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Abstract: Grocery retailers need accurate forecasts at Stock Keeping Unit (SKU) level to effectively manage their inventory. Previous studies have developed forecasting methods which incorporate the effect of various marketing activities including prices and promotions. These methods, however, have overlooked whether the effects of marketing activities on product sales may change over time. These methods may potentially be subject to the structural change problem as they are unable to capture any varying effect of the marketing activities. As a result, they could generate biased and less accurate forecasts. In this study, we propose effective forecasting methods for retailer product sales which take into account the problem of structural change. Our methods outperform conventional models based on a sample from a popular dataset for US retailers.

A list of responses to the reviewers' comments

We want to thank the two anonymous reviewers for their helpful comments and valuable suggestions. We have carefully read through the reviewers' reports and revised the manuscript based on their suggestions. We have now completely revised the manuscript, and we have positively taken into account all the comments. We believe that the paper has improved substantially with their contributions.

In addition to the modifications based on the reviewers' suggestions, we highlight the following major changes in the revised manuscript:

1. We have completely revised the introduction section to emphasize the purpose of our research and highlight the contributions.

2. We have completely revised the literature review section.

3. We have completely revised the sections which explain the structural change problem and the methods. We have now merged the two sections. We have replaced some of the analytical equations for the EWC method with intuitive explanations. We have also described the limitations of the EWC method and the IC method, and accordingly, we highlight that their performance for retailer product sales is an empirical question.

4. We have added a more explicit description for the dataset.

5. We have more explicitly described the rationale of the three stages of the modeling process including the details of how we detect the presence of structural change.

6. We have added the description for the Base-lift method.

7. We have also updated more appropriate presentations for the error measures across all the products.

8. We have now reconducted the whole evaluation using a different setting for the sequential Chow test. For example, we now conduct the test for up to 95% of the observations, compared to the previous version where we conduct the sequential Chow test for up to 70% of the observations. The results suggest little difference in the models' forecasting performance. Our proposed methods consistently have the best forecasting performance.

9. We have replaced he Wilcoxon SR test with the Diebold-Mariana Test.

10. We have described more explicitly, for each category, the improved forecasting performance by our proposed methods compared to the model with similar specifications but overlook the structural change problem. We show the distribution of the improved forecasting performance at SKU level for selected product categories.

11. We have now completely revised the section which explores the determinants of the improve

forecasting performance by the proposed methods compared to the ADL-intra model. We remove some of the statistical measures (e.g., Skewness and Kurtosis, etc.) and construct five factors based on the remaining nine measures. The findings are consistent compared to those in the previous version. However, we tune down our claim and emphasize that the findings are only exploratory.

Please see our detailed responses to the reviewers' comments as follows:

Reviewer #1: This is a nice paper that investigates the influence of structural change (see one point I make below) on retail data in the IRI data set. It proposes to augment established Autoregressive Distributive Lag (ADL) models, by either fitting multiple models to shorter and shorter terminal segments of the series, then averaging the forecast (so data points after the conjectured structural break are weighted more heavily), or by attempting to estimate a bias from the terminal in-sample fits and correcting for this estimated bias. The forecast accuracy is improved in either way. I have few important points to make and mostly recommend toning down some overly enthusiastic claims.

Medium points:

- Highlights: "Retailer product sales from a wide range of product categories" is not very useful.

We have now removed this point from the highlights.

- "Structural breaks" suggests a sudden and abrupt change in a parameter, like a step change in the overall level of the time series. I find this choice of words somewhat unhappy. On the one hand, in a retail environment, I would typically not expect a sudden abrupt change (except in exceptional cases, like a new store opening next door), but rather a gradual one, which would also be more consistent with drivers of such change that the authors discuss, e.g., shifts in lifestyle. On the other hand, there is a vast literature on detecting structural changes in time series (e.g., look at the documentation of the strucchange R package on CRAN), but the authors nowhere apply such a test (which would not be overly useful in my opinion, per above). Thus, maybe "structural change" instead of "structural break" would be a more useful word for the concept.

We thank the reviewer for this helpful advice. We change the term from structural break to structural change and add the following footnote:

"The term of 'structural change' is used interchangeably with the term of 'structural break' in the literature. In this study, we use the term "structural change" as in the retailer context we expect the effect of the marketing activities to change sometimes gradually rather than but sometimes in a sudden and abrupt way. We thank one of the anonymous reviewers for to pointing this out."

Previously we described the sequential Chow test we used to detect the presence of structural change in the Appendix of the supplementary material. We have now described how we conduct the test explicitly in section 6 and we also address the possibility of implementing alternative structural change tests.

- The EWC is very similar to estimating a single model with weighted observations (or residuals),

with the weights decreasing as we go further into the past. I wonder whether a direct approach like this would be feasible. It would have the advantage of returning a single parameter vector that could be examined and analyzed, whereas in EWC, one has to look at multiple such vectors, one from each of the models we average.

What the reviewer has mentioned is a possibility. We have evaluated the forecasting performance of ADL models with time-varying parameters (TVP) which has the same rationale described here. However, the preliminary results are mixed. One possible explanation is that the model may have some sophisticated structures which are not robust to the retailer data at SKU level. We add the following to the last section:

"Also, an alternative to the ADL-intra-EWC method and the ADL-intra-IC method is to directly model the change in the effect of the marketing activities, such as the time-varying parameter model. However, a disadvantage of this method is that we need to make strong assumptions of how the effects of the marketing activities change. For example, Foekens, Leeflang, and Wittink (1999) modeled the effect of marketing activities as a linear function of previous promotional activities. Their models were not developed for forecasting purposes."

- None of the accuracy measures used is minimized in expectation by an unbiased forecast (see the introduction of Kolassa, 2016, IJF). I am somewhat concerned that the increase in accuracy may have come at the cost of bias. I would recommend using either a measure that is minimized in expectation by an unbiased forecast, e.g., a scaled RMSE, or assessing bias in some way.

We have now added the scaled MSE as one of the error measures, and our proposed methods consistently have the best forecasting performance in general. The increase in the accuracy comes from the reduction of the bias but at the cost of increased forecasting error variance. The IC method adds the estimated bias back to the forecasts, which directly reduces the bias but increases the forecast error variance. The EWC method combines the forecasts from different estimation windows. Compared to the full estimation window, other estimation windows are all smaller but with more recent information (e.g., closer to the forecast origin). Forecasts based on these 'smaller' estimation windows are less biased (e.g., these estimation windows contain fewer pre-structural change data) but potentially with higher forecast error variance (e.g., fewer estimation information). Thus, the final forecasts will be less biased and potentially with higher forecast error variance. Whether or not the final forecasts by the EWC method can be more accurate depends on the trade-off between the reduced forecast bias and the potentially increased forecast error variance.

- I see no discussion of how the estimation was actually carried out. Was some third-party software used, e.g., an R package? Please cite software and packages used (with version numbers). Software authors are entitled to recognition.

We estimate the model parameters using the OLS estimator, and we implement the estimation using the MODEL procedure with macros in SAS. 9.4. We have added this in section 6 and section 7.

- p. 11: what is "four-week seasonality"? Does this refer to cutting the year into 13 four-week periods

(13*4=52), then expending 12 dummies? If so, this corresponds to fitting a periodic *step* function, which stays constant for four weeks and then may change sharply when we enter the next four-week bin. This is discretizing a continuous variable (namely, time). Don't do this. The disadvantages of discretization have been well documented over the years - apart from the almost certainly ecologically invalid step fit I discuss, it also expends far too many degrees of freedom. Instead, use a number of periodic spline transforms of time. Three or four parameters expended here would be much better invested than twelve in discretization. Further reading here:

https://stats.stackexchange.com/questions/230750/when-should-we-discretize-bin-continuous-independent-variables-features-and-when
https://stats.stackexchange.com/questions/41227/justification-for-low-high-or-tertiary-splits-in-anova (see the links in Glen_b's answer)

In this study, we use the deterministic four-week dummy variables (e.g., 12 four-week dummy variables for the 52 weeks) to capture the seasonality which cannot be captured by the holiday event dummy variables (e.g., Christmas, New Year's Day, etc.). This approach has the limitation that the effect is assumed to stay constant within the four-week bins and has a cost of degrees of freedom. However, in our context, the models are estimated with a comparably large sample (e.g., 160 weeks), where the loss of 12 degrees of freedom is not an issue.

We think the performance of alternative methods for the seasonality depends on the characteristics of the data. In our study, we focus on weekly retailer data at SKU level which have unique characteristics. e.g., product sales have high variations, the effect of marketing activities change overtime, and less 'seasonal' compared to data from other industries (e.g., the electricity demand data), and product sales may be more driven by promotional events. Also, we propose sophisticated multi-stage model specification strategies. The methods initially include a large number of independent variables and then attempt to recursively simplify the model's specification. Thus, the performance of any other methods to capture the seasonality for retailer product sales becomes an empirical question, especially when integrated with sophisticated model simplification strategies.

We thank the reviewer for the suggestion on how to improve the model's performance using the alternative methods for seasonality. For example, there are other methods such as periodic spline functions and the seasonal exponential smoothing etc., which have been found useful in modeling seasonality in other fields such as electricity demand. We also thank the reviewer for the reference where the natural splines method is compared with the traditional deterministic method based on the simulation data. We address the limitation of our current approach in the last section as an avenue for further research.

- p. 19: To be honest, I do not find the introduction and discussion of the ADL-EWC-IC model convincing, since it was created after analyzing the performance of the separate models on subsamples. It is always easy to build a new model ex post that appears to perform well, but this is little better than data snooping. Can the ADL-EWC-IC model be compared to the other models on previously unseen data? If not, please label this discussion explicitly as exploratory. Similarly, please revisit the discussion in the first paragraph on p. 25.

We thank the reviewer for this useful comment and suggestion. We have now evaluated the

forecasting performance of the ADL-EWC-IC model based on previously unseen data. That is, based on 1605 SKU's from the same product categories but from a different set of 28 stores. The results are consistent (the results are now shown in Table 5). We take the reviewer's suggestion and describe the ADL-EWC-IC model as "exploratory."

- p. 23: In discussing a statistically significant positive coefficient for "Randomness and growth" in ADL-intra-EWC, the authors write that "This suggests that our proposed models tend to be more advantageous for the SKUs which are difficult to forecast and exhibit a trend in sales". I do not understand this. The dependent value modeled is MASE, so a positive coefficient of 0.4 should mean that a unit increase in "Randomness and growth" should be associated with a 0.4 unit (up to multiplication by 100, per the footnote to Table 7) *increase* in MASE. That is, ADL-intra-EWC should perform *worse* than the benchmark for high-"Randomness and growth" series, not *better*. Please clarify. Same for the rest of the discussions on the same page, and the third paragraph on p. 25.

We have now completely revised this section. The dependent variable is not the MASE but the percentage reduction of the MASE by the ADL-intra-EWC model and the ADL-intra-IC model compared to the ADL-intra model. e.g.,

$$\mathrm{PctRed}(\mathrm{ADL}-\mathrm{intra}-\mathrm{EWC},i)=\frac{\mathrm{MASE}(\mathrm{ADL}-\mathrm{intra},i)-\ \mathrm{MASE}(\mathrm{ADL}-\mathrm{intra}-\mathrm{EWC},i)}{\mathrm{MASE}(\mathrm{ADL}-\mathrm{intra},i)}$$

$$\mathrm{PctRed}(\mathrm{ADL}-\mathrm{intra}-\mathrm{IC},i)=\frac{\mathrm{MASE}(\mathrm{ADL}-\mathrm{intra},i)-\ \mathrm{MASE}(\mathrm{ADL}-\mathrm{intra}-\mathrm{IC},i)}{\mathrm{MASE}(\mathrm{ADL}-\mathrm{intra},i)}$$

where $\mathrm{PctRed}(\mathrm{ADL}-\mathrm{intra}-\mathrm{EWC},i)$ and $\mathrm{PctRed}(\mathrm{ADL}-\mathrm{intra}-\mathrm{IC},i)$ are the percentage reduction of the MASE by the ADL-intra-EWC model and the ADL-intra-IC model compared to the ADL-intra model for SKU i.

Thus, in the updated results, a positive estimate of 0.21 indicates that one unit increase in "Randomness and growth" would cause a 0.21% more reduction in the MASE. We have now added a clearer description for the interpretation.

We have revised this section accordingly and make the description more explicit.

- p. 23, "All the results here indicate that we may pre-test these features for each SKU and then determine the optimal sales forecasting method specifically for that SKU." This is a very exploratory finding, not guided by prior hypotheses. Unless this can be verified on previously unseen data, please emphasize the tentative nature of this recommendation.

We thank the reviewer to point out the tentative nature of this indication. We have now revised the sentence: we only highlight the indications based on the current findings and we limit the scope of the finding by emphasizing that the determinants are only for the improved forecasting performance by the proposed methods compared to the model with similar specifications but overlook the structural

change problem “Overall, we attempt to provide exploratory insights on the situations where our proposed methods may gain most benefits compared to the ADL-intra model..”

- p. 24, " The improved forecasting accuracy for product sales substantially contributes to retailers' profit". This is a very strong claim, and not backed by anything the authors did in their paper. Whether forecast accuracy improvements actually translate into better profits is not this clear-cut, since forecasts must still be translated into operational plans, which are constrained by logistics. In addition, supply chain operations rely far more on quantile forecasts than on point forecasts, since the total order includes safety amounts, and whether these quantile forecasts can be improved by the authors' proposals is not obvious. Please tone this claim down.

We thank the reviewer for this comment, and we tone down the claim of our contribution- we remove this sentence and add “Therefore, our study may provide retailers more effective forecasting methods”

Minor points:

- p. 6, 1st equation: there is no intercept in the formula. If u_t is assumed to have mean 0, this implies that a price of x=0 is associated with sales of y=0. I assume the authors meant to include an intercept parameter.

We have revised this section and we do not treat the variables to be price or price reductions (as pointed out by the reviewer, the sales will not be zero even there is no price reduction). We show the analytical evidence for a simple example where the model does not have an intercept. We highlight that more sophisticated scenarios (e.g., with an intercept and with endogenous variables) can be demonstrated using simulations. In the supplementary material, we demonstrate the impact of structural change on forecast bias and forecasting performance where the model has an intercept.

- Table 3: why do different models serve as benchmarks?

We compare the proposed ADL-intra-EWC model and the ADL-intra-IC model with the ADL-intra model because the ADL-intra model has similar specifications but overlook the problem of structural change), so that we know how much improvement is contributed by taking into account the problem of structural change. We compared the proposed methods the Base-lift method because it is still being widely used by industrial practitioners. We have now highlighted this in the revised manuscript.

- Figure 3: please provide more information in the figure caption instead of in the text or even in footnotes - the reader should not need to hunt through the text to understand the figure. Are the diamonds joined by lines group means? Are box widths *proportional* to numbers of SKUs in each category? "Are determined by" can be a log transform, a square root or anything else. Please ensure that the horizontal axes have the same extension so the plots are comparable, and that the whiskers are not cut off by the figure bounding box.

We have now described the Figure explicitly. We have provided the detailed information and we have also reproduced the Boxplots. The box widths are now proportional to the number of SKU’s in each product category. The diamonds represent the group means for each product category and joined by

lines for illustration. The Boxplots are now with the same extension for the horizontal axes and without outliers being clipped.

- Table 7: please indicate in the table caption what "their counterparts" are. The entire table is unclear to me; how do the top and the bottom half differ? What does "Model with 5 factors and category dummy variables" as a caption to the bottom half (or is it?) refer to, in contrast to the top half? The text says on p. 23 that "the horizon is one to eight-week ahead", but the table says "Horizon = 8" - please clarify whether the horizon is eight weeks or *up to* eight weeks.

We have now completely revised Table 8 (the previous Table 7). It now shows the parameter estimates for the regression model with the five factors as independent variables. Previously We developed another regression model where the independent variables include the five factors and also category dummy variables. The parameter estimates of the five factors are consistent for these two models. The revised Table 8 now only includes the parameter estimates of the model which has the five factors as independent variables. This makes Table 8 more readable. Also, we put the following footnote:

"For robustness, we have developed an alternative regression model which also include dummy variables to capture potentially unobserved category effects, and we find the parameter estimate for the five factors to be consistent with those shown in Table 8."

We have also clarified the description for the horizons.

- References: please provide full details for Loeb (2015)
Revised

Typos:

- p. 3, 2nd para, l. 3: "The model which is subject to structural break" - either add "a" or change to "breaks"

Revised

- p. 3, 2nd para, l. 7: remove "in" after "including"
Revised

- p. 4, l. 2: "mention" -> "mentioned"
Revised

- p. 4, l. 3: "values" -> "value"
Revised

- p. 4, 2nd para, l. 2: "the change of" -> "changes in"

Revised

- p. 5, l. 5: "forecast" -> "forecasts"
Revised

- p. 6, 2nd para, l. 3: "structure" -> "structural"
Revised

- p. 6, third equation block: italic and upright versions of beta, X and Q are mixed, which is painful to me (also on p. 7)). Please ensure proper mathematical typesetting. Lowercase x_{T+h} and uppercase X_{T+h} is used inconsistently here.

We thank the reviewer for this correction. We have now revised those inconsistent versions of letters and symbols. We have now discarded the symbol "Q" and use the lowercase consistently.

- p. 7, equation for the bias correction: lowercase omega is used both as the starting index of the summation (with the ending index indicated by W - why mix Greek and Latin?) and as the summation index itself.

Revised

- p. 7: "The estimated bias are" should be "is"
Revised
- p. 10, equation: can be slightly simplified by removing "=\eta, \eta"

We thank the reviewer- we think it might be more readable if we keep it.

- p. 19/20: Figure 3(c) is not "in the bottom-right corner", but in the bottom left.

We have now removed the previous Figure 3(c). This is because that we now focus on the ADL-intra-EWC method and the ADL-intra-IC method. We only consider the ADL-EWC-IC model to be exploratory and thus we do not show too much of its details for simplicity.

Reviewer #2: This is an interesting paper that is trying to investigate the forecasting performance of several ADL models over retailer product sales. The study is particularly focusing on the effects of structural breaks originating from marketing activities over the products.

Main Comments:
1. I found the structure of this paper very confusing. For example, the introduction and literature review section are very poorly written with many overlaps and repetitions that are not at all informative for the reader. The contribution of the paper, as outlined, is very weak.

We have now completely revised the structure of the paper and we have taken out some of the arguments that may sound a bit repetitive. We have also highlighted explicitly our contributions.

2. In the introduction the authors should clearly indicate what is the model they are introducing and why. On top of that, it should be made clear to the reader why the specific models seem appropriate for the retail forecasting exercise. It is quite astonishing that the reader does not get a gist of what he/she is going to see unless he/she reaches page 10.

We have now introduced what is new in our research earlier in the paper than we did in the previous version. We have also highlighted the value of the work regarding how it might impact inventory management practices similar to other related work in the field of forecasting.

3. The literature review is very short and several references are packed all together without any meaningful commentary (for example in page 5). I would really be interested to see what are the findings of studies assuming constant marketing activities, as this would highlight/clarify/validate potentially comparisons with the models at hand.

We have now completely revised the literature review. In section 2.1., we summarize the findings of previous studies which forecast retailer product sales at SKU level. e.g., their proposed methods and the rationales in more detail. In section 2.2., we summarize the (changing) effect of the marketing activities.

4. The text is characterized by some generalizations that make the reader confused on what the authors are claiming. For example, in page 3 '… The data in retailer product sales… macroeconomics).' I would suggest a thorough read-through to the authors in order to make the text more to the point.

We take the reviewer's suggestions and we have now streamlined the manuscript in line with this comment and taking into consideration other comments/suggestions by the other reviewer too.

5. Section 3 and 4 seem a bit redundant the way they are presented. I would expect to see a methodology section, where these two sections could motivate/inform the selection of models in section 6. The ideal approach would be that section 3 and 4 are reduced substantially and included in the commentary of section 6 or if needed in an appendix.

We have now completely revised these sections.

6. In section 5, it should be explained what the display and feature percentage is along with the motivation of the selection of these inputs. In my view, the data section should have been after the intro/literature review.

We have now added descriptions below Table 4. We explain the motivation to include the promotional variables in the methodology section. We put the section for the structural change after the literature review. It explains what would happen if we overlook the change in the effect of the marketing activities, which was introduced in the literature review section.

7. In terms of the analysis during structural breaks, it is interesting that the authors do not make

explicitly clear how they detect, test or analyse their results for structural breaks. It would be expected that in that type of paper where forecasting performance is evaluated within the presence of structural breaks that vast emphasis would be given on that issue. The general information provided in section 4 are not enough in my opinion. What tests have been done and what was the result? Except from the Chow test, have the authors investigated the Andrews approach (2003 , Econometrica) or Fixed Regressor Boostrap? The vague analysis on that aspect is a main shortcoming of this paper.

We previously described how we conduct the sequential Chow test in the Appendix in the supplementary material - we have now included this in section 6 of the paper. We conduct the sequential Chow test for up to 95% of the weeks in the estimation period. Suppose that we have an estimation period of 160 weeks. We conduct the Chow test for each of the 160*0.95= 152 weeks (e.g., the 152 weeks in the centre of the 160 weeks, from week 5 to week 156). Each time we assume that there is a structural change occurring at one of these weeks. For example, we initially conduct the Chow test assuming a structural change occurring at week 5, and we obtain the p-value. We then conduct the Chow test for week 6, 7, and so forth until week 156 and each time we obtain the corresponding p-values. We reserve at least 5% of the weeks for the estimation of the test. Thus, we may obtain up to 152 p-values in total. The null hypothesis of no structural change will be rejected if any of these p-values is below the threshold. To mitigate the multiple comparison problem, we adopt a very small threshold, i.e., 0.001 instead of the commonly used 0.05.

In the revised manuscript, we highlight the fact that previous studies have proposed alternative tests (e.g., Donald W K Andrews, 1993; Donald W. K. Andrews & Ploberger, 1994; Bai & Perron, 1998, 2003; Brown, Durbin, & Evans, 1975). However, these tests have different focuses (e.g., the size and the location of the structural change) and more stringent assumptions (e.g., a known number of multiple changes as a priori knowledge). The estimation of the locations and the sizes using these tests were not satisfactory (Pesaran and Timmerman, 2005). In our study, the purpose is neither to detect the locations nor the number of structural changes, but focusing on investigating the presence of any structural change, so that we can estimate and then offset the bias (if using the IC method) or to accept a trade-off between the forecast bias and the forecast error variance (if using the EWC method). Therefore, we conduct a sequential Chow test which serves for this purpose and has the benefit of a simple implementation. The empirical results suggest that our models generate more accurate forecasts.

The Andrews' approach published in *Econometrica* in 2003 (e.g., the end‑of‑sample instability test) has an advantage that it can be used when there are very limited data (e.g., even one observation) before or after structural change within the estimation sample. In comparison, to implement the sequential Chow test, we need to reserve some observations before and after the structural change (e.g., it is an F-test which compares the fit of the model before and after the structural change). However, as pointed out by the other reviewer, the effects of the marketing activities tend to change in a gradual way rather than an abrupt way. Thus, it is unlikely that there is a sudden and abrupt structural change occurring exclusively for a very few observations which are close to the forecast origin or the beginning of the estimation window (and it matters only if there are so few observations that a Chow test cannot be conducted). Empirically, we tried conducting the sequential Chow test with different settings so that we know if this situation potentially matters. For example, in the revised manuscript, we update the results by conducting the sequential Chow test for up to 95% of the weeks in the estimation period. This is compared to the previous results where we conduct the sequential Chow test for up to 70% of the weeks. Our proposed methods consistently have superior forecasting

performance and the results for the two settings suggest little difference. Therefore, it is unclear if we could benefit from the advantage of the Andrews' instability test as we do not see benefit when we push the assumed location for the structural change towards the edges of the estimation window. Also, the Andrews' instability test assumes that explanatory variables must be strictly stationary. Otherwise the test will be associated with a distorted inference and mix the instability of the explanatory variables with the instability of the regression model. In the retailer context, the assumption of stationarity of the explanatory variables may not always be hold as product prices increase gradually during the two-to-three-year timeframe due to inflation, though intermittently associated with price reductions.

We thank the reviewer for pointing out the possibility of further improvement if a set of alternative tests can be evaluated and we leave the empirical question for future research.

8. In the modelling part, I would expect to see a small description at least of the benchmark model, the base-lift model. Also, it is not well explained why Lasso is used two times. What motivates the authors to double apply Lasso shrinkage? Is there any similar study suggesting that? What are the expected benefits of this approach? Given that this paper comes down to a horse-racing application between ADL models constrained by Lasso operators, it is important to clarify why the ADL-raw models is combined with the ADL-own model? Wouldn't be a logical question from the reader as to why the Lasso operator is not used in a third stage, for example? A lot of discussion is provided before-hand (in cases unnecessary), but at section 6 that the reader wants to understand the reasoning and process of modelling, he/she struggles to do so because of the lack of explanations. Another important shortcoming for this work.

We have now added an explicit description for the Base-lift benchmark model.

We have now added explicit explanations for the modeling process of the ADL-intra-EWC method and ADL-intra-IC method. The LASSO procedure was initially used as a variable selection method to identify the important marketing variables (e.g., Huang et al., 2014). It was then used as a model simplification strategy following Ma et al. (2016). The general ADL model becomes the ADL-raw model after being simplified by the LASSO procedure, as shown in Figure 2.

We choose the LASSO procedure as a model simplification strategy because it proves to be effective, and it is also automatic. However, it runs the risk of missing important variables (e.g., potentially the price and promotions of the focal product). If we miss important variables, the final forecasts will be biased, and the forecast error variance will also rise (and this bias is not the bias incurred by the structural change but from the bias of the parameter estimate). Missing important variables is far more serious compared to the cost of efficiency (Davidson & MacKinnon, 2004).
Thus, we try to avoid this as much as we can. For example, if the price and promotion variables of the focal product are not included in the ADL-raw model, we try to bring them back, but only if they are retained in the ADL-own model by the LASSO procedure (as this suggests that they are useful/important). The supplementary parallel ADL model, i.e., in equation (8), by definition, has fewer explanatory variables compared to the general ADL model, i.e., in equation (7), and is less likely to suffer from multicollinearity compared to the latter. Thus, if the price and promotions of the focal product truly have effects on the product sales, it is less likely that they will be removed by both the ADL-raw model and the ADL-own model. However, if we further implement the LASSO

procedure, we will bear the risk of missing important variables.

9. In the experimental design section, the representation of the competing models is not clear. The authors should have included perhaps a table or a clear text on what is the differences between models in a concise and transparent way. Additionally, I am not sure why the roll-forward period is equal to two weeks, while the forecasts are done for 1, 4 and 8 weeks. The authors should explain why they used sMAPE over MAPE or why MASE is more informative. In terms of statistical accuracy, RMSE and Theil-U statistics are also quite often used. One final point is why are the authors inclined to use the adjustment of Cooper et al. (2009). This was not quite clear to me.

We have now added a clear text which highlights the feature and the difference between the models.

We implement the models with 18 rolling events, and for each time we roll the full estimation window forward for two weeks. Therefore, we will be able to evaluate our models for a longer time span (e.g., under this condition, the initial full estimation window is [1:160] and the last estimation window is [35:194], thus the data we used have a time span from week 1 to week 194, compared to a shorter time span from week 1 to week 167 if we only roll forward one week each time). This may potentially make our results more robust as we evaluate our models for a longer time span.

We include various traditional error measures in the evaluation. These error measures capture different aspects of the unobserved loss function for the retailer. We have explained why we report the results for the symmetric MAPE in a footnote. For example, the MAPE does not have an upper bound and vulnerable to outliers. We have added the descriptions for the advantages for the more recently developed error measures including the MASE and the RelAvgMAE. For example, the MASE is symmetric (e.g., equally penalize positive and negative errors) while the RelAvgMAE is readily interpretable as the percentage improvement (or worsening) of the focal method compared to a benchmark. These error measures need to be used as a whole to form the broad picture of the model comparison. We have now added the scaled MSE as an additional error measure. It conveys the information of the RMSE and the Theil's U. Our methods consistently have the best forecasting performance.

We use the adjustment of Cooper et al. (2009) to mitigate the bias due to the logarithm transform (e.g., the expected value of the log-transformed variable does not equal to the log transform of the expected value). We have now added this in a footnote.

10. The section 8 is quite extensive in terms of results in tables, but the comments are quite limited and badly written. For example, is there consistency in ranking across statistical measures? What exactly is the importance of Table 3? At such a forecasting exercise, a Diebold-Mariano test is needed to assess the significance of the differences in performances. The Wilcoxon Sign Rank is not enough. It is also not quite clear what Table 4 is offering. In Figure 3, is there a particular reason why these six product categories are selected for analysis?

We have now highlighted that the results are consistent for all the error measures.

We have now replaced the Wilcoxon SR test with Diebold-Mariano (DM) test in Table 3. We include Table 4 to demonstrate the performance of the various models depending on whether the focal product

is being promoted. This is because the product sales exhibit very different characteristics (e.g., much higher variations) for the promoted period compared to the non-promoted period.

In Figure 3, we choose the six product categories for which the ADL-intra-EWC model and the ADL-intra-IC model have the highest advantage over the ADL-intra model (which has similar model specifications but overlook the problem of structural change), and we show the distribution of the improved forecasting performance using boxplots. We have highlighted this explicitly in the revised manuscript.

11. Table 5 should probably be within the analysis of the determinants of the forecasting performance. I also find the explanation of the process confusing. Why is this factor selection followed? Have the authors explored another factor analysis?

We have now completely revised the section. This section provides exploratory insights on the situations where our proposed methods may gain most benefits compared to the ADL-intra model.

Also, we now construct five factors using nine statistical measures and we remove some previous measures because they are not very informative (e.g., range, skewness, and kurtosis etc.) and they were previously allocated into different factors (which make the interpretation of the factors difficult). We have consistent findings from the updated results.

Minor comments:

1. The writing of the whole paper is not very good. A lot of proof-reading is required. Some examples:

* 'Under such a circumstance…activities' in the abstract.

Revised

* '…the generated forecasts may potentially…' in the abstract

Revised

* SKU abbreviation should be defined in the abstact and in text and then explained perhaps on a footnote.

Revised

* '…proposed holistic methods to generate…' page 4, line 57

Revised

* Footnote 7 should refer to figure 1.

Revised

2. Sometimes writing lack of academic standard. For example, there is no numbering in equations, there is extensive use of bullet points within text, tables are not explained with footnotes, many equations appear within text, the tables style is not uniform etc.

We have now taken on board the comment on the writing style of the paper and we have now completely revised the corresponding sections.

3. The paper is not well positioned in the OR forecasting literature.

We have now completely revised the manuscript. We have more explicitly and effectively positioned the work as one that can impact on the inventory management of retailers similar to related work in the domain of forecasting.

Overall, based on the above I am inclined to reject the paper due to its lack of solid contribution, convincing results, presentation and academic rigour.

Response to Technical Check Results

European Journal of Operational Research
Forecasting Retailer Product Sales in The Presence of Structural Change

Dear Editor,

Thank you for your useful suggestions.

We have highlighted the changes to the text in the revised manuscript by using the red color.

We have resubmitted the manuscript to the journal, and we look forward to your positive response.

Sincerely,

Tao Huang

***Highlights (for review)**

- ✓ We propose novel forecasting methods for retailer product sales at SKU level.
- ✓ Our proposed methods generate accurate forecasts by taking into account the problem of structural change.
- ✓ Our analysis offers insights into situations where our proposed methods work more effectively.

Forecasting retailer product sales in the presence of structural change

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Abstract

Grocery retailers need accurate forecasts at Stock Keeping Unit (SKU) level to effectively manage their inventory. Previous studies have developed forecasting methods which incorporate the effect of various marketing activities including prices and promotions. These methods, however, have overlooked whether the effects of marketing activities on product sales may change over time. These methods may potentially be subject to the structural change problem as they are unable to capture any varying effect of the marketing activities. As a result, they could generate biased and less accurate forecasts. In this study, we propose effective forecasting methods for retailer product sales which take into account the problem of structural change. Our methods outperform conventional models based on a sample from a popular dataset for US retailers.

Keywords:
Analytics, Forecasting, OR in marketing, Retailing

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1. Introduction

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

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

These studies assume that the impact of marketing activities such as the price and promotions on product sales remains constant over time. In practice, the effect of prices and promotions on sales may change because of external non-controllable factors which may include, for instance, changing economic conditions, changes in consumer tastes and the entry of new competitors, introductions of new products, and terminations of existing products etc. Some of these effects are also neither observable or measurable (Wildt, 1976; Wildt & Winer, 1983). For example, customers can become more sensitive to prices and promotions during an economic crunch. Customers may also change their tastes due to their familiarity with the product and their changing lifestyles and social status (Meeran, Jahanbin, Goodwin, & Quariguasi Frota Neto, 2017). When a new competitor enters the market, the effect of prices and promotions of the focal product may decrease not only because of the marketing activities launched by the new competitor but also because customers seek variety. In the year of 2014,

the German discounting retail chain Aldi opened more than 400 stores in the United States, leading to changes in customer grocery purchasing habits which exerted severe competitive pressure on other retail chains (Loeb, 2014).

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

Our research falls in the domain of retail forecasting and makes the following contributions. First, our research is, as far as we are aware, the first to investigate the problem of structural change in forecasting retailer product sales. The empirical results based on the data suggest that our proposed methods have superior forecasting performance compared to conventional models which do not account for the problem of structural change. Second, our proposed methods focus on effectively utilizing available promotional information and thus do not incur additional costs for data collection. Third, our research provides an evaluation of various forecasting methods, the results of which offers operational guidance to not only retailers but also to manufacturers when competitive promotional information is unavailable. Fourth, the methods we propose are fully automatic and easy to implement. Finally, the focus on structural change in the retailer context offers exploratory insights into those situations where our proposed methods work more effectively compared to models with similar specifications but overlook the problem of structural change.

The remainder of the paper is organized as follows: section 2 summarizes previous studies which forecast retailer product sales at SKU level and also summarize the effect of marketing activities including price and promotions. Section 3 explains the structural change problem and the rationale of the methods which may potentially mitigate the problem. Section 4 explores the data. In section 5, we describe our new three-stage forecasting methods. Section 6 introduces the design of the model evaluation. Section 7 summarizes and discusses the evaluation results to provide a convincing demonstration of their performance. In Section 8, we explore the characteristics of the situations where the proposed methods garner the greatest improvements compared to models with similar

specifications but overlook the problem of structural change. In the last section, we make recommendations for both manufacturers and retailers, address research limitations, and highlight directions for future research.

2. Literature review

2.1 Forecasting retailer product sales at SKU level

In practice, many retailers still forecast their product sales at the SKU level using a two-stage 'Base-lift' method. The method (and the software) entails dividing the data into promoted and non-promoted periods based on whether the focal SKU is being promoted. Specifically, they use simple univariate methods to generate the 'baseline' forecasts for the non-promoted period and then make adjustments for the 'lift' effect of any incoming promotional events. They estimate the 'lift' effect of the promotional events relying on the experience of the brand/category managers (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009; Fildes, Nikolopoulos, Crone, & Syntetos, 2008). A stream of studies have been devoted to helping managers to effectively tackle their own biases typically reflecting their understanding of the market conditions (Lee, Goodwin, Fildes, Nikolopoulos, & Lawrence, 2007; Petropoulos, Fildes, & Goodwin, 2016). Other studies try to estimate the 'lift' effect with model-based forecasting systems. For example, the PromoCast™ system relates the 'lift' effect to previous promotions of the focal product, the characteristics of product categories and stores, and manufacturer information etc. (L. Cooper et al., 1999; L. G. Cooper & Giuffrida, 2000; Trusov, Bodapati, & Cooper, 2006). Aburto and Weber (2007) used neural network models to estimate the 'lift' effect for the product sales for a Chilean supermarket. One limitation of these two-stage methods is that, as they split the data into two periods, they tend to overlook the information in the promoted period when forecasting the product sales in the non-promoted period, and vice versa. Other studies have proposed integrated methods to directly generate the final forecasts. Kuo (2001) used neural network models to forecast product sales of daily milk in convenience stores. Gür Ali et al. (2009) proposed the regression tree method and the support vector regression (SVR) method to forecast retailer product sales for the non-perishable food categories at SKU level. Their models incorporate variables constructed based on statistical measures of past information (e.g., the sales, prices, and promotions of the focal product). Their regression tree method has the best forecasting performance. However, it gets beaten by the Base-lift method for the time periods when the focal product is not being promoted. One of the limitations for the model is that it overlooks the effect of competitive promotions on the sales of the focal product. Divakar et al. (2005) proposed the CHAN4CAST method to forecast product volume sales for beverage manufacturers. Their method incorporates the promotional information of the main competitors of the focal product. However, their method is only applicable when there are a small number of competitors (e.g., just like Coca *versus* Pepsi). Huang et al. (2014) proposed two-stage Autoregressive Distributed Lag (ADL) methods to forecast retailer product sales at SKU level. Their methods were the first to account for the competitive promotional

information for the whole product category. They initially implemented a variable selection procedure to identify the most important variables for the competitive activities within the product category. They then specified general-to-specific ADL models based on these selected variables. Their methods has been found the best forecasting performance for five grocery categories such as *Bottled Juice*, *Soft Drinks*, and *Bath Soap* etc. Ma et al. (2016) proposed three-stage ADL methods which further integrate the promotional information not only from the same product category but also from other related product categories. Their methods are extensions of those in Huang et al. (2014) and also benefit from an automatic model specification procedure. Their methods outperform the Base-lift benchmark model for 15 food product categories. These studies suggest that promotional information are valuable in forecasting retailer product sales, and evidence shows that modern commercial software has also started to integrate promotional information (Fildes et al., 2018). However, all the studies described here assume constant effects of the marketing activities.

2.2 The effect of marketing activities including price and promotions

Previous studies have summarized the effect of marketing activities on product sales. For example, early studies have found that product sales can be increased in the short term by price reductions and promotions (e.g., Blattberg, Briesch, & Fox, 1995; Christen, Gupta, Porter, Staelin, & Wittink, 1997; L. Cooper et al., 1999; Gupta, 1988; Gür Ali et al., 2009; Lattin & Bucklin, 1989; Mulhern & Leone, 1991). Product sales after the price reduction and promotions may decrease because customers may stockpile their purchases (Mace & Neslin, 2004; H. J. Van Heerde, Gupta, & Wittink, 2003). Product sales may be negatively affected by the marketing activities of competitive products (Demirag, Keskinocak, & Swann, 2011; Rudolph W. Struse, 1987; Walters, 1991; Walters & Rinne, 1986). The effect of competitive marketing activities may not come from products within the same category but also from related categories. (R. L. Andrews, Currim, Leeflang, & Lim, 2008; Wedel & Zhang, 2004).

Further evidence also shows that the effect of marketing activities such as prices and promotions may change over time. For example, Wildt (1976) and Wildt and Winer (1983) suggest that the effect of the marketing activities may change due to the change in economic conditions, consumer tastes, and the competition environment, etc. Customers may find price reductions and promotions more attractive during the period of an economic crunch compared to other time periods. Mahajan, Bretschneider, and Bradford (1980) found that the effect of prices and promotions change during the different stages of the product lifecycle. Meeran et al. (2017) found that customers have different tastes and preferences when they accumulate more knowledge of the product, when they seek variety, and when they reach a different social status and then decide to adopt a different lifestyle. These individual changes lead to substantial aggregate effects on product sales. Other studies find that the introduction of store-own brands in a product category decreases the promotional elasticities of

premium national brands and increase promotional elasticities of the second tier national brands (e.g., Nijs, Dekimpe, Steenkamps, & Hanssens, 2001; H. J. Van Heerde, Srinivasan, & Dekimpe, 2008). The effect of the marketing activities can also change depending on how retailers communicate their marketing events. For example, they may promote the products through mobile applications and adopt new prominent promotion shelf tags, which could makes the promotions more effective (H. van Heerde, M. Dinner, & Neslin, 2015). In practice, retailers may record their marketing activities using aggregate terms such as Features and Displays (e.g., Bronnenberg, Kruger, & Mela, 2008). However, these terms may have various forms such as Buy One Get One free (BOGO), store flyers, billboard advertising, and temporary price reduction (TPR) for shopper card holders only etc. Under such conditions, the effect of the marketing activities may differentiate.

3. The problem of structural change

The problem of structural change has been addressed by previous forecasting studies[2] (e.g., Castle, Doornik, & Hendry, 2008; Hendry, 2018; Pesaran & Timmermann, 2007). Pesaran and Timmermann (2005) demonstrated analytically how a structural change leads to biased forecasts using a simple regression model without an intercept. For example, suppose that for the time periods of $[1{:}T]$, the unobserved data generating process is:

$$y_{t+1} = 1_{\{t \le T_1\}} \beta_1' x_t + \left(1 - 1_{\{t \le T_1\}}\right) \beta_2' x_t + u_{t+1} \qquad (1)$$

where, y_{t+1} and x_t are the vectors of the dependent variable and independent variable respectively. u_{t+1} is the vector of the error term. β_i (where *i*=1,2) are the vectors of the parameter coefficients. $1_{\{t \le T_1\}}$ is an indicator which equals to 1 before week T_1 (where $1 < T_1 < T$) and 0 afterwards. Therefore, we have a structural change where the true parameter of the independent variable changes from β_1 to β_2 after T_1. We can estimate a model with a functional form congruent with the data generating process (e.g., $y_t = \hat{\beta}' x_t + \hat{u}_t$) based on the data before and after the structural change, e.g., $[m{:}T]$, $where\ 1 \le m < T_1 < T$. Thus, the OLS estimate of the parameter is:

$$\hat{\beta}_T(m) = (x_{m,T}' x_{m,T})^{-1} x_{m,T}' y_{m,T} \qquad (2)$$

where $y_{m,T}$ and $x_{m,T}$ are respectively the vectors of the dependent variable and independent variable for the time periods from week *m* to week *T*. We assume that there is no structural change after week *T*. e.g., $y_t = \beta_2' x_t + u_t, when\ t > T$. Suppose that we are interested in the one-step ahead forecast, the one-step ahead forecast error is:

$$\hat{e}_{T+1}(m) = \left(\beta_2 - \hat{\beta}_T(m)\right)' x_T + u_{T+1}$$

[2] The term of 'structural change' is used interchangeably with the term of 'structural break' in the literature. In this study, we use the term "structural change" as in the retailer context we expect the effect of the marketing activities to change sometimes gradually rather than but sometimes in a sudden and abrupt way. We thank one of the anonymous reviewers for to pointing this out.

$$= (\beta_2' - y_{m,T}' x_{m,T} (x_{m,T}' x_{m,T})^{-1}) x_T + u_{T+1}$$

$$= (\beta_2 - \beta_1)' \, x_{m,T_1}' x_{m,T_1} (x_{m,T_1}' x_{m,T_1})^{-1} x_T - u_{m,T}' x_{m,T} (x_{m,T_1}' x_{m,T_1})^{-1} x_T + u_{T+1} \quad (3)$$

where x_{m,T_1} is the vector of the independent variable for the time periods from week m to T_1. $u_{m,T}$ is the vector of error term for the time periods from week m to T. u_{T+1} is the error term at week $T+1$. Therefore, the expected value of the equation (3) is:

$$E[\hat{e}_{T+1}(m)|x_T] = (\beta_2 - \beta_1)' x_{m,T_1}' x_{m,T_1} (x_{m,T_1}' x_{m,T_1})^{-1} x_T. \quad (4)$$

Equation (4) is unequal to zero as β_2 is unequal to β_1. This indicates that the forecast at week $T+1$ is biased. For more general cases where the model has an intercept term and endogenous explanatory variables, the forecast bias can be demonstrated using Monte Carlo simulation (see Clements & Hendry, 1999; Pesaran & Timmermann, 2005, 2007)[3].

In this study, we implement two methods to mitigate the problem of structural change. The first method is the Intercept Correction (IC) method which specifies non-zero values for the model's errors in the forecast period (Clark & McCracken, 2007; Clements & Hendry, 1994, 1999). If we identify that the model is subject to structural changes, we may try to estimate the forecast bias, e.g., by taking the average value of those most recent residuals, e.g., $\widehat{\text{Bias}}_{IC} = \sum_{i=1}^{\lambda} \hat{e}_{T-\text{i}}$, where λ is the number of residuals. When $\lambda = 1$, the estimated bias reduces to $\hat{e}_{T-1}$, which is the residual at the forecast origin (e.g., Chevillon, 2016). Ideally, we can simply add the estimated bias back to the out-of-sample forecasts. However, the IC method has a limitation. In practice, sales at SKU level sometimes exhibit large variations and unexpected outliers, which renders the task of estimating the forecast bias challenging. For example, the bias can be submerged by high variations in the product sales. As a result, it is possible that the average value of the most recent residuals may mostly represent random variations. Also, by adding the estimated bias back to the out-of-sample forecasts, we inevitably incur the cost of inflated forecast error variance (see the analytical evidence in Clements & Hendry, 1999). The second method is the Estimation Window Combining (EWC) method which combines the forecasts generated by the same model but with different estimation windows (e.g., Pesaran & Pick, 2011; Pesaran, Schuermann, & Smith, 2009; Pesaran & Timmermann, 2005). More specifically, we can combine those forecasts with equal weights as it has been found effective and easy to implement.(Clements & Hendry, 1998; Dekker, van Donselaar, & Ouwehand, 2004; Fildes & Stekler, 2002; Pesaran et al., 2009). In the example demonstrated in equation (1), we may estimate the model using the most recent ω observations to generate the first set of forecasts, e.g., $\hat{y}_{T+1,1} = \hat{\beta}_{T-\omega+1,T} x_T$, where $\hat{\beta}_{T-\omega+1,T}$ represents the parameters estimated based on the observation window $[T - \omega + 1, T]$. The value of ω can be arbitrarily chosen given there are enough observations to estimate the

[3] We demonstrate the impact of the structural change on the forecasting performance using a simulation example where the model has an intercept term. We include this in the supplementary material.

model and enough variations in the explanatory variable. We then add more observations (e.g., one) to the estimation window and generate the second set of forecasts, e.g., $\hat{y}_{T+1,2} = \hat{\beta}_{T-\omega,T}\, x_T$, and so forth, until we generate the $(T-\omega+1)^{th}$ set of forecasts based on the estimation window $[1, T]$. Thus, we may equally combine those forecasts to generate the final forecasts:

$$\hat{y}_{T+1}(T,\omega) = (T-\omega+1)^{-1} \sum_{m=1}^{T-\omega+1} \hat{y}_{T+1,m} = (T-\omega+1)^{-1} \sum_{m=1}^{T-\omega+1} \hat{\beta}_{m,T} x_T \tag{5}$$

Pesaran and Timmermann (2007) show analytic evidence that, for the example in equation (1), the forecasts generated by the models with smaller estimation windows tend to be less biased (e.g., the models will utilize fewer observations before the structural change). However, these forecasts inevitably bear a cost of inflated forecast error variance. This is because they are generated when the model is estimated with less data especially if the data before the structural change are more informative. The EWC method thus tries to generate more accurate forecasts by accepting a trade-off between the reduced forecast bias and the inflated forecast error variance. Compared to the IC method, the EWC method does not estimate the size of the bias.

The two methods described above have been found good forecasting performance by previous studies. For example, the IC method has good performance in forecasting wage, unemployment, and CPI inflation etc. (e.g., Clark & McCracken, 2007; Clements & Hendry, 1996), and the EWC method has good forecasting performance for exchange rate, inflation, and equity index futures etc. (e.g., Pesaran & Pick, 2011; Pesaran et al., 2009; Rapach & Strauss, 2008). For retailer product sales, whether accounting for structural change and which of the two methods, the IC method and the EWC method, could generates more accurate forecasts becomes empirical questions.

4. The data

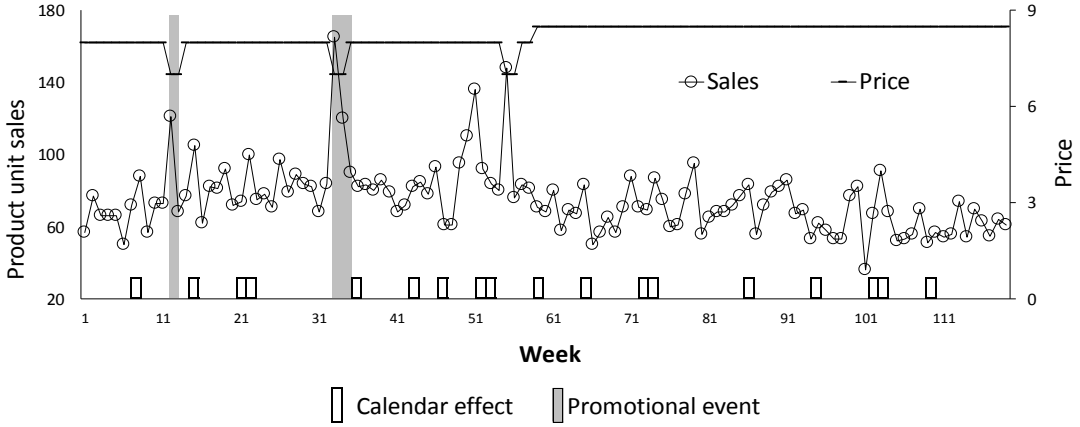
We evaluate the forecasting performance of various models using the retail dataset made available by the Information Resources, Inc. (IRI) company. A more comprehensive description of the dataset can be found in Bronnenberg et al. (2008). The dataset contains weekly data at SKU level with variables including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

Table 1. Statistical descriptions for each product category

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

* Sales mean represents the average unit sales for all the SKU's for the category for the specific store.
** ***Display percentage and Feature percentage indicate the percentage of weeks during the 202-week time periods when the focal product is being promoted for Display and Feature.

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



In Figure 1, week 1 indicates the first week in the year of 2001. The Calendar events include Halloween, Thanksgiving, Christmas, New Year's Day, President's Day, Easter,

Memorial Day, the 4th of July, and Labour Day. The Promotional events include Feature and Display.

5. Methodology

In this study, we propose two novel forecasting methods for retailer product sales at SKU level. Our methods consider the problem of structural change. The methods consist of three stages. During the first stage, we identify the most relevant competitive explanatory variables for the focal product within the product category. Grocery retailers typically sell hundreds of SKU's in a typical product category and also launch promotional activities for them. According to previous studies (e.g. those described in section 2.2), these promotional activities may all potentially have impact on the sales of the focal product. This leads to hundreds of potential competitive explanatory variables for the focal product. Incorporating all the variables into the model would easily overfit the model and render the estimation task infeasible (Martin & Kolassa, 2009). Therefore, we initially select the most relevant competitive explanatory variables using the Least Absolute Shrinkage and Selection Operator (LASSO) procedure (Tibshirani, 1996). That is, we construct the following model for each SKU:

$$\ln(y_{0,t}) = X\beta + u, subject\ to\ \sum_{j=1}^{N}|\beta_j| = \eta, \eta \leq \eta_0 \qquad (6)$$

where $\ln(y_{0,t})$ represents log product sales of the focal product for the store at week *t*. X is the matrix for the explanatory variables including prices, features, and displays of all the products in the same product category. u represents the identically distributed error term. β represents the vector of the parameter coefficients. N is the total number of SKUs for the category. η_0 is the shrinkage factor. The LASSO procedure imposes a constraint to the sum of the absolute values of the models' parameter coefficients. It removes the less relevant explanatory variables by pushing their parameter coefficients towards zero. We control the model simplification process using the shrinkage factor based on 10-fold cross validation (Ma & Fildes, 2017; Ma et al., 2016)[4].

During the second stage, we construct the General Autoregressive Distributive Lag (ADL) model following Huang et al. (2014) by incorporating the variables retained by the LASSO procedure during the first stage. The LASSO procedure has a limitation that it may potentially miss important variables especially under the condition of high multicollinearity (Fan & Lv, 2008; Ma et al., 2016). Previous studies suggest the product sales are usually mostly influenced by the prices and promotions of the products themselves (Bucklin, Gupta, & Siddarth, 1998). Thus, we intentionally incorporate the prices and promotions of the focal product in the general ADL model even these variables were not retained by the LASSO procedure during the first stage. We also incorporate the dynamic effects of these

[4] Huang et al. (2014) used alternative schemes such as the Akaike's Information Criterion. In this study, we find little difference in the results between these different schemes.

explanatory variables as well as a time variable to capture the potential trend, twelve deterministic four-week dummy variables to capture seasonality, and other dummy variables to capture calendar events. The constructed general ADL model for each product in a specific store can be demonstrated as follows:

$$\ln(y_{0,t}) = intercept + \tau * time + \sum_{j=1}^{L} \alpha_j \ln(y_{0,t-j}) + \sum_{j=0}^{L} \beta_{0,j} \ln(p_{0,t-j}) + \sum_{j=0}^{L} \gamma_{0,j} Feature_{0,t-j} + \sum_{j=0}^{L} \gamma_{0,j} Display_{0,t-j} + \sum_{m=1}^{M} \sum_{j=0}^{L} \beta_{m,j} \ln(p_{m,t-j}) + \sum_{n=1}^{N} \sum_{j=0}^{L} \gamma_{n,j} Feature_{n,t-j} \sum_{n=1}^{P} \sum_{j=0}^{L} \gamma_{n,j} Display_{n,t-j} + \sum_{d=1}^{12} \theta_d Four\_week\_dummy_d + \sum_{c=1}^{9} \sum_{v=0}^{1} \delta_{c,v} CalendarEvent_{c,t-v} + \varepsilon_t \quad (7)$$

where $\ln(y_{0,t})$ is the log sales of the focal product at week t. $time$ is the term which captures any potential trend during the estimation period (Song & Witt, 2003). $\ln(p_{0,t-j})$ and $\ln(p_{m,t-j})$ represent the log price of the focal product and a competitive product, m, at week $t-j$. $Feature_{0,t-j}$ and $Display_{0,t-j}$ represents the feature and the display dummy variables for the focal product at week $t-j$. $Four\_week\_dummy_d$ is the d^{th} four-week-dummy variable. $CalendarEvent_{c,t-v}$ is the dummy variable for the c^{th} calendar event at week $t-v$. The dummy variable represents the week of the calendar event when $v = 0$, and the week before the event if $v = 1$. c takes the values from 1 to 9 representing all the calendar events[5]. $\alpha_j, \beta_{0,j}, \gamma_{0,j}, \beta_{m,j}, \gamma_{n,j}, \theta_d, \delta_{c,v}, \tau$ are the parameters. ε_t is the error term and is assumed that $\varepsilon_t \sim iid(0, \sigma^2)$. L is the order of the lags and is set as 2. M, N, and P are the numbers of selected competitive price, Feature, and Display variables for the product category.

The general ADL model, as shown in equation (7), could have too many explanatory variables and lack parsimony. Thus, we simplify the model using the LASSO procedure following Ma et al. (2016) (we refer to the resulted model as the ADL-raw model thereafter). During this stage, we use the LASSO procedure as a model specification strategy rather than a variable selection method as previous studies indicate that models simplified by the LASSO procedure could have good forecasting performance and outperform traditional models specified based on statistical significance (Epprecht, Guegan, & Veiga, 2013; Ma et al., 2016). Also, the LASSO procedure enables the automation of the

[5] 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*.

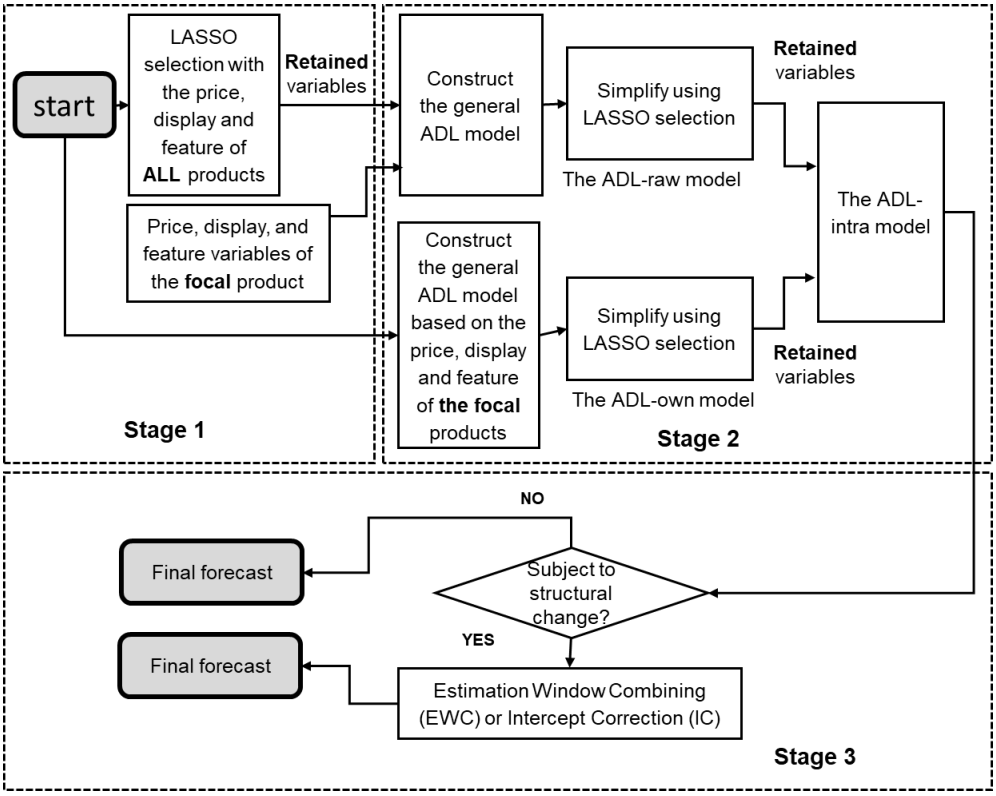
statistical forecasting task which becomes essential as typically grocery retailers stock a tremendous number of SKUs (L. Cooper et al., 1999). To prevent the LASSO procedure missing important variables, we initially construct a supplementary parallel ADL model which has a similar specification compared to the general ADL model but only includes the price and promotion variables of the focal product:

$$\ln(y_{0,t}) = intercept + \tau * time + \sum_{j=1}^{L} \alpha_j \ln(y_{0,t-j}) + \sum_{j=0}^{L} \beta_{0,j} \ln(p_{0,t-j}) + \sum_{j=0}^{L} \gamma_{0,j} Feature_{0,t-j} + \sum_{j=0}^{L} \gamma_{0,j} Display_{0,t-j} + \sum_{d=1}^{12} \theta_d Four\_week\_dummy_d + \sum_{c=1}^{9} \sum_{v=0}^{1} \delta_{c,v} CalendarEvent_{c,t-v} + \varepsilon_t \quad (8)$$

We simplify the supplementary parallel ADL model shown in equation (8) using the LASSO procedure (we refer to the resulted model as the ADL-own model thereafter). We then incorporate the marketing variables retained in the ADL-own model into the ADL-raw model (we refer to the resulted model as the ADL-intra model). This enables us to selectively retain the potentially important variables in the ADL-intra model, such as the price and promotions of the focal product and their dynamic terms. If these variables get removed by the ADL-raw model, they will be added back to the ADL-intra model if they are retained by the ADL-own model. That is, we try to prevent the ADL-intra model from missing important variables at the cost of reduced efficiency. The supplementary parallel ADL model, i.e., in equation (8), by definition, has fewer explanatory variables compared to the general ADL model, i.e., in equation (7), and is less likely to suffer from multicollinearity compared to the latter. Thus, if the price and promotions of the focal product truly have effects on the product sales, it is less likely that they will be removed by both the ADL-raw model and the ADL-own model[6].

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

[6]We do not further reduce the ADL-intra models using the LASSO procedure as further simplification using the LASSO procedure will potentially remove important variables.



During the final stage, we integrate the ADL-intra model with the EWC method and the IC method respectively to account for the structural change problem. We implement the EWC method and the IC method to the ADL-intra model only if the presence of the structural change is confirmed. If this is not the case, we keep the forecasts generated by the ADL-intra model as the final forecasts. In this study, we conduct a sequential Chow test for up to 95% of the weeks in the estimation period. That is, if we have an estimation period of 160 weeks, we conduct the Chow test for each of the 152 weeks. For example, we initially conduct the Chow test assuming a structural change occurring at week 5 and we obtain the corresponding p-value. We then conduct the Chow test for week 6, 7, and so forth until week 156 and each time we obtain the p-value accordingly. We keep at least 5% of the weeks for the estimation of the test. Thus, we may obtain up to 152 p-values in total. The null hypothesis of no structural change will be rejected if any of these p-values is below a threshold. To mitigate the multiple comparison problem, we adopt a very small threshold, i.e., 0.001[7].Previous studies have proposed alternative tests which focus on estimating multiple structural changes and their locations and are usually associated with very stringent assumptions (e.g., Donald W K Andrews, 1993; Donald W. K. Andrews & Ploberger, 1994; Bai & Perron, 1998, 2003; Brown, Durbin, & Evans, 1975). In our study, we only need to know if structural change is present in our data. Thus, we conduct the sequential Chow test which is appropriate for that purpose and is also simple to implement. We refer

[7] The results in our study suggest that for most scenarios (e.g., 99.8%) the ADL-intra models are subject to structural change if we conduct the Chow test for 95% of the observations. For robustness, we have conducted the whole evaluation by implementing the sequential Chow test for less observations (e.g., 70% of weeks). We find little difference in the final results.

to the final resulting models as the ADL-intra-EWC model and the ADL-intra-IC model respectively. Figure 2 provides a summary guide for the implementation of the ADL-intra-EWC model and the ADL-intra-IC model.

6. The experimental design

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

$$Forecast_t = \begin{cases} M_t, if\ the\ focal\ product\ is\ not\ being\ promoted \\ M_t + \ adjustment, if\ the\ focal\ product\ is\ being\ promoted \end{cases}$$
$$M_t = (1 - \ a)M_{t-1} + aS_{t-1} \tag{9}$$

where M_t represents the baseline forecast for week t by the simple exponential smoothing (SES) model. The SES model is estimated exclusively based on the data when the focal product is not being promoted. Thus, S_{t-1} represents the sales of the focal product for the previous time when the focal product was not promoted. a is the smoothing parameter of the simple exponential smoothing model, and is estimated by minimizing the in-sample mean squared errors. The adjustment for the 'lift' effect is calculated as the increased sales of the focal product during its most recent promotion compared to the corresponding baseline sales. We also have the following candidate models:

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

We specify the models with an estimation window of 160 weeks, and we evaluate their forecasting performance using 18 rolling origins for robustness (Tashman, 2000). For each rolling event, we move the estimation window two weeks forward and re-specify the model. We assume that the value of the price and any promotional information to be known as it is part of the retailer's inventory plan. We use the forecast value of product sales when the forecast horizon is beyond one week. We generate one to H week-ahead forecasts, where H is 1, 4, and 8, to approximate the situation retailers face in practice. For the EWC method, we generate the final forecasts by equally combining the

forecasts by the same model with ten estimation windows (e.g., for the estimation period, e.g., [1,160], we estimate the model with ten estimation windows including [1, 160], [3, 160], and so forth, until [19, 160]). This generates ten sets of forecasts). For the IC methods, we estimate the forecast bias as the average value of the sixteen most recent residuals and add the value to the forecasts of all the forecast horizons. We implement the models using the MODEL procedure with macros in SAS 9.4. The model parameters are estimated using the OLS estimator.

We evaluate the models with different error measures which approximate the unknown loss function of the retailer from different aspects. We include traditional error measures including the Mean Absolute Error (MAE), the symmetric Mean Absolute Percentage Error (sMAPE) and the scaled Mean Squared Error (scaled MSE)[8]. We also include more recently developed error measures including the Mean Absolute Scaled Error (MASE) and the Relative Average Mean Absolute Error (RelAvgMAE) respectively developed by Hyndman and Koehler (2006) and Davydenko and Fildes (2013). Such relative measures have more desirable properties, e.g., equally penalize positive and negative errors, more robust to outliers while the latter is readily interpretable as the percentage improvement (or worsening) of the focal method compared to a benchmark. The two latter error measures can be demonstrated as follows:

$$\mathrm{MASE}(H) = \frac{1}{S}\frac{1}{H}\frac{1}{K}\sum_{s=1}^{S}\sum_{h=1}^{H}\sum_{k=1}^{K}\left|\frac{y_{s,h,k}-\hat{y}_{s,h,k}}{\frac{1}{T_0-1}\sum_{t=2}^{T_0}|y_{s,t,k}-y_{s,t-1,k}|}\right| \tag{10}$$

$$\mathrm{AvgRelMAE}(H) = \left(\prod_{s=1}^{S}\mathrm{RelMAE}_{s,H,k}\right)^{\frac{1}{S}}, \text{ where } \mathrm{RelMAE}_{s,H,k} = \frac{\mathrm{MAE}^{C}_{s,H,k}}{\mathrm{MAE}^{B}_{s,H,k}},$$

$$\mathrm{MAE}^{C}_{s,H,k} = \frac{1}{h}\frac{1}{k}\sum_{h=1}^{H}\sum_{k=1}^{K}\left(\left|y_{s,h,k}-\hat{y}_{s,h,k}\right|\right) \tag{11}$$

where $\mathrm{MASE}(H)$ and $\mathrm{AvgRelMAE}(H)$ are the MASE and the AvgRelMAE based on one to H forecast horizon (H=1, 4 and 8) across S SKUs (e.g., S= 1831) for K rolling events (e.g., K=18). $y_{s,h,k}$ and $\hat{y}_{s,h,k}$ are respectively the h-step ahead actual value and forecast value for data series s based on the k^{th} rolling event. T_0 is the total number of observations in the estimation window (i.e., $T_0 = 160$). Before we transform the log values to levels for evaluation, we adjust the final forecasts by adding one-half mean squared error, which mitigate the bias caused by the logarithm transformation (e.g., L. Cooper et al., 1999; Ma et al., 2016).

7. Results and discussion

[8] Compared to the Mean Absolute Percentage Error (MAPE) which do not have an upper bound, the sMAPE is more robust to outliers.

In Table 2, we summarize the forecasting performance of the models across all the products. Table 3 shows the results of the Diebold-Mariana (DM) test for the statistical significance of the difference between the models' forecasting performance. (Diebold & Mariano, 1995; Harvey, Leybourne, & Newbold, 1997)[9]. The following findings emerge from the analysis:

(i) The Base-lift model generates the least accurate forecasts across all the error measures.

(ii) The ADL-intra model outperforms the ADL-own model across all the error measures, which is consistent with the findings in Huang et al. (2014).

(iii) The ADL-own-EWC model outperforms the ADL-own model for all the error measures.

(iv) The ADL-own-IC model generally outperforms the ADL-own model except for the MAE.

(v) The ADL-intra-EWC model outperforms the ADL-intra model for all the error measures.

(vi) The ADL-intra-IC model generally outperforms the ADL-intra model except for the MAE and the scaled MSE for longer forecast horizons (e.g., Forecast horizon is one to four weeks ahead and one to eight weeks ahead).

(vii) Overall, The ADL-intra-EWC model and the ADL-intra-IC model generate the most accurate forecasts.

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

Forecast horizon is one to eight weeks ahead

Model/measure	MAE	sMAPE	MASE	AvgRelMAE	scaled MSE
Base-lift	22.92	46.98%	0.775	1.1444	0.2234
ADL-own	15.75	40.81%	0.697	1.0000	0.1575
ADL-intra	15.44	40.51%	0.695	0.9941	0.1553
ADL-own-EWC	15.67	40.68%	0.696	0.9956	0.1570
ADL-own-IC	16.23	40.76%	0.694	0.9992	0.1596
ADL-intra-EWC	**15.35**	**40.41%**	0.694	**0.9905**	**0.1548**
ADL-intra-IC	15.59	40.46%	**0.693**	0.9936	0.1568

Forecast horizon is one to four weeks ahead

Model/measure	MAE	sMAPE	MASE	AvgRelMAE	scaled MSE
Base-lift	22.67	46.24%	0.762	1.1365	0.2186
ADL-own	15.63	40.45%	0.69	1.0000	0.1548
ADL-intra	15.16	40.12%	0.686	0.9913	0.1514
ADL-own-EWC	15.55	40.31%	0.688	0.9950	0.1540
ADL-own-IC	15.94	40.25%	0.684	0.9948	0.1553
ADL-intra-EWC	**15.09**	40.01%	0.685	0.9876	**0.1509**
ADL-intra-IC	15.21	**39.93%**	**0.681**	**0.9871**	0.1517

Forecast horizon is one week ahead

Model/measure	MAE	sMAPE	MASE	AvgRelMAE	scaled MSE
Base-lift	24.99	45.42%	0.762	1.1279	0.2261
ADL-own	16.66	39.87%	0.689	1.0000	0.1561
ADL-intra	15.66	39.43%	0.686	0.9883	0.1529
ADL-own-EWC	16.59	39.72%	0.686	0.9955	0.1549
ADL-own-IC	17.02	39.52%	0.68	0.9902	0.1552

[9] We conduct the DM test based on all the error measures except for the AvgRelMAE which does not fit into the framework of the DM test.

ADL-intra-EWC	**15.59**	39.33%	0.684	0.9850	0.1523
ADL-intra-IC	15.65	**39.15%**	**0.679**	**0.9804**	**0.1520**

We also investigate the models' forecasting performance for the time periods depending on whether the focal product is being promoted. This is because that retailer product sales tend to exhibit very high levels of variations when the focal product is being promoted, and tend to be comparably stable otherwise (Gür Ali et al., 2009). We refer these two periods as the promoted period and non-promoted period respectively afterward. Table 4 shows the forecasting performance of the models for the promoted forecast period and the non-promoted forecast period respectively for one to eight-week forecast horizon[10]. The following are particularly important. The ADL-intra-IC model has the best forecasting performance for the non-promoted period but only has moderate performance for the promoted period. A possible explanation is that the estimated bias added back to the error term in the forecast period may get submerged by the high variations of the product sales when the focal product is being promoted. In contrast, the ADL-intra-EWC model has the best performance for the promoted period. Therefore, we develop an exploratory combined method between these two methods, named as the ADL-EWC-IC model. The ADL-EWC-IC model is identical to the ADL-intra-EWC model for the promoted period and identical to the ADL-intra-IC model for the non-promoted period. To allow for a fair comparison, we evaluate the performance of the ADL-EWC-IC model based on previously unseen data (e.g., the data are based on 1605 SKU's for the same 28 product categories but from a new set of 28 stores). Table 5 shows the forecasting performance of the ADL-EWC-IC model compared to other three models[11]. The exploratory results indicate that the ADL-EWC-IC model generally generates the most accurate forecasts across all the models even when we consider previously unseen data.

We further explore the percentage reduction of the MASE by the ADL-intra-EWC method and the ADL-intra-IC method compared to the ADL-intra model for each product category. The comparison highlights the value for taking consideration of the structural change problem as the ADL-intra model has a similar specification compared to the two proposed methods but overlooks the problem of structural change. We calculate the percentage reductions of the MASE by the ADL-intra-EWC method and by the ADL-intra-IC method for product i as follows:

$$\mathrm{PctRed}(\mathrm{ADL}-\mathrm{intra}-\mathrm{EWC},i)=\frac{\mathrm{MASE}(\mathrm{ADL}-\mathrm{intra},i)-\ \mathrm{MASE}(\mathrm{ADL}-\mathrm{intra}-\mathrm{EWC},i)}{\mathrm{MASE}(\mathrm{ADL}-\mathrm{intra},i)} \quad (12)$$

[10] The results for other forecasting horizons are similar and are omitted for simplicity.
[11] Other models including the Base-lift method, the ADL-own model, the ADL-own-EWC model, and the ADL-own-IC model are outperformed by the four models in Table 5 and are not shown here for simplicity.

$$\text{PctRed}(\text{ADL}-\text{intra}-\text{IC}, i) = \frac{\text{MASE}(\text{ADL}-\text{intra}, i) - \text{MASE}(\text{ADL}-\text{intra}-\text{IC}, i)}{\text{MASE}(\text{ADL}-\text{intra}, i)} \quad (13)$$

We then take the average value of $\text{PctRed}(\text{ADL}-\text{intra}-\text{EWC}, i)$ and $\text{PctRed}(\text{ADL}-\text{intra}-\text{IC}, i)$ respectively across all the SKU's for each product category. Table 6 shows the results for each product category for one to eight weeks forecast horizon. The ADL-intra-EWC method and the ADL-intra-IC method outperform the ADL-intra model for most of the product categories (e.g., 18 and 16 respectively, out of 28 categories). They do not outperform the ADL-intra model for all product categories due to the heterogeneity of the data characteristics across different product categories (Ma et al., 2016). The comparison results for other error measures and horizons are similar and we omit them for simplicity. For each proposed method, we highlight the product categories where the method has its highest advantages compared to the ADL-intra model. For example, the ADL-intra-EWC method has its highest advantages compared to the ADL-intra model for six product categories including *Spaghetti sauce*, *Face Tissue*, and *Toothpaste* etc. Figure 3(a) shows the distributions of the percentage reduction of the MASE by the ADL-intra-EWC method compared to the ADL-intra model for these categories. The ADL-intra-IC method has its highest advantages compared to the ADL-intra model for another six product categories including *Peanut butter*, *Milk*, *Yogurt*,and *Toilet Tissue* etc. Figure 3(b) shows the distributions of the percentage reduction of the MASE by the ADL-intra-IC method compared to the ADL-intra model for these categories.

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

Model 1	Model 2	MAE			sMAPE			MASE			scaled MSE		
		H=1	*H*=1 to 4	*H*=1 to 8	*H*=1	*H*=1 to 4	*H*=1 to 8	*H*=1	*H*=1 to 4	*H*=1 to 8	*H*=1	*H*=1 to 4	*H*=1 to 8
ADL-own	Base-lift	0.000*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ADL-own	ADL-intra	0.000	0.001	0.015	0.000	0.000	0.000	0.233	0.026	0.157	0.443	0.380	0.453
ADL-own	ADL-own-EWC	0.106	0.005	0.002	0.000	0.000	0.000	0.000	0.104	0.294	0.148	0.335	0.258
ADL-own	ADL-own-IC	0.064	0.008	0.000	0.000	0.000	0.259	0.000	0.000	0.009	0.388	0.138	0.001
ADL-intra	ADL-intra-EWC	0.138	0.013	0.002	0.000	0.000	0.000	0.005	0.124	0.100	0.652	0.259	0.308
ADL-intra	ADL-intra-IC	0.946	0.469	0.021	0.000	0.000	0.277	0.000	0.000	0.030	0.169	0.011	0.001

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

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

Forecast horizon is one to eight weeks ahead, for the promoted period

Model/measure	MAE	sMAPE	MASE	AvgRelMAE	scaled MSE
Base-lift	119.33	87.26%	1.915	1.3705	2.4742
ADL-own	65.27	47.56%	1.329	1.0000	1.0719
ADL-intra	63.10	46.04%	1.307	0.9795	1.0265
ADL-own-EWC	65.01	47.43%	1.325	0.9955	1.0662
ADL-own-IC	69.68	47.95%	1.354	1.0208	1.1299
ADL-intra-EWC	**62.74**	**45.91%**	**1.303**	**0.9756**	**1.0196**
ADL-intra-IC	65.01	46.30%	1.327	1.0035	1.0651

Forecast horizon is one to eight weeks ahead, for the non-promoted period

Model/measure	MAE	sMAPE	MASE	AvgRelMAE	scaled MSE
Base-lift	8.84	41.10%	0.609	1.0083	0.0973
ADL-own	8.52	39.83%	0.605	1.0000	0.0921
ADL-intra	8.47	39.70%	0.606	0.9986	0.0922
ADL-own-EWC	8.47	39.70%	0.604	**0.9963**	0.0920
ADL-own-IC	8.43	39.71%	**0.598**	0.9995	**0.0916**
ADL-intra-EWC	8.43	39.61%	0.605	0.9964	0.0921
ADL-intra-IC	**8.38**	**39.61%**	0.600	0.9976	0.0918

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

Forecast horizon is one to eight weeks ahead, for all forecast period

Model/measure	MAE	sMAPE	MASE	AvgRelMAE	scaled MSE
ADL-intra	13.44	40.01%	0.770	1.0000	0.1689
ADL-intra-EWC	13.47	39.89%	0.769	0.9964	0.169
ADL-intra-IC	**13.34**	39.60%	0.76239	0.9885	**0.1674**
ADL-EWC-IC	13.39	**39.59%**	**0.76236**	**0.9876**	0.1677

Forecast horizon is one to eight weeks ahead, for the promoted forecast period

Model/measure	MAE	sMAPE	MASE	AvgRelMAE	scaled MSE
ADL-intra	**55.11**	45.96%	1.5694	1.0000	1.2509
ADL-intra-EWC	55.55	**45.90%**	**1.5689**	**0.9960**	1.2549
ADL-intra-IC	55.112	45.99%	1.5691	1.0090	**1.2477**
ADL-EWC-IC	55.55	**45.90%**	**1.5689**	**0.9960**	1.2549

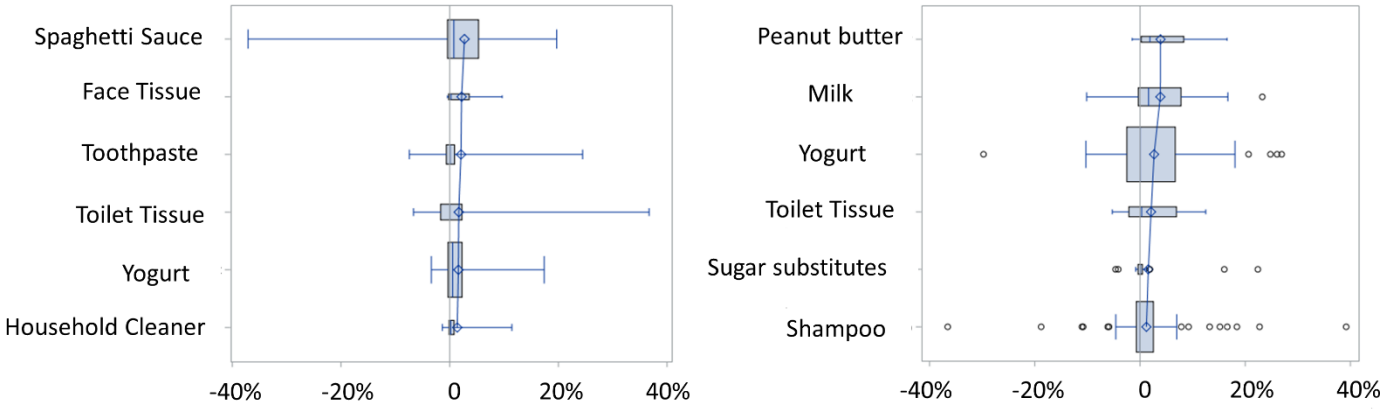
Forecast horizon is one to eight weeks ahead, for the non-promoted forecast period

Model/measure	MAE	sMAPE	MASE	AvgRelMAE	scaled MSE
ADL-intra	8.3	39.27%	0.671	1.0000	0.10473
ADL-intra-EWC	8.28	39.15%	0.67	0.9963	0.10472
ADL-intra-IC	**8.18**	**38.81%**	**0.663**	**0.9871**	**0.1036**
ADL-EWC-IC	**8.18**	**38.81%**	**0.663**	**0.9871**	**0.1036**

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

Category/MASE	ADL-intra-EWC	ADL-intra-IC	Category/MASE	ADL-intra-EWC	ADL-intra-IC
Beer	0.13%	-0.31%	Mayonnaise	-0.07%	0.04%
Blades	0.37%	1.30%	Milk	0.82%	**4.84%**
Carbonated Beverages	-0.33%	-2.13%	Mustard & Ketchup	0.45%	-0.84%
Cigarette	0.07%	0.72%	Peanut butter	-0.19%	**4.88%**
Coffee	-0.22%	0.89%	Photo	1.09%	1.05%
Cold Cereal	0.44%	-1.92%	Salty snacks	0.00%	0.56%
Deodorant	-0.04%	1.26%	Shampoo	0.19%	**1.52%**
Face Tissue	**2.19%**	-0.60%	Soup	0.97%	-4.04%
Frozen Dinner	-0.67%	-1.74%	Spaghetti sauce	**2.72%**	1.38%
Frozen pizza	-0.44%	-2.02%	Sugar substitutes	0.18%	**1.97%**
Hotdog	0.27%	-3.46%	Toilet Tissue	**1.67%**	**2.62%**
Household Cleaner	**1.40%**	0.89%	Toothbrush	-0.18%	-1.12%
Laundry Detergent	0.71%	-0.34%	Toothpaste	**2.09%**	0.55%
Margarine/Butter	-0.76%	-0.89%	Yogurt	**1.61%**	**3.35%**

Figure 3. The boxplots for the percentage reduction of the MASE by the ADL-intra-EWC method and the ADL-intra-IC method compared to the ADL-intra model for one to eight weeks forecast horizon for selected product categories (e.g., those with their relative performance highlighted in Table 6)



(a) the ADL-intra-EWC method (b) the ADL-intra-IC method

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

8. Exploring the determinants of the improvement in the forecasts

The results in Table 6 show that our proposed methods generate more accurate forecasts especially for some product categories (e.g., Yogurt, Toilet Tissue, and Spaghetti sauce etc.) compared to the

models with similar specifications but overlook the problem of structural change (e.g., the ADL-intra model). This is due to the unique characteristics of the data for the products in those categories. Thus, we may further explore the potential determinants of the improved forecasting performance by our proposed methods compared to the ADL-intra model at SKU level. This may potentially provide exploratory insights into what types of SKUs may most benefit from using the proposed methods. We consider the following data characteristics as potential determinants: 1) the average and standard deviation of both the prices and sales variables; 2) the frequency of the feature and display promotions for each of the focal products; 3) more advanced statistical measures suggested by Fildes (1992). For example, we include the proportion of outliers for the sales of each SKU. The value of the sales for product *i* will be identified as an outlier if $\Delta y_i < Q_1 - 1.5 * (Q_3 - Q_1)$ or $\Delta y_i > Q_3 + 1.5 * (Q_3 - Q_1)$, where Δy_i is the differenced value of the sales for product *i*. Q_1 and Q_3 are the first and third quantiles of Δy_i. For retailer product sales, these outliers are usually due to promotional activities. We also include the randomness measure by regressing $y'_{i,t}$ on $T, y'_{i,t-1}, y'_{i,t-2}, and\ y'_{i,t-3}$, where $y'_{i,t}$ is the sales value for product *i* at week *t* given that the outliers are removed and *T* is the time trend. The fitness of this autoregressive model (e.g., the R square) represents the systematic variation in the sales data which could be captured by simple models. Lastly, we include the linear trend of product sales measured as the absolute value of the correlation between $y'_{i,t}$ and the time trend. We then construct five orthogonal factors to represent the information originally contained in the nine explanatory variables described above, which mitigates the issue of multicollinearity[12]. Table 7 shows the correlation between the original fourteen explanatory variables and the constructed factors. We may interpret factor 1 as "Price level and variation", factor 2 as "Sales level and variation", factor 3 as "Randomness and trend", factor 4 as "Outliers and Feature intensity", and factor 5 as "Display intensity".

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

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

We then explore the relationship between these five factors and the forecasting improvement by the proposed methods using regression models. We consider the dependent variables as the percentage reductions of the MASE by the ADL-intra-EWC model and the ADL-intra-IC model compared to the

[12] We choose to retain five factors based on the Scree plot and 90.2% of the original information have been retained.

ADL-intra model for one to eight weeks forecast horizon for each SKU, as demonstrated in equation (12) and (13). Table 8 reports the estimate of the parameters. For example, the estimates of "Randomness and trend" are positive (e.g., 0.21 and 0.58) and statistically significant (e.g., with p-values of 0.01 for both parameters) for the models with the dependent variables of $\mathrm{PctRed}(\mathrm{ADL}-\mathrm{intra}-\mathrm{EWC}, i)$ and $\mathrm{PctRed}(\mathrm{ADL}-\mathrm{intra}-\mathrm{IC}, i)$[13]. This suggests that, adopting the ADL-intra-EWC method or the ADL-intra-EWC method leads to higher percentage reductions of the MASE for the SKU's which are associated with higher randomness and trend (e.g., those which are more difficult to forecast and tend to exhibit a trend in product sales). This is possibly because that the SKU's of this type are more heavily associated with the structural change problem and forecast bias. The results also show that the ADL-intra-IC model tends to have less of an advantage compared to the ADL-intra model for the SKU's with higher proportions of outliers and higher intensities for Feature promotions (e.g., the parameter is -1.13 with a p-value smaller than 0.01). This is possibly because of the fact that the 'intercept correction' for the bias can be submerged by high sales spikes which are usually 'outliers' and caused by the Feature promotional activities. This is consistent with the moderate forecasting performance of the ADL-intra-IC method for the promoted forecast period. We conduct the analysis for other error measures and forecast horizons and we have consistent findings. Overall, we attempt to provide exploratory insights on the situations where our proposed methods may gain most benefits compared to the ADL-intra model (i.e., to take into account the structural change problem for the ADL-intra model).

Table 8 The determinants of the percentage reduction of the MASE by the ADL-intra-EWC method and the ADL-intra-IC method compared to the ADL-intra model for one to eight weeks forecast horizon

Parameters/ Estimates and p-values/ Dependent variables	$\mathrm{PctRed}(\mathrm{ADL}-\mathrm{intra}-\mathrm{EWC}, i$		$\mathrm{PctRed}(\mathrm{ADL}-\mathrm{intra}-\mathrm{IC}, i$	
	Estimate	P-value	Estimate	P-value
Price level and variation	-0.11*	0.21	0.11	0.61
Sales level and variation	0.16	0.06	-0.17	0.43
Outliers and Feature intensity	-0.01	0.93	-1.13	0.00
Randomness and trend	0.21	0.01	0.58	0.01
Display intensity	-0.11	0.19	-0.06	0.77
Intercept	0.30	0.00	-0.38	0.08

*The estimates are all multiplied by 100.

9. Conclusions, limitations and future research

[13] For robustness, we have developed an alternative regression model which also include dummy variables to capture potentially unobserved category effects, and we find the parameter estimate for the five factors to be consistent with those shown in Table 8.

Grocery retailers need to effectively manage their supply chain and, to achieve that, they rely on effective forecasting models and welcome new approaches that will enable them to improve their current inventory management practices. Previous studies focus on incorporating additional information (e.g., Gür Ali et al., 2009; Huang et al., 2014; Ma et al., 2016). However, they assume the effect of marketing activities such as price and promotions (e.g., Feature and Display) to be constant over time. This assumption may not hold because of the impact of external factors such as the change in economic conditions, and the change due to consumers' taste and the entry of new competitors. The data on these external factors are typically not always available. Conventional models assuming constant effects of the marketing activities may be subject to the problem of structural change. As a result, they may generate biased and potentially less accurate forecasts.

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

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

In this study, we propose effective methods to forecast retailer product sales by taking into account the problem of structural change. We propose the ADL-intra-EWC method which combines various sets of forecasts by the ADL-intra method with different estimation windows under the condition when structural changes are detected. The method tries to achieve an effective trade-off between the reduced forecast bias and the inflated forecast error variance. We also propose the ADL-intra-IC method which attempts to offset the potential forecast bias. The method adds the estimate of the forecast bias back to the error term at the cost of inflated forecast error variance when structural changes are detected. Our models significantly outperform the industrial practice method. Table 9 shows the percentage reductions of various error measures by the ADL-intra-EWC method and the ADL-intra-IC model compared to the Base-lift method for one to eight-week forecast horizon. Specifically, by using the ADL-intra-EWC method and the ADL-intra-IC method, we can reduce the MASE by 10.5% and 10.6% respectively compared to the current practice of using the Base-lift method. Therefore, our study may provide retailers more effective forecasting methods. We have also evaluated the forecasting performance of the ADL-own-EWC method and the ADL-own-IC method . These methods are particularly valuable to manufacturers when competitive promotional information is not available (e.g., Mohammad M. Ali, Babai, Boylan, & Syntetos, 2017; M. M. Ali & Boylan, 2011). Table 9 also shows the percentage reductions of various error measures by the ADL-own-EWC method and the ADL-own-IC method compared to the Base-lift method for one to eight-week forecast horizon. Specifically, by using the ADL-own-EWC method and the ADL-own-IC method, we can reduce the MASE by 10.2% and 10.5% respectively compared to the current practice of using the Base-lift method. The improvements are consistent across different forecast horizons and such

improvements in accuracy are estimated to translate into a similar improvement in profits (Kremer, 2015).

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

We also explore the relationship between the improved forecasting performance of the proposed methods (compared to the methods with similar model specifications but overlook the structural break problem) and the data characteristics of the product SKU. We find that the ADL-intra-EWC model tends to have better forecasting performances compared to the ADL-intra model for the SKUs with higher levels of randomness and trend. This suggests that our methods are especially beneficial for the products which are more difficult to forecast and with a trend in their sales. We also find that the ADL-intra-IC model tends to accrue greater advantages compared to the ADL-intra model for the SKU's with a lower proportion of outliers and lower Feature promotion frequency. This may be due to the fact that the estimated bias can get submerged in the high sales variations caused by promotions. However, we note that the findings are still exploratory as we may capture the characteristics of the data by include more variables (e.g., those for seasonality). However, we leave this problem for future research.

The methods we propose in this study is new to the area of forecasting retailer product sales at SKU level, but we have also identified areas where we feel further improvements in forecasting performance could be found. For example, we may use alternative methods to capture the seasonality. Nagbe, Cugliari, and Jacques (2018) used the splines smoothing method to model the seasonality for electricity demand. For the EWC method, we equally combine the forecasts generated by the ADL-intra model with ten different estimation windows. We may further explore the model's forecasting performance with a different number of the estimation windows, and with different forecasting combination schemes (e.g., based on *k*-fold evaluation). For the IC method, we may explore the model's forecasting performance when using different correction schemes (Clements & Hendry, 1999). For example, one alternative correction scheme is to first make adjustments to the one-step-ahead forecast, and then calculate the two-step-ahead forecast based on the value of the one-step-

ahead forecast which has adjusted, and so forth. Ma et al. (2016) have proposed models which integrate both the intra- and the inter-category promotional information. Thus, it is possible that the forecasting performance might improve with both the intra- and the inter-category promotional information considering the structural change problem which we have brought to attention in this paper. Also, an alternative to the ADL-intra-EWC method and the ADL-intra-IC method is to directly model the change in the effect of the marketing activities, such as the time-varying parameter model. However, a disadvantage of this method is that we need to make strong assumptions of how the effects of the marketing activities change. For example, Foekens, Leeflang, and Wittink (1999) modeled the effect of marketing activities as a linear function of previous promotional activities. Their models were not developed for forecasting purposes. In summary, the methods we have proposed in this study produce consistently accurate forecasts. They also satisfy the practical requirements of retail forecasting in that they are intuitive, they can be developed and operated automatically and also use readily available data on marketing activities.

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