**Forecasting Retailer Product Sales at the SKU level with the impact by the unobserved factors**

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Abstract

Retailers need accurate sales forecasts for their inventory management. In this study, we propose more effective methods to generate more accurate forecasts by taking into account the unobserved change in the effectiveness of the price and promotional activities. We implement the intercept correction method and the estimation window combining method to mitigate the issue of structural breaks and forecast bias. We evaluate our models for retailer products at the SKU level and we found our proposed new models with intercept corrections with the best forecasting performance.

Check self- plagiarism (to rephrase) with previous two papers.

Key words:

Sales Forecasting, Marketing analytics, Promotion

1. **Introduction**

Grocery retailers rely on accurate sales forecasts at the SKU level for their inventory management. Poor forecasts of product sales lead to out-of-stock conditions or over-stock conditions. When the product is out-of-stock, retailers lose profit not only lose profits but also dissatisfy customers. In the long term, retailers may see customers switching to other retail chains and never return ([Corsten and Gruen 2003](#_ENREF_21)). Retailers may intentionally over-stock, which however significantly raises inventory costs (e.g., capital cost, warehousing, and deterioration etc.) and reduces profits ([Cooper, Baron et al. 1999](#_ENREF_19)). In the year of 2014, Retailers in North American lost $634.1 billion due to out-of-stocks and $471.9 billion due to over-stocks ([OrderDynamics 2015](#_ENREF_60)).

In practice, many retailers forecast their product sales at the SKU level using a two-stage ‘base-lift’ approach. The products are forecasted separately depending on whether or not the focal product is being promoted. The sales for the time period when the product is being promoted will be adjusted by brand/category managers based on their experience. In the literature, some studies focus on developing a procedure for managers to improve their judgments (e.g., [Goodwin 2002](#_ENREF_30), [Fildes, Nikolopoulos et al. 2008](#_ENREF_27), [Nikolopoulos 2010](#_ENREF_59)) or proposed models to determine the optimal judgment based on the data ([Cooper, Baron et al. 1999](#_ENREF_19), [Cooper and Giuffrida 2000](#_ENREF_20), [Trusov, Bodapati et al. 2006](#_ENREF_66)). Other studies directly generate the final forecasts of the product sales by proposing models with sophisticated structures and with additional information. For example, [Gür Ali, et al. (2009](#_ENREF_30)) proposed the regression tree model with a range of variables constructed from the sales, price, and promotion of the focal product in the previous time periods. [Huang, Fildes et al. (2014)](#_ENREF_35) proposed general-to-specific Autoregressive Distributed Lag models which incorporate the promotional information of not only the focal product but also of the competitive products within the same product category. [Ma, Fildes et al. (2016)](#_ENREF_48) further integrated the promotional information from the products not only within the same product categories but also across other related product categories.

One of the limitations for these studies is that they assume invariant effectiveness of the marketing activities (e.g., price reductions and promotions). In practice, the effectiveness of price reductions and promotions may change due to many influencing factors including the change of economic conditions, the change of consumer tastes, and media habits, and new competitor entry etc. which are normally not observable or measurable ([Wildt 1976](#_ENREF_72), [Wildt and Winer 1983](#_ENREF_73)). Customers may become more price/deal sensitive during an economic crunch. It may become more difficult to attract customers using the same budget of promotions and advertising when a new competitor enters the market. For example, the German low-price retail chain Aldi has opened more than 400 stores in the United States just in the year of 2014, which leaves great pressures to other existing retail chains ([Loeb 2015](#_ENREF_47)).

Under such circumstance, conventional models which assume no change of the effectiveness of the marketing variables may potentially be subject to structural break which is defined as large changes in the parameter coefficients of the model ([Allen and Fildes 2001](#_ENREF_3), [Armstrong 2001](#_ENREF_8)). The model which is subject to structural break may generate biased and less accurate forecasts. The issue of structural break and the opportunity to improve forecasting performance by mitigating the consequent forecast bias have been addressed in the macroeconomics literature ([see Clements and Hendry 1994](#_ENREF_16)). In this study, we aim to propose more effective forecasting models which generate more accurate forecasts by mitigating the forecast bias due to the structural break. The research problem is challenging for the following reasons: 1) the product sales data at the disaggregate SKU level contains more variations compared to macroeconomic data. It is possible for the improved forecasting accuracy to submerged in the noise of the data. 2) the methods we propose in the study try to mitigate the forecast bias at a cost of increased forecasting error variance which also affect the forecasting accuracy. Therefore, in the retailing context, whether or not the mitigation of potential forecast bias due to structural break could lead to higher forecasting accuracy becomes an empirical question.

Our research is significant for the following contribution: 1) unlike any earlier study which contributes higher forecasting accuracy by incorporating additional information (e.g., the promotional information of other products from the same product category or other related product categories), our methods focus on how the information can be effectively utilized by taking into account the issue of structural break and forecast bias potentially due to the change of the effectiveness of the marketing activities. 2) Our methods have superior forecasting performance compared to conventional models which assumes no change in the effectiveness of the marketing activities including prices and promotions. 3) Methodologically our study provides an evaluation of various methods which offers operational guidance to not only retailers as to how to produce more accurate forecasts but also manufacturers when competitive promotional information become not accessible. 4) we evaluate the forecasting performance of the models for 1834 SKUs from 30 product categories in 30 retail stores, which not only provide robust results but also allows us to further explore the relationship between the improved forecasting accuracy and the characteristics of the data series for each SKU. Our results suggest that it is more likely to obtained higher forecasting accuracy by implementing our methods for the data series which are difficult to forecast (e.g., with high variations in sales and price and high percentage of outliers).

The remainder of the paper is arranged as follows: section 2 summarizes previous research findings. Section 3 explains the issue of structural break and the subsequent forecast bias when conventional models overlook the change in the effectiveness of marketing activities. In section 4, we propose our models which may potentially improve the forecasting accuracy by mitigating the forecast bias due to structural break. Section 5 and section 6 explore the data and introduce the candidate models. Section 7 describes the design of the model evaluation. Section 8 summarizes and discusses the evaluation results. In section 9, we draw conclusions. We make recommendations for both manufacturers and retailers, address research limitations, and highlight directions for future research.

1. **Literature review**

2.1 Forecasting retailer product sales at the SKU level

In practice, many retailers produce forecasts for their product sales at the SKU level using a two stage ‘base-lift’ approach. They initially generate the ‘baseline’ forecasts using simple univariate methods with the data excluding the time periods when the focal product is being promoted. Then they make adjustments to the baseline forecasts if there is an incoming promotional event in the future ([Fildes, Nikolopoulos et al. 2008](#_ENREF_27), [Fildes, Goodwin et al. 2009](#_ENREF_26)). The adjustments are usually made by brand/category managers and therefore subject to human cognitive bias ([Fildes, Goodwin et al. 2009](#_ENREF_26)). A stream of studies has been devoted to helping managers with their adjustment procedure ([Fildes and Goodwin 2007](#_ENREF_25), [Arenas, Pedregal et al. 2013](#_ENREF_7)). Some other studies try to improve the adjustment with model-based forecasting systems. For example, they may estimate the ‘lift’ effect by the promotional event based on historical information related to previous promotions, store/category features, and manufacturers etc. ([Cooper, Baron et al. 1999](#_ENREF_19), [Cooper and Giuffrida 2000](#_ENREF_20), [Trusov, Bodapati et al. 2006](#_ENREF_66)). One of the common limitation for these methods of two stages is that they generate forecasts separately depending on whether or not the focal product is being promoted. Therefore, the information when the focal product is being promoted are inevitably overlooked when forecasting the sales of the product when the product is not being promoted, and vice versa.

Previous studies have also proposed holistic methods to forecast the grocery product sales at the same time. [Gür Ali, SayIn et al. (2009)](#_ENREF_31) evaluated the forecasting performance of the variants of support vector machine models and regression tree models. Their models incorporated a range of constructed variables based on the promotional information of the focal product. Divakar et al. (2005) proposed the CHAN4CAST system with models of a dynamic regression structure to forecast brand sales for manufacturers/channels. [Huang, Fildes et al. (2014)](#_ENREF_35) proposed to forecast retailer product sales using the general-to-specific Autoregressive Distributed Lag (ADL) model with selected competitive promotional information within the same product category. The competitive promotional information were selected with variable selection methods (e.g., the stepwise selection and the LASSO algorithm) or constructed using principle component analysis. [Ma, Fildes et al. (2016)](#_ENREF_48) further integrated the promotional information not only from the same category of the focal product but also from other related categories. They resorted to Granger causality test to indicate the relevant product categories and then relied on the LASSO algorithm not only as a variable selection procedure but also as a model simplification strategy.

[perhaps say more about the advantages of Huang et al 2014 and Ma et al 2016]

2.2 The changing effectiveness of marketing activities

Price reductions and promotions have significant impact on product sales. For example, price reductions and promotions significantly increase short-term sales of the focal product ([Blattberg, Briesch et al. 1995](#_ENREF_10)). Price reductions and promotions have positive (negative) impact on complementary (competitive) products ([Wittink, Addona et al. 1988](#_ENREF_75), [Dekimpe, Hanssens et al. 1999](#_ENREF_23), [Andrews, Currim et al. 2008](#_ENREF_6)). The impact of price reductions and promotions can be asymmetrical regarding different brands ([Wedel and Zhang 2004](#_ENREF_70)). Price reductions and promotions may either accelerate customers’ consumption or postpone their purchases if customers anticipate future promotional events ([Van Heerde, Gupta et al. 2003](#_ENREF_67), [Mace and Neslin 2004](#_ENREF_49)). The findings by these studies have been addressed by the most recent forecasting models (e.g., Gur Ali et al, 2009; Huang et al, 2014; Ma et al, 2016).

However, all the forecasting methods introduced in section 2.1 all presume invariant effectiveness of the marketing activities (e.g., price reductions, display promotions, and feature advertising). The potential change of the effectiveness of the marketing activities has been intensively explored in the literature (e.g. [Little 1966](#_ENREF_46), [Morrison 1966](#_ENREF_54), [Myers and Nicosia 1970](#_ENREF_57), [Myers 1971](#_ENREF_56), [Houston and Weiss 1975](#_ENREF_34), [Monroe and Guiltinan 1975](#_ENREF_53), [Moinpour, McCullough et al. 1976](#_ENREF_52), [Wildt 1976](#_ENREF_72), [Wichern and Jones 1977](#_ENREF_71), [Winer 1979](#_ENREF_74), [Mahajan, Bretschneider et al. 1980](#_ENREF_50)). The effectiveness of the marketing activities may change because of various reasons including the change in economic condition, legislation, consumer tastes, media habits, and advertising etc. ([Wildt 1976](#_ENREF_72), [Wildt and Winer 1983](#_ENREF_73)). The effectiveness of promotions may change during the different stages of the product life cycle ([Mahajan, Bretschneider et al. 1980](#_ENREF_50)). Marketing theory suggests that the elasticity of the marketing activities will tend to vary at each stage of the product life cycle ([Kotler 1997](#_ENREF_41)). The effectiveness of the marketing activities may change due to new competition. The introduction of new products (especially the store-owned brand) decrease promotional elasticities of premium national brands and increase promotional elasticities of the second tier national brands ([Nijs, Dekimpe et al. 2001](#_ENREF_58), [Van Heerde, Srinivasan et al. 2008](#_ENREF_68)). Evidence also suggests that intensive price reductions and promotions may decrease consumers responsiveness to these marketing activities by reducing their reference price ([Lattin and Bucklin 1989](#_ENREF_42), [Lichtenstein and Bearden 1989](#_ENREF_45), [Kalwani, Yim et al. 1990](#_ENREF_38), [Kalwani and Yim 1992](#_ENREF_37), [Foekens, Leeflang et al. 1999](#_ENREF_29), [Kopalle, Mela et al. 1999](#_ENREF_39), [Levy, Grewal et al. 2004](#_ENREF_44)). [Verhoef, Neslin et al. (2007)](#_ENREF_69) found the effectiveness of the marketing activities may be (negatively) affected by the introduction of a new distribution channel (e.g., online website).

Evidence also shows that consumers’ response to price reductions and promotions by competitive products may be affected by the introduction and termination of a loyalty programme as consumers included in the loyalty program may find the promotions of alternative brands less or more attractive. ([Melnyk and Bijmolt 2007](#_ENREF_51)). [Leenheer, van Heerde et al. (2007)](#_ENREF_43).

Some studies tried to model the change of the effectiveness of the marekting actitives. Foekens, S.H. Leeflang et al. ([1999](#_ENREF_29)) proposed an extended SCAN\*PRO model with time-varying parameters for the marketing activities including prices and promotions. In their model, the parameters of the marketing activities are modelled as functions of previous promotional information of the focal brand and other competitive brands. The model tried to capture how the effect of the marketing activities change over time, which may benefit managers with more effective budget allocation. Kopalle, Mela et al. ([1999](#_ENREF_40)) also proposed extensions of the SCAN\*PRO model to investigate the changing effectiveness of promotions on the baseline sales. These models, however, are all descriptive models and are not used in forecasting retailer product sales.

1. **The issue of structural break and potential forecast bias**

When the effectiveness of marketing activities on product sales change, as explained in the previous section, conventional models will be subject to structural break which is defined as large changes in the model’s parameters ([Allen and Fildes 2001](#_ENREF_3), [Armstrong 2001](#_ENREF_8)). The parameter estimates of the models then becomes the weighted average of the true parameters before and after the structural break. The forecasts generated by the model will potentially be biased and less accurate[[1]](#footnote-1). The impact of the structural break on the model’s forecasting performance has been addressed by many studies in the macroeconomics literature (e.g. [Cooper and Nelson 1975](#_ENREF_18), [Muellbauer 1994](#_ENREF_55), [Hendry 1995](#_ENREF_32), [Clements and Hendry 1999](#_ENREF_17), [Pesaran and Timmermann 2007](#_ENREF_61), [Castle, Doornik et al. 2008](#_ENREF_12)). [Pesaran and Timmermann (2005)](#_ENREF_63) provided an example using a simple regression model with a single structural break to indicate how structural break leads to forecast bias. In the retailing context, suppose that we have the sales and price information of the focal product from week 1 to week *T,* i.e.,, and we presume that the sales are driven by prices. We may assume that there is a structural break at week (where ), and the parameter of the price variable change from to after . In practice, this may be caused by the impact of a new brand entry, a new advertisement by other existing brands, or even the change of the temperature (e.g., for ice cream products) etc. which we cannot measure or do not have available data. Thus the unobservable real demand as follows:

where, is an indicator which equals to 1 before week and 0 otherwise. and are respectively the sales and the price of the product at week *t*. We assume that retailers do not change product price based on their short-term sales, thus we consider to be strictly exogenous[[2]](#footnote-2). and are the true parameters before and after the structural break at week . is the error term. when and when .

We may estimate a model with a functional form which is congruent with the demand (e.g., ) where the estimation window starts before the structural break, e.g., at week *m* . Thus the OLS estimate for the model based on the data [*m*,T] becomes:

where and are the matrices for the sales and price respectively for the time period from week *m* to week T. We assume no structural break after week T, and the true demand after week T remains as . Therefore, the *h*-step ahead forecast error at week *T*+*h* (with *m* as the starting observation of the estimation window) can be represented as:

where , is the matrix for the error term at week .

Therefore, the forecast bias at week can be represented as , which is unequal to zero as .

The structural break can further lead to less accurate forecasts. We illustrate this using a simulation example. We construct an artificial variable to represent price. The values of are 2.99 for most of the observations but occasionally reduced to 2.29 or 1.99[[3]](#footnote-3). i.e., or 2.29 or 1.99. We assume that we have the data of 100 weeks and we need to generate the forecast for the last 25 weeks based on the data of the first 75 weeks. The product sales to be determined by the price with two structural breaks at week 25 and week 50 respectively. Thus the unobserved real demand can be represented as follows:

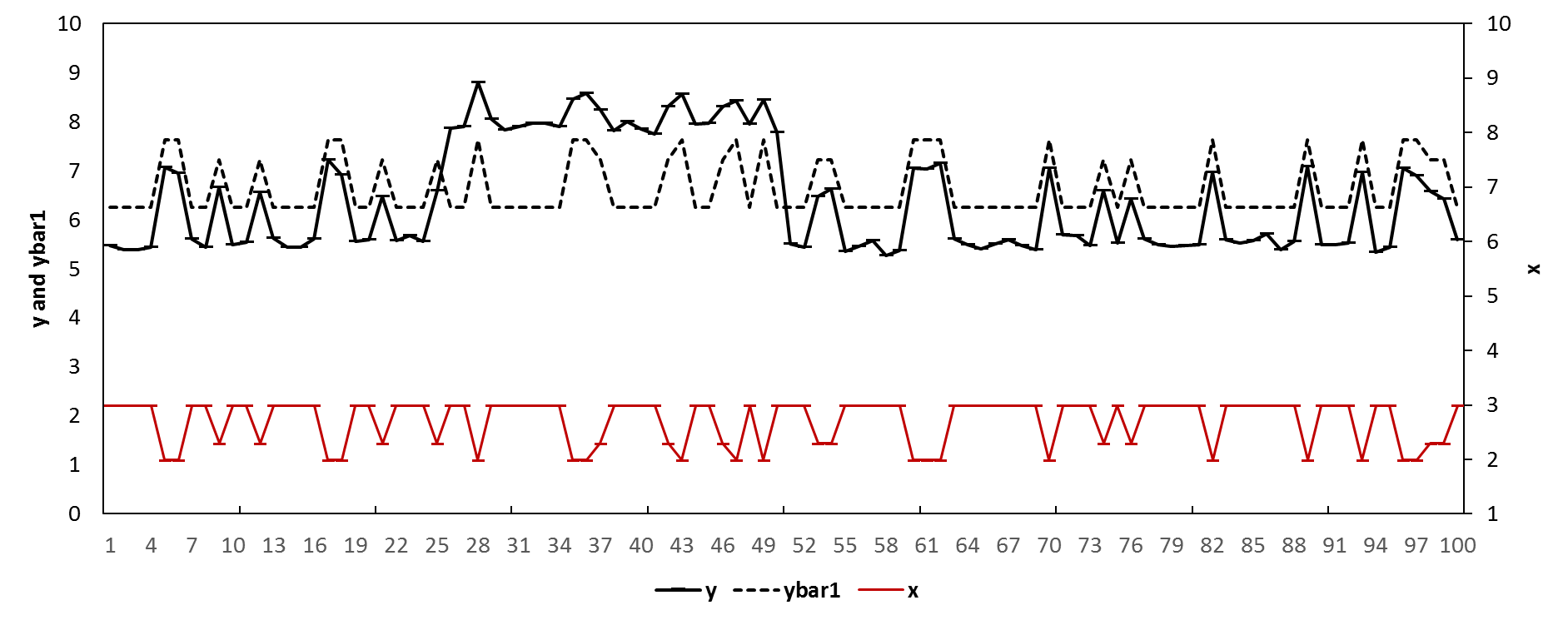
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where represents the sales at week t, represents the price at week t. is the error term. Therefore, the real demand may indicate that product sales increase after week 25 but also become less responsive to temporary price reductions after the break. This is reasonable especially for those products in the growth to mature stage in their product life cycle. After week 50, product sales decrease but become more responsive to temporary price reductions, which may simulate the situation of an economic crunch. The sales and price data from week 1 to week 100 are depicted in Figure 1 by the solid black line and the solid red line respectively.

Figure 1. Simulated sales with a structural break: model with full data



In Figure 1, the blue area represents the time period before the first structural break (e.g., week [1,25]), the yellow area represents the time period after the second structural break until the forecast origin (e.g., week [51, 75]), the green area represents the period between the two structural breaks (e.g., [26, 50]), and the red area represents the forecast period (e.g., week [76, 100]). Suppose we have the data from week 1 to week 75 and we want to forecast the product sales from week 76 to week 100. We may estimate the model with the function form as using the data from week 1 to week 75 while overlooking the changes of the effectiveness of the price at week 25 and week 50. Under such circumstance, we will have estimates as the weighted average of the true parameters in the three periods (e.g., blue, green, and yellow). As suggested by the graph, this would over-predict the product sales for the time period from week 1 to week 25, under-predict the product sales for the time period from week 26 to week 50, over-predict the product sales for the time period from week 51 to week 70, and finally would produce downwards-biased out-of-sample forecasts for the time period from week 76 to week 100. The predictions/forecasts are represented by the black dashed line (as *ybar1*) in Figure 1. Table 1 shows the forecasting performance of this model regarding various error measures (e.g., with MAE= 0.715, MSE= 0.520, MAPE= 12.2%, and SMAPE= 11.5%).

Alternatively, we may estimate the model exclusively using the data from week 51 to week 75 and generate unbiased forecasts, if we know there are structural breaks at week 25 and week 50. These unbiased forecasts are represented by the black dashed (as *ybar2*) line in Figure 2[[4]](#footnote-4). Table 1 shows the forecasting performance of the model which is estimated exclusively with post-break data (e.g., with MAE= 0.294, MSE= 0.184, MAPE= 5.0%, and SMAPE= 4.3%). The model exclusively estimated with post-break data outperforms the model estimated with all the data in the estimation sample. This indicate that the latter generates less accurate forecasts because of the structural break and forecast bias. However, in the retailing context. There are so many factors which may change the effectiveness of the price, as mentioned earlier in section 2.2. As a result, we are unable to observe the structural break at week 25 and week 50. For some occasions where structural breaks occur at the locations which are very close to the forecast origin, there will not be enough post-break observations to estimate the model.

Figure 2. Simulated sales with a structural break: model with post-break data

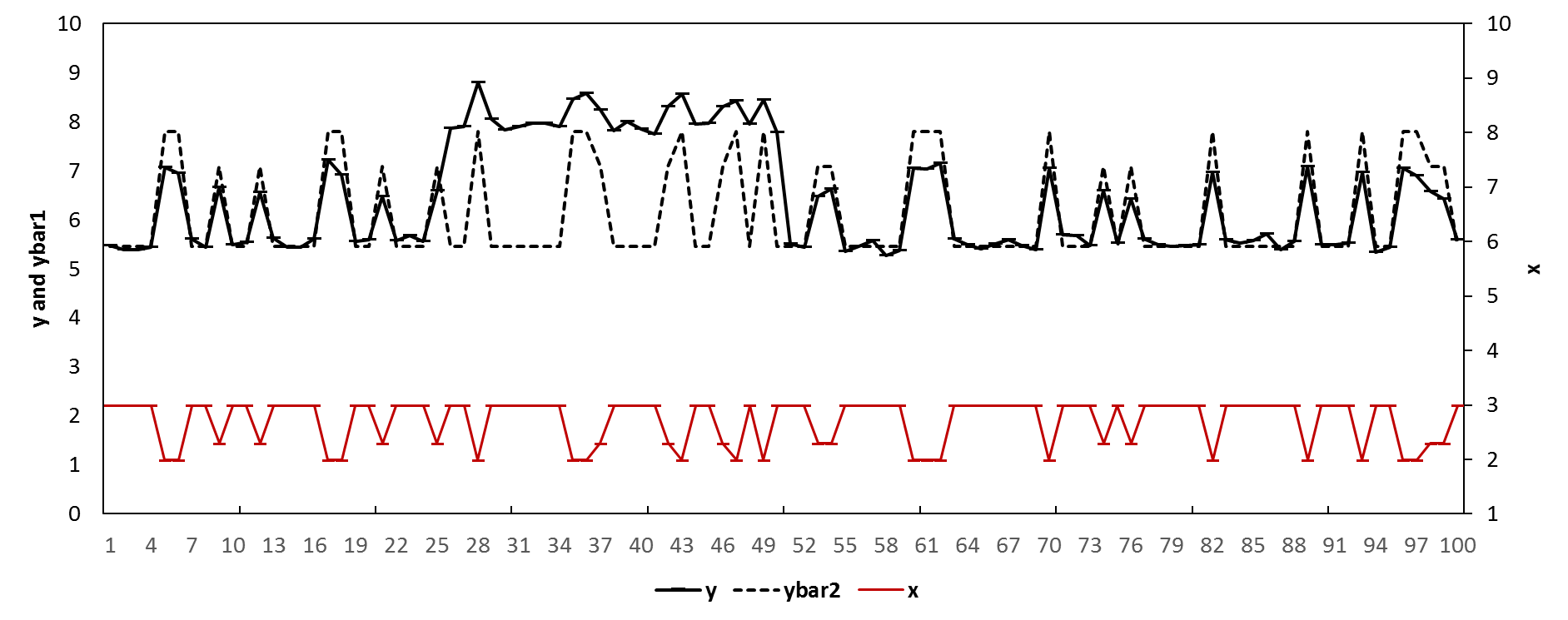


Table 1. The forecasting performance of different models in the simulation

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | MAE | MSE | MAPE | SMAPE |
| In Figure 1: Model with full data | 0.715 | 0.520 | 12.2% | 11.5% |
| In Figure 2: Model with Post-break data only | 0.294 | 0.184 | 5.0% | 4.3% |
| In Figure 3: Model with intercept correction | 0.101 | 0.015 | 1.7% | 1.8% |
| In Figure 4: Model with estimation window combining | 0.647 | 0.425 | 11.0% | 10.5% |

1. **Dealing with structural breaks**

4.1 The Intercept Correction method

One of the methods to deal with the forecast bias caused by structural break is the intercept correction method. The intercept correction method estimates the forecast bias and then offset the forecast bias (e.g., regime shifts) by specifying non-zero values for the model’s errors in the forecasting period ([Clements and Hendry 1994](#_ENREF_16), [Clements and Hendry 1999](#_ENREF_17), [Clark and McCracken 2007](#_ENREF_14)). The method may potentially improve the forecasting accuracy by mitigating the forecast bias through specify non-zero error terms but at the cost of inflated forecasting error variance ([Clements and Hendry 1999](#_ENREF_17)).

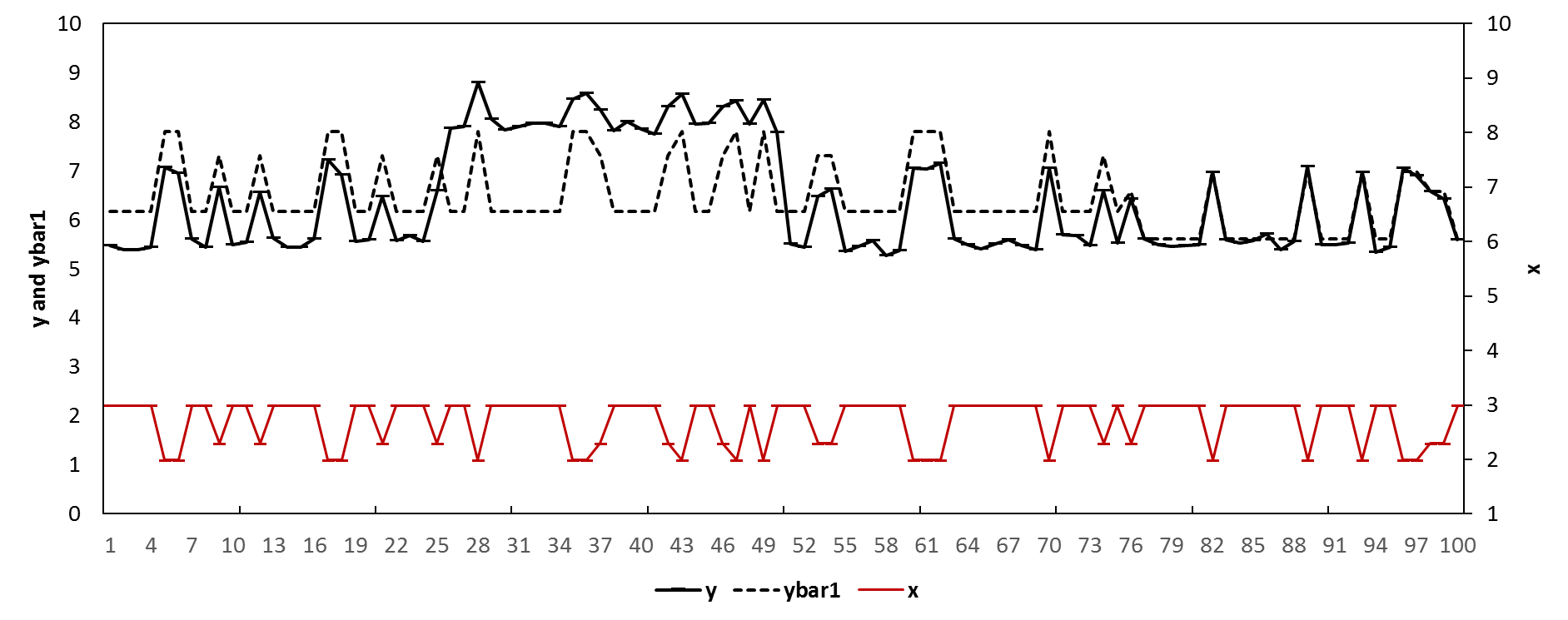
The IC method can be illustrated based on the same simulation example which is described in section 3. We assume that we have the congruent model as but with no prior knowledge related to the existence or the location of the structural break. A sequential [Chow (1960)](#_ENREF_13) test can be conducted for every observation in the whole estimation period[[5]](#footnote-5). The rejection of the null hypothesis of no structural break for any of the observation in the estimation sample would indicate that the model is subject to structural break (though it does not indicate how many structural breaks and their locations). Figure 4 shows the *p*-values of the sequential Chow test assuming there is one single structural break occurring at each week. The chow test rejects the null hypothesis of no structural break for some weeks (e.g., week 20) but fails to do so for some other weeks (e.g., week 35). Therefore, the results indicate that the model is subject to structural break with the estimation sample from week 1 to week 75, though do not indicate how many structural breaks and their locations[[6]](#footnote-6). More advanced statistic tests have been proposed to detect the locations of the structural breaks but they all need to assume additional priori knowledge such as the number of potential structural breaks ([Andrews 1993](#_ENREF_4), [Andrews and Ploberger 1994](#_ENREF_5), [Bai and Perron 2003](#_ENREF_9)).

Figure 4 P-values of the sequential Chow test



Therefore, we consider the model to be subject to structural break and we consider the forecasts as biased. We may estimate the forecast bias with different schemes. For example, as the predictive error at the forecast origin (i.e., , where *T* =75) or as the average value of an ad hoc number of predictive errors before the forecast origin (e.g. , where *i* can be arbitrarily chosen). In this example, we estimate the forecast bias as the average of the predictive errors for the most recent four observations in the estimation period. e.g., . We add the bias estimate back to the forecasts. e.g., , where represent the final ‘intercept corrected’ forecasts and are illustrated by the black dashed line (as *ybar3*) in Figure 5[[7]](#footnote-7). The results suggest that the intercept corrected model outperforms the original model (e.g., with MAE= 0.101, MSE= 0.015, MAPE= 1.7%, and SMAPE= 1.8%).

Figure 5. Simulated sales with a structural break: model with intercept correction



However, one of the limitations for the intercept correction method is that it heavily relies on the detection and the estimation of the forecasts bias. In the retailing context, the product sales at the SKU level have large variations, which may cause challenges to the estimation of the forecast bias. Also, the IC method mitigate the forecast bias by adding the estimated bias back to the forecasts but at a cost of inflated error variance of the forecasts (Clements and Hendry ([1999](#_ENREF_17)). Whether we can generate more accurate forecasts by implementing the IC method to conventional models for retailer product sales at the SKU level is an empirical question.

4.2 The Estimation Window Combining method

An alternative method to deal with the forecast bias due to structural break is the estimation window combining method ([Pesaran and Timmermann, 2005)](#_ENREF_63). The method does not estimate the forecast bias. It aims to take an effective trade-off between the forecast bias and the forecast error variance by combining the forecasts generated by the same model but with different estimation windows. In the simulation example in section 3, if we know the location of the structural break, we could estimate the model exclusively with the post-break data (e.g., the data from week 51 to week 75) and generate unbiased forecasts. In reality, we neither know whether structural breaks exist nor the location of the potential structural breaks. We may estimate the model with the most recent observations close to the forecast origin. It is less likely for the model to be subject to structural break as we keep *m* as large as possible (so that we discard more old data). When *m* by chance becomes larger than , the model will be estimated exclusively with post-break data and generate unbiased forecasts.

However, the reduction of the forecast bias comes with the cost of inflated forecasting error variance as we estimate the model with less information (e.g., the estimation sample is smaller). In the same example in section 3, the forecast error is:

The corresponding Mean Square Error (MSE), as one of the measures for the forecasting accuracy, at week can be represented as:

where

is interpreted as the squared forecast bias, and is interpreted as the efficiency term ( is the forecasting error variance). The change of the MSE for week when we include one more observation in the model estimation is:

where is the MSE for the model which is estimated with the data from week m-1 to week T. [Pesaran and Timmermann (2005)](#_ENREF_63) show that the bias term () (i.e., the change of the squared forecast bias) is always larger than or equal to zero (i.e., with one more observation before the structural break, the forecast will get more biased), but the sign for the efficiency term depends on the change of the error variance before and after the structural break (i.e., )). If (e.g., there are more post-break variations in the product sales which cannot be explained by the price variable), will be larger than or equal to , and the MSE may increase as both terms are non-negative. If (e.g., there are less variations in the product sales which cannot be explained by the price variable), may be smaller than or equal to . Under this condition, the MSE may either increase or decrease depending on how the non-negative squared bias term compares to the non-positive efficiency term. Therefore, when we exclude pre-break data in the model estimation, 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.

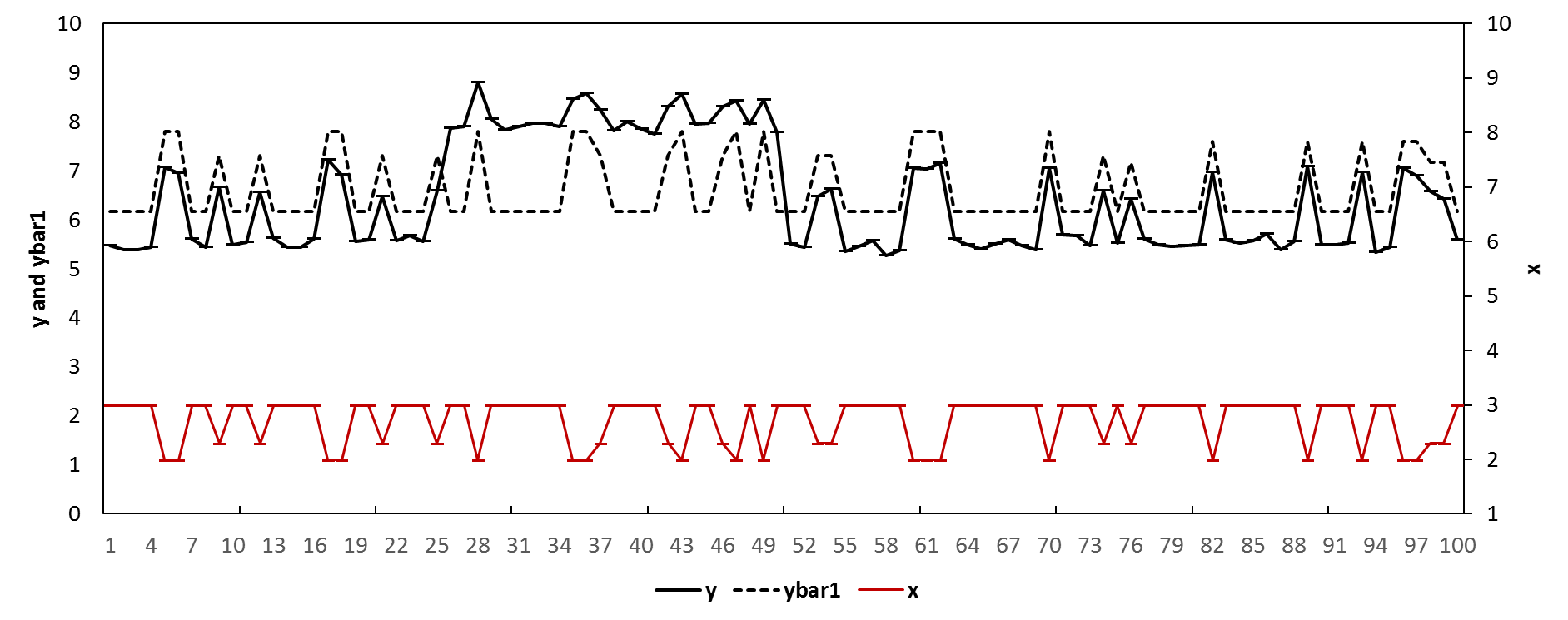
[Pesaran and Timmermann (2005)](#_ENREF_63) suggest combining the forecasts generated by the model of the same specification but estimated with different sample windows to potentially achieve an effective trade-off between the forecast bias the forecasting error variance. In this study, we combine these forecasts following a scheme of equal weights as combining forecasts with equal weights has been proved to be effective and easy to implement.([Clements and Hendry 1998](#_ENREF_15), [Fildes and Stekler 2002](#_ENREF_28), [Dekker, van Donselaar et al. 2004](#_ENREF_24), [Pesaran, Schuermann et al. 2009](#_ENREF_62)). Specifically, we 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 for the explanatory variables. We may then add one more observation to the estimation window and generate the 2nd set of the *h*-step-ahead forecast, e.g., and so forth. We have the set of the *h*-step-ahead forecasts, e.g., . Finally, we combine these () sets of *h*-step-ahead forecasts with equal weights:

where represents the final forecasts.

The method can be illustrated with the same simulation example in section 3. Suppose that there is a structural break within the estimation period but we do not know the date of the break is at week 31. We may estimate the model with different lengths of estimation windows and combine their forecasts. For example, we first estimate the model using the data from week 1 to week 75, and generate the forecasts for the period after week 75. We denote this set of forecasts as which are subject to the full bias. We then estimate the same model but using the data from week 2 to week 75, and generate forecasts for the period after week 75 and denote them as , and so forth. The forecasts such as will be less biased compared to but associated with inflated forecasting error variance because they were generated by models with less information. can be arbitrarily chosen given there are enough observations and variations to estimate the model. In this simulation, we choose *n* to be 60 and we combine the 60 sets of forecasts with equal weights. i.e.,. where is the forecasts by the EWC method for week *t*. are illustrated by the black dashed line in Figure 5. The forecasts are more accurate compared to the forecasts by the original model shown in Table 1. (e.g., 1.034 for MAE, 12.17% for MAPE, and 12.58% for SMAPE).

The EWC method relies on the trade-off between the reduced forecast bias and the inflated forecast error variance. In this study, we evaluate the empirical question that whether we can generate more accurate forecasts by implementing the EWC method to conventional models for retailer product sales at the SKU level.

Figure 6. Simulated sales with a structural break: model with estimation window combing



1. **The data**

In this study, we evaluate our models using the retail dataset made available by the IRI company. A description of the dataset can be found in [Bronnenberg, Kruger et al. (2008)](#_ENREF_11)[[8]](#footnote-8). The dataset contains weekly data at the SKU level including unit sales, price, features and displays etc. across over 30 product categories. We conduct our evaluation based on 1834 SKU’s with positive movements for at least 90% of time for 30 product categories from 30 stores. Table 2 shows the basic statistics for the selected SKU’s for each of the categories. The table indicates that some product categories (e.g., Carbonated beverages and Hotdog) have much higher promotional intensity compared to others (e.g., Margarine/Butter and Mayonnaise). Figure 6 depicts the sales data for a typical SKU in the Beer category. The product has occasional price reductions and feature/display events where the product sales exhibits spikes accordingly.

Table 2. Statistical description for the product in the categories

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Category | Price mean | Price standard deviation | Price coefficient of variation | Sales mean | Sales standard deviation | Sales coefficient of variation | Display percentage | Feature percentage | Outliers percentage | Randomness | Linear trend | Number of SKU's |
| Beer | 8.34 | 0.51 | 0.06 | 20.61 | 13.05 | 0.61 | 13.9% | 4.0% | 4.4% | 0.19 | -0.05 | 169 |
| Blades | 8.13 | 0.40 | 0.06 | 14.59 | 6.38 | 0.53 | 7.4% | 2.2% | 2.9% | 0.21 | -0.01 | 22 |
| Carbonated Beverages | 2.10 | 0.32 | 0.14 | 113.59 | 153.42 | 1.24 | 26.8% | 15.6% | 7.5% | 0.22 | 0.10 | 82 |
| Cigarette | 22.28 | 1.44 | 0.06 | 22.22 | 9.82 | 0.52 | 0.0% | 0.8% | 2.2% | 0.20 | 0.03 | 202 |
| Coffee | 5.19 | 0.67 | 0.12 | 14.50 | 10.19 | 0.68 | 5.2% | 2.9% | 5.0% | 0.15 | 0.04 | 86 |
| Coldcer | 3.45 | 0.61 | 0.18 | 70.70 | 127.58 | 1.68 | 4.0% | 18.1% | 14.1% | 0.24 | -0.36 | 125 |
| Deod | 2.66 | 0.19 | 0.07 | 6.94 | 4.42 | 0.65 | 4.1% | 5.2% | 4.4% | 0.09 | -0.07 | 126 |
| Factiss | 2.12 | 0.14 | 0.07 | 75.82 | 43.36 | 0.48 | 0.3% | 11.7% | 3.7% | 0.31 | 0.04 | 6 |
| Fzdinen | 2.04 | 0.31 | 0.15 | 43.79 | 58.50 | 1.31 | 5.3% | 23.7% | 14.9% | 0.16 | -0.10 | 87 |
| Frozen pizza | 3.44 | 0.31 | 0.09 | 31.17 | 28.92 | 0.94 | 8.9% | 9.1% | 8.9% | 0.13 | 0.08 | 147 |
| Household Cleaner | 2.48 | 0.16 | 0.06 | 29.92 | 10.63 | 0.39 | 0.3% | 3.6% | 3.0% | 0.15 | 0.02 | 18 |
| Hotdog | 3.99 | 0.67 | 0.19 | 68.63 | 110.50 | 1.41 | 13.2% | 15.6% | 12.3% | 0.16 | 0.02 | 35 |
| Laundry Detergent | 8.78 | 0.85 | 0.11 | 28.94 | 52.35 | 1.34 | 2.3% | 8.8% | 10.3% | 0.16 | -0.11 | 57 |
| Margarine/Butter | 1.95 | 0.21 | 0.12 | 71.36 | 57.56 | 0.66 | 0.1% | 6.3% | 8.0% | 0.18 | -0.03 | 36 |
| Mayonnaise | 2.97 | 0.21 | 0.07 | 79.74 | 29.69 | 0.41 | 3.0% | 0.4% | 2.1% | 0.39 | -0.20 | 22 |
| Milk | 2.45 | 0.16 | 0.07 | 222.26 | 49.37 | 0.38 | 2.1% | 1.8% | 2.7% | 0.35 | 0.01 | 30 |
| Mustard & Ketchup | 2.06 | 0.23 | 0.12 | 64.51 | 57.32 | 0.61 | 5.3% | 0.9% | 3.2% | 0.33 | -0.03 | 22 |
| Paptowl | 3.66 | 0.46 | 0.09 | 68.07 | 211.54 | 2.81 | 4.0% | 3.6% | 8.3% | 0.37 | -0.35 | 3 |
| Peanut butter | 3.67 | 0.32 | 0.10 | 34.23 | 19.01 | 0.42 | 3.2% | 0.6% | 2.2% | 0.27 | -0.21 | 15 |
| Photo | 7.18 | 0.97 | 0.12 | 9.19 | 6.85 | 0.71 | 4.6% | 5.1% | 4.3% | 0.27 | -0.19 | 13 |
| Razors | 5.60 | 0.33 | 0.06 | 7.99 | 6.07 | 0.66 | 22.6% | 2.1% | 3.6% | 0.32 | -0.24 | 4 |
| Salty snacks | 2.28 | 0.28 | 0.13 | 50.89 | 63.88 | 1.05 | 6.7% | 5.0% | 6.8% | 0.21 | -0.18 | 100 |
| Shamp | 3.51 | 0.32 | 0.11 | 9.89 | 8.00 | 0.74 | 12.8% | 7.1% | 6.1% | 0.11 | -0.14 | 70 |
| Soup | 1.54 | 0.18 | 0.12 | 61.59 | 71.38 | 1.01 | 1.2% | 9.7% | 9.0% | 0.20 | -0.09 | 139 |
| Spagsau | 2.43 | 0.15 | 0.07 | 39.14 | 36.22 | 0.80 | 1.6% | 6.5% | 5.6% | 0.24 | 0.06 | 51 |
| Sugar substitutes | 2.76 | 0.22 | 0.08 | 14.49 | 7.44 | 0.53 | 0.1% | 1.4% | 4.1% | 0.15 | -0.03 | 20 |
| Toilet Tissue | 5.42 | 0.65 | 0.12 | 89.13 | 164.24 | 1.57 | 4.3% | 8.3% | 9.6% | 0.30 | -0.25 | 20 |
| Toothbrush | 2.56 | 0.28 | 0.11 | 8.69 | 5.84 | 0.71 | 3.1% | 6.3% | 5.0% | 0.12 | -0.14 | 27 |
| Toothpaste | 2.77 | 0.26 | 0.10 | 35.49 | 65.65 | 1.42 | 11.0% | 12.5% | 12.4% | 0.10 | -0.03 | 25 |
| Yogurt | 1.13 | 0.07 | 0.07 | 115.07 | 48.15 | 0.43 | 0.7% | 6.3% | 3.6% | 0.25 | 0.21 | 75 |

Figure 7. Unit sales, price (in USD), and promotional events (feature and display) for an SKU in the Beer category at the store level.



1. **Models**

In this study, we include the base-lift method as the benchmark model. This method has been widely used by retailers to forecast product sales at the SKU level (Cooper et al., 1999; Huang et al., 2014). The method generates baseline forecasts using simple exponential smoothing method with data when there is no promotion for the focal product. It then makes adjustments for any incoming promotional event based on the lift effect by the most recent promotional event. The method can be represented as follows:

where is the final forecast for week *t* by the base-lift method, is the baseline forecast for week , is the actual sales for the previous week when the focal product is not being promoted, is the parameter for the simple exponential smoothing model. The adjustment is calculated as the increased sales by the most recent promotional event for the focal product.

We also include two autoregressive distributed lag (ADL) models which were introduced by Huang et al. (2014). The ADL model captures the dynamic effects of price reductions and promotional events with parsimonious specifications. The first ADL model is the ADL model initially constructed with the dynamic terms of the price and promotional information of the focal product (we refer this model as the ADL-own model thereafter). We initially construct the following model:

where:

is the log sales of the focal product at week

is the week number which captures the time trend

is the log price of the focal product at week

is the promotional index of 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 *[[9]](#footnote-9)*

are the parameters  
 is the error term and we assume

is the order of the lags and is set to as 2.

We then reduce the model with the Least Absolute Shrinkage and Selection Operator (LASSO) algorithm following Ma et al. (2016). The LASSO algorithm is a regularization algorithm which put a constraint to the sum of the absolute values of all the parameter coefficients of the initial ADL model ([Tibshirani 1996](#_ENREF_65)). It can be represented as follows:

where

is the vector of observations on the dependent variable  
 represents explanatory variables included in the initial ADL model

*u* is the identically distributed random error

is the vector of the parameter coefficients  
*N* is the number of parameters  
 is the shrinkage factor which equals to the sum of all the parameter coefficients.

The initial model will be reduced when some of the parameter coefficients are pushed towards zeros by the constraint. We control the model reduction process using a shrinkage factor based on 10-fold cross-validation following Ma et al. (2016). Therefore, the modelling procedure of the ADL-own model is illustrated by Figure 8a. For example, we estimate the model with the price and the promotional variables of the focal product (i.e., own predictors) and we reduce the model with the LASSO algorithm. The resulted model will be applied to generate the final forecasts.

We also include another ADL model with promotional information not only of the focal products but also of other competitive products within the same product category. The model is initially specified as follows:

where

is the log price of competitive product at week .

is the promotional index of competitive product at week .

is the number of competitive price variables in the product category.

is the number of competitive promotional variables in the product category.

We reduce the model with the LASSO procedure and then combine the retained explanatory variables with the variables retained in the corresponding ADL-own model so that it is less likely for the final reduced model to miss some important and relevant variables. We refer the model as the ADL-intra model thereafter and the modelling procedure can be illustrated in Figure 8b. For example, we conduct the LASSO selection procedure respectively for the models with own predictors and the models with both own predictors and competitive predictors. The final model will have explanatory variables from both sets of selected variables.

Figure 8a. An illustration for the ADL-own models

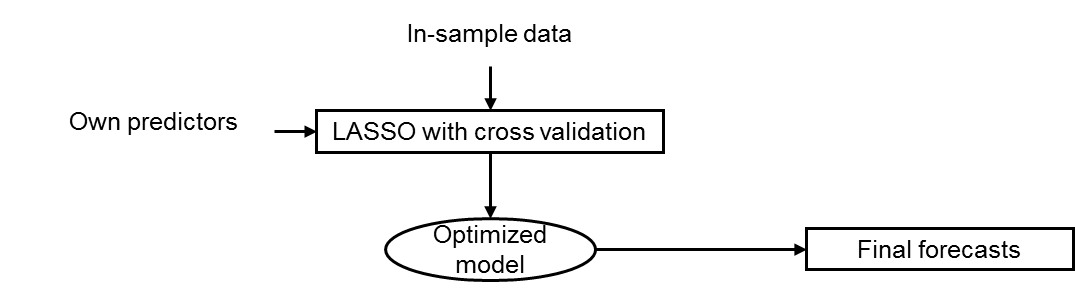


Figure 8b. An illustration for the ADL-intra models

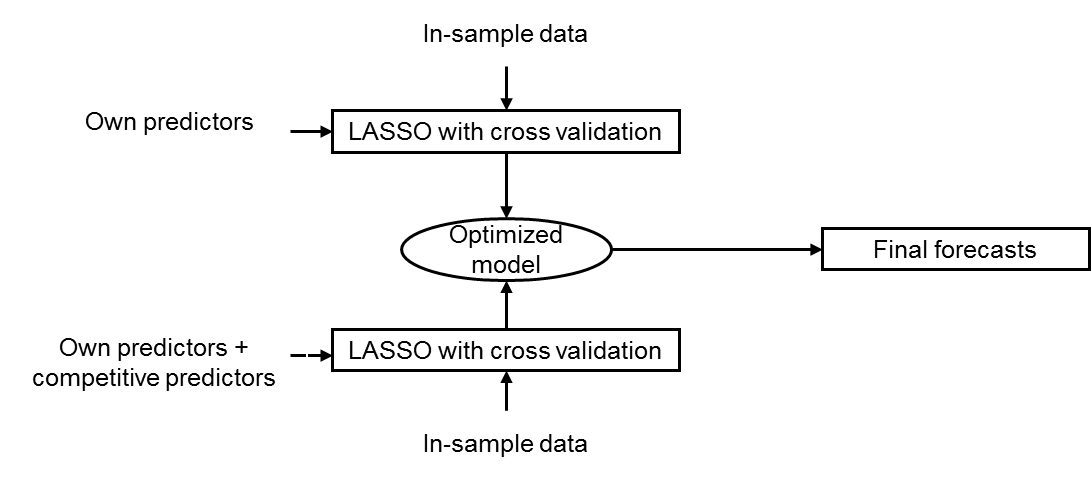


Figure 8c. An illustration for the ADL-intra-IC models

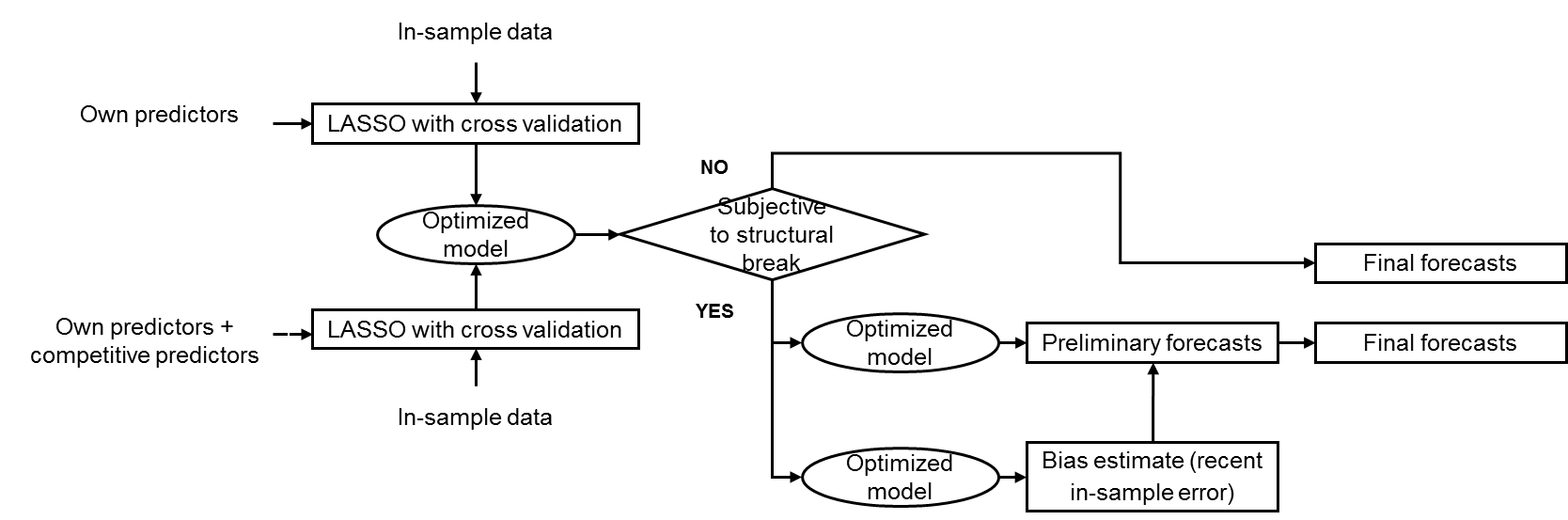


Figure 8d. An illustration for the ADL-intra-EWC models

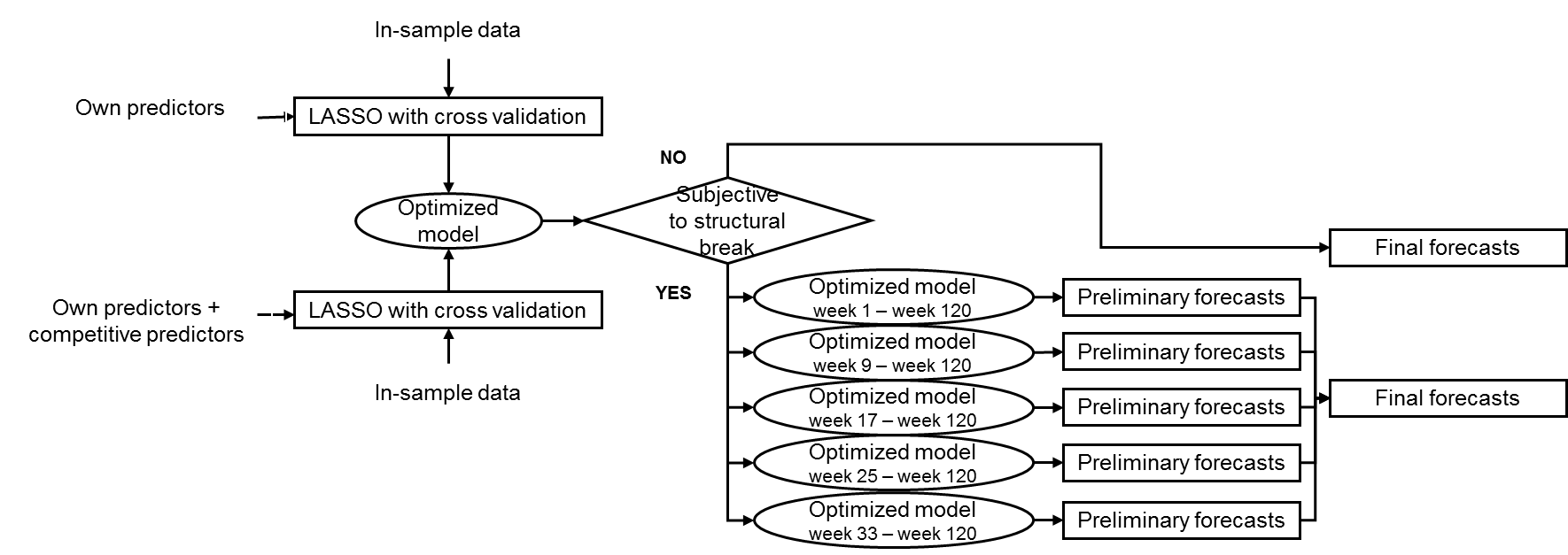


Figure 8e. An illustration for the ADL-own-EWC models

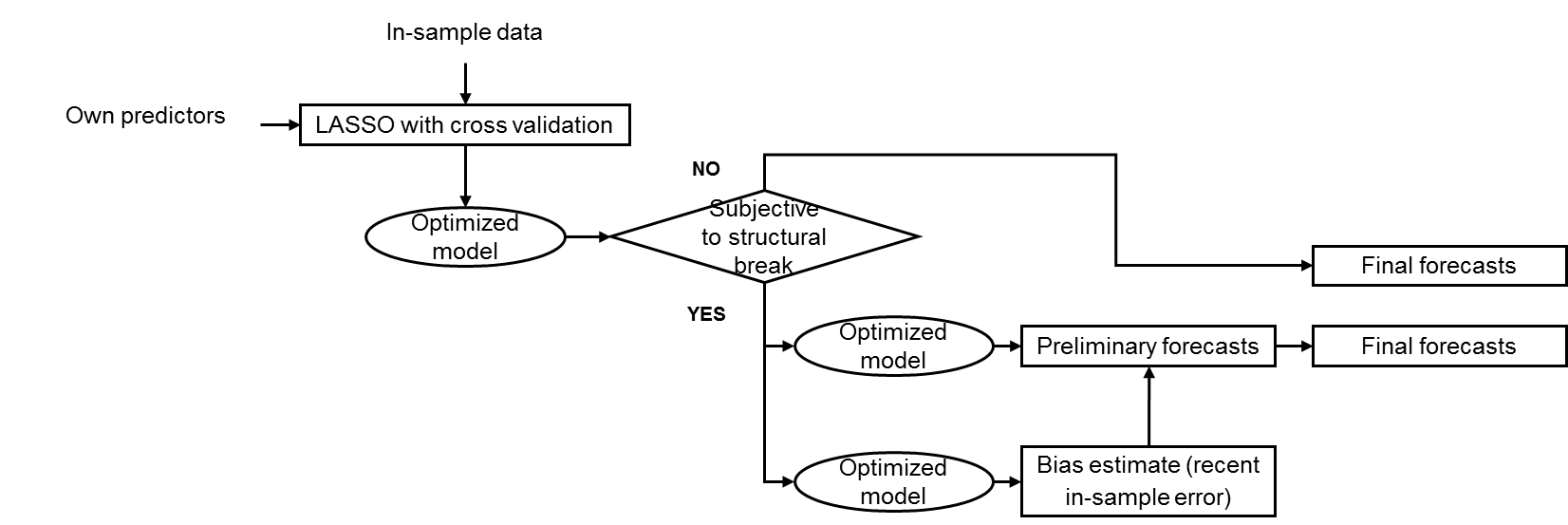
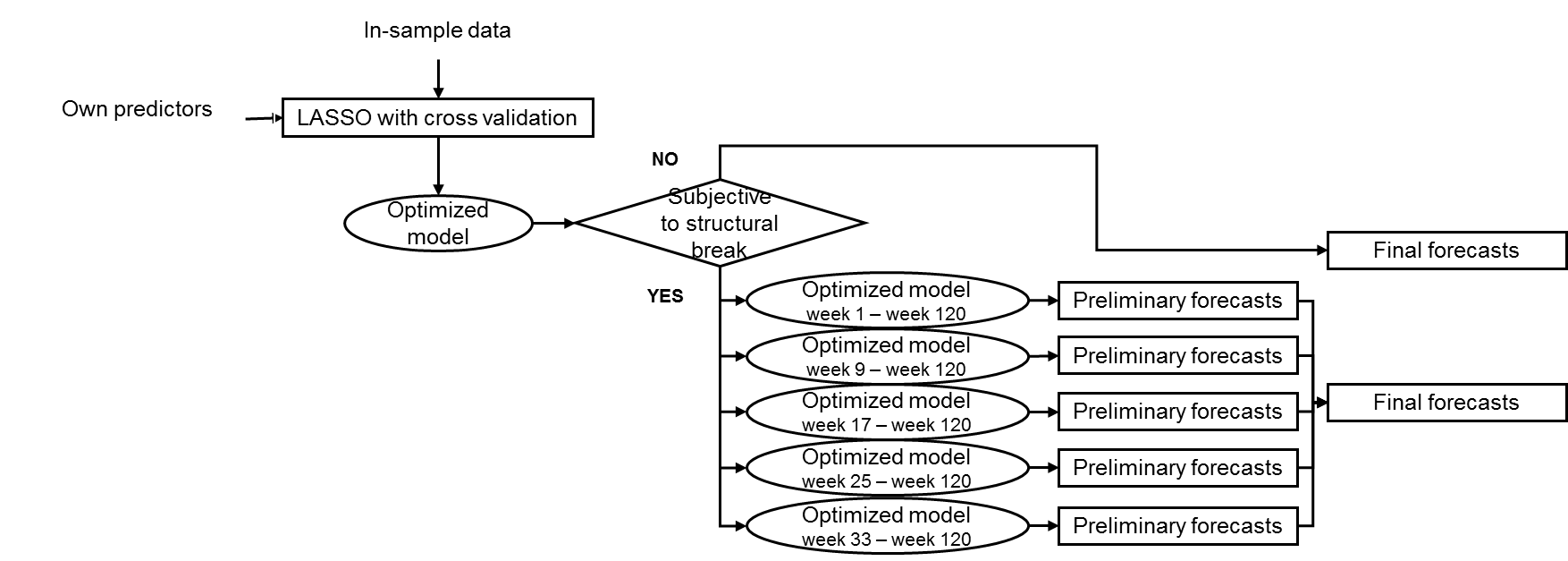


Figure 8f. An illustration for the ADL-own-EWC models



The ADL-own model and the ADL-intra model ignore the potential change in the effectiveness of the marketing activities. As a result, they may potentially be subject to structural break and generate biased and less accurate forecasts. In this study, we propose the following models which takes into account the change in the effectiveness of the marketing activities by resorting to the intercept correction method and the estimation window combining method: 1) the ADL-intra-IC method 2) the ADL-intra-EWC method 3) the ADL-own-IC method 4) the ADL-own-EWC method. The modelling procedure for the models are illustrated in Figure 8c, 8d, 8e, and 8f respectively. For the ADL-intra-IC model, we first construct the ADL-intra model as illustrated in Figure 8b and we then conduct the sequential Chow test based on all the observations in the estimation sample. If the test fails the reject the null hypothesis of no structural break, the forecasts by the ADL-intra model will be the final forecasts. Otherwise we estimate the forecast bias as the average value of four error terms which are close to the forecast origin. For the ADL-intra-IC model, we first construct the ADL-intra model as illustrated in Figure 8b and we then conduct the sequential Chow test based on all the observations in the estimation sample. If the test fails the reject the null hypothesis of no structural break, the forecasts by the ADL-intra model will be the final forecasts. Otherwise we estimate the forecast bias as the equal weighted average value of four error terms before the forecast origin. For the ADL-intra-EWC model, again we construct the ADL-intra model and then conduct the sequential Chow test. If the test results indicate no structural break, the forecasts by the ADL-intra model will be the final forecasts. Otherwise we re-estimate the ADL-intra model with five different estimation windows (e.g., if our initial estimation window is week 1 to week 120, then we re-estimate the model with the time period from week 1 to week 120, week 9 to week 120, week 17 to week 120, week 25 to week 120, and week 33 to week 120) and generate five sets of forecasts. The final forecasts will be the equal weighted average of these five sets of forecasts as equal weighting scheme has been proved to be effective and easy to implement ([Pesaran and Timmermann 2005](#_ENREF_63)). . The ADL-own-IC model and the ADL-own-EWC model are also built in the same way expect the models do not contain the competitive price and promotional information. The benchmark and the candidate models are described in Table 1. Compared to Huang et al. (2014) where the general-to-specific models were specified manually, all the models we propose in this study are specified automatically using the LASSO procedure in SAS 9.4.

|  |  |
| --- | --- |
| Model | Description |
| Base-lift | A two-stage method widely used in the industry |
| ADL-own | The ADL model with the promotional variables of the focal product only and then simplified by the LASSO algorithm. |
| ADL-intra | The ADL model with the promotional variables of the focal product only and all the competitive products within the same product category. The model is then simplified by the LASSO algorithm. and then the model will include the variables retained by the ADL-own model. |
| ADL-own-EWC | ADL-own model implemented with Estimation Window Combining |
| ADL-own-IC | ADL-own model implemented with Intercept Correction |
| ADL-intra-IC | ADL model implemented with Intercept Correction |
| ADL-intra-EWC | ADL model implemented with Estimation Window Combining |

1. **The experimental design**

In this study, we evaluate the forecasting performance of the models with rolling origins ([Tashman 2000](#_ENREF_64)). In Huang et al. (2016), the model estimation was updated in a rolling manner but the model specification was done with all the available data with a limitation of presuming prior knowledge of the data ([Fildes, Wei et al. 2011](#_ENREF_27)). In this study, we follow Ma et al. (2016) and re-specify the model for each rolling event. For example, we initially specify the models with the data from week 1 to week 120. we then re-specify the model respectively with updated data from week 9 to week 130, from week 17 to week 138, from week 25 to week 145, and from week 33 to week 153. For each rolling event, we generate one to week-ahead forecasts, where is 1, 4, and 12. Therefore, our evaluation truly represents the situation retailers face in practice. We use the actual values of the exogenous variables (e.g., price, promotion, or calendar events etc.) and the forecasts of the lagged dependent variables when the forecast horizon is beyond one week.

We evaluate the models’ forecasting performance using four error measures: the Mean Absolute Percentage Error (MAPE), the symmetric Mean Absolute Percentage Error (sMAPE), the Mean Absolute Scaled Error (MASE) proposed by [Hyndman and Koehler (2006)](#_ENREF_36), and the Relative Average Mean Absolute Error (RelAvgMAE) proposed by [Davydenko and Fildes (2013)](#_ENREF_22). These error measures approximate the loss function of the retailer from different aspects. The error measures for SKUs and rolling events based on forecast horizon of 1 to (i.e. , , and =1, 4 and 12) are as follows:

where is the actual value in the forecast period for data series based on the rolling event. is the forecast value for data series based on the rolling event[[10]](#footnote-10). is the total number of observations in the full estimation window.

1. **Results and discussion**

8.1 results for all the forecast period across categories

Table 4a shows the forecasting performance of the candidate models for all the forecast period. The Base-lift model generate the least accurate forecasts for almost all the scenarios. The ADL-own model gets outperformed by the ADL-intra model for all the scenarios, which highlights the value of competitive promotional information as suggested by Huang et al. (2014). However, in practice, competitive promotional information may not always be available especially for manufacturers ([Ali and Boylan 2011](#_ENREF_2)). Thus we propose the ADL-own-EWC model and the ADL-own-IC model which exclusively use the information of the focal product. In the results, the ADL-own-EWC model outperforms the ADL-own model for all the scenarios. The ADL-own-IC model has mixed forecasting performance compared to the ADL-own model: it has superior forecasting performance for short forecast horizons (e.g., when *h*=1 and *h*=4) but was losing advantages when forecast horizons get longer (e.g., when *h*=12). When competitive promotional information become available, we implement the EWC method and the IC method based on the ADL-intra model. The ADL-intra-EWC model outperforms the ADL-intra model for all the scenarios. The ADL-intra-IC model has mixed forecasting performance compared the ADL-intra model. The ADL-intra-IC model has superior forecasting performance for 1-week-ahead and 4-week-ahead forecast horizons but gets outperformed for 12-week-ahead forecast horizon. The forecasting performance are consistent across different error measures. Overall, the ADL-intra-EWC model and the ADL-intra-IC model are the most accurate models. The ADL-intra-EWC model has the best forecasting performance for 12-week-ahead forecast horizon, while the ADL-intra-IC model has the best forecasting performance for 1-week-ahead forecast horizon. They have comparable forecasting performance for 4-week-ahead forecast horizon.

Table 3a. The forecasting performance of candidate models for all forecast period for different forecast horizons

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| All forecast period, Forecast horizon= 12 | | | | | | | | |
| Model/measure | MAPE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank |
| Base-lift | 71.17% | 7 | 47.55% | 7 | 0.783 | 7 | 1.1458 | 7 |
| ADL-own | 67.99% | 5 | 41.16% | 5 | 0.700 | 5 | 1.0000 | 5 |
| ADL-intra | 67.00% | 2 | 40.84% | 2 | 0.696 | 3 | 0.9925 | 2 |
| ADL-own-EWC | 67.86% | 4 | 40.95% | 3 | 0.696 | 2 | 0.9932 | 3 |
| ADL-intra-EWC | 66.87% | 1 | 40.64% | 1 | 0.691 | 1 | 0.9856 | 1 |
| ADL-own-IC | 68.34% | 6 | 41.39% | 6 | 0.704 | 6 | 1.0031 | 6 |
| ADL-intra-IC | 67.27% | 3 | 41.05% | 4 | 0.700 | 4 | 0.9958 | 4 |
| All forecast period, Forecast horizon= 4 | | | | | | | | |
| Model/measure | MAPE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank |
| Base-lift | 66.41% | 7 | 45.94% | 7 | 0.751 | 7 | 1.0944 | 7 |
| ADL-own | 65.73% | 6 | 40.53% | 6 | 0.688 | 6 | 1.0000 | 6 |
| ADL-intra | 64.88% | 3 | 40.18% | 3 | 0.680 | 3 | 0.9907 | 3 |
| ADL-own-EWC | 65.54% | 5 | 40.31% | 4 | 0.683 | 5 | 0.9925 | 4 |
| ADL-intra-EWC | 64.70% | 2 | 39.96% | 1 | 0.676 | 1 | 0.9834 | 1 |
| ADL-own-IC | 65.15% | 4 | 40.47% | 5 | 0.682 | 4 | 0.9955 | 5 |
| ADL-intra-IC | 64.46% | 1 | 40.12% | 2 | 0.677 | 2 | 0.9866 | 2 |
| All forecast period, Forecast horizon= 1 | | | | | | | | |
| Model/measure | MAPE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank |
| Base-lift | 61.82% | 6 | 44.06% | 7 | 0.726 | 7 | 1.0062 | 7 |
| ADL-own | 62.04% | 7 | 39.53% | 6 | 0.666 | 6 | 1.0000 | 6 |
| ADL-intra | 61.44% | 4 | 39.22% | 4 | 0.657 | 4 | 0.9974 | 5 |
| ADL-own-EWC | 61.71% | 5 | 39.33% | 5 | 0.663 | 5 | 0.9954 | 4 |
| ADL-intra-EWC | 60.93% | 3 | 39.02% | 2 | 0.654 | 2 | 0.9836 | 3 |
| ADL-own-IC | 60.46% | 2 | 39.09% | 3 | 0.656 | 3 | 0.9707 | 2 |
| ADL-intra-IC | 60.15% | 1 | 38.82% | 1 | 0.650 | 1 | 0.9677 | 1 |

We conduct the Wilcoxon Sign Rank (WSR) test for the statistical significance of the difference between the models’ forecasting performance. Table 4 shows the results for each pair of models. In Table 4, column one and two highlight the benchmark model and the candidate model in the comparison. Column three, column four, and column five show the difference of the error measure between the models for various forecast horizons. For example, the difference between the performance of the ADL-intra model and the ADL-intra-EWC model for the MAPE is calculated as and it is statistically significant (with a p-value smaller than 0.01) according to the WSR test. The test results have the following indications: 1) the ADL-own model significantly outperforms the Base-lift model for all scenarios except for the MAPE when the forecast horizon is one week where they forecasting performance is not significantly different. 2) when the forecast horizon is four-week-ahead, the ADL-own-IC model significantly outperforms the ADL-own model, while the ADL-intra-IC model significantly outperforms the ADL-intra model. However, these improvements become less statistically significant when h=1. The ADL-own-IC model and the ADL-intra-IC model even get significantly outperformed by their counterparts when h=12. 3) For most occasions, the ADL-own-EWC model significantly outperforms the ADL-own model, while the ADL-intra-EWC model significantly outperforms the ADL-intra model. The only exception is for the MAPE when the forecast horizon is 12-week-ahead, where performance of these models and their counterparts are not significantly different (e.g., p-value= 0.184 and 0.414 respectively).

Table 4. Results for Pairwise Wilcoxon Sign Rank Test

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **model1** | **model2** | **Error measure** | **dif** | **P-value** | **dif** | **P-value** | **dif** | **P-value** |
| **h=1** | | **h=4** | | **h=12** | |
| ADL-intra | ADL-intra-EWC | MAPE | 0.5% | 0.002 | 0.2% | 0.000 | 0.1% | 0.414 |
| ADL-intra | ADL-intra-IC | MAPE | 1.3% | 0.144 | 0.4% | 0.002 | -0.3% | 0.000 |
| ADL-own | ADL-own-EWC | MAPE | 0.3% | 0.013 | 0.2% | 0.000 | 0.1% | 0.184 |
| ADL-own | ADL-own-IC | MAPE | 1.6% | 0.110 | 0.6% | 0.003 | -0.3% | 0.000 |
| ADL-own | ADL-intra | MAPE | 0.6% | 0.003 | 0.9% | 0.000 | 1.0% | 0.000 |
| ADL-own | Base-lift | MAPE | 0.2% | 0.268 | -0.7% | 0.039 | -3.2% | 0.000 |
| ADL-intra | ADL-intra-EWC | SMAPE | 0.2% | 0.000 | 0.2% | 0.000 | 0.2% | 0.000 |
| ADL-intra | ADL-intra-IC | SMAPE | 0.4% | 0.118 | 0.1% | 0.017 | -0.2% | 0.000 |
| ADL-own | ADL-own-EWC | SMAPE | 0.2% | 0.000 | 0.2% | 0.000 | 0.2% | 0.000 |
| ADL-own | ADL-own-IC | SMAPE | 0.4% | 0.134 | 0.1% | 0.028 | -0.2% | 0.000 |
| ADL-own | ADL-intra | SMAPE | 0.3% | 0.010 | 0.4% | 0.000 | 0.3% | 0.000 |
| ADL-own | Base-lift | SMAPE | -4.5% | 0.000 | -5.4% | 0.000 | -6.4% | 0.000 |
| ADL-intra | ADL-intra-EWC | MASE | 0.3% | 0.000 | 0.4% | 0.000 | 0.5% | 0.000 |
| ADL-intra | ADL-intra-IC | MASE | 0.7% | 0.247 | 0.3% | 0.003 | -0.4% | 0.000 |
| ADL-own | ADL-own-EWC | MASE | 0.4% | 0.000 | 0.5% | 0.000 | 0.5% | 0.000 |
| ADL-own | ADL-own-IC | MASE | 1.0% | 0.172 | 0.5% | 0.005 | -0.4% | 0.000 |
| ADL-own | ADL-intra | MASE | 1.0% | 0.010 | 0.7% | 0.000 | 0.4% | 0.030 |
| ADL-own | Base-lift | MASE | -6.0% | 0.000 | -6.4% | 0.000 | -8.3% | 0.000 |

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Benchmark | Candidate model | MAPE | | | SMAPE | | | MASE | | |
| h=1 | h=4 | h=12 | h=1 | h=4 | h=12 | h=1 | h=4 | h=12 |
| ADL-intra | ADL-intra-EWC | 0.002 | 0.000 | 0.414 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| ADL-intra | ADL-intra-IC | 0.144 | 0.002 | 0.000 | 0.118 | 0.017 | 0.000 | 0.247 | 0.003 | 0.000 |
| ADL-own | ADL-own-EWC | 0.013 | 0.000 | 0.184 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| ADL-own | ADL-own-IC | 0.110 | 0.003 | 0.000 | 0.134 | 0.028 | 0.000 | 0.172 | 0.005 | 0.000 |
| ADL-own | ADL-intra | 0.003 | 0.000 | 0.000 | 0.010 | 0.000 | 0.000 | 0.010 | 0.000 | 0.030 |
| ADL-own | Base-lift | 0.268 | 0.039 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

8.2 results for promoted forecast period and non-promoted forecast period across categories

Table 4b and Table 4c respectively shows the forecasting performance of the candidate models for the forecast period when the focal product is being promoted with either feature or display and when the focal product is not being promoted[[11]](#footnote-11). The results are overall in consistent with the results for all the forecast period described in section 8.1. For the promoted period, the Base-lift model has the least accurate forecasts but surprisingly have good performance for MAPE for 4-week-ahead and 12-week-ahead forecast horizons. The ADL-own model again gets outperformed by the ADL-intra model for all the scenarios. The ADL-own-EWC model outperforms the ADL-own model for most of the scenarios. The ADL-own-IC model has mixed forecasting performance compared to the ADL-own model: it outperforms the ADL-own model for short forecast horizons (e.g., when *h*=1). The ADL-intra-EWC model outperforms the ADL-intra model for most of the scenarios. The ADL-intra-IC model has superior forecasting performance for 1-week-ahead forecast horizon and mixed forecasting performance compared to the ADL-intra model, and gets outperformed by the ADL-intra model for the 12-week-ahead forecast horizon.

For the non-promoted period, as shown in Table 4c, the Base-lift model has the least accurate forecasts for most error measures except for the MASE and the AvgRelMAE for 1-week-ahead forecast horizon. The ADL-own model is outperformed by the ADL-intra model for all the scenarios. The ADL-own-EWC model outperforms the ADL-own model for all the scenarios. The ADL-own-IC model outperforms the ADL-own model for short and middle forecast horizons (e.g., when *h*=1 or 4) and has mixed forecasting performance with the ADL-own model for 12-week-ahead forecast horizon. The ADL-intra-EWC model outperforms the ADL-intra model for all the scenarios. The ADL-intra-IC model has superior forecasting performance for 1-week-ahead and 4-week-ahead forecast horizons and mixed forecasting performance compared to the ADL-intra model for 12-week-ahead forecast horizon.

Table 3b. The forecasting performance of candidate models for the promoted forecast period for different forecast horizons

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| promoted period, Forecast horizon= 12 | | | | | | | | |
| Model/measure | MAPE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank |
| Base-lift | 66.36% | 1 | 81.78% | 7 | 2.162 | 7 | 1.4518 | 7 |
| ADL-own | 74.93% | 4 | 49.89% | 5 | 1.656 | 4 | 1.0000 | 5 |
| ADL-intra | 73.89% | 3 | 48.82% | 2 | 1.633 | 2 | 0.9769 | 2 |
| ADL-own-EWC | 74.97% | 5 | 49.56% | 4 | 1.645 | 3 | 0.9906 | 3 |
| ADL-intra-EWC | 73.58% | 2 | 48.42% | 1 | 1.616 | 1 | 0.9659 | 1 |
| ADL-own-IC | 76.98% | 7 | 50.56% | 6 | 1.696 | 6 | 1.0265 | 6 |
| ADL-intra-IC | 75.35% | 6 | 49.28% | 3 | 1.668 | 5 | 0.9962 | 4 |
| promoted period, Forecast horizon= 4 | | | | | | | | |
| Model/measure | MAPE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank |
| Base-lift | 64.18% | 1 | 81.35% | 7 | 2.107 | 7 | 1.5123 | 7 |
| ADL-own | 73.50% | 6 | 50.05% | 5 | 1.617 | 6 | 1.0000 | 5 |
| ADL-intra | 72.02% | 3 | 48.46% | 2 | 1.560 | 2 | 0.9676 | 2 |
| ADL-own-EWC | 74.84% | 7 | 49.82% | 4 | 1.605 | 4 | 0.9897 | 4 |
| ADL-intra-EWC | 73.26% | 5 | 48.30% | 1 | 1.548 | 1 | 0.9593 | 1 |
| ADL-own-IC | 73.18% | 4 | 50.41% | 6 | 1.612 | 5 | 1.0131 | 6 |
| ADL-intra-IC | 71.92% | 2 | 48.65% | 3 | 1.563 | 3 | 0.9753 | 3 |
| promoted period, Forecast horizon= 1 | | | | | | | | |
| Model/measure | MAPE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank |
| Base-lift | 66.42% | 4 | 87.12% | 7 | 2.220 | 7 | 1.4461 | 7 |
| ADL-own | 67.11% | 7 | 50.14% | 5 | 1.603 | 5 | 1.0000 | 5 |
| ADL-intra | 66.63% | 5 | 48.56% | 3 | 1.510 | 1 | 0.9792 | 3 |
| ADL-own-EWC | 66.79% | 6 | 50.00% | 4 | 1.605 | 6 | 1.0044 | 6 |
| ADL-intra-EWC | 65.85% | 2 | 48.47% | 2 | 1.516 | 3 | 0.9715 | 2 |
| ADL-own-IC | 66.39% | 3 | 50.20% | 6 | 1.587 | 4 | 0.9902 | 4 |
| ADL-intra-IC | 65.71% | 1 | 48.30% | 1 | 1.511 | 2 | 0.9523 | 1 |

Table 3c. The forecasting performance of candidate models for the non-promoted forecast period for different forecast horizons

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| non-promoted period, Forecast horizon= 12 | | | | | | | | |
| Model/measure | MAPE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank |
| Base-lift | 72.83% | 7 | 42.44% | 7 | 0.600 | 7 | 1.0194 | 7 |
| ADL-own | 68.68% | 5 | 40.64% | 5 | 0.586 | 6 | 1.0000 | 5 |
| ADL-intra | 67.59% | 2 | 40.38% | 2 | 0.584 | 4 | 0.9940 | 3 |
| ADL-own-EWC | 68.47% | 4 | 40.44% | 3 | 0.581 | 2 | 0.9934 | 2 |
| ADL-intra-EWC | 67.37% | 1 | 40.20% | 1 | 0.579 | 1 | 0.9893 | 1 |
| ADL-own-IC | 68.82% | 6 | 40.83% | 6 | 0.585 | 5 | 1.0013 | 6 |
| ADL-intra-IC | 67.73% | 3 | 40.58% | 4 | 0.583 | 3 | 0.9978 | 4 |
| non-promoted period, Forecast horizon= 4 | | | | | | | | |
| Model/measure | MAPE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank |
| Base-lift | 67.42% | 7 | 40.73% | 7 | 0.571 | 6 | 0.9894 | 1 |
| ADL-own | 66.19% | 6 | 39.88% | 6 | 0.572 | 7 | 1.0000 | 7 |
| ADL-intra | 65.23% | 3 | 39.63% | 3 | 0.570 | 5 | 0.9962 | 6 |
| ADL-own-EWC | 65.85% | 5 | 39.67% | 4 | 0.567 | 4 | 0.9925 | 4 |
| ADL-intra-EWC | 64.93% | 2 | 39.43% | 1 | 0.566 | 2 | 0.9895 | 2 |
| ADL-own-IC | 65.55% | 4 | 39.73% | 5 | 0.566 | 3 | 0.9940 | 5 |
| ADL-intra-IC | 64.77% | 1 | 39.52% | 2 | 0.566 | 1 | 0.9905 | 3 |
| non-promoted period, Forecast horizon= 1 | | | | | | | | |
| Model/measure | MAPE | Rank | SMAPE | Rank | MASE | Rank | AvgRelMAE | Rank |
| Base-lift | 62.10% | 7 | 38.69% | 7 | 0.543 | 1 | 0.9614 | 1 |
| ADL-own | 61.36% | 6 | 38.59% | 6 | 0.552 | 7 | 1.0000 | 7 |
| ADL-intra | 60.52% | 4 | 38.39% | 5 | 0.550 | 6 | 0.9993 | 6 |
| ADL-own-EWC | 61.01% | 5 | 38.34% | 4 | 0.547 | 5 | 0.9945 | 5 |
| ADL-intra-EWC | 60.05% | 3 | 38.14% | 3 | 0.545 | 4 | 0.9848 | 4 |
| ADL-own-IC | 59.73% | 2 | 38.13% | 2 | 0.544 | 2 | 0.9694 | 2 |
| ADL-intra-IC | 59.19% | 1 | 38.00% | 1 | 0.544 | 3 | 0.9706 | 3 |

8.3 Results for all forecast period for each product category

Results shown in section 8.2 indicate that the EWC method and the IC method generate more accurate forecasts across the 30 product categories. We further explore their forecasting performance for each individual product category. Table 5a shows the improvement in term of the MAPE based on different forecast horizons for the following models over their counterparts: 1) the ADL-intra model versus the ADL-own model; 2) the ADL-own-EWC model versus the ADL-own model; 3) the ADL-own-IC model versus the ADL-own model; 4) the ADL-intra-EWC model versus the ADL- intra model; 5) and the ADL- intra -IC model versus the ADL-intra model. In the table, the values represent the percentage reduction (highlighted in green) or increase of the MAPE by one model over the other. For example, compared to the ADL-own model, we could achieve a MAPE value which is 1.40% lower by using the ADL-intra model. The value of 1.40% for “ADL-own - ADL-intra” in Table 5a is calculated as

Table 5a explores the results comparison between each pair of models for the MAPE. The positive values are highlighted in green which may indicate that the ADL-intra model outperforms the ADL-own model in the “ADL-own - ADL-intra” column or the ADL-intra-EWC model outperforms the ADL-intra model in the “ADL-intra - ADL-intra-EWC” column, and so forth. Table 5a suggests that for most of the product categories, the comparable forecasting performance of the various candidate models are in consistent with the results found in section 8.1 and 8.2. For example, 1) the ADL-intra model outperforms the ADL-own model for most of the categories; 2) the ADL-own-EWC model and the ADL-own-IC model generally outperform the ADL-own model, and the ADL-intra-EWC model and the ADL- intra -IC model generally outperform the ADL- intra model; 3) the advantage of the ADL-own-IC model and the ADL-intra-IC model over their counterparts (e.g., the ADL-own model and the ADL-intra model) are getting marginal as the forecast horizon increases. There are also some exceptional product categories including Carbonated Beverages, Frozen pizza, Hotdog, Razors, Margarine/Butter, Toothbrush, and Salty snacks where the ADL models combined with the EWC method and the IC method get outperformed by the ADL-own model or the ADL-intra model for most of the scenarios (e.g., error measures and forecast horizons). Table 5b and Table 5c have same indications for the MASE and the SMAPE. Table 5d shows the values of AvgRelMAE for the various pairs of models. The table either shows some of the original values of the AvgRelMAE (e.g., for the columns of “ADL-own - ADL-intra”, “ADL-own - ADL-own-EWC”, “ADL-own - ADL-own-IC”) which calculated based on the ADL-own model. The values below 1 are highlighted in green and indicate that the candidate models outperforms the ADL-own model. The table also shows the difference of the AvgRelMAE value for some other models. For example, the values in the column “ADL-intra versus ADL-intra-EWC” are calculated as , and the values in the column “ADL-intra versus ADL-intra-IC” are calculated as . The positive values are highlighted in green.

Table 4a Comparing forecasting performance for each product category for the MAPE.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Category/ MAPE | Horizon=1 | | | | | Horizon=4 | | | | | Horizon=12 | | | | |
| ADL-own - ADL-intra | ADL-own - ADL-own-EWC | ADL-own - ADL-own-IC | ADL-intra - ADL-intra-EWC | ADL-intra - ADL-intra-IC | ADL-own - ADL-intra | ADL-own - ADL-own-EWC | ADL-own - ADL-own-IC | ADL-intra - ADL-intra-EWC | ADL-intra - ADL-intra-IC | ADL-own - ADL-intra | ADL-own - ADL-own-EWC | ADL-own - ADL-own-IC | ADL-intra - ADL-intra-EWC | ADL-intra - ADL-intra-IC |
| Paptowl | 1.40% | -6.26% | 18.01% | -5.61% | 18.51% | 1.40% | -6.26% | 18.01% | -5.61% | 18.51% | 0.80% | -7.03% | 5.66% | -7.55% | 5.64% |
| Beer | 0.76% | 0.57% | 0.54% | 0.59% | 0.65% | 0.76% | 0.57% | 0.54% | 0.59% | 0.65% | 0.81% | 0.89% | -0.68% | 0.93% | -0.27% |
| Blades | -0.20% | 1.15% | -3.96% | 0.26% | -4.39% | -0.20% | 1.15% | -3.96% | 0.26% | -4.39% | 0.11% | 2.69% | 3.12% | 2.39% | 2.28% |
| Carbonated Beverages | 4.28% | -3.24% | -7.76% | -2.77% | -8.64% | 4.28% | -3.24% | -7.76% | -2.77% | -8.64% | 3.13% | -3.02% | -9.64% | -2.40% | -9.44% |
| Cigarette | -0.57% | 0.36% | -1.70% | 0.48% | -1.43% | -0.57% | 0.36% | -1.70% | 0.48% | -1.43% | -0.09% | 0.01% | -1.84% | -0.20% | -1.79% |
| Coffee | 0.80% | -0.39% | 7.74% | -0.44% | 6.52% | 0.80% | -0.39% | 7.74% | -0.44% | 6.52% | 0.87% | -0.91% | 3.14% | -0.79% | 3.16% |
| Coldcer | -2.28% | -0.54% | -2.90% | 1.05% | -2.92% | -2.28% | -0.54% | -2.90% | 1.05% | -2.92% | 0.28% | -2.39% | -6.96% | -1.88% | -6.85% |
| Deod | 0.74% | 0.87% | 3.34% | 1.04% | 3.50% | 0.74% | 0.87% | 3.34% | 1.04% | 3.50% | 0.85% | 0.75% | 3.67% | 0.74% | 3.65% |
| Factiss | -1.87% | 8.10% | 0.39% | 6.80% | 5.44% | -1.87% | 8.10% | 0.39% | 6.80% | 5.44% | 0.42% | 8.28% | -7.03% | 7.17% | -8.92% |
| Fzdinen | 2.60% | 2.75% | 15.27% | 3.19% | 12.72% | 2.60% | 2.75% | 15.27% | 3.19% | 12.72% | 3.17% | 2.68% | 7.32% | 2.22% | 6.54% |
| Frozen pizza | -0.62% | -2.58% | -6.15% | -1.69% | -5.06% | -0.62% | -2.58% | -6.15% | -1.69% | -5.06% | 0.94% | -2.17% | -6.90% | -2.27% | -6.19% |
| Household Cleaner | 2.89% | 2.26% | 7.35% | 1.70% | 4.87% | 2.89% | 2.26% | 7.35% | 1.70% | 4.87% | -0.48% | 3.45% | -0.24% | 3.44% | -0.77% |
| Hotdog | -2.24% | 1.35% | -6.24% | 2.17% | -4.49% | -2.24% | 1.35% | -6.24% | 2.17% | -4.49% | 1.58% | -3.50% | -13.66% | -3.16% | -11.69% |
| Laundry Detergent | 0.28% | 1.80% | 2.47% | 1.80% | 3.43% | 0.28% | 1.80% | 2.47% | 1.80% | 3.43% | 0.86% | 1.73% | -4.22% | 1.88% | -1.98% |
| Margarine/Butter | -1.39% | -0.64% | 3.19% | -0.94% | 3.43% | -1.39% | -0.64% | 3.19% | -0.94% | 3.43% | -0.11% | -0.46% | -1.28% | -0.72% | -1.68% |
| Mayonnaise | 1.50% | 1.71% | 5.79% | 1.19% | 5.53% | 1.50% | 1.71% | 5.79% | 1.19% | 5.53% | 0.93% | 0.94% | -6.24% | 0.62% | -6.16% |
| Milk | 0.64% | 3.43% | 6.14% | 3.01% | 5.89% | 0.64% | 3.43% | 6.14% | 3.01% | 5.89% | -1.17% | 4.16% | 7.82% | 3.90% | 7.62% |
| Mustard & Ketchup | -1.78% | 3.31% | 3.04% | 3.36% | 4.65% | -1.78% | 3.31% | 3.04% | 3.36% | 4.65% | 0.42% | 2.61% | 1.36% | 2.51% | 1.00% |
| Peanut butter | 0.14% | -0.83% | -2.52% | -1.60% | -2.49% | 0.14% | -0.83% | -2.52% | -1.60% | -2.49% | 0.30% | 3.22% | -2.14% | 3.05% | -2.48% |
| Photo | -0.16% | 2.21% | 8.54% | 1.86% | 7.79% | -0.16% | 2.21% | 8.54% | 1.86% | 7.79% | 0.10% | 2.12% | 4.12% | 1.84% | 4.62% |
| Razors | 0.00% | -1.74% | 3.38% | -1.74% | 3.38% | 0.00% | -1.74% | 3.38% | -1.74% | 3.38% | 0.00% | -3.85% | -1.98% | -3.85% | -1.98% |
| Salty snacks | -0.55% | -0.29% | 3.26% | -0.25% | 4.24% | -0.55% | -0.29% | 3.26% | -0.25% | 4.24% | -0.16% | -1.40% | -0.82% | -1.51% | -0.22% |
| Shamp | 1.21% | 1.97% | 4.91% | 1.47% | 3.78% | 1.21% | 1.97% | 4.91% | 1.47% | 3.78% | 1.61% | 2.86% | 5.34% | 2.61% | 4.66% |
| Soup | 7.06% | 1.70% | 8.78% | 1.19% | 5.52% | 7.06% | 1.70% | 8.78% | 1.19% | 5.52% | 4.59% | 1.23% | 0.86% | 1.09% | -0.19% |
| Spagsau | 2.76% | 8.66% | 8.37% | 6.81% | 6.79% | 2.76% | 8.66% | 8.37% | 6.81% | 6.79% | 1.88% | 8.66% | 4.36% | 7.87% | 3.92% |
| Sugar substitutes | 0.84% | 0.58% | 4.89% | 0.81% | 4.19% | 0.84% | 0.58% | 4.89% | 0.81% | 4.19% | 1.22% | 0.74% | 4.35% | 0.63% | 2.58% |
| Toilet Tissue | -0.37% | -0.62% | 8.45% | 1.24% | 11.86% | -0.37% | -0.62% | 8.45% | 1.24% | 11.86% | -1.59% | -0.13% | 2.73% | 0.47% | 4.54% |
| Toothbrush | 2.03% | -1.97% | -1.24% | -1.80% | -1.66% | 2.03% | -1.97% | -1.24% | -1.80% | -1.66% | 0.33% | -2.29% | -3.85% | -1.68% | -2.83% |
| Toothpaste | 0.65% | -1.59% | 2.83% | 1.66% | 2.48% | 0.65% | -1.59% | 2.83% | 1.66% | 2.48% | 5.72% | -1.09% | 3.96% | -0.46% | 5.25% |
| Yogurt | 0.16% | 3.52% | 5.99% | 3.30% | 4.75% | 0.16% | 3.52% | 5.99% | 3.30% | 4.75% | 0.60% | 1.03% | 2.20% | 0.65% | 1.04% |

Table 4b Comparing forecasting performance for each product category for the MASE.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Category/MASE | Horizon=1 | | | | | | Horizon=4 | | | | | | Horizon=12 | | | | | |
| ADL-own - ADL-intra | ADL-own - ADL-own-EWC | ADL-own - ADL-own-IC | ADL-intra - ADL-intra-EWC | ADL-intra - ADL-intra-IC | ADL-own - ADL-intra | | ADL-own - ADL-own-EWC | ADL-own - ADL-own-IC | ADL-intra - ADL-intra-EWC | ADL-intra - ADL-intra-IC | ADL-own - ADL-intra | | ADL-own - ADL-own-EWC | ADL-own - ADL-own-IC | ADL-intra - ADL-intra-EWC | ADL-intra - ADL-intra-IC |
| Paptowl | 2.18% | 10.03% | 1.54% | 12.01% | 2.22% | 2.32% | | 4.72% | 5.27% | 5.24% | 4.69% | 0.93% | | -4.43% | 9.85% | -4.26% | 9.85% |
| Beer | 2.13% | 0.03% | 0.33% | -0.17% | -0.66% | 1.00% | | 0.65% | -0.20% | 0.63% | -0.38% | 0.86% | | 0.59% | -1.07% | 0.55% | -1.08% |
| Blades | 0.46% | 0.93% | -1.07% | 0.02% | -1.93% | 1.42% | | 1.58% | 2.69% | 1.06% | 1.14% | 0.89% | | 2.01% | 2.95% | 1.79% | 1.38% |
| Carbonated Beverages | 2.58% | 0.06% | 2.05% | 0.83% | 1.40% | 0.49% | | 0.16% | 0.28% | 0.15% | -0.22% | 0.33% | | -0.10% | -1.16% | -0.05% | -1.27% |
| Cigarette | -0.50% | 0.22% | 0.39% | 0.47% | 0.31% | -0.13% | | 0.93% | 1.00% | 1.10% | 0.77% | -0.27% | | 0.49% | 1.16% | 0.55% | 1.20% |
| Coffee | 0.33% | -0.18% | 3.60% | -0.35% | 2.38% | 0.33% | | 0.12% | -0.22% | 0.02% | -0.63% | 0.24% | | -0.14% | -0.39% | -0.05% | -0.05% |
| Coldcer | 2.18% | -1.43% | 1.52% | -0.25% | 1.28% | 0.76% | | -0.96% | -3.40% | -0.28% | -3.36% | 0.53% | | -0.92% | -2.75% | -0.49% | -2.05% |
| Deod | 0.03% | 0.86% | 0.87% | 1.02% | 1.25% | 1.19% | | 0.69% | 1.23% | 0.62% | 0.94% | 0.84% | | 0.47% | 1.10% | 0.48% | 1.05% |
| Factiss | -0.06% | 5.97% | -4.64% | 4.81% | -1.27% | 0.11% | | 3.73% | -3.95% | 2.06% | -3.74% | -0.05% | | 4.37% | -5.24% | 2.85% | -6.04% |
| Fzdinen | 13.90% | 1.53% | 4.30% | 1.62% | -2.44% | 11.82% | | 0.24% | 1.74% | 0.00% | -3.42% | 4.77% | | 0.28% | -3.60% | -0.29% | -4.58% |
| Frozen pizza | -0.42% | -0.56% | -2.31% | -0.27% | -0.98% | 0.16% | | -0.47% | -0.93% | -1.43% | -0.60% | 1.04% | | -0.49% | -4.02% | -0.71% | -3.66% |
| Household Cleaner | 2.33% | 1.09% | 6.72% | 0.60% | 4.49% | 0.30% | | 1.32% | 4.24% | 1.53% | 3.57% | -0.62% | | 2.18% | 0.98% | 2.23% | 0.83% |
| Hotdog | 0.17% | 1.21% | -5.30% | 1.52% | -2.67% | 0.08% | | -4.13% | -5.43% | -3.57% | -4.63% | 0.22% | | -3.91% | -8.80% | -4.15% | -8.35% |
| Laundry Detergent | 1.36% | 0.69% | 3.69% | 0.26% | 3.89% | 1.67% | | 1.23% | 1.36% | 1.50% | 2.20% | 0.85% | | 1.20% | -1.33% | 1.46% | 0.46% |
| Margarine/Butter | -3.20% | -1.23% | -3.45% | -1.74% | -3.81% | -1.37% | | -1.36% | -1.93% | -1.54% | -1.22% | -1.06% | | -1.52% | -4.77% | -1.41% | -4.93% |
| Mayonnaise | 1.86% | 1.51% | 8.94% | 0.61% | 8.34% | -0.34% | | 0.11% | 2.78% | -0.18% | 1.82% | 0.22% | | 0.47% | -2.57% | 0.18% | -3.02% |
| Milk | 2.65% | 1.92% | 6.21% | 1.68% | 4.55% | 0.25% | | 1.89% | 5.66% | 1.59% | 4.69% | 0.09% | | 2.28% | 5.88% | 2.20% | 4.88% |
| Mustard & Ketchup | -0.67% | 1.92% | 1.27% | 2.75% | 1.81% | 0.01% | | 0.85% | -0.88% | 0.73% | -0.83% | 0.05% | | 1.16% | -1.46% | 1.25% | -2.22% |
| Peanut butter | -0.49% | -3.21% | 5.57% | -3.69% | 5.28% | 0.17% | | 0.32% | 6.49% | 0.21% | 5.93% | 0.30% | | 0.18% | 4.32% | 0.12% | 3.70% |
| Photo | -0.67% | 2.61% | 6.59% | 2.43% | 5.74% | 0.34% | | 2.32% | 3.76% | 2.00% | 4.00% | 0.30% | | 1.81% | 0.47% | 1.66% | 0.59% |
| Razors | 0.00% | -2.68% | -0.36% | -2.68% | -0.36% | 0.00% | | -1.96% | 0.58% | -1.96% | 0.58% | 0.00% | | -1.45% | -3.56% | -1.45% | -3.56% |
| Salty snacks | 0.09% | 1.89% | 2.16% | 1.80% | 2.68% | 2.29% | | 0.62% | -0.58% | 0.43% | -0.97% | 1.19% | | 0.82% | -0.58% | 0.67% | -0.76% |
| Shamp | 1.65% | 0.87% | 2.80% | 0.60% | 2.48% | -0.26% | | 1.07% | 1.38% | 0.93% | 1.15% | 0.66% | | 1.12% | 0.81% | 0.97% | 0.19% |
| Soup | 4.09% | 1.63% | 1.29% | 1.09% | 0.28% | 3.86% | | 1.91% | 0.62% | 1.38% | 0.66% | 1.16% | | 1.30% | -4.04% | 1.81% | -2.89% |
| Spagsau | 4.36% | 2.82% | 3.72% | 0.13% | 2.93% | -1.03% | | 5.31% | 0.52% | 5.13% | 0.37% | -0.26% | | 5.41% | 0.81% | 6.14% | 0.77% |
| Sugar substitutes | 0.91% | 0.73% | 5.01% | 0.92% | 4.80% | 0.82% | | 0.60% | 7.04% | 1.03% | 6.73% | 2.01% | | 1.21% | 6.65% | 1.39% | 4.97% |
| Toilet Tissue | -0.36% | -6.24% | -3.86% | -8.36% | -3.31% | 0.45% | | -2.44% | 4.04% | -3.34% | 3.80% | -0.55% | | -1.99% | 1.11% | -1.88% | 1.19% |
| Toothbrush | 5.13% | -0.25% | -4.82% | -0.44% | -5.06% | 0.99% | | -1.34% | -4.26% | -1.10% | -4.38% | 0.78% | | -1.02% | -4.53% | -0.67% | -4.21% |
| Toothpaste | -5.22% | -1.06% | 1.11% | 0.64% | 0.50% | -0.54% | | -2.21% | -1.30% | -1.43% | -0.16% | -1.42% | | -1.21% | -4.73% | 0.25% | -1.81% |
| Yogurt | -0.69% | 3.36% | 6.45% | 3.02% | 4.66% | 0.49% | | 3.87% | 6.52% | 3.51% | 5.46% | 0.54% | | 4.00% | 5.63% | 3.69% | 4.08% |

Table 4c Comparing forecasting performance for each product category for the SMAPE.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Category/SMAPE | Horizon=1 | | | | | Horizon=4 | | | | | Horizon=12 | | | | |
| ADL-own - ADL-intra | ADL-own - ADL-own-EWC | ADL-own - ADL-own-IC | ADL-intra - ADL-intra-EWC | ADL-intra - ADL-intra-IC | ADL-own - ADL-intra | ADL-own - ADL-own-EWC | ADL-own - ADL-own-IC | ADL-intra - ADL-intra-EWC | ADL-intra - ADL-intra-IC | ADL-own - ADL-intra | ADL-own - ADL-own-EWC | ADL-own - ADL-own-IC | ADL-intra - ADL-intra-EWC | ADL-intra - ADL-intra-IC |
| Paptowl | 1.98% | -0.57% | 14.78% | 1.17% | 15.23% | 1.31% | -0.62% | 1.69% | -0.09% | 1.18% | 0.38% | -2.90% | 4.70% | -2.73% | 4.67% |
| Beer | 1.26% | 0.30% | 1.04% | 0.20% | 0.54% | 0.60% | 0.58% | 0.39% | 0.54% | 0.45% | 0.57% | 0.52% | -0.33% | 0.46% | -0.31% |
| Blades | -0.29% | -0.22% | -2.36% | -0.81% | -2.26% | 0.81% | 0.70% | 0.36% | 0.29% | -0.32% | 0.58% | 1.21% | 1.44% | 0.98% | 0.51% |
| Carbonated Beverages | 3.01% | -1.19% | -1.57% | -1.01% | -2.18% | 1.92% | -1.19% | -2.63% | -1.01% | -3.05% | 1.44% | -1.04% | -2.38% | -1.04% | -2.39% |
| Cigarette | -0.58% | 0.25% | 0.83% | 0.34% | 0.92% | -0.12% | 0.70% | 0.73% | 0.69% | 0.52% | -0.17% | 0.46% | 0.89% | 0.44% | 0.77% |
| Coffee | 0.16% | -0.26% | 3.65% | -0.29% | 2.64% | 0.59% | -0.22% | 0.78% | -0.15% | 0.30% | 0.47% | -0.37% | 0.25% | -0.27% | 0.02% |
| Coldcer | 1.43% | -1.05% | -1.36% | -0.83% | -1.80% | 0.97% | -0.86% | -2.84% | -0.61% | -2.34% | 0.60% | -0.68% | -3.06% | -0.35% | -2.37% |
| Deod | 0.16% | 0.60% | -0.15% | 0.54% | 0.29% | 0.70% | 0.57% | 0.78% | 0.53% | 0.51% | 0.63% | 0.40% | 0.59% | 0.44% | 0.47% |
| Factiss | -0.26% | 6.66% | 1.78% | 5.40% | 5.22% | -0.52% | 4.51% | -1.28% | 2.67% | -2.00% | -2.67% | 4.75% | -4.00% | 3.24% | -5.18% |
| Fzdinen | 2.18% | 0.84% | 0.06% | 1.30% | -0.88% | 2.32% | 1.03% | -0.82% | 0.83% | -1.31% | 1.88% | 1.08% | -2.55% | 0.57% | -2.56% |
| Frozen pizza | -0.49% | -0.26% | -0.88% | 0.07% | 0.05% | 0.57% | -0.02% | -1.75% | 0.11% | -1.24% | 0.86% | 0.03% | -2.15% | 0.07% | -1.75% |
| Household Cleaner | 2.26% | 1.08% | 6.20% | 0.98% | 4.04% | -0.12% | 1.32% | 3.18% | 1.64% | 2.72% | -1.43% | 2.10% | 0.14% | 2.22% | 0.20% |
| Hotdog | -1.13% | 0.12% | -6.92% | 0.77% | -4.00% | -0.16% | -0.65% | -5.99% | -0.13% | -4.14% | 0.45% | -0.52% | -6.36% | -0.20% | -4.86% |
| Laundry Detergent | 1.20% | 1.63% | 2.81% | 1.47% | 2.37% | 1.55% | 0.99% | 2.10% | 1.17% | 2.30% | 1.06% | 0.79% | -0.45% | 0.89% | 0.33% |
| Margarine/Butter | -4.16% | -0.42% | 2.22% | -0.82% | 2.69% | -1.78% | -0.60% | 1.01% | -0.72% | 1.97% | -1.21% | -0.82% | -1.15% | -0.99% | -1.03% |
| Mayonnaise | 1.31% | 1.11% | 7.88% | 0.63% | 7.94% | 0.18% | 0.04% | 1.64% | -0.12% | 0.91% | 0.40% | 0.26% | -2.49% | 0.14% | -2.64% |
| Milk | 1.26% | 1.90% | 6.89% | 1.86% | 5.80% | -0.15% | 1.72% | 4.24% | 1.37% | 3.28% | 0.12% | 2.23% | 5.57% | 2.15% | 4.65% |
| Mustard & Ketchup | -0.44% | 1.10% | 5.17% | 1.81% | 4.86% | -0.11% | 0.53% | 1.60% | 0.54% | 1.61% | 0.15% | 0.71% | 0.56% | 0.87% | 0.06% |
| Peanut butter | -0.64% | -2.62% | 3.55% | -3.19% | 3.28% | 0.06% | 1.07% | 5.42% | 0.94% | 4.87% | 0.25% | 0.17% | 4.43% | 0.11% | 3.77% |
| Photo | -0.10% | 1.24% | 7.19% | 1.14% | 6.60% | 0.05% | 1.49% | 4.39% | 1.10% | 4.62% | 0.11% | 1.17% | 0.90% | 1.02% | 0.87% |
| Razors | 0.00% | -1.08% | -3.37% | -1.08% | -3.37% | 0.00% | -1.74% | -2.24% | -1.74% | -2.24% | 0.00% | -1.59% | -4.91% | -1.59% | -4.91% |
| Salty snacks | 0.00% | 1.74% | 0.74% | 1.84% | 1.79% | 0.93% | 0.74% | -0.20% | 0.77% | 0.10% | 0.50% | 0.84% | 0.29% | 0.80% | 0.02% |
| Shamp | 1.46% | 0.84% | 2.82% | 0.69% | 2.67% | 0.64% | 0.88% | 1.60% | 0.79% | 1.25% | 1.07% | 0.86% | 1.39% | 0.70% | 1.10% |
| Soup | 2.80% | 1.47% | 4.21% | 1.19% | 3.90% | 2.45% | 1.22% | 1.29% | 0.99% | 1.44% | 2.05% | 1.29% | -1.70% | 0.98% | -1.25% |
| Spagsau | 2.15% | 4.98% | 4.46% | 3.14% | 2.79% | 1.04% | 5.19% | 1.19% | 4.37% | 0.29% | 1.47% | 4.65% | 1.66% | 4.13% | 0.75% |
| Sugar substitutes | 0.73% | 0.50% | 1.31% | 0.59% | 0.96% | 0.83% | 0.60% | 3.92% | 0.80% | 3.84% | 1.19% | 0.75% | 3.54% | 0.78% | 2.40% |
| Toilet Tissue | -0.06% | -0.44% | 9.13% | -1.23% | 9.35% | -0.72% | 0.20% | 5.37% | -0.30% | 6.09% | -1.26% | -0.74% | -0.05% | -0.52% | 0.80% |
| Toothbrush | 3.43% | -0.27% | -2.63% | -0.44% | -3.23% | 0.48% | -0.89% | -2.60% | -0.94% | -2.58% | 0.29% | -0.60% | -3.07% | -0.55% | -2.95% |
| Toothpaste | -0.67% | 0.10% | -1.83% | 1.09% | -2.09% | 3.21% | 0.26% | -0.82% | 0.77% | -0.90% | 3.14% | -0.13% | -0.17% | 0.37% | 0.30% |
| Yogurt | -0.91% | 2.92% | 4.59% | 2.72% | 3.75% | 0.08% | 3.13% | 4.77% | 2.68% | 3.95% | 0.23% | 3.36% | 4.06% | 2.98% | 2.81% |

Table 4d Comparing forecasting performance for each product category for the AvgRelMAE

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Category | Horizon=1 | | | | | | Horizon=4 | | | | | | Horizon=12 | | | | | |
| RelAvgMAE | | | Improvement based on RelAvgMAE | | RelAvgMAE | | | | Improvement based on RelAvgMAE | | RelAvgMAE | | | | Improvement based on RelAvgMAE | |
| ADL-own versus ADL-intra | ADL-own versus ADL-own-EWC | ADL-own versus ADL-own-IC | ADL-intra versus ADL-intra-EWC | ADL-intra versus ADL-intra-IC | ADL-own versus ADL-intra | | ADL-own versus ADL-own-EWC | ADL-own versus ADL-own-IC | ADL-intra versus ADL-intra-EWC | ADL-intra versus ADL-intra-IC | ADL-own versus ADL-intra | | ADL-own versus ADL-own-EWC | ADL-own versus ADL-own-IC | ADL-intra versus ADL-intra-EWC | ADL-intra versus ADL-intra-IC |
| Paptowl | 0.982 | 1.028 | 0.874 | -0.013 | 0.141 | 0.988 | | 0.948 | 1.113 | 0.056 | -0.114 | 0.995 | | 1.019 | 1.033 | -0.018 | -0.033 |
| Beer | 0.997 | 1.006 | 0.990 | 0.023 | 0.004 | 0.991 | | 0.992 | 0.993 | 0.008 | 0.008 | 0.993 | | 0.993 | 1.004 | 0.007 | -0.004 |
| Blades | 1.004 | 1.056 | 0.981 | -0.056 | 0.030 | 0.987 | | 0.991 | 0.968 | 0.004 | 0.021 | 0.992 | | 0.982 | 0.966 | 0.014 | 0.021 |
| Carbonated Beverages | 0.971 | 1.029 | 1.000 | -0.016 | -0.037 | 0.987 | | 1.017 | 1.024 | -0.016 | -0.029 | 0.992 | | 1.019 | 1.023 | -0.016 | -0.021 |
| Cigarette | 1.011 | 1.022 | 0.988 | -0.011 | 0.022 | 1.001 | | 0.989 | 0.991 | 0.012 | 0.007 | 1.002 | | 0.995 | 0.993 | 0.006 | 0.007 |
| Coffee | 1.014 | 0.998 | 0.930 | 0.005 | 0.054 | 0.993 | | 1.002 | 0.987 | -0.004 | 0.006 | 0.997 | | 1.005 | 0.993 | -0.003 | 0.005 |
| Coldcer | 0.984 | 1.031 | 1.034 | -0.031 | -0.036 | 1.002 | | 1.018 | 1.039 | -0.011 | -0.029 | 0.994 | | 1.009 | 1.025 | -0.004 | -0.018 |
| Deod | 0.999 | 0.968 | 0.999 | 0.019 | 0.009 | 0.992 | | 0.990 | 0.980 | 0.009 | 0.016 | 0.994 | | 0.993 | 0.983 | 0.007 | 0.015 |
| Factiss | 0.978 | 0.965 | 1.045 | 0.062 | -0.012 | 1.007 | | 0.956 | 1.002 | 0.026 | 0.001 | 1.003 | | 0.950 | 1.028 | 0.033 | -0.037 |
| Fzdinen | 1.048 | 0.985 | 1.054 | 0.005 | 0.017 | 0.972 | | 0.989 | 1.038 | 0.016 | -0.028 | 0.977 | | 0.990 | 1.043 | 0.003 | -0.035 |
| Frozen pizza | 1.009 | 1.006 | 0.994 | 0.025 | 0.021 | 0.995 | | 1.005 | 1.033 | -0.003 | -0.029 | 0.988 | | 0.999 | 1.039 | 0.001 | -0.035 |
| Household Cleaner | 0.930 | 0.983 | 0.878 | 0.002 | 0.029 | 1.000 | | 0.979 | 0.955 | 0.026 | 0.038 | 1.011 | | 0.978 | 0.985 | 0.024 | 0.015 |
| Hotdog | 1.101 | 1.017 | 1.199 | 0.024 | -0.088 | 1.004 | | 1.008 | 1.092 | -0.002 | -0.069 | 0.985 | | 1.004 | 1.079 | -0.002 | -0.071 |
| Laundry Detergent | 0.988 | 0.971 | 0.929 | 0.031 | 0.064 | 0.980 | | 0.997 | 0.965 | 0.005 | 0.040 | 0.991 | | 0.991 | 1.010 | 0.011 | 0.008 |
| Margarine/Butter | 1.064 | 1.068 | 1.060 | -0.048 | -0.030 | 1.025 | | 1.024 | 1.009 | -0.019 | 0.009 | 1.013 | | 1.023 | 1.016 | -0.021 | -0.016 |
| Mayonnaise | 0.931 | 0.956 | 0.881 | 0.052 | 0.121 | 0.999 | | 0.997 | 0.990 | 0.000 | 0.003 | 0.995 | | 0.996 | 1.026 | 0.002 | -0.033 |
| Milk | 0.953 | 0.966 | 0.921 | 0.046 | 0.043 | 0.992 | | 0.978 | 0.935 | 0.018 | 0.044 | 0.995 | | 0.979 | 0.943 | 0.019 | 0.043 |
| Mustard & Ketchup | 1.110 | 1.067 | 0.955 | 0.013 | 0.141 | 1.012 | | 0.995 | 0.984 | 0.008 | 0.023 | 1.000 | | 0.988 | 0.993 | 0.014 | 0.003 |
| Peanut butter | 1.067 | 1.042 | 1.040 | -0.042 | 0.016 | 1.009 | | 0.982 | 0.979 | 0.016 | 0.025 | 0.995 | | 1.003 | 0.971 | -0.004 | 0.021 |
| Photo | 1.028 | 0.967 | 0.918 | 0.048 | 0.085 | 0.998 | | 0.981 | 0.946 | 0.015 | 0.058 | 0.997 | | 0.982 | 0.990 | 0.016 | 0.012 |
| Razors | 1.000 | 0.918 | 1.040 | 0.082 | -0.040 | 1.000 | | 1.034 | 1.003 | -0.034 | -0.003 | 1.000 | | 1.024 | 1.048 | -0.024 | -0.048 |
| Salty snacks | 0.992 | 0.970 | 1.029 | 0.045 | -0.018 | 0.977 | | 0.988 | 0.999 | 0.011 | -0.005 | 0.988 | | 0.995 | 0.991 | 0.005 | 0.000 |
| Shamp | 0.979 | 0.980 | 0.858 | 0.013 | 0.103 | 0.995 | | 0.989 | 0.970 | 0.011 | 0.023 | 0.990 | | 0.988 | 0.978 | 0.010 | 0.013 |
| Soup | 0.960 | 0.975 | 0.891 | 0.037 | 0.088 | 0.964 | | 0.986 | 0.976 | 0.010 | 0.016 | 0.977 | | 0.988 | 1.013 | 0.012 | -0.009 |
| Spagsau | 0.995 | 0.962 | 0.964 | 0.027 | 0.030 | 0.990 | | 0.915 | 0.975 | 0.071 | 0.015 | 0.994 | | 0.925 | 0.977 | 0.071 | 0.016 |
| Sugar substitutes | 0.990 | 0.973 | 0.973 | 0.049 | 0.005 | 0.986 | | 0.995 | 0.955 | 0.009 | 0.042 | 0.984 | | 0.992 | 0.953 | 0.008 | 0.030 |
| Toilet Tissue | 0.976 | 0.983 | 0.827 | -0.030 | 0.129 | 0.991 | | 1.002 | 0.921 | -0.025 | 0.069 | 0.997 | | 0.995 | 0.981 | 0.000 | 0.017 |
| Toothbrush | 0.932 | 1.037 | 1.007 | -0.040 | -0.005 | 0.993 | | 1.016 | 1.049 | -0.015 | -0.044 | 0.993 | | 1.009 | 1.040 | -0.007 | -0.040 |
| Toothpaste | 0.986 | 0.981 | 1.023 | 0.060 | 0.008 | 0.981 | | 1.002 | 1.061 | 0.011 | -0.030 | 1.025 | | 1.007 | 1.027 | 0.005 | 0.012 |
| Yogurt | 1.014 | 0.955 | 0.978 | 0.028 | 0.038 | 1.000 | | 0.967 | 0.951 | 0.033 | 0.050 | 0.999 | | 0.964 | 0.953 | 0.034 | 0.035 |

8.4 Explore the determinants of the forecasting improvement

The results in section 8.4 shows that our proposed models generate more accurate forecasts for most of the product categories. In this section, we further explore the determinants of the improvement of the forecasting performance at the SKU level. We regress the percentage improvement of the forecasting accuracy on the following explanatory variables 1) basic statistical measures for both prices and sales 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) Three statistical measures which capture the characteristics of the data series designed by Fildes et al. (1998). For example, we measure the proportion of outliers for the sales of the 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 . This measure may indicate the difficulty to generate accurate sales forecasts for this product. We also measure the randomness by regressing on , where is the sales value for product *i* at week *t* and *T* is the time trend. The fitness of this autoregressive model (e.g., the R square) may approximate the systematic variation in the sales data series which may be captured by simple models. Lastly, we measure the linear trend for the sales of the SKU as the absolute correlation between and the time trend. 4) dummy variables for each of the product category. Table 6 exhibits the explanatory variables.

Table 5. the explanatory variables (excluding category dummies) we use to explore the determinants of forecasting performance improvement.

|  |  |
| --- | --- |
| Variables | Descriptions |
| Price\_mean | Average price |
| Price\_std | Standard deviation of the unit sales |
| Price\_SKEWNESS | Sknewness of the price |
| Price\_range | Range of the price |
| Price\_kurtosis | Kurtosis of the price |
| Price\_coefficient of variation | Coefficient of variation of the price |
| Sales\_mean | Average sales |
| Sales\_std | Standard deviation of the unit sales |
| Sales\_SKEWNESS | Sknewness of the sales |
| Sales\_range | Range of the sales |
| Sales\_kurtosis | Kurtosis of the sales |
| Sales\_coefficient of variation | Coefficient of variation of the sales |
| D\_freq | Percentage of display |
| F\_freq | Percentage of feature |
| Outliers\_pct | Percentage of outliers |
| Randomness | Measure of randomness |
| Linear\_trend | Measure of linear trend |

We construct the following model:

where represents the percentage of improvement by model *A* over model *B* for product *i*. We assume that . Table 7 shows the estimated parameters for the four models based on error measures including the MAPE, the SMAPE, and the MASE. For example, column two to column are for ‘ADL- intra- IC versus ADL-Intra’ representing the model with the dependant variable for the various error measures. The results of the twelve models indicate: 1) the models tend to have better forecasting performance for the product with higher price for moderate and long forecast horizons (e.g., when h=4 and 12); 2) the models tend to have better forecasting performance for the product with low price variations, low sales variations, or low coefficients of variations for sales. One explanation is that the improved forecasting accuracy could be submerged in the variations in sales (which are to some extend caused by the variations in prices). 3) the models tend to have better forecasting performance for the product with less frequent display advertising. However, the evidence is significant for long forecast horizon (e.g., h=12) but insignificant for moderate and short horizons. 4) The models tend to have better forecasting performance for the product with low randomness. This also indicates that the improved forecasting accuracy could be submerged in the variations in the sales of the product with high randomness. 5) The models tend to have better forecasting performance for the product with stronger linear trend, especially when forecast horizons get longer (e.g., h=4 and 12).

The ADL-intra-IC model tends to outperform the ADL-intra-model for the SKU’s with the following characteristics: 1) with high coefficient of variations in product sales; 2) with high variations in product sales; 3) with lower sales volume; 4) with higher percentage of outliers in product sales; 5) with lower sales ranges 6) with frequent display promotions.

The ADL-intra-EWC model tends to outperform the ADL-intra-model for the SKU’s with the following characteristics: 1) with high variations in product prices; 2) with low randomness; 3) with high kurtosis in price 4)

Table 6a. The estimation results for the response model across 1 week-ahead forecast horizons

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Parameters | ADL- intra- IC versus ADL-Intra | | | ADL- intra- EWC versus ADL-Intra | | | ADL- OWN- IC versus ADL-OWN | | | ADL- OWN- EWC versus ADL-OWN | | |
| **MAPE** | **SMAPE** | **MASE** | **MAPE** | **SMAPE** | **MASE** | **MAPE** | **SMAPE** | **MASE** | **MAPE** | **SMAPE** | **MASE** |
| Intercept | 0.01376 | 0.00909 | 0.00751 | 0.03894\* | 0.03704\*\* | 0.03704\* | -0.01091 | -0.02527 | -0.03705 | 0.01707 | 0.01353 | 0.01205 |
| price\_mean | 0.00032 | -0.00132 | -0.00104 | -0.00037 | -0.00043 | -0.00043 | 0.00134 | -0.00036 | 0.00055 | 0.00037 | 0.00032 | 0.00033 |
| price\_std | 0.00376 | -0.00524 | 0.00654 | -0.0292\* | -0.03105\* | -0.03105\* | 0.01741 | -0.00501 | 0.00733 | -0.03064\* | -0.03481\*\* | -0.03814\*\* |
| price\_skewness | 0.01182\*\* | 0.00692 | 0.00433 | -0.00158 | -0.00070 | -0.00070 | 0.0131\*\* | 0.00828\* | 0.00465 | -0.00362\*\* | -0.00191 | -0.00237 |
| price\_range | 0.00021 | 0.00528 | 0.00135 | 0.00621 | 0.00821\* | 0.00821\* | -0.00468 | 0.00283 | -0.00185 | 0.00564 | 0.00794\* | 0.00825\* |
| price\_kurtosis | 0.00014 | 0.00007 | -0.00045 | -0.00058\*\*\* | -0.00043\*\* | -0.00043\*\* | 0.00015 | 0.00019 | -0.00030 | -0.00053\*\*\* | -0.0003\* | -0.00031\* |
| price\_c\_v | 0.02778 | -0.16634 | -0.11442 | 0.00611 | -0.02335 | -0.02335 | 0.18718 | 0.09596 | 0.24240 | 0.14554 | 0.13490 | 0.17125\* |
| sales\_mean | 0.00025\* | 0.00013 | 0.00017 | -0.00010 | -0.00012\* | -0.00012 | 0.00034\*\* | 0.00022\* | 0.00027\* | 0.00001 | -0.00001 | 0.00002 |
| sales\_std | -0.00087 | -0.00037 | -0.00071 | -0.00006 | 0.00007 | 0.00007 | -0.00118 | -0.00065 | -0.00096 | -0.00014 | -0.00003 | -0.00006 |
| sales\_skewness | 0.02787 | 0.00865 | 0.03242 | -0.00406 | -0.00425 | -0.00425 | 0.02088 | 0.00643 | 0.02762 | -0.00412 | -0.00498 | -0.00294 |
| sales\_range | 0.00016 | 0.00009 | 0.00015 | 0.00003 | 0.00002 | 0.00002 | 0.0002\* | 0.00012 | 0.00017\* | 0.00003 | 0.00001 | 0.00001 |
| sales\_kurtosis | -0.00304 | -0.00032 | -0.00294 | 0.00051 | 0.00057 | 0.00057 | -0.00238 | -0.00015 | -0.00276 | 0.00006 | 0.00028 | 0.00010 |
| sales\_c\_v | -0.08272\*\* | -0.06512\* | -0.0972\* | -0.01616 | -0.01378 | -0.01378 | -0.07632\*\* | -0.05326\*\* | -0.06779\*\* | 0.01630 | 0.01427 | 0.01574 |
| d\_freq | 0.04644 | 0.08848 | 0.12512 | 0.12806 | 0.11674 | 0.11674 | 0.02833 | 0.06400 | 0.03246 | 0.03496 | 0.02384 | 0.01095 |
| f\_freq | 0.14448 | 0.10533 | 0.10880 | 0.03332 | -0.00092 | -0.00092 | -0.00890 | -0.02536 | 0.07923 | -0.00274 | -0.01542 | 0.01748 |
| outliers\_pct | -0.40281\*\* | -0.27142\* | -0.49057\*\* | -0.13792\*\* | -0.10222\* | -0.10222\*\* | -0.40237\* | -0.32167\*\* | -0.61343\*\*\* | -0.19589\*\*\* | -0.13674\*\*\* | -0.20601\*\*\* |
| randomness | -0.08015 | -0.05858 | -0.12518\* | 0.05974\*\* | 0.05542\*\* | 0.05542\*\* | -0.09929 | -0.08380 | -0.14375\* | 0.02054 | 0.01515 | 0.00891 |
| linear\_trend | 0.02193 | 0.05712 | 0.11621\* | 0.00757 | 0.01449 | 0.01449 | 0.05685 | 0.09096\* | 0.13386\*\* | 0.00573 | 0.01758 | 0.01882 |
| category\_beer | 0.02982 | 0.03695 | 0.02571 | -0.02869 | -0.0319\* | -0.03190 | 0.03229 | 0.05478 | 0.04789 | -0.01291 | -0.01533 | -0.00968 |
| category\_blades | 0.02068 | 0.01757 | 0.03305 | -0.04537\* | -0.05195\*\* | -0.05195\*\* | 0.03899 | 0.03727 | 0.06051 | -0.02677 | -0.03274 | -0.02521 |
| category\_carbbev | -0.10256 | -0.08483 | -0.13123 | -0.15253\*\* | -0.13216\*\* | -0.13216\* | -0.05083 | -0.02483 | -0.08829 | -0.07271\*\*\* | -0.05555\*\* | -0.07316\*\*\* |
| category\_cigets | -0.03653 | 0.02318 | 0.01375 | -0.03431\* | -0.03664\*\* | -0.03664\* | -0.04331 | 0.02415 | 0.00580 | -0.04079\*\* | -0.03981\*\* | -0.03941\*\* |
| category\_coffee | 0.06984 | 0.07465 | 0.08693\* | -0.03856\*\* | -0.0345\* | -0.0345\* | 0.07900 | 0.07896 | 0.09187 | -0.04574\*\* | -0.03916\*\* | -0.0389\*\* |
| category\_coldcer | 0.05268 | 0.07716 | 0.07446 | -0.03665 | -0.02043 | -0.02043 | 0.07433 | 0.09265 | 0.06878 | -0.04911\*\* | -0.03857\*\* | -0.04324\*\* |
| category\_deod | 0.06222 | 0.04039 | 0.03905 | -0.01632 | -0.02005 | -0.02005 | 0.07251 | 0.04856 | 0.04097 | -0.01597 | -0.01706 | -0.01766 |
| category\_factiss | 0.03040 | 0.03999 | 0.03530 | 0.00903 | 0.00704 | 0.00704 | 0.04895 | 0.05716 | 0.04218 | 0.03230 | 0.02633 | 0.02345 |
| category\_fzdinen | 0.13672\*\* | 0.06542 | 0.11811\* | 0.03249 | 0.01278 | 0.01278 | 0.17492\*\* | 0.09146 | 0.14857\* | 0.02346 | -0.00235 | 0.00968 |
| category\_fzpizza | -0.02561 | 0.02913 | 0.01913 | -0.04088\*\* | -0.03049\* | -0.03049\* | -0.04740 | 0.00795 | -0.00275 | -0.04407\*\* | -0.03349\*\* | -0.03808\*\* |
| category\_hhclean | 0.06304 | 0.03901 | 0.03876 | -0.00491 | -0.01622 | -0.01622 | 0.08985 | 0.06091 | 0.05690 | 0.00242 | -0.01350 | -0.01611 |
| category\_hotdog | -0.13136 | -0.03862 | -0.10660 | -0.04056 | -0.03723 | -0.03723 | -0.14546 | -0.06387 | -0.13711 | -0.0642\*\* | -0.06149\*\*\* | -0.069\*\* |
| category\_laundet | 0.09452 | 0.10115\*\* | 0.12583\*\* | 0.03060 | 0.01452 | 0.01452 | 0.09720 | 0.10952\* | 0.11493\* | 0.01901 | 0.00326 | 0.00808 |
| category\_margbut | 0.04809 | 0.04395 | 0.04207 | -0.02892 | -0.02595 | -0.02595 | 0.03565 | 0.03237 | 0.02851 | -0.02901 | -0.02781 | -0.02773 |
| category\_mayo | 0.05001 | 0.06116 | 0.04397 | -0.04526\*\* | -0.04958\*\* | -0.04958\*\* | 0.07255 | 0.08759 | 0.08421 | -0.01765 | -0.02138 | -0.01651 |
| category\_milk | 0.05141 | 0.06492 | 0.06933 | -0.01833 | -0.02119 | -0.02119 | 0.06231 | 0.08615 | 0.09983 | -0.00384 | -0.01106 | -0.01188 |
| category\_mustket | 0.07751 | 0.08413\* | 0.07902 | -0.01618 | -0.02968 | -0.02968 | 0.07669 | 0.07960 | 0.06639 | -0.00974 | -0.02778 | -0.01611 |
| category\_Paptowl | 0.41567\*\*\* | 0.30778\*\*\* | 0.45264\*\*\* | -0.07408 | -0.06983 | -0.06983 | 0.41014\*\*\* | 0.29436\*\*\* | 0.41339\*\*\* | -0.11169 | -0.10607 | -0.11762 |
| category\_peanbut | -0.05670 | 0.01394 | 0.00183 | -0.05937\*\* | -0.06663\*\*\* | -0.06663\*\*\* | -0.05097 | 0.02422 | 0.01291 | -0.04163 | -0.0494\*\* | -0.04688\*\* |
| category\_photo | 0.10733\* | 0.11314\*\* | 0.12517\*\* | -0.02331 | -0.02500 | -0.02500 | 0.12426\* | 0.12911\*\* | 0.13836\*\* | -0.01308 | -0.01694 | -0.00324 |
| category\_razors | -0.15052 | -0.20781 | -0.15267 | 0.16607 | 0.16476 | 0.16476 | -0.12509 | -0.18177 | -0.11361 | 0.19559 | 0.19593 | 0.20428 |
| category\_saltsnc | 0.06820 | 0.06942 | 0.10062\*\* | 0.00068 | -0.00009 | -0.00009 | 0.06782 | 0.07216 | 0.09978\* | -0.00143 | -0.00213 | -0.00169 |
| category\_shamp | 0.00831 | 0.00407 | -0.00526 | -0.04567\* | -0.04971\*\* | -0.04971\*\* | 0.03688 | 0.01245 | 0.01988 | -0.04323 | -0.05247 | -0.04949 |
| category\_soup | 0.1156\*\* | 0.10707\*\* | 0.08825\* | 0.00130 | -0.00355 | -0.00355 | 0.14198\*\* | 0.12158\*\* | 0.09597 | 0.00099 | -0.00490 | 0.00138 |
| category\_spagsau | 0.12545\*\* | 0.09053\* | 0.11445\*\* | 0.05418\*\* | 0.02653 | 0.02653 | 0.16584\*\*\* | 0.12828\*\* | 0.14905\*\* | 0.06167\*\* | 0.03526 | 0.04538\* |
| category\_sugarsu | 0.05657 | 0.04913 | 0.05919 | -0.02244 | -0.02438 | -0.02438 | 0.07984 | 0.06653 | 0.07483 | -0.02231 | -0.02275 | -0.02077 |
| category\_toitisu | 0.15124\* | 0.17589\*\*\* | 0.18948\*\* | -0.04185 | -0.04437\* | -0.04437 | 0.14221\* | 0.17878\*\*\* | 0.16829\*\* | -0.04865\* | -0.04468\*\* | -0.05251\*\* |
| category\_toothbr | -0.05409 | -0.02407 | -0.02210 | -0.04619\*\* | -0.03247\* | -0.03247 | -0.02944 | -0.00370 | -0.01139 | -0.045\*\* | -0.02819 | -0.03221 |
| category\_toothpa | 0.05896 | 0.06279 | 0.06461 | 0.00978 | 0.00143 | 0.00143 | 0.10158 | 0.11074 | 0.11986 | -0.00328 | -0.00294 | -0.00276 |

Table 6b. The estimation results for the response model across 1 to 4-week-ahead forecast horizons

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Parameters | ADL- intra- IC versus ADL-Intra | | | ADL- intra- EWC versus ADL-Intra | | | ADL- OWN- IC versus ADL-OWN | | | ADL- OWN- EWC versus ADL-OWN | | |
| **MAPE** | **SMAPE** | **MASE** | **MAPE** | **SMAPE** | **MASE** | **MAPE** | **SMAPE** | **MASE** | **MAPE** | **SMAPE** | **MASE** |
| Intercept | 0.01474 | 0.00905 | 0.00335 | 0.01714\* | 0.01667\*\* | 0.01667\* | 0.00383 | -0.00099 | -0.00582 | 0.0175\* | 0.01548\* | 0.01867\* |
| price\_mean | 0.00455\*\*\* | 0.00239\*\*\* | 0.00324\*\*\* | 0.00040 | 0.00019 | 0.00019 | 0.00595\*\*\* | 0.00329\*\*\* | 0.00447\*\*\* | 0.00070 | 0.00039 | 0.00052 |
| price\_std | -0.02307 | -0.02994\* | -0.03676\* | -0.00823 | -0.01045 | -0.01045 | -0.02907 | -0.03929\*\* | -0.04768\*\* | -0.01073 | -0.01366\* | -0.01568 |
| price\_skewness | 0.00578\* | 0.00383 | 0.00367 | 0.00036 | -0.00005 | -0.00005 | 0.00591\* | 0.00377 | 0.00357 | -0.00151 | -0.00058 | -0.00057 |
| price\_range | -0.00267 | 0.00327 | 0.00187 | -0.00070 | 0.00158 | 0.00158 | -0.00574 | 0.00189 | -0.00019 | -0.00130 | 0.00161 | 0.00100 |
| price\_kurtosis | 0.00026 | 0.00026 | 0.00034 | -0.00029\*\* | -0.00018\*\* | -0.00018\*\* | 0.00007 | 0.00017 | 0.00022 | -0.00044\*\* | -0.00024\*\* | -0.00027\*\* |
| price\_c\_v | 0.28153 | 0.13466 | 0.21425 | 0.05921 | 0.01486 | 0.01486 | 0.33185\* | 0.21148\*\* | 0.30891\*\* | 0.08641 | 0.06066 | 0.06666 |
| sales\_mean | 0.00034\*\*\* | 0.00021\*\*\* | 0.0003\*\*\* | 0.00004 | 0.00000 | 0.00000 | 0.00037\*\*\* | 0.00025\*\*\* | 0.00031\*\*\* | 0.00006 | 0.00004 | 0.00005 |
| sales\_std | -0.00158\*\*\* | -0.00086\*\* | -0.00146\*\* | -0.00033\* | -0.00018 | -0.00018\* | -0.00175\*\*\* | -0.00101\*\* | -0.00163\*\* | -0.0004\*\* | -0.00027\* | -0.00044\*\* |
| sales\_skewness | 0.01512 | 0.00733 | 0.02004\* | -0.00013 | -0.00175 | -0.00175 | 0.00381 | 0.00309 | 0.01098 | -0.00083 | -0.00056 | 0.00135 |
| sales\_range | 0.00022\*\*\* | 0.00012\*\* | 0.0002\*\* | 0.00005\* | 0.00003 | 0.00003 | 0.00024\*\*\* | 0.00013\*\* | 0.00022\*\* | 0.00005\* | 0.00004 | 0.00006\* |
| sales\_kurtosis | -0.00218 | -0.00065 | -0.0024\* | -0.00005 | 0.00004 | 0.00004 | -0.00125 | -0.00038 | -0.00168 | -0.00018 | -0.00014 | -0.00037 |
| sales\_c\_v | -0.06666\*\*\* | -0.0296\*\* | -0.04637\*\* | -0.00454 | 0.00228 | 0.00228 | -0.07379\*\*\* | -0.02909\*\* | -0.04766\*\* | 0.00062 | 0.00442 | 0.00158 |
| d\_freq | -0.01673 | 0.00514 | -0.01334 | -0.00801 | -0.00717 | -0.00717 | 0.00473 | 0.01745 | -0.01185 | -0.01625 | -0.01277 | -0.00641 |
| f\_freq | 0.00114 | -0.00374 | 0.04186 | 0.03675 | -0.00174 | -0.00174 | 0.00621 | 0.01264 | 0.07757 | 0.00348 | -0.00837 | -0.03393 |
| outliers\_pct | -0.06953 | -0.04494 | -0.10339 | -0.01662 | 0.00259 | 0.00259 | 0.03519 | -0.02906 | -0.05825 | -0.04241 | -0.01615 | -0.00355 |
| randomness | -0.05824 | -0.02798 | -0.07278\* | 0.02175 | 0.02384\* | 0.02384\* | -0.01637 | -0.00188 | -0.03069 | 0.02517 | 0.02233\* | 0.02466 |
| linear\_trend | 0.01236 | 0.03624 | 0.07269\*\* | -0.00357 | 0.00390 | 0.00390 | 0.00677 | 0.03626 | 0.06402\* | -0.00979 | 0.00118 | 0.00052 |
| category\_beer | -0.00449 | -0.01043 | -0.01041 | -0.00813 | -0.01376\* | -0.01376\* | -0.00648 | -0.00761 | -0.00849 | -0.00611 | -0.01315\* | -0.01435 |
| category\_blades | 0.00062 | -0.01598 | -0.00513 | -0.00579 | -0.01747\* | -0.01747 | 0.01069 | -0.00935 | 0.00549 | -0.00365 | -0.01614 | -0.01557 |
| category\_carbbev | -0.04283 | -0.02988 | -0.0544\* | -0.05471\*\*\* | -0.03446\*\*\* | -0.03446\*\*\* | -0.03426 | -0.02532 | -0.05408\* | -0.05644\*\*\* | -0.03543\*\*\* | -0.04902\*\*\* |
| category\_cigets | -0.08773\*\*\* | -0.03909\* | -0.04737\* | -0.01375 | -0.01462\* | -0.01462 | -0.08231\*\* | -0.03371 | -0.04177 | -0.01535 | -0.01666\*\* | -0.01738\* |
| category\_coffee | -0.00190 | -0.01155 | -0.00357 | -0.03225\*\*\* | -0.0247\*\*\* | -0.0247\*\*\* | 0.01391 | -0.00459 | 0.00066 | -0.03411\*\*\* | -0.03002\*\*\* | -0.03223\*\*\* |
| category\_coldcer | -0.03821 | -0.02102 | -0.03309 | -0.04991\*\*\* | -0.03292\*\*\* | -0.03292\*\*\* | -0.03155 | -0.02431 | -0.02877 | -0.04482\*\*\* | -0.03736\*\*\* | -0.03955\*\*\* |
| category\_deod | 0.02738 | -0.00511 | -0.00486 | -0.00690 | -0.01251 | -0.01251\* | 0.04095 | 0.00221 | 0.00458 | -0.00908 | -0.01547\*\* | -0.01812\*\* |
| category\_factiss | -0.0494\* | -0.04237\* | -0.05493 | -0.00297 | -0.00683 | -0.00683 | -0.04470 | -0.03735 | -0.05986 | -0.00253 | -0.00471 | -0.00508 |
| category\_fzdinen | 0.10322\*\*\* | -0.00002 | 0.01132 | 0.00310 | -0.01182 | -0.01182 | 0.11636\*\*\* | 0.00431 | 0.02108 | 0.00796 | -0.01479 | -0.01056 |
| category\_fzpizza | -0.05018\* | -0.02191 | -0.02811 | -0.03589\*\* | -0.01811\*\* | -0.01811\*\*\* | -0.04685 | -0.02303 | -0.03081 | -0.02706\*\*\* | -0.0208\*\*\* | -0.02791\*\*\* |
| category\_hhclean | -0.02306 | -0.01203 | -0.01683 | 0.01638 | 0.00287 | 0.00287 | -0.01008 | -0.01272 | -0.01599 | 0.01415 | -0.00257 | 0.00187 |
| category\_hotdog | -0.14603\*\* | -0.08983\*\* | -0.14213\*\*\* | -0.03675\*\* | -0.02997\*\*\* | -0.02997\*\* | -0.16035\*\*\* | -0.11219\*\*\* | -0.16794\*\*\* | -0.04749\*\*\* | -0.04556\*\*\* | -0.05457\*\*\* |
| category\_laundet | 0.02624 | 0.01072 | 0.02021 | 0.00919 | -0.00883 | -0.00883 | 0.02449 | 0.01755 | 0.01853 | 0.01024 | -0.01156 | -0.00375 |
| category\_margbut | 0.00226 | -0.00594 | -0.01609 | -0.02775\*\* | -0.02199\*\* | -0.02199\*\*\* | -0.00379 | -0.01882 | -0.03081 | -0.02529\*\* | -0.02468\*\*\* | -0.02967\*\*\* |
| category\_mayo | -0.02794 | -0.02737 | -0.02967 | -0.02244\*\* | -0.0308\*\*\* | -0.0308\*\*\* | -0.01821 | -0.02510 | -0.02415 | -0.01929\* | -0.02923\*\*\* | -0.03227\*\*\* |
| category\_milk | -0.03644 | -0.02227 | -0.02546 | -0.01600 | -0.01479 | -0.01479 | -0.03857 | -0.01856 | -0.02245 | -0.01402 | -0.01637 | -0.01908 |
| category\_mustket | -0.01336 | -0.01677 | -0.01712 | -0.00504 | -0.02207\*\* | -0.02207\* | -0.00498 | -0.02316 | -0.02841 | -0.00347 | -0.02578\*\*\* | -0.02436\*\* |
| category\_Paptowl | 0.15085\*\*\* | 0.04691 | 0.18927\*\*\* | -0.04849 | -0.04648 | -0.04648 | 0.1804\*\*\* | 0.05795 | 0.19994\*\*\* | -0.04939 | -0.05450 | -0.07706 |
| category\_peanbut | -0.06817 | -0.01401 | -0.01825 | 0.00224 | -0.01591 | -0.01591 | -0.06253 | -0.00764 | -0.01362 | 0.00253 | -0.01683 | -0.01827 |
| category\_photo | 0.08039\*\* | 0.03789 | 0.05079 | -0.00518 | -0.01033 | -0.01033 | 0.08125\* | 0.03925 | 0.05062 | -0.00020 | -0.00965 | -0.00203 |
| category\_razors | 0.07685 | -0.02269 | 0.01243 | -0.05024\*\*\* | -0.04586\*\*\* | -0.04586\*\*\* | 0.07992 | -0.02427 | 0.01270 | -0.05037\*\*\* | -0.04641\*\*\* | -0.05489\*\*\* |
| category\_saltsnc | -0.02066 | -0.01677 | -0.01316 | -0.01346 | -0.01074 | -0.01074 | -0.02674 | -0.01728 | -0.01459 | -0.01187 | -0.01259 | -0.01550 |
| category\_shamp | 0.00531 | -0.00498 | -0.01478 | -0.00377 | -0.01041 | -0.01041 | 0.03393 | 0.00640 | 0.00332 | -0.00110 | -0.01305 | -0.01196 |
| category\_soup | 0.03747 | 0.00902 | -0.01938 | -0.00392 | -0.00602 | -0.00602 | 0.05886\*\* | 0.01021 | -0.02033 | -0.00038 | -0.00745 | -0.00406 |
| category\_spagsau | 0.05214 | 0.00004 | 0.01246 | 0.05006\*\*\* | 0.01544 | 0.01544 | 0.07061\*\* | 0.01101 | 0.02686 | 0.05404\*\*\* | 0.01934 | 0.02928\* |
| category\_sugarsu | 0.03297 | 0.02607 | 0.02553 | -0.00730 | -0.00957 | -0.00957 | 0.05371 | 0.03382 | 0.03459 | -0.01340 | -0.01602\*\* | -0.01874\*\* |
| category\_toitisu | 0.03950 | 0.04068 | 0.04714 | -0.02858 | -0.03111\*\* | -0.03111\*\* | 0.04199 | 0.03697 | 0.03866 | -0.02144 | -0.03298\*\*\* | -0.03923\*\* |
| category\_toothbr | -0.07157 | -0.04748\* | -0.07252\* | -0.04528\*\*\* | -0.03076\*\*\* | -0.03076\*\*\* | -0.06500 | -0.04714 | -0.07677\* | -0.04876\*\*\* | -0.03335\*\*\* | -0.04166\*\*\* |
| category\_toothpa | 0.04398 | 0.02968 | 0.03777 | -0.00879 | -0.01442 | -0.01442 | 0.04153 | 0.03776 | 0.04874 | -0.01290 | -0.0183\* | -0.01784 |

Table 6c. The estimation results for the response model for 1 to 12 week-ahead forecast horizon

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Parameters | ADL- intra- IC versus ADL-Intra | | | ADL- intra- EWC versus ADL-Intra | | | ADL- OWN- IC versus ADL-OWN | | | ADL- OWN- EWC versus ADL-OWN | | |
| **MAPE** | **SMAPE** | **MASE** | **MAPE** | **SMAPE** | **MASE** | **MAPE** | **SMAPE** | **MASE** | **MAPE** | **SMAPE** | **MASE** |
| Intercept | 0.00506 | 0.00267 | -0.00450 | 0.02943\*\*\* | 0.02556\*\*\* | 0.02556\*\*\* | 0.01205 | 0.00453 | -0.00099 | 0.02815\*\*\* | 0.02277\*\*\* | 0.02716\*\*\* |
| price\_mean | 0.00277\*\* | 0.00054 | 0.00137\* | 0.00101\*\* | 0.00037 | 0.00037 | 0.00379\*\*\* | 0.00114\* | 0.00226\*\*\* | 0.00103\*\* | 0.00059\*\* | 0.00079\*\* |
| price\_std | -0.01211 | -0.01597 | -0.02256 | -0.00562 | -0.00850 | -0.00850 | -0.01238 | -0.02074\* | -0.02808\* | -0.01100 | -0.01422\* | -0.01574 |
| price\_skewness | -0.00037 | -0.00068 | -0.00131 | 0.00051 | -0.00015 | -0.00015 | 0.00027 | -0.00079 | -0.00155 | -0.00109 | -0.00056 | -0.00032 |
| price\_range | 0.00025 | 0.00544\* | 0.00435 | -0.00193 | 0.00096 | 0.00096 | -0.00236 | 0.00436 | 0.00254 | -0.00176 | 0.00142 | 0.00065 |
| price\_kurtosis | -0.00046 | -0.00019 | -0.00019 | -0.0003\*\* | -0.00018\* | -0.00018\* | -0.0006\* | -0.00032\*\* | -0.00034 | -0.00045\*\* | -0.00023\* | -0.00026\* |
| price\_c\_v | 0.16111 | 0.02307 | 0.07248 | 0.03247 | 0.00240 | 0.00240 | 0.13770 | 0.04528 | 0.09883 | 0.04376 | 0.05094 | 0.05005 |
| sales\_mean | 0.00023\*\*\* | 0.00012\* | 0.00018\*\* | 0.00001 | -0.00002 | -0.00002 | 0.00025\*\*\* | 0.00015\* | 0.0002\*\* | 0.00003 | 0.00001 | 0.00002 |
| sales\_std | -0.00095\*\*\* | -0.00045\*\* | -0.00083\*\* | -0.00025\* | -0.00014 | -0.00014 | -0.00102\*\*\* | -0.00055\*\* | -0.00101\*\* | -0.00026\*\* | -0.0002\*\* | -0.00029\*\* |
| sales\_skewness | 0.00817 | 0.00499 | 0.01148 | -0.00155 | -0.00168 | -0.00168 | -0.00561 | -0.00257 | -0.00016 | -0.00019 | 0.00000 | 0.00012 |
| sales\_range | 0.00014\*\*\* | 0.00007\*\* | 0.00012\*\* | 0.00004\*\* | 0.00003\*\* | 0.00003\* | 0.00015\*\*\* | 0.00008\*\* | 0.00014\*\* | 0.00004\*\* | 0.00003\*\* | 0.00005\*\* |
| sales\_kurtosis | -0.00149 | -0.00058 | -0.00172\* | 0.00012 | 0.00005 | 0.00005 | -0.00035 | -0.00004 | -0.00080 | -0.00017 | -0.00018 | -0.00027 |
| sales\_c\_v | -0.03787\*\* | -0.01232 | -0.02140 | -0.00681 | -0.00047 | -0.00047 | -0.03765\* | -0.00607 | -0.02016 | -0.00033 | 0.00326 | 0.00352 |
| d\_freq | -0.06094 | -0.04879\* | -0.07097\* | -0.01749 | -0.01400 | -0.01400 | -0.04704 | -0.03746 | -0.07159\* | -0.03957\* | -0.03361\*\* | -0.04299\*\* |
| f\_freq | 0.01806 | -0.01197 | 0.01490 | 0.01541 | -0.01115 | -0.01115 | 0.01260 | -0.01339 | 0.02143 | -0.01009 | -0.02121 | -0.03593 |
| outliers\_pct | -0.12304 | -0.05428 | -0.06777 | -0.01266 | 0.00806 | 0.00806 | -0.02430 | -0.02144 | 0.01446 | -0.03710 | -0.01552 | 0.00039 |
| randomness | -0.05481 | -0.02020 | -0.06328\*\* | 0.03238\*\* | 0.02648\*\* | 0.02648\* | -0.03067 | -0.00795 | -0.04555 | 0.0386\*\* | 0.02251\*\* | 0.02833\* |
| linear\_trend | 0.03540 | 0.05163\*\*\* | 0.09356\*\*\* | -0.01630 | -0.00010 | -0.00010 | 0.02717 | 0.05497\*\*\* | 0.09635\*\*\* | -0.02463\* | -0.00159 | -0.00686 |
| category\_beer | -0.00815 | -0.01089 | -0.00825 | -0.01677\* | -0.0197\*\*\* | -0.0197\*\*\* | -0.02125 | -0.01733 | -0.01547 | -0.01208 | -0.01704\*\* | -0.01768\*\* |
| category\_blades | 0.01312 | -0.00694 | 0.00456 | -0.00786 | -0.01828\*\* | -0.01828 | 0.01639 | -0.00342 | 0.01155 | -0.00430 | -0.01572\* | -0.01380 |
| category\_carbbev | -0.04766\* | -0.02880 | -0.05304\*\* | -0.06275\*\*\* | -0.04149\*\*\* | -0.04149\*\*\* | -0.04845 | -0.02913 | -0.05087\* | -0.06598\*\*\* | -0.04143\*\*\* | -0.0602\*\*\* |
| category\_cigets | -0.07058\*\* | -0.02313 | -0.03228 | -0.03322\*\*\* | -0.02586\*\*\* | -0.02586\*\*\* | -0.08005\*\* | -0.02825 | -0.03731 | -0.02787\*\* | -0.0272\*\*\* | -0.03028\*\*\* |
| category\_coffee | 0.00669 | -0.00901 | -0.00260 | -0.04018\*\*\* | -0.03222\*\*\* | -0.03222\*\*\* | 0.01115 | -0.00938 | -0.00405 | -0.04136\*\*\* | -0.03569\*\*\* | -0.04018\*\*\* |
| category\_coldcer | -0.06608\*\* | -0.04065\*\* | -0.05768\*\* | -0.04667\*\*\* | -0.03397\*\*\* | -0.03397\*\*\* | -0.06105\*\* | -0.05044\*\* | -0.06296\*\* | -0.04558\*\*\* | -0.03944\*\*\* | -0.04373\*\*\* |
| category\_deod | 0.03077 | -0.00216 | 0.00305 | -0.01402 | -0.01914\*\*\* | -0.01914\*\* | 0.03389 | -0.00233 | 0.00417 | -0.01552\* | -0.0214\*\*\* | -0.02308\*\*\* |
| category\_factiss | -0.05763\* | -0.05602\*\* | -0.07821\*\* | 0.01368 | -0.00554 | -0.00554 | -0.05703\* | -0.05691\*\* | -0.08364\*\* | 0.01678 | -0.00123 | -0.00104 |
| category\_fzdinen | 0.07453\*\* | -0.01475 | -0.00299 | -0.00092 | -0.01873\*\* | -0.01873\* | 0.07618\*\* | -0.01871 | -0.00701 | 0.00976 | -0.01471 | -0.01367 |
| category\_fzpizza | -0.04258\* | -0.02127 | -0.02806 | -0.03927\*\*\* | -0.02457\*\*\* | -0.02457\*\*\* | -0.04766\* | -0.02828 | -0.03511 | -0.03199\*\*\* | -0.02457\*\*\* | -0.03123\*\*\* |
| category\_hhclean | -0.02752 | -0.01765 | -0.02169 | 0.01459 | 0.00255 | 0.00255 | -0.02292 | -0.02090 | -0.02384 | 0.01764 | 0.00145 | 0.00909 |
| category\_hotdog | -0.13098\*\*\* | -0.07739\*\*\* | -0.11451\*\*\* | -0.03969\*\*\* | -0.03048\*\*\* | -0.03048\*\* | -0.13798\*\*\* | -0.10324\*\*\* | -0.14931\*\*\* | -0.04137\*\*\* | -0.03894\*\*\* | -0.04287\*\*\* |
| category\_laundet | -0.02258 | -0.01647 | -0.01721 | -0.00141 | -0.01942\*\* | -0.01942 | -0.04104 | -0.02415 | -0.03253 | 0.00020 | -0.022\*\* | -0.01597 |
| category\_margbut | -0.02468 | -0.02627 | -0.03286 | -0.0371\*\*\* | -0.03334\*\*\* | -0.03334\*\*\* | -0.02238 | -0.02876 | -0.03478 | -0.03411\*\*\* | -0.03356\*\*\* | -0.03626\*\*\* |
| category\_mayo | -0.06908\*\* | -0.06247\*\*\* | -0.07134\*\* | -0.02723\*\*\* | -0.03499\*\*\* | -0.03499\*\*\* | -0.06984\*\* | -0.06618\*\* | -0.07297\*\* | -0.02198\*\* | -0.03238\*\*\* | -0.0353\*\*\* |
| category\_milk | -0.01847 | -0.00694 | -0.00978 | -0.01953 | -0.01679 | -0.01679\* | -0.02657 | -0.00894 | -0.01500 | -0.01659 | -0.01775 | -0.02188 |
| category\_mustket | -0.01962 | -0.02274 | -0.02416 | -0.01244 | -0.02576\*\*\* | -0.02576\*\* | -0.00935 | -0.02318 | -0.02305 | -0.01167 | -0.02937\*\*\* | -0.02873\*\*\* |
| category\_Paptowl | 0.11373 | 0.04271 | 0.16328\*\* | -0.08338\* | -0.07136\*\*\* | -0.07136\*\* | 0.12524 | 0.03535 | 0.16158\*\* | -0.08640 | -0.07801\*\*\* | -0.10176\*\* |
| category\_peanbut | -0.04227 | 0.00202 | -0.00302 | -0.01579 | -0.0418\*\*\* | -0.0418\*\*\* | -0.04389 | 0.00317 | -0.00315 | -0.01397 | -0.04197\*\*\* | -0.04499\*\*\* |
| category\_photo | 0.04757 | 0.00053 | 0.01537 | -0.01426 | -0.01718 | -0.01718 | 0.04424 | -0.00185 | 0.01333 | -0.00738 | -0.01547 | -0.01113 |
| category\_razors | 0.02646 | -0.04874 | -0.02441 | -0.0647\*\* | -0.05427\*\*\* | -0.05427\*\* | 0.02228 | -0.05612 | -0.02776 | -0.06199\*\* | -0.05109\*\*\* | -0.05903\*\* |
| category\_saltsnc | -0.01933 | -0.00794 | -0.00664 | -0.01753\* | -0.01664\*\* | -0.01664\* | -0.02354 | -0.00767 | -0.00949 | -0.01725 | -0.01775\*\* | -0.02032\*\* |
| category\_shamp | 0.01312 | 0.00291 | -0.00054 | -0.00457 | -0.01586\*\* | -0.01586 | 0.02764 | 0.00209 | 0.00222 | -0.00068 | -0.01676\*\* | -0.01346 |
| category\_soup | 0.00621 | -0.01846 | -0.03381 | -0.00858 | -0.01539\*\* | -0.01539 | 0.00835 | -0.02571 | -0.04135\* | -0.00483 | -0.01502\* | -0.01144 |
| category\_spagsau | 0.04126 | -0.00407 | 0.00907 | 0.04154\*\*\* | 0.00520 | 0.00520 | 0.05253\* | 0.00481 | 0.01900 | 0.04378\*\* | 0.00831 | 0.01694 |
| category\_sugarsu | 0.03236 | 0.02341 | 0.02407 | -0.01536 | -0.01695\*\* | -0.01695\* | 0.04993 | 0.03221 | 0.03858 | -0.0174\* | -0.02042\*\*\* | -0.02189\*\* |
| category\_toitisu | 0.00546 | -0.02564 | -0.02226 | -0.02838 | -0.0483\*\*\* | -0.0483\*\*\* | -0.00075 | -0.03684 | -0.03520 | -0.02567 | -0.05344\*\*\* | -0.06312\*\*\* |
| category\_toothbr | -0.04675 | -0.03803\* | -0.05146\*\* | -0.04618\*\*\* | -0.03197\*\*\* | -0.03197\*\*\* | -0.04736 | -0.04202\* | -0.05875\*\* | -0.05042\*\*\* | -0.03421\*\*\* | -0.04287\*\*\* |
| category\_toothpa | 0.06001 | 0.03106 | 0.05436 | -0.01720 | -0.02066\*\* | -0.02066 | 0.04427 | 0.02182 | 0.03959 | -0.02186 | -0.02396\*\*\* | -0.02444\*\* |

1. **Conclusions, limitations and future research**

Grocery retailers have been struggling with producing accurate sales forecasts to effectively manage their inventory planning and customer satisfaction. In practice, many retailers use simple univariate models with adjustments for incoming promotional events. Some recent studies focused on taking advantage of the impact of promotional activities. For example, Gur Ali et al. (2009) proposed models with sophisticated function forms (e.g., the regression tree model) with the price and promotional information of the focal product. Huang et al. (2014) incorporated the competitive promotional information within the same product category by resorting to variable selection methods and the principle component analysis which mitigated the problem of high dimensionality. Ma et al. (2016) integrated the promotional information both within the same product category and across difficult product categories.

These conventional forecasting models all presume invariant effectiveness of marketing activities such as price reductions and feature and display promotions which may actually change over time because of the impact of many influencing factors including the change of economic condition, the change of the consumer taste, and new competition entry etc. However, these factors may not be observable or at least difficult to measure. As a result, the conventional models will be subject to structural break and potentially generate biased and less accurate forecasts.

In this study, we propose the ADL-intra-EWC model and the ADL-intra-IC model which take into account the potential forecast bias caused by the structural break. The ADL-intra-EWC model generate forecasts which are the combine of various sets of forecasts by the ADL-intra model with different estimation windows under the condition when structural breaks are detected. The ADL-intra-EWC model tries to obtain an effective trade-off between the forecast bias and the forecast error variance. In our experiment, the ADL-intra-EWC model generate the most accurate forecasts across all 30 product categories for various scenarios (e.g., forecast horizons and error measures). Table 7 shows the percentage of reductions by the model compared to other models for all the scenarios. For example, the ADL-intra-EWC model reduces the MAPE of the ADL-intra model by 0.20%, and reduces the MAPE of the Base-lift model by 6.04% based on 12 week forecast horizon. The ADL-intra-IC model tries to offset the forecast bias by adding the estimate of the forecast bias back to the error term at a cost of inflated forecast error variance given that structural breaks are detected. The ADL-intra-IC model also has superior overall forecasting performance across all the product categories, though its advantages are getting marginal for longer forecast horizons (e.g., when *h*=12, as indicated in Table 7). At the category level, our proposed models have superior forecasting performance for most of the product categories.

In this study, we also propose the ADL-own-EWC model and the ADL-own-IC model. These models are especially valuable for manufacturers when competitive promotional information cannot be accessed ([Ali and Boylan 2011](#_ENREF_2)). Under such circumstance, manufacturers need to make the best use of the data they have and produce forecasts as accurate as possible. In our experiment, the ADL-own -EWC model outperforms the ADL-own model across all the product categories for various scenarios, while the ADL-own -IC model outperforms the ADL-own model across all product category for short forecast horizons. Table 7 shows that the ADL-own-EWC model reduces the MAPE of the ADL-own model by 0.20% based on the 12 week ahead forecast horizon. At the category level, again the results are in consistent with results across all product categories.

Table 7. Forecasting performance regarding percentage reductions in various error measures

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Forecast horizon | Proposed model | Benchmark | percentage of increase/decrease | | | |
| MAPE | SMAPE | MASE | AvgRelMAE |
| h=12 | ADL-intra-EWC | ADL-intra | -0.20% | -0.48% | -0.69% | -0.70% |
| ADL-intra-IC | ADL-intra | 0.40% | 0.51% | 0.55% | 0.33% |
| ADL-own-EWC | ADL-own | -0.20% | -0.52% | -0.65% | -0.68% |
| ADL-own-IC | ADL-own | 0.51% | 0.56% | 0.56% | 0.31% |
| ADL-intra | ADL-own | -1.46% | -0.78% | -0.61% | -0.75% |
| ADL-intra-EWC | Base-lift | -6.04% | -14.52% | -11.76% | -13.98% |
| ADL-intra-IC | Base-lift | -5.48% | -13.66% | -10.66% | -13.09% |
| h=4 | ADL-intra-EWC | ADL-intra | -0.28% | -0.53% | -0.61% | -0.74% |
| ADL-intra-IC | ADL-intra | -0.66% | -0.15% | -0.41% | -0.41% |
| ADL-own-EWC | ADL-own | -0.30% | -0.55% | -0.72% | -0.75% |
| ADL-own-IC | ADL-own | -0.89% | -0.16% | -0.76% | -0.45% |
| ADL-intra | ADL-own | -1.29% | -0.88% | -1.08% | -0.93% |
| ADL-intra-EWC | Base-lift | -2.58% | -13.00% | -10.03% | -10.14% |
| ADL-intra-IC | Base-lift | -2.95% | -12.67% | -9.85% | -9.85% |
| h=1 | ADL-intra-EWC | ADL-intra | -0.83% | -0.53% | -0.51% | -1.38% |
| ADL-intra-IC | ADL-intra | -2.11% | -1.02% | -1.01% | -2.98% |
| ADL-own-EWC | ADL-own | -0.53% | -0.52% | -0.56% | -0.46% |
| ADL-own-IC | ADL-own | -2.54% | -1.12% | -1.53% | -2.93% |
| ADL-intra | ADL-own | -0.96% | -0.78% | -1.43% | -0.26% |
| ADL-intra-EWC | Base-lift | -1.44% | -11.44% | -9.99% | -2.25% |
| ADL-intra-IC | Base-lift | -2.70% | -11.88% | -10.44% | -3.83% |

There are potentials to further improve the forecasting accuracy which we leave to future research. 1) In this study, we indiscriminately restrict the smallest estimation window for the EWC method to contains 120 weeks of observations for each SKU and we combine the various sets of forecasts based on different estimation windows using equal weights. The forecasting performance may potentially be improved by tubing the number of estimation windows and the number of the observations in 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) is a summary of different correction schemes which may have different effect on the trad-off of the bias and the error variance[[12]](#footnote-13). 2) Ma et al. (2016) proposed models which integrate both the intra and the inter category promotional information. We may investigate if we can further improve the forecasting performance of the ADL-intra-EWC model and the ADL-intra-IC model with inter-category information. 3) One of the alternative methods is to directly incorporate the changing process of the effectiveness of the marketing activities into the model. When the influencing factors are not observed, the changing process may be captured by an autoregressive process of the marketing activity parameters. For example, [Foekens, Leeflang et al. (1999)](#_ENREF_29) modelled the effectiveness (i.e., the parameters) of the price variables using the level of previous prices and the recency and the frequency of previous promotional events. The models were used to describe and evaluate the changing process of the effectiveness of the price and promotions, and their forecasting capacity was unknown. However, one of the challenges for this type of model is that it would easily go over-sophisticated when engaged with a second stage model for the parameters and therefore lose parsimony. 4) Another method alternative to the EWC method and the IC method is the impulse saturation method introduced by [Hendry and Krolzig (2001)](#_ENREF_33) and [Castle, Doornik et al. (2008)](#_ENREF_12). They proposed to saturate the ADL model with dummy variables for each of the observations and then recursively simplify the model with the *Autometrics* algorithm based on a general-to-specific modelling strategy[[13]](#footnote-14). The final model usually retains a large number of dummy variables to prevent the structural break and the subsequent forecast bias. However, this method inevitably loses information by retaining these dummy variables, which makes the forecasting performance of the method an empirical question. We leave all these potential opportunities to the next stage of our research.

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1. More specifically, the forecast bias comes from the change of the deterministic mean of the model due to the change of the model parameters. There is a possibility that the deterministic mean could retain unchanged even if the parameters change. Under such circumstance, there will be no forecast bias even when the model is subject to structural break. However, in this study we do not explain this situation as it only happens theoretically when very restrictive conditions are met. Details based on an example of a VAR model can be found in Clements and Hendry (1999). [↑](#footnote-ref-1)
2. Analytical evidence for the models with endogenous explanatory variables can be found in Clements and Hendry (1999) and Pesaran and Timmerman (2005, 2007). [↑](#footnote-ref-2)
3. This setting is very common in the retailer context. In this example we artificially make up the data series but we keep the data series to be stationary. [↑](#footnote-ref-3)
4. The values from week 1 to week 50 are predicted by the model estimated with the data from week 51 to week 75. [↑](#footnote-ref-4)
5. The Chow test is a variant of F-test which compares the fitting of the model before and after the structural break. It assumes the locations of one structural break known a priori and also invariant error variations before and after the break. For example, we conduct the Chow test assuming the break occurs at a specific week (e.g., week 30). A small p-value would reject the null hypothesis of no structural at week 30. [↑](#footnote-ref-5)
6. To mitigate the multiple comparison problem, we may adopt very small threshold (e.g., 0.0001) for the p-value of the sequential test. [↑](#footnote-ref-6)
7. In Figure 5, the black dashed line for the estimation period (e.g., week 1 to week 75) represents the predicted value of the original regression model which is estimated using the full sample. [↑](#footnote-ref-7)
8. All estimates and analyses in this paper based on Information Resources, Inc. data are by the author and not by Information Resources, Inc. [↑](#footnote-ref-8)
9. 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-9)
10. Note that, in this study, although our econometric models are based on log sales, we calculate all the error measures after we transform them back to original levels. [↑](#footnote-ref-10)
11. The values of the error measures we report in Table 4a, 4b, and 4c are all aggregate values. The values of the error measures for all forecast period may not necessarily drop in the range between the values for the non-promoted forecast period and the values for the promoted forecast period. This is because that the lengths of the promoted time periods are different across the SKU’s. As a result, the weights we use to combine the various data series for all forecast period, for the promoted forecast period, and for the non-promoted forecast period are all be different. [↑](#footnote-ref-11)
12. For example, in this study we generate the forecasts first and then add the estimated bias to all the forecasts. One of the alternative schemes 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 already adjusted, and so forth. [↑](#footnote-ref-13)
13. The algorithm recursively simplifies the model block by block pretending there are only a section of the dummy variable existing. The algorithm eventually combines all the retained dummy variables from every recursion. [↑](#footnote-ref-14)