FORECASTING DEMAND WITH POINT OF SALES DATA—A CASE STUDY OF FASHION PRODUCTS

By Bill Sichel

The retail industry is faced with increasingly shorter lead times due to changing customer-supplier relationships and overall competitive and profitability pressures. Many retailers utilize weekly POS data to improve forecasting accuracy of their products by store location. In this article we describe methods to improve weekly demand forecasts by using the Point of Sales (POS) data. This data, which represents retail store sales to their final consumers, are captured electronically from retail accounts. In forecasting consumer demand trends, POS data represents the most current indicator of actual consumer demand; in fact, it is the first indicator of changes in consumer demand patterns. In consideration of lead times and the potential short duration of trends, the fashion industry requires a weekly forecasting technique, which detects early changes in consumer demand so that it can quickly respond by revising forecasts, as well as production plans.

The Monet Group, acquired by Liz Claiborne, is the world leader in the design, production, and distribution of costume jewelry. End customers include most large retailers such as Macy’s (USA), Breuninger (Germany), Harrods (UK), Galeries Lafayette (France), and De Bijenkorf (Holland), as well as many other smaller retail outlets.

**METHODOLOGY**

POS data is transferred via EDI (Electronic Data Interchange), which is to say, it is transferred by way of computer-to-computer data transfers. Retail POS data is transmitted from retail stores to our computer facility once each week. The POS data is modeled for seasonality patterns and then an annual (single number) forecast of expected sales to POS accounts is produced, which is then broken down into 52 weekly periods. The derived annual forecast of retail POS sales is inflated for non-POS customers, such as international and military customers. Due to the difference in seasonality between retail POS sales and shipments from the distribution facility, the inflated annual estimate of POS sales is re-seasonalized into monthly buckets based on seasonality patterns derived from historical shipping patterns.

**EXPECTATIONS FROM IMPROVED FORECASTS**

The expectations from improved forecasts both by vendors and customers are:

- **Lower Inventory Cash Flow,** which will allow for increased expenditures in areas such as advertising and in-store displays to further promote sales.
- **Minimum store-level stock outs (lost sales)** with a rapid vendor replenishment system.
- **Maximum resource utility under constrained production environment** by producing the right product at the right time.

**HANDLING THE SEASONAL COMPONENT OF A FORECAST**

There are five components of a forecast: baseline, seasonality, promotions, events, and outliers. This article, however, discusses only the seasonality component of the entire forecast process. The procedure discussed here can be easily programmed into an automated system—particularly if it is written in a user-friendly programming language.

The costume jewelry business is a highly seasonal business. Therefore, the first step here should be to aggregate POS data to a highest product level by adding up all product items with similar

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characteristics. In the costume jewelry industry, products are categorized by pierced earrings, clip earrings, necklaces, bracelets, color pierced earrings, etc. This is called category level categorization (in comparison to the brand level, which would be a higher level, or the subcategory level, which would be lower). After aggregation along the product line, the weekly POS data needs to be aggregated into monthly buckets. Figure 1 gives the monthly seasonal indexes of POS data of two categories—Metal Pierced Earrings and Color Pierced Earrings. As can be seen in this figure, both have a different seasonal pattern. The sales of Color Pierced Earrings peak in June, while sales of Metal Pierced Earrings peak in December. This level of aggregation is sufficient for some products, but not for others. In particular, for Color Pierced Earrings (which include white earrings, black earrings, red earrings, and navy blue earrings) we needed to break it down further into subcategories such as a Black Pierced Earrings subcategory and a Red Pierced Earrings subcategory because of their different seasonal patterns. We have found that Color Pierced Earrings category peaks in the month of June because of large sales of White Earrings in that month, but the secondary peak is in December because of Black, Red, and Blue Pierced Earrings.

So far we have described two different types of aggregation—along product line (by brand level, category level, and subcategory level) and along time line (by week, month, and year). There is also a third type, aggregation along a geographical or regional line, which we found to be quite useful. We determined seasonal indexes of the White Pierced Earrings subcategory for two geographic regions—the South and the East—(although more could be considered), which are plotted in Figure 2. It shows that both regions have a different seasonality—sales peak in the month of March in the South and in the months of June and July in the East. This may be because the warm weather arrives earlier in the year in the South and later in the East. We also plotted two years of POS data for one popular gold pierced earring, and found that in the East sales peak out in June, whereas it is in March in the South.

The fashion industry, like jewelry, requires a weekly forecasting technique for a number of reasons. One, you can detect the change in the trend much quicker. Two, it is possible that data may have a weekly seasonal pattern, which was true in the case of our jewelry company. In that case, to improve forecasts we have to incorporate seasonality in the forecasts. To make that determination we wanted to know whether the rate of purchases differ for different weeks of a calendar quarter. In other words, do consumers tend to spend more in certain weeks and less in other weeks of every quarter? To find out the answer to this, each series was split into 13-week quarters, and weekly seasonal indexes were determined for each week within the quarter as if each quarter represented a year. After this kind of grouping, we used the equivalent of seven years of data. We found that a four-week cycle exists, the third week of each month has the highest seasonal index, and thus the highest sales. This may be because of the distribution of pay checks. Such paycheck dispersal often occurs two times a month. The first check might be used to pay for more necessary items (such as mortgage and car payments), and the second check for more non-essential items.

To determine whether these types of seasonal indexes improve forecasts, we prepared ex post facto forecasts. The results were quite favorable: The MAPE (Mean Absolute Percent Error) improved over relevant lead-times by 9.2%.

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