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WORKING PAPER

Dynamic cross-sales effects of price promotions: Empirical generalizations

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November 2004

2004/276

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D/2004/7012/62

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Abstract

In this research we use the framework of market-basket analysis and techniques from modern multivariate time-series analysis to measure and explain the dynamic impact of a price promotion on the sales of a complementary product. The large scale of this research enables us to derive empirical generalizations.

We contribute to the literature in drawing the following conclusions: Firstly, we illustrate that using an intense promotion strategy, characterized by deeper and more frequent price promotions, has a negative impact on the cross-price effect. Secondly, we show that using the same brand name (umbrella branding) for two complements has a beneficial influence on the cross-price effect. Finally, we show that price levels of the products are important moderators in explaining persistent cross-price effects.

Keywords: Empirical generalizations; market-basket analysis; cross-price elasticities; promotion strategy; multivariate time-series techniques; retailing.

Acknowledgements

We are indebted to the Fund for Scientific Research Flanders (FWO Vlaanderen) for financial support (Grant no.
G005501) and to the anonymous company that supplied the data to perform the analysis.

1. Introduction

It is well known that the response of marketing activities is not limited to the brand or the product itself [15]. Complementary products, for example, can benefit from external marketing activities, whereas substitute products can be harmed by such activities. The aim of this research is to derive empirical generalizations concerning the cross-sales effect of price promotions of complementary products. These generalizations in turn can help marketing managers in their decision-making process [30]. Moreover, they represent an important step towards building a decision support system. The level of analysis is the stock-keeping unit (sku). To the best of our knowledge, this is the first large-scale research that studies cross-price effects at the sku level.

Using market-basket analysis (association-rule discovery) allows us to select complementary products. For every selected product couple, we simulate successively two price promotions and measure the impact on the sales of the associated product using impulse-response functions. Finally, we explain the observed variations in cross-price effects using a set of moderating variables. We conduct hereby separate analysis for the short run and the long run.

The paper is organized as follows: We first discuss the relevant literature concerning cross-price effects of price promotions and show how this paper contributes to current literature. We then develop our methodological framework, followed by a description of the database. In part five, we discuss the results of our research. Part six summarizes the conclusions and we end with limitations and directions for future research.

2. Literature

As Neslin [20] points out in his monograph on sales promotions, research concerning cross-sales effects of promotions is rather scarce. [28] and [18] use sales-response models to measure cross-price effects in a limited set of predefined complement and substitute brands. Both studies report asymmetric cross-price effects. Promotions in cake mix, for example, have a bigger impact on the sales of frosting than the reverse.

Other studies use the shopping basket as unit of analysis for identifying cross-price effects. [17] and [24] use a multivariate logit model to predict and explain the composition of a shopping basket. They both add the price of complementary categories as an independent variable, and both studies find weak cross-price effects. [7] use bivariate hazard models to investigate the purchase timing behavior of households in two product categories. For the categories pasta and pasta sauce, they find that promoting one of the categories results in a higher purchase probability of both categories.

Although the aforementioned studies all find significant cross-price effects, they are not well suited to derive generalizations on why cross-price effects tend to differ for different categories, brands or products. This is due to the fact that in these studies only a limited set of predefined products is analyzed. The set of analyzed products in the aforementioned studies are summarized in Table 1.

INSERT TABLE 1 ABOUT HERE

However, a study by Nijs et al.[27] is of particular interest in the derivation of empirical generalizations concerning cross-price elasticities of complementary products. Nijs et al.[27] investigate the cross-sales effect of price promotions at the category level. More specifically, they study 79 food categories. They measure the effect of price promotions of the top two brands in each category on the sales of the 78 other categories. This design results in the computations of 12,324 cross-price elasticities.

This study differs from the study by Nijs et al.[27], since we measure cross-price effects at the sku level. This makes it possible to add different variables to our analysis, like the existence of an umbrella-branding effect.

3. Methodology

Market Basket Analysis

In this study, we measure the cross-sales effect of price promotions at the sku level. Since our database contains data concerning more than 15,000 different sku's, this results in more than 112,492,500 sku pairs that could be investigated. Since we make use of a bootstrap procedure in the derivation of the cross-price effect, this would lead to an unmanageable computational load. Hence, we first need a method to select combinations of sku's which could be potentially interesting in terms of cross-price effects. We use market basket analysis to select interesting product associations.

In the data-mining community, market baskets are typically analyzed using the framework of association rules. Association-rule discovery was introduced in [2]. They proposed two parameters to measure the strength of an association: support and confidence. [4] introduced a third parameter: interest.

More specifically, the three parameters are defined as follows:

Consider the association rule Y ➔ Z, where Y and Z are two products[1]. Y is called the antecedent en Z is called the consequent.

Support of the rule: the percentage of all baskets that contain both product Y and Z

Or support = $P(Y \wedge Z)$.

Confidence of the rule: the percentage of all the baskets containing Y that also contain Z. Hence, confidence is a conditional probability, i.e. $P(Z|Y)$

Or confidence = $P(Y \wedge Z)/P(Y)$.

Interest of the rule: measures the statistical dependence of the rule, by relating the observed frequency of occurrence ($P(Y \wedge Z)$) to the expected frequency of co-occurrence under the assumption of conditional independence of Y and Z ($P(Y)*P(Z)$)

Or interest = $P(Y \wedge Z)/(P(Y)*P(Z))$.

Association-rule discovery is the process of finding strong product associations with a minimum support and/or confidence and an interest of at least one.

Association-rule discovery has become a prevailing topic in the data-mining community, as can be deduced from the large number of publications based on the proposed framework in [2]. However, it should be noted that most of these publications focus on algorithms to find association rules [14]. Only a small portion of the association-rule literature is concerned with applications of the framework[2]. This research attempts to fill this void, by describing and explaining how a price promotion of a product influences the sales of the associated product.

Multivariate Time-Series analysis

A four-equation Vector Autoregressive (VAR) model is estimated for each selected product couple. The four equations constitute of the weekly price series and the weekly sales series of both products, which are the four endogenous variables in the model. Three exogenous variables were added to the model, in order to control for factors that could have influenced the sales of the two products. Firstly, a variable measuring the total weekly sales of the retailer was added, which controls for possible events that influenced sales of the two products, as Christmas peaks. For both products, a dummy variable is added, which indicates whether the product was featured in the weekly folder of the retailer. Hence, for every product association, the following system was estimated:

$$\begin{bmatrix} \ln(Sa_t) \\ \ln(Sb_t) \\ \ln(Pa_t) \\ \ln(Pb_t) \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} + \begin{bmatrix} \delta_{Sa} \\ \delta_{Sb} \\ \delta_{Pa} \\ \delta_{Pb} \end{bmatrix} t + \sum_{i=1}^{8} \begin{bmatrix} a_{11}^i & a_{12}^i & a_{13}^i & a_{14}^i \\ a_{21}^i & a_{22}^i & a_{23}^i & a_{24}^i \\ a_{31}^i & a_{32}^i & a_{33}^i & a_{34}^i \\ a_{41}^i & a_{42}^i & a_{43}^i & a_{44}^i \end{bmatrix} \begin{bmatrix} \ln(Sa_{t-i}) \\ \ln(Sb_{t-i}) \\ \ln(Pa_{t-i}) \\ \ln(Pb_{t-i}) \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \\ b_{41} & b_{42} & b_{43} \end{bmatrix} \begin{bmatrix} Fa_t \\ Fb_t \\ \ln(S_t) \end{bmatrix} + \begin{bmatrix} \varepsilon_{Sa,t} \\ \varepsilon_{Sb,t} \\ \varepsilon_{Pa,t} \\ \varepsilon_{Pb,t} \end{bmatrix}$$

Sa_t = Sales in units of product A in period t
Sb_t = Sales in units of product B in period t
Pa_t = Price of product A in period t
Pb_t = Price of product B in period t
t = Deterministic trend variable
Fa_t = a dummy-variable that takes the value one if product A was featured in the folder in t.
Fb_t = a dummy-variable that takes the value one if product B was featured in the folder in t.
S_t = total sales of all products in period t.

We conducted unit-root tests on the four endogenous variables to decide whether these variables should enter the system in levels or in differences. We hereby followed the testing procedure as proposed in [9], which is based on the augmented Dickey-Fuller test. This procedure classifies a series as being a stationary, a unit root or a trend-stationary process. Series with a unit root enter the system in differences, whereas stationary series enter the system in levels. If at least one of the variables appears to be trend-stationary, a deterministic trend is added in all four equations[3].

To estimate the over-time impact of a price promotion of a product on the associated product, we derived the impulse-response function. More specifically, we operationalized a price promotion as a one-time unit shock of the price variable. The dynamic effect is then estimated as the over-time impact of this price shock on the sales of the associated product. For example, to estimate the effect of a price promotion of product A on the sales of product B, we set $\varepsilon_{Pa,t}$ to -1 and measure the over-time response of ln(Sb) of this shock.

To assess whether a response is significant or not, we used a bootstrap procedure [16]. In this procedure, we create new series of the endogenous variables, based on a random draw of the original errors and the estimated parameters of the VAR system. We then re-estimate the VAR based on the new series. Finally, an impulse-response function is derived, based on the new estimates of the VAR. We repeated this procedure 500 times for each VAR system. The sample standard error is computed based on the 500 outcomes of each response. This sample standard error enables us to compute the t-values of a response. We label a response as significant, if the absolute t-value is bigger then one.

Instantaneous responses are not estimated directly in a VAR, but are reflected in the variance-covariance matrix of the error terms. We estimate these responses using the method proposed by Evans & Wells [11]. Formally, by assuming multivariate normality, the instantaneous response of variable j to a shock k of variable i is estimated as:

$$E(\varepsilon_j \mid \varepsilon_i = k) = k^*\sigma_{ij}/\sigma_{ii}$$

Where σ_{ij} is the corresponding element in the variance-covariance matrix.

Applying this method to our setting, a price promotion of product A is operationalized as a shock in the residual vector of $[- \sigma_{Pa,Sa}/\sigma_{Pa,Pa}, - \sigma_{Pa,Sb}/\sigma_{Pa,Pa}, -1, - \sigma_{Pa,Pb}/\sigma_{Pa,Pa}]'$.

Following [22], we derive two summary statistics based on the computed responses. Firstly, we derive a long-run or persistent response. A persistent response occurs when the asymptotic value ($t \rightarrow \infty$) of the impulse-response function is significantly different from zero. Short-run effects are the summation of all the responses over the dust-settling period. The dust-settling period ends at the first period which is followed by four non-significant impulses[4].

Concluding, four summary statistics are derived from each VAR model. Firstly, a short-run and a long-run response of the sales of product B to a price promotion of product A. And secondly, the other way around, i.e. a short-run and a long-run response of the sales of product A to a price promotion of product B.

Moderator Analysis

We use the computed cross-price elasticity to classify the relationships as being independent, substitute or complementary. More specifically, the sign of the cross-price elasticity determines the nature of the relationship. A positive sign is associated with a complementary relationship, whereas a negative sign is associated with a substitution relationship. In cases where the long-run elasticity has a different sign than the short-run elasticity, the long-run elasticity determines the nature of the relationship. In absence of both a significant short-run and long-run elasticity, the relationship is classified as being independent.

For relationships classified as complementary, we use several moderators to explain the observed variation in cross-price effects. These moderators can be classified in four groups:

Promotion intensity

- Joint promotion frequency (JPF): the number of weeks that the two products were simultaneously promoted.
- Promotion frequency (PFa, PFb): for both the initiating and the responding product, we computed the total numbers of weeks they were sold on promotion.
- Promotion depth (PDa, PDb): the depth of the average promotion for both products

Private labels (PLa, PLb)

Dummy variables that take the value one if the product is a private label.

Umbrella branding (UMB)

If the two products are national brands with the same brand name, this variable takes the value one (zero in all other cases).

Price levels

Both the price level of the initiating product (PRa) and the responding product (PRb) as well as the relative price (RP) of the initiating product versus the associated product are considered as independent variables.

We use a multiple linear regression framework for the estimation of the moderating effects. This yields a total of two regressions: both the short-run and long-run cross-price effect of the complementary relationships. For the short-run cross-price effect of the complements ($\eta_{sr,c}$), for example, the following equation is estimated:

$$\eta_{sr,c} = \beta_0 + \beta_1 {*}JPF + \beta_2 {*}PFa + \beta_3 {*}PFb + \beta_4 {*}PDa + \beta_5 {*}PDb + \beta_6 {*}PLa + \beta_7 {*}PLb \\ + \beta_8 {*}UMB + \beta_9 {*}PRa + \beta_{10} {*}PRb + \beta_{11} {*}RP$$

For the regression of the short-run dynamics, we observed heteroscedasticity (White-test, $p = 0.0012$). This may result in biased estimates of the standard errors of the parameter estimates, which makes inferences about their significance unreliable. Therefore, we used White's heteroscedasticity-consistent estimator [29] to estimate the standard errors for this regression. This method has proven to result in reliable estimates in large samples [13]. Heteroscedasticity was not observed in the long-run model (White test, p = 0.94).

4. Description of the data

The transactional database of a big European retailer was used to perform our analyses. This database contains the sales transactions between July 7th 1999 and March 26th 2003 concerning 15,017 different sku's, resulting in 194 weekly observations.

We started our analysis with a market basket analysis to find associated products between all possible combinations of two products. In order to reduce the computational load, this market basket analysis was carried out on a sub-sample of all the transactions during 2002. A product pair is classified as a product association if it has an interest larger than two and a support exceeding 0.0157[5].

Moreover, we required that the price series of both products contain at least one price promotion in the 194 weeks. A price promotion was defined following the heuristic procedure in [1]. They define a price promotion when the price is reduced by at least five percent, and then is raised again by at least three percent within the following eight weeks. If there were weeks in which the product was featured in the folder, these weeks do not count in the calculation of the eight weeks period. The same procedure was used to measure the number of promotion periods (promotion frequency: PFa and PFb) in the moderating variable analysis.

Applying these restrictions results in 1,350 selected product associations. Since we successively simulate a price promotion in both products, this results in the estimation of 2,700 cross-price elasticities, both for the short and the long run.

5. Results

5.1. Descriptive Findings

Classification

Applying the aforementioned classification scheme to classify the relationship as being independent, complement or substitute, the 2700 relationships are classified in the following way:

- 1112 (41.19%) relationships are classified as being complements.
- 1212 (44.89%) relationships are classified as being substitutes, and
- 376 (13.93%) relationships are classified as being independent.

Complements

Persistent positive cross-price elasticities are rather exceptional, since they only occur in 60 instances. The mean value of this persistent cross-price elasticity is 0.89. 1,052 relationships were classified as being complements based on a positive short-run cross-price elasticity. The mean short-run elasticity is 4.56. On average, it takes 13 weeks for the short-run cross-price dynamics to stabilize.

Substitutes

Persistent negative cross-price elasticities only occurred in 42 cases. The mean value of the 42 elasticities is -0.62. The short-run dynamics have a mean value of -4.59, which took on average 16 weeks to stabilize.

The relatively infrequent occurrence of persistent effects of price promotion is consistent with previous research that applied multivariate time series techniques to measure the impact of price promotions. For example [8], [25], [22] and [23] find none or few persistent responses.

The high occurrence of substitutes in a market basket analysis may seem to be surprising, but can be explained by the concept of horizontal variety seeking [27].

We will only conduct a moderator analysis on the group of complements. In this way and following the classification in [3] our analysis derives empirical generalizations concerning purchase complements, which are complements that are purchased together and not concerning use complements, which are products that are used together.
Theoretically, we could perform a similar moderator analysis on the group of substitutes. From a practical point of view, however, this analysis would suffer from a sample bias, since this group only contains substitutes which are bought frequently together. Hence, inferences concerning this group would not enable us to derive conclusions for all substitute products.

5.2. Moderator Analysis

This section describes the effect of the moderators on the cross-price elasticity of the 1,112 complementary products. As mentioned before, we present are separate analyses for both the short-run and the long-run effects.

5.2.1. Moderators of Short-Run Cross-Price Effects

Promotion Intensity

A high occurrence of joint promotions ($b = 0.077$, $p < 0.01$) has a positive impact on the cross-price effect of complementary product pairs. This effect will be mainly attributable to the competitive effect [21], since promoting two complementary products together is conceptually identical to an instantaneous promotion reaction from the complement to a promotion of the initiating product, which yields obviously higher sales of the complement.

INSERT TABLE 2 ABOUT HERE

Interestingly, after controlling for joint-promotion activity, there is still an effect of the promotion intensity of both products on the cross-price effect.
Both the frequency ($b = -0.034$, $p < 0.01$) and depth ($b = -10.85$, $p < 0.01$) of promotions of the initiating product have a negative effect on the cross-price effects. This relationship can

be explained by recent research concerning cherry-picking behavior [12]. Cherry pickers tend to spread their purchases across multiple shopping trips to different stores in order to minimize their total shopping spending. Cherry pickers are attracted to the store by deep and frequent promotions. They are less inclined to buy complements that are not on deal, however. Consequently, products characterized by a high promotion intensity exhibit a lower cross-price effect, by attracting more cherry pickers. This finding also discourages the strategy of loss-leader pricing. In loss-leader pricing, a retailer sells a particular product at a very high discount, resulting in a negative profit margin. In doing so, the retailer depends on the sales of complementary products to make a profit per shopping basket. However, as shown, deeper promotions result in a lower cross-price effect.

The promotion depth of the complement ($b = 3.791$, $p < 0.10$), on the other hand, has a weakly significant positive impact on the cross-price effect. A possible explanation is that by running deep promotions, the complement becomes a part of the consideration set of the cherry picker, and is bought more easily on next shopping occasions.

Umbrella Branding

Umbrella branding ($b = 2.088$, $p < 0.01$) has a positive impact on the cross-price effect. Consequently, a product that is promoted tends to have a higher impact on the sales of a complementary product with the same brand name. This conclusion supports the current literature on umbrella branding. [10] show for the categories toothbrushes and toothpaste that there is a positive cross-price effect for umbrella brands. By confirming this effect across multiple products, this research provides an empirical generalization of the findings in [10].

5.2.2. Moderators of Long-Run Cross-Price Effects

Promotion Intensity

Whereas we observed a positive impact of the joint promotion frequency in the short run, this effect disappears in the long run.

The effect of the promotion intensity of both products separately, however, remains the same as in the short run. This means that both the promotion frequency ($b = -0.00082$, $p < 0.05$) and depth ($b = -0.171$, $p < 0.10$) of the initiating brand have a lower persistent effect on the sales of the complement. When the complement is characterized by deeper promotions, it benefits more from price promotions of the initiating products in the long run ($b = 0.324$, $p < 0.01$). Hence, the same reasoning concerning cherry picking applies to the long run.

Umbrella Branding

The positive effect of umbrella branding observed in the short run, also disappears in the long run. Whereas two complements with the same brand name show higher cross-price effects in the short run, there is no such advantage in the long run.

INSERT TABLE 3 ABOUT HERE

Price Levels

Both the interaction effect and the main effects of the price levels have a significant impact on the level of persistent cross-price effects. The relative price ($b = 0.029$, $p < 0.01$) affects the persistent cross-price effect positively. As the price of the initiating product gets larger relative to the price of the complement, the persistent cross-price effect increases. However, this interaction effect needs to be corrected for the two main effects of the price levels (price A, $b = -0.015$, $p < 0.01$, price B; $b = 0.006$, $p < 0.1$). Indeed, the total effect of the price variables on the level of persistent cross-price effects is estimated by the following equation:

$$\text{Persistent cross-price effect} = -0.015*\text{Price A} + 0.006*\text{Price B} + 0.029*\text{Price A/Price B}$$

Given a constant price of the complement (price B), one can assess the impact of the price of the initiating product (price A) on the persistent cross-price effect. For a price level of one Euro of the complement, for example, the relation between the cross-price effect and the price of the initiating brand can be written as:

$$\text{Persistent cross-price effect} = 0.006 + 0.014*\text{Price A}$$

which yields a positive relationship between the price of the initiating brand and the cross-price effect. It can easily be shown that price A has a positive influence on the cross-price effect for values of price B smaller than 1.93 Euro. If the price of B is fixed at a higher level than 1.93 Euro, the effect of price A on the cross-price effect becomes negative. Figure 1 shows a visual representation of this relationship.

INSERT FIGURE 1 ABOUT HERE

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6. Conclusions

In this research we used multivariate time-series techniques to measure the cross-sales effect of a price promotion on purchase complements. We classified the relationships as being complements, substitutes or independent. The observed variation in the cross-price elasticities of the complements was explained in a moderator analysis.

Three major conclusions can be drawn from this empirical work.

Firstly, pursuing an intense sales-promotion strategy seems to be rather disadvantageous, especially for retailers. A high cross-price effect for complementary products is of interest to the retailer, since promoted items induce the sales of full-margin, non-promoted products. However, products that are promoted more frequently and more deeply lose their ability to encourage the purchase of complementary goods. On the other hand, products that are promoted deeper tend to be purchased more if a complement is promoted.

Secondly, from a cross-sales point of view, umbrella branding is a favorable strategy for the manufacturer. Using the same brand name over different categories for complementary products has a positive effect. The complementary product will benefit more from a price promotion of its namesake in the short run. This effect does not apply, however, to persistent cross-sales effects.

Finally, prices of the products have especially an impact on the persistent cross-price effects. The relative price of the initiating product versus the associated product leads to a stronger impact on the persistent cross-price effect. That is, the higher the price difference between the initiating product and its complement/substitute, the higher the cross-price effect. This effect only holds for low-priced products of the complementary product, however. If the complement has a high price, the main effect of the price of the initiating product dominates. In those instances, a higher price of the initiating product results in a lower impact on the cross-price effect.

7. Limitations and directions for future research

A limitation of this study is the fact that we do not have a lot of marketing spending variables at our disposal. In fact, we could only control for the fact whether the article was featured in the weekly folder, but we miss data on marketing spending and display information. This can in some instances lead to biased estimates of the cross-price elasticity.

Moreover, the moderator analysis can be extended with more independent variables. A variable that could be included in future analyses is the degree to which a particular product is purchased on the basis of impulse buying (see [19]).

Finally, as mentioned, the generalizations are only valid for purchase complements and not for complements in use. The selection of purchase complements is possible through a data driven method as market basket analysis. To select a large set of complements in use to derive empirical generalization, one should use survey measurements.

FOOTNOTES

[1] More general, Y and Z can be sets of products in stead of single products.

[2] Examples of applications are the PROFSET model for assortment decisions (Brijs et al.,2004), or a model for web document categorization (Boley et al., 1999). Van den Poel et al. (2004) investigate the impact of associations on sales and profits.

[3] Including a trend variable in all equations allows us to estimate the system using OLS. Only including a trend variable in the equations which are trend-stationary would oblige us to estimate the system with SUR, which results in a heavy computational load given the number of systems to be estimated (see [22] for a similar approach).

[4] When there is no persistent effect, significant means significantly different from zero. When there is a persistent effect, significant means significantly different from the persistent effect.

[5] The 0.0157 results from the fact that we imposed that the two products should have been sold at least 1000 times together in the observation period. Since there were 6,368,614 baskets in total, this is the same as demanding a minimum support of 0.0157.

REFERENCES

[1] M. Abraham and L. Lodish, An Implemented System for Improving Promotion Productivity using Store Scanner Data, Marketing Science, Vol.12(3) (1993) 248-269.

[2] R. Agrawal, T. Imielinski, and A. Swami, Mining Association Rules between sets of items in large databases, in: Proceedings of the 1993 ACM SIGMOD International Conference on Management of Data, Washington DC (1993) 207-216.

[3] F.E. Balderston, Assortment Choice in Wholesale and Retail Marketing, Journal of marketing, Vol.21(2) (1956) 175-183.

[4] S. Brin, R. Motwani, and C. Silverstein, Beyond Market Baskets: Generalizing Association Rules to Dependence Rules, in: Data Mining and Knowledge Discovery, Vol.2(1) (1998) 39-68.

[5] T. Brijs, G. Swinnen , K. Vanhoof, and Wets G., Building an Association Rules Framework to Improve Product Assortment Decisions. Data Mining and Knowledge Discovery, Vol.8(1) (2004) 7-23.

[6] D. Boley, M. Gini, R. Gross, E.-H. Han, K. Hastings, G. Karypis, V. Kumar, B. Mobasher, and J. Moore, Partitioning-based Clustering for Web Document Categorization, Decision Support Systems, Vol.27(3) (1999) 329-341.

[7] P.K. Chintagunta, and S. Haldar, Investigating Purchase Timing Behavior in Two Related Product Categories, Journal of Marketing Research, Vol.35(1) (1998) 43-53.

[8] M. Dekimpe, D.Hanssens, and J.Silva-Risso, Long-run Effects of Price Promotions in Scanner Markets, Journal of Econometrics, Vol.89 (1999) 269-291.

[9] W. Enders, Applied Econometric Time Series (John Wiley & Sons,1995).

[10] T. Erdem, and B.Sun, An Empirical Investigation of the Spillover Effects of Advertising and Sales Promotions in Umbrella Branding, Journal of Marketing Research, Vol.39(4) (2002) 408-420.

[11] L. Evans, and G. Wells, An Alternative Approach to Simulating VAR Models, Economic Letters, Vol.12(1) (1983) 23-29.

[12] E.J. Fox and S.J. Hoch, Cherry Picking, Working Paper, Wharton School, University of Pennsylvania (2003).

[13] W.H. Greene, Econometric Analysis, (Prenctice Hall,2003)

[14] D. Hand, H.Mannila , and P. Smyth, Principles of Data Mining, (Massachusetts Institute of Technology, 2001)

[15] D. Hanssens, L. Parsons and R. Schultz. Market Response Models, Econometric and Time Series Analysis, 2nd edition (Kluwer Academic Publishers, 2001)

[16] H. Lütkepohl, Introduction to Multiple Time Series Analysis, Second Edition, (Springer-Verlag, 2001)

[17] P. Manchanda, A. Ansari, and S. Gupta, The “Shopping Basket”: A Model for Multicategory Purchase Incidence Decisions, Marketing Science, Vol.18(2) (1999) 95-114.

[18] F.J. Mulhern, and R.P. Leone, Implicit Price Bundling of Retail Products: A Multiproduct Approach to Maximizing Store Profitability, Vol.55(4) (1991) 63-76.

[19] C. Narasimhan, S.A. Neslin, and S.K. Sen, Promotional Elasticities and Category Characteristics, Journal of Marketing, Vol.60(2) (1996) 17-30.

[20] S.A. Neslin, Sales Promotions, Marketing Science Institute, Relevant Knowledge Series (2002)

[21] V.R. Nijs, M.G. Dekimpe, J.-B. E.M. Steenkamp, and D.M. Hanssens, Tracing the Impact of Price Promotions across Categories, Working Paper, Kellogg School of Management (2001a)

[22] V.R. Nijs, M.G. Dekimpe, J.-B. E.M. Steenkamp, and D.M. Hanssens, The Category-Demand Effects of Price Promotions, Marketing Science, Vol.20(1) (2001b) 1-22.

[23] K. Pauwels, D. Hanssens, and S. Siddarth, The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice, and Purchase Quantity, Journal of Marketing Research Vol.39(4) (2002) 421-439.

[24] G. Russell, and A.Petersen, Analysis of Cross Category Dependence in Market Basket Selection, Journal of Retailing, Vol.76(3) (2000) 367-392.

[25] S. Srinivasan, P. Leszczyc, and F. Bass, Market Share Response and Competitive Interaction: The Impact of Temporary, Evolving and Structural Changes in Prices, International Journal of Research in Marketing, Vol.17(4) (2000) 281-305.

[26] D. Van den Poel, J. De Schamphelaere, and G. Wets, Direct and Indirect Effects of Retail Promotions on Sales and Profits in the Do-It-Yourself Market, Expert Systems with Applications, Vol. 27 (1) (2004) 54-62.

[27] B. Vindevogel, D. Van den Poel, and G. Wets, Why promotion Strategies Based on Market Basket Analysis do not Work, Working Paper, Ghent University (2004).

[28] R.G. Walters, Assessing the Impact of Retail Price Promotions on Product Substitution, Complementary Purchase, and Interstore Sales Displacement, Journal of Marketing, Vol.55(2) (1991) 17-28.

[29] H. White, A Heteroscedasticity-Consistent Covariance Matrix and a Direct Test for Heteroscedasticity, Econometrica, Vol. 48(4) (1980) 817-838.

[30] B. Wierenga, On academic marketing knowledge and marketing knowledge that marketing managers use for decision-making, Marketing Theory, Vol. 2(4) (2002) 355-362.

Table 1: Previous research concerning cross-price effects

Reference	**Set of analyzed products**
[28] Walters (1991)	Cake mix and cake frosting Spaghetti and spaghetti sauce
[18] Mulhern & Leone (1991)	Cake mix and cake frosting
[17] Manchanda et al.(1999)	Cake mix and cake frosting Laundry detergent and fabric softener
[24] Russell & Petersen (2000)	Paper towels, toilet paper, facial tissue and paper napkins
[7] Chintagunta & Haldar (1998)	Pasta and pasta sauce

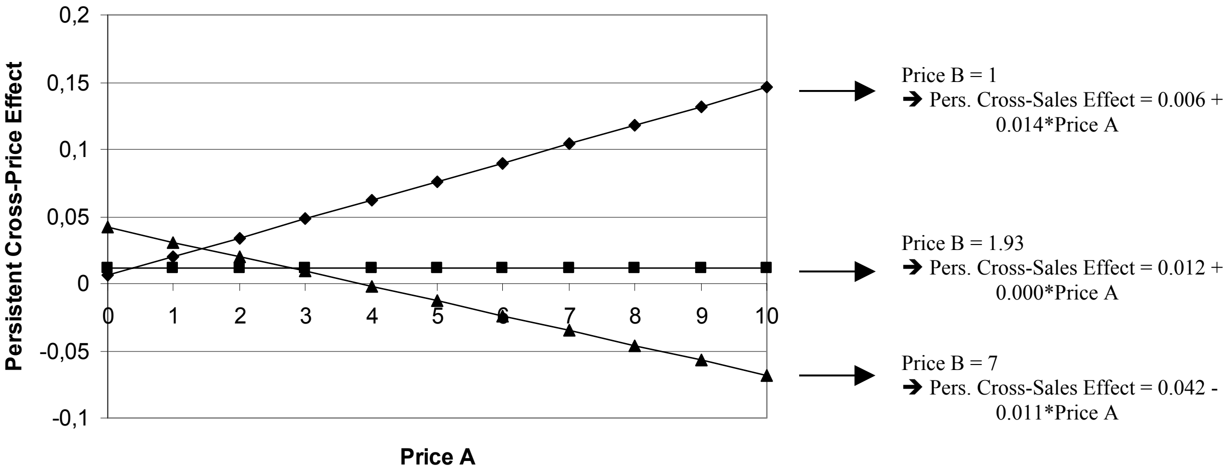
Table 2: Moderators of the short-run cross-price effects

	B	*Error*	*t-value*	*Prob.*
Intercept	3.617	0.508	7.12	0.0000
Promotion Intensity				
Joint promo freq	0.077	0.028	2.78	0.0055
Promo freq A	-0.034	0.006	-6.05	0.0000
Promo depth A	-10.85	1.701	-6.38	0.0000
Promo freq B	0.001	0.008	0.13	0.8945
Promo depth B	3.791	1.935	1.96	0.0503
Private Labels				
Private label A	0.047	0.206	0.23	0.8205
Private label B	0.022	0.236	0.10	0.9246
Umbrella Branding	2.088	0.753	2.77	0.0057
Price Levels				
Price A	-0.007	0.055	-0.13	0.8962
Price B	0.014	0.053	0.26	0.7935
Relative Price	-0.011	0.079	-0.14	0.8895

Table 3: Moderators of the long-run cross-price effects

	B	*Error*	*t-value*	*Prob.*
Intercept	0.016	0.029	0.58	0.5643
Promotion Intensity				
Joint promo freq	0.001	0.002	0.76	0.4473
Promo freq A	-0.000820	0.00036	-2.28	0.0228
Promo depth A	-0.171	0.104	-1.65	0.0993
Promo freq B	-0.000589	0.00036	-1.63	0.1042
Promo depth B	0.324	0.110	2.94	0.0034
Private Labels				
Private label A	-0.007	0.017	-0.39	0.6968
Private label B	-0.022	0.018	-1.24	0.2161
Umbrella Branding	0.003	0.030	0.09	0.9288
Price Levels				
Price A	-0.015	0.004	-4.23	0.0000
Price B	0.006	0.003	1.89	0.0584
Relative Price	0.029	0.005	6.51	0.0000

Figure 1: The influence of the price level on the persistent cross-price effect



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