

# INVESTIGATING THE CROSS-SALES EFFECT OF PRODUCT ASSOCIATIONS

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## **Abstract**

In this research, we use the framework of association rule discovery to find 1,350 interesting product associations between two sku's. Using multivariate time series techniques, we successively simulate a price promotion in both products and measure the impact on the sales of the associated product. This approach allows us to model both the short run and long run cross-sales effect. For both complement and substitute relationships, we investigate the moderating effect of several covariates on the size of the cross-sales effect.

## **1. Introduction**

In a recent Journal of Marketing article, Shocker and colleagues call for a better understanding of the connectedness among products (Shocker et al., 2004, p. 29). Indeed, it is clear and well known that the purchase of one product can influence purchases of other products. The underlying dynamics of these processes however remain less clear. 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 an associated product.

Using market-basket analysis and association rules allows us to select interesting pairs of products in terms of their cross-sales effects. 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. In a third phase, we explain the observed variations in cross-sales effects using a set of moderating variables. We conduct hereby separate analysis for the short run and the long run and for complements and substitutes.

We contribute to the marketing literature in drawing following conclusions:

First, we show that association-rule discovery is not a good technique when pursuing positive cross-sales effect. While it is intuitively appealing to think that a price promotion will favor the sales of the associated product, we show that there is a higher probability that sales of the associated product will drop.

Secondly, we show that using the same brand name for two complements has a beneficial influence on the cross-sales effect. However, using the same brand name for substitute

products results in a permanent cannibalization effect when one of the two products is promoted.

Thirdly, we illustrate that using an intense promotion strategy, characterized by deeper and more frequent price promotions, has a negative impact on the cross-sales effect.

Finally, we show that price levels of the products are an important moderator in explaining persistent cross-sales effects.

The paper is organized as follows: we first discuss the relevant literature concerning cross-sales 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 (2002) points out in his essay on sales promotions, literature on cross-sales effects of promotions is rather scarce.

Walters (1991) and Mulhern & Leone (1991) use sales response models to measure cross-sales effects in a limited set of predefined complement and substitute brands. Both studies report asymmetrical cross-sales 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 analyses for identifying cross-sales effects. Manchanda et al. (1999) and Russell & Petersen (2000) 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. Chintagunta & Haldar (1998) 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-sales effects, they are not well suited to derive conclusions on why cross-sales effects tend to differ for different categories, brands or products. This is mainly due to the fact that in most studies only a limited set of predefined products are analyzed, which makes them not very well suited to derive empirical generalizations.

However, in recent research, we found two studies which are of particular interest to the pursuit of empirical generalizations. Both studies are methodologically similar to this study, since they both use multivariate time-series techniques to measure cross-sales effects of promotions and derive empirical generalizations in a second phase.

Steenkamp et al. (2002) conducted a large-scaled study to investigate competitive reactions and cross-sales effects of advertising and promotion. For the cross-sales effects, they investigated the impact of a price promotion of each top-three brand of 442 categories on the sales of the other two brands. They show that especially the brand-equity and the private-label nature of the brands are the most important variables in explaining the cross-sales effects.

A similar study by Nijs (2001b) investigates the cross-sales effect of a price promotion on a category level. Hence, they study how a price promotion in one category induces an expansion or a contraction of another category.

This study differs from the two latter studies since we measure cross-sales effects at the SKU level. This makes it possible to add different variables to our analysis, like the existence of an umbrella-branding effect for substitute products.

In this study we are also able to run separate analyses for complement and substitute product pairs, as is done in the paper of Nijs (2001b), whereas the study of Steenkamp et al. (2002) is limited to substitute relationships due to the research design.

Moreover, we add different variables to explain observed variations in the cross-sales effect, like the promotion intensity, enabling us to derive distinct conclusions, which contribute to the marketing literature.

### 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 of over 15,000 different SKU's, resulting in more than 112,492,500 SKU pairs, we first need a method to select combinations of SKU's which could be potentially interesting in terms of cross-sales effects. We use the framework of market basket analysis to select interesting product associations.

Market-basket analysis is a generic term for methodologies that study the composition of a basket of products purchased by a household during a single shopping trip.

Agrawal et al. (1993) first introduced the association rule framework to study market baskets. Originally, this framework consisted of two parameters: support and confidence. Brin et al. (1998) extended this framework by a third parameter: interest.

More specifically, the three parameters are defined as follows:

Consider the association rule  $Y \rightarrow Z$ , where  $Y$  and  $Z$  are two products<sup>1</sup>.  $Y$  is called the antecedent and  $Z$  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.

Since the publication of the paper by Agrawal (1993), literally hundreds of publications followed based on the proposed framework. However, as Hand et al. (2001, p.447) state: "*It is fair to say that there are far more papers published on algorithms to discover association rules than there are papers published on applications of it*"<sup>2</sup>.

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<sup>1</sup> More general,  $Y$  and  $Z$  can be sets of products in stead of single products.

<sup>2</sup> An exception of this rule is the work of Brijs (2004), who used market basket analysis to create the PROFSET model for optimal product assortment selection as well as Van den Poel et al. (2004).

This research attempts to fill this void, by describing and explaining how a price promotion of the antecedent influences the sales of the consequent of the product association.

### *A rationale for using multivariate time-series techniques*

Recent research concerning the effects of price promotions is characterized by an increasing use of multivariate time-series techniques. Dekimpe et al. (1999) examine the long-run impact of a price promotion on sales. In most cases, they find a short-run effect of price promotion. Long-run effects are only observed exceptionally. Srinivasan et al. (2000) analyze the impact of temporary, evolving and structural changes in price on market share. They conclude that temporary price changes, or price promotions, have only a short-run effect on market share, whereas structural changes or evolving prices have long-run effects on market share. Nijs et al. (2001a) conducted a large-scale research to investigate the influence of price promotions on category demand. They find a short run impact in 58% of the cases, with a duration of ten weeks on average. They also conclude that long-run effects are exceptional, since it is only observed in two percent of the cases. Pauwels et al. (2002) decompose promotional effects into category incidence, brand choice and purchase quantity. They find significant short-term effects for each of the sales components, with duration of up to eight weeks. On the long run, however, they conclude that each sales component lacks a persistent promotion effect.

Although long-term effects are rather exceptional in most of these studies, there is still a rationale for the use of multivariate time series techniques in analysing the effect of price promotions.

First of all, although the occurrence of a persistent effect of price promotions is exceptional, these exceptional cases are, evidently, of a high strategical relevance. Hence, being able to measure and explain these rare occurrences is of interest to the marketing community. Secondly, time-series techniques are more flexible in measuring the short-run dynamics, which are observed in all studies. Indeed, time-series analysis is able to detect the most irregular fluctuations in the short-run promotional effects, whereas other techniques, like the Koyck model, necessitate an a priori specification of the response, which is usually a gradually decaying response.

Finally, in measuring the cross-price elasticity, the use of multivariate time-series techniques shows another benefit. As Nijs et al. (2001b) argue, a cross-sales effect can have two sources. First, a price promotion results in an increase in demand of the promoted product. This increase in demand can cause changes in the demand of complement and substitute products, which Nijs et al. (2001b) call the consumer-demand effect. On the other hand, a price promotion can possibly cause marketing reactions of the associated product, which obviously also results in a change in demand of the associated product. This effect is called the competitive effect. An advantage of time-series techniques is that it simultaneously accounts for the two effects through the derivation of impulse-response functions.

### *Unit root tests*

The first step of our analysis involves the testing for unit roots. Those tests are necessary, since variables that appear to be non-stationary have to be put in differences before entering the model, whereas stationary variables enter the model in levels. Moreover, the presence of a unit root is a necessary condition for the existence of long-run effects (Dekimpe & Hanssens, 1995b).

Augmented Dickey-Fuller tests were used to test for the presence of a unit root. We used the testing scheme proposed by Enders (1995) (see appendix). The optimal lag length for the autoregressive part of the test was chosen using the Schwarz Bayesian Criterion (SBC). This testing procedure classifies each series as a unit root process, a stationary process or a trend stationary process.

### ***VARX models***

For each selected product couple, we estimate a four-equation VAR model, with the prices and sales of both products as endogenous variables. We thereby controlled for factors that could influence sales, which were estimated as exogenous variables. More specifically, we estimated the effect of the featuring of the two products in the weekly folder of the retailer and the effect of the total sales per week of the retailer, which controls for external factors that could have influenced the sales of the two products. When one of the endogenous variables appeared to be trend-stationary, a trend variable was included in all equations<sup>3</sup>. 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.

As mentioned before, endogenous variables that have a unit root enter the system in differences.

### ***Impulse-response functions.***

The effects of a price promotion on the sales of the associated product were estimated by deriving impulse-response functions from the estimated VARX-systems.

Formally, price promotions are operationalized as one-time unit shocks of the price variable in the VARX-model in levels. The impact of a price promotion of product A on the sales of product B, for example, is operationalized by setting the value  $\varepsilon_{Pa,t}$  at -1 and measuring the over-time impact on  $\ln(Sb)$  of this one-time unit shock. From each VARX-model we derive two impulse-response functions, measuring cross elasticities. First, we estimate the response of the sales of product B to a price promotion of product A, and second we estimate the response of the sales of product A to a price promotion of product B.

<sup>3</sup> 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 Nijs et al. (2001a) for a similar approach).

In a VAR system, the instantaneous effects can not be estimated directly, but are reflected in the variance-covariance matrix of the residuals. For example, if we observe a high covariance between the errors of the sales of product A and B, we can infer that there is a high instantaneous effect between sales of product A and B. A problem, however, remains that we can not directly observe the direction of these instantaneous effects. In our example, we do not directly know whether it is the sales of product A that have an immediate effect on the sales of product B, or whether it is the other way around, i.e. sales of product B that influence the sales of product A. This problem is traditionally solved by imposing restrictions on the instantaneous effects. These restrictions impose a priori a causal ordering of the instantaneous effects. In a system with  $n$  endogenous variables, we need  $(n^2-n)/2$  restrictions for identification, which resolves to six restrictions in our four-equation model. Imposing these six restrictions in our particular setting seems to be problematic however. While we could reasonably assume that feedback effects from sales to price take some time to materialize<sup>4</sup>, and hence restrict the instantaneous effects from price to sales to zero, this only yields four restrictions (sales A does not have an instantaneous effect on price A and price B, and sales B does not have an instantaneous effect on price A and price B). Imposing further restrictions can not be done on a theoretical basis. If we observe an instantaneous effect between the price of A and B, for example, there are no theoretical grounds to impose that price A has an instantaneous effect on price B, while price B can only affect price A after one week. To circumvent this problem, we use the method proposed by Evans & Wells(1983) (See Dekimpe & Hanssens (1999) for an application in marketing) to estimate the instantaneous effects, since this method does not imply to impose restrictions.

This method models instantaneous effects as the expected value of the error term given a particular shock and by assuming a multivariate normal distribution of the error terms. Formally, the expected instantaneous effect of variable  $j$  as a result of a shock  $k$  of variable  $i$  is computed as:

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

Where  $\sigma_{ij}$  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  $[-\sigma_{Pa,Sa}/\sigma_{Pa,Pa}, -\sigma_{Pa,Sb}/\sigma_{Pa,Pa}, -1, -\sigma_{Pa,Pb}/\sigma_{Pa,Pa}]'$ .

In order to derive confidence intervals for the estimated responses, we used a bootstrap method. Therefore, elements from the residuals were randomly drawn with replacement. Based on these residuals and the parameters estimated for the VARX-model, we created new values for the four endogenous time series. We then re-estimate the parameters of the VARX-model using these new time series, and impulse-response functions are derived based on this model. This procedure is repeated 500 times. Finally, the sample standard error is computed for these 500 response values. Using this standard error, we compute the t-values of each response. Responses with an absolute t-value higher than 1.65 are labelled as significant.

We follow Nijs et al. (2001a) in deriving a short-term and a long-term effect from the estimated impulse-response function. A long-term or persistent effect occurs when the asymptotic value of the response ( $t \rightarrow \infty$ ) is significantly different from zero. Short-run effects are the summation of all the impulses over the dust-settling period. The dust-settling period ends at the first period which is followed by four non-significant impulses<sup>5</sup>.

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<sup>4</sup> This assumption gives marketing mix variables causal priority over sales variables. For an application of this assumption see Dekimpe & Hanssens, 1995a.

<sup>5</sup> 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.

## *Moderator Analysis*

The relationship between the promoted product and the associated product is classified as being independent, substitutes or complements depending on the direction of the cross-price elasticity. First, we investigate the persistent cross elasticity. If this measure appears to be positive, we label the relationship as being complementary, whereas a negative persistent effect indicates a substitution relationship. In the absence of a long-run effect, we use the short-run estimates to classify the relationship. Again, a positive cross-sales effect is classified as being complementary, while a negative effect is classified as substitute. In the absence of a short-run effect, we classify the relationship as being independent.

For both substitutes and complements, we use several moderators to explain the observed variation in cross-sales 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.

### *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 linear regression framework for the estimation of the moderating effects. This yields a total of four regressions. Both the short-run and long-run cross-sales effect for the complements and for the substitutes. For the short-run cross-sales 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 both regressions of the short-run dynamics, we observed heteroscedasticity (White-test: complements,  $p = 0.0012$ , substitutes,  $p = 0.0003$ ). 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 (White, 1980) to estimate the standard errors for these two regressions. This method has proven to result in reliable estimates in large samples (Greene, 2003). Heteroscedasticity was not observed in the long-run models (White test, complements,  $p = 0.94$ , substitutes,  $p = 0.97$ ).

## 4. Description of the data

For our analysis, we used the transactional database of a big Belgian retailer, which contains the sales transactions of six outlets between July 7<sup>th</sup> 1999 and March 26<sup>th</sup> 2003 of 15,017 different sku's.

First, we took a sample of all the transactions of 2002, and computed the support and interest measure for all possible combinations of two sku's. We labelled a combination as a product association if it has an interest larger than two and a support exceeding 0.0157<sup>6</sup>. For the selected product associations we computed six variables on a weekly basis, which results in 194 weekly observations of the price of the two products, the sales in units of the two products, and the dummy variable that indicates whether the product featured in the folder for both products.

Since we are interested in the impact of price promotions on the sales of the associated product, 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 Abraham & Lodish (1993). 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 where the product was featured in the folder, these weeks do not count in the calculation of the eight weeks period. This same procedure was used to measure the number of promotion periods (promotion frequency: PFa and PFb) in the moderating variable analysis.

These restrictions result in 1,350 selected product associations. As mentioned, we successively simulate a price promotion in both products and measure the impact of the promotion on the sales of the associated product, which 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 relationships are classified as being complements.
- 1212 relationships are classified as being substitutes, and
- 376 relationships are classified as being independent.

#### *Complements*

In 60 instances, a price promotion had a persistent positive effect on the sales level of the associated product. Following our classification scheme, these instances were classified as complements. The mean value of this persistent cross-price elasticity is 0.89. The other 1052 complementary relationships were classified as being complements based on a positive short-run cross-price elasticity. The mean short-run elasticity is 4.56. These short-run dynamics took on average 13 weeks to stabilize.

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<sup>6</sup> 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.



## ***Substitutes***

42 cross-price elasticities showed a persistent negative sign, meaning that the price promotion had a persistent negative effect on the sales of the associated product. The mean value of the 42 elasticities is -0.62. The short-run dynamics have a mean value of -4.59. It took on average 16 weeks for the short-run dynamics to stabilize.

Although we only considered product couples that can be labeled as product associations, it is remarkable that we can classify even more relationships as substitutes (1212) than as complements (1112). This finding denies the intuitively appealing business idea that association rules can be used by retailers to implement more effective promotion strategies. Indeed, the underlying hypotheses that product associations necessarily show a positive cross-price elasticity does not seem to hold. A reflection of this belief can be illustrated by the following citation of an article by two data-mining consultants in the popular business press: *'Business managers or analysts can use a market basket analysis to plan couponing and discounting. It is probably not a good idea to offer simultaneous discounts on [two products] if they tend to be bought together. Instead, discount one to pull in sales of the other.'* (Brand & Gerritsen, 1998). As we have shown, however, there is a bigger probability that the sales of associated products will drop. Indeed, observing that customers tend to buy two products on the same shopping occasion does not imply a complementary relationship between these two products. Consumers can buy products together for a variety of reasons (see Manchanda et al. (1999) or Böcker (1978)). Variety-seeking behavior or habit formation, for example, can result in an association rule between two substitutes.

### **5.2. Moderator analysis**

For the moderator analysis of cross-price elasticities, we included the 376 independent relationships in both the substitute and the complement equations, in order to have some instances of zero elasticities. The inclusion of this sample does not have any effects on our findings, however, since analyses without this sample result in the same findings.

#### **5.2.1. Moderators of Short-Run Cross-Sales Effects - Complement Products**

##### ***Promotion Intensity***

A high occurrence of joint promotions ( $b = 0.077$ ,  $p < 0.01$ ) has a positive impact on the cross-sales effect of complement product pairs. This effect will be mainly attributable to the competitive effect, since promoting two complement 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.

	<i>b</i>	<i>Error</i>	<i>t-value</i>	<i>Prob.</i>
Intercept	3.617	0.508	7.12	0.0000
<i>Promotion Intensity</i>				
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
<i>Private Labels</i>				
Private label A	0.047	0.206	0.23	0.8205
Private label B	0.022	0.236	0.10	0.9246
<i>Umbrella Branding</i>	2.088	0.753	2.77	0.0057
<i>Price Levels</i>				
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

Interestingly, after controlling for joint-promotion activity, there is still an effect of the promotion intensity of both products on the cross-sales 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-sales effects. This relationship can be explained by recent research concerning cherry-picking behavior (Fox and Hoch, 2003). 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 complement products that are not on deal, however. Consequently, products characterized by a high promotion intensity show a lower cross-sales 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 complement products to make a profit per shopping basket. However, as shown, deeper promotions result in a lower cross-sales 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-sales 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-sales effect. Consequently, a product that is promoted tends to have a higher impact on the sales of a complement product with the same brand name. This conclusion supports the current literature on umbrella branding. Erdem and Sun (2002) show for the categories toothbrushes and toothpaste that there is a positive cross-price effect for umbrella brands. By confirming this effect across multiple categories, this research provides an empirical generalization of the findings of Erdem and Sun (2002).

## 5.2.2. Moderators of Long-Run Cross-Sales Effects - Complement Products

### *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.

	<i>b</i>	<i>Error</i>	<i>t-value</i>	<i>Prob.</i>
Intercept	0.016	0.029	0.58	0.5643
<i>Promotion Intensity</i>				
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
<i>Private Labels</i>				
Private label A	-0.007	0.017	-0.39	0.6968
Private label B	-0.022	0.018	-1.24	0.2161
<i>Umbrella Branding</i>	0.003	0.030	0.09	0.9288
<i>Price Levels</i>				
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

### *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-sales effects in the short run, there is no such advantage in the long run.

### *Price Levels*

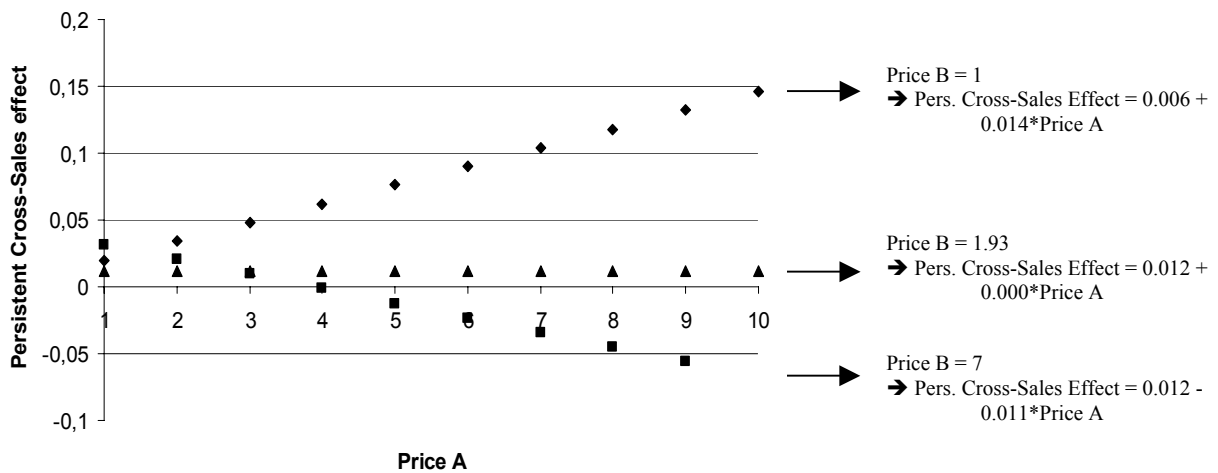
Both the interaction effect and the main effects of the price levels have a significant impact on the level of persistent cross-sales effects. The relative price ( $b = 0.029$ ,  $p < 0.01$ ) affects the persistent cross-sales effect positively. As the price of the initiating product gets larger relative to the price of the complement, the persistent cross-sales effect increases. For example, the persistent effect on the sales of spaghetti (less expensive product) as a result of a price promotion of spaghetti sauce (more expensive product) is expected to be higher than the reverse. 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 effects is estimated as the following equation:

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

Given a constant price of the complement, one can assess the impact of the price of the initiating product on the persistent cross-sales effect. For a price level of 1 Euro of the complement, for example, the relation between the cross-sales effect and the price of the initiating brand can be written as:

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

which yields a positive relationship between the price of the initiating brand and the cross-sales effect. It can easily be shown that price A has a positive influence on the cross-sales 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-sales effect becomes negative. Figure 1 shows a visual representation of this relationship.



**Figure 1: The moderating effect of price - Complements**

Concluding, we can state that when the price of the complement product is low, the positive interaction effect of the relative price dominates the relationships. This means that higher price levels of the initiating product, resulting in a higher relative price, have a higher impact on the persistent cross-sales level. On the other hand, for high prices of the complement product, the main effect of price A dominates the relationship. In this setting, an increase of price A results in a lower impact on the persistent cross-sales effect.

### 5.2.3. Moderators of Short-Run Cross-Sales Effects - Substitute Products<sup>7</sup>

#### *Promotion Intensity*

The promotion intensity, both frequency ( $b = 0.041$ ,  $p < 0.01$ ) and depth ( $b = 13.87$ ,  $p < 0.01$ ), of the attacker results in less negative cross-sales effects. Otherwise stated, an attacker that has an intensive promotion strategy is less able to deteriorate the sales of the defender. An explanation of this effect can be found in the concept of brand equity. The power of brand equity lies in what customers have learned felt, seen, and heard about the brand as a result of their experiences over time and can be formally defined as ‘the differential effect that brand knowledge has on customer response to the marketing of that brand’ (Keller, 2003).

	<i>b</i>	<i>Error</i>	<i>t-value</i>	<i>Prob.</i>
Intercept	-4.265	0.645	-6.61	0.0000
<i>Promotion Intensity</i>				
Joint promo freq	0.032	0.035	0.90	0.3660
Promo freq A	0.041	0.007	6.00	0.0000
Promo depth A	13.87	2.438	5.69	0.0000
Promo freq B	-0.025	0.010	-2.41	0.0162
Promo depth B	-3.205	2.458	-1.30	0.1925
<i>Private labels</i>				
Private label A	-0.412	0.417	-0.99	0.3230
Private label B	-0.581	0.419	-1.38	0.1663
<i>Umbrella Branding</i>	-0.502	0.738	-0.68	0.4965
<i>Price Levels</i>				
Price A	-0.114	0.076	-1.50	0.1337
Price B	-0.167	0.062	-2.68	0.0074
Relative Price	0.141	0.087	1.62	0.1058

Jedidi et al. (1999) have shown that price promotions have a negative effect on brand equity. Hence, products characterized by high promotion intensity will have lower brand equity than similar products with lower promotion intensity. Moreover, Steenkamp et al. (2002) show that brand equity influences the cross-sales effects between substitutes. They argue that an attacker with high brand equity can further deteriorate sales of the defender.

Concluding, we can state that an intensive promotion strategy weakens the competitive position of a product, since the product is less able to pull sales of its competitors with price promotions. This reasoning does not only apply for the attacker, but also for the defender. Implementing frequent price promotions (Promo frequency B,  $b = -3.205$ ,  $p < 0.05$ ) weakens the competitive position even more, since a product loses more sales by a price promotion of a competitor.

#### *Price Levels*

Only the price level of the defending product shows a significant negative impact (Price B,  $b = -0.167$ ,  $p < 0.05$ ). Concluding, a defender with a higher price level loses more sales due to a promotion action of the attacker.

<sup>7</sup> In the substitute relationships, we are explaining a negative cross-sales elasticity. Hence, a negative sign associated with a moderator is an indication of a stronger cross-sales effect.

## 5.2.4. Moderators of Long-Run Cross-Sales Effects - Substitute Products

### *Promotion Intensity*

Most of the promotion intensity parameters confirm our reasoning about the negative impact of an intense promotion strategy on the competitive position of a product. Both the frequency ( $b=0.000526$ ,  $p < 0.05$ ) and the depth ( $b = 0.208$ ,  $p < 0.01$ ) of promotions of the attacker result in a lower ability to harm the sales of the defender in the long run. From a defender's point of view, running deep promotions (Promo depth B,  $b = -0.233$ ,  $p < 0.01$ ) weakens the competitive position, since sales are more harmed by a promotion of a competing product.

There are two effects for which we do not have a clear interpretation, however. Firstly, the positive effect of the promotion frequency ( $b = 0.000695$ ,  $p < 0.01$ ) of the defender on his competitive position. This effect does not seem to fit in our framework on the negative impact of intensive promotion strategies on the competitive position.

Secondly, products that are promoted together more often (joint promo frequency,  $b = -0.002$ ,  $p < 0.05$ ) show a stronger cross-sales effect in the long run. We do not have an explanation for the sign of this effect.

	<i>b</i>	<i>Error</i>	<i>t-value</i>	<i>Prob.</i>
Intercept	-0.028	0.017	-1.60	0.1098
<i>Promotion Intensity</i>				
Joint promo freq	-0.002	0.001	-2.32	0.0206
Promo freq A	0.000526	0.000229	2.30	0.0218
Promo depth A	0.208	0.066	3.18	0.0015
Promo freq B	0.000695	0.000234	2.97	0.0030
Promo depth B	-0.233	0.071	-3.29	0.0010
<i>Private Labels</i>				
Private label A	-0.009	0.011	-0.77	0.4440
Private label B	0.007	0.011	0.62	0.5321
<i>Umbrella Branding</i>				
	-0.038	0.019	-2.01	0.0443
<i>Price Levels</i>				
Price A	0.009	0.002	4.26	0.0000
Price B	-0.017	0.00184	-1.24	0.2160
Relative Price	-0.017	0.00308	-5.36	0.0000

### *Umbrella Branding*

Two competing products with the same brand name is a very common situation. For example, two flavors of salad dressing of the same brand are obviously substituting products. Having the same brand name, increases the persistent negative effect of a sales promotion of the attacker on the sales level of the defender. Hence, this clearly shows the cannibalization effect of a price promotion in one flavor at the expense of another flavor of the same brand.

### *Price Levels*

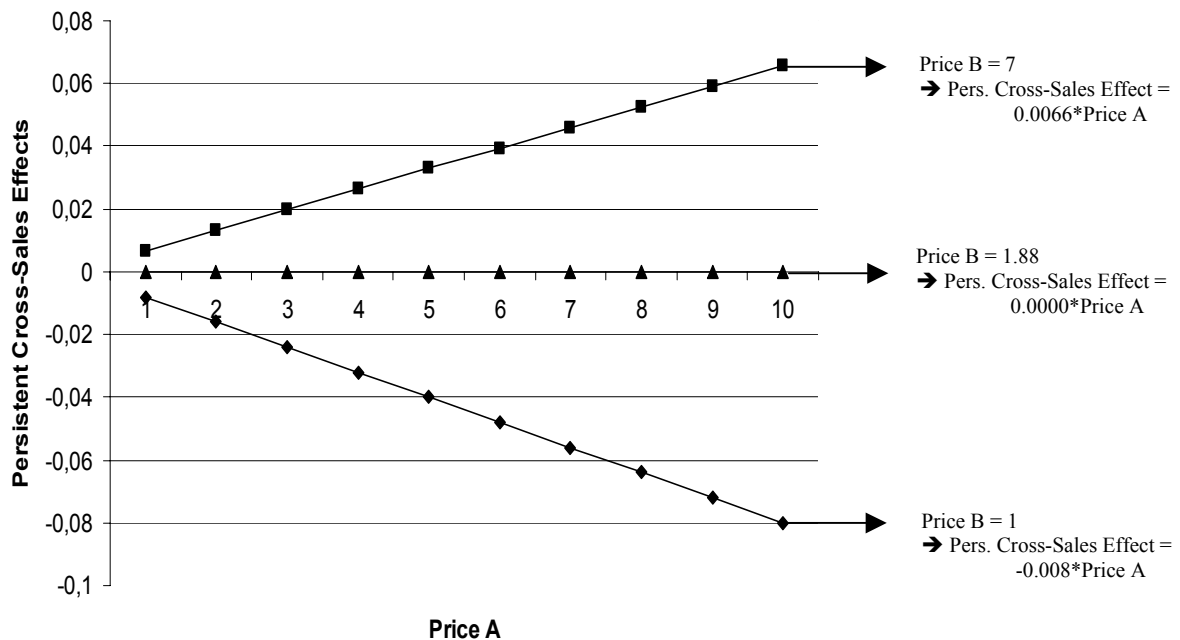
Both the level of the price ( $b = 0.009$ ,  $p < 0.01$ ) of the attacker and the interaction effect, measured as the relative price ( $b = -0.017$ ,  $p < 0.01$ ) of the attacker versus the price of the defender have a significant impact on the persistent cross-sales effect. If the price of the attacker increases, this has a negative effect on the attacking power via the main effect. On

the other hand, an increasing price of the attacker yields a higher relative price, which results in a higher attacking power. We depict this relationship in the same manner as we did in explaining the price effect for complementary products, i.e. by considering the price effect of product A for different fixed levels of price B.

Since the main effect of the price of the defender is insignificant, the relationship between the price levels and the persistent cross-sales effect can be written as

$$\text{Persistent cross-sales effect} = 0.009 * \text{Price A} - 0.017 * \text{Price A} / \text{Price B}.$$

This means that for prices of the defender smaller than 1.88 Euro, the relative price effect dominates, and the attacking power gets larger as the price of A increases. When the price of B exceeds 1.88 Euro, the main effect dominates the relationship, which means that products with a higher price have a smaller influence on the persistent loss in sales of the defender. Figure 2 depicts this relationship graphically.



**Figure 2: The moderating effect of price - Substitutes**

In literature, the fact that a high priced product has a stronger effect on a low-priced substitute than the reverse is known as the asymmetric price effect (see Sethuraman et al.(1999)). In our setting, we only observe an asymmetric price effect when the price of the substitute is low. For higher prices of the substitutes, the main price effect dominates the relationship, and the long-term impact becomes less strong as the price of the initiating brand increases.

## 6. Conclusions

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

Four major conclusions can be drawn from this empirical work. Firstly, we have shown that association-rule discovery is not a good technique when pursuing positive cross-sales effects. Although it is intuitively appealing to think that a price promotion favors the sales of associated products, we have shown that there is a bigger probability that the sales of the associated product eventually will drop.

Secondly, Umbrella branding has mixed properties for a manufacturer. Using the same brand name over different categories for complement products has a positive effect. The complement product will benefit more from a price promotion of its namesake in the short run. When the two products are substitutes, however, a price promotion will cause more persistent damage to the substitute. This clearly shows that price promotions have a cannibalization effect from the manufacturer's point of view in the long run.

Thirdly, pursuing an intense sales promotion strategy seems to be rather disadvantageous, both for manufacturers and for retailers. A high cross-sales effect for complement products is of interest of 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 complement goods. On the other hand, products that are promoted deeper tend to be purchased more if a complement is promoted. But this positive effect is smaller in magnitude than the negative effect of promoting deeper. For manufacturers, the negative effect that a promotion has on the sales of its substitutes is of vast strategic importance. Of the eight<sup>8</sup> estimated parameters, six have a negative impact on the competitive position, whereas only one has a positive impact. We therefore argue that, from a strategic perspective, it is better to execute price promotions occasionally on well considered moments.

Finally, both for complements and substitutes, prices of the products have especially an impact on the persistent cross-sales 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-sales effect. This effect only holds for low-priced products of the reacting product, however. If the complement/substitute 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-sales effect.

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<sup>8</sup> Both promotion frequency and depth for both the attacker and the defender in both the short and the long run



## **7. Limitations and directions for future research**

Since this is still a research in progress, there is still some potential in fine-tuning the methodology of the estimation of the cross-sales elasticities. The power of the unit root procedure, for example, can be enhanced by allowing for structural breaks at unknown periods, by using the method of Zivot & Andrews (1992). We also did not account for possible cointegration relationships in specifying the VARX models (Johansen, 1995). In a next phase of our research, we will apply these techniques and observe whether our results stand firm.

Another 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.

Thirdly, we wish to draw attention to the fact that all product couples are selected on their high probability to be sold together. This procedure was chosen in order to make the computational load manageable. However, this means that the results strictly only hold for product associations, since we can not guarantee external validity.

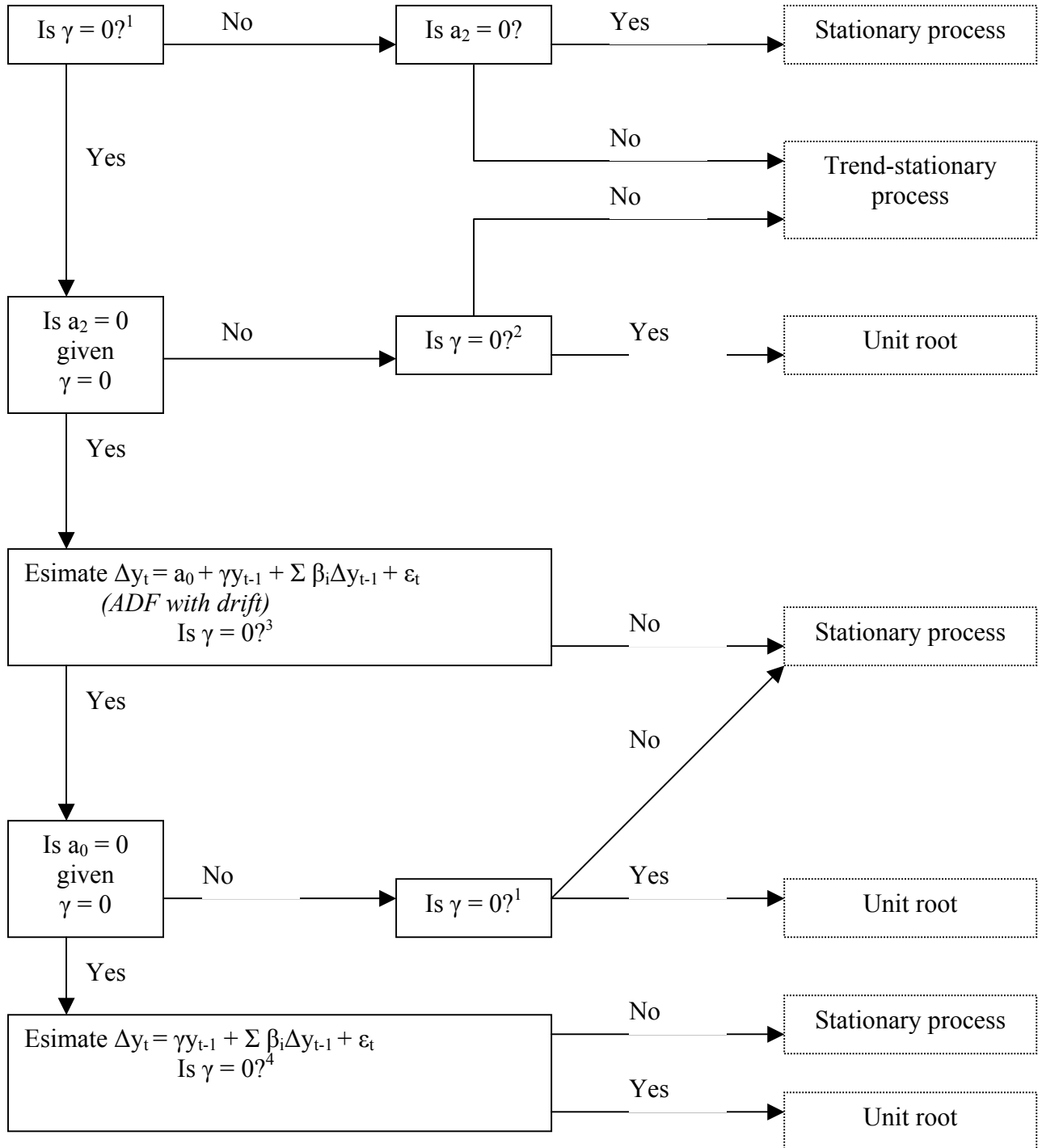
Moreover, the moderator analysis can be extended with more independent variables. A variable that will be included in future analyses is the degree to which a particular product is purchased on the basis of impulse buying (see Narasimhan et al., 1996).

Finally, we will conduct research concerning the cherry-picking behavior observed in the cross-sales effect of complement products. Results of this research will be reported in a future version of this paper.

**APPENDIX**

Testing for unit roots using ADF-tests following Enders(1995,pp.257) and Dolado et al. (1990).

Estimate  $\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \sum \beta_i \Delta y_{t-1} + \varepsilon_t$   
*(ADF with trend and drift)*



1. Using the normal distribution
  2. Using  $\tau_\tau$
  3. Using  $\tau_\mu$
  4. Using  $\tau_\mu$
- All test were conducted at a .05 significance level.

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