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The impact of forecasting methods on the bullwhip effect

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Abstract

This paper considers the impact of forecasting methods on the bullwhip effect for a simple replenishment system in which a first-order autoregressive process describes the customer demand and an order-up-to inventory policy characterizes the replenishment decision. A bullwhip effect measure is derived for the optimal forecasting procedure that minimizes the mean-squared forecasting error for the specified demand process. Similar measures are obtained for the moving average and exponential smoothing methods. The findings indicate that different forecasting methods lead to bullwhip effect measures with distinct properties in relation to lead time and underlying parameters of the demand process. Moreover, a simple rule is established to help managers select a forecasting method that yields the lowest inventory cost.

Keywords: Bullwhip effect; Forecasting; Supply chain; Inventory control

1. Introduction

Many companies have followed the footsteps of Dell, Chrysler, and Wal Mart in streamlining their supply chains and reducing operational costs. With its focus on integrating and synchronizing business activities across traditional organization boundaries, supply chain management has attracted the attention of researchers and practitioners alike. One active area of investigation is the bullwhip effect, which was brought to the forefront of research by the works of Lee et al. (1997a, b). It refers to the empirical and theoretical observation that the demand variability is magnified as a customer demand signal is transformed through various stages of a serial supply chain. The magnification can potentially cause instability in the supply chain and increase the cost of supplying end-customer demand.

The first recognition of the bullwhip effect can be traced back to Forrester (1958, 1961). Other earlier papers including Blanchard (1983), Blinder (1982, 1986), and Kahn (1987) also found evidence of inventory volatility similar to the bullwhip effect. The beer game (Sterman, 1989) that has been used in teaching inventory management exhibited the same phenomenon. Lee et al. (1997a, b) established five possible sources that may lead to the bullwhip effect, including demand signal processing, non-zero lead time, batched order, rationing game under shortage, and price fluctuations and promotions. They considered a first-order autoregressive AR(1) demand process

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with simple supply chain structures including a two-echelon serial and one-warehouse distribution systems. In contrast, Baganha and Cohen (1995) specified a more complex model with an AR(p) demand and a multi-echelon manufacturing and distribution system. They showed that a centralized distribution system tends to reduce the demand variability and have a stabilizing effect.

Chen et al. (2000a) made an important contribution in recognizing the role of demand forecasts as a filter for the bullwhip effect. Using an AR(1) demand process similar to Lee et al. (1997a), they derived a lower bound for the bullwhip effect in a two-stage serial supply chain when the downstream retailer uses the moving average (MA) method to forecast lead-time demand. In a sequel, Chen et al. (2000b) extended their results to the case in which a simple exponential smoothing (ES) method is used to forecast lead-time demand. Recognizing that ES forecast is optimal for a demand represented by an integrated MA process of order (0, 1, 1) (Goodman, 1974; Muth, 1960). Graves (1999) quantified the bullwhip effect for this class of demand process.

This paper continues to study the role of forecasting in relation to the bullwhip effect. It seeks to derive a bullwhip effect measure using a forecasting procedure that minimizes the mean-squared forecast error for the underlying demand process. The MA and ES forecasting methods do not share this optimal property in general for a time series process. The popularity of the MA and ES methods is due to their ease of use, flexibility, and robustness in dealing with non-linear demand processes (Silver et al., 2000). However, they can lead to specification error for pre-specified demand processes (Badinelli, 1990). The paper examines the differences in bullwhip effect measures when the MA and ES methods are used to forecast lead-time demand. The findings suggest that different forecasting methods lead to bullwhip effect measures with fundamentally different properties in relation to lead-time and demand autocorrelation. In addition, the paper shows that these forecasting methods affect the average inventory cost in a straightforward manner, providing a manager with a simple rule for selecting the best forecasting method.

The following section presents a simple replenishment model similar to the one used by Chen et al. (2000a, b) and Goodman (1974). In Section 3, the bullwhip effect measure for the minimum mean-squared error (MMSE) forecasting method is derived. Sections 4 and 5 develop similar measures for the MA and ES forecasts. They are compared to the case of the MMSE forecast in relation to the lead-time and demand autocorrelation. Section 6 discusses the economic impact of using different forecasting methods and the relationship between the bullwhip effect measure and the inventory cost. The paper concludes with discussions on the managerial implications of our findings.

2. Replenishment model

Consider a retailer that maintains a single-item inventory. It orders and replenishes its stock from a manufacturer on a fixed time interval to supply customer demand. All shortages are backordered. We assume that the demand can be described by an AR(1) model such as

$$d_t = \mu + \rho d_{t-1} + \varepsilon_t, \quad |\rho| < 1, \tag{1}$$

where d_t is the demand during period t, μ is a constant that determines the mean of the demand, ε_t is an i.i.d. normally distributed random error with mean 0 and variance σ^2, and ρ is the first-order autocorrelation coefficient. The assumption of $|\rho| < 1$ assures that the demand process is covariance stationary.

Let H_t represent the history of demand observed up to period t,

$$H_t = \{d_t, d_{t-1}, d_{t-2}, \ldots\}. \tag{2}$$

In the rest of the paper, we assume that there is an infinite number of observed demand data and the underlying parameters of the demand model are known. This assumption precludes any sampling variations and estimation errors in our analysis, and greatly simplifies the derivations. In practice, all parameters of the demand model in Eq. (1) must be estimated with a finite sample using the