**Forecasting retailer product sales in the presence of structural change**

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Abstract

Grocery retailers need accurate sales forecasts at Stock Keeping Unit (SKU) level to effectively manage their inventory. Previous studies have proposed forecasting methods which incorporate the effect of various marketing activities including prices and promotions. However, their methods have overlooked that the effects of the marketing activities on product sales may change over time. Therefore, these methods may potentially be subject to the structural change problem and generate biased and less accurate forecasts. In this study, we propose more effective methods to forecast retailer product sales which take into account the problem of structural change. Our methods outperform conventional forecasting models based on the data from a well-known US retailer.

Keywords:

Analytics, Forecasting, OR in marketing, Retailing

1. **Introduction**

Grocery retailers rely on accurate sales forecasts to coordinate their supply chains (Syntetos, Babai, Boylan, Kolassa, & Nikolopoulos, 2016). Inaccurate forecasts of product sales lead to out-of-stock conditions or inflated costs due to overstocking. When a specific item is out-of-stock, retailers directly lose the profit from the missed sale of the item. If out of stocks situations happen on a regular basis, it can further lead to consumer dissatisfaction which, in the long term, can lead customers permanently switching to other retail chains (Corsten & Gruen, 2003). To avoid such situations, retailers may intentionally overstock to maintain a high customer satisfaction level. However, this significantly raises inventory costs (e.g., capital cost, warehousing, and deterioration, etc.) and reduces profits (Cooper, Baron, Levy, Swisher, & Gogos, 1999). In 2014, retailers in North America had a loss of $634.1 billion due to out-of-stock and spent $471.9 billion on overstocking (OrderDynamics, 2015). One of the solutions to mitigate this dilemma is to generate more accurate sales forecasts at Stock Keeping Unit (SKU) level which improves the effectiveness of the supply chain management by reducing the bullwhip effect and enabling the Just-In-Time delivery (Ouyang, 2007; Sodhi & Tang, 2011).

Some recent studies have proposed effective methods to forecast retailer product sales at SKU level. For example, Gür Ali, SayIn, van Woensel, and Fransoo (2009) proposed the regression tree method with a range of variables constructed from sales, price, and promotion of the focal product. Huang, Fildes, and Soopramanien (2014) proposed two-stage general-to-specific Autoregressive Distributed Lag (ADL) methods. Their methods incorporate the promotional information not only of the focal product but also of competing products within the same product category. Ma, Fildes, and Huang (2016) further proposed three-stage forecasting methods which integrate the promotional information of the products across related product categories. The various methods in the literature have been explicitly surveyed by Fildes, Ma, and Kolassa (2018).

These studies assume that the impact of marketing activities such as the price and promotions on product sales remains constant over time. However, in practice, the effect of prices and promotions may change because of many external uncontrollable factors. For example, customers may become more sensitive to prices and promotions during an economic crunch period (Wildt, 1976; Wildt & Winer, 1983). Customers may change their tastes due to a change in familiarity with the product, a change in lifestyles, and aechange in social status (Meeran, Jahanbin, Goodwin, & Quariguasi Frota Neto, 2017). When a new competitor enters the market, the effect of prices and promotions of the focal product may decrease not only because of the marketing activities launched by the new competitor but also because customers seek variety. In 2014, the German discounter retail chain Aldi opened more than 400 stores in the United States, leading to changes in customer grocery purchasing habits which exerted severe competitive pressure on other retail chains (Loeb, 2014).

Under any of these circumstances described above, these forecasting models assume constant effects of the price and promotions but may potentially be subject to the problem of structural changes (Allen & Fildes, 2001). As a result, the forecasts generated by these models might be biased and less accurate. The structural change problem has been addressed by previous studies (see a summary in Clements & Hendry, 1999) but overlooked in the domain of forecasting retailer product sales. In this study, we propose novel methods to forecast retailer product sales by taking into account the problem of structural change. Specifically, we examine the forecasting performance of the Autoregressive Distributed Lag (ADL) models with the Estimation Window Combining (EWC) method and the ADL model with the Intercept Correction (IC) method. The former combines different sets of forecasts generated by the same ADL model but with different estimation windows. The latter makes corrections to the final forecasts based on the estimate of the forecast bias.

Our research falls into the domain of retail forecasting and makes the following contributions. First, our research is, as far as we are aware, the first to investigate the problem of structural change in the area of forecasting retailer product sales. The empirical results based on the data suggest that our methods have superior forecasting performance compared to conventional models which do not account for the problem of structural change. Second, our methods focus on effectively utilizing available promotional information and thus do not incur the costs of collecting additional data (also, in reality, collecting additional data may not even be possible). Third, our research provides an evaluation of various forecasting methods. The results offers operational guidance to not only retailers but also to manufacturers when competitive promotional information becomes unavailable. Fourth, our methods are fully automatic (e.g., the specification of the model for each product does not rely on human intervention but algorithms) and are easy to implement, which meets the requirement by retailers who nowadays sell tens of thousands of products. Finally, we shed light upon the characteristics of the products for which our proposed methods have even more superior forecasting performance compared to the conventional model which overlook the problem of structural change.

The remainder of the paper is organized as follows. Section 2 initially summarizes previous studies which forecast retailer product sales at SKU level and then discusses the findings of previous studies which justifies why the effect of marketing activities, including price and promotions, may change over time. Section 3 describes the structural change problem and the methods which can be applied to mitigate the problem. Section 4 explores the data that we use for empirical analysis. In section 5, we introduce our proposed three-stage forecasting methods. Section 6 describes the design of the model evaluation. Section 7 summarizes and discusses the evaluation results to compare the methods’ performances. In Section 8, we highlight the characteristics of the product for which our proposed methods garner the greatest improvements compared to conventional models which overlook the problem of structural change. In the last section, we provide recommendations for both manufacturers and retailers, address research limitations, and highlight directions for future research.

## Literature review

2.1 Forecasting retailer product sales at SKU level

In practice, retailers may forecast their product sales at SKU level using a two-stage ‘Base-lift’ method (Cooper et al., 1999; Fildes, Ma, et al., 2018). The method entails dividing the data into promoted and non-promoted periods based on whether the focal SKU is being promoted. Specifically, they may use simple univariate methods to generate the ‘baseline’ forecasts for the non-promoted period and then make adjustments for the ‘lift’ effect of any incoming promotional events. The adjustment could be estimated relying on the experience of brand/category managers or based on the lift effect by the previous promotional event (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009; Fildes, Nikolopoulos, Crone, & Syntetos, 2008). A stream of research studies has been devoted to helping retail managers effectively tackle their own cognitive biases when they make the adjustment typically reflecting their understanding of the market conditions (Fildes, Goodwin, & Önkal, 2018; Petropoulos, Fildes, & Goodwin, 2016). Also, Lee, Goodwin, Fildes, Nikolopoulos, and Lawrence (2007) used an experiment to suggest that a forecasting support system (FSS) could help users recall and understand more appropriately the similarity between past analogous events and thus make more effective judgments. Some other studies also divide the data into promoted and non-promoted periods but estimate the ‘lift’ effect with model-based forecasting approaches. For example, the PromoCast™ system relates the ‘lift’ effect to various driving factors including previous promotions of the focal product, the characteristics of product categories and stores, and manufacturer information etc. (Cooper et al., 1999; Cooper & Giuffrida, 2000; Trusov, Bodapati, & Cooper, 2006). Aburto and Weber (2007) used Neural Network models to estimate the ‘lift’ effect for the product sales for a Chilean supermarket though their evaluation is only based on very limited numbers of products. A limitation for all these methods is that, as they split the data into two periods, they tend to overlook the information in the promoted period when forecasting the product sales in the non-promoted period, and vice versa.

Some other studies have proposed holistic methods which directly generate the final forecasts. Kuo (2001) used Fuzzy Neural Network models to forecast product sales of daily milk in convenience stores. However, their models have been evaluated based on a very limited number of products. Gür Ali et al. (2009) proposed the regression tree method and the support vector regression (SVR) method to forecast retailer product sales for the non-perishable food categories at SKU level. Their methods incorporate variables constructed based on statistical measures of past information (e.g., the sales, prices, and promotions) of the focal product and have overall superior forecasting performance. Their methods do not perform better than the Base-lift method for the time period when the focal product is not being promoted. One of the limitations for their methods is that they overlook the effect of competitive promotions on the sales of the focal product. Divakar, Ratchford, and Shankar (2005) proposed the CHAN4CAST method to forecast product volume sales for beverage manufacturers. Their method incorporates the promotional information for a small number of known competitors of the focal product (e.g., the main competitors, Coca *versus* Pepsi). Their method, however, is not applicable to retailers where there are hundreds of competitive products. Huang et al. (2014) proposed two-stage Autoregressive Distributed Lag (ADL) methods to forecast retailer product sales at SKU level, which is the first to account for the competitive promotional information for the whole product category where there is a large number of competitive products. They initially implemented a variable selection procedure to identify the most important variables for the competitive activities within the product category. Then they specified the ADL models following a general-to-specific modeling strategy based on these selected variables. Their methods have superior forecasting performance for five grocery categories such as *Bottled Juice*, *Soft Drinks*, and *Bath Soap,* etc. However, their methods specify the models relying on the intervention by human expertise and thus do not directly meet the need for automatic modeling which is essential by today’s retailers. Ma et al. (2016) proposed three-stage ADL methods which further integrate the promotional information not only from the same product category but also from other related product categories. Their methods are extensions of those in Huang et al. (2014) and also benefit from an automatic model specification procedure. Their methods outperform the Base-lift benchmark model for 15 food product categories. These studies suggest that promotional information are valuable in forecasting retailer product sales, and evidence shows that modern commercial software has also started to integrate promotional information (Fildes, Ma, et al., 2018). However, all the studies described here assume the constant effects of the marketing activities.

2.2 The changing effect of marketing activities

Previous studies suggest that the effect of marketing activities can change over time. Wildt (1976) and Wildt and Winer (1983) find that the effect of the marketing activities may change due to the change in economic conditions, consumer tastes, and the competition environment, etc. Customers may find price reductions and promotions more attractive during an economic crunch compared to other time periods. Mahajan, Bretschneider, and Bradford (1980) found that the effect of prices and promotions changes during different stages of the product lifecycle. Meeran et al. (2017) find that customers have different tastes and preferences when they accumulate more knowledge of the product, when they seek variety, and when they reach a different social status and then decide to adopt a different lifestyle. The change in the behavior of individual customers may eventually lead to substantial change in the aggregate effect by the marketing activities on product sales. Pauwels and Srinivasan (2004) find that the introduction of store-own brands in a product category reduces the price elasticities of premium national brands and increase price elasticities of the second-tier national brands. The effect of the marketing activities can also change depending on how retailers communicate their marketing events. For example, retailers may promote the products through mobile applications and adopt new prominent promotion shelf tags, which can make the promotions more effective (van Heerde, M. Dinner, & Neslin, 2015). The effect of the marketing activities can also change due the change in the content of the promotional event. For example, retailers tend to record promotional events as feature and display (e.g., Bronnenberg, Kruger, & Mela, 2008). However, the content of the events may change across various types such as Buy One Get One free (BOGO), store flyers, billboard advertising, and temporary price reduction (TPR), or TPR for shopper-card holders only, etc.

## The problem of structural change

The problem of structural change has been addressed by previous studies in the forecasting literature[[2]](#footnote-2) (e.g., Castle, Doornik, & Hendry, 2008; Hendry, 2018; Pesaran & Timmermann, 2007). Pesaran and Timmermann (2007) demonstrated analytically how a structural change could lead to forecast bias using a simple regression model without an intercept. For example, suppose that for the time period of , the unobserved data generating process (DGP) is:

(1)

where, and are respectively the vectors of the dependent variable at week *t*+1 and independent variable at week *t*. is the vector of the error term at week *t*+1. (where *i*=1,2) are the vectors of the parameter coefficients. is an indicator which equals to 1 before week (where ) and 0 afterwards. Therefore, the DGP has a structural change where the true parameter of the independent variable changes from to after . We can estimate a model with a functional form congruent with the DGP (e.g., ) based on the data before and after the structural change, e.g., ,. Thus, the OLS estimate of the parameter is:

(2)

where is the vectors of the dependent variable for the time period from week *m* to week *T*, and is the vector of the independent variable for the time period from week *m* to week *T*. We assume that there is no structural change after week *T*. e.g., . Thus, the one-step ahead forecast error is:

(3)

where is the vector of the independent variable for the time period from week *m* to . is the vector of error term for the time period from week *m* to *T*. is the error term at week . The conditional mean of equation (3) is:

(4)

Equation (4) is unequal to zero as is unequal to , which indicates that the forecast at week is biased. The forecast bias may subsequently lead to lower forecast frequency (Clements & Hendry, 1999). Previous studies also demonstrated the bias for more general cases (e.g., models with an intercept term and endogenous explanatory variables) using Monte Carlo simulation (see Clements & Hendry, 1999; Pesaran & Timmermann, 2005, 2007)[[3]](#footnote-3).

In this study, we implement two methods to mitigate the problem of structural change. The first method is the Intercept Correction (IC) which specifies non-zero values for the model’s errors in the forecast period given that the model is subject to structural change (Clark & McCracken, 2007; Clements & Hendry, 1994, 1999). If the model is subject to structural changes, we can estimate the forecast bias, e.g., by taking the average value of the most recent residuals, e.g., , where is the number of residuals. When , the bias will be estimated to be the residual at the forecast origin, i.e., , (e.g., Chevillon, 2016). We then add the estimated bias back to the out-of-sample forecasts. The final forecasts would be less biased and may potentially be more accurate. However, the IC method comes with limitations. For example, by adding the estimated bias back to the out-of-sample forecasts, we inevitably incur the cost of inflated forecast error variance (see the analytical evidence in Clements & Hendry, 1999). Also, in practice, product sales at SKU level often exhibit large variations and unexpected outliers caused by marketing activities, which renders the task of estimating the forecast bias challenging. The bias could be submerged by high variations in the product sales. Under this circumstance, it is possible that the average value of the most recent residuals may predominatly represent random variations rather than the bias caused by the structural change. The second method is the Estimation Window Combining (EWC) which combines the forecasts generated by the same model but with different estimation windows (e.g., Pesaran & Pick, 2011; Pesaran, Schuermann, & Smith, 2009; Pesaran & Timmermann, 2005). The forecasts can be combined based on equal weights, which has been found effective and easy to implement (Clements & Hendry, 1998; Dekker, van Donselaar, & Ouwehand, 2004; Fildes & Stekler, 2002; Pesaran et al., 2009). For the example demonstrated in equation (1), we may estimate the model using the most recent observations to generate the first set of forecasts, e.g., , where represents the parameter estimated based on the observation window . The value of can be arbitrarily chosen provided that there are enough observations to estimate the model and enough variations in the explanatory variable. We may then add more observations (e.g., one) to the estimation window and generate the second set of forecasts, e.g., , and so forth, until we generate the set of forecasts based on the estimation window . Thus, we may obtain the final forecast by equally combining all the sets of forecasts:

(5)

Pesaran and Timmermann (2007) show that, for the example in equation (1), the forecasts generated by the models with smaller estimation windows tend to be less biased (e.g., the models will utilize fewer observations before the structural change). However, these forecasts may bear a cost of inflated forecast error variance. This is because the models with smaller estimation windows tend to ignore some of the data before the structural change (which may potentially be more informative compared to the data after the structural change). The EWC method thus tries to generate more accurate forecasts by taking a trade-off between the reduced forecast bias and the potentially inflated forecast error variance. Compared to the IC method, the EWC method does not estimate the size of the bias.

The two methods described above have been found effective in previous studies. For example, the IC method has been applied to forecast wage, unemployment, and CPI inflation, etc. (e.g., Clark & McCracken, 2007; Clements & Hendry, 1996), and the EWC method has superior forecasting performance for exchange rate, inflation, and equity index futures etc. (e.g., Pesaran & Pick, 2011; Pesaran et al., 2009; Rapach & Strauss, 2008). However, in the case of retailer product sales, whether we account for structural change and which of the two methods (i.e., the IC method, and/or the EWC method) would generate more accurate forecasts remain empirical questions.

## The data

In this study, we use the retail dataset which is publicly available from the Information Resources, Inc. (IRI) company. A more comprehensive description of the dataset can be found in Bronnenberg et al. (2008). The dataset contains weekly data at SKU level with variables including product unit sales, price, features, and displays, etc. We initially evaluate the forecasting performance of various models based on 1831 SKU’s for 28 product categories from 28 different stores. We select the SKU’s for the same category from the same store, and we select the SKU’s with positive movements for at least 90% of the time. Table 1 shows basic statistical measures for the selected SKU’s during a period of 202 weeks for each product category, which suggests a wide variety in the marketing activities across different product categories. Figure 1 shows the data series for a typical SKU in the Beer category. e.g., the product sales spikes are usually associated with the price reductions, feature, or display of the focal product, as well as calendar events (e.g., Halloween, Thanksgiving, and Christmas, etc.).

Table 1. Statistical descriptions for each product category

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Category | Price mean | Sales mean\* | Display percentage\*\* | Feature percentage\*\*\* | Number of SKU's |
| Beer | 8.3 | 20.6 | 13.9% | 4.0% | 169 |
| Blades | 8.1 | 14.6 | 7.4% | 2.2% | 22 |
| Carbonated Beverages | 2.1 | 113.6 | 26.8% | 15.6% | 82 |
| Cigarette | 22.3 | 22.2 | 0.0% | 0.8% | 203 |
| Coffee | 5.2 | 14.5 | 5.2% | 2.9% | 86 |
| Cold cereal | 3.5 | 70.7 | 4.0% | 18.1% | 125 |
| Deodorant | 2.7 | 6.9 | 4.1% | 5.2% | 126 |
| Face Tissue | 2.1 | 75.8 | 0.3% | 11.7% | 6 |
| Frozen Dinner | 2 | 43.8 | 5.3% | 23.7% | 87 |
| Frozen pizza | 3.4 | 31.2 | 8.9% | 9.1% | 147 |
| Household Cleaner | 2.5 | 29.9 | 0.3% | 3.6% | 18 |
| Hotdog | 4 | 68.6 | 13.2% | 15.6% | 35 |
| Laundry Detergent | 8.8 | 28.9 | 2.3% | 8.8% | 57 |
| Margarine/Butter | 2 | 71.4 | 0.1% | 6.3% | 36 |
| Mayonnaise | 3 | 79.7 | 3.0% | 0.4% | 22 |
| Milk | 2.5 | 222.3 | 2.1% | 1.8% | 30 |
| Mustard & Ketchup | 2.1 | 64.5 | 5.3% | 0.9% | 22 |
| Peanut butter | 3.7 | 34.2 | 3.2% | 0.6% | 15 |
| Photo | 7.2 | 9.2 | 4.6% | 5.1% | 13 |
| Salty snacks | 2.3 | 50.9 | 6.7% | 5.0% | 101 |
| Shampoo | 3.5 | 9.9 | 12.8% | 7.1% | 70 |
| Soup | 1.5 | 61.6 | 1.2% | 9.7% | 139 |
| Spaghetti sauce | 2.4 | 39.1 | 1.6% | 6.5% | 52 |
| Sugar substitutes | 2.8 | 14.5 | 0.1% | 1.4% | 20 |
| Toilet Tissue | 5.4 | 89.1 | 4.3% | 8.3% | 20 |
| Toothbrush | 2.6 | 8.7 | 3.1% | 6.3% | 28 |
| Toothpaste | 2.8 | 35.5 | 11.0% | 12.5% | 25 |
| Yogurt | 1.1 | 115.1 | 0.7% | 6.3% | 75 |

\* Sales mean represents the average unit sales for all the SKU’s for the category for the specific store.

\*\* \*\*\*Display percentage and feature percentage indicate the percentage of weeks during the 202-week time period when the focal product is being promoted for display and feature respectively.

Figure 1. Store level data for an SKU in the Beer category



In Figure 1, week 1 indicates the first week in the year of 2001. The Calendar events include Halloween, Thanksgiving, Christmas, New Year’s Day, President’s Day, Easter, Memorial Day, the 4th of July, and Labour Day. The Promotional events include feature and display.

## Methodology

We propose two novel methods to forecast retailer product sales at SKU level by taking into account the problem of structural change. Both methods consist of three stages. During the first stage, we identify the most relevant competitive explanatory variables for the focal product within the product category. In practice, grocery retailers typically sell hundreds of SKU’s in a product category. This leads to hundreds of potential competitive explanatory variables (e.g., competitive price and competitive promotions) for the focal product. Incorporating all the variables into the model can easily overfit the model and render the estimation task infeasible (Martin & Kolassa, 2009). Therefore, we select the most relevant competitive explanatory variables using the Least Absolute Shrinkage and Selection Operator (LASSO) procedure (Tibshirani, 1996). That is, we construct the following model for each SKU:

(6)

where represents log sales of the focal product for a store at week *t.* is the matrix for the explanatory variables including prices, features, and displays of all the products in the same product category. *u* represents the error term. represents the vector of the parameter coefficients. *N* is the total number of SKUs for the category. is the shrinkage factor. The LASSO procedure thus imposes a constraint to the sum of the absolute values of the models’ parameter coefficients. It removes the less relevant explanatory variables by pushing their parameter coefficients towards zero. We control the model simplification process using the shrinkage factor based on a 10-fold cross validation (Ma & Fildes, 2017; Ma et al., 2016)[[4]](#footnote-4).

During the second stage, we construct the General Autoregressive Distributive Lag (ADL) model following Huang et al. (2014) based on the variables retained by the LASSO procedure during the first stage. The LASSO procedure has a limitation in that it may potentially miss important variables especially under the condition of high multicollinearity (Fan & Lv, 2008; Ma et al., 2016). Previous studies suggest that product sales are usually mostly influenced by the prices and promotions of the products themselves (Bucklin, Gupta, & Siddarth, 1998). Thus, we intentionally incorporate the prices and promotion variables of the focal product in the general ADL model even if these variables were not retained by the LASSO procedure during the first stage. We also incorporate the dynamic effects of these explanatory variables as well as a time variable to capture the potential trend, four trigonometric variables to capture the seasonal effect, and other dummy variables to capture the calendar effect. The constructed general ADL model for each product in a specific store can be demonstrated as follows:

where is the log sales of the focal product at week . We include the time as a variable to capture any potential trend during the estimation period (Song & Witt, 2003). and respectively represent the log price of the focal product and the log price of a competitive product, *m*, at week . and represents the feature and the display dummy variables for the focal product at week . The first two trigonometric variables, e.g., and captures the month of the year effect, and the other two trigonometric variables, e.g., , and captures the week of the month effect (A. Harvey, 2006)[[5]](#footnote-5). is the dummy variable for the calendar event at week . The dummy variable represents the week of the calendar event if , and the week before the event if . takes the values from 1 to 9 representing all the calendar events*[[6]](#footnote-6)*. are the parameters. is the error term and we assumed that . is the order of the lags and is set as 2. *, ,* and are the numbers of selected competitive price, feature, and display variables for the product category.

The general ADL model, as shown in equation (7), contains too many explanatory variables and lack parsimony. Therefore, we simplify the model using the LASSO procedure following Ma et al. (2016) (we refer to the resulting model as the ADL-raw model thereafter). During this stage, we use the LASSO procedure as a model specification strategy rather than a variable selection method as previous studies show that models simplified by the LASSO procedure could have good forecasting performance and outperform traditional models specified based on statistical significance (Epprecht, Guegan, & Veiga, 2013; Ma et al., 2016). Also, the LASSO procedure enables the automation of the statistical forecasting task which becomes essential as typically grocery retailers stock a large number of SKUs (Cooper et al., 1999). To mitigate the limitation of the LASSO procedure in that it may potentially miss important variables, we specify a supplementary parallel ADL model which has a similar specification compared to the general ADL model but only includes the price and promotion variables of the focal product:

(8)

We simplify the supplementary parallel ADL model using the LASSO procedure (we refer to the resulting model as the ADL-own model thereafter). We incorporate the explanatory variables retained in the ADL-own model into the ADL-raw model (we refer to the resulting model as the ADL-intra model). This enables us to selectively retain potentially important variables such as the price and promotions of the focal product and their dynamic terms only at a cost of efficiency. The supplementary parallel ADL model, by definition, has fewer explanatory variables compared to the general ADL model and thus is less likely to suffer from multicollinearity compared to the latter. Thus, if the price and promotions of the focal product truly have effects on the product sales, it would be less likely for these variables to be removed from both the ADL-raw model and the ADL-own model[[7]](#footnote-7).

Figure 2. An illustration for the three-stages of our proposed methods



During the final stage, we integrate the ADL-intra model with the EWC method and the IC method respectively to account for the structural change problem. We implement the EWC method and the IC method only when the ADL-intra model is subjected to structural changes, and we keep the forecasts generated by the ADL-intra model as the final forecasts otherwise. In this study, we conduct a sequential Chow test for up to 95% of the weeks in the estimation period[[8]](#footnote-8). Suppose we have an estimation period of 160 weeks, we conduct the Chow test for each of the central 152 weeks. For example, we conduct the Chow test each time assuming a structural change occurring at a specific week from week 5 to week 156 and we obtain the p-values. The null hypothesis of no structural change will be rejected if any of these p-values is below a threshold. To mitigate the multiple comparison problem, we adopt a very small threshold, i.e., 0.001[[9]](#footnote-9). Previous studies have proposed alternative tests which focus on estimating multiple structural changes and their locations but are usually associated with stringent assumptions (e.g., Andrews, 1993; Andrews & Ploberger, 1994; Bai & Perron, 1998, 2003; Brown, Durbin, & Evans, 1975). In our study, we only need to identify the presence of structural change. Thus, we conduct the sequential Chow test which meets the requirement and also benefits from simple implementation. We refer to these two three-stage methods as the ADL-intra-EWC method and the ADL-intra-IC method respectively. Figure 2 provides a guide for the implementation of the two methods.

## The experimental design

In this study, we consider the Base-lift method as the benchmark model. The method has been used in previous studies (e.g., Cooper et al., 1999; Gür Ali et al., 2009; Huang et al., 2014; Ma et al., 2016). The forecasts for week *t* by this method can be described as follows:

(9)

where represents the baseline forecast for week by the simple exponential smoothing (SES) model. The SES model is estimated exclusively based on the data when the focal product is not being promoted. Thus, represents the sales of the focal product for the previous time when the focal product was not promoted. is the smoothing parameter of the SES model, and is estimated by minimizing the in-sample mean squared errors. The adjustment for the ‘lift’ effect is calculated as the increased sales of the focal product during its most recent promotion compared to the corresponding baseline sales. In this study, we have the following candidate models:

1. The ADL-own model, i.e., the model in equation (8) simplified by the LASSO procedure
2. The ADL-intra model; i.e., the model in equation (7) simplified by the LASSO procedure and then include the explanatory variables retained in the ADL-own model.
3. The ADL-own-EWC model: the ADL-own model with the EWC method
4. The ADL-own-IC model: the ADL-own model with the IC method
5. The ADL-intra-EWC model: the ADL-intra model with the EWC method
6. The ADL-intra-IC model: the ADL-intra model with the IC method

We specify the models with an estimation window of 160 weeks, and we evaluate their forecasting performance using 18 rolling origins for robustness (Tashman, 2000). For each rolling event, we move the estimation window two weeks forward and re-specify the model. We assume that the value of the price and any promotional information to be known as it is part of the retailer’s inventory plan. We use the forecast value of product sales when the forecast horizon is beyond one week. We generate one to week-ahead forecasts, where is 1, 4, and 8, to approximate the situation retailers face in practice. For the EWC method, we generate the final forecasts by equally combining the forecasts by the same model with ten estimation windows (e.g., for the estimation period, e.g., [1,160], we estimate the model with ten estimation windows including [1, 160], [3, 160], and so forth, until [19, 160]). Thus, we have ten sets of forecasts in total. For the IC methods, we estimate the forecast bias as the average value of the sixteen most recent residuals and add the value directly to the forecasts of all the forecast horizons. We implement the models using the MODEL procedure with macros in SAS 9.4. The model parameters are estimated using the OLS estimator.

We evaluate the models’ forecasting performance using different error measures which approximate the unknown loss function of the retailer from different perspctives. We include traditional error measures including the Mean Absolute Error (MAE), the symmetric Mean Absolute Percentage Error (sMAPE) and the scaled Mean Squared Error (scaled MSE)[[10]](#footnote-10). We also include relative measures including the Mean Absolute Scaled Error (MASE) proposed by Hyndman and Koehler (2006) and the Relative Average Mean Absolute Error (RelAvgMAE) proposed by Davydenko and Fildes (2013). These measures have more desirable properties, e.g., equally penalizing positive and negative errors and being more robust to outliers. Also, the RelAvgMAE is readily interpretable as the percentage improvement (or worsening) of the focal method compared to a benchmark. The MASE and the RelAvgMAE can be demonstrated as follows:

(10)

, where ,

(11)

where and are the MASE and the AvgRelMAE based on one to *H* forecast horizon (=1, 4 and 8) across SKUs (e.g., *S*= 1831) for *K* rolling events (e.g., *K*=18). and are respectively the *h*-step ahead actual value and forecast value for data series based on the rolling event. is the total number of observations in the estimation window (i.e., ). The measures the forecasting performance of one model relative to another and the corresponding and are the MAE by these two models based on one to *H* forecast horizon across SKUs for *K* rolling events. In this study, we use the to measure the forecasting performance of each model relative to the ADL-own model. Thus the is the MAE by the candidate model and the is the MAE by the ADL-own model. Before we transform the log values to levels for evaluation, we adjust the final forecasts by adding one-half mean squared error, which mitigate the bias caused by the logarithm transformation (e.g., Cooper et al., 1999; Ma & Fildes, 2017; Ma et al., 2016).

## Results and discussion

In Table 2, we summarize the forecasting performance of the models across all the products with respect to different forecast horizons. Table 3 shows the results of the Diebold-Mariano (DM) test for the statistical significance of the difference between the models’ forecasting performance (Diebold & Mariano, 1995; D. Harvey, Leybourne, & Newbold, 1997)[[11]](#footnote-11). The following findings emerge from this analysis:

1. The Base-lift model generates the least accurate forecasts across all the error measures.
2. The ADL-intra model outperforms the ADL-own model across all the error measures, which is consistent with the findings in Huang et al. (2014).
3. The ADL-own-EWC model outperforms the ADL-own model for all the error measures.
4. The ADL-own-IC model generally outperforms the ADL-own model except for the MAE.
5. The ADL-intra-EWC model outperforms the ADL-intra model for all the error measures.
6. The ADL-intra-IC model generally outperforms the ADL-intra model except for the MAE and the scaled MSE for longer forecast horizons (e.g., Forecast horizon is one to four weeks ahead and one to eight weeks ahead).
7. Overall, The ADL-intra-EWC model and the ADL-intra-IC model generate the most accurate forecasts.

Table 2. The forecasting performance of the models for all forecast period

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Forecast horizon is one to eight weeks ahead | | | | | |
| Model/measure | MAE | SMAPE | MASE | AvgRelMAE | scaled MSE |
| Base-lift | 22.92 | 46.98% | 0.775 | 1.1508 | 0.2234 |
| ADL-own | 15.70 | 40.74% | 0.693 | 1.0000 | 0.1552 |
| ADL-intra | 15.36 | 40.39% | 0.692 | 0.9934 | 0.1530 |
| ADL-own-EWC | 15.61 | 40.61% | 0.691 | 0.9954 | 0.1542 |
| ADL-own-IC | 16.14 | 40.67% | 0.690 | 0.9986 | 0.1570 |
| ADL-intra-EWC | **15.27** | **40.29%** | 0.690 | **0.9893** | **0.1525** |
| ADL-intra-IC | 15.54 | 40.37% | **0.690** | 0.9935 | 0.1545 |
| Forecast horizon is one to four weeks ahead | | | | | |
| Model/measure | MAE | SMAPE | MASE | AvgRelMAE | scaled MSE |
| Base-lift | 22.67 | 46.24% | 0.762 | 1.1413 | 0.2186 |
| ADL-own | 15.62 | 40.39% | 0.687 | 1.0000 | 0.1530 |
| ADL-intra | 15.11 | 40.02% | 0.684 | 0.9908 | 0.1498 |
| ADL-own-EWC | 15.53 | 40.25% | 0.684 | 0.9948 | 0.1519 |
| ADL-own-IC | 15.88 | 40.19% | 0.681 | 0.9941 | 0.1533 |
| ADL-intra-EWC | **15.02** | 39.91% | 0.682 | **0.9865** | **0.1492** |
| ADL-intra-IC | 15.19 | **39.87%** | **0.679** | 0.9877 | 0.1502 |
| Forecast horizon is one week ahead | | | | | |
| Model/measure | MAE | SMAPE | MASE | AvgRelMAE | scaled MSE |
| Base-lift | 24.99 | 45.42% | 0.762 | 1.1294 | 0.2261 |
| ADL-own | 16.67 | 39.86% | 0.687 | 1.0000 | 0.1551 |
| ADL-intra | 15.65 | 39.40% | 0.685 | 0.9892 | 0.1525 |
| ADL-own-EWC | 16.60 | 39.72% | 0.684 | 0.9952 | 0.1540 |
| ADL-own-IC | 16.97 | 39.49% | 0.678 | 0.9895 | 0.1539 |
| ADL-intra-EWC | **15.58** | 39.29% | 0.683 | 0.9849 | 0.1515 |
| ADL-intra-IC | 15.62 | **39.12%** | **0.678** | **0.9810** | **0.1514** |

We also investigate the models’ forecasting performances for the time periods depending on whether the focal product is being promoted. In practice, retailer product sales tend to exhibit high levels of variations when the focal product is being promoted and tend to become comparably stable otherwise (Gür Ali et al., 2009). We refer these two periods as the promoted period and non-promoted period respectively afterward. Table 4 shows the forecasting performance of the models for the promoted forecast period and the non-promoted forecast period respectively for one to eight-week forecast horizon[[12]](#footnote-12). The following findings are particularly important. The ADL-intra-IC model has the best forecasting performance for the non-promoted period but only has the moderate performance for the promoted period. A possible explanation is that the estimated bias added to the error term in the forecast period may get submerged by the high variations of the product sales when the focal product is being promoted. In contrast, the ADL-intra-EWC model has the best performance for the promoted period. Therefore, we develop an exploratory combined method across these two methods and we refer this model as the ADL-EWC-IC model. The ADL-EWC-IC model is identical to the ADL-intra-EWC model for the promoted period and the ADL-intra-IC model for the non-promoted period. To allow for a fair comparison, we evaluate the performance of the ADL-EWC-IC model based on previously unseen data (e.g., the data for 1605 SKU’s for the same 28 product categories but from a different set of 28 stores). Table 5 shows the forecasting performance of the models[[13]](#footnote-13). The exploratory results indicate that the ADL-EWC-IC model generally generates the most accurate forecasts across all the models even when we consider previously unseen data.

We further explore the benefit of taking account for the problem of structural change by focusing on the percentage reduction of the MASE by the ADL-intra-EWC method and the ADL-intra-IC method compared to the ADL-intra model for each product category. The ADL-intra model has a similar specification compared to the ADL-intra-EWC method and the ADL-intra-IC method but overlooks the problem of structural change. The percentage reductions of the MASE by the ADL-intra-EWC method and by the ADL-intra-IC method for product can be demonstrated as follows[[14]](#footnote-14):

(12)

(13)

We then take the average value of and respectively across all the SKU’s for each product category. Table 6 shows the results for each product category for one to eight weeks forecast horizon[[15]](#footnote-15). The ADL-intra-EWC method and the ADL-intra-IC method outperform the ADL-intra model for most of the product categories (e.g., 18 and 16 respectively, out of 28 categories). They do not outperform the ADL-intra model for all product categories due to the heterogeneity of the data characteristics across different product categories (Ma et al., 2016). Figures 3(a) and 3(b) show the boxplots for the percentage reduction in the MASE for selective product categories where the two methods respectively produce the biggest improvement in forecasting performance compared to the ADL-intra model.

Table 3. The results of the Diebold-Mariano (DM) test

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Model 1 | Model 2 | MAE | | | sMAPE | | | MASE | | | scaled MSE | | |
| *H*=1 | *H*=1 to 4 | *H*=1 to 8 | *H*=1 | *H*=1 to 4 | *H*=1 to 8 | *H*=1 | *H*=1 to 4 | *H*=1 to 8 | *H*=1 | *H*=1 to 4 | *H*=1 to 8 |
| ADL-own | Base-lift | 0.000\* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| ADL-own | ADL-intra | 0.000 | 0.000 | 0.007 | 0.000 | 0.000 | 0.000 | 0.555 | 0.100 | 0.294 | 0.352 | 0.973 | 0.304 |
| ADL-own | ADL-own-EWC | 0.092 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.669 | 0.604 | 0.388 |
| ADL-own | ADL-own-IC | 0.106 | 0.022 | 0.000 | 0.000 | 0.000 | 0.175 | 0.000 | 0.000 | 0.007 | 0.554 | 0.469 | 0.019 |
| ADL-intra | ADL-intra-EWC | 0.165 | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.061 | 0.048 | 0.488 | 0.368 | 0.301 |
| ADL-intra | ADL-intra-IC | 0.791 | 0.296 | 0.009 | 0.000 | 0.002 | 0.532 | 0.000 | 0.000 | 0.078 | 0.590 | 0.059 | 0.006 |

\*0.000 indicates that the p-value is smaller than 0.001.

Table 4. The forecasting performance of the models for the promoted and non-promoted forecast period

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Forecast horizon is one to eight weeks ahead, for the promoted period | | | | | |
| Model/measure | MAE | sMAPE | MASE | AvgRelMAE | scaled MSE |
| Base-lift | 119.33 | 87.26% | 1.915 | 1.381 | 2.474 |
| ADL-own | 64.80 | 47.49% | 1.319 | 1.000 | 1.048 |
| ADL-intra | 62.57 | 45.95% | 1.294 | 0.981 | 0.999 |
| ADL-own-EWC | 64.58 | 47.36% | 1.315 | 0.996 | 1.043 |
| ADL-own-IC | 68.95 | 47.94% | 1.344 | 1.022 | 1.104 |
| ADL-intra-EWC | **62.16** | **45.79%** | **1.289** | **0.975** | **0.992** |
| ADL-intra-IC | 64.62 | 46.32% | 1.316 | 1.009 | 1.040 |
| Forecast horizon is one to eight weeks ahead, for the non-promoted period | | | | | |
| Model/measure | MAE | sMAPE | MASE | AvgRelMAE | scaled MSE |
| Base-lift | 8.84 | 41.10% | 0.609 | 1.0120 | 0.0973 |
| ADL-own | 8.53 | 39.76% | 0.602 | 1.0000 | 0.0912 |
| ADL-intra | 8.47 | 39.58% | 0.604 | 0.9977 | 0.0914 |
| ADL-own-EWC | 8.46 | 39.62% | 0.599 | **0.9957** | 0.0905 |
| ADL-own-IC | 8.43 | 39.61% | **0.594** | 0.9984 | **0.0904** |
| ADL-intra-EWC | 8.42 | 39.49% | 0.602 | 0.9950 | 0.0912 |
| ADL-intra-IC | **8.37** | **39.50%** | 0.598 | 0.9961 | 0.0909 |

Table 5. The forecasting performance of the models based on previously unseen data for one to eight-week forecast horizon for 1605 SKU’s for the same 28 product categories from a different set of 28 stores

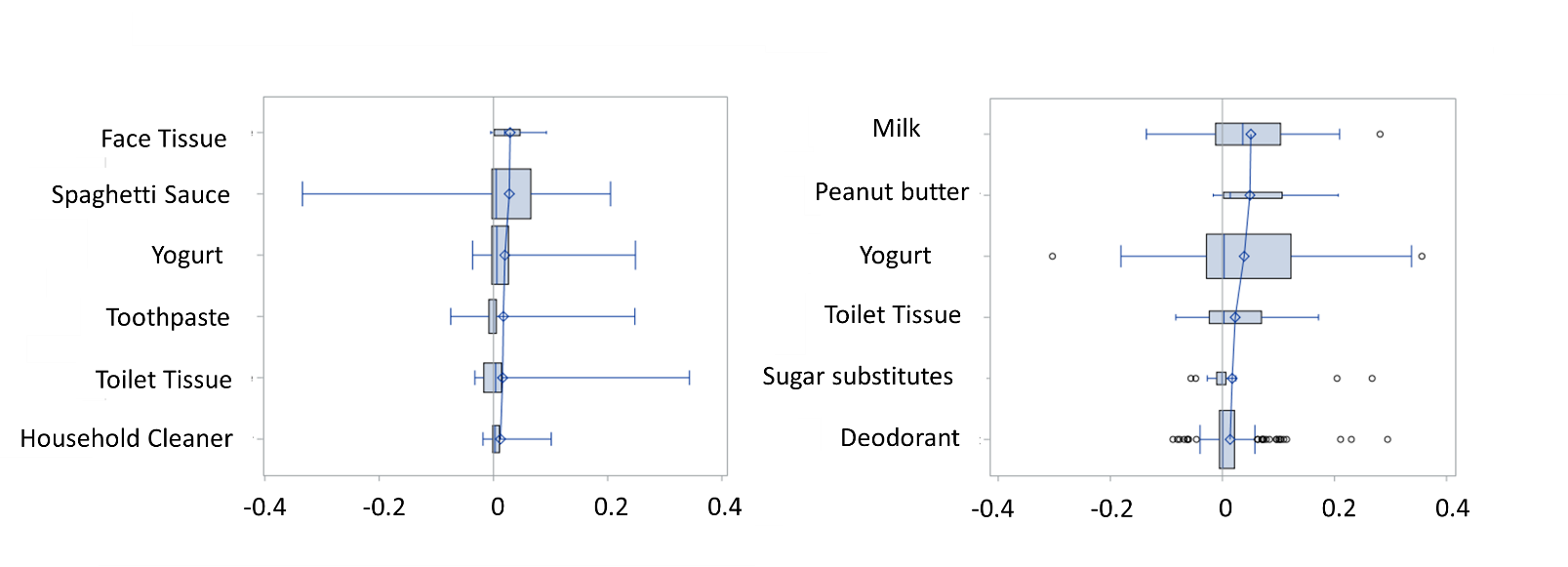
|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| All forecast period, for 1 to 8 weeks ahead | | | | | |
| Model/measure | MAE | SMAPE | MASE | AvgRelMAE | scaled MSE |
| ADL-intra | 13.46 | 39.91% | 0.7669 | 0.997 | 0.1674 |
| ADL-intra-EWC | 13.47 | 39.79% | 0.7650 | 0.993 | 0.1674 |
| ADL-intra-IC | **13.39** | 39.50% | 0.7592 | 0.986 | **0.1660** |
| ADL-EWC-IC | 13.41 | **39.49%** | **0.7588** | **0.985** | 0.1661 |
| promoted period, for 1 to 8 weeks ahead | | | | | |
| Model/measure | MAE | SMAPE | MASE | AvgRelMAE | scaled MSE |
| ADL-intra | **55.02** | 45.88% | 1.566 | 0.988 | 1.2459 |
| ADL-intra-EWC | 55.36 | **45.83%** | **1.564** | **0.982** | 1.2482 |
| ADL-intra-IC | 55.23 | 45.93% | 1.567 | 0.993 | **1.2451** |
| ADL-EWC-IC | 55.36 | **45.83%** | **1.564** | **0.982** | 1.2482 |
| non-promoted period, for 1 to 8 weeks ahead | | | | | |
| Model/measure | MAE | SMAPE | MASE | AvgRelMAE | scaled MSE |
| ADL-intra | 7.692 | 38.28% | 0.622 | 0.989 | 0.0904 |
| ADL-intra-EWC | 7.644 | 38.13% | 0.618 | 0.985 | 0.0897 |
| ADL-intra-IC | **7.451** | **37.46%** | **0.605** | **0.967** | **0.0869** |
| ADL-EWC-IC | **7.451** | **37.46%** | **0.605** | **0.967** | **0.0869** |

Table 6. The percentage reduction of the MASE by the ADL-intra-EWC model and the ADL-intra-IC model compared to the ADL-intra model for one to eight-week forecast horizon for each product category

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Category/MASE | ADL-intra-EWC | ADL-intra-IC | Category/MASE | ADL-intra-EWC | ADL-intra-IC |
| Beer | 0.18% | -0.53% | Mayonnaise | 0.00% | -0.11% |
| Blades | 0.32% | 1.08% | Milk | 1.06% | 5.09% |
| Carbonated Beverages | -0.30% | -2.44% | Mustard & Ketchup | 0.31% | -0.62% |
| Cigarette | 0.11% | 0.80% | Peanut butter | -0.18% | 4.90% |
| Coffee | -0.22% | 0.13% | Photo | 1.00% | -0.98% |
| Cold Cereal | 0.61% | -1.88% | Salty snacks | 0.10% | 1.12% |
| Deodorant | 0.11% | 1.39% | Shampoo | 0.31% | 1.34% |
| Face Tissue | 2.93% | -1.31% | Soup | 0.97% | -4.39% |
| Frozen Dinner | -0.39% | -2.15% | Spaghetti sauce | 2.79% | 0.70% |
| Frozen pizza | -0.46% | -2.16% | Sugar substitutes | 0.09% | 1.75% |
| Hotdog | -0.45% | -4.88% | Toilet Tissue | 1.61% | 2.29% |
| Household Cleaner | 1.24% | 0.66% | Toothbrush | -0.14% | -1.11% |
| Laundry Detergent | 1.14% | -0.17% | Toothpaste | 1.75% | -0.83% |
| Margarine/Butter | -0.84% | -2.70% | Yogurt | 2.01% | 3.89% |

\* positive numbers refer to forecast improvements by our proposed methods with respect to the ADL-intra model.

Figure 3. The boxplots for the percentage reduction of the MASE by the ADL-intra-EWC method and the ADL-intra-IC method compared to the ADL-intra model for one to eight weeks forecast horizon for selected product categories.



1. the ADL-intra-EWC method (b) the ADL-intra-IC method

The box widths are proportionate to the number of SKU’s for the category. The square symbols, which are joined by lines for illustration, indicate the group means for the category. Positive numbers refer to forecast improvements by our proposed methods with respect to the ADL-intra model.

## SKU characteristics and Forecasting Performance

In this section, we wish to explore if our proposed methods, the ADL-intra-EWC method and the ADL-intra-IC method, have greater advantages for products with some specific characteristics. We consider the following data characteristics for each SKU : 1) the average and standard deviation of both the prices and sales variables; 2) the frequency of the feature and display promotions for each of the focal products; 3) more advanced statistical measures suggested by Fildes (1992). Furthermore, we include the proportion of outliers for the sales of each SKU. The value of the sales for product *i* will be identified as an outlier if or , where is the differenced value of the sales for product *i*. and are the first and third quantiles of . For retailer product sales, these outliers are usually due to promotional activities. We also include the randomness measure by regressing on , where is the sales value for product *i* at week *t* given that the outliers are removed and *T* is the time trend. The fitness of this autoregressive model (e.g., the R square) represents the systematic variation in the sales data which could be captured by simple models. Lastly, we include the linear trend of product sales measured as the absolute value of the correlation between and the time trend. We then conduct the principle component analysis to summarize the information contained in those the nine explanatory variables described above, which mitigates the issue of multicollinearity[[16]](#footnote-16). Table 7 shows the correlation between the original nine explanatory variables and the five constructed components, and we may interpret components 1 as “Price level and variation”, components 2 as “Sales level and variation”, components 3 as “Randomness and trend”, components 4 as “Outliers and Feature intensity”, and components 5 as “Display intensity”.

Table 7. The pattern of the factors (small values are omitted for simplicity)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Factor1 | Factor2 | Factor3 | Factor4 | Factor5 |
| Standard deviation of price | 0.956 |  |  |  |  |
| Average price | 0.930 |  |  |  |  |
| Average sales |  | 0.940 |  |  |  |
| Standard deviation of sales |  | 0.898 |  |  |  |
| Proportion of outliers |  |  | 0.921 |  |  |
| Frequency of Feature |  |  | 0.849 |  |  |
| Trend |  |  |  | 0.922 |  |
| Randomness |  |  |  | 0.913 |  |
| Frequency of Display |  |  |  |  | 0.961 |

We then consider two regression models. The dependent variables are the percentage reduction of the MASE by the two proposed methods compared to the ADL-intra model, as defined in equation (12) and equation (13) respectively. The independent variables are the five constructed components described above. Table 8 shows the estimation results of the two regression models. The independent variable for “Randomness and trend” has positive and statistically significant effect on the dependent variable for both regression models (e.g., 0.26 with a p-value of smaller than 0.01 and 0.57 with a p-value of 0.01 respectively) [[17]](#footnote-17). This suggests that the two proposed methods have greater advantages compared to the ADL-intra models for SKU’s associated with higher levels of randomness and trend (e.g., those which are more difficult to forecast and tend to exhibit a trend in product sales), possibly because products of this type tend to be more heavily influenced by structural changes and the resulting forecast bias. The ADL-intra-IC method tends to have less advantages compared to the ADL-intra model for SKU’s with higher proportions of outliers and higher levels of feature intensity (e.g., -1.08 with a p-value smaller than 0.01). A possible explanation is that the adjustment for the forecast bias may get submerged by high sales variations which are usually ‘outliers’ and caused by the feature promotional activities. This is also consistent with the moderate forecasting performance of the ADL-intra-IC method for the promoted forecast period. We also conduct the regression analysis for other error measures and forecast horizons, and we have consistent findings.

Table 8 The estimation results for the two regression models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Parameters/ Estimates and p-values/ Dependent variables |  | |  | |
| Estimate | P-value | Estimate | P-value |
| Price level and variation | -0.15\* | 0.07 | 0.07 | 0.73 |
| Sales level and variation | 0.19 | 0.02 | -0.19 | 0.36 |
| Outliers and Feature intensity | 0.03 | 0.74 | -1.08 | 0.00 |
| Randomness and trend | 0.26 | 0.00 | 0.57 | 0.01 |
| Display intensity | -0.15 | 0.07 | -0.22 | 0.31 |
| Intercept | 0.35 | 0.00 | -0.43 | 0.05 |

\*All the estimates are multiplied by 100.

## Conclusions, limitations and future research

Grocery retailers need to effectively manage their supply chain and, to achieve that, they welcome new approaches that will improve their forecasting accuracy. Previous studies focus on incorporating additional information to build better forecasting models (e.g., Gür Ali et al., 2009; Huang et al., 2014; Ma et al., 2016) but they assume the effect of marketing activities such as price and promotions (e.g., feature and display) to be constant over time. This assumption may not hold because of the impact of external factors such as the change in economic conditions, the change in consumers’ taste, and the entry of new competitors, etc. The data on these external factors are typically not available. Thus, conventional models that assume constant effects of the marketing activities may be subject to the problem of structural change. As a result, these models may generate biased and potentially less accurate forecasts.

Table 9. The percentage reductions of different error measures compared to the Base-lift method

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Models | MAE | SMAPE | MASE | AvgRelMAE | Scaled MSE |
| ADL-own-EWC | -31.9% | -13.6% | -10.9% | -13.5% | -31.0% |
| ADL-own-IC | -29.6% | -13.4% | -11.0% | -13.2% | -29.7% |
| ADL-intra-EWC | -33.4% | -14.2% | -11.0% | -14.0% | -31.7% |
| ADL-intra-IC | -32.2% | -14.1% | -11.1% | -13.7% | -30.8% |

In this study, we propose novel methods to forecast retailer product sales by taking into account the problem of structural change. We propose the ADL-intra-EWC method which combines various sets of forecasts by the ADL-intra method with different estimation windows when structural changes are present. The method tries to achieve an effective trade-off between the reduced forecast bias and the inflated forecast error variance. We also propose the ADL-intra-IC method which attempts to offset the potential forecast bias. The method adds the estimate of the forecast bias back to the error term at the cost of inflated forecast error variance when structural changes are detected. Our models significantly outperform the industrial practice method. Table 9 shows the percentage reductions of various error measures by the ADL-intra-EWC method and the ADL-intra-IC model compared to the Base-lift method for one to eight-week forecast horizon. Specifically, by using the ADL-intra-EWC method and the ADL-intra-IC method, we can reduce the MASE by 11.0% and 11.1% respectively compared to the Base-lift method. We have also evaluated the forecasting performance of the ADL-own-EWC method and the ADL-own-IC method. These methods are particularly valuable to manufacturers when competitive promotional information is not available (e.g., Mohammad M. Ali, Babai, Boylan, & Syntetos, 2017; M. M. Ali & Boylan, 2011). Table 9 also shows the percentage reductions of various error measures by the ADL-own-EWC method and the ADL-own-IC method compared to the Base-lift method for one to eight-week forecast horizon. Specifically, by using the ADL-own-EWC method and the ADL-own-IC method, we can reduce the MASE by 10.9% and 11.0% respectively compared to the Base-lift method. The improvements are consistent across different forecast horizons and such improvements in accuracy are estimated to translate into a similar improvement in profits (Kremer, 2015). In this study, we also compare the forecasting performance of our proposed methods with conventional econometric models which have similar specifications but overlook the structural change problem. For example, we compared the ADL-intra-EWC method and the ADL-intra-IC method with the ADL-intra model, and we compared the ADL-own-EWC method and the ADL- own -IC method with the ADL- own model. We conduct the comparison to highlight the benefit of taking into account the problem of structural change and because, as suggested by Fildes, Ma, et al. (2018), industrial practitioners now tend to take advantages of conventional econometric models.

In this study, we evaluate the models’ forecasting performance depending on if the focal product is being promoted. We find that the ADL-intra-EWC method has the best performance for the promoted forecast period and the ADL-intra-IC method dominates the non-promoted forecast period. We, therefore, forge an exploratory ADL-EWC-IC model which is a combination of the ADL-intra-EWC method and the ADL-intra-IC method based on whenever the focal product is being promoted. We evaluate the forecasting performance of the ADL-EWC-IC model based on previously unseen data for 1605 SKU’s from a different set of 28 stores, and we find that the ADL-EWC-IC model generates the most accurate forecasts overall.

We also explore the relationship between the improved forecasting performance of the proposed methods (compared to the methods with similar model specifications but overlook the structural break problem) and the data characteristics of the product SKU. We find that the ADL-intra-EWC model tends to have greater forecasting performance advantages compared to the ADL-intra model for the SKUs with higher levels of randomness and trend. This may suggest that our methods have outperformed conventional econometric models especially for the products which are more difficult to forecast and have a trend in sales. We also find that the ADL-intra-IC model tends to have greater advantages compared to the ADL-intra model for the SKU’s with a lower proportion of outliers and lower feature promotion intensity. A possible explanation is that the estimated bias we add back to the forecasts gets submerged in the high sales variations caused by promotions. We note that the findings are based on post hoc results and have the limitation of information loss associated with the construction of the principal components.

The methods proposed in this study are new in the domain of forecasting retailer product sales at SKU level, but there are areas where further improvements in forecasting performance can be acheived. For the ADL-intra-EWC method, we equally combine the forecasts generated by the ADL-intra model with ten different estimation windows. It is possible to further explore the model’s forecasting performance with different numbers of the estimation windows, and with different forecasting combination schemes (e.g., based on *k*-fold evaluation). For the ADL-intra-IC method, it is possible to explore the model’s forecasting performance when using different correction schemes (Clements & Hendry, 1999). One of the alternative correction schemes is to make adjustments to the one-step-ahead forecast and then calculate the two-step-ahead forecast based on the value of the one-step-ahead forecast which has been adjusted, and so forth. In this study, we have brought the problem of structural change to attention. An alternative method to account for this problem is to directly model the change in the effect of the marketing activities, such as using time-varying parameter models. However, a disadvantage of this type of models is that we need to make strong assumptions concerning the effects of the marketing activities change. For example, Foekens, Leeflang, and Wittink (1999) modeled the effect of marketing activities as a linear function of previous promotional activities. Their models were not developed for forecasting purposes. In summary, the methods we have proposed in this study produce consistently accurate forecasts. They also satisfy the practical requirements of retail forecasting in that they are intuitive, they can be developed and operated automatically and also use readily available data on marketing activities.

**Acknowledgments**

We thank the IRI company for making the data available. All the analysis and findings in this paper based on the IRI dataset are by the authors and not by the IRI company.

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   (d.soopramanein) [↑](#footnote-ref-1)
2. The term of ‘structural change’ is used interchangeably with the term of ‘structural break’ in the literature. In this study, we use the term “structural change” as in the retailer context we expect the effect of the marketing activities to change gradually rather than but in a sudden and abrupt way. We thank one of the anonymous reviewers for pointing this out. [↑](#footnote-ref-2)
3. We demonstrate the impact of the structural change on the forecasting performance using a simulation example where the model has an intercept term. We include this in the supplementary material. [↑](#footnote-ref-3)
4. Huang et al. (2014) used alternative schemes such as the Akaike’s Information Criterion. In this study, we find rare difference in the results between these different schemes. [↑](#footnote-ref-4)
5. We thank one of the anonymous reviewers for this suggestion to capture the seasonal effect using trigonometric variables. We find that models with trigonometric variable generally have higher forecasting accuracy compared to models which capture the seasonal effect using four-week dummy variables. [↑](#footnote-ref-5)
6. We include the following US calendar events including *Halloween*, *Thanksgiving*, *Christmas*, *New Year’s Day*, *President’s Day*, *Easter*, *Memorial Day*, the *4th of July*, and *Labour Day*. [↑](#footnote-ref-6)
7. We do not further reduce the ADL-intra models using the LASSO procedure as further simplification using the LASSO procedure will potentially remove important variables. [↑](#footnote-ref-7)
8. We keep at least 5% of the weeks for the estimation of the test. [↑](#footnote-ref-8)
9. The results in our study suggest that for most scenarios (e.g., above 99%) the ADL-intra models are subject to structural change if we conduct the Chow test for 95% of the observations. For robustness, we have conducted the whole evaluation by implementing the sequential Chow test for less observations (e.g., 70% of weeks). We find the final results consistent. [↑](#footnote-ref-9)
10. The sMAPE is more robust to outliers compared to the Mean Absolute Percentage Error (MAPE) as the latter does not have an upper bound. We have also conducted the analysis for the MAPE and the results are consistent with the results based on the sMAPE. We do not report the results for the MAPE for simplicity. [↑](#footnote-ref-10)
11. We conduct the DM test based on all the error measures except for the AvgRelMAE which does not fit into the framework of the DM test. [↑](#footnote-ref-11)
12. The results for other forecasting horizons are similar and are omitted for simplicity. [↑](#footnote-ref-12)
13. The results based on the unseen data for the 1605 SKU’s are consistent with the results based on the previous 1831 SKU’s. In Table 5, we do not show the forecasting performance for the Base-lift method, the ADL-own model, the ADL-own-EWC model, and the ADL-own-IC model for simplicity. [↑](#footnote-ref-13)
14. In Equation (12) and (13), all the MASE’s have the same denominator, thus the percentage reductions of the MASE is equivalent to the percentage reductions of the MAE. [↑](#footnote-ref-14)
15. The comparison results for other error measures and horizons are similar and thus omitted for simplicity. [↑](#footnote-ref-15)
16. Five principal components are retained based on the Scree plot and retain 90.2% of information contained in the original nine variables. [↑](#footnote-ref-16)
17. For robustness, we have developed alternative regression models which also include dummy variables to capture potentially unobserved category effects, and we find the parameter estimate for the five components to be consistent with those shown in Table 8. [↑](#footnote-ref-17)