Interaction between Pricing and Inventory Management

Julie Watson and Manuel Rossetti
Department of Industrial Engineering
University of Arkansas
Fayetteville, AR 72701

Abstract

This paper examines the effect that product pricing has on the dynamics and variability of a supply chain, with a focus in retail inventory. Pricing policies and strategies and the impacts of prices on demand and inventories within the retail supply chain environment are reviewed. Recent pricing and markdown research is examined. An example model is presented that is stochastic and uses simulation to study a two-echelon multi-period inventory system. The simulation methodology and the experimental design used are described. Then, the summary of the experimental results with discussion is presented. The last section outlines future research directions. Results show that large markdowns can produce significant losses, with revenues not covering ordering and product costs. Observations of these supply chain dynamics produce many additional research questions.

Keywords Pricing, Demand, Inventory

1 Introduction and Motivation of the Problem

Kent Monroe [12] states that the ultimate objective of a pricing decision is to influence buyer behavior. In recent years, the pressure for retailers to markdown prices has skyrocketed. Excessive markdowns are frequently cited as a key factor contributing to unexpected earnings shortfalls among retailers. The average markdowns as a percentage of total sales have increased from around 6% in the mid-1960s to over 33% currently [9]. Impact to the bottom line is $300 million for every billion dollars in sales. Even worse, consumers have become conditioned to expect markdowns, with only 50% of items sold at full retail price [9]. With this, successful retailers will be those that can most effectively manage markdowns and price changes.

A better understanding of the effect of price changes within supply chains, especially in the areas of demand variability, inventory and total costs, needs to be established. Pricing actions significantly impact demand, inventory, and logistics management throughout the supply chain. In addition to excess inventory, inadequate demand management leads to poor product forecasts, insufficient/excess capacities, poor customer service and high costs for corrections. Understanding the impacts of price changes can lead to lower costs and increased asset utilization resulting in improved profits, inventory turns, and overall service for all supply chain partners.

This work examines the effect that product pricing has on the dynamics and variability of a supply chain, with a focus in retail inventory. The model given extends a previous study [17] to observe system supply chain impacts of arrival rates dependent on price changes. The following section contains a review of the literature organized by pricing policies and strategies, the impacts of pricing on demand and inventories within the retail supply chain environment and recent pricing and markdown research. Section 3 describes the stochastic model that uses simulation to study a two-echelon multi-period inventory system. The simulation methodology, the experimental design used, and a summary of the experimental results are presented in Section 4. The last section summarizes conclusions and outlines future research directions.

2 Literature Review

Pricing policies are the broad guidelines used by the retailers in making pricing decisions, which reflects the retailer's position regarding factors such as competing stores, costs and promotional expenditures [13]. The pricing policy/philosophy of one entity within a supply chain has an affect on its members. Overall, pricing policies are designed to modify customer demand patterns, enhance competitiveness, encourage traffic (other purchases), and increase profitability.

Specific price reductions are initiated for a variety of different reasons, primarily motivated for promotion and inventory closeout. Pricing errors result in either loss of potential revenue or excess inventory for liquidation [4]. Price reduction categories include: clearances, promotional markdown, promotional discount, and rollbacks (semi-permanent reductions.)

Information sources for making pricing decisions include historical data, market research data and expertise of one's key managers [14]. Pricing decision challenges have increased in the last decade with the growth of demand unpredictability due to product variety expansion on the supply side and consumer taste diversification on the demand side [10]. Some of the key parameters to consider when making pricing decisions include: demand intensity, demand elasticity , competitive structure, seasonality/perishablility/selling horizon, velocity of market, product life cycle stage, and inventory level/forecasting performance**.**

Promotions offered during a short period of time can hurt the manufacturer with uneven production schedules, unnecessary inventory costs and distorted demand information. Lee et al [7] credits price variations as one of the four major causes of the bullwhip effect. (The other causes are demand signal processing, order batching and rationing gaming.) The bullwhip effect, resulting from this distorted information within supply chains, has led every entity in the supply chain, including the plant warehouse, a manufacturer's shuttle warehouse, distributor's central and regional warehouses and retail store's storage space to stockpile because of high demand uncertainties and variability. Forward buying, when items are bought in advance of requirements, results from price fluctuations [8]. If the cost of holding inventory is less than the price differential, then it is advantageous; however, purchases do not reflect their immediate needs and stock ups result. When price returns to normal, buying stops until inventory is depleted. Common symptoms from demand variations include excess inventory, poor product forecasts, insufficient or excess capacities, poor customer service, uncertain production planning and high costs for corrections (i.e., expedited shipments and overtime) [8].

Effort has been made to identify ways to improve supply chain performance. The Efficient Consumer Response (ECR) grocery supply chain initiative reports an estimated a potential $30 billion opportunity from streamlining the inefficiencies of the grocery supply chain [8]. Given appropriate conditions, Metters [11] stated that eliminating the bullwhip effect can increase product profitability by 10-30%. Chen, et al [2] developed a model for simple, two stage supply chains consisting of a single retailer and a single manufacturer that measures demand forecasting and order lead time. They determined that the bullwhip effect can be reduced, but not eliminated by centralizing demand information. Lee [6] designed models to study the effect of inter-organization coordination in the supply chain's stocking, return, and clearance sales operations, demonstrating the benefits of supply chain entity joint optimal decision making. Sugiyama et al. [16] developed an analytical model to study the relationship between price fluctuation and demand variability and quantify the benefits of the Every Day Low Price (EDLP) Strategy.

Considerable work has been done on pricing policies and their impacts on demand. These pricing policies have only been tested in a limited scope that do not represent the complex nature of the supply chain. Work done in this area has been concentrated on very specific product characteristics (i.e. grocery, fashion) in a simplistic setting, some using extensive mathematical optimization models. Several recent papers have focused on optimal pricing for marking down and selling out a fixed amount of inventory of a fashion or style good. Gallego and Van Ryzin [3] determined the optimal price path (as a function of the stock level and length of the horizon). They accomplished this by formulating a continuous-time model with a current price-dependent Poisson demand-arrival process and applied intensity-control theory. Feng and Gallego [**Error! Reference source not found.**] extended this work with a continuous-time model Markov process formulation to determine the optimal timing and duration of a single price change markdown or markup. Urban and Baker [18] developed a single-period inventory model, where product demand is a deterministic, multivariate function of price, time, and level of inventory. They provide models for the basic pricing case and a seasonal price markdown case. Walker [19] developed a heuristic procedure for quickly identifying and highlighting items for review to make decisions in determining the timing and magnitude of price markdowns. Simple rules determined three inventory segments: slow moving, economically viable for price markdown and review action needed.

3 Retail Supply Chain Model

The simulation model in this study is a two-echelon one warehouse and multiple retailers system using (R,Q) inventory policies. The distribution network consists of one warehouse and N retailers, where the retailers directly serve the customers and the warehouse replenishes all the retailers. When the inventory position (the net inventory on hand including stock on order minus backorders) is less than the reorder point R, a replenishment order batch size of Q is placed. Many have suggested using the continuous review (R,Q) inventory control policy on the slow moving type A items (Silver [15], Tee and Rossetti [17]).

Tee and Rossetti [17] present details of the simulation model including logic, structure, data inputs, outputs, verification and validation. A single location model was initially built and expanded into a warehouse-retailer model in Arena 5.0 Professional Edition. The simulation models were verified and validated to give performance measures that are an accurate and valid representation of the system. When demand occurs, units demanded are determined and the system checks for stock availability. If sufficient quantity is on-hand, the demand is filled and quantity on-hand is decreased. If stock on-hand will not satisfy the order, the entire order is backordered. Backorders are accumulated in a queue and will be filled on a first-come-first-serve basis after arrival of replenishment order. The inventory position is evaluated at each customer demand and backorder fulfillment. If the inventory position falls under the reorder point, a replenishment order is placed. The replenishment order takes an established time to arrive, increases on-hand inventory and fills any backorders at the retailer. Retailer orders are sent directly to the warehouse model. The demand process at the warehouse depends on the retailer order frequencies and order quantities. When the demand is filled at the warehouse, stock is transferred to the retailers. When the warehouse is out of stock, retailer demand is backordered and effective lead time is extended. Other model assumptions are as follows:

- Each demand was assumed to be a single unit of product.
- The demand process at the retailer is established by the specification of the time between arrivals and demand quantity.
- All unsatisfied demand is backordered and no partial order filling is allowed.
- Warehouse replenishment lead-time is constant.
- Retailer lead-time can be stochastic or deterministic.

The Tee and Rossetti model [17] was extended in order to examine system performance with price changes and demand fluctuations based on price. This step was taken to develop insights into the dynamics of price changes in order to develop more comprehensive modeling and experimental designs for extended research.

4 Experimental Design

This study modifies the (Tee and Rossetti [17]) simulation model in two significant areas: price is determined weekly based on inventory level and age and demand varies as a function of price. The objective is to observe the impact of changing prices on demand, system profit, cost and service in a (R,Q) inventory system. Heuristics were developed to evaluate updates to pricing weekly based on an inventory ratio and time in inventory. The interarrival time was determined based on current price. The literature review did not produce comparable supply chain modeling in this area. As a consequence, parameters set in this model may be questioned, such as profit margins and cost estimates. It is emphasized that this work is intended to investigate impacts on the supply chain of price and demand changes and to raise future research questions and direction. Model assumptions are listed:

- All customers that come buy or back order; no lost sales.
- Backorders are priced at the current price when the demand takes place.
- Pricing is adjusted back to full price (for entire retailer inventory) after retailer replenishment for all future sales.
- Product used can be thought to stimulate traffic, store activity. None are wasted (disposed of).
- Discount maximum is 80%, regardless of length of time in inventory.

Three scenarios were performed in the study, a base case (no price changes), a moderate price change case and an aggressive price change model. The input was used from the Axsater [1] formulation, as performed in the Tee and Rossetti study. Pricing and demand heuristics and formulations were developed and tested in Excel to reflect reasonable trends and relationships. A "checking" or review system was triggered at every retailer replenishment to weekly evaluate the inventory level with respect to inventory age. Walker [19] provides an example of inventory evaluation heuristic development. A two stage calculation methodology established the inventory level assignment and length of time in inventory determines the markdown percentage. Price changes are evaluated at the retailer level, with unique pricing based on location inventory levels/age. The inventory ratio was calculated by the following formula:

$$I_{ratio} = \text{Current On Hand Inventory(RetailerNum) / OnHand Inventory at Replenishment(RetailerNum)} \quad (1)$$

An inventory bracket was assigned (IB=InvBracket(max(1, integer(10* I_{ratio})) based on inventory level and age to generate a markdown assignment by the formulation:

$$\text{Markdown(RetailerNum)=max((InvWeek(RetailerNum)+2)*.10-(.10*(IB-1)), 0)} \quad (2)$$

The following tables represent these relationships for the aggressive and moderate markdowns. For example, in moderate pricing, an inventory ratio of 65% would be assigned an inventory bracket 2. With an inventory age of 6 weeks, the discount assignment would to .40 or 40%

Table 1 - Discount assignment under aggressive markdown

I_{ratio}	Inventory Bracket	Weeks held in Inventory							
		1	2	3	4	5	6	7	8
70-90%	1	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.80
50-69%	2	0.00	0.20	0.30	0.40	0.50	0.60	0.70	0.80
30-49%	3	0.00	0.00	0.20	0.30	0.40	0.50	0.60	0.70
20-29%	4	0.00	0.00	0.00	0.20	0.30	0.40	0.50	0.60
11-19%	5	0.00	0.00	0.00	0.00	0.20	0.30	0.40	0.50

Table 2 - Discount assignment under moderate markdown

I_{ratio}	Inventory Bracket	Weeks held in Inventory							
		1	2	3	4	5	6	7	8
70-90%	1	0.00	0.20	0.20	0.30	0.40	0.40	0.50	0.60
50-69%	2	0.00	0.00	0.20	0.20	0.30	0.40	0.40	0.50
30-49%	3	0.00	0.00	0.00	0.20	0.20	0.30	0.40	0.40
20-29%	4	0.00	0.00	0.00	0.00	0.20	0.20	0.30	0.40
11-19%	5	0.00	0.00	0.00	0.00	0.00	0.20	0.20	0.30

The demand function is from Gallego and Van Ryzin [3] D~Poisson (λ(p)):

$$\lambda(p)=ae^{-\alpha p} \quad \text{with p=price, and a and } \alpha \text{ are arbitrary constants} \quad (3)$$

The factors used to calculate the parameter a and α were determined by taking the markdown mu ltiplied by a constant to derive a mean interarrival time (at full price) equal to the Tee and Rossetti study [17] value of 10.

Table 3 - Calculation of the demand interarrival rates

		Arbitrary	Mean Interarrival		Arbitrary	
		Parameter	Time		Parameter	Demand Rate
Price($)	Markdown	a	1/ λ (p)	%chg	α	$\lambda(p)=ae^{-ap}$
3.00	80%	65300	0.003391	100%	1.800000	294.932736
4.50	70%	97950	0.021446	100%	1.700000	46.628522
6.00	60%	130600	0.113053	99%	1.600000	8.845373
7.50	50%	163250	0.470934	95%	1.500000	2.123441
9.00	40%	195900	1.513826	85%	1.400000	0.660578
10.50	30%	228550	3.707989	63%	1.300000	0.269688
12.00	20%	261200	6.868586	31%	1.200000	0.145590
15.00	0%	326500	10.012304	0%	1.000000	0.099877

Model input parameters are listed in the following table:

Table 4 - Simulation input parameters

ATTRIBUTES		
Attribute Name		**Description**
AmtDemanded=1		quantity demanded in each order by the customer from the retailer.
VARIABLES		
Variable Name		**Description**
MeanInterarrivalTime		EXPO(1/(326500*(1-Markdown(RetailerNum))*ex(- PriceCur(RetailerNum)* (1+ Markdown(RetailerNum)))))/NumR
Supply Chain Entity-specific		
Retail	**Warehouse**	
NumR=4		total number of retailers. It is used in the Order Arrival of the Create Module to determine the aggregate arrival rate for all retailers (input).
RetailerLT=1	*WhsLT*=1	replenishment lead-time between entities of the supply chain (input).
Qr=4	*Qw*=4	replenishment order quantity for the entity in units (input).
Rr=1	*Rw*=1	reorder point at the entity in units (input).
OnHand(NumR)=1		one-dimensional variable array represents the actual inventory on-hand at each retailer.
	WhsOnHand =20	actual warehouse inventory on-hand.
hold_r=1	*hold_w*=1	holding cost factor at the entity in $/unit/period (input parameter).
back_r=4.60		backordering cost factor at the retailer in $/unit/period (input parameter).
PriceFull=15.00		full retailer price (input parameter).
ProductCost=6.70		retailer product cost (input parameter).
Order_r=5.00		ordering cost per retailer order (input parameter).
Global Calculations		
RINV=4		keeps track of the total inventory on-hand at the retailer level, i.e. the sum of inventory on-hand at all retailers.
TotalCost		tracks of the total system cost, i.e. *TotalCost =RINV*hold_r + RBack * back_r + whsOnHand * hold_w*.

Three levels of total profits were tested:

Base θ_1 $\lambda = .10$ per day constant price = $15.00

Moderate θ_2 $\lambda = .10$/day full price and price changes conservative

Aggressive θ_3 $\lambda = .10$/day full price and price changes aggressive

Tests on the means were performed on system profit θ_i, comparing base total profit to both pricing levels: $\theta_1 - \theta_2$ and $\theta_1 - \theta_3$. A sample of five runs, each containing one year (365 days) of system activity was run to determine the sample size. A sample size of 813 replications was determined for a confidence level of 95% ($10 total profit). The output is the yearly average of 813 runs.

Table 5 - Experimental results – annual (average of 813 runs)

	Base θ_1 $\lambda = .10$ per day constant price = $15.00	Moderate θ_2 $\lambda = .10$/day full price, Price Changes Conservative	Aggressive θ_2 $\lambda = .10$/day full price, Price Changes Aggressive
Total Profits	940.43 ± 5.96	793.12 ± 45.20	-4714.50 ± 559.68
Total Revenue	2201.20 ± 12.32	2700.80 ± 29.51	6094.80 ± 332.75
Total Ordering Costs	195.59 ± 1.04	297.31 ± 11.22	1692.90 ± 139.52
Total Avg. Backorder Costs	.00 ± .00	.04 ± .05	5.75 ± .60
Total Product Costs	1048.30 ± 5.58	1593.50 ± 60.15	9074.30 ± 747.86

The 95% confidence interval on $\theta_1 - \theta_2$ is [102.47, 192.14]; the 95% confidence interval on $\theta_1 - \theta_3$ is [5094.89, 6214.99]. The results indicate that there is a significant difference between the comparisons of the differences of the means, and the conclusions $\theta_1 > \theta_2$ and $\theta_1 > \theta_3$ can be made. It may seem surprising to see the large difference between the profits, with no price change with an average of about $140 above moderate pricing. In comparison, aggressive pricing posts a huge profit loss for $4714.50. Looking at the cost components, the aggressive pricing scenario ordering and product costs exploded at the high discount levels. It could be said that they are giving away the "store." Backorders were not a real factor and are highest in the aggressive case. As mentioned in the introduction, the input parameters in this model can be argued and adjusting them could have large impacts on the performance. The strength of simulation models allows future experiments with ease, such as sensitivity analysis of cost and profit parameters.

5 Conclusions and Future Research

There is significant opportunity for the advancement of quantifying the effect of pricing on demand and inventory. Further study should be done to quantify how price changes affect the entire supply chain, even incorporating the addition of vendor price changes. Other areas to investigate include:

- Measure aggregate inventory at retailers to determine synchronized pricing changes.
- Test other inventory policies. In addition, the (R,Q) policy could be updated at price change.
- Stratification of price based on inventory age.
- Demand dependant on price changes and seasonality, cyclical behavior.
- Examine other methodologies for triggering price changes.

References

1. Axsater, S., 2000, "Exact Analysis of Continuous Review (R,Q) Policies in Two-Echelon Inventory Systems with Compound Poisson Demand," *Operations Research*, 48(3), 686-696.
2. Chen, F., Drezner, Z., Ryan, J., and Simchi-Levi, D, 2000, "Quantifying the Bullwhip Effect in a Simple Supply Chain: The impact of forecasting, lead times and information." *Management Science*, 46(3), 436-443.
3. Gallego, G., and Van Ryzin, G., 1994, "Optimal Dynamic Pricing of Inventory with Stochastic Demand over Finite Horizons," *Management Science*, 40(8), 999-1020.
4. Hopp, W. J., and Spearman, M.L., 2000, Factory Physics: Foundations of Manufacturing Management, 2nd edition, Irwin/MacGraw-Hill, New York.
5. Lazear, E.P., 1986, "Retail Pricing and Clearance Sales." *The American Economic Review*, 76(1), 14-32.
6. Lee, C. H., 2001, "Coordinated Stocking, Clearance Sales, and Return Policies for a Supply Chain," *European Journal of Operational Research*, 131(3), 491-513.
7. Lee, H.L., Padmanabhan V., and Whang, S., 1997, "Information Distortion in a Supply Chain: The Bullwhip Effect," *Management Science*, 43(3), 546-558.
8. Lee, H.L., Padmanabhan V., and Whang, S., 1997, "The Bullwhip Effect in Supply Chains," *Sloan Management Review*, Spring, 93-102.
9. Levy, M., and Weitz, B. A., 1992, Retailing Management, Irwin, Homewood, IL.
10. Mantrala, M.K.. and Rao, S., 2001, "A Decision-Support System that Helps Retailers Decide Order Quantities and Markdowns for Fashion Goods," *Interfaces*, 31(3) Part 2 of 2, S146-S165.
11. Metters, R., 1997, "Quantifying the Bullwhip Effect in Supply Chains," *Journal of Operations Management*, 15, 89-100.
12. Monroe, K.B., 1979, *Making More Profitable Decisions*, McGraw Hill., New York.
13. Rosenberg, J. M., 1995, *Dictionary of Retailing and Merchandising*, John Wiley & Sons, New York.
14. Singh, M.G., and Bennavail, J-C, 1994, "Price-strat a Knowledge Support System for Profitable Decision-Making During Price Wars," *Information and Decision Technologies*, 19(4) 277-296.
15. Silver, E.A., Pyke, D. F., and Peterson, R. 1998, Inventory Management and Production Planning and Scheduling, 3rd edition, John Wiley & Sons, New York.
16. Sugiyama, T.T., Sengupta, S., and Noda, K., 2001, "Bullwhip Effect and Every Day Low Price (EDLP) Strategy in a Supply Chain," *Proceedings of the 6th Annual International Conference on Industrial Engineering, Applications and Practice*, San Francisco, CA, November 19-20.
17. Tee, Y., and Rossetti, M.D., 2001, "Using Simulation to Evaluate a Continuous Review (R,Q) Two-Echelon Inventory Model," *Proceedings of the 6th Annual International Conference on Industrial Engineering*, Nov. 18-20, San Francisco, CA.
18. Urban, T.L., and Baker, R. C., 1997, "Optimal Ordering and Pricing Policies in a Single-Period Environment with Multivariate Demand and Markdowns," *European Journal of Operational Research*, 103(3), 573-583.
19. Walker, J., 1999, "A Model for Determining Price Markdowns of Seasonal Merchandise," *Journal of Product & Brand Management*, 8(4), 352-361.