**Forecasting Retailer Product Sales in The Presence of Structural Change**

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Abstract

Grocery retailers need accurate forecasts at SKU level for their inventory management decisions. Previous studies have developed forecasting models which incorporate the effect of various marketing activities including prices and promotions. These models, however, do not consider that the effect of these marketing activities on product sales may not be constant over time. Under such a circumstance, the models could be subject to the structural change problem, i.e., the models with constant parameters are unable to capture the varying effect of the marketing activities. As a result, the generated forecasts may potentially be biased and less accurate. In this study, we propose new forecasting methods for retail product sales by taking into account the problem of structural change. Our methods generate more accurate forecasts compared to conventional models which assume constant parameters for various marketing activities.

Keywords:

Forecasting, OR in marketing, Analytics, Retailing

1. **Introduction**

Grocery retailers rely on accurate sales forecasts for their inventory management (Petropoulos, Makridakis, Assimakopoulos, & Nikolopoulos, 2014). Poor forecasts of product sales lead to poor service arising from out-of-stock conditions or, alternatively, inflated costs due to overstocking. When a specific item is out-of-stock, retailers directly lose the income and profit from the sale of the item. If the out of stock situation happens on a regular basis, it can lead to consumer dissatisfaction. In the long term, retailers may see customers switching to other retail chains (Corsten & Gruen, 2003). To avoid such situations, retailers may intentionally overstock to maintain a high customer satisfaction level but this significantly raises inventory costs (e.g., capital cost, warehousing, and deterioration etc.) and reduces profits (L. 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 overstock (OrderDynamics, 2015). One of the solutions to mitigate the dilemma is to generate more accurate sales forecasts at 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).

In practice, many retailers generate forecasts at SKU level using a two-stage ‘base-lift’ approach. The forecasts are generated separately depending on whether or not the focal product is being promoted. The ‘base’ forecasts are generated using simple univariate models, while the ‘lift’ effect, which is effectively caused by marketing activities including price reductions and promotions, is estimated by the brand/category manager based on his/her experience. In this context, some previous studies have proposed procedures to help managers improve the accuracy of their judgments (e.g., Fildes, Nikolopoulos, Crone, & Syntetos, 2008; Goodwin, 2002; Nikolopoulos, 2010). Others have developed models to estimate the ‘lift’ effect based on data (L. Cooper et al., 1999; L. G. Cooper & Giuffrida, 2000; Trusov, Bodapati, & Cooper, 2006). A third type of approach develops methods to directly generate the final forecasts of the product sales. For example, Gür Ali, SayIn, van Woensel, and Fransoo (2009) proposed the regression tree method with a range of variables constructed from the sales, price, and promotion of the focal product. Huang, Fildes, and Soopramanien (2014) proposed two-stage general-to-specific Autoregressive Distributed Lag (ADL) models which incorporated the promotional information of not only the focal product but also of the competitive products within the same product category. Ma, Fildes, and Huang (2016) further integrated the promotional information of the products from related product categories.

However, all these studies assume that the impact of marketing activities on product sales remains constant over time. In practice, the effect of prices and promotions may change due to the many non-controllable factors which may include, for instance, changing economic conditions, changes in consumer tastes, and the entry of new competitors etc., some of which are neither observable or measurable (Wildt, 1976; Wildt & Winer, 1983). Customers may become more sensitive to prices and promotions during an economic crunch. They may change their tastes due to factors including their familiarity with the product, and their changing lifestyle and 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 be reduced not only because the new competitor launches their marketing activities but also because customers seek variety. In the year of 2014, the German low-price retail chain Aldi opened more than 400 stores in the United States, leading to changes in customer grocery purchasing habits, which then put pressures on existing retail chains (Loeb, 2014).

Under any of the circumstances described above, conventional models which use constant parameters to represent the effect of the price and promotions may potentially be subject to the structural change problem (Allen & Fildes, 2001; Armstrong, 2001). The model which is subject to a structural change may generate biased and less accurate forecasts. The structural change problem has been historically addressed in the macroeconomics literature (see M. B. Clements & Hendry, 1994; H. M. Pesaran & Timmermann, 2005). As an example, Ang and Bekaert (2002) explored the change of the effect of the financial interest rate on stock market returns due to exogenous factors including market sentiment shifts and new regulations. The problem of the structural change has been totally overlooked in forecasting retailer product sales, In this study, we propose Autoregressive Distributed Lag (ADL) models with techniques including Intercept Correction and estimation window combining. Our new methods generate more accurate forecasts by taking into account the structural change problem.

Our research in the domain of retail forecasting in particular at SKU level is significant for the following reasons. First, our research is the first research which investigates the structural change problem in forecasting retailer product sales. The data in retailer product sales at SKU level exhibit unique characteristics compared to data in other areas (e.g., macroeconomics). Also, the methods which deal with the structural change problem by reducing the associated forecast bias come with the cost of inflated forecast error variance (which also affects the forecasting accuracy, as discussed in later sections). Under such circumstances, whether or not we can improve the forecasting accuracy by dealing with the structural change problem becomes an empirical question. The final results indicate that our models have superior forecasting performance compared to conventional models which assume no change in the effect of product prices and promotions. Second, unlike any earlier studies which rely on incorporating additional information on the marketing mix (which leads to additional cost), our methods rely on how limited promotional information could be effectively utilized. In practice, the change of the effect of the marketing activities may be caused by many factors (as mentioned above) for which the data are difficult or infeasible to collect or measure. Therefore, our methods add value without incurring additional costs to retailers. Third, our research provides an evaluation of various forecasting methods which offers operational guidance to not only retailers but also to manufacturers when competitive promotional information is unavailable. Fourth, the methods we propose are fully automatic and easy to implement compared to Huang et al. (2014).

The remainder of the paper is organised as follows: section 2 summarizes previous studies in the literature related to forecasting retailer product sales and the change of the effect of marketing activities. Section 3 explains the origins and the consequence of the structural change problem. In section 4, we introduce two methods which are used in the macroeconomics area to deal with the structural change problem. Section 5 explores the data. In section 6, we propose our new three-stage forecasting methods. Section 7 describes the design of the model evaluation. Section 8 summarizes and discusses the evaluation results in order to provide a convincing demonstration of their performance. In Section 9, we explore the characteristics of the situations where the proposed models garner the greatest improvements. In the last section, we make recommendations for both manufacturers and retailers, address research limitations, and highlight directions for future research.

## Literature review

In practice, many retailers forecast their product sales at SKU level using a two-stage ‘base-lift’ method. The method entails dividing the data into promoted and non-promoted periods based on whether the focal SKU is being promoted. The method is a combination of simple univariate methods (for the non-promoted period) and human judgments by brand/category managers (for the promoted period) (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009; Fildes et al., 2008). A number of studies has been devoted to helping managers with better adjustment procedures by overcoming their cognitive biases (Lee, Goodwin, Fildes, Nikolopoulos, & Lawrence, 2007; Petropoulos, Fildes, & Goodwin, 2016). Other studies try to improve the adjustment with model-based forecasting systems. e.g., they estimate the ‘lift’ effect by the promotional event based on information related to previous promotions, store/category features, and manufacturers etc. (L. Cooper et al., 1999; L. G. Cooper & Giuffrida, 2000; Trusov et al., 2006). One limitation of 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.

Other studies have proposed more holistic methods to generate the forecasts. Divakar et al. (2005) developed the CHAN4CAST system with models of dynamic regression structures to forecast brand volume sales for the manufacturer/channel. Gür Ali et al. (2009) evaluated the forecasting performance of support vector machine (SVM) models and regression tree models. Huang et al. (2014) proposed two-stage general-to-specific ADL models which incorporate competitive promotional information within the same product category of the focal product. Ma et al. (2016) further integrated the promotional information not only from the same category but also from other related categories. These studies tried to generate accurate sales forecast by capturing the effect of marketing activities. For example, the short-term effect of prices and promotions (Blattberg, Briesch, & Fox, 1995), the (asymmetrical) competitive effect (R. L. Andrews, Currim, Leeflang, & Lim, 2008; Dekimpe, Hanssens, & Silva-Risso, 1999; Wedel & Zhang, 2004; Wittink, Addona, Hawkes, & Porter, 1988), and the dynamic effects which lead to purchase acceleration and anticipation (Mace & Neslin, 2004; Van Heerde, Gupta, & Wittink, 2003).

The studies above all assume constant effect of marketing activities. However, evidence has accumulated and shows that the effect of marketing activities including prices and promotions may change over time (e.g. Houston & Weiss, 1975; Little, 1966; Mahajan, Bretschneider, & Bradford, 1980; Moinpour, McCullough, & MacLachlan, 1976; Monroe & Guiltinan, 1975; Morrison, 1966; Myers, 1971; Myers & Nicosia, 1970; Wichern & Jones, 1977; Wildt, 1976; Winer, 1979). Wildt (1976) and Wildt and Winer (1983) attribute the change in the effect of the marketing activities to the change in economic conditions, consumer tastes, and the competitive environment etc. Customers may find price reductions and promotions more attractive when there is an economic crunch compared to other time periods. Customers may also display a change in their tastes and preferences. This can occur when customers accumulate more knowledge of the product, when they seek variety, and when they reach a different social status and decide to adopt a different lifestyle (Meeran et al., 2017). These individual changes may then lead to substantial aggregate effects. Research at store level finds that the introduction of new brands in a product category (e.g., the store-owned brand) decreases the promotional elasticities of premium national brands and increase promotional elasticities of the second tier national brands (Nijs, Dekimpe, Steenkamps, & Hanssens, 2001; Van Heerde, Srinivasan, & Dekimpe, 2008). Lastly, the effect of prices and promotions may change during the different stages of the product lifecycle (Mahajan et al., 1980). Overall, changes in the effect of marketing activities and consumer responses on sales, however, has been overlooked by previous studies in the forecasting literature.

## 3. Structural change and potential forecast bias

Conventional models with constant parameters tend to overlook the change in the effect of the marketing activities at different points in time such as price changes and promotions on product sales. As a result, the generated forecasts will potentially be biased and less accurate (Allen & Fildes, 2001; Armstrong, 2001). This is referred to as the structural change problem and has been addressed by previous studies especially in the macroeconomics literature[[2]](#footnote-2) (e.g., Castle, Doornik, & Hendry, 2008; Hendry, 2018; H. M. Pesaran & Timmermann, 2007). H. M. Pesaran and Timmermann (2005) demonstrate analytically how a structural change may lead to forecast bias using a simple regression model without an intercept[[3]](#footnote-3). For example, for the time period of , the unobserved data generating process is:

(1)

where, is an indicator which equals to 1 before week and 0 afterwards. and are the vectors for the dependent variable and independent variable. Suppose that there is a structural change at week (where ), where the true parameter of the independent variable changes from to after . We may estimate a model with a functional form congruent with the data generating process (e.g., ) based on the data before and after the structural change, e.g., ,. The OLS estimate of the parameters is:

(2)

where and are respectively the matrices of the independent variable and dependent variable for the time periods from week *m* to week *T*. We assume no structural change after week *T*. e.g., . Then, the *h*-step ahead forecast error at week *T*+*h* can be represented as:

(3)

where is the matrix of the intercept and the price variable for the time period from week *m* to . is the vector of error terms for the time periods from week *m* to *T*. and are the vectors for the price variable and the error term at week . Therefore, the forecast at week is biased as the expect value of the equation (3) is unequal to zero. e.g.,

. In Appendix A in the supplementary material, we illustrate the impact of the structural break on the forecasting performance using a simulation example. For more general cases where the model has an intercept term or has endogenous explanatory variables, the forecast bias can be demonstrated using Monte Carlo simulation (M. P. Clements & Hendry, 1999; H. M. Pesaran & Timmermann, 2005, 2007).

## 4. Dealing with structural change

The bias due to the structural change may be mitigated by specifying non-zero values for the model’s errors in the forecasting period, which is referred as the intercept correction (IC) method (Clark & McCracken, 2007; M. B. Clements & Hendry, 1994; M. P. Clements & Hendry, 1999). For example, if we believe that the model is subject to structural change and forecasts are biased, we may estimate the bias as the average value of the most recent residuals, i.e., , where is the number of residuals being used to estimate the forecast bias. When , the estimate reduces to , which is the residual at the forecast origin (e.g., Chevillon, 2016). The estimated bias is then added back to the out-of-sample forecasts, which may potentially improve the forecasting accuracy but at a cost of inflated forecasting error variance (M. P. Clements & Hendry, 1999). In the retailer context, product sales at SKU level often exhibit large variations, unexpected outliers, and missing values, which makes estimating the forecast bias a difficult task.

An alternative method is to combine the forecasts which are generated by the same model but with different estimation windows while expecting a trade-off between reduced forecast bias and potentially increased forecast error variance (H. M. Pesaran & Timmermann, 2005; M. H. Pesaran & Pick, 2011). Ideally, if we know that there is a structural change at , we can estimate the model exclusively with the post-break data, i.e., , and generate unbiased forecasts.In reality, as the location of the break is unknown. We can estimate the model using the data which are closest to the forecast origin (e.g., we keep *m* as large as possible) in conformity with maintaining the degrees of freedom so that that there are enough observations to estimate the model. If *m* by chance becomes larger than , the model will be exclusively estimated with the post-break data and will generate unbiased forecasts. However, this does not necessarily lead to improved forecasting accuracy because the forecasting error variance would increase due to smaller estimation window (e.g., we are using fewer observations to estimate the model). The Mean Squared Error (*MSE*) at week can be represented as , where , and can be interpreted as the squared forecast bias; , and can be interpreted as the efficiency term ( is the forecasting error variance), μ, , and ψ. H. M. Pesaran and Timmermann (2005) show analytically that the change of the *MSE* for week when we estimate the model with data compared to with the data is:

(4)

where is the *MSE* at week based on the estimation window [m+1, *T*]. When the observation at week *m* is excluded in the estimation, the change of the squared bias term (e.g., ) will always be non-positive (i.e., the bias will decrease), but the change of the efficiency term (e.g., ) depends on the error variance before and after the structural change. If (e.g., there are more pre-break variations compared to post-break variations in the product sales which cannot be explained by the price variable), will be smaller than or equal to , and the *MSE* will decrease as the change for both the squared bias term and the efficiency term are non-positive. However, if , will be larger or equal to . Under this condition, the *MSE* may either increase or decrease depending on how the non-positive change of the squared bias term compares to the non-negative change of the efficiency term. As a result, when we exclude pre-break data and adopt a smaller estimation window, we may have either better or worse forecasting performance depending on the trade-off between the reduced forecast bias and the potentially inflated forecasting error variance. Therefore, the forecasts generated by the model with larger estimation windows may be subject to larger bias (contains more pre-break data) but associated with smaller forecast error variance (with more observations), and vice versa. As it is difficult to find the location of the structural change, we can combine the forecasts generated by the models with different estimation windows, which may potentially lead to higher forecasting accuracy by making an effective trade-off between the forecast bias and the forecasting error variance (Clemen, 1989; Jose & Winkler, 2008).

For example, we may combine the forecasts with equal weights as it has been found effective and easy to implement.(M. Clements & Hendry, 1998; Dekker, van Donselaar, & Ouwehand, 2004; Fildes & Stekler, 2002; M. H. Pesaran, Schuermann, & Smith, 2009). We may estimate the model using the most recent observations to generate the 1st set of the *h*-step-ahead forecast, e.g., , where represents the parameters estimated with the sample window . The value of is arbitrarily chosen given there are enough observations to estimate the model and there are enough variations in the explanatory variables. We then add more observations (e.g., one) to the estimation window and generate the 2nd set of the *h*-step-ahead forecast, e.g., and so forth. We may have the set of the *h*-step-ahead forecasts, e.g., . We calculate the final forecasts as the average value of the () sets of *h*-step-ahead forecasts:

(5)

This method is referred as the estimation window combining (EWC) method and has been used to help VAR models forecast financial variables (M. H. Pesaran et al., 2009)[[4]](#footnote-7).

## The data

In this study, we evaluate the forecasting performance of various models using the retail dataset made available by the Information Resources, Inc. (IRI) company. A description of the dataset can be found in Bronnenberg, Kruger, and Mela (2008). The dataset contains weekly data at SKU level with variables including product unit sales, price, features, and displays etc. We initially conduct our evaluation based on 1831 SKU’s for 28 product categories from 28 different stores. Table 1 shows the basic statistics of the selected SKU’s during a period of 202 weeks for each product category[[5]](#footnote-8). Some product categories (e.g., Carbonated Beverages and Hotdog) exhibit much higher promotional intensity compared to others (e.g., Margarine/Butter and Mayonnaise). Figure 1 exhibits the data series for a typical SKU in the Beer category as an example: it indicates that sales spikes are usually associated with the price reductions and feature/display promotions of the focal product, as well as calendar events (e.g., Halloween, Thanksgiving, and Christmas etc.).

Table 1. Statistical description of different product categories

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Category | Price mean | Sales mean | Display percentage | Feature percentage | Number of SKU's |
| Beer | 8.3 | 20.6 | 13.90% | 4.00% | 169 |
| Blades | 8.1 | 14.6 | 7.40% | 2.20% | 22 |
| Carbonated Beverages | 2.1 | 113.6 | 26.80% | 15.60% | 82 |
| Cigarette | 22.3 | 22.2 | 0.00% | 0.80% | 203 |
| Coffee | 5.2 | 14.5 | 5.20% | 2.90% | 86 |
| Cold cereal | 3.5 | 70.7 | 4.00% | 18.10% | 125 |
| Deodorant | 2.7 | 6.9 | 4.10% | 5.20% | 126 |
| Face Tissue | 2.1 | 75.8 | 0.30% | 11.70% | 6 |
| Frozen Dinner | 2 | 43.8 | 5.30% | 23.70% | 87 |
| Frozen pizza | 3.4 | 31.2 | 8.90% | 9.10% | 147 |
| Household Cleaner | 2.5 | 29.9 | 0.30% | 3.60% | 18 |
| Hotdog | 4 | 68.6 | 13.20% | 15.60% | 35 |
| Laundry Detergent | 8.8 | 28.9 | 2.30% | 8.80% | 57 |
| Margarine/Butter | 2 | 71.4 | 0.10% | 6.30% | 36 |
| Mayonnaise | 3 | 79.7 | 3.00% | 0.40% | 22 |
| Milk | 2.5 | 222.3 | 2.10% | 1.80% | 30 |
| Mustard & Ketchup | 2.1 | 64.5 | 5.30% | 0.90% | 22 |
| Peanut butter | 3.7 | 34.2 | 3.20% | 0.60% | 15 |
| Photo | 7.2 | 9.2 | 4.60% | 5.10% | 13 |
| Salty snacks | 2.3 | 50.9 | 6.70% | 5.00% | 101 |
| Shampoo | 3.5 | 9.9 | 12.80% | 7.10% | 70 |
| Soup | 1.5 | 61.6 | 1.20% | 9.70% | 139 |
| Spaghetti sauce | 2.4 | 39.1 | 1.60% | 6.50% | 52 |
| Sugar substitutes | 2.8 | 14.5 | 0.10% | 1.40% | 20 |
| Toilet Tissue | 5.4 | 89.1 | 4.30% | 8.30% | 20 |
| Toothbrush | 2.6 | 8.7 | 3.10% | 6.30% | 28 |
| Toothpaste | 2.8 | 35.5 | 11.00% | 12.50% | 25 |
| Yogurt | 1.1 | 115.1 | 0.70% | 6.30% | 75 |

Figure 1. Store level data for an SKU in the Beer category[[6]](#footnote-9)



## The models

In this study, we propose new forecasting methods which take into account the problem of structural change. The new methods consist of three stages. At the first stage, we identify the most informative competitive explanatory variables for the focal product. Grocery retailers typically sell hundreds of SKU’s in a typical product category and this leads to hundreds of potential competitive explanatory variables for the focal product. Incorporating all the variables into the model would easily overfit the model and even make the estimation infeasible (Martin & Kolassa, 2009). Therefore, we initially select the most relevant variables using the Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani, 1996). In the LASSO procedure, we specify the following model for each SKU:

(6)

where represents log product sales of the focal product at week *t.*  
 is the matrix for the explanatory variables including product prices, features, and displays of all the products in the same product category.

*u* represents the identically distributed error term.

represents the vector for the parameter coefficients.  
*N* is the total number of SKUs for the category.  
 is the shrinkage factor.

The LASSO procedure imposes a constraint to the sum of the absolute values of the models’ parameter coefficients. It removes less relevant explanatory variables by pushing their parameter coefficients towards zero. We control the model simplification process using the shrinkage factor based on 10-fold cross validation (Ma & Fildes, 2017; Ma et al., 2016)[[7]](#footnote-10).

At the second stage, we construct the General Autoregressive Distributive Lag (ADL) model based on the variables selected by the LASSO procedure with their dynamic terms (Huang et al. 2014). One limitation of the LASSO procedure is that it potentially misses important variables under the condition of high multicollinearity (Fan & Lv, 2008; Ma et al., 2016). In practice, retailers tend to promote relevant products at the same time. Therefore, we include the marketing variables of the focal product in the general ADL model. The general ADL model takes into account the dynamic effect of the (LASSO retained) marketing activity variables as well as a time variable which captures the potential trend, 12 four-week dummy variable to capture seasonality, and other dummy variables to capture calendar events. We refer this model as the general ADL model:

(7)

where is the log sales of the focal product at week .

is the term which captures any potential trend during the estimation period (Song & Witt, 2003).

and represent the log price of the focal product and a competitive product, *m*, at week .

and represents the Feature dummy for the focal product at week .

is the four-week-dummy variable.  
 is the dummy variable for the calendar event at week . The dummy variable represents the week of the calendar event when , , and the week before the event if . takes the values from 1 to 9 representing all the calendar events*[[8]](#footnote-11)*.

are the parameters.  
 is the error term and we assume .

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.

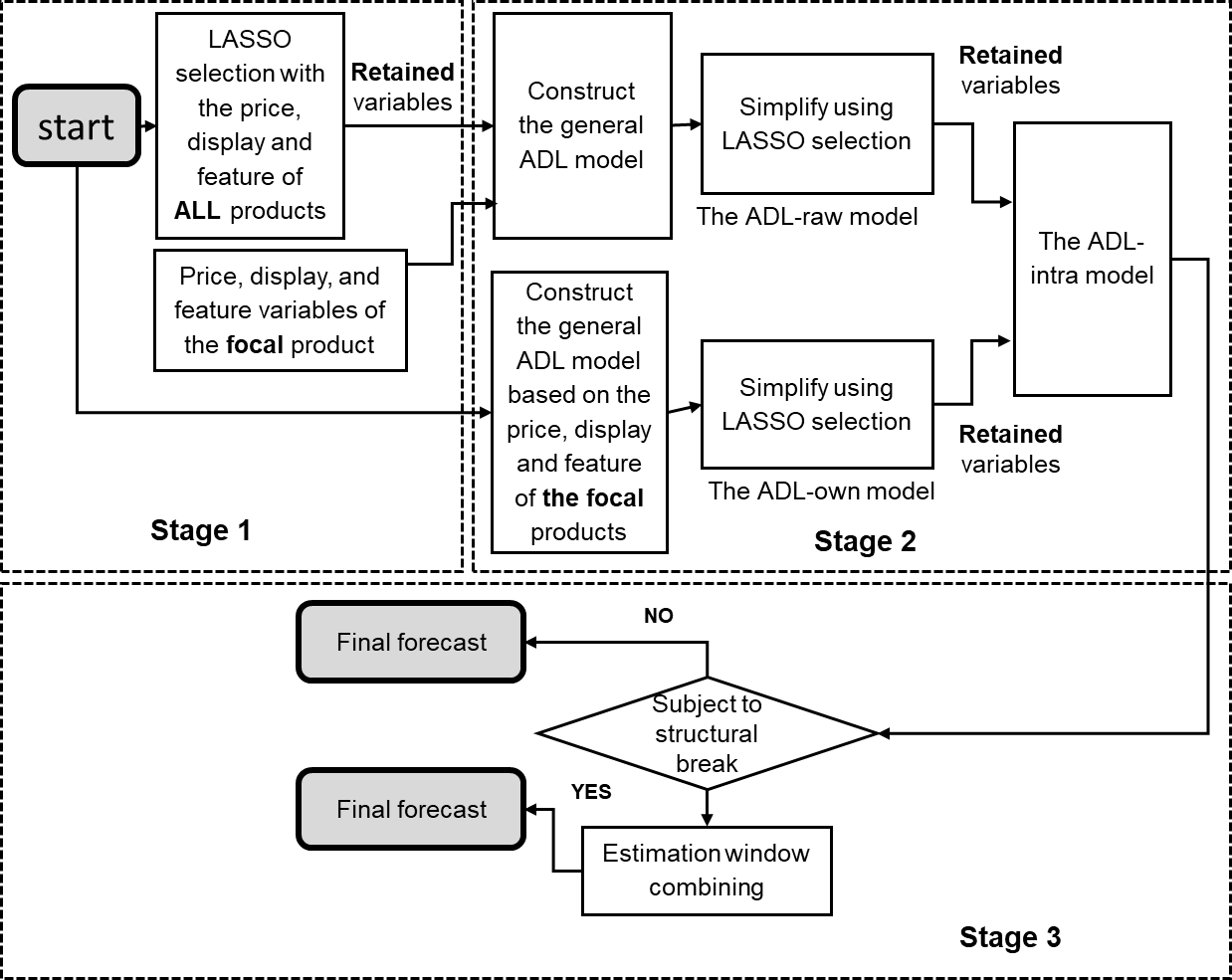
The specified general ADL model may have a large number of explanatory variables and some of them may be correlated with other variables or do not convey any effective information. Therefore, we simplify the general ADL model by again conducting the LASSO procedure (we refer to this simplified ADL model as the ADL-raw model thereafter). At this stage, we use the LASSO procedure as a model specification strategy rather than a variable selection method because previous studies indicate that models simplified by the LASSO procedure have good forecasting performance and outperform traditional models specified based on statistical significance (Epprecht, Guegan, & Veiga, 2013; Ma et al., 2016). The LASSO procedure also enables the automation of the statistical forecasting task which becomes essential as typically grocery retailers stock a tremendous number of SKUs (L. Cooper et al., 1999). However, as mentioned previously, the LASSO procedure has a critical limitation of missing important variables when it is exposed to high multicollinearity. Therefore, to mitigate the problem, we construct a supplementary parallel ADL model which only includes the price and promotion variables of the focal product:

(8)

We also simplify this model using the LASSO procedure (we refer to this simplified model as the ADL-own model thereafter). We then incorporate the variables retained by the ADL-own model into the ADL-raw model (we refer the resulted model as the ADL-intra model). There are two benefits to use this parallel model: 1) we concern that the ADL-raw model may have missed important variables. However, we do not want to force the model to include variables which should not be included.

We include the variables in the ADL-own model because previous studies suggest that promotional variables of the focal variable are usually more important compared to variables of other products (Bucklin, Gupta, & Siddarth, 1998). We, therefore, reduce the probability of (wrongfully) discarding them at a cost of efficiency.

Figure 2. An illustration for the three-stages of the ADL-intra-EWC model



At 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 to the ADL-intra model if the sequential Chow test indicates the existence of structural change, and we keep the forecasts generated by the ADL-intra model as the final forecasts otherwise. In the sequential Chow test, we conduct separate Chow tests for the central 95% of the weeks within the estimation sample, each time assuming there is a structural change at one of the weeks[[9]](#footnote-12). Therefore, we obtain a set of p-values. For example, we may have 160 weeks in the estimation sample. Thus, we conduct separate Chow tests each time assuming there is a structural change at week 5, 6, 7, until 156. We obtain 152 p-values in total. The null hypothesis of no structural change will be rejected if none of those p-value is below the threshold. To mitigate the multiple comparison problem, we adopt a very small threshold (e.g., 0.001) rather than the usual 0.05 for the p-value. Previous studies have proposed alternative tests which focus on estimating the number of the multiple structural changes and their exact locations, though these tests were usually poor (e.g., Donald W K Andrews, 1993; Donald W. K. Andrews & Ploberger, 1994; Bai & Perron, 1998, 2003; Brown, Durbin, & Evans, 1975). In this study, as we only need to investigate if there is any structural change existing or not, we conduct a sequential Chow test which serves for this purpose and has the benefit of simple implementation. We refer the models as the ADL-intra-EWC model and the ADL-intra-IC model respectively and we expect these models to generate more accurate forecasts by taking into account the structural change problem. Figure 2 provides a guide to implementing the ADL-intra-EWC model[[10]](#footnote-13).

## The experimental design

In this study, we consider the Base-lift method as the benchmark model. The method is widely used in practice and evaluated in previous studies(e.g., L. 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:

where represents the initial baseline forecast for week by the simple exponential smoothing model. represents the actual sales of the focal product during the previous week given that the it was not promoted. is the parameter of the simple exponential smoothing model. It is estimated by minimizing the in-sample mean squared errors. The adjustment is therefore calculated as the increased sales of the focal product by its most recent promotion compared to the corresponding initial baseline.

We have the following candidate models: 1) The ADL-own model; 2) The ADL-intra model; 3) The ADL-intra-EWC model; 4) The ADL-own-EWC model: similar to the ADL-intra-EWC model except that the ADL-intra model is replaced by the ADL-own model at the final stage; 5) The ADL-intra-IC model; 6) The ADL-own-IC model: similar to the ADL-intra-IC model except that the ADL-intra model is replaced by the ADL-own model at the final stage. with macros

In this study, we evaluate the forecasting performance of these models with 18 rolling origins for robustness (Tashman, 2000). We specify the model with an estimation window of 160 weeks. For each rolling event, we move the estimation window two weeks forward and re-specify the model. We presume the value of the price and promotional information to be known, as it is part of the retailer’s inventory plan, and we use the forecast value of the 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 engage ten estimation windows with different lengths (e.g., for the initial estimation period [1,160], we estimate the model with ten estimation windows including [1, 160], [3, 160], and so forth, until [19, 160]), and generate ten sets of forecasts accordingly). We combine the ten sets of forecasts with equal weights. For the IC methods, we estimate the forecast bias as the average value of the sixteen most recent residuals and add the value equally to the forecasts of all the forecast horizons.

We evaluate the models with various error measures which approximate the loss function of the retailer from different aspects. We include traditional error measures including the Mean Absolute Error (*MAE*) , the symmetric Mean Absolute Percentage Error (*sMAPE*) and the scaled Mean Squared Error (sMSE). We also include recently developed error measures including the Mean Absolute Scaled Error (*MASE*) developed by Hyndman and Koehler (2006) and the Relative Average Mean Absolute Error (*RelAvgMAE*) developed by Davydenko and Fildes (2013). The two latter error measures for SKUs based on a forecast horizon of 1 to (e.g., and =1, 4 and 8) are as follows:

, where

Where

Where and are the MASE and the AvgRelMAE based on one to *H* forecast horizon (=1, 4 and 8). and are respectively the *h*-step ahead actual value and forecast value for data series based on the rolling event. There are *S* data series and *K* rolling events (*S*= 1831 and *K*=18). is the total number of observations in the estimation window (i.e., ). 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 log transformation (e.g., L. Cooper et al., 1999; Ma et al., 2016)

## Results and discussion

In Table 2, we summarize the forecasting performance of the models across all the product categories. Table 3 shows the results of the Diebold-Mariana (DM) test for the statistical significance of the difference between the models’ forecasting performance. (Diebold & Mariano, 1995; Harvey, Leybourne, & Newbold, 1997)[[11]](#footnote-16). We find the following from the analysis of the comparisons of forecasts from the different models:

1. The Base-lift model generates the least accurate forecasts.
2. The ADL-intra model outperforms the ADL-own model, 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* which is scale dependent.
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 *MSE* error measures for longer forecast horizons (e.g., *h*=4 and 8).

Overall, The ADL-intra-EWC model and the ADL-intra-IC model generate the most accurate forecasts. In Table 6, we compare the forecasting performance of the ADL-intra-EWC model and the ADL-inter-IC model to the ADL-intra model for each individual product category based on the MASE for one to eight-week forecast horizon. We focus on the ADL-intra-EWC model and the ADL-inter-IC model because they have the best forecasting performance overall and the ADL-intra model has a similar model specification expect that it overlooks the issue of structural change. The comparison results for other error measures and horizons are similar. The ADL-intra-EWC model and the ADL-intra-IC model outperforms the ADL-intra model for the majorities of product categories (e.g., 20 and 17 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 (e.g., Ma et al., 2016).



|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Forecast horizon is 1 to 8 weeks ahead, for all forecast period | | | | | | | | | | |
| Model/measure | MAE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank | scaled MSE | Rank |
| Base-lift | 22.919 | 7 | 46.98% | 7 | 0.775311 | 7 | 1.1444 | 7 | 0.2234 | 7 |
| ADL-own | 15.755 | 5 | 40.81% | 6 | 0.697303 | 6 | 1.0000 | 6 | 0.1575 | 5 |
| ADL-intra | 15.436 | 2 | 40.51% | 3 | 0.695222 | 4 | 0.9941 | 3 | 0.1553 | 2 |
| ADL-own-EWC | 15.673 | 4 | 40.68% | 4 | 0.695964 | 5 | 0.9956 | 4 | 0.1570 | 4 |
| ADL-own-IC | 16.233 | 6 | 40.76% | 5 | 0.694034 | 3 | 0.9992 | 5 | 0.1596 | 6 |
| ADL-intra-EWC | 15.354 | 1 | 40.41% | 1 | 0.693915 | 2 | 0.9905 | 1 | 0.1548 | 1 |
| ADL-intra-IC | 15.595 | 3 | 40.46% | 2 | 0.692854 | 1 | 0.9936 | 2 | 0.1568 | 3 |
| Forecast horizon is 1 to 4 weeks ahead, for all forecast period | | | | | | | | | | |
| Model/measure | MAE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank | scaled MSE | Rank |
| Base-lift | 22.669 | 7 | 46.24% | 7 | 0.761699 | 7 | 1.1365 | 7 | 0.2186 | 7 |
| ADL-own | 15.630 | 5 | 40.45% | 6 | 0.690272 | 6 | 1.0000 | 6 | 0.1548 | 5 |
| ADL-intra | 15.157 | 2 | 40.12% | 3 | 0.686329 | 4 | 0.9913 | 3 | 0.1514 | 2 |
| ADL-own-EWC | 15.546 | 4 | 40.31% | 5 | 0.688358 | 5 | 0.9950 | 5 | 0.1540 | 4 |
| ADL-own-IC | 15.942 | 6 | 40.25% | 4 | 0.683757 | 2 | 0.9948 | 4 | 0.1553 | 6 |
| ADL-intra-EWC | 15.089 | 1 | 40.01% | 2 | 0.684993 | 3 | 0.9876 | 2 | 0.1509 | 1 |
| ADL-intra-IC | 15.211 | 3 | 39.93% | 1 | 0.681286 | 1 | 0.9871 | 1 | 0.1517 | 3 |
| Forecast horizon is 1 week ahead, for all forecast period | | | | | | | | | | |
| Model/measure | MAE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank | scaled MSE | Rank |
| Base-lift | 24.990 | 7 | 45.415% | 7 | 0.762 | 7 | 1.1279 | 7 | 0.2261 | 7 |
| ADL-own | 16.662 | 5 | 39.873% | 6 | 0.689 | 6 | 1.0000 | 6 | 0.1561 | 6 |
| ADL-intra | 15.661 | 3 | 39.434% | 3 | 0.686 | 4 | 0.9883 | 3 | 0.1529 | 3 |
| ADL-own-EWC | 16.588 | 4 | 39.720% | 5 | 0.686 | 5 | 0.9955 | 5 | 0.1549 | 4 |
| ADL-own-IC | 17.015 | 6 | 39.519% | 4 | 0.680 | 2 | 0.9902 | 4 | 0.1552 | 5 |
| ADL-intra-EWC | 15.595 | 1 | 39.329% | 2 | 0.684 | 3 | 0.9850 | 2 | 0.1523 | 2 |
| ADL-intra-IC | 15.653 | 2 | 39.148% | 1 | 0.679 | 1 | 0.9804 | 1 | 0.1520 | 1 |

Table 3. The p-values of the Diebold-Mariana (DM) test

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | MAE | | | SMAPE | | | MASE | | | MSE | | |
|  |  | *H*=1 | *H*=4 | *H*=8 | *H*=1 | *H*=4 | *H*=8 | *H*=1 | *H*=4 | *H*=8 | *H*=1 | *H*=4 | *H*=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 | 0.001 | 0.015 | 0.000 | 0.000 | 0.000 | 0.234 | 0.026 | 0.157 | 0.259 | 0.289 | 0.637 |
| ADL-own | ADL-own-EWC | 0.078 | 0.004 | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 | 0.120 | 0.341 | 0.503 | 0.586 | 0.201 |
| ADL-own | ADL-own-IC | 0.065 | 0.008 | 0.000 | 0.000 | 0.000 | 0.208 | 0.000 | 0.000 | 0.002 | 0.015 | 0.006 | 0.002 |
| ADL-intra | ADL-intra-EWC | 0.080 | 0.005 | 0.001 | 0.000 | 0.000 | 0.000 | 0.006 | 0.128 | 0.110 | 0.965 | 0.612 | 0.140 |
| ADL-intra | ADL-intra-IC | 0.576 | 0.645 | 0.048 | 0.000 | 0.000 | 0.070 | 0.000 | 0.000 | 0.002 | 0.621 | 0.075 | 0.052 |
| ADL-intra | ADL-EWC-IC | 0.005 | 0.000 | 0.000 | 0.000 | 0.000 | 0.003 | 0.000 | 0.000 | 0.000 | 0.858 | 0.496 | 0.125 |







We also investigate the models’ forecasting performance for the time periods depending on whether the focal product is being promoted because the corresponding sales tend to exhibit very different levels of variations[[12]](#footnote-18). We refer these two periods as the promoted period and non-promoted period respectively. Table 4 shows the forecasting performance of the models for the promoted period and the non-promoted forecast period respectively for one to eight-week forecast horizon[[13]](#footnote-19). The results are similar compared to those in Table 2. Of the many detailed comparisons possible, the following seem particularly important: the ADL-intra-IC model has the best forecasting performance for the non-promoted period but only has moderate performance for the promoted period. A possible explanation is that the estimated bias used for the correction gets 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 forge a combined model between these two models, named as the ADL-EWC-IC model. The ADL-EWC-IC model will be identical to the ADL-intra-EWC model for the promoted period and to the ADL-intra-IC model for the non-promoted period. To make a fair comparison, we further evaluate the performance of the ADL-EWC-IC model based on previously unseen data (e.g., the data from the same 28 product categories but from a set of different 28 stores). Table 5 shows the forecasting performance of the ADL-EWC-IC model compared to other three models[[14]](#footnote-20). The results indicate that the ADL-EWC-IC model generally generates the most accurate forecasts across all the models even for previously unseen data.



Table 4.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Forecast horizon is 1 to 8 weeks ahead, for the promoted period | | | | | | | | | | |
| Model/measure | MAE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank | scaled MSE | Rank |
| Base-lift | 119.330 | 7 | 87.26% | 7 | 1.915 | 7 | 1.3705 | 7 | 2.4742 | 7 |
| ADL-own | 65.272 | 5 | 47.56% | 5 | 1.329 | 5 | 1.0000 | 4 | 1.0719 | 5 |
| ADL-intra | 63.100 | 2 | 46.04% | 2 | 1.307 | 2 | 0.9795 | 2 | 1.0265 | 2 |
| ADL-own-EWC | 65.010 | 3 | 47.43% | 4 | 1.325 | 3 | 0.9955 | 3 | 1.0662 | 4 |
| ADL-own-IC | 69.677 | 6 | 47.95% | 6 | 1.354 | 6 | 1.0208 | 6 | 1.1299 | 6 |
| ADL-intra-EWC | 62.737 | 1 | 45.91% | 1 | 1.303 | 1 | 0.9756 | 1 | 1.0196 | 1 |
| ADL-intra-IC | 65.013 | 4 | 46.30% | 3 | 1.327 | 4 | 1.0035 | 5 | 1.0651 | 3 |
| Forecast horizon is 1 to 8 weeks ahead, for the non-promoted period | | | | | | | | | | |
| Model/measure | MAE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank | scaled MSE | Rank |
| Base-lift | 8.837 | 7 | 41.10% | 7 | 0.609 | 7 | 1.0083 | 7 | 0.0973 | 7 |
| ADL-own | 8.523 | 6 | 39.83% | 6 | 0.605 | 5 | 1.0000 | 6 | 0.0921 | 5 |
| ADL-intra | 8.475 | 5 | 39.70% | 4 | 0.606 | 6 | 0.9986 | 4 | 0.0922 | 6 |
| ADL-own-EWC | 8.467 | 4 | 39.70% | 3 | 0.604 | 3 | 0.9963 | 1 | 0.0920 | 3 |
| ADL-own-IC | 8.427 | 2 | 39.71% | 5 | 0.598 | 1 | 0.9995 | 5 | 0.0916 | 1 |
| ADL-intra-EWC | 8.433 | 3 | 39.61% | 2 | 0.605 | 4 | 0.9964 | 2 | 0.0921 | 4 |
| ADL-intra-IC | 8.377 | 1 | 39.61% | 1 | 0.600 | 2 | 0.9976 | 3 | 0.0918 | 2 |

Table 5. The forecast results based on previously unseen data from a different set of 28 stores.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| All forecast period, for 1 to 8 weeks ahead | | | | | | | | | | |
| Model/measure | MAE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank | scaled MSE | Rank |
| ADL-intra | 13.441 | 3 | 40.01% | 4 | 0.770 | 4 | 1.0000 | 4 | 0.1689 | 3 |
| ADL-intra-EWC | 13.473 | 4 | 39.89% | 3 | 0.769 | 3 | 0.9964 | 3 | 0.1690 | 4 |
| ADL-intra-IC | 13.339 | 1 | 39.60% | 2 | 0.762 | 2 | 0.9885 | 2 | 0.1674 | 1 |
| ADL-EWC-IC | 13.387 | 2 | 39.59% | 1 | 0.762 | 1 | 0.9876 | 1 | 0.1677 | 2 |
| promoted period, for 1 to 8 weeks ahead | | | | | | | | | | |
| Model/measure | MAE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank | scaled MSE | Rank |
| ADL-intra | 55.110 | 1 | 45.96% | 3 | 1.569417 | 4 | 1.0000 | 3 | 1.2509 | 2 |
| ADL-intra-EWC | 55.549 | 3 | 45.90% | 1 | 1.568883 | 1 | 0.9960 | 1 | 1.2549 | 3 |
| ADL-intra-IC | 55.112 | 2 | 45.99% | 4 | 1.569142 | 3 | 1.0090 | 4 | 1.2477 | 1 |
| ADL-EWC-IC | 55.549 | 3 | 45.90% | 1 | 1.568883 | 1 | 0.9960 | 1 | 1.2549 | 3 |
| non-promoted period, for 1 to 8 weeks ahead | | | | | | | | | | |
| Model/measure | MAE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank | scaled MSE | Rank |
| ADL-intra | 8.296 | 4 | 39.27% | 4 | 0.67148 | 4 | 1.0000 | 4 | 0.1047 | 4 |
| ADL-intra-EWC | 8.279 | 3 | 39.15% | 3 | 0.670104 | 3 | 0.9963 | 3 | 0.1047 | 3 |
| ADL-intra-IC | 8.182 | 1 | 38.81% | 1 | 0.66279 | 1 | 0.9871 | 1 | 0.1036 | 1 |
| ADL-EWC-IC | 8.182 | 1 | 38.81% | 1 | 0.66279 | 1 | 0.9871 | 1 | 0.1036 | 1 |

In Table 6, we compare the forecasting performance of the ADL-intra-EWC model and the ADL-inter-IC model to the ADL-intra model for each individual product category based on the MASE for one to eight-week forecast horizon. We focus on the ADL-intra-EWC model and the ADL-inter-IC model because they have the best forecasting performance overall and the ADL-intra model has a similar model specification but overlooks the issue of structural change. The comparison results for other error measures and horizons are similar. The ADL-intra-EWC model and the ADL-intra-IC model outperforms the ADL-intra model for the majorities of the product categories (e.g., 20 and 17 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 (e.g., Ma et al., 2016). Figure 3 show further details using boxplots for their best performing product categories. In the figures, positive values indicate the percentage reduction of the MASE by the ADL-intra-EWC model and by the ADL-intra-IC model compared to the ADL-intra model.

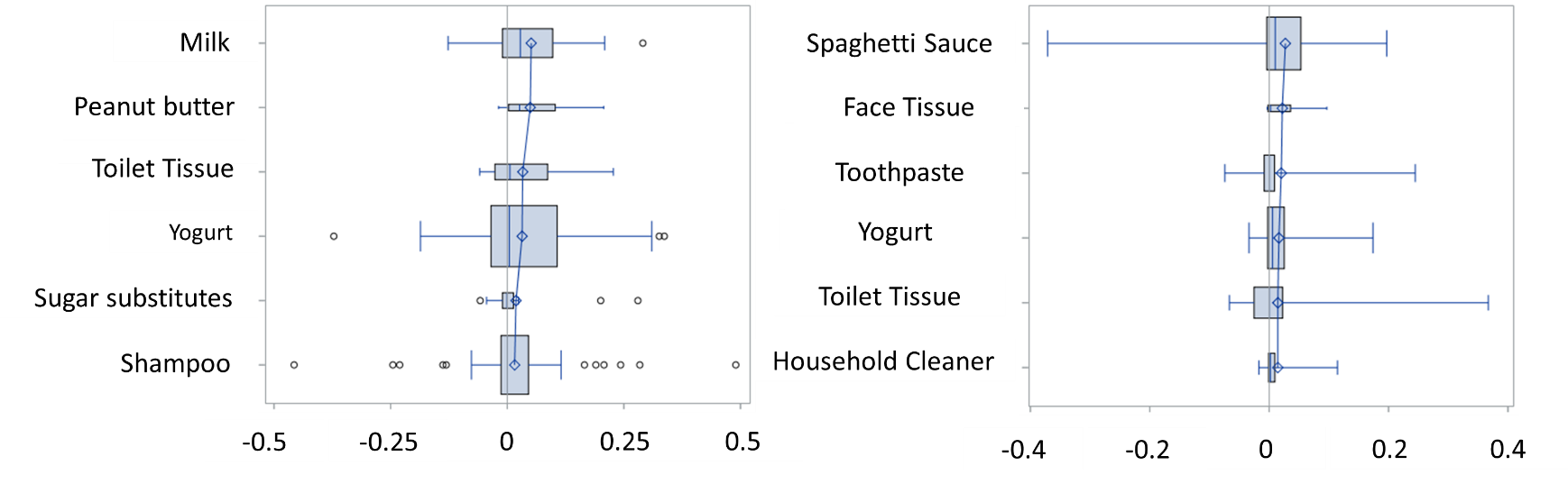
Table 6. The percentage reduction by the ADL-intra-EWC model and the ADL-intra-IC model compared to the ADL-intra model for each product category for the MASE for one to eight-week forecast horizon



|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Category/MASE | ADL-intra-EWC | ADL-intra-IC | Category/MASE | ADL-intra-EWC | ADL-intra-IC |
| Beer | 0.12% | -0.58% | Mayonnaise | 0.07% | 0.58% |
| Blades | 0.20% | 2.19% | Milk | 1.04% | 6.25% |
| Carbonated Beverages | 0.40% | 0.10% | Mustard & Ketchup | 0.64% | -1.04% |
| Cigarette | 0.17% | 1.29% | Peanut butter | -0.15% | 5.11% |
| Coffee | -0.01% | 0.38% | Photo | 1.16% | 0.20% |
| Cold Cereal | 0.11% | -2.29% | Salty snacks | 0.02% | 0.25% |
| Deodorant | -0.01% | 1.74% | Shampoo | 0.38% | 1.56% |
| Face Tissue | 1.80% | -0.47% | Soup | 1.03% | -3.29% |
| Frozen Dinner | -0.67% | -0.70% | Spaghetti sauce | 1.61% | 1.67% |
| Frozen pizza | -1.71% | -1.73% | Sugar substitutes | 0.39% | 3.41% |
| Household Cleaner | 1.25% | 0.72% | Toilet Tissue | 0.04% | 2.45% |
| Hotdog | -0.44% | -4.05% | Toothbrush | -0.02% | -2.12% |
| Laundry Detergent | 0.43% | 0.62% | Toothpaste | 1.66% | -1.80% |
| Margarine/Butter | -0.57% | -0.76% | Yogurt | 1.78% | 4.47% |



Figure 3. Compare three models with the ADL-intra model for six product categories: results at SKU level, for the MASE, and for one to eight-week forecast horizon.



The box widths are proportionate to the number of SKU’s for each product category. The square symbols, which are joined by lines for illustration, indicates the group means.

1. the ADL-intra-EWC model (b) the ADL-intra-IC model,

## Exploring the determinants of the forecasting improvement

The results in Table 6 show that our proposed models generate more accurate forecasts especially for some product categories (e.g., Yogurt, Milk, Toilet Tissue etc.). We further explore the determinants of the improvement of the forecasting performance of our proposed models. This provides insights into for what types of SKUs we may get most benefit by using the proposed models. We consider the following data characteristics as potential determinants: 1) basic statistical measures for both the prices and sales variables including the average, standard deviation, skewness, range, kurtosis, and coefficient of variation; 2) the frequency of the feature and display promotions for each SKU; 3) more advanced statistical measures suggested by Fildes (1992). For example, 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 . 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) approximates 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 construct five orthogonal factors to represent the information originally contained in the fourteen explanatory variables described above, which mitigates the issue of multicollinearity[[15]](#footnote-23). Table 6 shows the correlation between the original fourteen explanatory variables and the constructed factors[[16]](#footnote-24). We interpret factor 1 as “Outliers and general variations”, factor 2 as “Sales level and variation”, factor 3 as “Central tendency of sales”, factor 4 as “Price level and variation”, and factor 5 as “Randomness and growth”. We regress the percentage improvement by the models based on these five factors at SKU level. For robustness, we construct the model with and without dummy variables for product categories.

Table 6. The pattern of the factors

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Factor1 | Factor2 | Factor3 | Factor4 | Factor5 |
| Proportion of outliers | 0.855 |  |  |  |  |
| Coefficient of variation (price) | 0.759 |  |  |  |  |
| Coefficient of variation (sales) | 0.714 |  |  |  |  |
| Frequency of Feature | 0.703 |  |  |  |  |
| Standard deviation of sales |  | 0.964 |  |  |  |
| Range of sales |  | 0.929 |  |  |  |
| Average sales |  | 0.807 |  |  |  |
| Frequency of Display |  | 0.281 |  |  |  |
| Kurtosis of sales |  |  | 0.973 |  |  |
| Skewness of sales |  |  | 0.881 |  |  |
| Standard deviation of price |  |  |  | 0.987 |  |
| Average price |  |  |  | 0.831 |  |
| Randomness |  |  |  |  | 0.992 |
| Trend |  |  |  |  | 0.703 |
|  |  |  |  |  |  |
|  |  |  |  |  |  |



Table 7 The determinants of reductions of the MASE for one to eight weeks ahead horizon

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| parameter estimate for the model without category dummy variables | | | | | | | | |
| Horizon = 8 | ADL-intra-EWC | | ADL-own-EWC | | ADL-intra-IC | | ADL-own-IC | |
| Parameter/estimate and p-values | Estimate | P-value | Estimate | P-value | Estimate | P-value | Estimate | P-value |
| Outliers and promotional variations | 0.07 | 0.434 | 0.11 | 0.303 | -1.09 | 0.000 | -1.45 | 0.000 |
| Sales level and variation | 0.12 | 0.173 | 0.16 | 0.105 | -0.21 | 0.340 | -0.93 | 0.000 |
| Central tendency of sales | -0.06 | 0.460 | -0.07 | 0.511 | -0.68 | 0.002 | -0.84 | 0.001 |
| Price level and variation | -0.12 | 0.149 | -0.17 | 0.092 | 0.07 | 0.742 | -0.09 | 0.721 |
| Randomness and growth | 0.38 | 0.000 | 0.45 | 0.000 | 0.63 | 0.004 | 0.80 | 0.001 |
| Intercept | 0.30 | 0.001 | 0.37 | 0.000 | -0.38 | 0.082 | -0.46 | 0.060 |



Table 7 reports the estimated parameters of the regression models for the percentage reductions of the MASE for one to eight weeks ahead horizon[[17]](#footnote-25). Specifically, the dependent variables are the percentage reductions of the MASE by the ADL-intra-EWC model or the ADL-intra-IC model compared to the ADL-intra model, and the percentage reductions of the MASE by the ADL-own-EWC model or the ADL-own-IC model compared to the ADL-intra model. For the percentage reduction of the MASE by the ADL-intra-EWC model and by the ADL-intra-IC model, the estimates of the parameter “Randomness and growth” are positive (e.g., 0.38 and 0.63) and statistically significant (e.g., a p-values smaller than 0.001, displayed as “0.000”, and 0.004). This indicates that, , using the ADL-intra-EWC model and the ADL-intra-IC model lead to higher percentage reductions of the MASE for the SKU’s with higher randomness and trend (e.g., being difficult to forecast and exhibit a trend in sales), possibly because the SKUs of this type are more heavily associated with the structural change problem and forecast bias. The results also indicate that the ADL-intra-IC model and the ADL-own-IC model tend to have disadvantages compared to the ADL-intra model and the ADL-own model respectively for the SKUs with a higher proportion of outliers, possibly because that the ‘intercept correction’ for the bias can be submerged by high sales spikes which are usually ‘outliers’ and caused by promotions. The results here may indicate a possibility of determining the optimal sales forecasting method specifically for an SKU. However, the findings are only exploratory, and we leave it to future research.

## Conclusions, limitations and future research



Grocery retailers need to effectively manage their inventory and, to achieve that, they rely on effective forecasting models and welcome new approaches that will enable them to improve their current practices. Previous studies focus on incorporating additional information (e.g., Gür Ali et al., 2009; Huang et al., 2014; Ma et al., 2016). However, they all assume that the effect of the marketing activities such as price reductions and feature and display promotions remain unchanged over time. This assumption may not hold because of the impact of external factors including the change in economic conditions, the change in consumer taste, and new competition entry etc. The data on these factors are not always available, or, we do not actually know which of these external factors are causing the structural change. As a result, conventional models may be subject to the problem of structural change and potentially generate biased and less accurate forecasts.

Table 8. The percentage reductions for different error measures

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | MAE | SMAPE | MASE | AvgRelMAE | scaled MSE |
| ADL-own-EWC | -31.6% | -13.4% | -10.2% | -13.0% | -29.7% |
| ADL-own-IC | -29.2% | -13.3% | -10.5% | -12.7% | -28.6% |
| ADL-intra-EWC | -33.0% | -14.0% | -10.5% | -13.4% | -30.7% |
| ADL-intra-IC | -32.0% | -13.9% | -10.6% | -13.2% | -29.8% |

Our research focuses on how to mitigate the problem based on the data of marketing activities which retailers typically have control over. We propose models which take into account the potential forecast bias caused by structural change. The ADL-intra-EWC model generates forecasts which are the combination of various sets of forecasts by the ADL-intra model with different estimation windows under a condition when structural changes are detected. It tries to achieve an effective trade-off between the forecast bias and the forecast error variance. The ADL-intra-IC model tries to offset the potential forecast bias by adding the estimated forecast bias back to the error term at a cost of inflated forecast error variance when structural changes are detected. In the retailer context, the data at SKU level exhibit very different characteristics across different product categories and usually exhibit high levels of variations. Based on our empirical results, we find that these models outperform the ADL-intra model across all the 28 product categories. Table 8 shows the percentage reductions of various error measures by the ADL-intra-EWC model and the ADL-intra-IC model for one to eight-week forecast horizon[[18]](#footnote-26). Specifically, by using the ADL-intra-EWC model we can reduce the MASE by 10.6% compared to the current practice Base-lift method. Therefore, our study provides retailers more effective forecasting methods.

In this study, we have also evaluated the forecasting performance of the ADL-own-EWC model and the ADL-own-IC model. These methods are especially valuable to manufacturers since, under certain circumstances, competitive promotional information may not be available (M. Ali & Boylan, 2011; M. M. Ali, Babai, Boylan, & Syntetos, 2017). In our study, the ADL-own -EWC model and the ADL-own -IC model both outperform the ADL-own model across all the product categories. Table 8 also shows the percentage reductions of various error measures by the ADL-own-EWC model and the ADL-own-IC model for one to eight-week forecast horizon. Therefore, our study provides also manufacturers more effective forecasting methods.

In our study, the ADL-intra-EWC model has the best performance for the promoted forecast period while the ADL-intra-IC model dominates the non-promoted forecast period. We, therefore, forge a model combining the ADL-intra-EWC model and the ADL-intra-IC model based on if the focal product is being promoted. The resulted ADL-EWC-IC model thus generates the most accurate forecasts across all the candidate models for the original data and even for previously unseen data from another set of 28 stores.

We also explore the relationship between the relative advantage of the proposed models and the data characteristics of the product SKU. We find that the models with the estimation window combining method (e.g., the ADL-intra-EWC model and the ADL-own-EWC model) have better forecasting performances compared to their counterparts for the SKU’s with high randomness and trend, while the models with intercept corrections (e.g., the ADL-intra-IC model, the ADL-own-IC model, and the ADL-EWC-IC model) tend to have more advantages compared to their counterparts for the SKU’s with high randomness and trend, with a low proportion of outliers and low level of general variations, and with a low level of sales central tendency.

The approach that we propose in this study is new to the area of retailer product sales forecasting, but we have also identified some areas where we feel further improvements could be beneficial. For example, there are studies which use splines smoothing method to model seasonality, which were found useful for electricity data (Nagbe, Cugliari, & Jacques, 2018). For the EWC method, we combine five sets of forecasts based on ten different estimation windows using equal weights. The forecasting performance may potentially be improved by changing the number of the estimation windows, by changing the minimum length of the estimation windows, and by exploring alternative forecasting combination schemes (e.g., based on k-fold evaluation). For the IC method, Clements and Hendry (1999) summarize various correction schemes each of which may have different effects on the trade-off between the bias and the error variance[[19]](#footnote-27). Furthermore, Ma et al. (2016) propose models which integrate both the intra- and the inter-category promotional information. Thus, we may further investigate how we can improve the forecasting performance with both the intra- and the inter-category promotional information while taking into account the structural change problem. A method alternative to the ADL-intra-EWC method and the ADL-intra-IC method is to directly model the changing process of the effect of the marketing activities. For example, the time-varying parameter model. However, a disadvantage of this method is that we need to make very strong assumptions of how the effect of the marketing activities change overtime. e.g., Foekens, Leeflang, and Wittink (1999) modelled the effect of the marketing activities a linear function of previous promotional activities. The model has a sophisticated structure and was not developed for forecasting. Therefore, we leave the exploration of the potential of this type of model to future research. assumed that the effect of the marketing activities is a linear function of previous promotional activities. In summary, the models we proposed in this study produce consistently accurate forecasts. They also suffice 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.

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2. The term ‘structural change’ is also used interchangeably with the term of ‘structural break’ in the literature. In this study, we use the term “structural change” as in the retail context we expect the effect of the marketing activities to change gradually rather than in a sudden and abrupt way. We thank one of the anonymous reviewers to point this out. [↑](#footnote-ref-2)
3. We demonstrate a simple example with an intercept using simulation in later sections. [↑](#footnote-ref-3)
4. In Appendix B in the supplementary material, we demonstrate how we can achieve more accurate forecasts with the IC method and the EWC method using simulation examples. [↑](#footnote-ref-7)
5. We select the SKUs with positive movements for at least 90% of the time. [↑](#footnote-ref-8)
6. In Figure 6, 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. [↑](#footnote-ref-9)
7. Alternative schemes including information criteria are also available (e.g., Huang et al., 2014). We find little difference between the results by these schemes. [↑](#footnote-ref-10)
8. 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-11)
9. We replicate the whole evaluation where we conduct the sequential Chow test for the central 70% of weeks and the results are consistent. [↑](#footnote-ref-12)
10. The ADL-intra-IC model can be implemented analogously when the EWC method is replaced by the IC method if we confirm that the model is subject to structrual change. [↑](#footnote-ref-13)
11. We conduct the DM test based on all the error measures except the AvgRelMAE which does not fit into the framework of the DM test. [↑](#footnote-ref-16)
12. We refer these two periods as the promoted period and non-promoted period respectively. [↑](#footnote-ref-18)
13. The results for other forecasting horizons are similar and are not shown here for simplicity. [↑](#footnote-ref-19)
14. Other models including the Base-lift method, the ADL-own model, the ADL-own-EWC model, and the ADL-own-IC model are all outperformed by the four models in Table 5 and we do not show them for simplicity. [↑](#footnote-ref-20)
15. We choose to retain five factors based on the Scree plot and 77% of the original information have been retained. [↑](#footnote-ref-23)
16. In Table 6, we omit all small values for simplicity. [↑](#footnote-ref-24)
17. The results are consistent for other error measures and forecast horizons and also for an alternative regression model which includes dummy variables for each product category. [↑](#footnote-ref-25)
18. The results are similar for other forecast horizons. [↑](#footnote-ref-26)
19. For example, one of the alternative is to first 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 adjusted, and so forth. [↑](#footnote-ref-27)