The International Journal of Digital Accounting Research
Vol. 7, N. 13-14, 2007, pp. 121- 152
ISSN: 1577-8517

Strategic pricing Possibilities of Grocery Retailers – An empirical study

Aapo Länsiluoto. Seinäjoki University of applied sciences. Finland.
aapo.lansiluoto@seamk.fi

Barbro Back. Åbo Akademi University. Finland.
barbro.back@abo.fi

Hannu Vanharanta. Tampere University of Technology. Finland.
hannu.vanharanta@pori.tut.fi

Abstract. The right pricing of products is one of the most important issues concerning the development of companies' financial performance. Prices should be low enough to attract customers and at the same time high enough to cover all the emerged costs and expected profits. This research illustrates how self-organizing maps (SOM) can be used for pricing purposes. We show how changes in a company's pricing policies would affect the company's pricing position. The study illustrates clearly that companies have different possibilities to change their pricing positions. The SOM method is new and can be applied in many different ways through different pricing simulations.

Key words: *Grocery retailers, pricing, self-organizing maps.*

Submitted May 2006
Accepted March 2007

1. INTRODUCTION

The pricing of products is one of the most important and difficult strategic decisions in companies because it generally affects sales volumes, market shares and the overall profitability of companies (cf. Avlonitis & Indounas 2005, Bhattacharya & Friedman 2001, Richards et al. 2005, Simmonds 1982 and Steed & Gu 2005). Sales volumes and market shares are general important business factors. Profitability is important because it enables companies to survive, i.e. to invest and to guarantee jobs and the payment of dividends. Subsequently the sales price must be high enough to yield a needed profit (i.e. the price should cover the costs) for companies and shareholders and low enough to give possible customers a sufficient incentive and advantage to buy (Avlonitis & Indounas 2005, Bourne 1999 and Pitt et al. 2001). Accounting information systems should help to set up the needed prices of products. However, the accounting systems have not been able to provide valuable enough information for these pricing decisions from the marketing manager's point of view (Foster & Gupta 1994). According to Foster and Gupta (1994) valuable pricing information relates, for instance, to the monitoring of competition and competitors pricing policies and the difference between the listed prices and actual sales prices.

Strategic management accounting (SMA), which has been a response to Johnson and Kaplan's (1987) critique of the lost accounting relevance, has also emphasized the importance of pricing information in the decision-making process. SMA differs from traditional management accounting by focusing on competitors, marketing and future (Bromwich 1990, Guilding et al. 2000 and Roslender & Hart 2003), whereas, traditional management accounting focuses more on production and history. Competitor accounting (competitive position monitoring, competitor cost assessment and competitor performance appraisal based on published financial statements) and strategic pricing (competitor price reaction, price elasticity) are some famous SMA practices (Guilding et al. 2000).

In this study we focus on strategic pricing since it is more interesting than competitor accounting for the purposes of this study and furthermore it is a widely used technique in the field of SMA (Guilding et al. 2000). Strategic pricing covers many kind and type of strategic analyses such as competitor price reaction (how do competitors react to the new prices, what are their financial possibilities to react), price elasticity (how does the demand change if the prices change), projected market growth (what are the effects of growth on the industry and its profitability, do the market shares change as a result of the growth) and economies of scale and scope (do the competitors have some kind of economic advantages) (cf. Simmonds 1982). Therefore, successful strategic pricing need information concerning customers, competitors and costs (Richards et al. 2005).

Another widely used new practice of SMA, which emphasizes the importance of competitive pricing, is target costing. This specific SMA practice highlights the external perspective in the pricing of products and is a technique of market-driven pricing (i.e. congruence with the SMA philosophy) rather than cost-based pricing, i.e. congruence with the traditional management accounting (cf. Guilding et al. 2000, Roslender & Hart 2003 and Yu-Lee 2002). Target costing starts by analyzing the target price, i.e. the price that the customers are willing to pay, or the product price of the competitors, and possible income. After that target costs are determined. If the target costs are higher than actual costs, the cost structure and processes have to be reengineered so that the actual and target costs are consistent (Yu-Lee 2002). Target costing helps companies to prevent the launch of a low profitability product by emphasizing market conditions and capacity utilization (cf. Yu-Lee 2002).

Strategic pricing and the price level assessment of competitors and the effects of changing prices in target costing are daunting tasks when there is a need to analyze many products (e.g. grocery industry). These kinds of assessments are almost impossible to conduct within an acceptable time without computational tools. The assessments can be performed with indexes (cf. Aalto-Setälä 1999, 34-51). According to Aalto-Setälä (1999, 34-36) the use of these indexes poses some difficulties in cases when consumer utility function should be known and when the function varies between people. The requirements for the tool are demanding when it should not only handle huge amounts of data but also visualize this data effectively. The visualization is especially important in the current information-rich era (Kohavi et al. 2002).

The method of self-organizing maps (SOM), in particular, has been developed to improve the capabilities of information visualization (e.g. Churilov et al. 2005).

The SOM is a neural network technique that can use multidimensional data and after the training maps it onto a topological two dimensional grid. The technique maps similar items of data close to each other on the grid, preserving the relationships between the data in the form of the topological display. The SOM has been used in over five thousand applications (Oja et al. 2003), in many different areas where the visualization capability is important, such as in breast cancer diagnosis (e.g. Chen et al. 2000), customer profiling and segmentation (Ultsch 2002), economic environment analysis (e.g. Länsiluoto et al. 2002a), industrial cycle comparisons (e.g. Länsiluoto et al. 2002b) and classification of prostate cancer patients into risk groups (e.g. Churilov et al. 2005). However, there are only some studies of financing where the SOM has been used. Kiviluoto (1998) and Serrano-Cinca (1996) have used the SOM for predicting bankruptcies, Tan et al. (2002) for credit rating and Eklund et al. (2002) for financial benchmarking of pulp and paper companies. Although there are thousands of different applications for which the SOM has been used, it has not been used before for strategic pricing purposes.

This study discusses the ways in which a strategic accountant can produce and deliver information in the pricing process, also considering the price level of competitors. The purpose of the study is to illustrate how the SOM[1] can be used to assess the effects of changing pricing policy (i.e. simulation) on the price position of some Finnish grocery retailers. This kind of assessment is interesting because retailers can evaluate the gap between the current and desired pricing position and assess how much they can or have to change the pricing policy to achieve the desired position. When the assessment has been conducted the retailers and their strategic accountants can evaluate how their cost structures should be changed to achieve the desired new profitable strategic position. On the other hand, accountants can conduct the assessment of a price position to analyze how much they can raise the prices still retaining the current price position. Strategic accountants can also evaluate how competitors' positions change as a result of the changing pricing policy. There are also many other possibilities for strategic pricing although we only show some of these possibilities with real market prices.

[1] This kind of assessment can be also performed with different price indexes (cf. Aalto-Setälä 1999, 34-51).

The structure of the rest of the paper is as follows. First, we introduce our data and the variables used. Second, we present the SOM technique which we have used in this research, and give some reasons why we used the chosen technique. In the last section we interpret our results and draw conclusions.

2. METHODOLOGY

In the methodology chapter we introduce the empirical data and variables, the choice of appropriate technique for the study, the technique of self-organizing maps as well as the used parameters in the network training.

2.1. Empirical data and variables

Our data is gained from the National Consumer Research Centre (Finland). The institution is independent i.e. it is not allied in any way to any group of the grocery retailers. The data is from the year 1995 and it includes the prices of 237 grocery products (see Appendix 1). The price range of the products is between EUR 0.12 (Fazer liquorice/#221) and EUR 27 (inner fillet of cattle/#20).

Our database contains 135 grocery retailers whose turnover was between EUR 940 thousand million and EUR 30.1[2] million in 1995. The data consists of the five groups of Finnish grocery retailers; K-group (40 retailers), S-group (32), T-group (27), Eka (15), Elanto (3), both independent grocery retailers (3) and finally fifteen retailers whose groups were unknown.

Because the purpose of the study is to illustrate how changing pricing policy affects the position of a retailer, we will focus on some retailers. The illustrations focus on the retailers in one town[3] because our database includes several competitors from different retailer groups in that town. They also had close locations and were of quite the same size, which gave another reason to focus on these retailers.

---

[2] The first quartile is EUR 5.2 million, median EUR 8.7 million and the third quartile EUR 13.8 million.

[3] We do not have possibility to mention the name of the town due to the data confidentiality

The database contains six retailers with turnovers of grocery products between EUR 2 million and EUR 16 million. Retailers 53, 54, 55 and 56 are over median size retailers in the Finnish grocery industry and all of them belong to different groups of retailers. We do not know the size and group of 57 but we assume it is quite a small retailer because we can estimate the size of the retailer by the location of 57. 58 is a small retailer and it is in the same group with 56.

Retailers 53 and 55 belong to different groups and are geographically very close to each other. 53 and 55 also have the same turnover and can therefore be considered to be competitors. Retailer 54 is located at a distance of some kilometers from 53 and 55 but 54 is a competitor for 55 because they have almost equal turnover of grocery products. The closest geographical competitor for 54 is 56 with the distance of less than three kilometers. On the other hand retailers 57 and 58 are also close competitors since they have quite the same turnover and are located in the same area; the distance between the retailers is less than three kilometers. The closest competitors of 56 are 53, 54 and 55 within a distance of some kilometers.

We limited the maximum prices of the products in the analyses so that they could not exceed the maximum price of that product after the rise of the product price. Thus if the price of the product has been raised by some retailer by 10 percent in the analyses then some price can exceed the maximum price of that product and this exceeded price has been adjusted so that it does not rise over the maximum price of the product in the whole dataset. The same limitation was applied to reduced prices.

2.2. Choice of appropriate technique for the study

Three most commonly used clustering techniques are partitioning techniques (k-means), hierarchical techniques (decision trees) and model-based techniques (self-organizing maps) (Han & Kamber 2001, 346-81 see also Berry & Linoff 2000, 93-94 and 102-21). In the following paragraphs we briefly discuss the reasons for the selection of the SOM as a clustering technique for our research purposes.

The most well-known and commonly used partitioning algorithm is k-means (Han & Kamber 2001, 349 and Wang 2001). The users have to specify k, i.e. the number of clusters, in advance, which is one disadvantage concerning k-means. The k-means technique is not suitable for discovering clusters with nonconvex shapes or clusters of very different size. Furthermore, it is sensitive to noise and outlier data points. (Han & Kamber 2001, 350 and Kiang & Kumar 2001 see also Wang 2001)

The second group of techniques is hierarchical clustering (i.e. decision trees) techniques. They work by grouping data objects into a tree of clusters. The quality of a pure hierarchical clustering technique suffers from its inability to perform adjustment once a merge or split decision has been executed, which is the biggest problem concerning hierarchical techniques. (Han & Kamber 2001, 354-6) The greatest benefit of decision tree approaches is their understandability (Groth 1998, 25). Especially, if the perceptions are similar with each other, then the size of the decision tree is compact and, hence, the results are easily understandable (Berry & Linoff 2000, 120 and Cios et al. 1998, 256).

The third group is model-based clustering techniques which follow a neural network approach[4] (e.g. self-organizing maps). (Han & Kamber 2001, 376-81). The number of clusters does not need to be identified a priori when using the SOM technique which is one advantage of the technique. Kiang & Kumar's (2001 see also Wang 2001) results indicate that the SOM networks provide a robust alternative to clustering techniques (k-means), especially, when the input data is skewed (i.e. the data do not have normal distribution).

The introduced clustering techniques have their own strengths and weaknesses. We chose the SOM technique because we did not want to determine the number of clusters a priori (as we should do by the using of k-means). Furthermore, we wanted to utilize a properly performing technique if the size of the clusters varies (this would not be a case when using k-means). Although decision tree technique produces easily understandable clusters, it can also sometimes produce quite

[4] Han & Kamber (2001, 376-379) introduce also a statistical approach as another model-based clustering technique.

complex cluster constructs especially if the data is multidimensional (as it is in our case). We also wanted to use a technique that has a good visualization ability and performs well if the data is skewed. These reasons impacted on the selection of the SOM technique which is described in more detail in the next chapter.

2.3. Self-organizing maps

The network in a self-organizing map usually consists of two layers of neurons: an input layer and an output layer. The neurons in the output layer are arranged in a grid and are influenced by their neighbors in this grid. The goal is to automatically cluster the input patterns in such a way that similar patterns are represented by the same output neuron, or by one of its neighbors. The inputs are 237 product prices of 135 grocery retailers. The outputs in our case are clusters of retailers which have a similar price level. These clusters are not known when the training process starts, i.e., during the training process the network has no knowledge of the desired outputs. The training process is characterized by a competition between the output neurons. The input patterns (a grocery retailer's product prices) are presented to the network one by one, in random order. The output neurons compete with each other to be activated or fired. The output neuron with a reference vector that is closest to the input vector is called the winner (Haykin 1999, 58). The reference vector of the winner is adjusted in the direction of the input vector, and so are the reference vectors of the surrounding neurons in the output array (Ultsch 1993, 308). The size of adjustment in the reference vectors of the neighboring neurons is dependent on the distance of that neuron from the winner in the output array. There are several different metrics for expressing the distance between two vectors (Han & Kamber 2001, 339-341). We have used the Euclidean distance, which is often used in quantitative analysis (Kiang & Kumar 2001). It is defined as $\mathrm{Min}\{|x - mi|\}$, where x is the input data vector and mi is the reference vector (Kohonen 1997, 86).

Usually, neurons on the output layer are arranged in either a rectangular or hexagonal grid (Ripley 1996, 323). A neuron in a rectangular grid has four neighbors and a neuron in a hexagonal grid has six neighbors, except for the ones at the edges of the grid.

There are two learning parameters that have to be stated: the learning rate and the neighborhood width parameter. The learning rate influences the size of the reference vector adjustments after each training step, whereas the neighborhood width parameter determines to what extent the surrounding neurons, the neighbors, are affected by the winner. An additional parameter is the training length, which measures the processing time, i.e. the number of iterations through the training data.

The stopping criterion of a training iteration is a number: the average quantization error. The error in turn, is an average of the Euclidean distances of each input vector and its best matching reference vector in the SOM. The clusters of the data are formed by identifying neurons on the output layer that are close to each other using the reference vectors as a starting point. A tool called U-matrix (Ultsch 2002) is used to visualize the distances between neighboring neurons (Figure 1). In the U-matrix presentation, relative distances between the neighboring SOM vectors are represented by shades in a gray scale. Lighter shades of gray represent smaller distances and darker shades larger distances. A "cluster landscape" formed over the SOM clearly visualizes the classification (Kohonen 1997). The clusters are groups of neurons surrounded by dark bordering nodes. The U-matrix is an accumulated description of all the inputs.

The interpretation of the clusters is given by analyzing the reference vectors, the so called feature planes (Figure 2) where the weight for each neuron is visualized by gray scale imaging – light shades representing high values and dark shades representing low values.

2.4. Training

We utilized the Self-Organizing Map Program Package (SOM_PAK) version 3.1 in the map training. The SOM Programming Team of the Helsinki University of Technology has developed the SOM_PAK. (Kohonen et al. 1995) The program uses the competitive learning algorithm, as described in the previous section. The trained maps are visualized by using NENET demo version 1.1 whereby we have better visualization abilities than the abilities of SOM_PAK 3.1.

We started by standardizing the input variables to the range [-1,1] because we attempt to give all variables an equal weight and to improve the accuracy and efficiency of the map training (Han & Kamber 2001, 105 & 339 see also Kaski & Kohonen 1998). We constructed several maps - all maps included the whole database with 135 retailers and the prices of 237 grocery products- and chose the map with the lowest quantization error. We chose a network topology that was hexagonal with 4 x 5 neurons. The training length was 10 000 in the first part, 100 000 in the second part and in the last part 200000. The learning rate was 0.5 in the first part, 0.05 in the second part and 0.01 in the last part. We used these values because after several different training sets we found that these values brought the best results. The Euclidean distance of each input vector and its best matching reference vector (quantization error) was 4.521150.

3. RESULTS

In this part of the study we identify the clusters and illustrate the effects of changing pricing policy on the retailers' price positions. First we illustrate how the changes in all the prices affect the positions and after that we illustrate how the price changes in one specific product group affect the positions of the retailers. The specific product groups are milk (products 55-65 in Appendix 1), fruits and vegetables (89-109), meat (7-28) and biscuits and candies (128-138 and 200-224).

The analyses of specific product groups are interesting when the retailers are analyzing the possible effects on the price position in a case when they are able to (or have to) change their prices in one specific product group as a result of more efficient operations. On the other hand retailers would be interested to know whether their position will change if they want to raise their prices in one specific product group when aiming at improving their profitability. This kind of smaller product group specific changes are more realistic in the price setting of the retailer because these changes are easier to implement than the price changes of all the products. On the other hand, it can be difficult to choose the products prices of which would be changed. This difficulty gives a reason to analyze the changes of all the product prices and their possible effects on the position.

3.1. Identifying clusters

The training of the SOM yields the map presented in Figure 1a where the numbers indicate the original price position of the retailers. When we have received this kind of a map we might firstly be interested in the reasons why the specific retailer is located for instance in the bottom right-hand corner (i.e. retailer 55). We might also be interested if some of the retailers are in the same cluster (i.e. they have similar price level).

Figure 1a shows for instance the horizontal black areas between two neurons in the middle of the map, which indicates a difference between two cells i.e. the border of a cluster. By using feature planes (see Figure 2) and U-matrix we were able to define and explain the properties of the clusters and after that we drew the clusters in Figure 1b manually. In general, Figure 1b and Table 1 show all the variables increasing from the right-hand (or down) to the left-hand (up) side of the map.

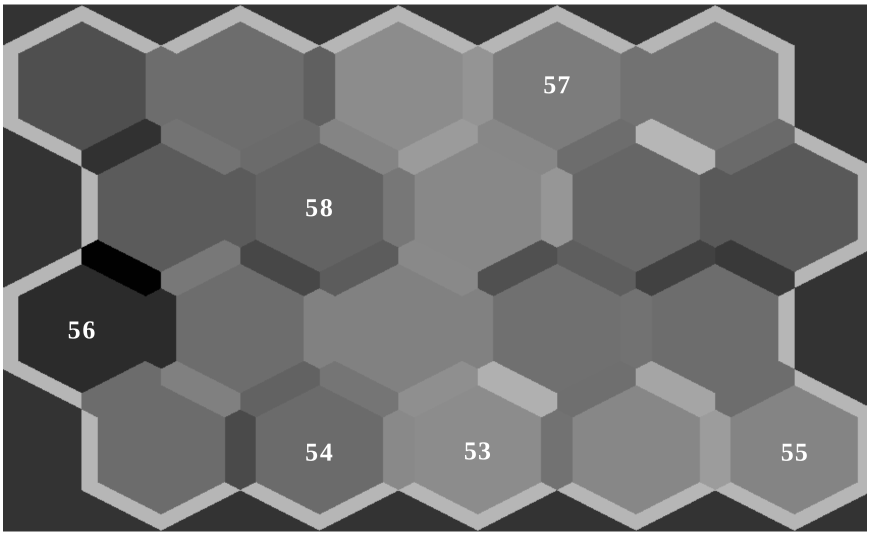

Figure 1. a) SOM after training

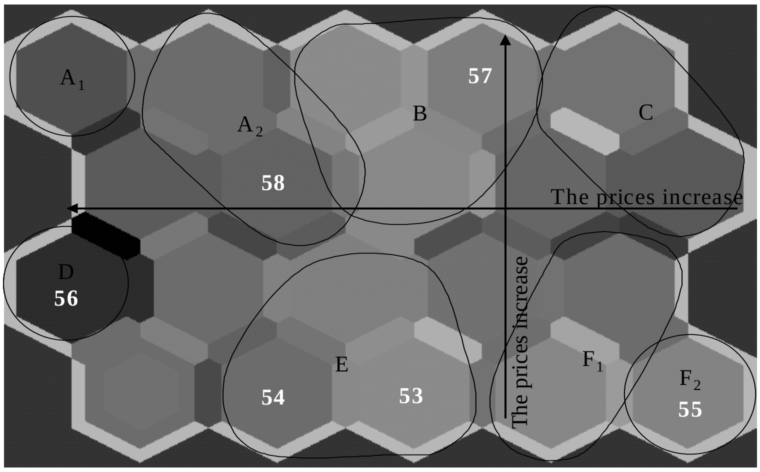

Figure 2. b) clusters of the SOM (clusters and arrows are manually drawn)

Figure 1b shows eight clusters A-F2 with 237 variables (i.e. the prices of grocery products). We derived the properties of the clusters from the feature planes manually. Some of these planes, in particular the unusual maps which have been referred to in Table 1, are presented in Figure 2. We can understand the linkage between feature planes (Figure 2) and U-matrix (Figure 1) in a way that the U-matrix is achieved when all the feature planes are put together. Therefore, when retailer 55 is located in the lower right-hand corner in Figure 1 it will also be in the same place in all the feature planes in Figure 2. This means that almost all the prices of retailer 55 are low when looking at the presented feature planes. In Figure 2 we present the unusual feature planes which have been referred to in Table 1. Feature planes increase usually in the way as presented in Figure 1b.

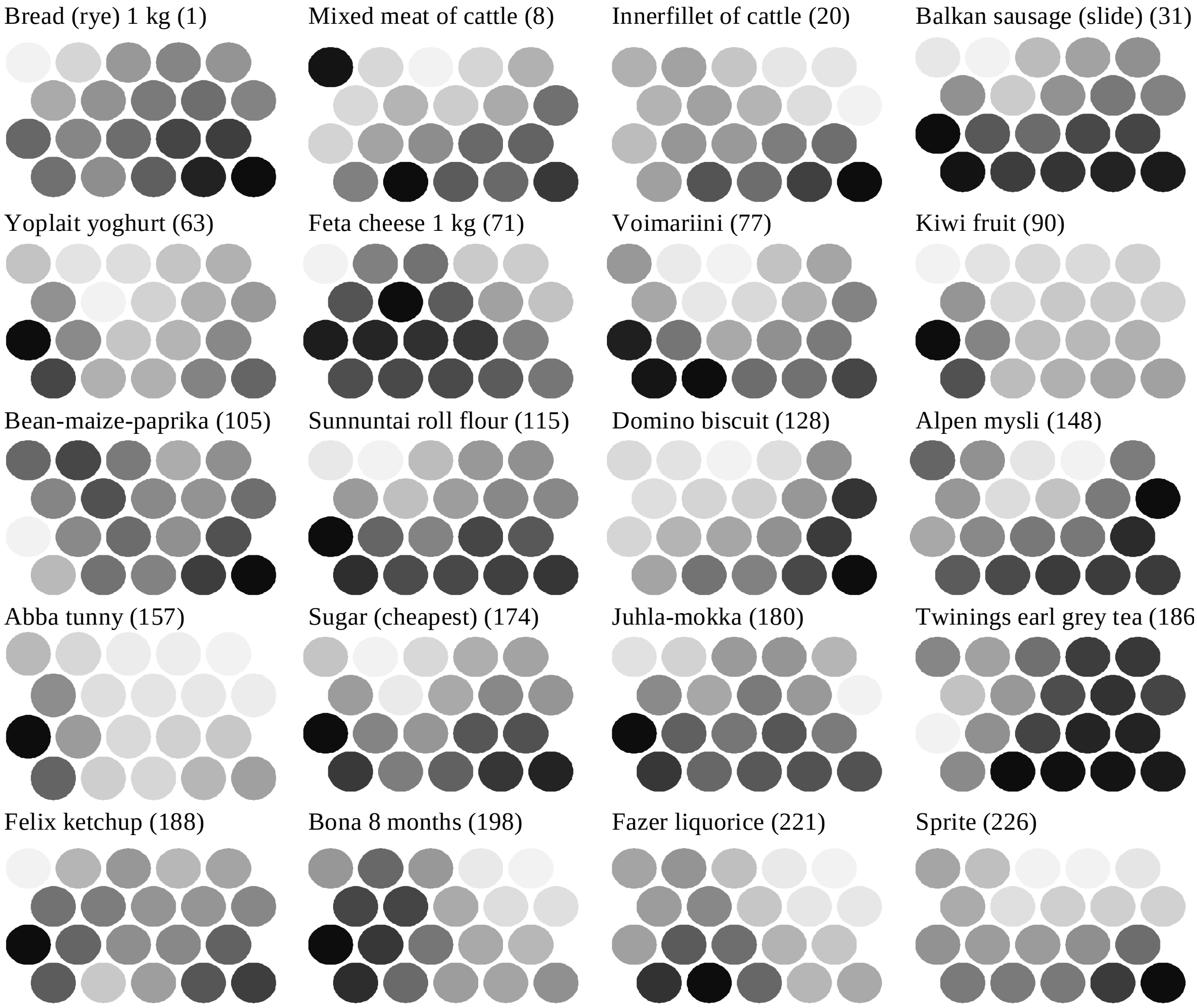

Figure 2. Feature planes (black describes cheap and white expensive prices)

Table 1 describes the price levels of the different clusters. Table 1 shows that the retailers with the most expensive products are in cluster A1 whereas the retailers with the cheapest products are in cluster F2 (cf. Porter (1985, 11-16) who proposes that the competitive advantage can be based on low cost). Table 1 also shows that the most expensive retailers have some campaign products (e.g. mixed meat and strip beef of cattle) that try to increase the customer traffic and subsequently the profit to the retailer. On the other hand the cheapest retailers (F2) have also some products (e.g. jelly and bona) which are not the cheapest although they are still quite cheap compared to the other retailers (cf. Aalto-Setälä 1999, 5 and 50-51).

Feature/ Cluster	**General price level**	**Exceptional cheap products compared to the general price level of the cluster**	**Exceptional expensive products compared to the general price level of the cluster**
A_1	1	Mixed meat of cattle and strip beef of cattle, meat paste casserole	-
A_2 (58)	2	Feta cheese	Yoghurts, plum, raisins and sugar
B (57)	3	Cream cheese	Milk, yoplait yoghurt, butter, Voimariini, oil, Domino biscuits, mueslis, Abba tunny, pineapple, Koti mustard, Bona 5 months, Orbit xylitol and Sprite
C	4	-	Innerfillet of cattle, liver of cattle, Kellog's frosties, Abba tunny, Juhla-Mokka, Bona 8 months, Emmental and Fazer Liqourice
D (56)	(4/) 5	Strip beef of cattle, shoulder of cattle, meat paste casserole, stock cube, satsumas, twining earl grey tea)	Balkan sausage, feta cheese, Becel margarine, kiwi, Anni Helene wheat flour and Sunnuntai roll flour
E (53&54)	6	-	Yoplait yoghurt, kiwi, Abba tunny, Felix ketchup, Bona 5 months, halva mixed candies
F_1	7	-	-
F_2 (55)	8	-	Some biscuits, jelly, bona and gum

Table 1. The specifications of different clusters

Table 1 (see also Figure 1b) shows also the original price positions of the retailers in the study when the cheapest retailer was 55 and the most expensive 58. Table 1 and Figure 1 show the close original price level position of retailers 53, 54 and 55 when 53 is cheaper than 54 although they are in the same cluster. When we compare the close geographical competitor retailers 53 and 55, we notice the latter being less expensive. We can also see that the competitor retailers 57 and 58 are also close price competitors; the former is in the less expensive cluster. In the next paragraphs we illustrate what will happen in the position when the pricing policy of retailers is changed.

3.2. Changing prices of all the products

In this subchapter, we illustrate the movements in price positions when the changing pricing policy affects all the products. This means that the prices of all the products have been raised or reduced in the illustration of Figure 3.

First we investigate what will happen to the original position (see cluster F2) if the cheapest retailer 55 (white solid arrows in Figure 3 and all the rest figures) is planning to raise the prices of all its products. We can see that if all the prices of retailer 55 are raised only by three percent, retailer 55 will move to cluster to F1. This is interesting because if 53 (black solid arrows; originally in cluster E), competitor of 55, is planning to reduce its prices at the same time by three percent they will end in the same cluster F1. On the other hand, if retailer 53 is able to reduce its prices by seven percent, this will drive 53 to the same cluster with the original price position (F2) of 55. Therefore, the situation of 55 seems to be quite safe because only a seven percent reduction in the prices of 53 and 54 (ten percent decrease in 56; white dashed arrows) will make them close price competitors to 55.

Finally we can see the movement if retailer 58 (A2) is able to reduce the prices by 10 percent. This 10 percent reduction moves 58 (white dashed arrows with the number 58) to be a price competitor to 54 (black dashed arrows, originally in cluster E) if it decides to raise its prices by five percent at the same time. We can also see that if 57 (black dashed arrows with the number 57, originally in cluster B) reduces its prices by 5 percent it moves quite far away from its geographical competitor 58. This five percent drop moves 57 to the same cluster with 53 (E). If 57 is able to reduce its prices by 10 percent it will move to the cheapest cluster (F2). Figure 3 clearly illustrates that the decrease in price level affects the position of 57 much more than that of 58. We also observe the unfavorable situation of 58 (originally in cluster A2) when at least a 10 percent reduction in the prices would move 58 to the cheaper cluster but already a three percent rise of the prices moves it to the more expensive cell. Therefore, it seems that if 57 can reduce its prices, the effects would be more favorable than in the case of its close competitor 58.

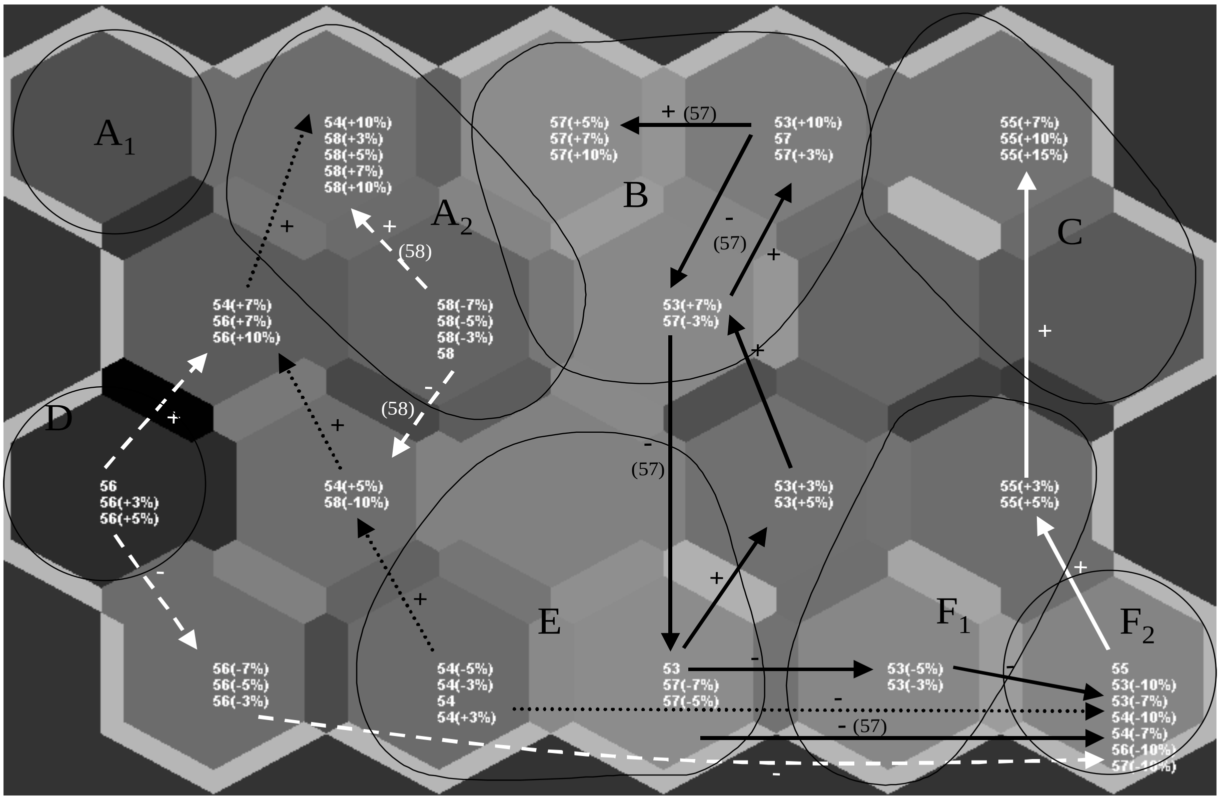

Figure 3. The positions of retailers after changes in all the product prices

Figure 3 shows that a seven percent rise in the prices of 53 will bring it to the same cluster with 57 (B). Their geographical distance is only a few kilometers and this possible rise in the prices may stimulate customers with high price sensitivity to change their grocery retailer. The situation of retailer 54 (originally in cluster E) is quite amazing and unfavorable because if it changes its prices between –5 and +3 percent its location does not change. Then only a seven percent reduction in prices will bring 54 to the cheapest cluster (F2). On the other hand, a ten percent raise of prices brings 54 to the second most expensive cluster (A2). In the next subchapters we focus on the changes in the specific product groups and their effects on the price positions of the retailers. We start by analyzing the price level changes of milk products.

3.3. Changing prices of milk products

Figure 4 illustrates a situation where the prices of milk products (i.e. product 55-65) have been changed and all the prices of other products have stayed on the original level. First of all we can see that the changes on the map are smaller (although the product group specific price level changes are larger) in Figure 4 than in Figure 3 as a result of the changes in the smaller number of product prices.

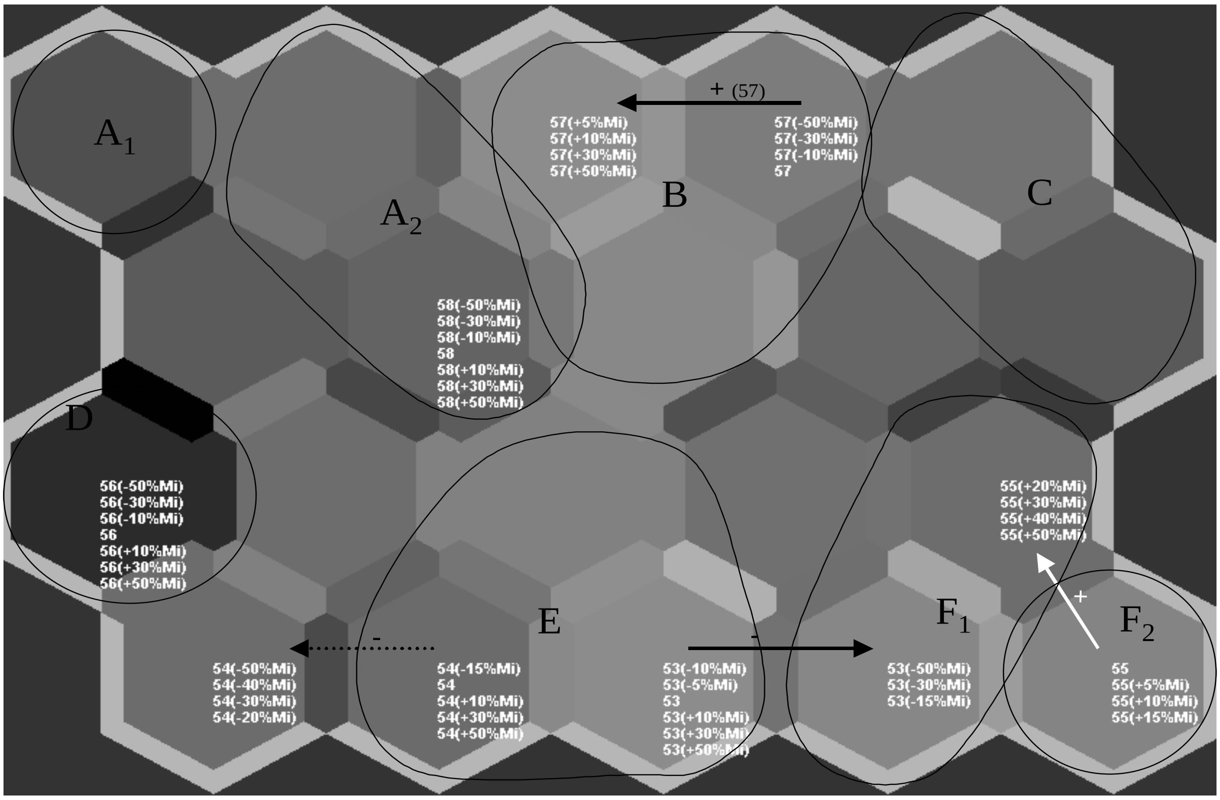

Figure 4. The retailer's positions after changes in milk products

Figure 4 shows that the cheapest retailer 55 (F2) can raise its milk product prices by even 15 percent and still remain in the cheapest cluster. On the other hand, retailer 53 has to reduce its milk product prices by 15 percent to change its location closer to retailer 55. It is amazing in Figure 4 that if retailer 54 reduces its prices of milk products by 20 percent its location changes to the opposite direction that would be expected by Figure 3. We verified this surprising movement from the feature planes of milk products (they are not presented in this study) and noticed the reliability of the movement. We can also see that if 57 raises the prices by only five percent it will achieve almost the price level of its competitor retailer 58 (A2). Finally, Figure 4 shows that retailers 58 and 56 cannot change their positions by decreasing or increasing only their milk product prices.

3.4. Changing prices of fruits and vegetables

Next, we investigate the impacts of fruit and vegetables (i.e. products 89-109) price changes on the position of the retailers. Generally, Figure 5 shows that the price changes of fruits and vegetables have more effects on the position of a retailer than the price changes of milk products. One reason for the effect can be the greater number of products than in the earlier analysis.

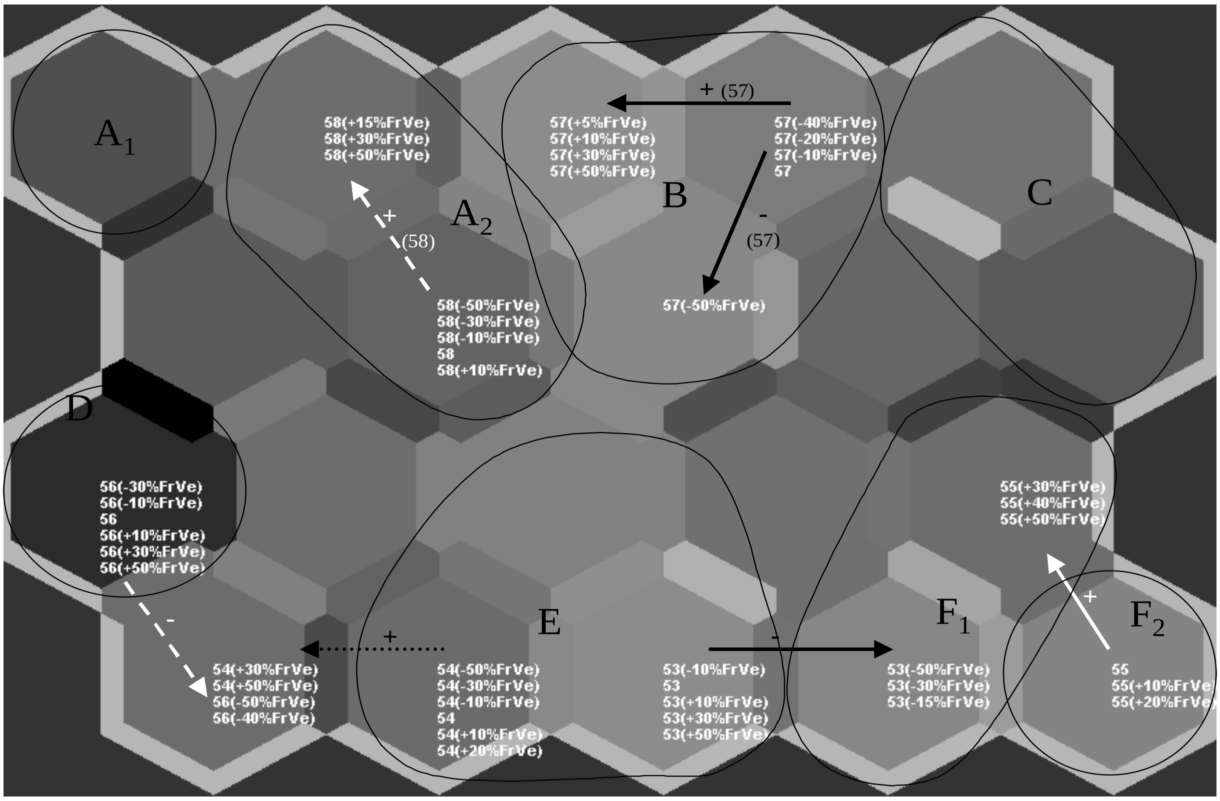

Figure 5. The positions after the price changes in f ruits and vegetables

According to Figure 5 the fifteen percent price reduction of fruits and vegetables moves retailer 53 (see cluster F1) closer to its competitor retailer 55 (F2). We can also see that not even 50 percent rise in the prices changes the position of 53 (E) to the more expensive cluster, which indicates quite a safe pricing policy position for 53. Retailer 55 can raise its fruit and vegetables prices even 20 percent still remaining in the same cheapest cluster. 54 (E) is not able to change its location by decreasing the prices of fruits and vegetables. However, a 30 percent rise moves 54 closer to its geographical competitor retailer 56 (D). If 56 reduces and 54 raises the prices of fruits and vegetables by 40 percent and 30 percent respectively, they get similar price levels.

The most expensive retailer, 58 (A2), is not able to alter its position by reducing fruit and vegetables prices whereas a 15 percent rise moves 58 toward the most expensive corner on the map. If 57 (B) raises the prices only 5 percent, it will come closer to its competitor 58 although they will not be in the same cluster even though 57 would raise the prices until 50 percent.

3.5. Changing prices of meat products

Now we illustrate how the position of retailers changes when the prices of meat products (i.e. product 7-28) have been changed. Figure 6 illustrates a case when 53 (in cluster E) wants to know how much it has to reduce the prices to change its position closer its competitor 55 (in cluster F2). We notice that it has to reduce the prices of meat products by twenty percent. On the other hand if 53 raises meat product prices by 20 percent, it will change its position to cluster F1 but lower than a 50 percent rise in prices does not change the position anymore. The reducing prices cannot change the position of 54 toward a cheaper cluster whereas already more than a five percent increasing of the prices of meat products moves 54 closer to its geographical competitor retailer 56.

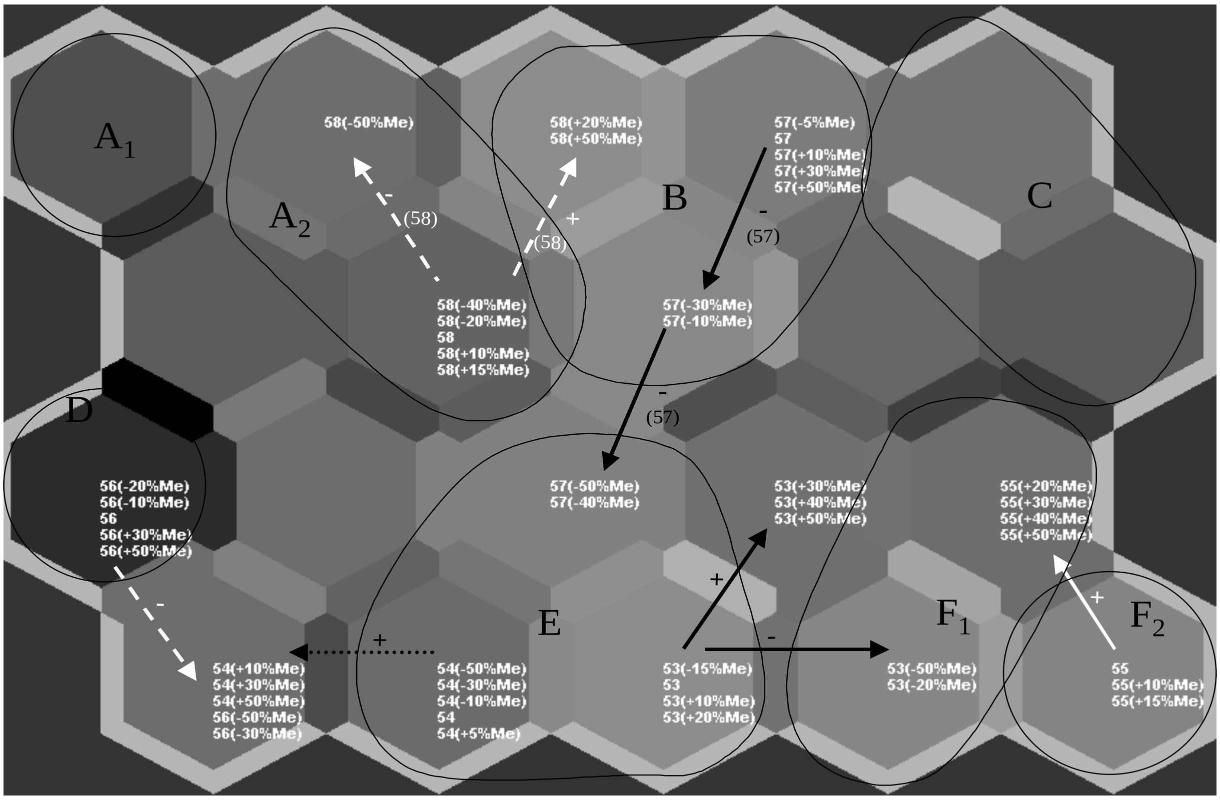

Figure 6. The positions after the price changes of meat products

The rise in meat product prices until 50 percent does not cause any movement for 56 (cluster D). Contrary to this price stability, a thirty percent decrease in meat product prices leads 56 close to 54. They will be at the same neuron actually if 56 reduces its meat prices by 30 percent and 54 raises its prices by 10 percent simultaneously. Therefore, if 54 is planning to raise its meat product prices they have to be aware of the final result if 56 is able to reduce the prices at the same time.

The cheapest retailer 55 (F2) has quite a safe position again since it can raise its meat prices up to 15 percent still being in the cheapest cluster. But if 55 plans to raise its meat product prices by 20 percent and simultaneously 53 plans to reduce meat prices by 20 they will be in the same cluster F1. Figure 6 shows that it is easiest for retailer 57 to change the position by reducing meat product prices because already a ten percent reduction in the meat product prices moves 57 to the less expensive area in cluster B. When comparing this with the earlier figures, this kind movement has required a larger price reduction in other product groups of 57. If 57 can reduce its meat product prices by 40 percent, it moves close to retailers 53 and 54 in cluster E.

The analyses of changing pricing policy suggest quite an interesting result for retailer 58 when comparing Figures 1b and 6. According to Figure 6 if retailer 58 (A2) raises its meat prices by twenty percent it moves to a cheaper area (cluster B) and if it reduces its prices by 50 percent it will move to a more expensive area when looking at Figure 1b. But when we examined these interesting movements from the feature planes (all of these feature planes are not presented in Figure 2) where all the meat products were visualized we found out logic for these movements.

3.6. Changing prices of biscuits and candies

Finally, we illustrate the movements of the price positions when we are changing the prices of biscuits and candies (i.e. products 128-138 and 200-224). In general Figure 7 illustrates that the positions of retailers change when they reduce or raise the prices. Therefore, the retailers are able to affect their position by changing the prices of biscuits and candies. Candies and biscuits are combined because they can be understood as the titbit unnecessary products.

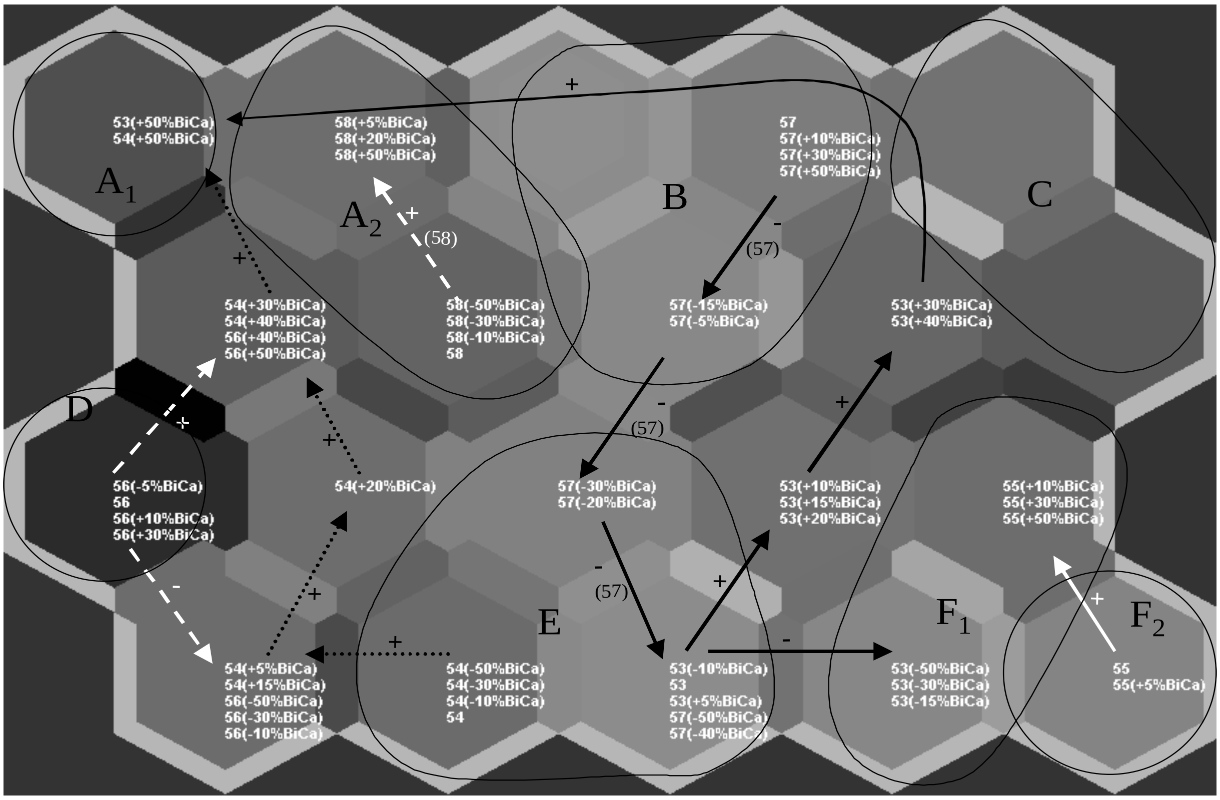

Figure 7. The positions after the price changes of biscuits and candies

Figure 7 shows that if retailer 53 is able to reduce the prices of biscuits and candies by fifteen percent it moves closer to its competitor 55. We can also see that it does not make sense to 53 to reduce the product prices more than fifteen percent if they are trying to change their position because even fifty percent cheaper products do not move the position of 53 any closer to its competitor 55. On the contrary, these are minor possibilities to change the position of 53 by decreasing the prices whereas the position changes by raising the prices sensitively. Therefore even a 10 percent rise moves 53 to a more expensive position, a thirty percent rise close to 57 and finally a 50 percent rise moves it to the most expensive cluster A1.

Figure 7 shows quite difficult situations for retailers 54 (cluster E) and 58 (A2) because they are not able to improve their price positions by decreasing the prices of biscuits and candies. On the other hand both of them change their positions if they raise the prices only by 5 percent. Figure 7 clearly illustrates that if 54 raises the prices by 30 percent and 58 does not change its prices they will be very close to each other. If 54 decides to raise the prices by 50 it moves to the most expensive cluster A1.

Figure 7 shows again the favorable position of the cheapest retailer 55 since it can raise the prices by five percent without any effect on the position. If they decide to raise the prices between 10 or 50 percent, their position changes only one cell to the second cheapest cluster F2. If 56 (D) can and is willing to reduce the prices by 10 percent, their position will change. On the other hand, the larger reductions are not grounded from the view of changing pricing position because they do not have any impact on the position. We can also observe that 54 and 56 will be at the same neuron if 54 raises the prices by five percent and simultaneously 56 decreases its prices by 10 percent. A 40 percent rise in the prices of biscuits and candies moves 56 close to the original position of 58.

The competitor retailers 57 (B) and 58 (A2) have opposite possibilities to move their positions by changing the prices of biscuits and candies. The situation is more favorable to 57 than 58. The raising of prices of 57 does not have any effect on its position when only a five percent reduction moves 57 to the cheaper neuron. If 57 is able to reduce the prices by 40 percent they will move to the same neuron with 53 (E). Contrary to the situation of 57, 58 does not have any possibilities to change its position by reducing the prices whereas already a five percent rise moves 58 to the more expensive neuron.

4. CONCLUSIONS

In this research we have illustrated several different ways to change the strategic pricing position of some Finnish grocery retailers. As would be expected the greatest movements are achieved by changing the prices of all products. This kind of a total change can be very difficult to conduct in practice since the position can also be moved by doing minor changes in specific product groups. The study also showed that not all the product pricing policy changes affected the price positions of retailers, which emphasizes the importance of individual analyses of each retailer. Some pricing policy changes did not affect the position at all and some larger changes did not affect the position any more than minor changes had already done. However, in some cases even minor pricing policy changes affected the position of the retailer. This shows clearly that some retailers have less possibilities to change their pricing position by reducing grocery product prices than others.

We also found that if a retailer is planning to raise the prices of some product group it should consider the plans of the competitor retailers so that they do not move close to others unexpectedly. Therefore, the accountants of retailers should also try to analyze the cost structure of their competitors[5] (Guilding et al. 2000), their possibilities to reduce the prices or the competitors' pressures to raise the prices of their products as a result of unprofitable business. These kinds of assessments can be very difficult in practice.

When the presented price sensitivity analysis of products is performed and its effect on the price position is evaluated, strategic accountants should analyze how the planned changes affect companies' profitability and what kind of operative arrangements should be performed to achieve the desired results. We propose that accountants should produce illustrations presented earlier because they know the cost structure of the company and subsequently they can estimate, first, how possible it is to improve the cost structure and, second, how much costs it is possible to cut to achieve the desired price position of the retailer. Accountants can also make action plans so that the desired price level could be achieved. On the other hand, we also think that if accountants provide the presented price sensitivity illustrations it will be valuable information to the marketing managers (cf. Foster & Gupta 1994) who have not been satisfied with the information produced by accountants. The illustrations are usable also when the popular strategic management accounting practices (see Guilding et al. 2000), such as target costing and strategic pricing, are utilized.

Although we used the prices of grocery products as an evaluation factor in the study, we have to remember that the purchasing decisions of customers are not only affected by price. Therefore, the most expensive retailers can still be profitable and successful because customers value also other factors than price, e.g the location of retailer when they are buying grocery goods (cf. Aalto-Setälä 1999, 2-3 and Pitt et al. 2001).

[5] In this study we were not able to do this kind of assessment because we did not have cost data available.

By using the SOM instead of indexes in the price assessments we can overcome a number of problems: 1) We do not need to assess the consumer utility function which varies between people. In this study, the function need not be assessed because the starting point of this study is that retailers have huge databases including the prices of the products of the different grocery retailers. And thus the basic problem is to analyze and assess the pricing position of the retailer compared to other retailers correctly and rapidly. After the assessments the retailer can evaluate the possible effects of the changing prices on the sold quantities, i.e. how customers respond to the changing price level. When using price indexes we have to know the real quantities of the sold products if we want to use the "reasonable" price indexes (cf. Aalto-Setälä 1999, 40) but in our approach we do not have to know the quantities of the sold products (the used database did not even include the information of sold quantities). 2) The price indexes, as well as the SOM, do not consider the price elasticities of products, i.e. how product demand changes when the price changes (cf. Aalto-Setälä 1999, 45). But as we mentioned, the retailer can analyze the price elasticities after the pricing position assessments. 3) The effect of the changing prices in a specific product group cannot be as easily visualized and evaluated as can be done with feature maps in the SOM.

The study left and created some interesting questions that could be answered in the future. The first interesting question would be to investigate the correlation between retailers' price level and their profit. The second interesting question would be to examine what kind of possibilities from the point of view of cost structure grocery retailers have to change their pricing policy. Third, it would be interesting to study if the illustrations really help in the formulation of retailers' pricing policy. Finally, it would be valuable to compare the situation of today's pricing policy and the presented illustrations. The validation of the method, i.e. to answer questions two and three, will be difficult to perform in practice due to the data confidentiality. The verification of the SOM method is performed through simulations where the SOM showed the effects of changes in the strategic pricing positions as a result of changing of all and product specific prices.

5. REFERENCES

AALTO-SETÄLÄ, V. (1999): *Economies of Scale, Product Differentiation, and Market Power*, Serie A-162, Helsinki School of Economics and Business Administration.

AVLONITIS, G.J.; INDOUNAS, K.A. (2005): "Pricing objectives and pricing methods in the services sector", *The Journal of Services Marketing*, vol.19, n. 1: 47-57.

BERRY, M.J.A.; LINOFF, G. (2000): *Mastering Data Mining – The Art and Science of Customer Relationship Management*, John Wiley & Sons.

BHATTACHARYA, A.; FRIEDMAN, H. (2001): "Using 'Smart' Pricing to Increase Profits and Maximize Customer Satisfaction", *National Public Accountant*, vol. 46, n. 6: 34-38.

BOURNE, H. (1999): "Pricing - The Strategic Implications", *Management Accounting*, vol. 77 n. 3: 26.

BROMWICH, M. (1990): "The Case for Strategic Management Accounting: The Role of Accounting Information for Strategy in Competitive Market", *Accounting, Organizations and Society*, vol. 15, n. 1&2: 27-46.

CHEN, D.-R.; CHANG R-F.; HUANG Y.-L. (2000): Breast Cancer Diagnosis Using Self-Organizing Map for Sonography, *Ultrasound in Medicine and Biology*, vol. 26 n. 3: 405-411.

CHURILOV L.; BAGIROV, A.; SCHWARTZ, D.; SMITH, K.; DALLY, M; (2005): Data Mining with Combined Use of Optimization Techniques and Self-Organizing Maps for Improving Risk Grouping Rules: Application to Prostate Cancer Patients, *Journal of Management Information Systems*, vol. 21 n. 4: 85-100.

CIOS, K.; PEDRYCZ W.; SWINIARSKI R. (1998): *Data Mining Methods for Knowledge Discovery*, Kluwer Academic Publishers.

EKLUND, T.; BACK, B.; VANHARANTA, H.; VISA A. (2002): Assessing the Feasibility of Self-Organizing Maps for Data Mining Financial Information, in

Proceedings of The Xth Euro-pean Conference on Information Systems (ECIS 2002), Gdansk, Poland, June 6-8, Vol. 1: 528-537.

FOSTER, G.; GUPTA, M. (1994): "Marketing, Cost Management and Management Accounting", *Journal of Management Accounting Research*, vol. 6(Fall): 43-77.

GUILDING, C.; CRAVENS K.; TRAYLES M. (2000): "An International Comparison of Strategic Management Accounting Practices", *Management Accounting Research*, vol. 11 n. 1: 113-135.

GROTH, R. (1998): *Data Mining: A Hands-On Approach for Business Professionals*, Prentice Hall, New Jersey.

HAN, J.; KAMBER M. (2001): *Data Mining: Concepts and Techniques*, Academic Press.

HAYKIN, S. (1999): *Neural Networks: A Comprehensive Foundatio*n, Prentice-Hall inc., 2nd edition.

JOHNSON, T.H.; KAPLAN, R.S. (1987): *Relevance Lost – The Rise and Fall of Management Accounting*, Harvard Business School Press, Boston.

JOHNSON, G.; SCHOLES, K. (1997): *Exploring Corporate Strategy*, the 4th edition, Prentice Hall Europe.

KASKI, S.; KOHONEN T. (1998). Tips for Processing and Color-coding of Self-Organizing Maps, Chapter in the book: *Visual Explorations in Finance*, Deboeck G. and Kohonen T. (eds.), Springer-Verlag.

KIANG, M.Y.; KUMAR, A. (2001): "An Evaluation of Self-Organizing Map Networks as a Robust Alternative to Factor Analysis in Data Mining Applications", *Information Systems Research*, vol. 12 n. 2: 177-194.

KIVILUOTO, K. (1998): "Predicting Bankruptcies with Self-Organizing Maps", *Neurocomputing*, vol. 21, n. 1-3: 191-201.

KOHAVI, R.; ROTHLEDER, N.J.; SIMOUDIS, E. (2002): “Emerging Trends in Business Analytics”, *Communications of the ACM*, vol. 45, n. 8: 45-48.

KOHONEN, T. (edit.) (1997): *Self-Organizing Maps*, second edition, Springer.

KOHONEN, T.; HYNNINEN, J.; KANGAS, J.; AND LAAKSONEN, J. (1995): *The Self-Organizing Map Program Package, Helsinki University of Technology: Laboratory of Computer and Information Science*, http://www.cis.hut.fi/research/som_pak/som_doc.txt (April 12, 2006)

LÄNSILUOTO, A.; BACK, B.; VANHARANTA, H.; VISA, A. (2002a): “Multivariable Business Cycle Analysis with Self-Organizing Maps - Are the Cycles Similar?”, *An article in the proceedings of European Conference Accounting Information System (ECAIS)*, http://accountingeducation.com/subsites/ecais/2002/back.pdf. (April 12, 2006)

LÄNSILUOTO A., BACK, B.; VANHARANTA, H.; VISA, A. (2002b): ”An Analysis of Economic Trends in the Pulp and Paper Sector Using Self-Organizing Maps”, *Pulp and Timber*, vol. 84, n. 4: 246-252.

OJA, M.; KASKI, S.; KOHONEN, T. (2003): ”Bibliography of Self-Organizing Map (SOM) Papers: 1998-2001 Addendum”, *Neural Computing Surveys*, vol. 3: 1-156. Available http://www.soe.ucsc.edu/NCS/ (April 12, 2006)

PITT, L.; BERTHON, P.; WATSON, R.; EWING, M. (2001): “Pricing Strategy and the Net”, *Business Horizons*, vol. 44, n. 2: 45-54.

PORTER, M. (1985): *Competitive Advantage: Creating and Sustaining Superior Performance*, Free press, New York.

RIPLEY, B.D. (1996): *Pattern Recognition and Neural Networks*, Cambridge: Cambridge University Press.

RICHARDS J.D.; REYNOLDS, J.; HAMMERSTEIN, M. (2005): “The Neglected Art of Strategic Pricing”, *Financial Executive*, vol. 21, n. 5: 26-29.

ROSLENDER, R.; HART, S.J. (2003): "In search of strategic management accounting: Theoretical and field study perspectives", *Management Accounting Research*. Vol. 14, n. 3: 255-279.

SERRANO-CINCA, C. (1996) : "Self Organizing Neural Networks for Financial Diagnosis", *Decision Support Systems*, vol. 17, n. 3: 227-238.

SIMMONDS, K. (1982): "Strategic Management Accounting for Pricing: A Case Example", *Accounting and Business Research*, vol. 12, n. 42: 206-214.

STEED, E.; GU Z. (2005): "An examination of hotel room pricing methods: Practised and proposed", *Journal of Revenue and Pricing Management*, Vol.3, n. 4: 369-379.

TAN, R. G.; VAN DEN BERG, H., J.; VAN DEN BERGH, W.H. (2002): "Credit Rating Classification Using Self-Organizing Maps", in Smith, K.; Gupta, J. (Eds.), *Neural Networks in Business: Techniques and Applications*, Idea Group Publishing, Hershey, pp. 140-153.

ULTSCH, A. (2002): "Emergent Self-Organising Feature Maps Used for Prediction and Prevention of Churn in Mobile Phone Markets", *Journal of Targeting, Measurement and Analysis for Marketing*, vol. 10, n. 4: 314-324.

ULTSCH, A. (1993): "Self-Organizing Neural Networks for Visualization and Classification", In the book Opitz, O.; Lausen, B.; Klar, R. (edit.): *Information and Classification*, Springer-Verlag.

WANG, S. (2001): "Cluster Analysis Using a Validated Self-Organizing Method: Cases of Problem Identification", *International Journal of Intelligent Systems in Accounting, Finance and Management*, vol. 10, n. 2: 127-138.

WANG, S.; WANG, H. (2002): "Knowledge Discovery through Self-Organizing Maps: Data Visualization and Query Processing", *Knowledge and Information Systems*, vol. 4, n. 1: 31-45.

YU-LEE, R.T. (2002): "Target costing: What you see is not what you get", *Cost Management*, Vol. 16, n. 4: 23-28.

APPENDIX 1. THE LIST OF GROCERY PRODUCTS

1. bread (rye) 1 kg	41. grill sausage 1 kg (cheapest)	81. keiju margarine 400 g
2. bread (rye with hole) 1 kg	42. HK:n small sausage 1 kg	82. kultarypsi margarine 400 g
3. pieces of bread (rye) 1 kg	43. small sausage of Atria 300 g	83. becel margarine 400 g
4. bread (wheat) 1 kg	44. small sausage 1 kg (cheapest)	84. kevyt linja margarine 400 g
5. mixed bread 1 kg	45. liver casserole 400 g	85. sunnuntai margarine 500 g
6. toast 1 kg	46. meat-paste casserole 400 g	86. milda margarine 500 g
7. mixed meat of cattle 1 kg	47. meat balls 400 g	87. kultasula oil 0.5 l
8. mixed meat of cattle (beef) 1 kg	48. pizza 400 g	88. kultaryosi oil 0.5 l
9. mixed meat of pork-cattle 1 kg	49. canned cattle-pork 400 g	89. orange 1 kg
10. chop of pork 1 kg	50. canned bean soup 450 g	90. kiwi 1 kg
11. fillet of pork (outer) 1 kg	51. stock cube 12 psc.	91. satsumas 1 kg
12. shoulder of pork (with bones) 1 kg	52. chicken balls 1 kg	92. golden delicious apple 1 kg
13. back of pork 1 kg	53. meat pie 1 kg	93. apple 1 kg (cheapest)
14. side of pork (without bones) 1 kg	54. karjala pie 1 kg	94. paprika 1 kg
15. strip beef of pork 1 kg	55. 1.5 % milk 1 l	95. tomato 1 kg
16. pork kassler 1 kg	56. 3 % milk 1 l	96. cucumber 1 kg
17. outerbeef of cattle 1 kg	57. 0 % milk 1 l	97. chinese cabbege 1 kg
18. strip beef of cattle 1 kg	58. 0 % sour milk 1 l	98. cabbage 1 kg
19. innerbeef of cattle 1 kg	59. asidofilus sour milk 1 l	99. carrot 1 kg
20. innerfillet of cattle 1 kg	60. processed sour whole milk 200 g	100. onion 1 kg
21. outerfillet of cattle 1 kg	61. light processed sour whole milk 200 g	101. garlic 1 kg
22. shoulder of cattle (without bones) 1 kg	62. yoghurt 200 g	102. leek 1 kg
23. liver of cattle 1 kg	63. yoplait yoghurt 4 * 125 g	103. cauliflower 1 kg
24. breast of chicken 1 kg	64 pudding 120 g	104. salad 1 kg
25. quarterpieces of chicken 1 kg	65. tutteli milk 2 dl	105. kesäpöytä bean-maize-paprika 200 g
26. frozen chicken 1 kg	66. edam cheese 1 kg	106. kesäpöytä vegetables mix 250 g
27. boiled ham (slide) 1 kg	67. emmental cheese 1 kg	107. potato 1 kg
28. smoked ham (slide) 1 kg	68. olterman cheese 1 kg	108. frenc fries, frozen 1 kg
29. metwursti sausage (slide) 1 kg	69. bla castello cheese	109. potato-onion mix, frozen 1 kg
30. wursti sausage (slide) 1 kg	70. brie cheese 1 kg	110. vegetable fat ice-cream 1 l
31. balkan sausage (slide) 1 kg	71. feta cheese 1 kg	111. ice-cream 1 l
32. balkansausage 1 kg	72. cream cheese 200 g	112. ice cream 2 dl
33. gouter sausage 1 kg	73. fresh cheese 100 g	113. sunnuntai wheat flour 2 kg

34. jahti sausage (slide) 1 kg	74. rae cheese 200 g	114. anni helene wheat flour 2 kg
35. jahti sausage 1 kg	75. eggs 1 kg	115. sunnuntai roll flour 2 kg
36. lauantai sausage of Saarioinen (slide) 300 g	76. butter 500 g	116. uncle ben's rice 1 kg
37. lauantai sausage 1 kg (cheapest)	77. voimariini 400 g	117. risella porrage rice 1 kg
38. HK:n sininen sausage 1 kg	78. voilevi 400 g	118. elovena oat flakes 1 kg
39. owen sausage of Atria 1 kg	79. voimix 400 g	119. nalle 4-corn flakes 700 g
40. sausage 1 kg (cheapest)	80. flora margarine 400 g	120. vaasan maukas 500 g
121. koulunäkki 360 g	161. tropic orange juice 1 l	201. marabou chocolate 170 g
122. pieni pyöreä 250 g	162. valio orange juice 1 l	202. royal chocolate 150 g
123. vaasan voima 430 g	163. dole juice 1 l	203. panda chocolate 200 g
124. maitonäkki 460 g	164. apple juice (cheapest) 1 l	204. chymos rice chocolate 80 g
125. vaasan rapeat crispbread 400g	165. tropic orange drink 1,5 l	205. mars chocolate bar 58 g
126. crispbread of oululainen 350 g	166. black currant drink (cheapest) 0,5 l	206. maxi-tupla 57 g
127. ryvita crispbread 400 g	167. drink (cheapest) 2 dl	207. royal 45 g
128. domino biscuit 350 g	168. dronningholm strawberry/raspberry jelly 1 kg	208. dajm duppel 57 g
129. jaffa biscuit 300 g	169. saarioinen jelly 720 g	209. geisha chocolate ber 38 g
130. lu pims biscuit 300 g	170. orange marmelad (cheapest) 1 kg	210. fazer chocolate bar 40 g
131. jyväshyvä suklaapisara 500 g	171. plum marmelad (cheapest) 1 kg	211. big cat 40 g
132. fafer kaunis veera biscuit 350 g	172. plum (cheapest) 227 g	212. lauantaipussi 90 g
133. fazer cream cracker 400 g	173. raisins 250 g	213. hyvää makumaasta 160 g
134. jyväshyvä oat biscuit 500 g	174. sugar (cheapest) 1 kg	214. maxi salmiakki/hedelmäaakkoset 100 g
135. tuc biscuit 300 g	175. lumps of suger 1 kg	215. pantteri salmiakki 100 g
136. Mc Vities Digestive 400 g	176. felix mashed potatoes 214 g	216. marianne 90 g
137. marie biscuit (cheapest) 1 kg	177. mummon mashed potatoes 210 g	217. halva mixed candies 200 g
138. waffle 1 kg	178. estrella chips 200 g	218. fazer best 95 g
139. torino macaroni 400 g	179. taffel chips 250 g	219. halva lakritsimatto 60 g
140. myllyn paras rakettispagetti 350 g	180. juhla-mokka 500 g	220. panda iso pepe 38 g
141. milano spagetti 500 g	181. presidentti 500 g	221. fazer liquorice 10 g
142. barilla spagetti 500 g	182. gevalia 500 g	222. xylitol-jenkki 6,5 g
143. kellogg's rce crispies 375 g	183. o'boy cocoa 500 g	223. xylitol-jenkki 32 g
144. kellogg's frosties 375 g	184. paulig tea 50 ps	224. orbit xylitol chewing-gum 13

		g
145. kellogg's corn flakes 500g	185. lipton tea 50 ps	225. coca-cola 1 l
146. weetabix 430 g	186. twinings earl grey tea 25 ps	226. sprite 1 l
147. finax perhemysli 1 kg	187. heinz ketchup 570 g	227. hartwall jaffa 1 l
148. alpen mysli 375 g	188. felix ketchup 500 g	228. aurinko jaffa 1 l
149. mysli (cheapest) 1 kg	189. turun mustard 125 g	229. pepsi 1 l
150. salmon (whole) 1 kg	190. koti mustard 300 g	230. frisco 1 l
151. salmon fillet 1 kg	191. felix pickles 380 g	231. seven up 1 l
152. herring 1 kg	192. piltti 3 months 125 g	232. koff aqua 1 l
153. fish sticks 250 g	193. piltti 5 months 125 g	233. hartwall vichy 1 l
154. ahti herring 250 g	194. piltti 8 months 190 g	234. koff I-bier 0,33 l
155. boy herring 640 g	195. piltti 1-3 year 190 g	235. lapin kulta I-bier 0,33 l
156. abba mustard herring 260 g	196. bona 3 months 125 g	236. spice cucumber 1 kg
157. abba tunny 150 g	197. bona 5 months 125 g	237. mushrooms 115 g
158. tunny (cheapest) 185 g	198. bona 8 months 190 g	
159. pineapple 227 g	199. bona 1-3 years 190 g	
160. peach 850 g	200. fazer chocolate 170 g	