonal Index	1	0.007309	0.002002	3.65	0.0004
Lagged Δ Commodity Price	1	-0.0168	0.007402	-2.28	0.0243
ec1	1	-0.8184	0.2951	-2.77	0.0063

Market II- Brand C

Ordinary Least Squares Estimates					
SSE	7.45445901	DFE	147		
MSE	0.05071	Root MSE	0.22519		
SBC	9.85337166	AIC	-14.494029		
Regress R-Square	0.5439	Total R-Square	0.5439		
Durbin-Watson	1.0715	Pr < DW	<.0001		
Pr > DW	1				
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	5.6312	0.2646	21.28	<.0001
ΔPc	1	-0.1523	0.2219	-0.69	0.4934
ACV_Distribution_Brand C	1	0.0204	0.002497	8.17	<.0001
ACV on Any Promotion_Brand B	1	0.003542	0.001225	2.89	0.0044
Price_Discount_Brand C	1	0.005545	0.00153	3.62	0.0004
ACV on Any Promotion_Brand A	1	-0.004387	0.000929	-4.72	<.0001
Seasonal Index	1	0.003079	0.001833	1.68	0.0951
ec2	1	-0.1454	0.1838	-0.79	0.4303

Market II- Brand C Adjusted for Autoregressive Error

Maximum Likelihood Estimates					
SSE	5.63004207	DFE	146		
MSE	0.03856	Root MSE	0.19637		
SBC	-28.278734	AIC	-55.66956		
Regress R-Square	0.3899	Total R-Square	0.6555		
Durbin-Watson	1.9599	Pr < DW	0.3768		
Pr > DW	0.6232	0			
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	5.7453	0.3342	17.19	<.0001
ΔPc	1	-0.0695	0.187	-0.37	0.7106
ACV_Distribution_Brand C	1	0.0183	0.003015	6.06	<.0001
ACV on Any Promotion_Brand B	1	0.003388	0.001588	2.13	0.0345
Price_Discount_Brand C	1	0.003657	0.00144	2.54	0.0121
ACV on Any Promotion_Brand A	1	-0.003044	0.000889	-3.42	0.0008
Seasonal Index	1	0.002729	0.002545	1.07	0.2854
ec2	1	-0.1134	0.2124	-0.53	0.5942
AR1	1	0.5317	0.0736	-7.23	<.0001

Market III- Brand A

Ordinary Least Squares Estimates					
SSE	21.9211828	DFE	149		
MSE	0.14712	Root MSE	0.38356		
SBC	166.955883	AIC	148.695333		
Regress R-Square	0.5602	Total R-Square	0.5602		
Durbin-Watson	1.7917	Pr < DW	0.0729		
Pr > DW	0.9271				
Intercept	1	8.5964	0.1977	43.47	<.0001
ΔPa	1	-2.3259	0.2742	-8.48	<.0001
ACV on Any Promotion_Brand A	1	0.0129	0.001823	7.07	<.0001
ACV on Any Promotion_Brand B	1	-0.004147	0.001924	-2.16	0.0327
Seasonal Index	1	0.008025	0.002113	3.8	0.0002
ec1	1	0.4308	0.4263	1.01	0.3139

Market III- Brand B

Ordinary Least Squares Estimates					
SSE	11.6606243	DFE	149		
MSE	0.07826	Root MSE	0.27975		
SBC	69.1143497	AIC	50.853799		
Regress R-Square	0.5527	Total R-Square	0.5527		
Durbin-Watson	1.6578	Pr < DW	0.0136		
Pr > DW	0.9864				
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	8.6315	0.1541	56.01	<.0001
ΔPb	1	-1.2963	0.2232	-5.81	<.0001
ΔPc	1	0.159	0.1411	1.13	0.2616
ACV on Any Promotion_Brand B	1	0.0141	0.001408	9.99	<.0001
Seasonal Index	1	0.003196	0.001481	2.16	0.0325
ec2	1	0.239	0.1784	1.34	0.1824

Market III- Brand C

Ordinary Least Squares Estimates					
SSE	5.01991347	DFE	146		
MSE	0.03438	Root MSE	0.18543		
SBC	-46.390154	AIC	-73.78098		
Regress R-Square	0.7409	Total R-Square	0.7409		
Durbin-Watson	1.5349	Pr < DW	0.001		
Pr > DW	0.999				
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	5.9531	0.4334	13.73	<.0001
ΔPc	1	-1.1276	0.1251	-9.01	<.0001
ACV_Distribution_Brand C	1	0.0212	0.007753	2.74	0.0069
ACV on Any Promotion_Brand B	1	0.005713	0.002263	2.52	0.0127
Price_Discount_Brand C	1	0.007139	0.001166	6.12	<.0001
Price Discount_Brand B	1	-0.002612	0.001452	-1.8	0.0742
Difference of Commodity Price	1	-0.0129	0.005804	-2.22	0.0278
ec1	1	-0.4074	0.209	-1.95	0.0532
ec2	1	-0.6357	0.1344	-4.73	<.0001

Market IV- Brand A

Ordinary Least Squares Estimates					
SSE	10.03242	DFE	148		
MSE	0.06779	Root MSE	0.26036		
SBC	50.8464153	AIC	29.5424394		
Regress R-Square	0.5249	Total R-Square	0.5249		
Durbin-Watson	1.8389	Pr < DW	0.1208		
Pr > DW	0.8792				
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	8.466	0.1936	43.72	<.0001
ΔPa	1	-0.345	0.2162	-1.6	0.1127
ACV on Any Promotion_Brand A	1	0.009935	0.001285	7.73	<.0001
Price Discount_Brand A	1	0.003317	0.001835	1.81	0.0728
RMH_GRP	1	0.000579	0.000324	1.79	0.0755
ACV on Any Promotion_Brand B	1	-0.003102	0.001273	-2.44	0.016
Seasonal Index	1	0.009027	0.002112	4.27	<.0001

Market IV- Brand B

Ordinary Least Squares Estimates					
SSE	7.15429635	DFE	147		
MSE	0.04867	Root MSE	0.22061		
SBC	3.48297798	AIC	-20.864423		
Regress R-Square	0.5612	Total R-Square	0.5612		
Durbin-Watson	1.8564	Pr < DW	0.1392		
Pr > DW	0.8608				
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	8.3652	0.1645	50.86	<.0001
ΔPb	1	-0.8216	0.157	-5.23	<.0001
ACV on Any Promotion_Brand B	1	0.008836	0.001111	7.95	<.0001
RFG_DC1	1	0.0287	0.009281	3.1	0.0023
ACV on Any Promotion_Brand A	1	-0.003009	0.001002	-3	0.0031
Seasonal Index	1	0.00845	0.001825	4.63	<.0001
ΔCommodity Price	1	-0.0202	0.007041	-2.87	0.0048
ec2	1	0.4696	0.1855	2.53	0.0124

Market IV- Brand B

Ordinary Least Squares Estimates					
SSE	6.09292363	DFE	150		
MSE	0.04062	Root MSE	0.20154		
SBC	-36.537977	AIC	-51.755102		
Regress R-Square	0.4683	Total R-Square	0.4683		
Durbin-Watson	1.2747	Pr < DW	<.0001		
Pr > DW	1				
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	6.2005	0.1811	34.24	<.0001
ΔPc	1	-0.1419	0.1517	-0.94	0.351
ΔPa	1	0.0528	0.1362	0.39	0.699
ACV_Distribution_Brand C	1	0.0114	0.003161	3.6	0.0004
ACV on Any Promotion_Brand B	1	0.0188	0.002141	8.76	<.0001

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