



Yet, many Collaborative Planning, Forecasting and Replenishment (CPFR) projects focus on routine replenishment rather than promotions. Only a few projects, such as Metro's pilot CPFR programme with Procter & Gamble (P&G) focus solely on promotions.

Such research is beginning to show that by improving information sharing between the manufacturer and the retailer, and by developing a smart customer choice model that is part of the forecasting process, performance can improve significantly.

A smart customer choice model is a model that takes detailed account of the effects of temporary price changes on consumer behaviour. One way of doing this is via the concept of consumer level stockpiling: how do consumer stocks of goods at home affect their reactions to promotions? Understanding the model requires us to explain three concepts – the reservation price, holding cost and a customer breakeven calculation.

#### Understanding consumer stockpiling

Let us assume that all the shoppers coming into a store can be divided into two segments (we use two as an example – more segments may be used to model more complex environments). One segment purchases at a constant rate and is indifferent to retail prices as long as they are below a certain level.

The second segment will not purchase unless prices are below a certain level (their reservation price) and in addition, will typically stockpile product (when retail prices are low) and then consume from individual inventory. This is the segment we focus on.

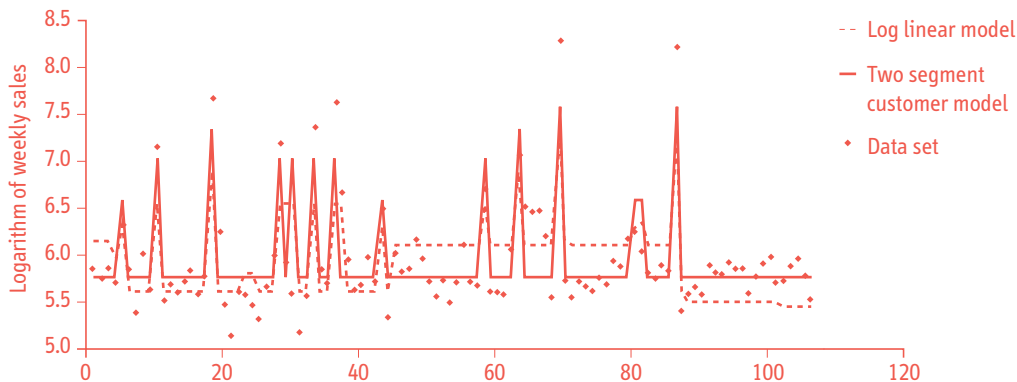
How does this segment decide how much to buy? Consider the following calculation that these consumers may carry out. They have a reservation price above which they will not purchase. They have a holding cost they posit to capture the limitations on their storage space (at home or in the car), their liquidity constraint and so on.

When such consumers are faced with a promoted product whose price is below their reservation price, they have to decide how many days' worth of consumption to purchase. This is their (intuitively calculated) breakeven number of days' consumption – after which the cost of buying and holding the promoted item begins to exceed the reservation price.

For example, if the reservation price is €1.0, the holding cost is €0.01 and the price during promotion is €0.9, then the breakeven number of days is (reservation cost - promotion price) / holding cost or  $(€1.0 - €0.9) / €0.01 = 10$  days. Thus, faced with a price of €0.9, this consumer will buy 10 days' worth of consumption today. It is clear that the lower the holding cost,

#### Exhibit 1: Predicting weekly sales of canned tomato soup in a store over two years

A data set showing the logarithm of weekly sales of canned tomato soup in a store over two years. Also shown is a fitted log-linear model as well as a model with parameters fitted to a two-segment model. The associated  $R^2$  for the log-linear model was 52%, the  $R^2$  for the fitted two-segment model was 68%.



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the greater the purchase for the same retail price. It is also clear, of course, that a lower promotion price encourages greater purchases from the same customer segment.

Now suppose the promotion price was €0.9. How should a retailer promote in such an environment? If the retailer followed a strategy of promoting the item once every breakeven number of days of consumption, this would prompt our first segment of price-insensitive shoppers to pay the regular price most of the time, and for our second segment of price-sensitive buyers to pay the promoted price every period, for instance, every 10 days in this example.

Exhibit 1 shows sales of canned soup in a supermarket over a period of two years. The dots show fluctuations in actual sales as prices rise or fall. The dotted line models demand according to the log-linear regression model of prices against demand suggested by most marketers and economists. And the line graph shows expected demand levels when using this consumer stockpiling model.

This extremely simple model explains over 74 per cent of demand variations. But there are still a number of cases where actual sales are different from the model's predictions. This requires us to know the forecast accuracy of the model and thus know the associated forecast error suggested by the model.

Once we get that information, we can choose the right amount of retail inventory to include a hedge against this forecast error and thus guarantee a relatively high in-stock availability at the store.

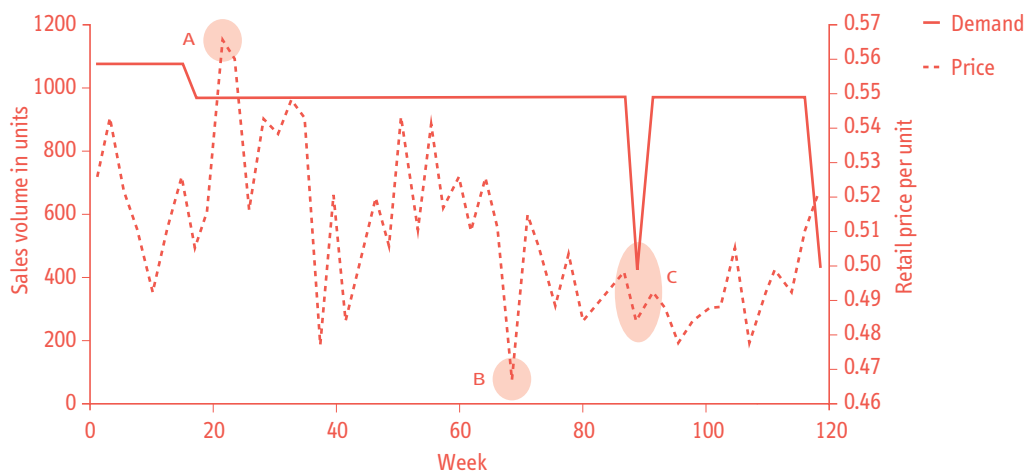
#### Are accurate forecasts for single stock-keeping-units possible?

Consider a typical retail environment where shoppers are presented with the same product in different package sizes with different per-unit prices, and where these per-unit prices vary from time to time. As the relative value of different pack sizes changes, we would expect to see shoppers switching their preference from one size to another. They might also withhold purchases until prices are low enough, to stockpile inventory when prices fall, and to continue to observe price levels to prompt such decisions<sup>3</sup>.

We tested this hypothesis with Procter & Gamble's diaper brand Pampers. MADAKOM, a German Point-of-Sales-Data Service Provider, provided us with weekly point-of-sales data from several grocery retailers located throughout Germany.

Pampers is a good product to study because it accounts for 81 per cent of sales in its category, is an expensive and promotion-intensive item, and triggers store traffic. We plotted price against demand over a period of one year for one Pampers stock-keeping-unit (see Exhibit 2).

Exhibit 2: Retail price versus demand of a single SKU



As can be seen, there is no clear relationship between customer demand and price variations. Points A and B have the same price level but significantly different demand levels. At point C the price decreases and the quantity sold decreases as well.

These counter-intuitive observations show how important it is to develop a consumer choice model that takes account of price differences between package sizes each period. Consequently, we aggregated demand of all packages and determined the average price paid as the demand-weighted price across the various package sizes. We then used the consumer stockpiling model to test actual sales against prediction. Exhibit 4 shows the results for one particular diaper type, Jumbo diapers. The model determines the fraction of customers who switch during promotions, including those switching to the larger (most economical) package size.

#### Accurate demand forecast for individual SKUs

Disaggregating the forecasts for individual SKUs is straightforward. The aggregate demand is multiplied with the fraction of (price-sensitive) customers reacting to promotions. We call this number the “a”-factor where the level of “a” may be very different across retail environments or micro-markets (and certainly across Euro-land).

From the WHU-INSEAD shopper research study, we see that the German, French and Dutch population is far more price-sensitive than the Italian or Spanish. In our data analysis, we observed the following: demand for the large (and promoted) package size(s) can be predicted very accurately (see Exhibit 3). Across all stores, the forecast error for the large package item is around 24 per cent with 87 per cent of all cases exhibiting a forecast error of less than two per cent<sup>3</sup>! Forecast error for the small package items is around 35 per cent.

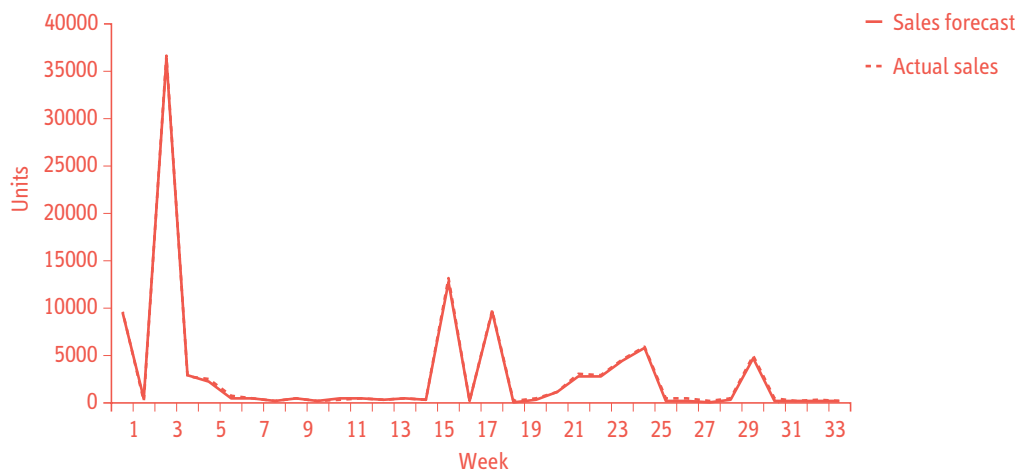
Exhibit 4 shows how radical the possible improvements over current levels of forecasting error can be. Traditionally, forecast errors varied from 30-140 per cent. Now this error is being brought down to a much more manageable level 4.

#### How does this help CPFR and promotions?

By taking account of the consumer response to promotions through stockpiling and package switching, forecast error can be reduced significantly. For CPFR to be successful in reducing forecast error and days of supply this is an imperative. We suggest the following approach:

- Aggregate the sales data to see unexplainable issues at the SKU level
- Model the customer reaction to

Exhibit 3: Actual demand versus demand forecast for the large package size



- promotions, that is, switching across package sizes
- c. Synchronize shipments with demand-pull information to make promotions work for both the manufacturer and the retailer.

In addition, as suggested by practitioners from Metro and Procter & Gamble at the 2nd ECR Research Symposium at the WHU, the order fulfilment process – which is not part of the standard CPFR framework – must be carefully managed during times of promotion<sup>4,5</sup>.

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**Exhibit 4: Weighted absolute percentage (forecast) error observed by Procter & Gamble**

