Evaluating promotional pricing effectiveness using convenience store daily sales data

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Received: 13 August 2022 / Accepted: 7 November 2022 / Published online: 23 November 2022
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Abstract
One of the activities that can grab customers attention and rise sales for convenience stores is promotional pricing strategy. Our study aims to examine the effects of promotional pricing and other factors on sales. Six categories of products with 286 SKUs are explored. Four models are compared, and the results show that autoregressive-distributed lag model provides the lowest mean absolute percentage error (MAPE). This model can also capture the interaction between promotion and non-promotion products. Price elasticity of each product is found to be different, and it results different optimal prices for the maximum profit. Moreover, factors like holidays, the beginning of the month, or weekend, can uplift sales at a specific time. Unlike previous literature, this paper focuses on daily sales and related recent factors such as the number of COVID-19 cases. The methodology presented in this research provides guidelines for retailers to measure their pricing strategy and can be managerial insights for other retailers’ future strategy.

Keywords Promotion effectiveness · Autoregressive-distributed lag model · Demand forecasting · Retail pricing · Price elasticity

Introduction
Nowadays, convenience stores seem to have more impact on our daily lives, especially urban life, because of their availability, number of stores, variety of products, and distribution across the country. According to the Thai Retailers Association, convenience stores have dominated the number of outlets by a retailer with 93.8% share with over 17,000 convenience stores (Tunpaiboon 2021). This is a competitive industry for those retailers, who keep challenging themselves to take market share from each other. Even more, this industry was growing at around 2–3% per year, which is an interesting performance compared to its price value in the modern trade market (Tunpaiboon 2021). Therefore, there are many of issues in the field of convenience stores to concern, such as where the best location for their next store is and what product they should sell, but the most popular one is what they should do with their promotion strategy.

There are many different types of promotions, such as price reduction, coupon, cashback, buy one get one free, or packed for a special price (Khouja et al. 2020). Among those strategies, a price reduction might be the basic and the easiest way to track from a numerical point of view (Wolters and Huchzermeier 2021). However, the promotions always have their price in terms of cost. If you lower your product price as a discount, it will result in a lower profit per piece. Not only does it produce a lower profit per piece, but it also produces a brand-switching effect, known as a cross-brand effect, and an effect on a brand image. This effect of frequent price promotions will set the lower reference price of the product and lower sales in the regular price period as customers tend to wait for the promotion as it comes frequently (Mela et al. 1998). Figure 1 presents an example of daily sales and promotion prices of an SKU in Bird nest category from a leading case-study convenience store chain in Thailand. It can be seen that there is a shift in sales when the price is reduced. However, not all products will be in the same pattern. Launching a promotion must be a thoughtful decision for all the reasons mentioned before because many trade-off issues exist.

Since how, what, and when to do price promotion has been a popular question for a long time, there have been
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many studies in the fields of promotion performance, promotion frequency, duration of the promotion, and promotion effectiveness (Van Heerde et al. 2004; Ailawadi et al. 2007). However, most previous studies were in supermarkets or grocery stores which have different behavior from the convenience stores, especially in Thailand where this industry is blooming, in both retailers and customers. Thus, the behavior of convenience stores is interesting and has the potential for different insights.

Our study aims to examine the effects of promotional pricing on sales of main product categories of a convenience store chain in Thailand, along with the implicated effects such as holiday, beginning of the month, or weekend effects. Besides the own effects of promotion on each product, cross-effects between promotion and non-promotion products during the promotional period are also explored. Six categories of products (Detergent, Bird nest, Essence of chicken, Drinking water, Milk Powder for Baby, Liquid Milk) with 286 SKUs are considered in this study. As the complexity of promotion analysis, autoregressive-distributed lagged model (ADL) is used in the first step to capture the relationship of sales and variables from both lagged parts and explanatory variables (Ma and Fildes 2017). Other less complicated models like top down with market share decomposition and promotional index model are also examined. Our goal is to identify models providing the lowest mean absolute percentage error (MAPE).

After getting the equations presenting relationship between promotion prices and sales, an interesting question like what is the most suitable promotion price for each product for the highest profit. This insight can be useful for business to examine their past strategy and for better strategy in the future. The remainder of the paper is structured as follows. In “Literature review” section, we review the literature and studies that are the foundation of our study. In “Methodology” section, the methodology is explained. “Results” section the empirical results and insights are reported. In “Conclusion” section, we conclude the output of this study, discuss the limitation, and suggest issues for the future work.

Literature review

Promotion effect

MELA et al. (1998) studied the long-term impact of promotions on consumer stockpiling behavior and found that customers tend to buy products more when the price is lower than usual. However, the sales will decrease in the normal price period because they already have stock which is called stockpiling effect. Van Heerde et al. (2002) studied a SCAN*PRO-based evolutionary model building and summarized the generated knowledge about how promotions work, based on this process. Sun et al. (2003) studied the impact of promotions on brand switching and found that more accurate estimates of brand-switching elasticities can be obtained by incorporating forward-looking consumer behavior into structural models. Van Heerde et al. (2004) proposed a system of store-level regression models that decomposed the sales promotion bump into three parts which are cross-brand effects, cross-period effects, and category-expansion effects and found that sales promotion is likely to increase sales in the promotional period but increase in sales does not mean that it is beneficial directly to the retailer because of the stockpiling effect. Ailawadi et al. (2007) studied the differential effect of promotion-induced stockpiling and developed a model for measuring the four sales of promotion-induced stockpiling which are consumption, preemptive switching, loyal acceleration, and repeat purchased.

After all, a promotion strategy can be truly useful and beneficial to the retailer if consideration of those mentioned topics is included. The right model will point those topics

Fig. 1 An example of sales and promotion price of a product in Bird nest category from a case-study convenience store chain in Thailand
out by considering the entire category of product for the brand-switching effect and observing the lagged sales for stockpiling effect. This will result in a well-rounded tool to help retailers plan their thoughtful strategies.

Price elasticity

The responsiveness of the quantity desired or supplied of an item to a change in its price is measured by price elasticity. It is calculated by dividing the percentage change in quantity demanded (or supplied) by the percentage change in price. Elasticity can be classified into three types: elastic (or highly responsive), unitary elastic, and inelastic (no responsive). Elastic demand or supply curves show that the amount wanted or supplied responds to price changes in a higher than proportionate way. A demand or supply curve that is inelastic is one in which a given percentage change in price results in a lesser percentage change in the quantity desired or supplied. A unitary elasticity is one in which a given percentage change in price results in an equal percentage change in quantity demand or supplies (Greenlaw et al. 2018).

Autoregressive-distributed lag model

An autoregressive-distributed lag model is an ordinary least-square (OLS)-based model which forecasts one variable in two parts, the first part is lagged itself called the autoregressive part, and another part is an explanatory variable called distributed part. For these components, the model is able to capture widely effects which we are interested in such as the lagged itself can observe the stockpiling effect, the explanatory can take a role for a special event or a related number of things that affects sales (Sloboda and Sissoko 2020).

Ma and Fildes (2017) summarized that the complexity of the ADL model can lead to three major mathematical problems. First, as there are many variables, the sample size may not be large enough for the OLS requirement that needs a great sample size to validate the OLS. Second, the correlation between variables can be easily found in the high dimension model like in this study, and this will be multicollinearity which resulted in difficulty to distinguish the effect of each variable. Third, the higher the aggregation level, the noisier data would be. Therefore, the cross-SKU and cross-period effect in promotion effect may be too weak to measure, resulting in the incorrect sign which will affect the interpreting process, especially in the application session. They had dealt with these issues by sign-constrained regularization. The sign-constrained regularization uses the L1 regularization called LASSO, which separates into two parts, the first part is the minimization of the sum of square and the second part is the LASSO regression penalty which is responsible for the issues mentioned before. In this study, the optimal LASSO regression penalty ($\lambda$) for each SKU is determined by 20-fold cross-validation. There are two steps of regularization, the first one is own effect followed by cross-effect. After regularizing, it can cope with the high dimensionality as in the model. This method has been popular for decades because of its convexity and the sparsity of its parameter space solutions as demonstrated in the original lasso paper (Tibshirani) and the implemented one (Tibshirani and Taylor 2011).

Thus, we chose the ADL model for many reasons. First, the ADL model offers the advantage of addressing rooms for the effect of price and promotional variables. Second, the elastic modeling technique ensures the model’s parsimony and data congruence which can be adapted depending on user requirement and specification. Third, the ADL model is understandable and explainable due to the straightforward cause–effect model structure (Fader et al. 2005).

Contribution of this research

The most related research is Ma and Fildes (2017), who has captured the promotional impacts on demand via an ADL model. However, there are several differences compared to our study in this paper. Our contributions are as follows: (i) the data considered in this work are daily sales, unlike the weekly sales in previous studies (Ma and Fildes 2017; Gauri et al. 2017). The daily sales have potential in responsiveness which has quicker reaction compared to weekly sales (Martínez-Ruiz et al. 2006). (ii) Festival/holiday dummy variables, the beginning of month, weekend, etc. are added to the models to capture effects from those features. (iii) Recent events like the daily number of COVID-19 cases in Thailand is included in the models to see how it impacts convenient stores sales. (iv) The number of store branches are also added to the models, as we use the total sales data, the increasing of a number of store branches may affect the sales.

Methodology

Source of data

We received organized data from a case-study company which contains nine properties of data including sales date, category, SKU, sales unit, total sales, including the regular sale, promotion sale, promotion price, and regular price. Data were gathered daily from 1 January 2020 to 30 September 2021, 639 days in total. The data were split into two parts, the training set used for model training starting from 1 January 2020 to 31 May 2021 which are 517 days in total (80% of the data), and the testing set used for model
validation starting from 1 June 2021 to 30 September 2021 which are 122 days in total (20% of the data).

There are six product categories with various sales units depending on products such as piece, bottle, box, carton, and pack; however, we only use piece as sales units in this study. The categories of products are as follows: Detergent, Bird nest, Essence of chicken, Drinking water, Milk Powder for Baby, Liquid Milk, 286 SKUs in total. Table 1 summarizes the number of SKUs for each category of the studied products.

Models

The main promotional effects on demand are considered, which are the promotional effect on the demand of focal SKU in the model, the promotional effect on the demand of focal SKU in later periods, and the effect on the demand of other SKUs in the same category in the current period as a high-dimensional autoregressive-distributed lag model. As the data are daily, we propose to add weekend dummy variable \( W_t \) and beginning of the month dummy variable \( B_t \) to the model. In addition, since there was COVID-19 crisis in the past 2 years, the number of COVID-19 cases variable \( Co_t \) is added. The number of branches variable \( Nb_t \) is also included to capture trend effect as time goes by. These factors have not been considered in the previous study.

Autoregressive-distributed lag model (ADL-CROSS model)

We model the demand of SKU \( j \) of category \( k \) on day \( t \) as an autoregressive-distributed lag (ADL) model, which reflects the promotional impacts on demand, using the model demonstrated in previous studies (Huang et al. 2014; Ma et al. 2016) as base model. However, unlike weekly sales considered previously, we focus on daily sales in this paper. Thus, four additional variables [weekend dummy variable \( (W_t) \), beginning of the month dummy variable \( (B_t) \), the number of COVID-19 cases variable \( (Co_t) \), and the number of branches variable \( (Nb_t) \)] are added to the model below.

\[
\begin{align*}
\ln(Y_{kjt}) &= \eta_{kj} + \sum_{l=0}^{1} \phi_{klj} \ln(Y_{kjt-l}) + \alpha_{kj} \ln(Y_{kjt-1}) + \rho_{kj} \ln(\widehat{Y}_{kjt-1}) + \sum_{i=1}^{n} \left( \beta_{kij} X_{kit} + \alpha_{kij} \ln(Y_{kjt-1}) \right) + \sum_{c=1}^{24} \sum_{t=0}^{1} \delta_{kjc} C_{c-t} + \epsilon_{kjt},
\end{align*}
\]

where \( \ln(Y_{kjt}) \) is the log sales of the focal product \( j \) in category \( k \) on day \( t \). \( \eta_{kj} \) is the product \( j \)'s specific constant. \( X_{kjt} = \left[ PR_{kjt}/P_{kj} \right] \) is a promotional explanatory variable of the ratio of the regular price, and the selling price of the product \( i \) in category \( k \) on day \( t \). \( \ln(\widehat{Y}_{kjt}) \) is the log seven days moving average sales of the focal product \( j \) in category \( k \) on day \( t \), for capturing a trend. \( C_{c-t} \) is the dummy variable for the company’s event plan on day \( t-l \). When \( l = 0 \), the dummy variable represents the day of the calendar event, and the day before the event if \( l = 1 \); \( c \) takes the values from 1 to 24 representing all the calendar events including Children’s Day, Chinese New Year, Valentine’s Day, Makha Bucha, Summer season, Chakri, Songkran, Labor Day, Rainy season, Visakha Bucha, Asalha Bucha, Buddhist Lent, The King Birthday, Mother’s Day, Chinese Ghost Festival, Vegetarian Festival, The Late King Memorial Day, The End of Buddhist Lent Day, Chulalongkorn Memorial Day, Winter, Loy Krathong, The Late King Birthday, Constitution Day, and New Year, respectively.

\( W_t \) is the dummy variable of weekend of day \( t \). When it is Saturday or Sunday, \( W_t = 1 \); otherwise, \( W_t = 0 \).

\( B_t \) is the dummy variable of the beginning of the month, starting from the first day to the tenth day of the month, \( B_t = 1 \) when it is the beginning of the month; otherwise, \( B_t = 0 \).

\( Co_t \) is the number of COVID-19 cases in Thailand on day \( t \).

\( Nb_t \) is the number of the case-study’s store branches on day \( t \).

The \( \beta_{kij} \) is equal to 0 or 1, is a coefficient variable of the promotion multiplier, the \( \alpha_{kij} \) is the multiplier for sale lag of product \( j \) in category \( k \), \( \delta_{kjc} \) is the calendar multiplier for event \( c \), \( \sigma_{kj} \) is the weekend multiplier for day \( t \), \( \upsilon_{kj} \) is the beginning of month multiplier for day \( t \). \( \varphi_{kj} \) is the multiplier of the number of COVID-19 cases, \( \omega_{kj} \) is the multiplier of the number of branches on day \( t \), and the disturbance term is represented by \( \epsilon_{kjt} \).

Table 1

| Category            | Number of SKUs |
|---------------------|----------------|
| Essence of chicken  | 13             |
| Detergent           | 109            |
| Drinking water      | 15             |
| Bird nest           | 8              |
| Liquid milk         | 38             |
| Milk powder         | 103            |

ADL-OWN model

The ADL-OWN model (Ali and Yaman 2003; Lang et al. 2015; Williams et al. 2014) represents the model using only the focal SKU’s own predictors without taking cross-SKU promotional effects into account. By ignoring all
promotional information from other SKUs, this is a lower-dimension form of ADL-CROSS shown in (1).

\[
\ln(Y_{kt}) = \eta_j + \sum_{l=0}^{1} \beta_{kj}^l X_{kt-l} + \alpha_j^l \ln(Y_{kt-l}) + \rho_j \ln(\bar{Y}_{kt-l}) + \sum_{c=1}^{24} \sum_{l=0}^{1} \delta_{jkl} C_{t-l} + \sigma_j W_t + \nu_i B_t + \varphi_j C_t + \omega_j Nb_t + \epsilon_{kt-l}.
\]  

(2)

Top down with market share decomposition

Let \( Y_{kt} \) be the aggregate demand of category \( k \) on day \( t \), and \( X_{kt} \) be the weighted average of the price across SKUs in the category. The weight is the daily average sales in the calibration period. Then the demand at category level can also be modeled as an ADL model with calendar event dummy variables (\( C_l \)), weekend dummy variable (\( W_t \)), beginning of the month dummy variable (\( B_t \)), the number of COVID-19 cases variable (\( C_t \)), and the number of branches variable (\( Nb_t \)) included as in the previous models.

\[
\ln(Y_{kt}) = \eta_k + a_k \ln(Y_{kt-l}) + \rho_k \ln(\bar{Y}_{kt-l}) + \sum_{c=1}^{24} \sum_{l=0}^{1} \delta_{kjl} C_{t-l} + \sigma_k W_t + \nu_k B_t + \varphi_k C_t + \omega_k Nb_t + \epsilon_{kt}.
\]  

(3)

Ma and Flides (2017) presented the following equation for decomposing the aggregate category level demand to SKU level demand. Since our data are daily, we model the market share of SKU \( j \) in the category \( k \) with the following market attraction model:

\[
A_{kj} = \exp \left[ \eta_j + a_j \ln(M_{kj,t-1}) + \sum_{l=0}^{1} \beta_j X_{kj,t-l} + \epsilon_{kj} \right],
\]  

(4)

where \( A_{kj} \) is the attraction of SKU \( j \) on day \( t \), and \( M_{kj,t-1} \) is the market share of SKU \( j \) in category \( k \) on day \( t-1 \).

The market share of SKU \( j \) on day \( t \) is equivalent to its attraction relative to the total attractions, which is

\[
M_{kj} = \frac{A_{kj}}{\sum_{j=1}^{n} A_{kj}}.
\]  

(5)

This model had been shown in the literature to be useful for analyzing competitive structures (Cooper 1993). In addition, it can be used to estimate the cross-effects of marketing-mix variables (Fok et al. 2003). To be able to estimate the parameters of model shown in (4), one SKU in the category has to be set as a benchmark, then the natural logarithm of the ratios between the market shares of the reminder SKUs and the benchmark is taken and then yields a \((n_k-1)\)-dimensional system of equations estimated using a seemingly unrelated regression estimator (Zellner 1962).

Promotional index model

Lastly, an SKU level promotional index model is considered. We model the demand of SKU \( j \) in category \( k \) on day \( t \) as an ADL model as ADL-CROSS model, but we use the promotional intensity indexes of the category as the predictors instead of SKU level promotional variables. Therefore, the dimension of the explanatory variable is reduced. The model is described as follows:

\[
\ln(Y_{kt}) = \eta_j + a_j \ln(Y_{kt-l}) + \sum_{l=0}^{1} \beta_{j}^l X_{kt-l} + \rho_j \ln(\bar{Y}_{kt-l}) + \sum_{c=1}^{24} \sum_{l=0}^{1} \delta_{jkl} C_{t-l} + \sigma_j W_t + \nu_j B_t + \varphi_j C_t + \omega_j Nb_t + \epsilon_{kt}.
\]  

(6)

Weighted averaging of the price across SKUs in a category is used to calculate all promotional intensity indexes. The weight represents the SKU’s daily average sales. That is, the larger an SKU’s market share in a category is, the more weight it has in determining promotional intensities.

Models evaluation and comparison

To compare the forecasting performance of the candidate demand models, mean absolute error (MAE), MAPE, and mean percentage error (MPE) are measured. MAE is a well-known and widely used scale-dependent error measure that is simple to calculate, understand, and apply. MAPE is the most widely used measure for checking forecast accuracy. It comes under percentage errors which are scale independent and can be used for comparing series on different scales. MPE is used to measure forecasting error bias, which is potentially relevant in stocking decisions and is defined here as the arithmetic means of the total error to total sales per SKU ratio.

Results

Model comparison

As explained in “Source of data” section, the data were split into two parts: the training set (80%) and the testing set (20%). After all four models are estimated in the training set, the error measurement in the testing set is captured.
Table 2 presents a summary of MAE, MAPE, and MPE for each product category from all models.

The results show that the ADL-CROSS model has the best performance, according to the least measurement error value: MAE and MAPE, compared to all other alternative models including ADL-OWN model, TOP-DOWN model, and Promotional index model. According to the MAPE, the results also show that all models are negatively biased except the TOP-DOWN model. Even though there are not many error differences among models, the ADL-CROSS model still has an advantage since it has the highest resolution of the variables, an SKU level. With this scale of resolution, we can observe the interaction between each SKU. Thus, the ADL-CROSS model will be focused on for the remaining part of this paper. Figure 2 illustrates the MAE of each SKU in each category as Violin plot. Drinking water category has the lowest MAPE maybe due to the characteristics of the category that have low price elasticity and are low in price in general, which means variables do not affect the sales in this category very much. Therefore, the sales can be accurately predicted by the past sales. On the other hand, Detergent category, which has the highest MAPE, is higher in price and is more sensitive to many variables such as promotions and beginning of the month and also has more SKUs. These can be the causes of higher errors. Figure 3 illustrates an example of predicted sales versus actual sales of an SKU in the Drinking water category for the testing periods.
Price elasticity from the model

Since doing promotion is a trade-off activity, the question is how well it performs; price elasticity can measure that. Price elasticity takes an important role when it comes to promotion effectiveness studies because it can tell the percentage of rising sales for each percent the price is reduced.

After fitting the data for every SKU in the ADL-CROSS model, all independent variables' coefficients are estimated. The first focused parameter is price elasticity which can be gained from the negative price discount coefficient divided by its average price (Ma and Fildes 2017). Figure 4 illustrates each SKU's own and cross-price elasticities. The colors show the direction and magnitude of price elasticity. The blue represents positive value, while the red represents negative value. The magnitude of price elasticity can be told by the weight of the color, light or dark, together with the area. The darker color and wider means the bigger magnitude. There are rows and columns of SKU in the figure. To find the own-price elasticity of the SKU is to match the targeted SKU in both rows and columns which is diagonal in the figure. From Fig. 4, the SKU with the highest negative own-price elasticity is SKU19. For cross-price elasticity, the row SKU is on price promotion while the column SKU is non-promotion, for example, when SKU33 does a price promotion, it affects the sales of non-promotion SKU19 to be decreased 0.13% from every 1% of price reduction of SKU5. However, most cross-price effects have small to insignificant value compared to the absolute own-price elasticity, which means price reduction in each SKU does not or insignificantly decreases other SKU sales. Therefore, as retailers, they can consider a promotion for each SKU that has an insignificant CROSS-price effect without concern effect on other SKUs. Price elasticity of other categories is illustrated in Figs. 4, 5, 6, and 7.

Figure 8 summarizes the own-price elasticity of every category including minimum value, maximum value, and average value. Most own-price elasticity has negative values which means the lower price is, the higher the sales are. The liquid milk category has the widest range with one SKU having a significant negative value of own-price elasticity (−0.46). This implies that price reduction can much increase sales. However, other SKUs in the Liquid milk category have price elasticity to be close to 0. Another observation is that only few SKUs in all product categories appear to have price elasticities less than −0.1. Thus, most SKUs’ sales cannot be lifted up that much compared to the price reduction offered. This presentation helps managers or promotion planners to get an overview of the own- and cross-price elasticities of each category.

Fig. 4 The own-price elastics and cross-price elastics of Liquid milk category

Fig. 8 The own-price elasticities of each category
Holiday and festival effects

Since the ADL-CROSS model outperforms other models and has the advantage ability mentioned before, we will further explore insights from this model. Besides the price elasticity, there are holiday and festival effects as well. These effects can tell how the sales uplift during the festival or holiday period by looking at the coefficient of each dummy variable. The more coefficient value, the more sales uplift.

Since the predicted variable is modeled as a log function, it can be interpreted for every coefficient value, it will be \( e^{\text{coefficient value}} \) times of sales, while \( e \) is Euler’s number (2.71828, briefly). For example, if the New Year’s dummy variable of SKU X has its coefficient equal to 0.5 when the New Year comes, sales will be lifted by \( e^{0.5} \) times which is equal to 1.648 times compared to sales on other normal days. If the coefficient is negative, it means sales decrease during that festive or holiday.

Table 3 shows the main holidays and festivals from the case-study convenience store. For Bird nest category, the coefficient of Mother’s day has the highest value which is 0.7340, meaning the sales increase approximately \( e^{0.734} \) or 2 times compared to other days. In addition, for this bird nest category, New Year, King Bhumibol’s Birthday (known as Father’s Day), Makha Bucha Day (Buddhist’s day), and Chinese New Year (Lunar New year) show a high positive impact. This is because this group of products is recognized for being good for health, especially for the elder who need extraordinary nutrients; so, they are common gifts for these holidays. This effect is similar to the essence of chicken but lighter. Moreover, the Winter (1 Nov) coefficient has the highest value for overall categories. Not only the high value of the coefficient can tell the insight, the low one can too. For the drinking water category, all the coefficient in the holiday and festival effects is low, this can tell that necessary products like drinking water have no or little relationship with holiday or festival. Thus, the retailers can plan their promotion strategy independently from the holiday or festival. On average, the effect of holidays and festivals can uplift sales by approximately 25% compared to other normal days.

Fig. 5 The own-price elastics and cross-price elastics of Bird nest category

Fig. 6 The own-price elastics and cross-price elastics of Drinking water category

Fig. 7 The own-price elastics and cross-price elastics of Essence of chicken category
As we had extended the ADL-CROSS model (Ma and Fildes 2017) by adding more variables to explain daily sales, it is interesting to explore how these factors affect sales. The interpretation of the coefficient is the same as the holidays and festivals effect which the sales will be lifted by $e^{\text{coefficient value}}$. Insights are explained below.

### Early of the month dummy variable

Detergent category has the highest impact from the early of the month factor as its coefficient value is higher than other product categories. A reason is that at the beginning of the month, middle-income customers, which seems to be the target group of this case-study company, just got their salaries, then they spend on the necessary products like detergent.

### Weekend dummy variable

All product categories considered in this paper are positively affected by the weekend dummy variable. This is intuitive since the majority of customers go shopping during weekends. However, it can be observed that detergent and bird nest categories have been significantly impacted compared to other product groups.

### COVID-19 cases

Surprisingly, the COVID-19 cases variable has insignificant effects on all focused product categories. A reason may be that these groups of products are every-day used.
so they might be not directly related to the COVID-19 situation like a surgical mask, alcohol spray, or medicine (Table 4).

**Number of stores**

Even though our data come from every store, sales do not seem to increase much when the number of stores increases. This result shows an insignificant value of the coefficient of the number of stores for the overall category. This could be an issue that the case-study company has to work on in the future.

**Numerical experiments for recommended promotion prices**

In this section, the ADL-CROSS model is used to capture sales behavior through focused variables. The equations from the model are applied to compute profit for each option of price to the most profitable price for the highest profit. The profit equation basically comes from the difference between price and cost per unit, times the sales quantity which is a function of price obtained from the ADL-CROSS model. From our discussion with the case-study company, the average cost is assumed to be 60% of the regular price for each product. The profit function is presented below:

\[
\text{Profit}(\text{price}) = (\text{price} - \text{Cost}) \times \text{Sales}(\text{price}).
\]

Table 5 shows profit results from different levels of promotion prices from three example SKUs, representing high, medium, and insignificant price elasticity, respectively. The bold letter represents the price option providing the highest total profit. Figure 9 illustrates price and profit relationships in more clear pictures. The results show that for the SKU with high price elasticity, the optimal promotion price (in percentage reduction) is lower than the medium and insignificant price elasticity items. Especially, for the insignificant elasticity, the offer promotion price is considered to be a disadvantage to the store. Thus, classifying products according to price elasticity is useful so that the store can choose effective products for price promotion.

From Table 5, the highlight in the price row means the current promotion price often used by the case-study convenience store, while the highlight in the profit row means the highest profit, which is gotten from the ADL-CROSS model and the profit equation. If the highlight in price and the highlight in profit are matched, the retailer currently chooses the proper promotion price yielding the most profit. It also means that price promotion does its best performance in terms of uplift sales which can beat its lower profit per

| Table 4 | The coefficient of additional variables for each product category |
|---------|---------------------------------------------------------------|
| Coefficient | Detergent | Drinking water | Milk powder | Essence of Chicken | Bird Nest | Liquid Milk |
| Early.month | 0.1896 | -0.0020 | 0.0026 | 0.0407 | 0.0202 | 0.0347 |
| Weekend | 0.1577 | 0.0425 | 0.0405 | 0.0781 | **0.1609** | 0.0174 |
| Covid.case | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Number.of.stores | -0.0001 | 0.0003 | 0.0003 | 0.0008 | 0.0016 | 0.0002 |

The bold numbers in the table represents the method providing the lowest average error measurements

| Table 5 | Profit results from different choices of prices from three example SKU |
|---------|---------------------------------------------------------------|
| SKU5 of liquid milk (insignificant price elasticity) |
| Price | 12 | 11.5 | 11 | 10.5 | 10 | 9.5 | 9 | 8.5 | 8 | 7.5 |
| Profit | 1542.68 | 1381.98 | 1221.29 | 1060.59 | 899.89 | 739.20 | 578.50 | 417.81 | 257.11 | 96.42 |
| SKU11 of liquid milk (medium price elasticity (−0.25)) |
| Price | 15 | 14.5 | 14 | 13.5 | 13 | 12.5 | **12** |
| Profit | 1876.70 | 1949.17 | 2025.69 | 2104.94 | 2184.29 | 2259.02 | 2320.74 |
| SKU19 of liquid milk (high price elasticity (−0.46)) |
| Price | 10 | 9.5 | 9 | 8.5 | 8 | 7.5 | **7** | **6.5** |
| Profit | 790.85 | 880.58 | 986.53 | 1108.93 | 1242.26 | 1364.54 | **1406.97** | 1163.54 |

The bold numbers in the table represents the method providing the lowest average error measurements.
piece and result in overall higher profit. On the other hand, if the highlights are not matched, they can be interpreted in two different ways. The first one is the highlighted price is higher than the highlighted profit, this means that the retailer still has the capability to lower their promotion price to meet the highest profit. The second one is the highlighted price is lower than the highlighted profit, this means that the retailer gets a disadvantage from their price promotion in terms of optimal profit. By the way, profit in sales is not the only measurement of promotion effectiveness because there are still many reasons behind doing promotion, for example, clearing stock, developing awareness of the new product, or boosting traffic in their store. Therefore, being not at the highest profit with promotion price still need to look at other dimensions to ensure that there is a benefit to the retailer when doing promotion. However, our study mainly focuses on profitability which is easy to measure and understand in a promotion effectiveness study.

**Conclusion**

In this research, the ADL-CROSS model, ADL-OWN model, TOP-DOWN model, and Promotional index model are explored to capture the relationship between sales quantity and price, as well as other factors. The results showed ADL model (ADL-CROSS model) provides the lowest MAPE. This model could also capture the interaction between promotion and non-promotion products. The coefficients of variables in the model gave us perspective and empirical results for all of the dimensions we had addressed earlier. Because of a wide range of coefficients, we chose to focus on price elasticity which could give a straightforward insight into promotion effectiveness. While own-price elasticities were significant, most cross-price elasticity had small values meaning there was insignificant effects between those promotional and non-promotional products which is easier for the retailer to plan their strategy in the future. After that, we had linked the model with the profit estimated equation to get more insights. The profit equation could reflect those previous promotions in terms of optimal profit. This could tell whether the previous promotion was at its best or not, and there was a possibility to get their profit higher or they are not the right tasks. Besides the complexity of the model, using the ADL-CROSS model together with the profit equation could help the retailer look back at their promotion effectiveness and plan their future promotion strategy.

There are many possibilities for future research. For example, since there is a COVID-19 cases independent variable in this model, it is useful in the pandemic situation because the customer has changed their behavior from shopping at the market, supermarket, or grocery to the convenience store which is less crowded and less risk in pandemic point of view. It is interesting to continuously measure this effect when the number of cases reduces in

![Fig. 9 The relationship between profit and price in line charts](image-url)
the future. Another possible extension is considering more product categories for further insights. Also, since the data obtained for this work are limited, extending data to capture more than 2 years of daily sales can clearer identify holidays and festivals effect. Overall, this paper provided a guideline for convenience stores for their promotional pricing effectiveness evaluation and can help select the most effective products for their future promotions.

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Publisher’s Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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