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TIME SERIES ANALYSIS FOR SMALL-MEDIUM ENTERPRISES STRATEGIC PRICING: A CASE STUDY FROM ROMANIAN SMALL CONVENIENCE STORES

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ABSTRACT. This paper illustrates how time series analysis can support regular price decision making for small convenience grocery stores. The existing literature indicates an increasing importance of strategic pricing. However, small-medium enterprises (SMEs) lack both the know-how and the financial capabilities required for advanced price analysis. The carried research illustrates a relatively simple approach for forecasting the impact of different pricing strategies. A case study based on a Romanian SME: SM, operating in the retail sector, was selected. The collected sales data and financial performance indicators provide an interesting insight into both practices and problems faced by SMEs. Following a detailed investigation, a particular category of products: bread and pastry products, was identified as having a major impact on both sales and gross profit. Based on a series of analyses which include: forecasts, best and worst case scenarios, impacts on revenues and gross profit, SM was recommended to increase their mark-ups with 10% for all bread and pastry products. The change is predicted to produce a 9.86% increase in total gross profit and 1.31% increase in all revenue, with minimum risks and minimal loss of sales.

Key words: pricing strategies, forecasting, time series analysis, cost-plus pricing

JEL Classification: L11

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Introduction

The Romanian grocery market is characterized by high competition and thin margins. Moreover, the industry continues to expand, especially on the proximity, supermarket and discounter formats (Retail&FMCG, 2018). Small and medium companies (SMEs) operating in the grocery market face a fierce competition. They are clearly not capable of competing with the hypermarkets (e.g. Auchan, Carrefour, Cora, Real), discount hypermarkets (Penny, Lidl), or Cash&Carry formats (Metro, Selgros) on price. Their main competitive advantage relies on proximity and convenience. However, certain supermarkets e.g. Profi, Carrefour, Mega Image, Auchan, invest heavily in expanding their proximity format stores. The most aggressive expansion is exhibited by Profi. They are by far the leading retailers in terms of number of units and coverage, at the end of March, having over 741 stores nationwide (OverviewProfi, 2018). They also hold the record for the number of units opened in a single month: 32 stores (ProfiPress, 2017).

Given the fierce competition, SMEs must offer great consideration to pricing. Existing studies emphasise the importance of adequate pricing policies, which is argued to be the most important lever in profit improvements (Dolan and Simon, 1997). Literature presents a variety of pricing strategies, the most popular is also the simplest one: everyday low price (EDLP), which, as its name suggests, implies offering low stable prices across all the products (Hoch et al., 1994). The alternative strategies will be presented in the literature review section. EDLP seems the obvious choice for SMEs, which are not capable of investing large sums in marketing campaigns.

A case study was conducted based on a proximity store belonging to a SMEs from a medium-sized city in Romania. Data presented in this paper was collected over a period of over two and a half years. Collected data monitors: daily sales, sales on groups of articles, daily number of customers, and average value of shopping basket. Moreover, these results were associated with the company's financial performance (e.g. cost of goods, other direct & indirect costs, profit margins).

For predicting the impact of price increases, this paper employs time series analysis. First of all, the data is decomposed into its corresponding basic components: trend, seasonal variation, and irregular variation using a moving average smoothing method. Secondly, the quality of the developed model is tested using data from the last three months. Finally, confidence intervals are employed to approximate the impact of price changes on the future sales.

The remainder of this paper is structured as follows. Section 2 is dedicated to reviewing the existing literature on Romanian grocery market and the most popular pricing strategies. Section 3 briefly presents the collected data and the selected methodology. The findings are presented in Section 4 along with a recommendation for the store. Finally, this paper concludes in Section 5, which mentions the limitations and suggestions for further research.

Literature review

Most models of grocery retail decision making are developed based on case studies or data pertaining to either US or UK. In this section we will review the existing literature on pricing strategies, but we will also examine the particularities of the Romanian grocery retail market. This section will start with an analysis on traditional retail pricing, followed by more recent approaches, and it will conclude with the links to the local grocery retail market.

Phillips (2005) suggests that there are three major 'traditional' approaches to pricing: cost-plus, market based, and value based (see table 1). As its name suggests, cost-plus pricing is based on adding a certain percentage to the cost you incur with the product. As indicated by Phillips (2005), and illustrated in table 1, this approach completely ignores the needs of the customers and the prices of the competition, being a completely inward-focused and disregarding towards the market. On the other hand, market based pricing presents an approach which relies entirely on the prices of the competitors. Phillips (2005) indicates that this approach is particularly popular in commodity markets or markets dominated by a clear market leader. Under these circumstances he indicates that the market dictates the price, and companies must take it as a given. Finally, value-based pricing implies that price should be entirely based on the customer perception of the product. In other words, through this approach the value that customers attribute to products is extracted (e.g. surveys, focus groups) and is reflected into the price (Phillips 2015). Most frequent examples of value-based pricing are found in the case of new, innovative products, with minimal competitive pressure.

Table 1. Traditional pricing approaches

Approach	Based on	Ignores
Cost-plus	Costs	Competition, customers
Market based	Competition	Cost, customers
Value based	Customers	Cost, competition

Source: Phillips, 2005

Clearly the above presented traditional pricing approaches are quite simplistic and they represent extremes. In practice, retailers use a combination of these approaches. Moreover, recent practices incorporate new aspects into pricing e.g. price variation, deals and promotions. Bolton and Shankar (2003) identify five major pricing strategies employed by branded retailers in the US: EDLP, HiLo, Exclusive, Moderately promotional, and Aggressive. The pricing strategies are described in table 2 (Bolton and Shakar, 2003, and Bolton et al., 2010). The two price-related dimensions distinguish between the pure price and the promotion price, captured through relative price and variation of price. The deal-related dimensions indicate the deal depth, frequency and duration (deal intensity) and the feature and/or display (deal support).

Table 2. Pricing strategies

Pricing strategy	Relative price	Price variation	Deal intensity	Deal support
EDLP	Average	Low	Medium	Medium
HiLo	Average	High	High	High
Exclusive	High	Medium	Low	Low
Moderately promotional	Average	Medium	Medium	Medium
Aggressive	Average	High	Low	Medium

Source: Bolton et al. (2010)

In the case of EDLP pricing, the companies focus on providing consistent low prices, without running sales or promotions (Hoch et al., 1994). Almost opposite to EDLP we can place the HiLo pricing which consists of retailers charging high prices for products, followed by big discounts in sales clearance, once their popularity has passed. Exclusive pricing was found to be the least adopted strategy, as it is targeted for high-end stores which address a wealthy customer segment (Bolton and Shankar, 2003). As Zielke (2010) argues, the pricing impacts the way the customers perceive a particular retailer. Another customized pricing strategy: the moderately promotional pricing, which relies as its name suggests on average implication in deals and promotions, has a relatively low popularity. Finally, the most popular hybrid strategy, which actually was found to surpass the HiLo pricing, is the aggressive pricing (Bolton and Shankar, 2003). Retailers adopting this strategy use the price as a weapon, offering a low price and medium deal support coupled with high price variation and a low deal intensity.

The above mentioned popularity of pricing strategies is restricted, as previously emphasised, to the US. Similar scientific enquiries have been carried for the UK in conjunction with the US (Watson et al., 2015). However, the existing literature does not provide any comprehensive study that addresses the retail pricing strategies for the Romanian market. This enquiry is also beyond the purpose of this research; nevertheless, this paper will present a detailed overview of the current retail market in Romania e.g. main competitors, market share, and type of stores.

According to a study carried by Euler Hermes and cited by ESM (2017), based on revenues towards the end of 2017, Romanian retail market is dominated by four major players: Kaufland, Carrefour, Metro, and Auchan, with a cumulated market share of over 60%. However, the picture changes drastically if the players are judged based on their respective number of stores, on this criterion, as expected, the supermarkets outperform the hypermarkets. At the end of January 2018 Profi is reported to have the highest number of stores: 705, followed by Mega Image: 599 units, and Carrefour: 311 (Retail&FMCG, 2018). In this paper, the focus is placed on supermarkets, since they compete directly with SMEs on convenience/ proximity. Clearly, hypermarkets outperform both supermarkets and SMEs on price, promotions, and variety.

Even though Profi is now clearly the leader, having the highest number of stores and the highest rate of store openings, the market looked very different 4 years ago. At the end of 2014 Mega Image operated with 410 stores, whilst Profi only had 275 (ZF, 2015). The gap between the two was narrower one year before, the figures are presented in table 3. It is clear that both companies followed a very aggressive expansion strategy, even though Mega Image managed a slightly slower growing pace after 2014.

Table 3. Profi vs Mega Image

Supermarket	Stores Dec. 2013	Stores Dec. 2014	Stores Jan. 2018	Increase (%)
Profi	204	275	705	345.58%
Mega Image	293	410	599	204.43%

Source: Retail&FMCG (2018) and ZF (2015)

Another retailer which tries to capture the proximity/ convenience market is Metro, through their LDP stores. They are reporting to have over 500 store nationwide (LDP, 2018). The reason for their exclusion from the above presented statistics is that they operate a very different business model. As opposed to their competitors, they franchise their stores. In other words, they do not deal with the daily operations. In fact, their role is quite limited: they offer consultancy, marketing, design features, and training, but the actual decision making is taken by the SME that bought the franchise (LDP, 2018). The SME franchise holder will take all the operating and strategic decisions such as: pricing, acquisition, opening hours, number of staff. The franchisor imposes a minimal number of operating rules, which are rarely enforced e.g. an agreed upon amount of goods must come from Metro (can be under 10% of sales), the store must have good availability for products that are part of their bi-monthly marketing campaign, the products on their bi-monthly campaign have maximal prices.

Moreover, it is important to emphasise that Metro LDP stores have a very low minimum threshold on store floor space, the accepted minimum is 40 square meters (LDP, 2018). The supermarkets are generally inclined to opt for larger floor space. For example, Profi accepts a minimum of 180 square meters for their smallest store format: Profi City (BM, 2013), and their regular-format stores can have up to 700 square meters of total floor space.

Following a local analysis for the specific case study addressed in this paper, it was revealed that the city in question holds 2 hypermarkets: Unicarm and Carrefour, and three Profi supermarkets. In addition, there are two local stores which hold LDP franchises, one being the SME addressed in the case study. It could be argued that the existing local retail market is underdeveloped. Interviews with experts reveal plans for three extra hypermarkets: Lidl, Kaufland, and Penny to be opened by 2020, and at least one extra Profi supermarket, which will be launched in June 2018. Consequently, in terms of proximity stores, Profi and the LDP franchises are the only competitors to local SMEs.

As previously mentioned, this paper is supported by data gathered from a Romanian-based small medium enterprise (SME) referred in this paper by the acronym SM. The company was recently funded: first store was opened in the third quarter of 2015. The main challenge for SM is to react to the impact of multi-national and local competitors. In close proximity: under 50 m and respectively under 200 m, there are two other local SMEs with slightly smaller store floor spaces. A Profi supermarket is scheduled to be launched in June 2018, at a distance of 300m from SM. The distance to the two existing local hypermarkets: Unicarm and Carrefour, is under one kilometre.

The limited number of hypermarkets and supermarkets can be explained by the size of the city. As previously emphasised, SM activates in a small-medium city (D). According to the 2011 census (Census, 2011), D has a population of only 33,497. Given its spread of 109km^2, it can be deducted that D has a very small density: approximately 307 people/km^2. By contrast, the largest city in the county: Cluj-Napoca had a population of over 324,576, with a density of 1808 people/km^2 (Census, 2011).

Nevertheless, SM faces extreme pressure from both local and multi-national competition. One on hand, the multi-national companies like Profi, exert high pressure on pricing due to their economies of scale (higher volumes), larger store sizes (larger variety of goods), relatively good proximities. On the other hand, the local SMEs which are in close proximity are family-run businesses which also possess certain competitive advantages e.g. lower costs (e.g. wages), lower indirect costs (e.g. accounting, fuel), and sometimes lower acquisition costs (e.g. one-off promotions). SM has exclusivity to a segment of goods: pastry and confectionary specialties, which is supplied by a company from its own group. The other goods are supplied by independent suppliers.

As previously emphasised, there are no comprehensive academic studies that address the pricing strategies adopted in the Romanian retail market. For the addressed case study, of most relevance are the pricing practices of Profi, LDP franchises and local SMEs. From the available information (LDP, 2018) it can be concluded that LDP franchises face similar challenges as SMEs in terms of pricing, except for the few products that have imposed maximal prices. A research into pricing practices of local SMEs would be most beneficial. As far as Profi is concerned, their pricing strategies are undisclosed. They seem to adopt a hybrid approach, which varies among products but also from one store format to another. An informal interview carried with one of their suppliers provided some generalities which he was at liberty to disclose. For their particular product, Profi had no mark-up per see, rather they are charging the supplier a set of fees: shelf space fixed fee, shelf stocking fee (variable), and admin fees (variable). However, this pricing technique, must be very different from other products from their portfolio e.g. own brand products.

Material and Methods

The data employed in this paper was collected from three major sources, and it covers a period of two and a half years. First of all, sales and other statistic data was collected form SM’s IT software system. All this data is strictly quantitative. Secondly, financial data was collected from company’s official balance sheets and income statements; this data is also quantitative. Finally, other information required to process or interpret the data was collected, as qualitative data, through a series of informal interviews carried with key SM staff members.

As previously emphasised, time series analysis and forecasting constitute the main methodology of this paper. Given the nature of the data: quantitative historical data, time series was identified as the most appropriate method (Anderson et al., 2007). The main assumption behind the time series approach is that up to four components can be extracted from the data: trend, seasonal, irregular, and cyclical (Anderson et al., 2007). As it will be showed in the following chapter, the cyclical component is disregarded in this paper, as the collected data does not cover a sufficiently large period of time so as to be able to identify any cyclical patterns. However, both interviews and an in-depth analysis of the historical data indicates a strong seasonal pattern; also, both trend and irregular components are present.

In order to extract the seasonal component the moving average approach is employed. Given the fact that historical data and interviews indicated a strong seasonal (weekly) pattern, moving averages (MA) is preferred to smoothing methods. According to Anderson et al. (2007) simple smoothing methods e.g. exponential smoothing should only be employed on stable time series, which exhibit little trend or seasonality, for shot-range forecasts. On the other hand, MA offers a simple way of firstly deseasonalizing, secondly capturing, and finally extracting any seasonal pattern. The MA can be defined as follows: MA=[∑(most recent data values)]/n, where n is the selected window, for example, in the case of data that follows a weekly seasonal pattern, n=7.

For modelling the trend component, simple linear regression is employed. The underlying equation is given by: $T_t = b_0 + b_1 * t$, where T_t is the trend value of the series at period t, b_0 is the intercept of the trend line, b_1 is the slope of the trend line, and t is the time. The quality of the trend line fit is judged based on the coefficient of determination (R^2). For a perfect fit R^2 has a value of 1, while lower values mean a worse fit (Anderson et al., 2007).

As far as the specific time series model is concerned, a multiplicative model was selected for this paper. Even though both multiplicative and additive models can offer good representations of the interaction between the components, according to Dewhurst (2006), the multiplicative models have generally registered better performances. The model is described by the following equation: $TS_t = T_t * S_t * I_t * C_t$, where TS_t is the value of the time series, T_t is the value of the trend component, S_t is the value of the seasonal component, I_t is the value of the irregular component, and C_t is the cyclical component, at time period t.

The forecasts are generated using the fitted trend line and the captured seasonal component. The underlying equation is given by: $F_t=T_t*S_t$, where F_t is the forecasted value for the time series, T_t is the forecasted value of the trend component, and S_t is the value of the seasonal component (seasonal index), at time period t. The quality of the forecasts is judged based on visual inspection and a paired t-test. The paired t-test is employed to check if there is a significant difference between the two sets of observations: the forecasts and actual data (Anderson et al., 2007). The hypothesis are expressed as follows: $H_0:\mu_1=\mu_2$ or $H_0:\mu_1-\mu_2=0$ (the population means are equal) and $H_1:\mu_1\neq\mu_2$ or $H_1:\mu_1-\mu_2\neq0$ (the population means are not equal). If H_0 cannot be rejected at the selected confidence interval percentage, it can be concluded that data does not provide enough evidence that the two data sets (forecasts and actual data) are significantly different (Anderson et al., 2007).

Results and Discussions

The purpose of this section is to analyse the impact that difference pricing levels would have on the future sales and suggest the most appropriate strategy for SM. It will commence with an in-depth analysis of the collected data. This will be followed by the decomposition of sales data into relevant time-series components: trend, seasonal, and irregular. Additionally, forecasts for a period of 3 months will be provided. Finally, the results are going to be discussed and recommendations for SM are going to be suggested.

Since its opening, SM exhibited significant increases in Total Sales and steady increase in Profits, as illustrated in fig. 1. The discrepancy between 2015 and 2016 is given by the fact SM opened its first shop in the third quarter of 2015, consequently the figures correspond to approximately 5 months of commercial activity. As far as year 2018 is concerned, the presented figures represent the total sales and profit at the end of the first quarter. Clearly, the financial results for 2018 give raise to many concerns. Even though the Q1 target for sales: 600000lei was achieved, the profit fell well below the target and SM made a loss. The unsatisfactory Q1 results are attributed to a rise in costs e.g. rise in costs with employees (tax changes), repairs, and other indirect costs, which correlated with a very low profit margin lead to a loss of almost 6000lei.

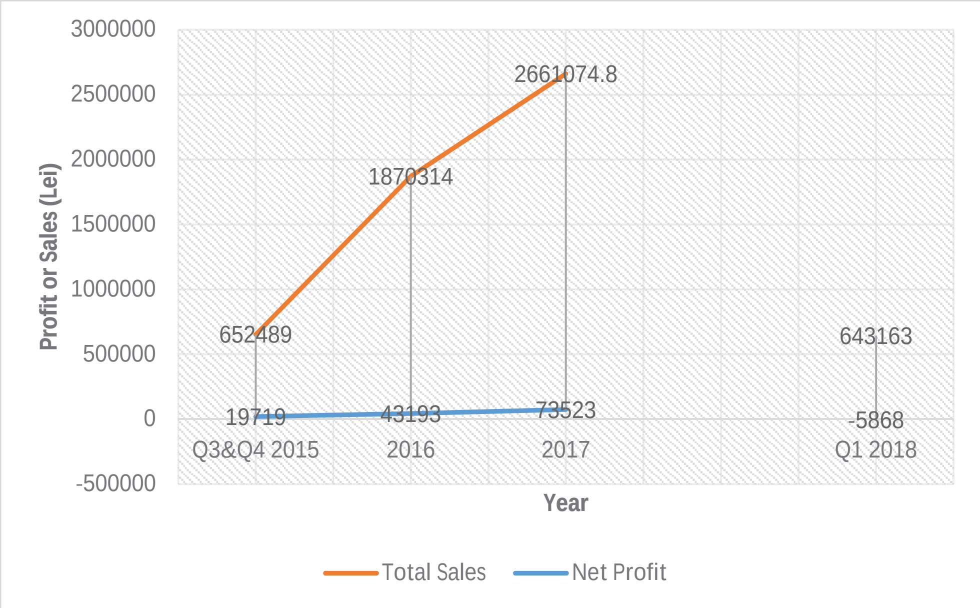

Fig. 1. SM Total Sales and Net Profit for 2015-2018

The retail industry is generally characterized by very low net profit margins (NPM), as a result of large sales coupled with low mark-ups, and, consequently high cost of goods. The industry standard for NPM is thought to be in the interval 3-5%. Available statistics indicate that, in 2010, top 250 retailers in Europe averaged a net profit margin of 3.3% (Statista, 2018), for UK the margin was slightly higher 3.6% and the US registered an average net profit margin of 4.3%. As indicated by fig. 2, SM fell short of the industry standard, registering lower NPM in all years since its opening. SM performed particularly poor in 2016, when it registered a NPM of only 2.31%.

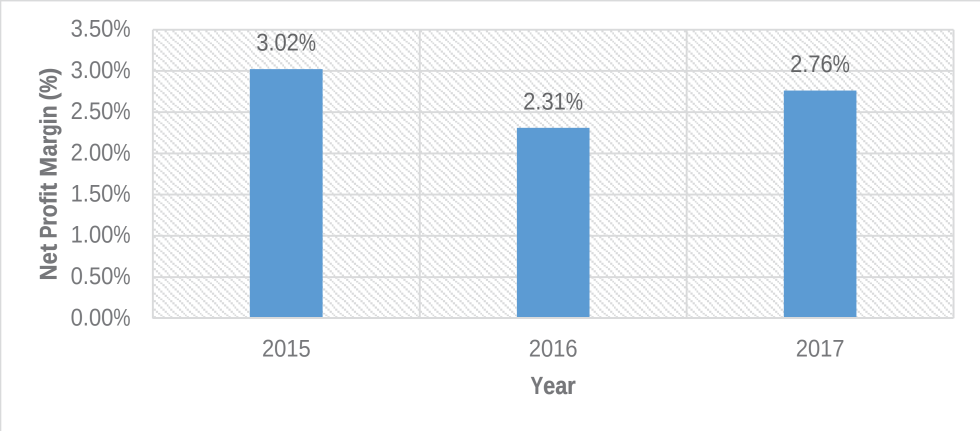

Fig. 2. SM Net Profit Margins 2015-2017

In order to improve the performance on the NPM indicator, SM can either reduce their costs or increase their revenues. The highest proportion of costs, generally around 85%, is given by the costs of goods. This variable can generally be reduced by negotiating with suppliers or changing suppliers. The remaining 15% of the total costs consist in a very high proportion of salaries and tax, the rest being indirect costs such as repairs, bank charges, and telecom. As far as the revenue improvement is concerned, the strategies can be twofold, either increasing the quantity of goods sold or increase their price. The quantity of sold goods can be raised either by increasing the number of consumers e.g. through marketing and promotions (can also negatively impact NPM), or determining the customers to buy more (increase the shopping basket value). However, all these approaches are inter-related e.g. if we invest in marketing: revenue might increase due to increased customers, however the overall costs will also increase due to the new marketing costs.

This paper will focus on improving the NPM indicator through optimizing the pricing strategy. An increase in price will clearly have a very high impact on profit and NPM, Dolan and Simon (1996) illustrate how a 10% increase in price can result in a 33% improvement in profit. However, the price elasticities of the products must be considered, sometimes a too high increase in price can lead to a significant loss of customers which can lead even to a decrease in NPM.

First of all, the daily sales data is collected from the store under investigation, referred in this paper as S1. Fig. 3 illustrates the daily sales data for the period: 01.07.2015 to 30.03.2018 for S1. As it can be observed straight away there are quite a few outliers and quite a lot of noise in the data. On a close analysis, we can observe that outliers are associated with major yearly celebrations: Christmas, New Year, and Easter. There are few days around this days which act as outliers, these are expected as sales are rising exponentially the days before the event and then they decrease or even go to 0 if the store is closed during and/ or after the national holiday. The added trend line exhibits an upper slopping trend, however, as indicated by the coefficient of determination (R^2), does not present a good fit because of the present irregularities and potential seasonal variation. Consequently, a detailed analysis of the data is required.

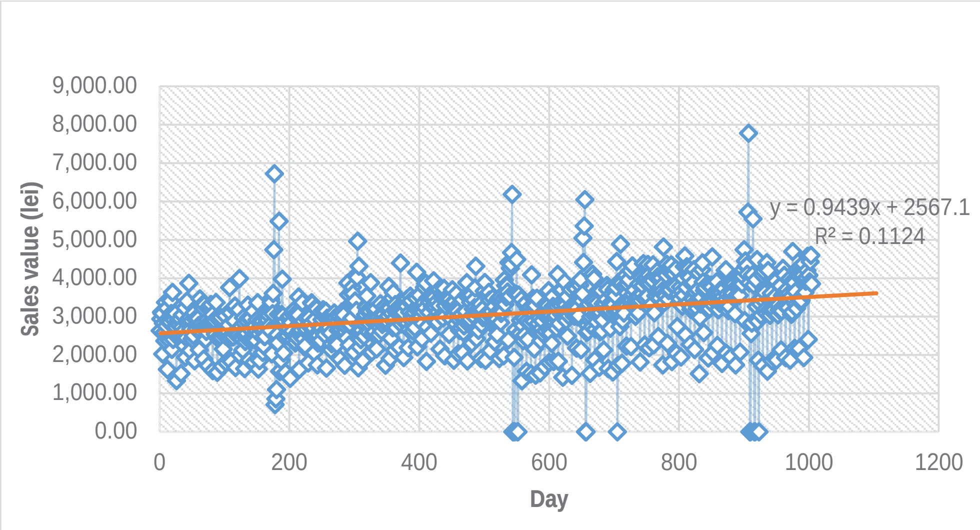

Fig. 3. S1 Daily Sales

Looking at the sales of Q1 2018, which are depicted in fig. 4, we can identify the same outliers as mentioned above. The 1st and 2nd of January indicate no sales as a result of S1 being closed for the two days following the New Year. Moreover, the date of 8th of January also represents an outlier with 0 sales. Following an informal interview with SM's financial team, the date 08.01.2018 was identified as the date in which they conducted the yearly law required inventory, hence, S1 was closed for the whole day. The trend line exhibits a similarly poor fit as for the previous (complete) dataset. However, from the more restricted data-set, the presence of a certain seasonality is apparent. On a close analysis, it can be observed that all data-points which represent daily sales values below or around 2000lei are registered on Sundays. This recursive trend suggests the existence of a weekly seasonal pattern.

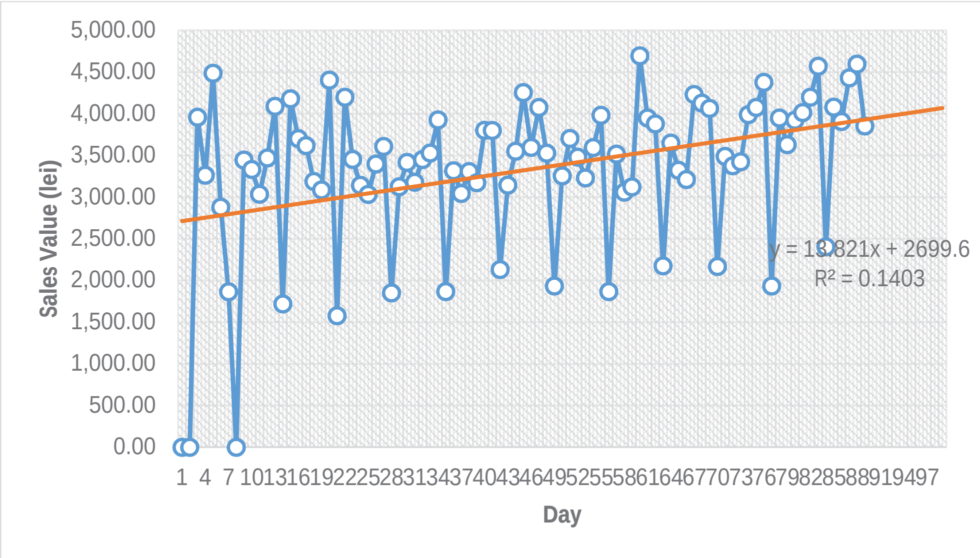

Fig. 4. S1 2018 Q1 Daily Sales

The existence of a weekly seasonal pattern is further illustrated in fig. 5. Except for the three outliers: two in week 1 (blue) and one in week 2 (red), the remaining data seems to follow quite a similar weekly pattern. There seems to be slightly larger sales on Fridays and Saturdays, followed by very low sales on Sundays. This information is extremely valuable in extracting the seasonal component from the time series.

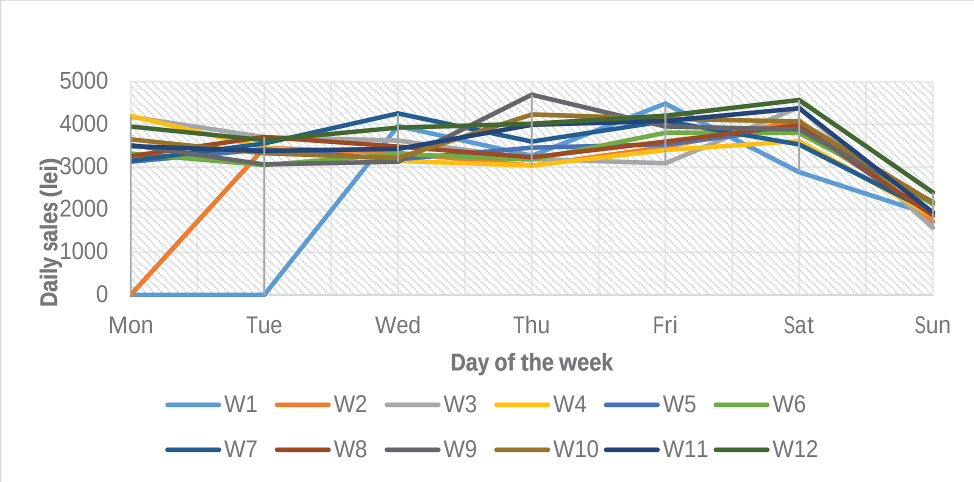

Fig. 5. Weekly pattern S1 2018 Q1

As previously emphasised, the work carried in this paper employs a time series analysis methodology for forecasting. In a classical view a time series is composed of four basic components: trend, seasonal variation, cyclical variation, and irregularities (Anderson et al., 2007). Considering the above presented data-set, the cyclical will be disregarded, as the interval for data collection is not long enough: slightly under 3 years. As previously emphasised, a multiplicative model will be employed, as they are considered to generally outperform the additive models (Dewhurst, 2006).

Since it has already been established that the data follows a seasonal pattern, smoothing methods, e.g. simple exponential smoothing, cannot be employed (Anderson et al., 2007). Consequently, in order to identify and remove the seasonal component a moving average (MA) approach is proposed. As the pattern is correlated to the weekdays (see fig. 5) a 7-period MA is selected. An illustration of original data vs MA(7) is provided in fig. 6. As it can be observed, MA(7) does well to remove the irregular components; however, it can be observed that it is still impacted by the outliers. It must be mentioned that data pertaining to Q1 2018 (3 months in total) was not included, as it was kept for testing. This testing set will be excluded from all analysis, until the forecasts are produced.

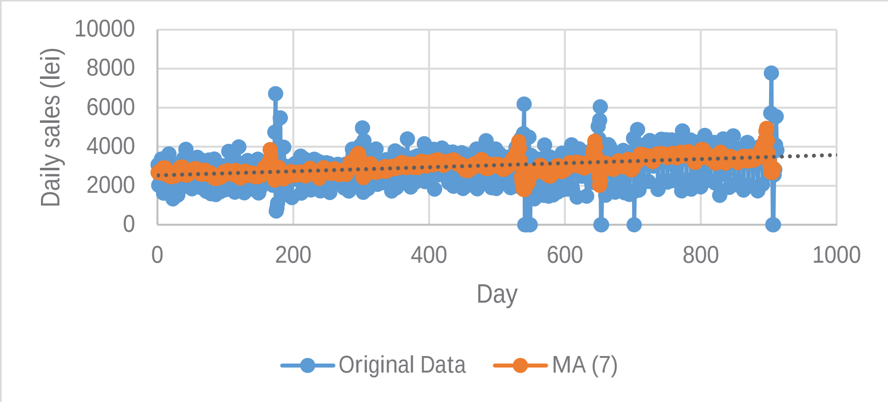

Fig. 6. Original data vs MA (7)

The resulting seasonal indices are presented in fig. 7. The seasonal indices clearly follow the pattern indicated in fig. 5, displaying average sales for the first four days of the week, followed by a slight increase in sales during Fridays and Saturdays and a very sharp decrease on Sundays. This is consistent with the information gathered during informal interviews with the staff.

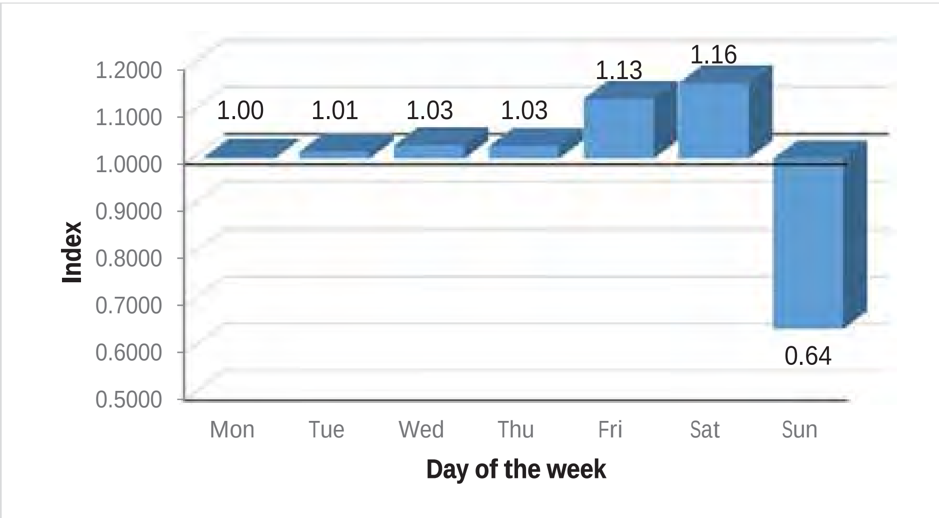

Fig. 7. Seasonal indices

Following the identification of seasonal indices, the data is deseasonalized, so as to extract the trend component. In order to reduce their impact on the trend line, the known outliers e.g. days around Christmas, New Year, and Easter, have been removed. Clearly, as it can be observed from fig. 8, there is still significant noise in the data, given by the irregular component. As previously emphasised, in order to test the accuracy of the developed model, a testing dataset consisting of Q1 2018 (three months in total) has not been included in the trend fitting either. The coefficient of determination indicates a significant improvement in trend line fit, when compared with initial seasonal data (see fig. 3). Nevertheless, it is clear that its accuracy could be improved: for a more accurate fit the R^2 value should be closer to 1. Unfortunately, the irregular variation and various outliers, coupled with the large size of the dataset, did not facilitate a better fit. However, the fit could be potentially improved if a larger window-size was to be tested for the MA. This was not desired in the current research as the MA window-size would lose its significance; following a number of informal interviews and a detailed analysis of the data, it is clear that the exhibited seasonality is weekly and, hence, a 7 window MA should be used.

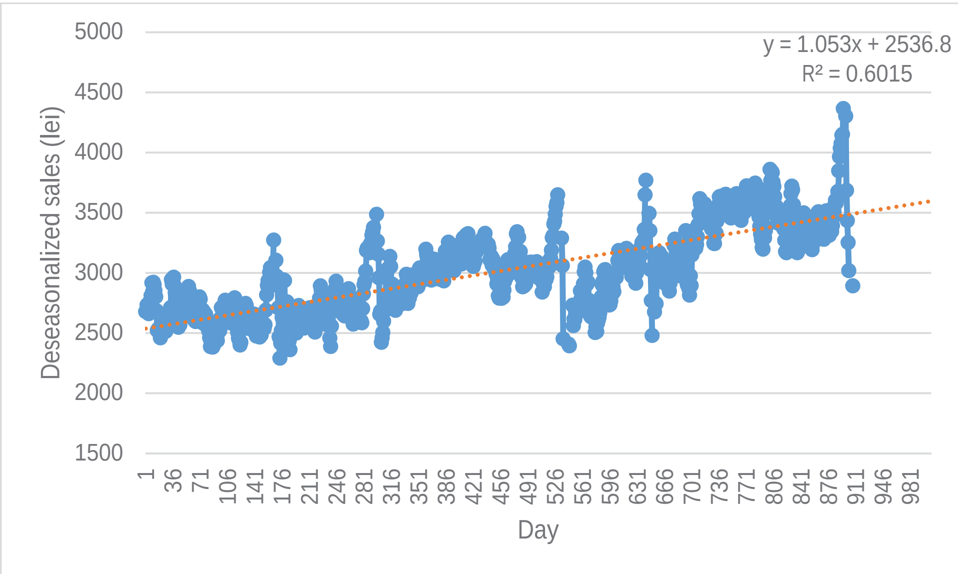

Fig. 8. Deseasonalized data

The accuracy of the developed model has been assessed on the testing set using visual inspection and a paired t-test (Anderson et al., 2007), to ensure there is no significant difference between the mean of the actual data and the mean of the forecasts. The first eight days were excluded from the testing set, as they contained a high number of outliers: the days following the New Year when the store was closed, and the day in which the law-required inventory was carried (08.01.2018). A visual inspection of the two datasets plotted in fig. 9 (actual vs forecasts) indicate small differences between the two. Main differences occur mainly because of lower than estimated sales on Sundays, but also due to certain variations during weekdays; nevertheless the predicted pattern seems to fit quite well with the actual data. This is also supported by the conducted paired t-test which indicated that there is not enough evidence to reject the null hypothesis H_0 at a 0.05 significance level. In other words, there is not enough statistical evidence to say that the mean of the actual data is significantly different than the mean of the forecasts.

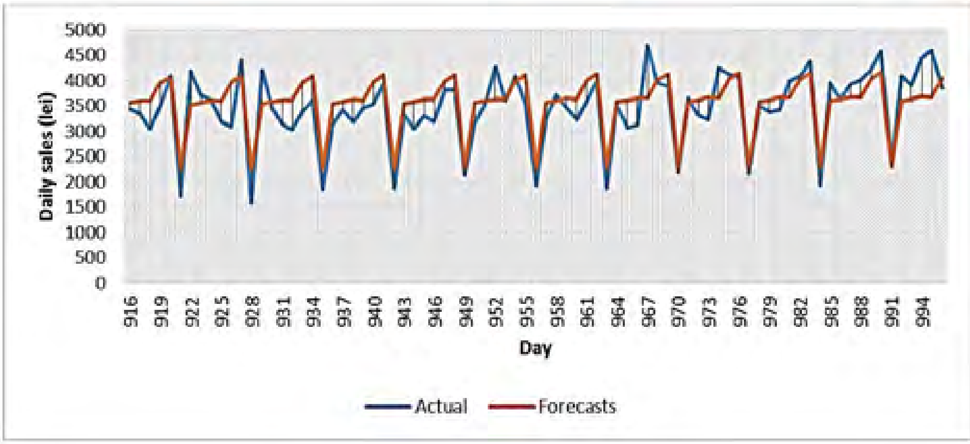

Fig. 9. Actual vs Forecasts on testing set (Q1 2018)

As the forecasting model is constructed and tested, the impact of certain price changes can be analysed. First of all, a detailed analysis of the main groups of products, which contribute to the daily sales, must be carried. An illustration of total sales for the period 01.07.2015-

30.03.2018, based on the main groups of products is provided in fig. 10. As it can be observed tobacco products are by far the biggest source of revenues, followed by bread and pastry products, and coffee & sweets. Quite a significant amount of sales is also hold by beverages and non-food products. However, this figure does not provide a complete picture, as different product groups have different contributions towards the gross profit (GP). SM currently employs different mark-ups according to the group of products e.g. sweets, beverages, and alcoholic drinks are marked-up 30% while pastry, meats, milk, and dairy products are marked-up 20%.

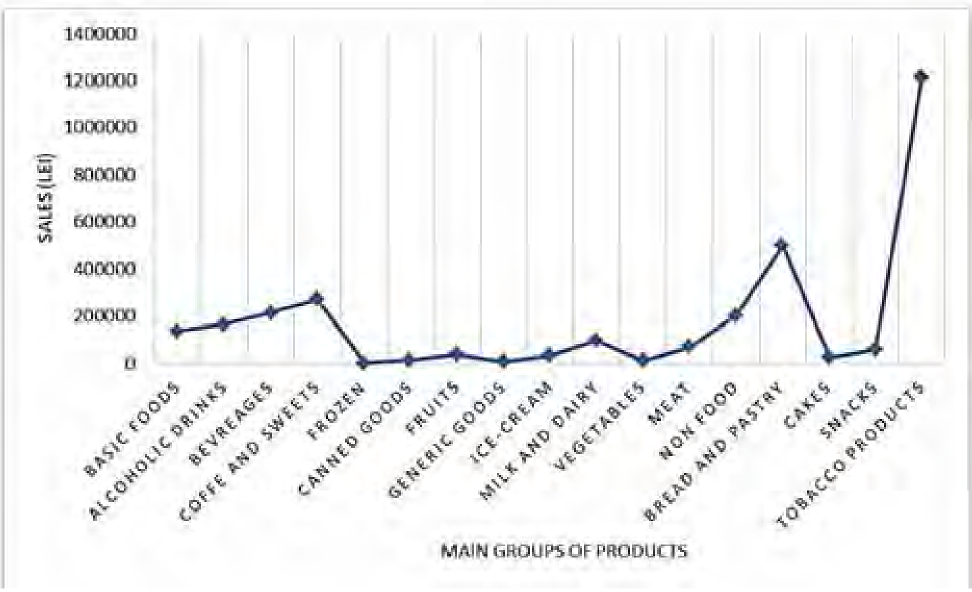

Fig. 10. S1 Sales (main groups of products)

From a gross profit point of view, the main top contributors change. As indicated by fig. 11, even though tobacco products account for an extremely large percentage (39.7%) of the total sales, they contribute with less than 11% towards the total GP. This is due to the fact that mark-up for tobacco products is restricted by law and generally reaches around 4%. The main contributor towards the GP is the bread and pastry category, which generates almost 20% of the GP. That is almost twice the contribution to GP made by tobacco products with less than half of the sales (bread and pastry amount only to 16.4% out of total sales). Other main contributors towards the GP are: coffee and sweets with 16% of the GP (only 9% of total sales), non-food: 12% of GP (6.7% of total sales), and beverages: 9.9% of GP (7.1% of total sales).

Fig. 11. S1 Percentage Sales and Gross Profit

Clearly, the categories which hold the highest percentage of total sales can generate the greatest impact of gross and net profits. However, the category that holds the highest percentage of sales: tobacco products (39.7%) has a law imposed selling price and, consequently, no adjustments can be made in this regard. As previously discussed the following categories are: bread and pastry with 16.4% out of total sales and coffee and sweets with 9% of total sales. In this paper the impact of a price change for bread and pastry will be analysed. First of all, this category was selected for its potential: since it holds the second highest percentage of total sales, it has the potential of generating the highest impact on total gross profit. Secondly, its mark-up is only 20%, as opposed to coffee and sweets which have a mark-up of 30%; consequently, the perceived impact on price (from consumers' point of view) can be smaller. Finally, since the supplier for bread and pastry is a company from SM's group, it can provide support in case the price change has an undesired effect/ deviates from the forecasts e.g. help with promotions, price reductions and other discounts. Clearly, the pricing strategy can be analysed across multiple product categories; however, that will be the grounds of future analysis. The work carried in this paper will be limited to one category of products. From the case study/ company perspective, this is important for testing the forecasts and minimizing the impact of any deviations.

By employing the developed forecasting model, the sales for the next 3 months, more precisely the next 93 days, are predicted, as illustrated in fig. 12. Following a set of informal interviews with key members of staff, the impact of various price increases on customer spending was estimated using best and worst case scenarios. The results are presented in table 1.

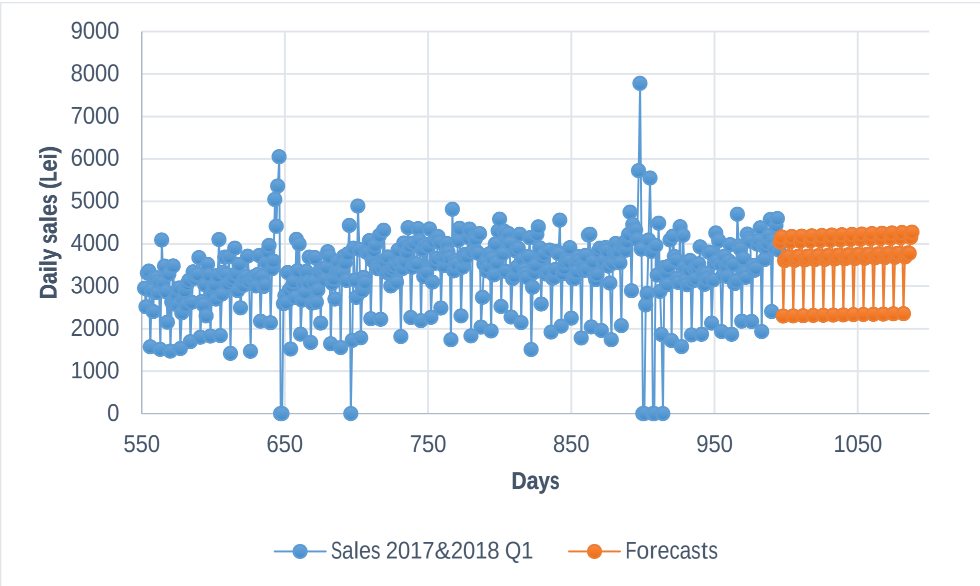

Fig. 12. S1 Percentage Sales and Gross Profit

The potentially negative customer impact is analysed from two different perspectives. On one hand we consider the potential loss in bread and pastry sales, but on the other, we also consider potential impact on overall sales. For supporting this required assessment, the data pertaining to customer baskets for February 2018 were analysed. The sum of all shopping baskets that contained 700gr white bread for Feb 2018 was 10187lei while all the 700gr white bread sold in Feb 2018 was 3462lei. In other words, for every 1leu spent on bread there were additional products worth 2.94lei in the basket. However, this data does not prove causality, it cannot be inferred that bread was the main driver for shopping, it could have been a side-product. For the purpose of this paper we estimate that for every 1leu (or 1%) lost in sales of bread due to price raise, we have a total of 1.5lei (or 1.5%) loss from total revenue.

Table 4. Pricing level analysis

Price raise (Mark-up)	Example of impact (700gr White bread)		Calculated positive impact (greater revenues)	Estimated overall negative impact on sales Best Case (BC)	Estimated overall negative impact on sales Worst Case (WC)	Overall impact on GP
	Before (lei)	After (lei)				
5%	3 (2.5)	3.125	0.69%	0.15%	0.30%	4.93%
10%	3 (2.5)	3.25	1.31%	0.15%	0.60%	9.86%
15%	3 (2.5)	3.375	2.05%	0.75%	1.50%	14.79%
20%	3 (2.5)	3.50	2.74%	2.25%	4.75%	19.73%
30%	3 (2.5)	3.75	4.10%	4.50%	10.50%	29.59%

An example is employed in table 4 to illustrate the impact of potential price changes. By adding an additional 5% to the original mark-up, the 700gr white bread increases its total gross margin to 25% (from 20%) leading to a price raise of 0.125lei: from 3lei to 3.125lei. The impact of the price raise on total revenues is presented in column 4. The impact on the bread and pastry revenues are calculated using the following formula: increase= [(1.20+markup)/1.20-1]. For example, for the 5% increase in mark-up there will be a 4.2% increase for bread and pastry revenues. In order to obtain the impact on total revenue the previous percentage is multiplied by percentage contribution that bread and pastry holds from total revenue (16.4%). Hence for the 5% increase in mark-up there will be a 4.2%*16.4%=0.69% increase in total revenues. In columns 5 and 6 the best and worst case scenarios are estimated for negative impact on sales due to loss of consumers. The previously mentioned rule was considered during the informal interviews: a 1% loss in revenues of bread and pastry translates in 1.5% loss in total revenues. Finally, in the last column (7), the impact on overall GP is calculated. For calculating the impact on bread and pastry GP the following formula can be used: GP increase= [(0.20+markup)/0.20-1]. For example, for the 5% increase in mark-up, there is a 25% increase in bread and pastry GP. In order to calculate the impact on the overall GP the previously calculated increase is multiplied with the percentage contribution that bread and pastry holds from total GP (19.73%). Hence, a 5% increase in mark-up will generate a 25%*19.73%=4.93% increase in total GP.

It can be observed that, when compared to impact on GP, the price change impact on overall revenue is relatively small. An increase with 5% of the mark-up will raise the total revenue with only 0.69% while the overall GP will be raised by a significant 4.93%. It must be noted that the proposed increase in price mark-up is only for a category (bread and pastry) and even though this category is one of the main contributors to both revenue (16.4%) and GP (19.73%), it clearly implies a diminishing impact on overall results. If we analyse the contribution to the category's own revenue: 4.2% and GP: 25%, we are clearly presented with a significantly different impact.

As far as the price change impact on GP is concerned, it can be argued that the major increase is expected. Since the cost of the goods remains constant, all the increase given by the rise in the mark-up will become directly gross profit. Consequently, even though the percentage increase in overall revenue is not very small, the percentage increase in GP will raise exponentially. These results are consistent with the literature, as previously emphasised, Dolan and Simon (1997) found that a 10% rise in price can generate a 33% increase in profits.

In order to select the appropriate pricing level, the potential impact on loss of sales is illustrated in fig. 13. Based on the figures extracted in table 4, the predictions for 10%, 20%, and 30% change in mark-up were graphed. Understandably, as the increase in price becomes larger, the loss of sales along with the predicted uncertainty raise exponentially. From a predicted loss, for the whole 3 month period, of only 508lei (BC) -2034lei (WC) in the case of a 10% raise in mark-up to an expected loss between 15256lei (BC) - 35597lei (WC) for a 30% raise. Judging strictly based on the figures from table 4, we might be inclined to think that even under the dire conditions of significant loss of customers, given the high impact on the GP, greater benefits are obtained when very high price changes are applied. This judgement is correct for the short term, but such a strategy is not recommended as we risk losing a significant number of customers in the long run, or even more drastic impacts (than predicted) in the short term.

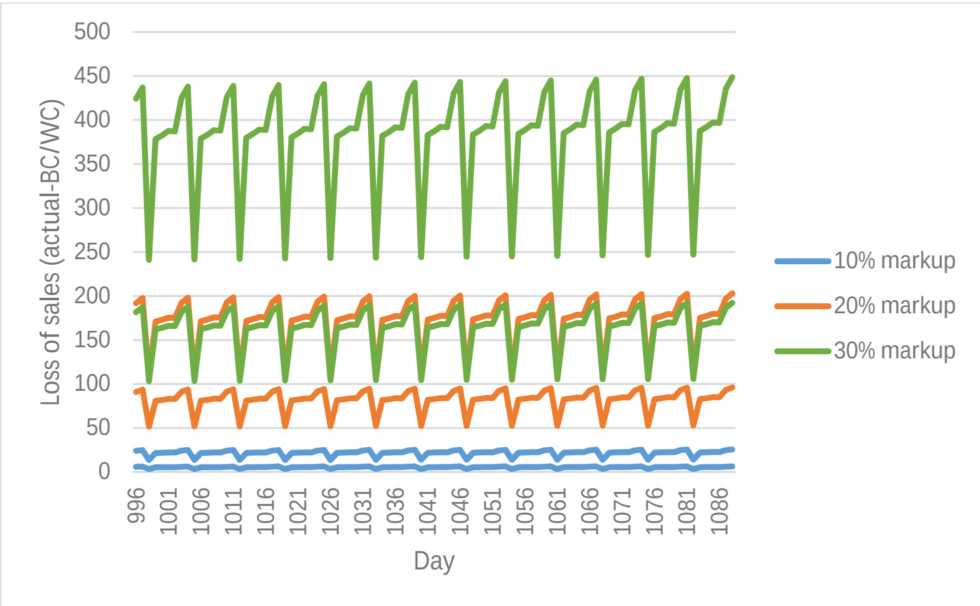

Fig. 13. Forecasted daily potential loss of sales

Subsequent to the presentation of the results, another set of informal interviews were carried, including with the CEO of SM's supplier for bread and pastry products. Following these discussions, the 10% increase in pricing mark-up was recommended and selected to be implemented. It represents the optimum alternative for SM as it predicts significant increase in overall GP (9.86%), a small increase in total revenue (1.31%), but, at the same time, minimal forecasted risks: just 0.15%- 0.60% decrease in sales. The second favourite option: the 15% increase in pricing mark-up was also considered as potentially viable, but was dismissed for its corresponding slightly higher associated risks. The experts subjectively appreciated that, for the higher mark-ups, the risk of sale loss could be even larger than forecasted. The predictions will be checked over 3 month intervals; after 6 months a re-evaluation will be conducted.

Conclusions

This paper analysed the feasibility of employing time series analysis to support pricing decision making for SMEs which activate in the convenience sector of the retail market. The literature review revealed that increasing importance is paid to strategic pricing. Moreover, many consecrated approaches, as well as, hybrids have been developed. However, very few of these techniques are actually implemented, especially in the case of SMEs, which lack the knowledge and financial resources of analysing large datasets. It is also the case of a Romanian based SME: SM, which was selected as a case study for this research. SM's current practices rely on cost-plus pricing and historic data is rarely analysed.

As far as the Romanian retail market is concerned, there are limited publications that discuss pricing strategies, there are no overviews to indicate which methods are preferred. After a detailed literature review, an overview of the market structure became apparent. The four major players: Kaufland, Carrefour, Metro, and Auchan, which dominate the market, were identified. However, these top retailers are focused on the hypermarket sector, the proximity sector was found to be dominated by Profi and Mega Image, with Metro franchises "La doi pasi" offering an interesting, yet, currently, inefficient alternative.

As far as SM is concerned, they were found to face competition from hypermarkets: Unicarm and Carrefour, supermarkets: Profi, and other local SMEs, which operate as family businesses. Even though they generally experienced an upward sloping trend in terms of sales, SM was found to face problems with their net profit margins, which are below the industry standards. This is thought to be mainly attributed to their efforts of being competitive and keeping the prices low, but it is judged to be also the effect of a somewhat lax pricing policy.

Following an analysis of historic sales and a detailed investigation into groups of products, it was found that SM also exhibits quite a low gross margin (13.7%). This is mainly due to the fact that the main driver of sales: tobacco products (almost 40% of revenues) have a very low gross margin (around 4%). The biggest contributors to GP were found to be the bread and pastry products, which, even though, have a gross margin of only 20% and contribute to only 16.4% of the total sales, they amount to almost 20% of all GP. This category was selected for further analysis and price optimization.

Based on forecasts, estimations of worst and best case scenarios, impacts on GP and total sales, different pricing levels were analysed. Subsequent to a set of discussions and informal interviews with key personnel from SM and their bread and pastry supplier, a consensus has been reached and a 10% increase in mark-up was identified as optimal strategy and selected for implementation. The main deciding factor was constituted by the low predicted risks. Given the relatively low price of the products, a 10% increase in mark-ups was estimated to have a very minor impact on the buying patterns of consumers e.g. for the 700gr white bread a 10% increase in mark-up means raising the price from 3lei to 3.25lei.

Nevertheless, it must be mentioned that the carried work relies on a number of assumptions, and its robustness could be further improved. Consequently, a number of important directions are suggested for further research. First of all, in order to have a more comprehensive understanding of Romanian retail market, a research into existing empirical pricing strategies should be carried. This could prove quite challenging because of the reluctance, of major retail companies, to disclose their practices. Secondly, in order to improve the accuracy of forecasts for SM, the impact of price changes across different categories should be analysed. In order to evaluate such elasticities data needs to be collected from various price changes and correlations to potential losses (in sales) should be sought. Thirdly, more case studies (e.g. more shops) should be analysed in order to be able to formulate a framework which can later be generalized and applied to any SME. Finally, a procedure should be devised for reacting to the results that the pricing strategy holds. Pricing is not a linear procedure, rather a cyclical one, the market is always changing and adapting, the feedback received from a certain price change must be analysed and frequent re-evaluations need to be conducted.

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