The Impact of Service Level Requirements and Product Perishability Information on Demand Forecasting Bias

Behnam Fahimnia (behnam.fahimnia@sydney.edu.au)
The University of Sydney, Australia

Tarkan Tan
Eindhoven University of Technology, The Netherlands

Meysam Arvan
The University of Sydney, Australia

Enno Siemsen
University of Wisconsin-Madison, USA

Abstract

Motivated by forecasting practices in the Fast-Moving Consumer Goods (FMCG) industry, this research aims to understand the extent to which sales forecasts are treated as the most likely sales quantities, and not demand plans. We study the impact of retailer service level on demand forecasts, and the moderating impact of product perishability and sales promotions. A laboratory experiment is designed using empirical sales data and promotional events from two FMCG companies. Data is collected form 248 subjects (over 85% experienced forecasters) across four treatment groups. Our analysis arrives at interesting results on how forecasters respond to different mix of information.

Keywords: Judgmental demand forecasting, Service level, Laboratory Experiment

Introduction

Demand-driven supply chain management (SCM) has gradually replaced the traditional forecast-push production and capacity planning practices. In a demand-driven SCM, demand forecasts are used to develop demand plans which are accordingly used as key ingredients of Sales & Operations Planning (S&OP). S&OP is the core of demand-driven SCM which facilitates the execution of Integrated Business Planning (IBP) transformation programs. By definition, S&OP is a process that aims to maximise operational performance through continuous alignment between demand plans and supply/manufacturing plans at the tactical planning level, and alignment between the tactical plans and the business plan at the strategic planning level.

Essentially, S&OP provides a holistic view of the business and how best the available capacity can be utilised to deliver against the consensus demand plan. Hence, it is a must for S&OP managers and SCM executives to understand what constitutes the demand plan. There is a consensus in the FMCG industry that the demand plan constitutes of (1) sales forecasts, (2) service level requirements and replenishment constraints, and (3) revenue projections. Sales forecasts, as the most important ingredient of the demand plan, are prepared by the forecasters. In generating the sales forecasts, they consider sales history and trends as well as contextual information , most importantly the type and scale of sales promotions and other events that contribute to demand fluctuations.

Statistical methods – which are theoretically based on extrapolating the historical sales data – have been historically used for sales forecasting. However, forecasters increasingly intervene to use their intuition and expert judgment to produce the forecasts. Judgmental forecasting allows a forecaster to incorporate the factors that are not fully captured by the statistical models. Such factors are associated with contextual information that are more dynamic in nature or not easily quantifiable (Sanders & Manrodt 1994; Sanders & Ritzman 2001; Sanders & Manrodt 2003).

S&OP managers are quite familiar with the concept of 'loss function'. Marketing managers focus on customer satisfaction by giving more weight to supply chain responsiveness and improving the service level. Operations and inventory managers, on the other hand, focus on efficiency and productivity aiming to maximise the output with minimise use of the available resources. Loss function is defined differently in these two departments. In demand planning, asymmetric loss function has two sides: (1) satisfying customer/retailer service level triggers over-forecasting, and (2) minimising inventory triggers under-forecasting. Using this function, forecast error cannot be linearly correlated to the costs. Thus, under- and over-forecasting may have different cost functions. These are the typical daily challenges of demand planners. But this should not be the case in sales forecasting!

In forecasting, human interventions aim to only incorporate contextual information (primarily, information related to sales promotions and special events) into the statistical models (Sanders & Ritzman 1992; Goodwin & Fildes 1999). Hence, a loss function has no place in sales forecasting. In fact, that's what differentiates sales forecasting from demand planning and other supply chain decisions. Forecasting purely relies on historical data – including previous sales, promotional data, and information related to special events and market dynamics – while demand planners consider a range of internal and external factors to prepare the forecast plan (factors such as service level requirements, product perishability and inventory obsolescence, and storage and shipping constraints). It is of paramount importance to understand these differences to avoid double counting and ineffective S&OP. Scanty literature exist on how different factors – within and outside the supply chain – could potentially influence the judgmentally made forecasts.

This research is grounded on several years of industry observations and discussions with sales forecasters, demand planners and S&OP managers within the FMCG industry. We were challenged by two questions for which we have no answers that are strongly supported by the academic literature and/or related industry practice. (1) To what extent do forecasters factor in retailer/consumer service level requirements into their forecasts? The industry is unaware of potential forecast bias caused by service level consideration given its stressed significance in the FMCG industry. (2) To what extent factors such as product perishability and the presence of sales promotion can moderate the impact of service level consideration? In other words, the industry is interested to know whether presenting side information to a forecaster would distract the service level consideration.

To explore these, we design a lab experiment replicating the sales forecasting process in two giant FMCG companies in Australia. Empirical data related to sales history and promotional events was gathered from these companies. The data was manipulated to produce unique time series (statistically replicable) for each subject. Collected data from

248 subjects – comprising fresh graduates (less than 15%) and experienced forecasters (over 85%) – is used to investigate how forecasters respond to different mix of information presented to them.

Background and Literature Review

Historically, human has used mind heuristics to simplify complex problems (Tversky & Kahneman 1974). Sales forecasting has been no exception. Our observation and discussions with forecasters from over 50 companies within the FMCG industry indicates that human judgment is commonly used to generate forecasts, with no formal statistical forecasting tool in place. American survey results confirm our observations by recognising judgmental forecasting as the most commonplace demand forecasting approach in industry (Sanders & Manrodt 1994, 2003; Klassen & Flores 2001). Even when statistical methods are used to generate base forecasts, forecasters intervene and apply personal judgment to the base forecasts (a process that is commonly referred to as 'judgmental forecast adjustments') in order to incorporate contextual information incorporated in the base forecasts (Webby, O'Connor & Edmundson 2005; Fischer & Harvey 1999). Contextual information relates to any event that could potentially prompt sudden fluctuations in demand.

The use of heuristics in forecasting comes with personal biases (Hogarth & Makridakis 1981). Anchoring (Tversky & Kahneman 1974), wishful thinking (Saxena 1973), illusion of control (Langer 1975), Hindsight bias (Fischhoff 1975) are examples of these biases. Nevertheless, recent research reinforces that effectiveness of judgmentally made or judgmentally adjusted forecasts when individuals are adequately informed and/or trained (Alvarado-Valencia et al. 2017; Fildes et al. 2009)(Nikolopoulos & Fildes 2013; Seifert et al. 2015). We follow this line of thinking and ask the participating subjects in our experiment to make judgmental forecasts based on the provided historical data and certain contextual information.

Another literature that we need to touch upon is the use of loss functions in demand planning, S&OP and SCM. In a demand planning context, a loss function is used to describe the extent to which a decision maker favours over-forecasting or under-forecasting (Lawrence & O'Connor 2005). In simple terms, the relationship between the size and direction of a forecast error and the cost to the organization is referred to as a 'loss function'. Demand plans are developed using a loss function because each unit of forecast error may not cost the same to the company. Quantitative model and decision-support tools assume that loss functions are symmetrical (Lawrence & O'Connor 2005). However, judgmental planning – including any decision that involves human judgment – is based on asymmetrical loss functions. Goodwin (2005) studied how providing different forms of support can help demand planners to better utilise an asymmetric loss function that describes the cost of shortage vs. surplus. The study finds that providing demand planners with the statistical forecasts can be more helpful in informing human judgment when sudden fluctuations occur in the series. Other studies have examined the behaviour of decision makers using different loss functions (Elliott, Timmermann & Ivana 2008, 2005, Franses, Legerstee & Paap 2017).

However, the primary goal in demand forecasting is error minimisation. Using a loss function in forecasting makes no sense because all units of forecast error should appear the same to a forecaster. But, since human judgment is an inevitable part of demand forecasting (predominantly to incorporate the impact of promotional and other contextual information), it is highly likely that forecasters unconsciously use loss functions to compare the cost of an under-forecast with the cost of an over-forecast. If this happen to be the case, the same factors that are incorporated into the loss functions of demand planning and S&OP could be already considered in the judgmentally made forecasts. This signals the potential for an unobserved double counting and what we aim to investigate in this research.

Our particular interest is the impact of service level on judgmentally made forecasts. Research has shown that stockouts can seriously jeopardize customer loyalty (Heim & Sinha 2001) and decrease the size and frequency of customer orders (Silver 1976; Shih 1980). Unsatisfied customers could switch to suppliers of substitutable products, and the profit loss could be even more pronounced when customers are the major retailers where majority of the sales occur. We argue that service level consideration may instinctively affect the sales forecasts (recalling that, theoretically, forecasters are supposed to ignore service levels as it will be part of the loss functions in demand planning and S&OP). Therefore, we hypothesise:

H1. A high service level requirement creates over-forecasting bias.

H2. A low service level requirement creates under-forecasting bias.

Service level could play a more central role in promotional periods. Promotions are an important part of the marketing mix in the FMCG industry. A substantial portion of sales occur in cyclic promotions. Even for medium-size enterprises, the costs associated with unmet service level in promotions can be up to millions of dollars (Craig, Dehoratius & Raman 2013). For that reason, promotions are not always profitable. Survey results show that only 18% of promotions have been profitable (Srinivasan et al. 2004). Another survey of the FMCG industry carried out by Efficient Consumer Response Australasia (ECRA) reported that stock-out rates significantly increase in promotional periods which makes promotions not as profitable as they are perceived to be (ECR Australia 2010). Supply chain practitioners are frequently informed about the immediate and long-term profits associated with maintaining the service levels (no just through the increased sales in promotions, but also through the improved customer satisfaction and business reputation in the long term). While maintaining service level in promotions is a logical consideration in demand planning and S&OP, a forecaster who is frequently exposed to this information may also instinctively care more about service level in promotional periods. Our next hypothesis is developed on this basis.

H3. Service level influence forecasts more strongly during promotional periods than during regular periods.

Forecasting for food and other perishable products could be even more challenging. While under-forecasting is associated with lost sales and damage to the business reputation, over-forecasting prompts wastage and sales markdowns. Food manufacturers and retailers have witnessed these consequences. Waste generation has turned into a major concern in food chains, to the point that half of all food grown is wasted before and after it reaches the consumer (Lundqvist, Fraiture & Molden 2008). Food chain experts believe that poor forecasting and planning is one of the primary contributors to food wastage (Mena, Adenso-Diaz & Yurt 2011). This has been a widespread discussion topic in the media and executive publications/seminars/forums. Waste consideration is imperative to the classic newsvendor problem (Petruzzi 1999), where optimal inventory decisions are determined considering such factors as waste generation, lost sales, holding costs and capacity constraints (Qin et al. 2011). Due to the significance of this topic to organizations – food producers, in particular – we think that there is a good chance for a forecaster to be influenced by product perishability information when making judgmental forecasts (also see Sanders & Ritzman 2001). If so, this would be the opposite side of service level consideration which triggers over-forecasting. Therefore, we hypothesize:

H4. Service level influence forecasts less strongly for perishable products.

Section 3 presents the design of a laboratory experiment that will be used in Sections 4 and 5 to collect data to test these hypotheses.

Experimental Design

This section presents the design of a laboratory experiment to test the four hypotheses articulated in the previous section. Controlled laboratory experiments are the most common research approach in the literature of judgmental forecasting (Bendoly, Donohue & Schultz 2006; Arvan et al. 2018). An important aspect of our experiment is that we use a mix of naïve students (15%) and experienced forecasters (85%) from the FMCG industry as participating subjects.

The experiment starts with providing all subjects with general information about the case industry and their role as sales forecasters. The difference between sales forecasting and demand planning and supply chain decision making is explicitly reinforced in the task description. All subjects are adequately notified that their forecasts should only reflect the most likely value for product demand in the forthcoming week based on the historical sales data and possible sales promotions, and that their forecasts will then be forwarded to other departments where additional factors will be taken into consideration to make related supply chain decisions.

Each subject is assigned to one of the four treatment groups. Treatment 1 is the control group in which forecasts are made for a non-perishable product (shelf life of 9 months) where service level information is not revealed to the subjects. Treatment 2 aims to test the impact of high service level (testing H1: the impact of high service level). In this treatment, forecasts are made for a non-perishable product and the subjects are informed about a retailer service level of 98.5% (which is the standard service level requirement of large retailers). In treatment 3 the forecasts are still made for a non-perishable product, but the subjects are informed about a low service level requirement of 85% (testing H2: the impact of low service level). Treatment 4 is characterized by forecasting for a highly perishable product (shelf life of 1 day) where service level is also high (testing H4: the impact of product perishability).

Each subject prepares four forecasts. For each forecast, a subject is provided with 30 weeks of sales data with both normal and promotional weeks. The promotional weeks are highlighted as ‘Promo’. The subjects are asked to provide their forecasts for week 31. In two out of four attempts, the subjects forecast for a promotional period (testing H3: the impact of promotional information). Additional information about product shelf life and retailer service level is provided to the forecasters depending on the treatment group to which a subject is assigned.

The experiment starts with a set of questions to collect some demographic information from the subjects related to their gender, age, qualifications and related work experience. At the end of the experiment, the subjects are asked to state the factors they considered when making the forecasts. The options could be (1) the historical sales data, (2) the past promotional information, (3) the upcoming promotions, (4) product shelf life, (5) the retailer service level, (6) seasonality in the past sales, (7) trend in the past sales, (8) noise (sudden fluctuations) in the past sales, and (9) personal industry insights.

For each forecast, a subject receives a unique historical sales data. We used real data from two giant food and beverage companies to generate the historical sales data. The sales data and promotional information for the non-perishable product (9-month shelf life) was obtained from a giant beverage company. Data for the perishable product (1-day shelf life) was obtained from a large bread manufacturing company. The characteristics of the real datasets were used to be replicated in all sales data. Such parameters as noise, frequency of promotions, and the impact of promotions on sales uplift were estimated to replicate the real data characteristics. Therefore, each subject receives four unique datasets to produce four forecasts (two promotional and two non-promotional weeks).

To encourage the participating subjects to perform attentively, we offered monetary incentives to all subjects. All participants in our experiment received a show-up fee of $5 as well as an additional payment of up to $10 depending on their forecast accuracy. Mean absolute percentage error (MAPE) was used to assess the accuracy of the forecasts. MAPE is calculated relative to the normative benchmark forecast (F) using equation (1).

$$MAPE = 100\frac{\sum_t \left|\frac{A_t - F}{A_t}\right|_t}{n} \tag{1}$$

A normative benchmark was used to calculate the accuracy of the forecasts made (based on which the amount of cash incentives are calculated) and to calculate statistical forecast bias. To calculate the normative benchmark, an exponential smoothing approach with lift adjustment was adopted (Ali et al. 2009). When there is no promotion, the benchmark forecast is calculated using exponential smoothing for previous non-promotional periods. In the presence of promotions, the average uplift amount is added to the exponential smoothing figure for non-promotional periods.

$$\begin{cases} F_t = (1-\alpha)F_{t-1} + \alpha A_{t-1} & x_t = 0 \\ F_t = (1-\alpha)F_{t-1} + \alpha A_{t-1} + UP_{t-1} & x_t = 1 \end{cases} \tag{2}$$

Where the optimal value for α is obtained from equation (3) (Harrison 1967):

$$\alpha = \frac{[\sqrt{(1+4R)}]-1}{2R}, \qquad where\ \ R = \frac{c^2}{n^2} \tag{3}$$

The most important parameter in equation (3) is R. An optimal value is less sensitive to noise and reacts more significantly to permanent changes (c) in the series. R is the change-to-noise ratio for this purpose. α can be found according to change-to-noise ratio (R). A larger value for R means that variations in the series are mainly due to the permanent change and hence α should be higher. Similarly, lower value of R implies more noise hence smaller α. Since we assume no level change (i.e., c=0), α becomes equal to 0. This transforms the exponential smoothing to a simple average method.

Results

Data was collected in 12 experiment runs, 3 runs for each treatment. Each subject prepared four forecast attempts; that is, treatment 1 with 60 subjects provided 240 data points, 120 forecasts for non-promotional periods and 120 forecasts for promotional periods. Initial statistics are presented in Table 1.

Various metrics have been introduced to statistically measure the forecast bias. We adopted the metric introduced by (Petropoulos, Fildes & Goodwin 2015) which calculates the relative deviation from the actual point (i.e., the normative benchmark detailed in previous section). Percentage forecast bias is calculated using equation (4). This measure is scale free and easy to interpret. A percentage bias of 0% means that there is no deviation from the benchmark. Negative and positive numbers imply under-forecasting and over-forecasting, respectively.

$$\text{Forecst percentage bias} = 100\frac{forecast}{actual} \tag{4}$$

Table 1. The initial statistics of the number of subjects and their overall performance

Treatment	No. of subjects		Average Statistical Bias	MAPE
		Non-promotional period	99.7%	5.45%
		Promotional period	98.8%	3.52%
		Non-promotional period	103.4%	6.21%
		Promotional period	107.2%	7.72%
		Non-promotional period	96.1%	6.44%
		Promotional period	97.1%	4.20%
		Non-promotional period	105.1%	5.69%
		Promotional period	105.9%	7.64%

Based on the ANOVA test results in Table 2, we find that service level requirements to the subjects would significantly affect the forecast bias (when other factors are average out). Promotions are also shown to have significant influence on forecast bias, so is the interaction between service level and promotions. Although perishability information alone is not seen to have significant impact on the forecast bias, the interaction between 'service level and perishability' and 'promotions and perishability' does have significant impact on the forecast bias.

Table 2. ANOVA test results for statistical forecast bias (over vs under forecasting).

Factor	F	P.value
Service Level	97.03	<.0001***
Perishability	0.00	0.99
Promotions	10.56	0.001**
Service Level: Perishability	3.16	0.04*
Service Level: Promotions	20.55	0.0001***
Perishability: Promotions	39.14	0.0001***
Service Level: Perishability: Promotions	3.94	0.02

$*p \leq 0.05$; $** p \leq 0.01$, $*** p \leq 0.001$

Testing the four hypotheses we find that:

1. Comparing the forecast bias in high service level treatments (T2 and T4) with the control treatment (T1), we find that revealing service level requirement to the subjects results in significant forecast bias (over-forecasting). The results show a t.ratio of 11.293 and a p-value of <.0001.
2. Comparing the forecast bias in the low service level treatment (T3) with the control treatment (T1) indicates that a low service level has insignificant impact on the forecast bias. For this we get a t.ratio of -1.25 and a p-value of 0.42. There is slight difference between providing no SL information and revealing a low SL requirement (i.e., there is a slight under-forecasting behaviour when service level is low), but we find no meaningful impact.
3. The forecast bias comparison between forecasting for promotional and non-promotional weeks in T2 and T3 shows that the presence of sales promotions has moderation impact on service level consideration (t-ratio = 5.259 and p-value = <.0001 for low level consideration, and t-ratio = -3.275 and p-value = 0.0012 for high service level consideration in the presence of promotions). What is interesting is that when service level is high (treatment 2), the subjects are more biased to over-forecast when forecasting for promotional weeks. When service level is low, there is more tendency to under-forecast in promotional weeks.
4. Our results do not prove the moderating impact of product perishability on service level consideration (H4 is not confirmed). The significant forecast bias caused by high service level requirements remains unchanged when the product shelf life is changed from 9 months to 1 day (t-ratio = -0.356 and p-value = 0.7219).

Conclusions

While both sales forecasting and demand planning use sales history, the sales forecast does not consider constrained supply, pent-up demand, service level requirements, product obsolescence and perishability issues, or money lending market policy. In this paper, we studied the extent to which forecasters realise the difference between sales forecasting and decisions that are informed by the forecasts such as demand planning and S&OP. In particular, we examined how service level requirements affect the forecasts and whether sales promotions and product perishability information moderate this impact.

Our results from a laboratory experiment confirm our hypothesis that service level information significantly affects the forecast bias. Promotions are proved to have significant influence on forecast bias, but perishability information alone is not confirmed to have significant moderating impact. An interesting extension of this study would be to design and test a forecasting support system that is capable of (1) graphicly informing the sales forecasters about the use of their forecasts in supply chain decision making including demand planning and S&OP, and (2) providing personalised set of information to the forecasters to help mitigate personal biases.

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