A multidimensional clustering on Fuzzy metrics to classify CPG pricing and price promotion strategies: the case of pasta in Italy

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Abstract

While retailers compete along many dimensions, pricing strategy is clearly one of the most important drivers to increase sales especially in the field of Consumer Packaged Goods (CPG). Previous studies reveal that the classification of pricing and price promotion strategies has a complexity that may not be reduced to a binary choice between high reliance on price promotions (HiLo) and every-day-low-price (EDLP) approach.

This paper suggests a fuzzy and multidimensional framework for analyzing price promotion strategies in the CPG market over time and geographical areas. A dataset of weekly prices and price promotions for pasta brands across different retailers and geographical areas in Italy has been used. Retailers' promotion strategies are classified according to five dimensions: price level, price variability, price promotion frequency, price promotion intensity and price promotion variability. Membership functions have been designed to transform those metrics into fuzzy measures. We obtained nine groups which identify different pricing and price promotion strategies and described their distribution across brands, retailers and geographical areas.

Introduction

Price promotions, which are temporary price changes offered by a seller, play a crucial role in retail, especially in the field of Consumer Packaged Goods (CPG) (Gómez, Rao, & McLaughlin, 2007) (Besanko, Dubé, & Gupta, 2005) (Gedenk, Neslin, & Ailawadi, 2010). Their importance for CPG manufacturers is well represented by the share of total revenue dedicated to trade promotions[1], which

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[1] Retail price promotions are generally backed by trade price promotions offered by CPG manufacturers to retails. The degree of price reduction passed from retailers to consumers may vary widely over brands, categories (Besanko, Dubé, & Gupta, 2005) and time (Meza & Sudhir, 2006).

varies between 10% and 25% (Boston Consulting Group, 2012) (Gartner, 2015) and by the long term impact of price promotion on consumers' habit (Mela, Gupta, & Lehmann, 1997).

Products on discount are generally a minority on the store shelves compared to regularly priced ones (McShane, Chen, Anderson, & Simester, 2016), but they contribute to a proportionally larger share of sales. According to different sources and definitions, the share of sales for goods in promotion over total grocery sales varies across countries. For example, in the UK the share of products in promotion accounted for 32% in 2009 (Nielsen, 2009a) and for 51.5% in 2015 (IRI, 2016) while in the US it accounted for 42.8% in 2009 (Nielsen, 2009b) and for 34.9% in 2015 (IRI, 2016). The share of turnover for products in price promotion in Australia was 40.6% in 2015 (IRI, 2016) and 40% in 2017 (Nielsen, 2018a) whereas in New Zealand it accounted for 55.8% in 2015 (IRI, 2016) and for almost 60% in 2017 (Nielsen, 2018b). Finally, in Italy, the share of sales for goods in price promotion accounted for 27.9% in 2015 (IRI, 2016).[2]

Empirical evidence regarding price promotions' profitability is controversial. Several studies reveal that promotions not only influence retailers' revenues (Jedidi, Mela, & Gupta, 1999) (Drèze & Bell, 2003) but also positively impact key intangible assets, such as brand equity (Buil, de Chernatony, & Martínez, 2012) and brand loyalty (Gedenk & Neslin, 1999). Contrastingly, various studies demonstrated that the long-term effects of price promotions tend to be much weaker (Srinivasan, Pauwels, Hanssens, & Dikempe, 2004). A recent study by Nielsen shows that 67% of trade promotions in the US in 2014 had a negative return for the manufacturer (Nielsen, 2015a). In addition, the positive impact on sales, sometimes, comes with negative effects on brands (Zoellner & Schaefers, 2015) (DelVecchio, Henard, & Freling, 2006).

Yet, various types of price promotion are used by retailers to increase sales as a result of complex managerial decision processes (Bogomolova, Szabo, & Kennedy, 2017). In order to shed light on the most frequent pricing strategies adopted in Italy we suggest using fuzzy metrics which allow us to better identifying and understanding the different commercial strategies adopted by retailers and brands. We focus on Pasta given the importance of this CPG category in Italy and the complex competitive landscape (Cacchiarelli & Sorrentino, 2019).

Since retailers are likely to have different pricing strategies for different category-brand combinations, by focusing on a single product category, i.e. "Pasta", which in Italy represents a so-called

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[2] Different sources may use slightly different definitions in order to calculate the above-reported values.

"destination category", we are able to capture the differences in pricing and price promotion strategies amongst retailers and geographical areas.

Therefore, this paper aims at providing answers to the following research questions:

1. What are the strategies for pricing and price promotion in the Italian pasta retail market?
2. How are the strategies for pricing and price promotion distributed across geographical areas, retailers and brands?

Pasta products represent the ideal sector of analysis to derive answers to those questions which are relevant for marketing practitioners in CPG manufacturing and retail. Indeed, Italy is the world's leading pasta producer and the largest consumer of pasta (International Pasta Organisation, 2014).

Therefore, brand managers need to overview the overall positioning their products present toward consumers, spotting potential inconsistencies that may create confusion or strategies not in line with their overall plan (Bolton, Shankar, & Montoya, 2010). Retailers need to control and evaluate their pricing and promotional strategies versus their competitors, in order to ensure they can transmit the right message to consumers choosing which store they'll visit next time.

The geographical element is particularly relevant, since the local competitive scenario is considered a key determinant for retailers' strategy results, and there is evidence that retailers' strategies tends to be homogeneous in a given area (Ellickson & Misra, 2008).

In this article we leverage a unique dataset of prices and temporary price reductions[3] for retailers across the Italian territory and consider the combination type-brand-retailer-area as statistical unit. Our empirical analysis is based on 738 weekly average price data from January 2011 to June 2015 segmented across 16 retailers, 18 brands and 5 geographical areas.

In order to explore the various pricing and price promotions strategies applied to pasta we refer to the fuzzy set theory approach (Zadeh L. A., 1965) (Zadeh L. A., 1968) (Zadeh L. A., 1977) (Dubois & Prade, 1980) (Zimmermann, 2001), as properly designed membership functions may enable us to achieve a better classification of the data, smoothing distortions caused by outliers while still including them into the analysis. Another advantage of the fuzzy set theory approach is to overcome the limits of discrete classifications of data, preserving a higher degree of information for analysis.

[3] TPR is only one of the possible promotional strategies in CPG. However, several studies show how TPR is widely prevalent compared to other promotional options (Multi-Buy, Extra Product Free, etc.) (Gedenk, Neslin, & Ailawadi, 2010) (Bogomolova, Dunn, Trinh, Taylor, & Volpe, 2015). Therefore, for our research, we will concentrate on TPRs.

We propose a multidimensional clustering that takes into account regular prices and temporary price reductions to derive the strategies implemented by retailers on the different brands and classify them according to the characteristics revealed.

The remaining of this article is structured as follows. First, we review the studies related to price promotions to determine the relevant dimensions to consider for our analysis. In Section 3 we present the research methodology and describe the data used. Results are presented in Section 4. Finally, we come to managerial implications, limitation and future research scope and conclusion.

Conceptual Framework

Price promotions are perceived as the only tool that can drive an increase in sales in the short term, compared to the generally longer term returns of advertising spending[4]. They are also perceived as less risky for small brands since the return on trade promotion spending is considered more certain in terms of demand generation (Anderson & Fox, 2019) (Bogomolova, Szabo, & Kennedy, 2017). Furthermore, price promotions are another tool for manufacturers to keep brand awareness, as they go virtually always alongside with communication efforts by the retailer (Anderson & Fox, 2019) (Brito & Hammond, 2007) (Blattberg & Briesch, 2012). Manufacturers that produce private label products for retailers also allocates trade funds for promotional activities to support their sales. This may happen because product volume declines dramatically when products are not promoted (Anderson & Fox, 2019).

As already mentioned, the effects on retailers' revenue are generally regarded as positive, especially for retailers in CPG, where a majority historically relies heavily on price promotions as competitive weapon, i.e. the type of strategy known as "HiLo" ("High Price, Low Price") referring to retailers who offer periodic, temporary price discounts (low prices) that contrast with regular prices (high prices). Other retailers, including Walmart, effectively built their success using an Every-Day-Low-Price (EDLP) strategy which refers to retailers who tend to maintain a constant price without offer discounts.

[4] This bias towards short term returns is deeply criticized by the faction of academics and practitioners that advocates the superiority of advertising in building a loyal share of customers, as their view – using the words of Ken Roman of Ogilvy & Mather – is that *"Promotions rent customers, advertising owns them"* (Pettie & Pettie, 2003). Recent studies, however, show that brand loyalty is at an all-time low, despite increases in advertising spending (Jedidi, Mela, & Gupta, 1999) (Nielsen, 2019).

There are also evidences that HiLo strategies lead to a better profit margin, and high switching costs exist from moving from HiLo to EDLP (Ellickson, Misra, & Nair, 2012). Retailers' economic results are also highly influenced by the local context, as competitive actions and socio-economic background may effectively alter the payout from a HiLo or EDLP strategy. Stores from the same chain in different locations may implement different strategies to better compete in the local market (Ellickson & Misra, 2008).

Moreover, promotions may be strongly habit forming for consumers. For instance, when JC Penney tried to switch from a "coupon sales" pricing strategy to an EDLP strategy, they experienced a dramatic decline in shop visits and sales (Mourdoukoutas, 2017) and it was eventually forced to return to the previous HiLo strategy. Even when prominent manufacturers like Procter and Gamble tried to reduce their spending in price promotions and move toward an EDLP strategy, they encountered a fierce backfire as consumers' perception was that P&G brands became suddenly more expensive (Slater, 2001). The EDLP strategy carried out in the 1990s costed P&G a fair percentage of market share, also because competing brands insisted on their HiLo strategy thus effectively eroding P&G position across several categories. Eventually, P&G moved back to a HiLo strategy, even if some studies show EDLP improved its profits figures as a percentage of sales. Probably, the drop of sales volume was considered a more worrisome metric that needed to be addressed (Ailawadi, Lehmann, & Neslin, 2001).

The attractiveness of a price promotion is generally related to the magnitude of discount versus the regular price level. However, a particularly deep discount ("hot price") is a concern for brand managers. A retailer may offer an extremely low price to increase store traffic, but such move could also *"disrupt the marketplace, anger competing retailers, and damage brand equity"* (Anderson & Fox, 2019), with a detrimental long-term effect on the overall brand performance (DelVecchio, Henard, & Freling, 2006). According to Nielsen, price promotion is a driver that 45% of consumers report as important for store switching (Nielsen, 2015b). It is widely documented that shoppers generally buy a basket of products that includes both items on promotion and regularly priced ones (Anderson & Fox, 2019). Therefore, maximizing the shoppers' traffic to a store, the retailer can use the price promotion as a magnet to increase overall sales.

Frequency of price promotion, i.e. the average number of times a specific brand is promoted over a specific time period, is a key decision for brand managers and retailers (Allender & Richards, 2012).

In the retail context, a "product category" is defined as "*a distinct manageable group of products that consumers perceive to be related and/or substitutable in meeting a consumer need*" (Blattberg & Fox, 1995). Specific product categories, particularly well-suited to attract consumers in a store, are called "destination categories". Within those categories, the items that are most important for attracting shoppers are called "key value items" (Briesch, Dillon, & Fox, 2013). Considerations by retail managers in pricing and promoting those categories and items go beyond simple margin targets, as the main target is to leverage those categories for attracting shoppers in store and generate beneficial spillovers in other categories (the so-called "basket building effect") (Chevalier, Kashyap, & Rossi, 2003).

Therefore, pricing and price promotion strategies represent a key element of the overall sales strategy for CPG manufacturers and retailers. The research on this subject is vast and consolidated, as ascertained in several literature reviews over time (Kuntner & Teichert, 2016) (Blattberg & Neslin, 1989) (Blattberg, Briesch, & Fox, 1995) (Neslin, 2002) (Ailawadi, Beauchamp, Donthu, Gauri, & Shankar, 2009) (Grewal, et al., 2010) (Fassnacht & El Husseini, 2013).

Bolton and Shankar (2003) derived an empirical taxonomy of pricing and price promotion strategies for grocery retailers in the US across several product categories using a multidimensional approach. Their study represent a departure from the traditional classification of strategies (Zwanka, 2017) focused on the HiLo and EDLP, either as a binary classification (Johnson, 2003) (Bailey, 2008) (Lal & Rao, 1997) or as a continuum of with several intermediate strategies between those two extremes (Hoch, Drèze, & Purk, 1994) (Gauri, Trivedi, & Grewal, 2008) (Ellickson & Misra, 2008).

Previous literature on price promotions (Bolton & Shankar, 2003) (Hoch, Drèze, & Purk, 1994) (Blattberg & Briesch, 2012) allows us to identify the following strategic dimensions to be considered for analyzing retailers' price strategies regarding Pasta in Italy: Regular Price level, Regular Price variability, Price Promotion level, Price Promotion variability, and Price Promotion frequency. In the next section we will report the metrics used to capture these dimensions

Data and Methods

The dataset we used for this study is an elaboration on a dataset provided by ISMEA, manipulated for removing inconsistencies and imputing missing data[5] [6]. The dataset includes 738 statistical units

[5] We thank ISMEA and in particular, dr. Maria Nucera for giving us the dataset. We performed several elaborations to correct reporting inconsistencies in the dataset, such as: remove price promotions points inconsistent with regular prices; reclassify regular price points which were following a price promotion pattern; remove anomalous regular price points; impute missing regular price points.

[6] In our elaboration we identified as TPRs – in addition to the ones self-reported by the retailers – a price reduction of at least 10% (Nielsen, 2020) compared to the regular price that lasts for less than 5 weeks and is followed by an increase in the shelf price. In a series of studies on the German food retail market, a TPR is defined as a reduction of at least 5%

on regular prices (RP) and temporary price reductions (TPR) prices – divided in two different tables – for pasta Stock Keeping Units (SKU) in different retail chains divided in NUTS1 areas in Italy. In this case, the 738 statistical units are the type-brand-retailer-area combination[7]. Data are reported for 234 weeks, starting in January 2011, and provide information on RP and TPR for 18 pasta brands across 16 retailers in 5 NUTS1 areas. The total data points are 153.182 for the RP table, and 16.910 for the TPR table. RPs and TPRs are list prices for the retailers' chain in each geographical area where they have stores.

The dataset is particularly valuable, as it enables us to follow the brand positioning across multiple retailers and geographical areas. The addition of the pasta format to define the statistical units increase the granularity of our analysis and enable us to provide more insights for brands which have more SKUs on the retailer's shelves. Pasta itself, being a destination category with a large number of manufacturers of very different scale, provides us with the ideal landscape to explore different commercial strategies.

We propose a multidimensional clustering that takes into account regular prices and temporary price reductions to derive the strategies implemented by retailers on the different brands and classify them according to the characteristics revealed. We used the partitioning around medoids (PAM) clustering algorithm, as it provides a higher level of robustness for noise and outliers compared to other methods like k-means. Furthermore, being the medoids identified in the PAM procedure actual elements of our dataset, we are also able to use them as reference points for our membership functions.

As a first step of our procedure for analyzing the dataset and searching the answers to our research questions, we calculate the following set of synthetic metrics (Table 1) which capture the dimensions identified above:

a) Average RP, calculated as the arithmetic mean of RP time series;
b) RP variability, calculated as the Relative Standard Deviation (RSD) of RP time series;
c) TPR percentage, calculated as the difference between RP and TPR values divided by RP, and multiplied by 100;
d) TPR variability, calculated as the RSD of the TPR percentage time series;

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compared to the regular price that lasts for a maximum of 4 weeks and it is followed by an increase of the shelf price. The regular price is observed in the four weeks preceding a sales promotion (Empen, Loy, & Weiss, 2015) (Herrmann, Moeser, & Weber, 2005). Combining this information with the reference from Nielsen (2020) on the Italian market and the metrics derived from our data, we feel confident about the consistency of our TPR definition metrics.

[7] The combination of format and brand defines the SKU.

e) TPR frequency, calculated as the number of TPR data points over the number of RP data points.

Dimension	Metric	Min	Median	Max	RSD
Regular Price level	Average RP	0,460	1,780	3,392	28,04%
Regular Price variability	RP Variability	0,000	3,460	18,074	71,87%
Price Promotion level	Average TPR%	0,000	18,489	55,556	80,53%
Price Promotion variability	TPR% Variability	0,000	0,197	1,124	100,25%
Price Promotion frequency	TPR Frequency	0,000	5,556	98,291	120,21%

Table 1 - Pricing and price promotion metrics

A quick graphical analysis of the five metrics shows the presence of outliers and skewed distributions that could potentially affect the analysis performed on the data, as showed in Figure 1 for RP Variability and TPR Frequency.

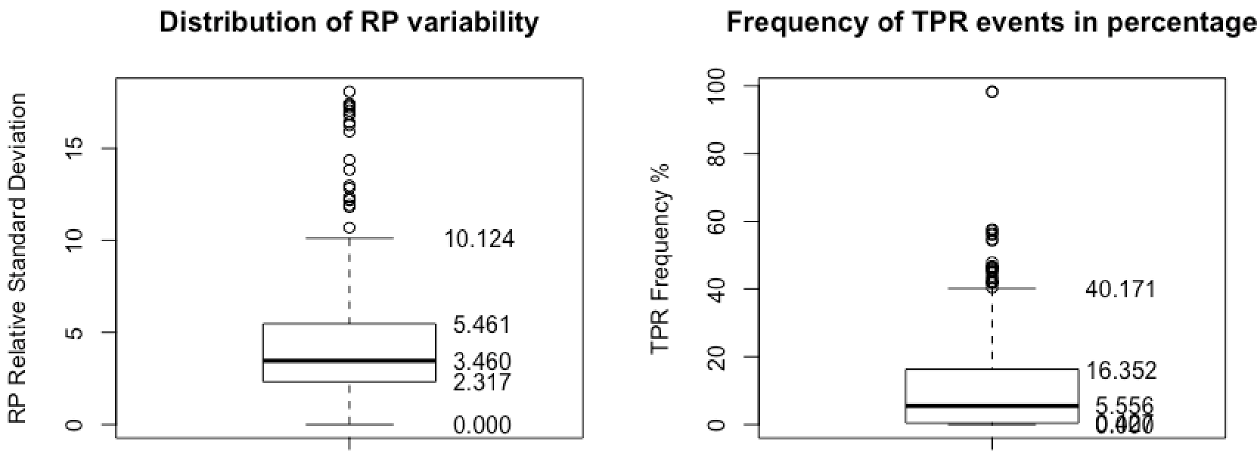

Figure 1 - Pricing and price promotion metrics dispersions

We use the PAM algorithm to cluster the statistical units in two sets – representing Low and High clusters – according to each metric listed above. This operation aims at dividing the dataset into clusters characterized by the low (or high) value of the metric under evaluation, as a base for the following empirical definition of pricing and price promotion strategies. For instance, we aim at identifying the statistical unit characterized by a high RP, compared to the rest of our sample. This transformation, that associate to every statistical unit a High or Low classification, effectively remove the potential bias caused by outliers in the distribution of each metric.

In order to overcome the limitations entailed in the binary classification performed in the previous step, we leverage the fuzzy set theory approach to smooth the transition from Low to High classification in each metric, defining a membership function that will associate for each statistical unit a degree m_L of belonging to the Low classification, and consequently a degree $1-m_L$ of belonging to the High classification.

In literature there are many types of membership functions for fuzzification of a dataset. Many of the simplest forms – for instance, triangular, trapezoidal, or gaussian – rely on arbitrary values for definition of the membership function, which makes them prone to subjective evaluations. Other more sophisticated forms, for instance the ones based on the Lorentz distribution and its derivatives, offer a more objective approach to fuzzification.

In our case, we need our membership function to address the following points:

- Avoid excessive change in membership levels at the edges of the distribution, as some metric presents outliers and hard limits at zero [8];
- Avoid reliance on any external parameter for the definition of the function.

Keeping those points in consideration, we define our membership function in a staged approach, and only basing on information derived from the dataset. The medoids found in the previous PAM procedure are used as partitioning points for the fuzzification. For each metric, data points below the Low Medoid will be considered as fully belonging to the Low cluster ($m_L = 1$) and data points above the High Medoid will be considered as fully belonging to the High cluster ($m_L = 0$). For the data points between the two Medoids, we define the degree of belonging to the Low cluster for the data point i as the proportion of data points between the two Medoids with a value higher than i.

$$m_{Li} = \begin{cases} if \;\; y_i < y_{Lmed} & \rightarrow \quad 1 \\ if \; y_{Lmed} < y_i < y_{Hmed} & \rightarrow \quad \dfrac{\sum_{k=i+1}^{n} y_k > y_i}{\sum_{k=2}^{n} y_k > y_1} \\ if \;\; y_i > y_{Hmed} & \rightarrow \quad 0 \end{cases}$$

The results of membership functions are the basis for our PAM clustering aimed at discovering the different commercial strategies in the market. We select the optimal number of clusters for this operation based on average silhouette width.

For control purposes, we also perform the same clustering operation on the original metrics values, both selecting the optimal number of clusters according to average silhouette width and forcing the same number of clusters but we found optimal for clustering on membership values.

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[8] We assume that variability towards the edges of the distribution has actually less impact in differentiating two strategies rather than variability in the middle of the distribution.

We then move on to characterize each strategy individuated in our procedure according to dimensions, geographical area, retailers and brands.

Results

Table 2 represent the results from the initial clustering of values in High and Low classification according to each dimension. We can note how some dimension present a fairly skewed distribution of its values.

Metric	Low Medoid	Low N	High Medoid	High N	Silhouette[9]
Average RP	1,515	393	2,385	345	0,709
RP Variability	2,875	527	6,982	211	0,607
Average TPR%	0,000	337	28,495	401	0,708
TPR% Variability	0,000	361	0,387	377	0,588
TPR frequency	1,282	460	21,264	278	0,667

Table 2 - Clustering results on each dimension

Our membership function attenuate – to a certain extent – this skewness, resulting in a relative majority of statistical units being classified with a membership value which blends High and Low classification as showed in Table 3 and Figures Figure 2-Figure 6.

Metric	$M_L = 1$	M_L]0:1[	$M_L = 0$
Average RP	197	368	173
RP Variability	264	368	106
Average TPR%	178	360	200
TPR% Variability	248	302	188
TPR frequency	228	368	142

Table 3 - Membership function results on each dimension

[9] The Silhouette index is related to PAM clustering with 2 clusters for each metric. This is not necessarily the maximum Silhouette index achievable in each metric, as a different number of clusters may deliver a better performance. However, for our purpose of classifying pricing and price promotion strategies, this binary clustering allows to link our analysis with business practices.

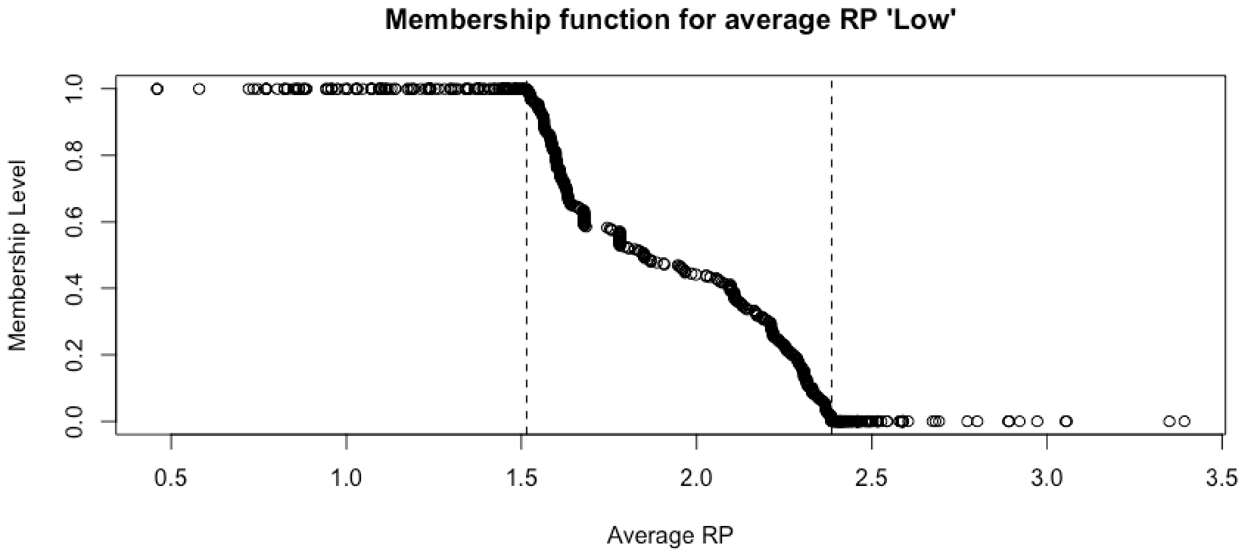

Figure 2 - Membership function for Average RP Low

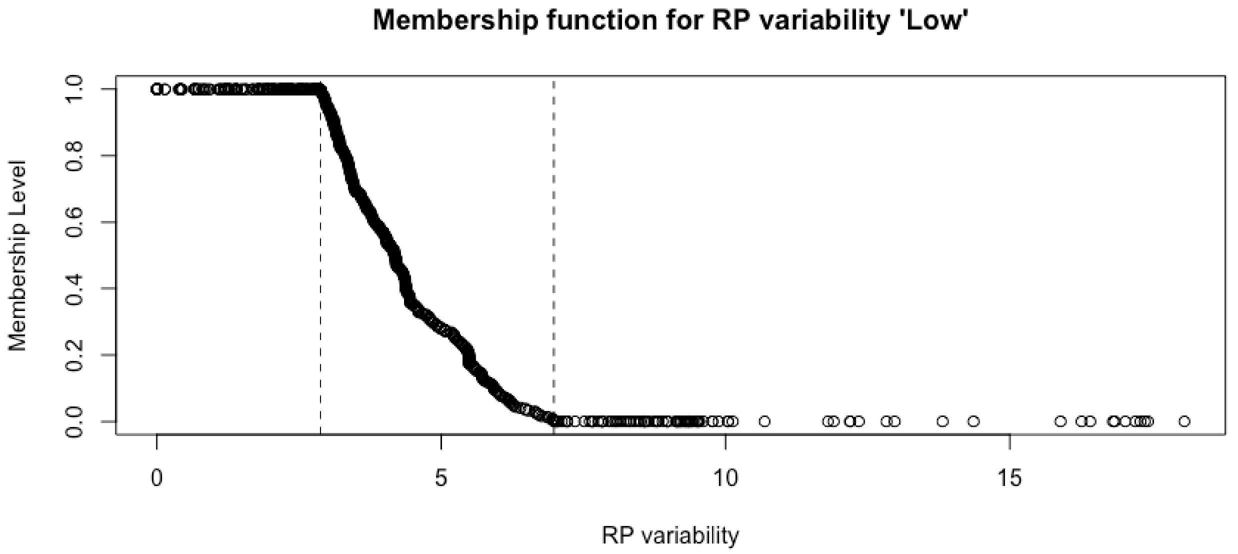

Figure 3 - Membership function for RP Variability Low

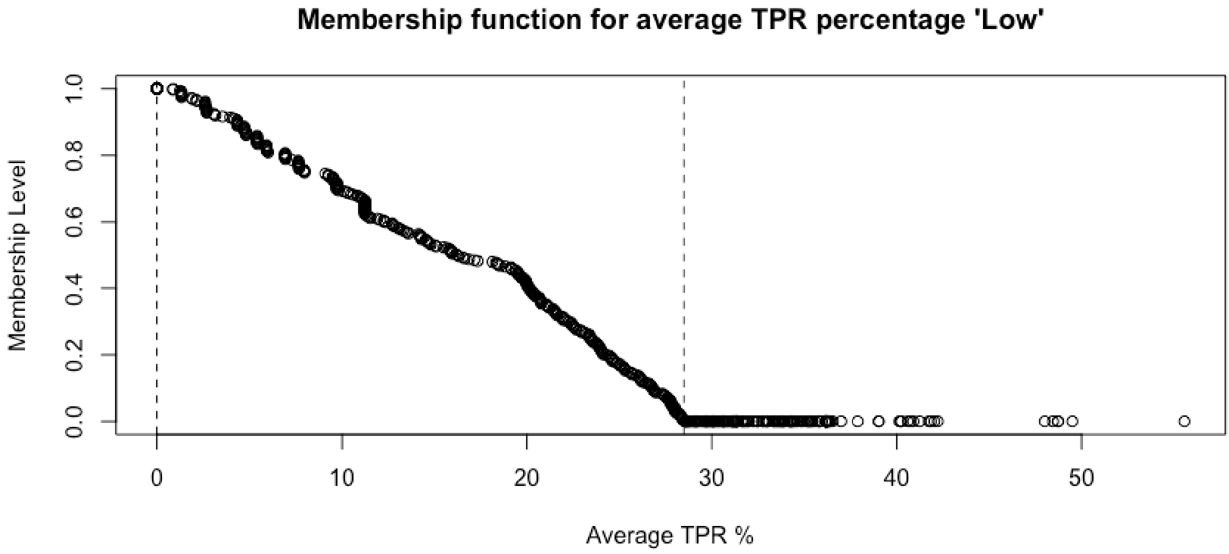

Figure 4 - Membership function for TPR Percentage Low

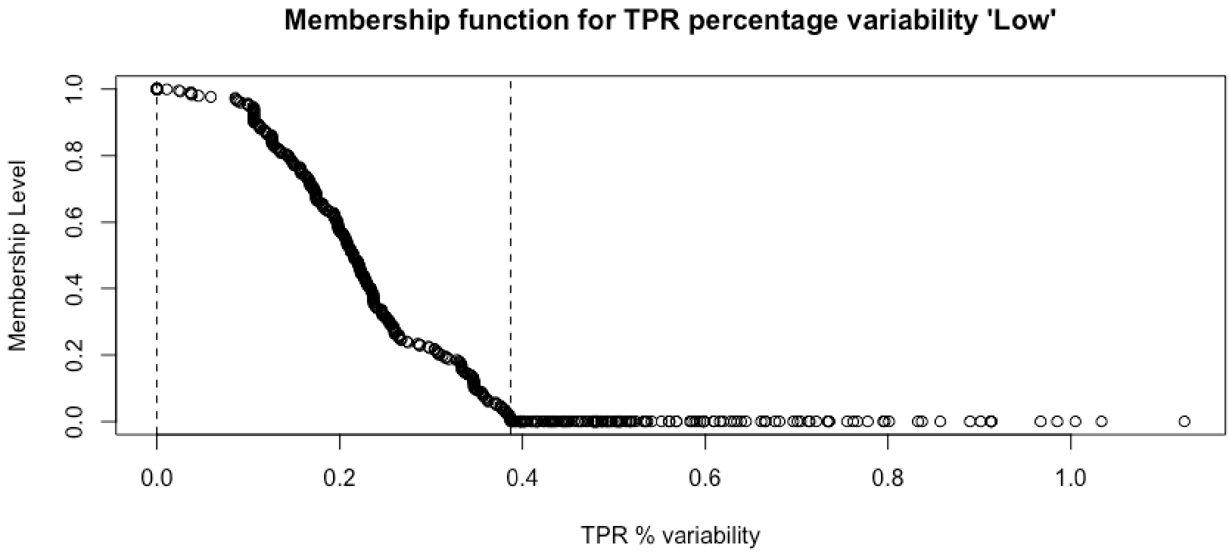

Figure 5 - Membership function for TPR Percentage Variability Low

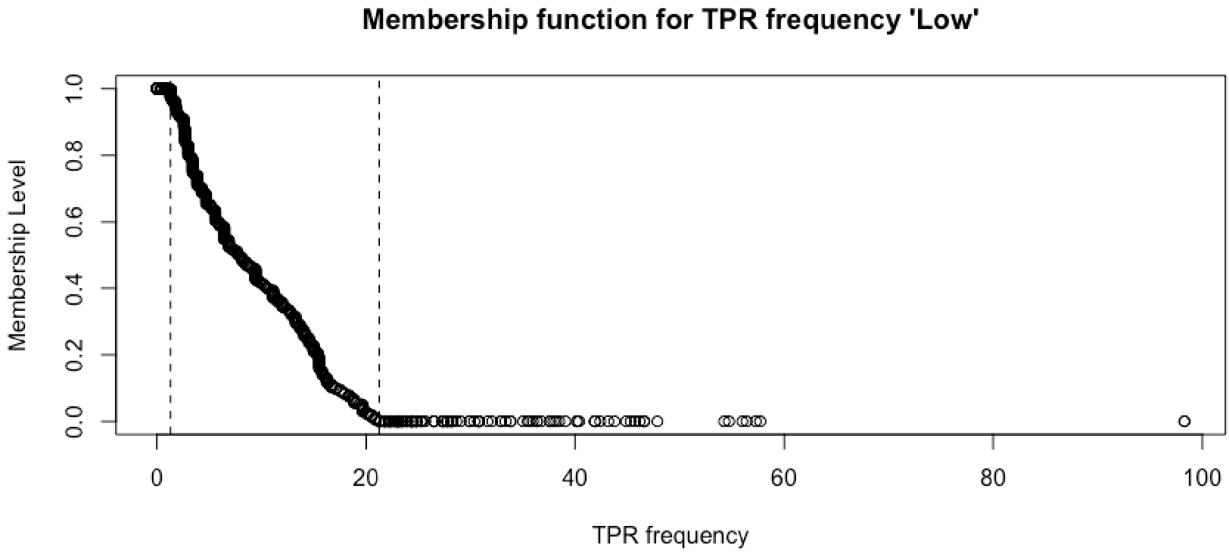

Figure 6 - Membership function for TPR Frequency Low

Moving on with the results of our study, in the comparison of the different clustering procedures aimed to identify pricing and price promotion strategies two results are evident:

- Clustering on membership values seems capable of capturing a deeper level of variability across the dataset, identifying 9 clusters as optimal division rather than the 4 clusters supposed optimal when clustering on the original metrics;
- Clusters calculated on membership values appear more consistent with the business logic behind pricing and price promotion strategies.

As an example, to support this second point we report the mapping of the different clusters versus the average RP. The clustering derived on the membership values (Figure 7) appears much more consistent with business logic than the one calculated on original metrics values. Contrastingly, the "traditional" approach do not show a clear pattern consistent with the business logic both when applying the optimal number of clusters according to the original metric values (Figure 8) and when forcing the same number of clusters found optimal by clustering the Fuzzy membership values (Figure 9).

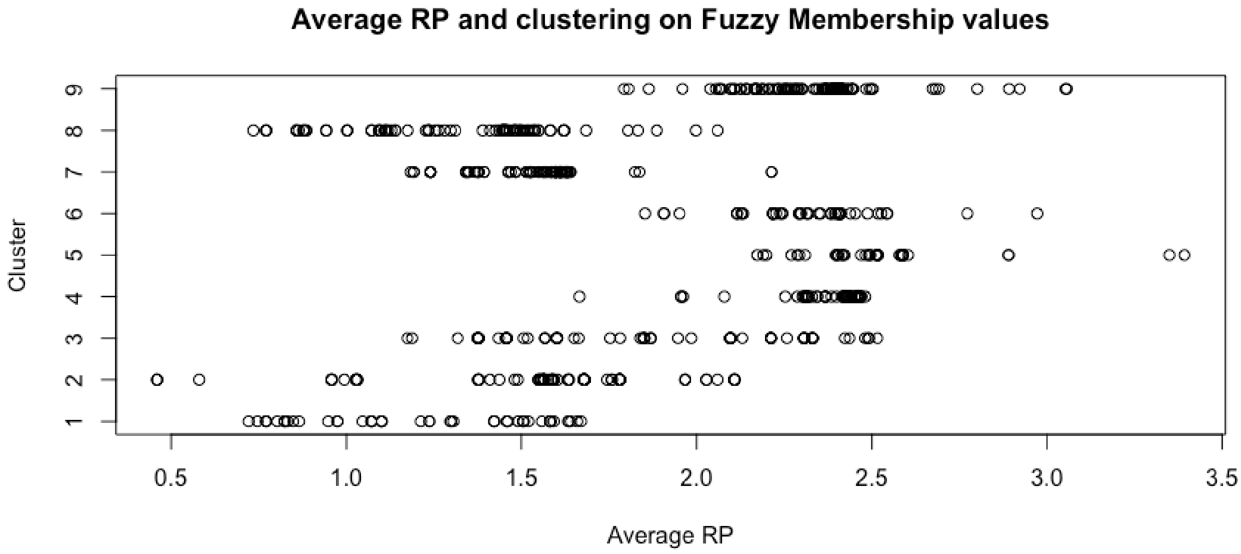

Figure 7 - Average RP and clustering on Fuzzy Membership values

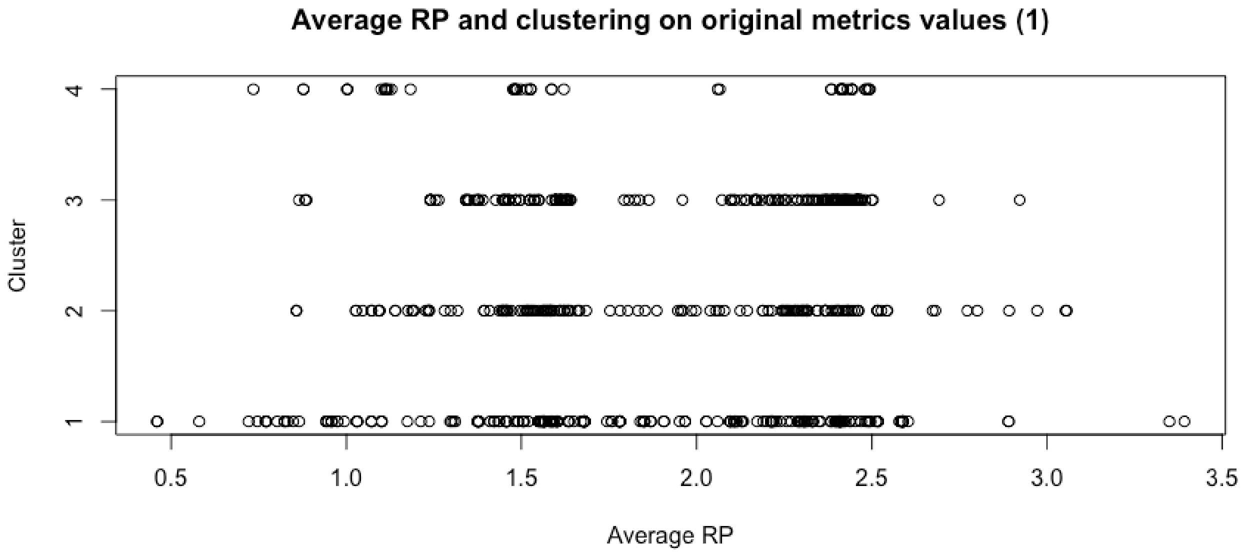

Figure 8 - Average RP and clustering on original metrics values

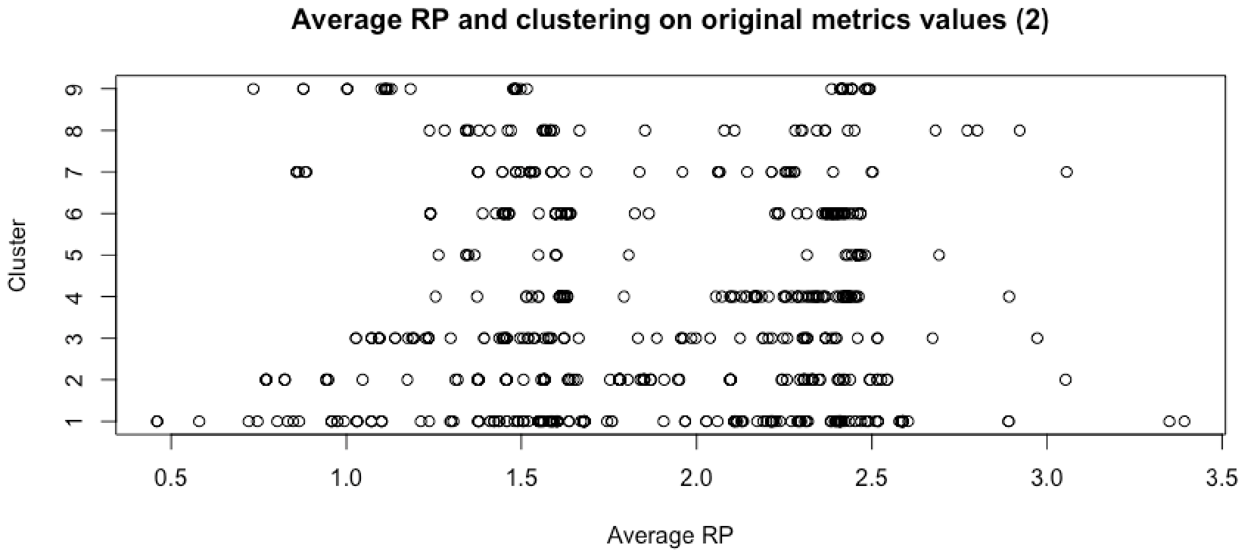

Figure 9 - Average RP and clustering on original metrics values, forcing the same number of clusters identified with the clustering on Fuzzy Membership Values

The results from cluster analysis based on fuzzy membership values measured on our statistical units appear in Table 4, where mean scores of each original metric are reported.

	Metric					
	Average RP	RP Variability	Average TPR%	TPR% Variability	TPR frequency	N
Min	0,460	0,000	0,000	0,000	0,000	738
Median	1,780	3,460	18,489	0,197	5,556	738
Max	3,392	18,074	55,556	1,124	98,291	738
Cluster						
1	1,225	6,502	5,661	0,013	0,509	52
2	1,569	1,437	3,507	0,010	0,793	104
3	1,874	2,803	6,702	0,520	6,691	81
4	2,378	3,119	32,353	0,147	13,229	73
5	2,540	2,123	2,048	0,001	0,107	51
6	2,325	6,374	5,214	0.027	0,636	59
7	1,530	2,349	29,979	0,222	17,647	102
8	1,316	5,474	22,283	0,405	18,675	98
9	2,330	7,311	26,780	0,435	20,815	118

Table 4 - Mean scores on the dimensions for each cluster

We provide a graphical summary of the 9 clusters in Figure 10, standardizing the cluster average metrics over each metric overall average, in order to easily compare the relative differences amongst clusters.

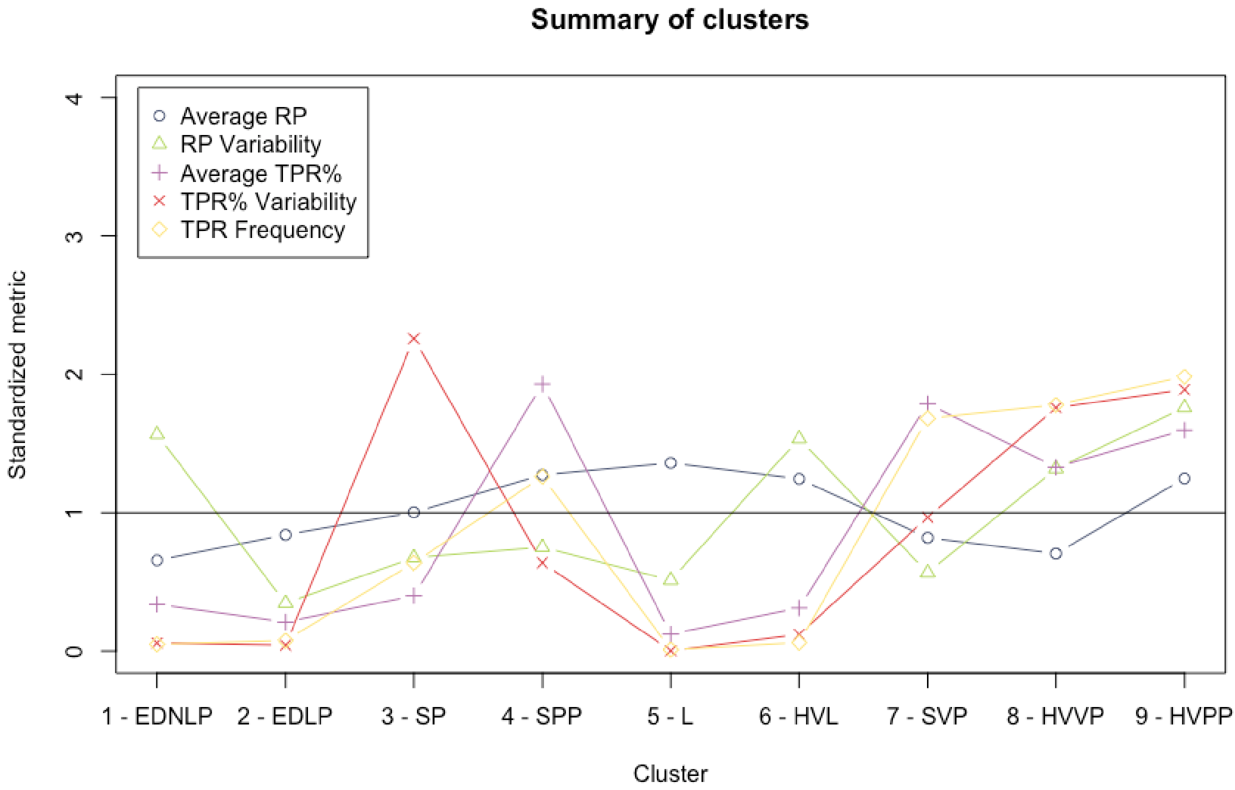

Figure 10 - Graphical summary of pricing and price promotion strategies

According to fuzzy clustering, we can then derive our empirical taxonomy regarding the different pricing and price promotion strategies based on the peculiarities of each cluster. We have labeled them: Every Day New Low Price (EDNLP), Every Day Low Price (EDLP), Surprise Promo (SP), Stable Premium Promo (SPP), Luxury (L), High Variability Luxury (HVL), Stable Value Promo (SVP), High Variability Value Promo (HVP), and High Variability Premium Promo (HVPP).

Table 5 shows the combinations of pricing dimensions for each pricing strategy. The characterization of those clusters according to the business domain and the numerosity of each cluster are the following:

Cluster	**N**	**Label**	**Description**	**TPR reliance**	**RP positioning**
1	52	Every Day New Low Price	Low RP, extremely High RP Variability, extremely Low TPR%, Frequency and Variability	Low	Value
2	104	Every Day Low Price	Low RP and RP Variability, extremely Low TPR%, TPR Frequency and TPR variability	Low	Value
3	81	Surprise Promo	Average RP, extremely High TPR variability, relatively low RP Variability, TPR%, and TPR frequency	Low	Average

4	73	Stable Premium Promo	Extremely High TPR%, high TPR Frequency, Low TPR and RP Variability, high RP	High	Premium
5	51	Luxury	High RP, Low RP Variability, extremely Low TPR%, Frequency, and Variability	Low	Premium
6	59	High Variability Luxury	High RP and RP Variability, extremely Low TPR%, Frequency, and Variability	Low	Premium
7	102	Stable Value Promo	Extremely High TPR% and Frequency, Low TPR Variability and RP, medium RP Variability	High	Value
8	98	High Variability Value Promo	High TPR%, Frequency, and Variability, High RP Variability, Low RP	High	Value
9	118	High Variability Premium Promo	High TPR%, Frequency, and Variability, High RP and RP Variability	High	Premium

Table 5 - Characterization of pricing and price promotion strategies

The picture that derive from this clustering represent a fairly balanced panel, with a wide variety of strategies. Being pasta a market characterized by fierce competition and a large number of very different competitors, this finding is in line with the overall business scenario. There is a roughly equivalent amount of High TPR frequency and TPR% value items aimed respectively to the value (cluster 7 and 8) and premium segments (cluster 4 and 9), which are probably frequently and deeply promoted in order to attract shoppers promotions (Bolton & Shankar, 2003). Contrastingly, the number of infrequently changing prices – with both low RP and low TPR frequency – are remarkably higher in the value segments (cluster 2) compared to the premium ones (cluster 5). A considerable share of statistical units shows an extremely high variability, probably a replacement for TPR events, in both the value (cluster 1) and premium segments (6). Finally, a large cluster shows a characteristic trait of the category, with average pricing, relatively infrequent TPR events, and an extremely high TPR% variability (cluster 3). This may mean that some TPR event may be much more attractive than others for customers, but others will have much less appeal in term of monetary savings.

Some underlying macro groups emerges from this clustering, with some strategy that heavily relies on TPR (clusters 4, 7, 8, and 9) and others that instead refrain to use this promotional lever (clusters 1, 2, 3, 5, and 6). Another characterization, this time according to RP positioning, shows that some cluster has a premium price positioning (cluster 4, 5, 6, and 9), while others have a definite value positioning (cluster 1, 2, 7, and 8), and the remaining group position itself around the average market price (cluster 3).

Having classified all our statistical units according to our empirically derived taxonomy, we now move on to analyze how those classifications are distributed across areas, retailers and brands. We first analyzed group characteristics according to the NUTS1 areas, still standardizing each metric over the metric overall average for easier comparisons (Table 6).

Area	Average RP	RP Variability	Average TPR%	TPR% Variability	TPR frequency	N
CENTER	1,024	0,662	0,992	0,730	0,826	226
ISLANDS	0,980	1,032	0,569	1,334	0,417	64
NORTH-EAST	1,032	1,194	1,066	0,738	0,760	180
NORTH-WEST	1,022	1,175	1,063	1,094	0,898	113
SOUTH	0,921	1,127	1,066	1,491	1,848	155

Table 6 - Summary metrics by Area

Average regular prices are quite similar across macro-areas. More evident differences appear in comparing TPR frequencies, with South presenting extremely high use of this promotional tool, followed at distance by all other regions. Islands, in particular, stands out for the exceptionally low TPR frequency and TPR percentage compared to other regions.

To compare the composition of strategies across areas, we plotted in each macro-region the percentage of statistical units classified according to our taxonomy (Figure 11).

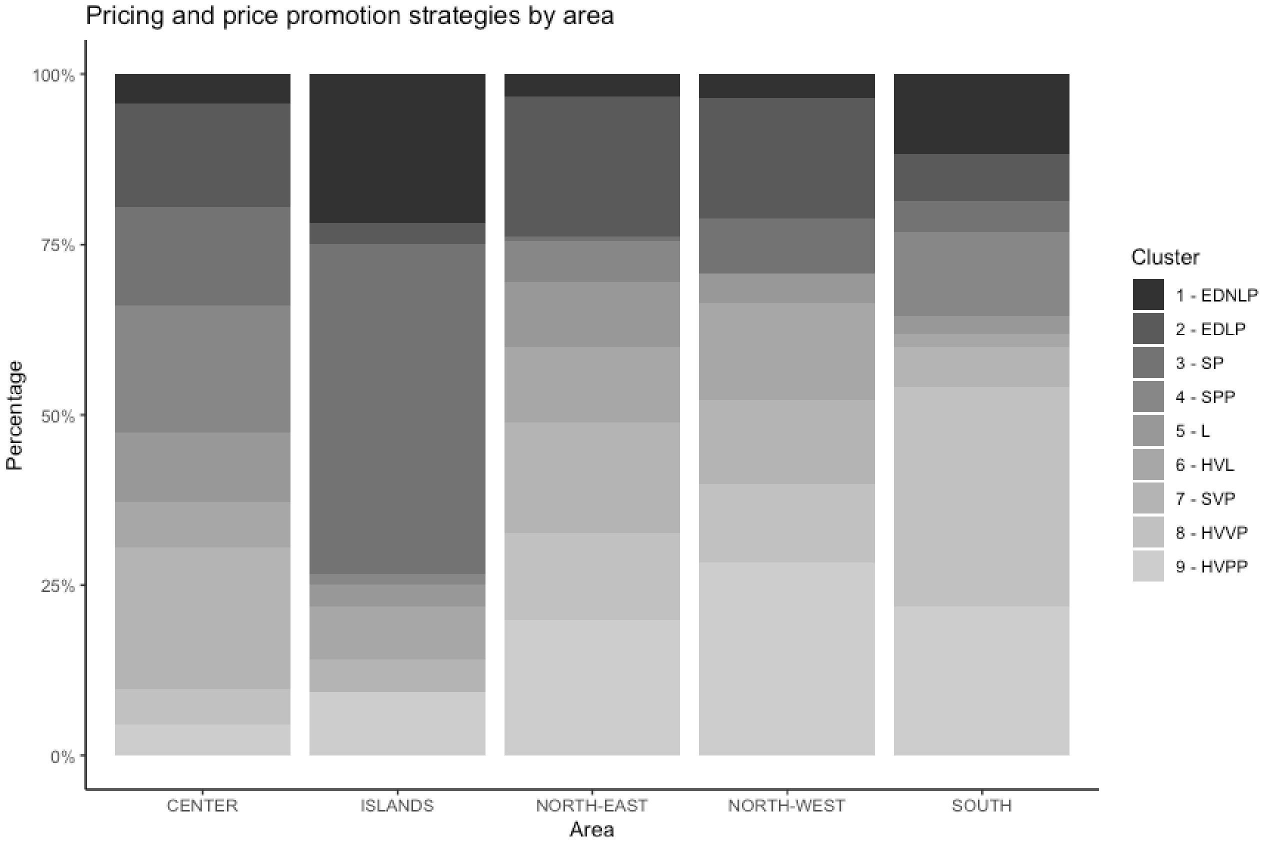

Figure 11 - Pricing and price promotion strategies by area

In Southern regions there is a prevalence of strategies that rely highly on TPR, while these are almost absent in the Islands. Another notable characteristic to note is that in the Islands there is a much lower presence of strategies that rely on Value or Premium pricing and a much higher proportion of strategies that position the RP near the market average.

We then move on analyzing our results by Retailer chain, with standardized metrics listed in Table 7. It is worth noting that the distribution of stores by retailers' chain is not uniform across territorial areas[10].

Retailer	Average RP	RP Variability	Average TPR%	TPR% Variability	TPR frequency	N
Auchan	0,927	1,269	1,302	1,105	0,782	86
AZ	0,687	1,075	1,160	1,034	2,160	11
SISA	0,974	0,816	1,650	0,844	0,789	79
Codè CRAI Ovest	1,091	0,623	0,067	0.000	0,030	8
Conad – Iper	1,047	1,251	1,588	1,540	2,150	178
Conad del Tirreno	0,986	0,680	0,335	1,743	0,460	89
Coop Centrale Adriatica	0,835	1,092	0,039	0,110	0,010	46
Etruria – SMA	1,065	1,104	1,558	0,678	1,175	7
Gabrielli	0,934	1,065	1,271	1,196	1,761	22
Il Gigante	0,892	1,174	1,415	1,795	1,221	12
Megamark	0,780	0,936	0,644	0,476	1,025	8
Multicedi	0,875	1,126	1,162	1,840	2,582	14
Nealco	1,153	0,417	0,125	0,000	0,047	86
SMA	1,083	1,279	0,423	0,237	0,088	55
Unicomm	1,031	1,285	1,451	1,023	1,369	15
Unicoop Tirreno	0,967	0,918	1,592	0,910	1,127	22

[10] As a result, in some cases a higher number of observations may be attributed to retailers by reporting RP and TPR of more Brands and SKUs and/or across multiple areas. Some retailing chains in the analysis only have presence in a single area, resulting then in a smaller representation.

Table 7 - Summary metrics by Retailer

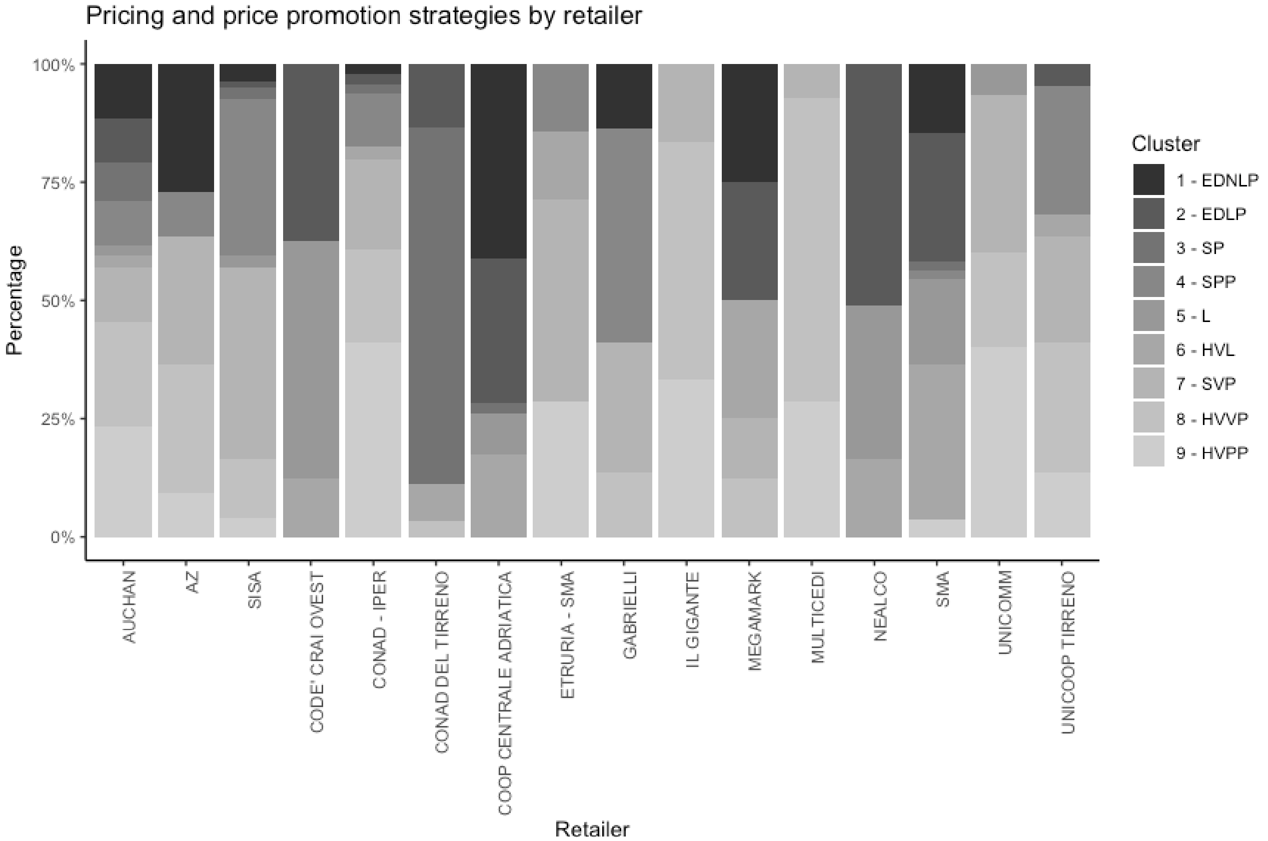

Figure 12 - Pricing and price promotion strategies by Retailer

Figure 12 represents the proportion of the different strategies observed for each retailer. The retailers' profiles vary wildly, from the ones taking a more balanced approach – like Auchan – to the ones that clearly chose sides in terms of price positioning and use of TPR – like Il Gigante and Multicedi.

Finally, we analyze the strategies observed for each Brand. Standardized metrics are listed in Table 8.

Brand	Average RP	RP Variability	Average TPR%	TPR% Variability	TPR frequency	N
Agnesi	0,987	0,523	0,693	0,647	0,502	11
Amato	0,801	0,709	0,494	0,608	0,214	10
Barilla	0,863	0,778	0,905	1,039	1,062	206
Bianconi	0,386	1,064	0,000	0,000	0,000	1
Ceccato	0,438	1,992	0,000	0,000	0,000	5
Colavita	0,412	1,887	0,438	1,047	0,122	4
Coop	0,625	0,717	0,018	0,000	0,004	20
De Cecco	1,290	1,066	1,189	1,048	1,263	218
Divella	0,699	0,932	1,414	1,136	1,442	82
G/Passione	1,748	0,688	0,254	1,241	0,434	3
Garofalo	1,297	0,787	1,375	0,780	1,244	27
Il Gigante	0,586	1,138	1,300	1,804	0,377	4

Jolly	0,929	0,288	1,014	0,180	0,199	26
Multicedi	1,164	1,791	1,132	2,369	0,835	2
Pallante Reggia	0,468	1,556	0,750	1,058	1,111	17
Sisa	0,653	0,808	1,349	1,394	0,334	9
Valdigrano	0,316	0,044	0,000	0,000	0,000	5
Voiello	1,155	1,709	0,738	1,285	0,593	88

Table 8 - Summary metrics by Brand

We observe again large differences in size for each group. A smaller size may represent a private label, which is then only distributed in a single retailer – or a local brand with a limited distribution, often in a single area. Pricing strategies are strongly heterogeneous among the various brands.

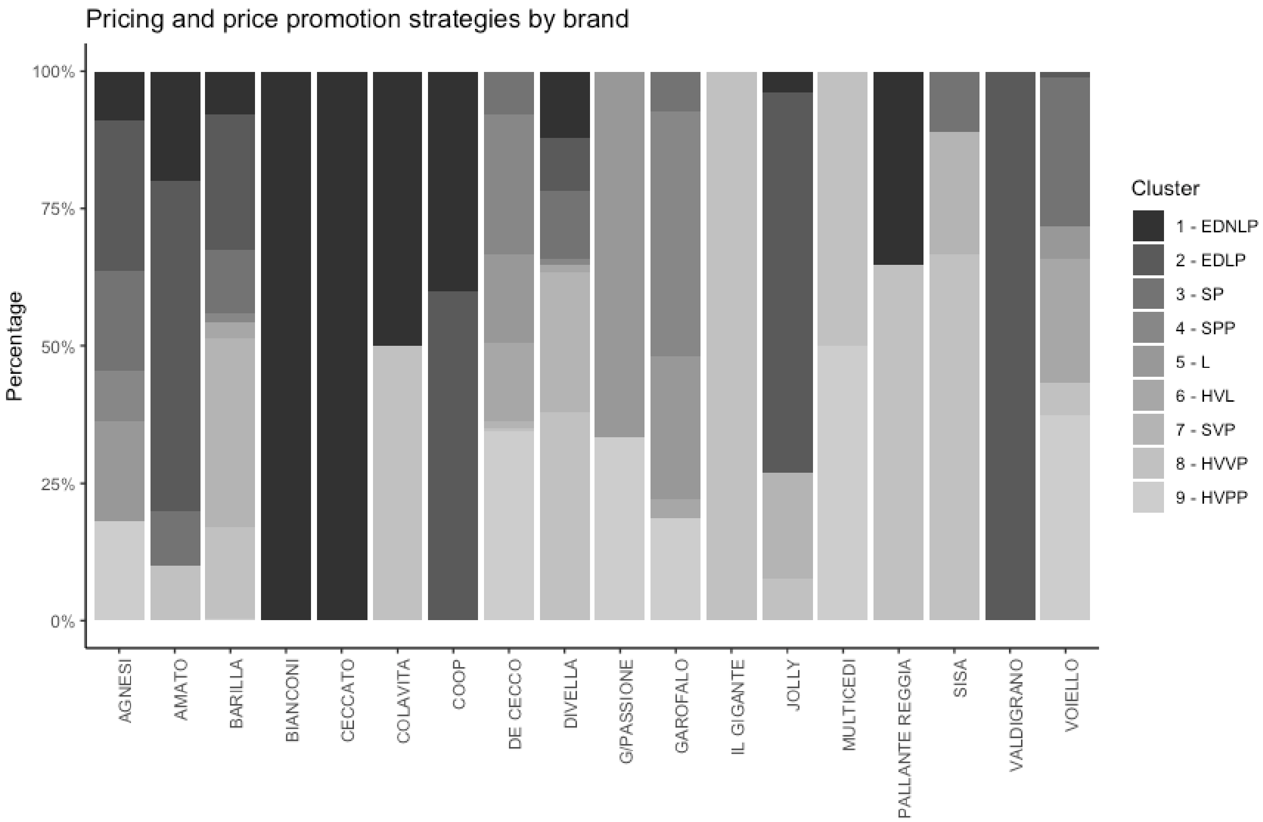

Figure 13 - Pricing and price promotion strategies by Brand

Figure 13, representing the proportion of pricing and promotional price strategies for each brand, shows a number of interesting facts regarding each brand positioning. We see a number of brands takes a clear EDLP approach (namely, Bianconi, Ceccato, Coop, and Valdigrano), positioning with a Value pricing and refraining from the use of TPR. On the contrary, other brands, rely heavily on TPR for their commercial strategies, positioning their pricing as Value (Il Gigante, Sisa) or at a mixed level (Multicedi). All the brands mentioned so far, however, are also amongst the ones with the smaller representation in our analysis. It is reasonable to expect that brands with a larger diffusion may adopt a wider portfolio of strategies.

The remaining brands have different levels of reliance on TPR, with the brands more represented (Barilla, De Cecco, Divella, and Voiello) presenting a slight prevalence for the use of TPR in their marketing strategies.

Regarding the pricing level, most brands show a good consistency, pursuing strategies with common characteristics. However, a few brands present strategies with antithetical characteristics. This may affect the clarity of the brand's image towards the consumers, being the same brand positioned very differently across different areas or retailers within the same area.

Conclusions

In this work we identified empirically nine different pricing and price promotion strategies for pasta brands in Italy, characterized by different levels and mix of RP and TPR positioning. Those strategies are: Every Day New Low Price, Every Day Low Price, Surprise Promo, Stable Premium Promo, Luxury, High Variability Luxury, Stable Value Promo, High Variability Value Promo, and High Variability Premium Promo.

We also showed that a fuzzification of the metrics underlying the clustering enabled us to identify clusters more consistent with the business logic underlying pricing and price promotions strategies.

We developed a novel membership function approach, based on preliminary clustering of the single metrics and leveraging their medoids to derive membership values that: (1) are not influenced by arbitrary or exogeneous values, (2) minimize the effect of outliers, and (3) preserve the maximum information from the original metric.

We used a dataset with weekly reported prices which has been consistently wrangled to remove inconsistencies and impute missing data. However, a limitation of our research may derive from the fact that dataset does not contain information about display and features, which are two aspects that previous literature considers important to augment TPR results. In addition, data refer to wide geographical areas, which may be characterized by a high level of heterogeneity in pricing strategies across sub-areas.

Further research using scanner data may be able to provide additional insights on retailers' and brands' pricing and price promotion strategies. Moreover, our clustering approach treats all variables as equally relevant for classifying the strategies. A clustering on weighted variables – thus allocating more relevance to certain dimensions of the marketing mix – may provide further insights and different points of view on pricing and price promotion strategies.

Bibliography

Ailawadi, K. L., Beauchamp, J., Donthu, N., Gauri, D. K., & Shankar, V. (2009). Communication and Promotion Decisions in Retailing: A Review and Directions for Future Research. *Journal of Retailing, 85*(1), 42-55.

Ailawadi, K. L., Lehmann, D. R., & Neslin, S. A. (2001). Market Response to a Major Policy Change in the Marketing Mix: Learning from Procter & Gamble's Value Pricing Strategy. *Journal of Marketing, 65*(1), 44-61.

Allender, W. J., & Richards, T. (2012). Brand loyalty and price promotion strategies: an empirical analysis. *Journal of Retailing, 88*(3), 323–342.

Anderson, E. T., & Fox, E. J. (2019). How price promotions work: A review of practice. In J.-P. Dubé, & P. E. Rossi, *Handbook of the Economics of Marketing* (1 ed., Vol. 1, pp. 497-552). Amsterdam: North-Holland.

Bailey, A. A. (2008). Evaluating consumer response to EDLPs. *Journal of Retailing and Consumer Services, 15*(3), 211-223.

Besanko, D., Dubé, J.-P., & Gupta, S. (2005). Own-Brand and Cross-Brand Retail Pass-Through. *Marketing Science, 24*(1), 110-122.

Blattberg, R. C., & Briesch, R. A. (2012). Sales Promotions. In O. Özer, & R. Phillips, *The Oxford Handbook of Pricing Management* (pp. 585-619). Oxford, UK: Oxford University Press.

Blattberg, R. C., & Fox, E. J. (1995). *Category Management: A Series of Implementation Guides* (Vols. I-V). Washington DC: Food Manegement Institute.

Blattberg, R. C., & Neslin, S. A. (1989). Sales promotion: The long and the short of it. *Marketing Letters*(1), 81-97.

Blattberg, R. C., Briesch, R., & Fox, E. J. (1995). How Promotions Work. *Marketing science, 14*(3), G1-G236.

Bogomolova, S., Dunn, S., Trinh, G., Taylor, J., & Volpe, R. J. (2015). Price promotion landscape in the US and UK: Depicting retail practice to inform future research agenda. *Journal of Retailing and Consumer Services, 25*, 1-11.

Bogomolova, S., Szabo, M., & Kennedy, R. (2017). Retailers' and manufacturers' price-promotion decisions: Intuitive or evidence-based? *Journal of Business Research, 17*, 189-200.

Bolton, R. N., & Shankar, V. (2003). An empirically derived taxonomy of retailer pricing and promotion strategies. *Journal of Retailing, 79*(4), 213-224.

Bolton, R. N., Shankar, V., & Montoya, D. Y. (2010). Recent Trends and Emerging Practices in Retailer Pricing. In M. Krafft, & M. K. Mantrala, *Retailing in the 21st Century* (pp. 301-318). Berlin, Heidelberg: Springer.

Boston Consulting Group. (2012). Consumer products trade spend benchmark.

Briesch, R. A., Dillon, W. R., & Fox, E. J. (2013). Category positioning and store choice: the role of destination categories. *Marketing Science, 32*(3), 488–509.

Brito, P. Q., & Hammond, K. (2007). Strategic Versus Tactical Nature of Sales Promotions. *Journal of Marketing Communications, 13*(2), 131-148.

Buil, I., de Chernatony, L., & Martínez, E. (2012). Examining the role of advertising and sales promotions in brand equity creation. *Journal of Business Research, 66*(1), 115-122.

Cacchiarelli, L., & Sorrentino, A. (2019). ricing Strategies in the Italian Retail Sector: The Case of Pasta. *Social Sciences, 8*(4), 113.

Chevalier, J. A., Kashyap, A. K., & Rossi, P. E. (2003). Why don't prices rise during periods of peak demand? Evidence from scanner data. *The American Economic Review, 93*(1), 15–37.

DelVecchio, D., Henard, D. H., & Freling, T. H. (2006). The effect of sales promotion on post-promotion brand preference: A meta-analysis. *Journal of Retailing, 82*(3), 203-213.

Drèze, X., & Bell, D. R. (2003). Creating Win-Win Trade Promotions: Theory and Empirical Analysis of Scan-Back Trade Deals. *Marketing Science, 22*(1), 16-39.

Dubois, D., & Prade, H. (1980). Systems of linear fuzzy constraints. *Fuzzy Sets and Systems, 3*(1), 37-48.

Ellickson, P. B., & Misra, S. (2008). Supermarket pricing strategies. *Marketing Science, 27*(5), 811-828.

Ellickson, P. B., Misra, S., & Nair, H. S. (2012). Repositioning Dynamics and Pricing Strategy. *Journal of Marketing research, 49*(6), 750-772.

Empen, J., Loy, J.-P., & Weiss, C. (2015). Price promotions and brand loyalty: Empirical evidence for the German ready-to-eat cereal market. *European Journal of Marketing, 49*(5/6), 736-759.

Fassnacht, M., & El Husseini, S. (2013). EDLP versus Hi–Lo pricing strategies in retailing—a state of the art article. *Journal of Business Economics, 83*, 259-289.

Gartner. (2015). Market guide for trade promotion management and optimization.

Gauri, D. K., Trivedi, M., & Grewal, D. (2008). Understanding the Determinants of Retail Strategy: An Empirical Analysis. *Journal of Retailing, 84*(3), 256-267.

Gedenk, K., & Neslin, S. A. (1999). The role of retail promotion in determining future brand loyalty: its effect on purchase event feedback. *Journal of Retailing, 75*(4), 433-459.

Gedenk, K., Neslin, S. A., & Ailawadi, K. L. (2010). Sales promotion. In M. Krafft, & M. K. Mantrala, *Retailing in the 21st Century* (2nd ed., pp. 393–408). Berlin: Springer.

Grewal, D., Janakiraman, R., Kalyanam, K., Kannan, P., Ratchford, B., Song, R., & Tolerico, S. (2010). Strategic Online and Offline Retail Pricing: A Review and Research Agenda. *Journal of Interactive Marketing, 24*(2), 138-154.

Gómez, M. J., Rao, V. R., & McLaughlin, E. W. (2007, Aug.). Empirical Analysis of Budget and Allocation of Trade Promotions in the U.S. Supermarket Industry. *Journal of Marketing Research, 44*(3), 410-424.

Herrmann, R., Moeser, A., & Weber, S. A. (2005). Price Rigidity in the German Grocery-Retailing Sector: Scanner-Data Evidence on Magnitude and Causes. *Journal of Agricultural & Food Industrial Organization, 3*(1), 1-35.

Hoch, S. J., Drèze, X., & Purk, M. E. (1994). EDLP, Hi-Lo, and Margin Arithmetic. *Journal of Marketing, 58*(4), 16-27.

International Pasta Organisation. (2014). *The World Pasta Industry Status Report 2013.*

IRI. (2016, 11). *Price and Promotion in Western Economies.* Retrieved 02 23, 2020, from Iriworldwide.com: https://www.iriworldwide.com/IRI/media/IRI-Clients/International/Price-Promotion-in-Western-Economies-a-Pause-in-Promotion-Escalation.pdf

Jedidi, K., Mela, C. F., & Gupta, S. (1999). Managing advertising and promotion for long-run profitability. *Marketing Science, 18*(1), 1-22.

Johnson, L. K. (2003). Dueling Pricing Strategies. *MIT Sloan Management Review, 44*(3), 10-11.

Kuntner, T., & Teichert, T. (2016). The scope of price promotion research: An informetric study. *Journal of Business Research, 69*(8), 2687-2696.

Lal, R., & Rao, R. (1997). Supermarket Competition: The Case of Every Day Low Pricing. *Marketing Science, 16*(1), 60-80.

McShane, B. B., Chen, C., Anderson, E. T., & Simester, D. I. (2016). Decision stages and asymmetries in regular retail price pass-through. *Marketing Science, 35*(4), 619–639.

Mela, C. F., Gupta, S., & Lehmann, D. R. (1997). The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice. *Journal of Marketing Research, 34*(2), 248-261.

Meza, S., & Sudhir, K. (2006). Pass-through timing. *Quantitative Marketing and Economics, 4*(4), 351–382.

Mourdoukoutas, P. (2017, 2 24). *A strategic mistake that still haunts JC Penney.* Retrieved January 11, 2020, from Forbes: https://www.forbes.com/sites/panosmourdoukoutas/2017/02/24/a-strategic-mistake-that-still-haunts-jc-penney/#4968b5041bcf

Neslin, S. A. (2002). Sales Promotions. In B. A. Weitz, & R. Wensley, *Handbook of Marketing* (pp. 310-338). London: SAGE Publications Ltd.

Nielsen. (2009a, 06 17). *Promotions Spur Growth In UK Grocery Sales.* Retrieved 02 23, 2020, from Nielsen.com: https://www.nielsen.com/us/en/insights/article/2009/promotions-spur-growth-in-uk-grocery-sales/

Nielsen. (2009b, 10 05). *Almost Half of U.S. Supermarket Purchases are Sold on Promotion.* Retrieved 02 23, 2020, from Nielsen.com: https://www.nielsen.com/us/en/insights/article/2009/almost-half-of-u-s-supermarket-purchases-are-sold-on-promotion/

Nielsen. (2015a, 02). *The Path to Efficient Trade Promotions.* Retrieved 02 23, 2020, from Nielsen.com: https://www.nielsen.com/wp-content/uploads/sites/3/2019/04/the-path-to-efficient-trade-promotions-feb-2015.pdf

Nielsen. (2015b, 06 25). *Consumer Loyalty Is Not Much Deeper Than Our Pockets.* Retrieved 03 05, 2020, from Nielsen.com: https://www.nielsen.com/us/en/insights/article/2015/consumer-loyalty-is-not-much-deeper-than-our-pockets/

Nielsen. (2018a, 08 03). *Are We Really Getting Value From Our Promotions?* Retrieved 02 23, 2020, from Nielsen.com: https://www.nielsen.com/au/en/insights/article/2018/are-we-really-getting-value-from-our-promotions/

Nielsen. (2018b, 05 15). *The $470M Opportunity: Changing The Game With Price And Promotions.* Retrieved 02 23, 2020, from Nielsen.com: https://www.nielsen.com/nz/en/insights/article/2018/the-470m-opportunity-changing-the-game-with-price-and-promotions/

Nielsen. (2019, 08 07). *Global Ad Spending Is Up, But You Can't Buy Loyalty in CPG.* Retrieved 03 05, 2020, from Nielsen.com: https://www.nielsen.com/us/en/insights/article/2019/global-ad-spending-is-up-but-you-cant-buy-loyalty-in-cpg/

Nielsen. (2020). *The Ultimate Guide to Nielsen Retail Measurement Services.* Retrieved 03 05, 2020, from Nielsen.com: https://www.nielsen.com/us/en/client-learning/retail-measurement-services/analyzing-promotion/

Pettie, S., & Pettie, K. (2003). Sales Promotion. In M. J. Baker, *The Marketing Book* (5th ed., pp. 458-484). Oxford, UK: Butterworth Heinemann.

Slater, J. (2001). Is couponing an effective promotional strategy? An examination of the Procter & Gamble zero-coupon test. *Journal of Marketing Communications*, *7*(1), 3-9.

Srinivasan, S., Pauwels, K., Hanssens, D., & Dikempe, M. (2004). Do promotions benefit, manufacturers, retailers, or both? *Management Science, 50*(5), 617–629.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338-353.

Zadeh, L. A. (1968). Probability Measures of Fuzzy Events. *Journal of Mathematical Analysis and Applications*, *23*, 421-427.

Zadeh, L. A. (1977). Fuzzy Sets and Their Application to Pattern Classification and Clustering Analysis. *Classification and Clustering. Proceedings of an Advanced Seminar Conducted by the Mathematics Research Center, the University of Wisconsin–Madison, May 3–5, 1976* (pp. 251-299). New York, San Francisco, London: Academic Press.

Zimmermann, H.-J. (2001). *Fuzzy Set Theory - and Its Applications* (4th ed.). New York: Springer Sience+Business Media.

Zoellner, F., & Schaefers, T. (2015). Do Price Promotions Help or Hurt Premium-product Brands? The Impact of Different Price-promotion Types on Sales and Brand Perception. *Journal of Advertising Research*, *55*(3), 270-283.

Zwanka, R. J. (2017). Everyday Low Pricing: A Private Brand Growth Strategy in Traditional Food Retailers. *Journal of Food Products Marketing, 24*(4), 373-391.