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Enriching demand forecasts with managerial information to improve inventory replenishment decisions: Exploiting judgment and fostering learning

Yacine Rekik^a, Christoph H. Glock^b, Aris A. Syntetos^{c,*}

^a EMLYON Business School, DISP Lab, France

^b Technische Universität Darmstadt, Germany

^c Panalpina Centre for Manufacturing and Logistics Research, Cardiff Business School, UK

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ABSTRACT

This paper is concerned with analysing and modelling the effects of judgmental adjustments to replenishment order quantities. Judgmentally adjusting replenishment quantities suggested by specialized (statistical) software packages is the norm in industry. Yet, to date, no studies have attempted to either analytically model this situation or practically characterize its implications in terms of 'learning'. We consider a newsvendor setting where information available to managers is reflected in the form of a signal that may or may not be correct, and which may or may not be trusted. We show the analytical equivalence of adjusting an order quantity and deriving an entirely new one in light of a necessary update of the estimated demand distribution. Further, we assess the system's behaviour through a simulation experiment on theoretically generated data and we study how to foster learning to efficiently utilize managerial information. Judgmental adjustments are found to be beneficial even when the probability of a correct signal is not known. More generally, some interesting insights emerge into the practice of judgmentally adjusting order quantities.

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1. Introduction and motivation

In most contemporary organizations, the size and complexity of the inventory management task at the individual Stock Keeping Unit (SKU) level necessitates the employment of statistical theory as far as both forecasting and stock control are concerned. The advantage of doing so is that the resulting methods can be fully automated. This, in conjunction with recent IT processing developments, means that demand forecasts and replenishment decisions can be made for hundreds or thousands of SKUs in as little time as just a few seconds and as regularly as daily or even every half day, in the case of large stores or supermarkets. In principle, the automation of the inventory management task frees up managerial time that may be used at higher decision-making levels and/or for personally superimposing judgement on the quantities suggested by the automated system for the most important SKUs. Those would be items associated with a current promotion or any other special event (Goodwin & Fildes, 1999). However, research studies have demonstrated that managers personally inter-

* Corresponding author. E-mail address: SyntetosA@cardiff.ac.uk (A.A. Syntetos).

http://dx.doi.org/10.1016/j.ejor.2017.02.001 0377-2217/© 2017 Elsevier B.V. All rights reserved. vene in the process far more than what one might expect. As an example, consider the following situation. In a study conducted by Syntetos, Nikolopoulos, Boylan, Fildes, and Goodwin (2009) and Syntetos, Nikolopoulos, and Boylan (2010) for a branch of a major pharmaceutical company, sales forecasts were updated monthly for about 270 SKUs. The forecasts served both the inventory management task but also higher-level considerations and as such, extrapolation/estimation covered the subsequent 36 months (36 steps ahead). That is to say, at the end of every month, forecasts were produced for each single SKU for the subsequent 36 months. It is surprising that managers had adjusted about 65% of the forecasts examined in that research (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009). Franses and Legerstee (2011b) looked at the linkage between judgmental adjustments of statistical forecasts and the forecast horizon. They also found, through an empirical study in the pharmaceutical industry, that all horizons (short term and long term) were associated with managerial interventions in forecasting.

The practice of judgmentally adjusting statistical sales/demand forecasts has received much attention in the academic literature in recent years. The increasing number of relevant studies reflects the importance of this area in terms of both necessary theory development and practical implications. Sales forecasts constitute an





input into a stock control model that suggests when and how much to order. However, incorporating managerial judgment directly into such stock replenishment decisions has become the norm in industry (Kolassa, Shütz, Boylan, & Syntetos, 2008). Practitioners may directly adjust re-order and Order-Up-To (OUT) levels and/or order quantities (without this implying that forecasts are not also subject to such adjustments) for the purpose of achieving better trade-offs between achieved service levels and inventory costs.

Despite the fact that replenishment decisions may often be subject to judgmental intervention, the effect of judgmentally adjusting replenishment quantities has not attracted much attention in the academic literature, either in modelling or in empirical terms. Concerning the latter, we are aware of only one study that attempts to throw light on this area (Syntetos, Kholidasari, & Naim, 2016b). The researchers considered the effects of superimposing judgement into statistically derived OUT levels and evaluated the implications of doing so through an empirical dataset from the electronics industry. Concerning the former, the only attempt we are aware of to model such a situation relied upon a System Dynamics (SD) methodology (Syntetos, Georgantzas, Boylan, & Dangerfield, 2011). The researchers considered, by means of SD simulation, the joint effects of adjusting forecasts and inventory replenishment decisions. They acknowledged the fact that an analytical representation of the problem in hand, i.e. the joint consideration of judgmental adjustments at both the forecasting and inventory control process, is virtually impossible. Although this is true, analytical modelling of the effects of judgement replenishment decisions is feasible and very much needed also for the purpose of deriving insights into relevant situations. Conducting such modelling is our main objective.

This paper contributes to closing the research gap identified above and develops a single selling season model that provides insights into the practice of judgmentally adjusting order quantities. The scenario considered here can be described as follows. First, a forecast is produced based on past sales data and an initial order quantity is specified. Subsequently, a signal is observed that contains some important information not reflected in the historical sales data. Contrary to other modelling attempts presented in the literature (e.g. single season models with information updating), the signal may or may not be correct. Finally, the order quantity is adjusted based on the observed signal, it is released and the order is received prior to the beginning of the season. Due to long lead times, no further opportunities for ordering are available. The development of our model (and the specification of optimality conditions for the order quantity (Q) and the adjustment (A)) is followed by a numerical analysis that allows us to obtain some key insights into the process of adjusting the order quantity and an appreciation of how learning to efficiently utilize the signal can be fostered.

An Excel file has been made available as an electronic companion to enable interested readers to experiment with the learning processes discussed in this paper. Instructions on how to use the Excel file are provided in an on-line supplement. Such material would enable other researchers to reproduce our results (Boylan, 2016) and 'play' with different control parameter combinations, but also extend our results should they wish to take this research further.

The remainder of the paper is structured as follows. The next section presents the research background of this work. We structure the section around two main issues: (i) modelling research on (forecasting) judgmental adjustments and (ii) research on single selling season models. The inventory model developed for our research purposes, along with the notation and assumptions used, is presented in Section 3. This is followed by a detailed numerical analysis in Section 4. Section 5 discusses some alternative

techniques for learning to efficiently utilize the observed signal. Finally, the conclusions of our work along with its implications for Operational Research theory and practice and some natural avenues for further research are presented in Section 6.

2. Research backward

This section discusses the thematic and methodological background of our work. We first focus on studies that relate to the practice of judgmentally adjusting sales forecasts and make the case for the extension of the current state of knowledge into the area of inventory control. We then move to the methodological motivation behind our research by discussing the literature on single selling season modelling exercises that consider information updating and/or behavioural aspects.

2.1. Modelling of judgement in an inventory forecasting context

This section focuses on modelling attempts in the area of judgmentally adjusting statistical forecasts. As discussed in the previous section, there is a plethora of empirical studies in this area and we refer interested readers to Syntetos, Babai, Boylan, Kolassa, and Nikolopoulos (2016a) for a review of recent developments. Here we focus on the few studies that have attempted to model such practices statistically.

Franses and Legerstee (2009) examined whether we can predict expert adjustments using the forecasters' own past interventions and past model-based forecast errors at various lags. They did so by means of constructing an auxiliary regression model based on which they calculated the impact of one's own past adjustments (persistence) and their relevant size, taking into account the effects of past variance. They found that adjustments occurred a staggering 90% of the time, while such adjustments were more often than not, upward. Interestingly, they noted that the percentage size of expert adjustments is predictable for about 44% of its variation, and even the direction of those adjustments is predictable to some extent. The size of expert adjustments depends strongly on past adjustments, about three times as much as it depends on past model-based forecast errors.

Franses and Legerstee (2010) expressed model-based SKU-level forecasts as a linear function of past sales. The expert-adjusted forecasts were also assumed to be a linear function of past sales leading essentially to the forecasting scheme of the experts nesting the forecasting scheme of the model. They constructed a test regression to assess if the expert forecasts differ from the model forecast, and followed Clark and McCracken (2001)'s recommendation in conducting an ENC-NEW test to assess whether the Root Mean Squared Prediction Error (RMSPE) of the expert is significantly lower than that of the model. They concluded that more often than not experts' forecasts differ significantly from model forecasts. They also found that when the expert yields a significant positive contribution to forecast quality, the final forecast's improvement in terms of RMSPE is about equally large, as is the deterioration in case the expert does not significantly outperform the model. So, in general, expert forecasts are not necessarily better than the model forecasts.

In another paper, Franses and Legerstee (2011a) examined linear combinations of expert and model-based forecasts, with the aim of improving the final forecast (judgmentally adjusted one). For this reason, they calculated the RMSPE of a cohort of different combinations of the forecasts. To gauge how the optimal weights can be explained by experts' characteristics and their behaviour (age, position, number of products, etc.) they created a weighted summation of such variables and estimated the weights through OLS. They concluded that the combination leads to improvements in 90% of Download English Version:

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