FORECASTING CONSUMER PRODUCT DEMAND WITH WEATHER INFORMATION: A CASE STUDY

By Joel K. Sivillo and David P. Reilly

Describes how one can incorporate weather information into a forecasting model to improve the accuracy of demand forecasts ...it is preferable to use weather forecasts which are objectively (not subjectively) derived ... explains the findings of a study of consumer products company where weather information was used to forecast demand.

W eather plays a major role in our day-to-day life. It is an important factor in planning our leisure and making our purchasing plans. Most product demand patterns have a logical dependence on weather. Therefore, it is important to assess the significance of weather on demand. If it does have an impact, we have to include it in the forecasting model. In this article, we report the results of a study of daily consumer product demand forecasts where weather was incorporated into the model.

WHY WEATHER FOR DEMAND FORECASTS

Why blame weather when you can plan for it? Many corporations cite weather as a reason when earnings estimates are not met. While this seems to be a logical and acceptable explanation to some investors and analysts, the fact remains that companies should plan for, rather than react to, weather's impact. Hedging for an enterprise's weather exposure is one way to mitigate weather impacts. Another way is to include it in forecasting models. In this article, we demonstrate how one can incorporate weather information into a forecasting model to improve the accuracy of demand forecasts.
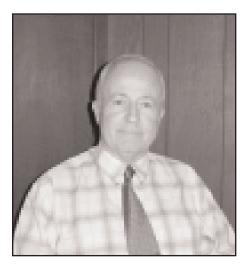
HOW TO USE WEATHER INFORMATION

In using weather in a forecasting model, two things are important: (1) Using the right weather information. (2) Using the right forecasting model and software.

Using The Right Weather Information: Before deciding to incorporate weather information into a demand forecasting model, one must consider which weather variables are most likely to impact consumer demand. Anecdotal information, common sense, and experience are likely to be the guide. Also, one must consider the locations where weather is important, as well as the types of weather

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TABLE 1
FORECAST DATES FOR DEMAND STUDY

Forecast Period	First Date of Period	Last Date of Period	Holiday
1	Mon 6/14/04	Sun 6/20/04	
2	Tue 6/22/04	Mon 6/28/04	
3	Wed 6/30/04	Tue 7/6/04	Independence Day
4	Thu 7/8/04	Wed 7/14/04	
5	Sat 7/17/04	Fri 7/23/04	
6	Mon 8/16/04	Sun 8/22/04	
7	Tue 8/24/04	Mon 8/30/04	
8	Wed 9/1/04	Tue 9/7/04	Labor Day
9	Wed 9/8/04	Tue 9/14/04	
10	Sat 9/18/04	Fri 9/24/04	

that have both enhancing and detrimental effects on consumer demand.

Provided that one is dealing with a sales forecasting problem for a manageable amount of first or second tier cities, adequate historical weather information is likely to be available via the National Weather Service, or through commercial weather information vendors. Correlation studies can be performed to determine how closely demand follows weather patterns. Further, one can test correlations between specific weather variables (such as Temperature, Precipitation, Dewpoint, Relative Humidity and Cloud Cover) and the demand for goods, which can guide in selecting the best variable for a given demand data.

Great care must be taken in establishing a complete dataset of observed historical weather, so that the demand model can properly represent the relationships between demand and weather conditions. Also, important consideration must be given to the type of weather forecast that is used. Weather forecasts can be prepared either subjectively or objectively. Many weather forecasting companies offer weather forecasts that have been subjectively constructed by meteorologists. Objective weather forecasts are those that are generated without human intervention. This means that the outputs are systematic and reliable, and error statistics are quantifiable and stable.

Using The Right Demand Model And Forecasting Software: Selecting the best weather variable is not enough. One must use the right demand model and forecasting software. The software should automatically select the best from the user's suggested variables, consider lead and lag relationships, and account for outliers and unusual values in the data. Outliers often give very important information, provided they are fully understood and properly used. They can help to improve further the quality of final forecasts. Some important outliers (unusual values) can be characterized as: (1) Pulses – one-time unusual values, (2) Seasonal Pulses – repetitive pulses over time, (3) Level Shifts –step like changes in the mean to a lower or higher level, and (4) Time Trends – systematic increases or decreases in the mean over time.

STUDY DESIGN

The objective of this study is to see if the weather variable can improve the forecasts for a consumer products company. The study is confined to twenty individual SKUs or UPCs, selected for eight retail outlets that represented a cross-section of the United States. Forecasts were made for ten different, non-overlapping one-week periods from June through September. Thus, we had to develop 1600 (20 × 8 ×10) individual model forecast equations. Each forecast equation was solved by Autobox to make a 7-day period forecast. Table 1 shows the forecast periods used in this demand study. While every effort was made to include forecasts that started on each weekday, the participating consumer products company could not share Friday data.

In order to compare demand forecast errors, we used three versions of Autobox model forecasts, one without weather information, and the other two with weather information. Therefore, we came out with a grand total of 4800, 7-day period forecasts. For the two model versions with weather information, two different weather information providers were used. Weather Predict, Inc. provided objectively constructed, daily maximum temperature forecasts. Another private weather forecasting company provided subjectively constructed, daily maximum temperature forecasts.

In this forecasting effort, we started out with daily forecasts, which were then aggregated into weekly forecasts. There were three reasons for doing that:

First, price changes occur on different days of a week, which can dramatically change the daily distribution of sales. Also, many stores receive two or more deliveries per week, while others will have one delivery per week on a fixed store-specific day. Further, delivery schedules often change; for some distributors, the delivery schedule is basically random.

Two, daily forecasts enabled the company to identify potential stock outs on a daily basis, thereby enabling the company to schedule emergency deliveries if needed.

Three, holidays substantially change weekly distribution of sales. Each holiday has a different effect. Furthermore, holidays that do not always fall on the same day of the week may have different effects. The weekly forecasts helped to overcome this problem.

In short, it was difficult to develop explicit weekly forecasts that accounted for all of these factors. Producing aggregate weekly forecasts from the individual, daily data appeared to be the best option. Here is the information that was incorporated into the demand forecasting model:

- Store-level daily sales to consumers for each of the 20 UPCs – a historical data set, beginning on January 1, 2002, and ending on the day prior to the forecasts' start date.
- Prices that consumers paid for the UPCs at each of the stores
- Past-observed, daily maximum temperatures at the physical locations of the stores beginning on January 1, 2002
- Day of the week for each sale
- Dates of holidays
- Special discounts that were in effect, including prices of products from the same company that could cannibalize sales for the SKU of interest
- Prices to be charged for the next 7 days
- Maximum temperature forecasts for the next 7 days, leading to 3 test cases: forecasts with weather information from Weather Predict, Inc., forecasts with weather information from a competing weather forecast company, and a case with no weather input

The following information was not known at the time of forecast generation:

- How sales respond to each holiday
- The price effects, and whether they were contemporaneous, or had lead or lag relationships with sales

Forecast Period	Solution with Info. from other Weather Provider	Solution with Weather Predict Information	Solution without Weather Information	Observed Sales Volume
	TABLE 2			
	VOLUME WEIGHTED MAPE			
1	43	42.8	45.7	10037
2	37.1	36.7	36.6	8118
3	25.6	24.3	25.5	14629
4	44.9	44.7	45.9	6772
5	31.1	31.2	32.4	6347
6	36.7	36.4	36.7	5646
7	37.9	39.6	39.5	6326
8	40.8	40.8	41.7	13177
9	32.9	32.4	32.7	5724
10	26.4	27	27.1	6687
WMAPE	**35.4**	**35.3**	**36.2**	**83463**

- The potential effect of a level shift in demand from factors not considered, such as the opening of a large competing chain store nearby
- The potential effect of sales trends resulting from factors not considered, such as the number of consumers in the geographical area of the store
- The potential effect of a shift in sales distribution over the days of the week

Regarding the total data requirements for this study, there were 1600 forecasts generated for the aforementioned forecast periods, SKUs, and Geographic areas. Further, for each forecast, a matrix was generated that contained a column for the dependent variable (the sales volume), plus 16 causal variables. In order to include historical observations back to January 1, 2002, the matrix contained upwards of 900 discrete rows. Therefore, each solution incorporated roughly 24,480,000 ($1600 \times 900 \times 17$) data points. We then multiply this by 3 because there were three solutions that varied according to the types of weather information that were used. Autobox had to manage roughly 73 million data points.

RESULTS

Here is what we learned from the 10 different forecast periods and three different model versions. The model versions were: (1) demand forecasts using a different weather forecast company's information, (2) demand forecasts using Weather Predict's information, and (3) demand forecasts using no weather input.

1. Forecasts improve when a reliable weather variable is included in the model. In this study, we chose Weighted Mean Absolute Percent Error (WMAPE) as our metric. (MAPE without weighting does not give a complete picture of the error because a small SKU with a large error gets the same weight as a large SKU with a small error.) The WMAPE of the model without weather was 36.2. The WMAPE from the model forecasts with subjective weather forecast information was 35.4. Finally, the WMAPE from the model forecasts with Weather Predict's objective information was 35.3.

In each case, the WMAPE, when

TABLE 3
NUMBER OF FORECAST WINS WEATHER PREDICT SOLUTION VS. OTHER WEATHER SOLUTION

Origin	Other Weather Solution	Weather Predict Solution	Tie	Total Number Of Forecasts
1	57	53	50	160
2	43	61	56	160
3	44	64	52	160
4	58	45	57	160
5	52	54	54	160
6	46	68	46	160
7	62	52	46	160
8	53	61	46	160
9	55	66	39	160
10	62	64	34	160
Total	**532**	**588**	**480**	**1600**

weather was included in the model, was lower than when it was not included. In a head to head comparison of the two weather information providers, Weather Predict's WMAPE was only slightly better than the other company (35.3 compared to 35.4). However, when we look at the model forecasts in which Weather Predict data was included, it outperformed the model with the other weather data 6 out 9 times. In one case, there was a tie. (See Table 2).

In terms of the magnitude of WMAPEs in Table 2, the forecast errors appear somewhat large because the individual errors are averaged over each store-city-SKU combination. MAPEs at this level of granularity are naturally higher. If we were to aggregate the total forecasts and total volumes first, and then calculate the WMAPEs, we would expect smaller numbers. Since we were bound by the data provided by the consumer goods company, we report the WMAPEs as they were reported to us.

It is difficult to assess the amount of savings that a CPG company can realize due to a better forecast,

because it depends on their cost structures. However, a better forecast will prove to be beneficial by increasing supply chain efficiency and reducing the amount of safety stocks.

2. Many individual forecasts were aggregated to study WMAPE. There were 160 weekly forecasts for each of the solutions that used Weather Predict and the other company's weather information. For each of these 160 demand forecasts, we counted how many times Weather Predict had the lowest absolute error (wins), how many times the other weather solution had the lowest absolute error (losses), and how many times the two solutions had the same error (ties).

From Table 3, we see that Weather Predict's solution produced 10% more wins than the other vendor. This means it does make a difference which weather information one uses in the forecasting model.

CONCLUSION

From the above study, we can conclude:

1. Weather plays an important role in the forecast of consumer products' demand. So, it should be included in the forecasting model.

2. Who is the provider of weather information also makes a difference. It is preferable to use weather forecasts which are objectively (not subjectively) derived, and for which error statistics can be readily verified. Ask the weather forecast company to provide error histories, or past forecasts that can be verified.

3. In this study, only maximum temperatures were included. It is possible that the forecasts may improve further if other variables such as humidity, minimum temperatures, and other weather factors are included either individually or collectively.

4. It would be interesting to extend this study to other seasonal items that have stronger temperature responses, such as canned soups, bottled water, and snow blowers. The consumer product used in this study has a relatively small response to temperature, which is about a 0.01% increase in sales for every degree Fahrenheit increase in temperature. ■