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A Joint Pricing, Supplier Selection And Inventory Replenishment Model Using The Logit

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Abstract:

The value of customers has evolved into a crucial component of preserving competitive edge in the retail sector. In the age of new retail, the value of customers is intimately tied to innovations like services with value and original business models in addition to how much a product costs.

In this article, we examine how revenue-sharing agreements and customer value affect the collaborative investment in innovation and pricing decisions made in a retailer-supplier supply chain. First, we discover that only the provider Stackelberg game achieves equilibrium in the non-cooperative game. Contracts for revenue sharing, however, are unable to synchronise the supply chain in a competitive game. We discover that there is a particular equilibrium for the Nash bargaining product when taking into account the bargaining strength of supply chain participants. Additionally, revenue sharing agreements can synchronise the supply chain to maximise consumer excess. When the supply chain is coordinated, the profit is divided among the participants according to their negotiating strength.

3. Introduction

A retail operating cash flow is significantly and critically determined by decisions regarding price and inventory management, particularly in the highly competitive global marketplace of today. Starting with price fixing in the marketing team, the industry's standard chronological decision-making process moves on to the purchasing unit or supply chain department, which sets all tactical and strategic options on inventory and purchasing policy in accordance. This decision-making procedure doesn't really systematically ensure optimum for the business in its entirety. As a result, synchronization of pricing and supply filament strategies, particularly simultaneous determination of the selling price and the stock strategy, has attracted significant interest from both the corporate world and academia. Integrated optimum approaches to the pricing and manufacturing problems outperform decentralised ones, according to Deng and Yano (2006).The traditional quantity of economic order (EOQ) model, on the other hand, has been suggested and developed for years. However, the EOQ model's fundamental assumption of a fixed demand rate is blatantly impractical. Actually, a variety of factors, such as cost, a reduction, lead time, available space, product quality, and marketing, affect sales (Huang et al. 2013). Among these variables, product pricing is frequently utilised to successfully leverage demand through sales and promotions. As a result, both in theory and in reality, there has been much research done on the combined pricing and stock management problem, which links price theory and inventory control.

Given the required made his first attempt to add price into to the classic EOQ model (1955). This article introduces a linear price-demand relationship for final consumers. In an EOQ scenario for a single product, the purpose is to establish the optimal pricing and order quantities again for company. Later, Kunreuther and Schrage (1971) evaluated the relationship between price and inventories choices by examining the decentralised and centralised decision-making processes within a company. Abad (1988) attempted a similar situation in which the supplier provides the store with an all-unit quantity discount. Kim and Lee (1998). Provided both fixed and dynamic capacities models in order to evaluate appropriate pricing, lot size, and capacity.In a labor-constrained environment, choices for the combined pricing and lot size problem are made by taking capacity restrictions manufacturing environment. Viswanathan and Wang (2003) analysed a single-vendor, single-retailer market structure. As coordinating methods, the seller offers quality or discount offers through the distribution platform. Ray et al. (2005) created a comprehensive profit maximisation model for a company selling a single item to final consumers. Customers can choose between two pricing strategies: establishing pricing as a variable or as a markup depending on the operating cost per unit. Kim et al. (2011) investigated four distinct supply chain coordinating methods chain of the a particular retailer and producer to establish the sales price and purchasing requirements of the retailer policies based on the price-sensitive demand. Yaghin et al. (2014) presented a collaborative marketing inventory model in a two-tier supply chain with discount advertising and price-sensitive demand for the purpose of identify the optimum regulations for ordering, shipping, and pricing. Price-sensitive stochastic demand was present. Jadidi et al. (2017), dealing with a simultaneous price and inventory dilemma, also explore the provider offering discounted rates. One subject of study that attracts the interest of academics is the expansion to numerous time periods. Thomas (1970) initially investigated an inter depends on both motivation production, inventory, and pricing issue for a particular element with a valuation, predictable demand. In that research, an effective forward. The algorithm is proposed for the model of maximizing profits. Kunreuther and Schrage (1973), Gilbert (1999),Van den Heuvel and Wagelmans (2006) investigated a pricing production issue involving a consistent price to be paid sustained for the duration of the planning horizon Bhattacharjee and Ramesh (2000) examined a price and demand model. The stock dependent in which a product's quality has a fixed shelf life. Biller et al. (2005) created pricing structure alongside the Direct-to-Customer business model for the car industry, in which production costs are proportional to output volume. Deng and Yano (2006) introduced a retail prices production model with start up costs but instead capacity issues for a particular device with price changes over a finite amount of time horizon and demonstrated that optimum results with the much increased margins can be acquired from modelling as opposed to decentralised models with a sequences making decision process. Güler et al. (2015) investigated a pricing and inventory dilemma in which the market for a particular item is based both the current market price and the case the cost. Bernstein et al. (2016) examined a combined inventories and priced problem inside the condition of advance notice and delivery delays for an unified system, providing a heuristic to simultaneously determine the restocking choice and the selling price. Recently, Wu et al. (2017) provided variable good bit and price models for newly introduced goods and evaluated the impact of price strategies and new product dissemination on the important for marketing.

Since provider choice and command allotment have indeed been recognised as major and significant tasks in supply chain management, researchers have recently incorporated supplier selection into the integrated pricing and production/inventory planning model in an effort to increase the overall supply chain's efficiency and the company's profitability. Qi (2007) suggested an integrated procurement, manufacturing, and pricing model for a manufacturer that sources from several finite capacity suppliers and faces price-sensitive consumer needs for a single item. The author suggested a heuristic method and a nonlinear programming technique to concurrently estimate the market value, production amount, and order number from a subset of providers. Rezaei and Davoodi (2012) presented a situation in which a single customer faces suppliers, lot size, and pricing considerations in a multi-product, multi-period setting.

They created a multi-objective non - linear programming model with the goals of maximising profit while minimising total consistency and overall insufficiency. Later, Adeinat and Palma (2015) examined a single-item EOQ model featuring price-dependent demand and various providers offering a discount on all unit quantities.

In the preceding studies, the price elasticities functional is typically believed to be linear or a powers functional for convenience. Although Lau and Lau (2003) noted that modest modifications in the supply curve could result in considerable changes in optimal solutions, there are only few articles (Huang et al. 2013 and Yaghin et al. 2014) that provide the rationale for selecting one demand function over others. According to Oum (1989), both the linear .financial and the log-linear system . the model have limitations that are unacceptable. Phillips (2005) also stated that both the linear model nor the isoelastic functional accurately represents the price-demand connection. In addition, Huang et al. (2013) published a detailed evaluation of linear equations employed in decision modelling and echoed Phillips's observation (2005). Companies must now modify their prices more often in order to compete on the world market; consequently, a much more precise demand curve is required for management of supply chains including marketing. In this chapter, we suggest applying a believable functional form, the logistic regression functional form, also known as the flipped S quantity demanded, to worldwide represent the pattern of requirement variability with price and to examine a combined pricing, supplier evaluation, and time inventory issue for a single product subject to suppliers' ability and constraints. In addition to the selling price, the best order regularity and order number from the chosen suppliers are computed to maximise the overall profit per unit of time. In the meantime, the influence of various demand curves on sourcing strategies is also studied. In the operations management literature, supply chain management (SCM) and the supplier selection processes have garnered considerable attention during the past three decades . Several researchers have stressed the multidisciplinary nature of supply chains and indicated that the application of economics and marketing-based methodologies can further enhance the efficacy of SCM . As outsourcing gains importance in numerous industries, for instance, the supplier selection procedure also evolves . In addition, the rapid spread of information sharing throughout supply chains has heightened the significance of supplier management in recent years . Moreover, a number of empirical research indicate that managers consider the role of the supplier to be crucial for greater business success.

While the academic literature is extensive, many sectors continue to struggle with the evaluation and selection of suppliers for essential raw materials. In this context, prior research demonstrates that firms use price and a variety of other dimensions, including quality, flexibility, delivery, and service, in the supplier selection process . In general, supplier selection trade-offs align well with diverse competitive priorities recognised and thoroughly investigated in operations strategy research .

In terms of conceptual models, decision support systems, simulation studies, and empirical analyses related to vendor evaluation, the literature on supplier selection is also abundant, As advised by both classic and contemporary research in operations strategy , however, relatively little work has been done to integrate market utility-based techniques into supplier selection processes.

To the best of our knowledge, we have been the first to concurrently examine the effects of several linear equations on strategic sourcing, order frequency, and order amount choices.Using the idea of point price elasticity of demand (PED), which is the proportional change in demand given a change in price, a lower constraint on the optimal retail price for this integrated pricing, supplier selection, and inventory replenishment model is established (See Anderson et al. 1997).The remaining sections of this chapter are structured as follows. In Section 3.2, the logit demand function and pertinent features are introduced. In Section 3.3, a formulation for mixed integer nonlinear programming is presented, taking into account two scenarios in which the retailer placed orders of equal or different sizes with the selected suppliers. Section 3.4 examines the model's properties and presents heuristic strategies for solving the two scenarios. The outcomes of two numerical results for the suggested are presented in Section 3.5.

3.2 The Demand Function Logit:

The Demand Function Logit:are increasingly offering "layered" contracts, which provide Internet access to resellers in bundles at prices dependent on the cost of the lines traversed by the traffic in the bundle. Although providers have begun implementing and deploying different pricing agreements, very little known about the impact of such price on The Demand Function Logit:and their users. Although agreements that sell connection on a finer granularity increase efficient markets, they are more expensive for The Demand Function Logit:to execute and harder for consumers to comprehend. In this paper, we make two donations: (1) we establish a novel method for tracing traffic and topography data to a demand and cost model; and (2) we match this model on three large network systems: a European transit The Demand Function Logit: an information distribution system, and a relevant academic network, and run counterfactuals to evaluate the effects of various pricing strategies on both the The Demand Function Logit: financial gain and the consumer. We emphasise three key conclusions. First, The Demand Function Logit: get the majority of their earnings with three or four price tiers and probably have no reason to expand pricing specificity. Second, we demonstrate that customer surplus nearly, if not precisely, parallels the rise in The Demand Function Logit: profit as the number of price tiers increases. Lastly, the prevalent The Demand Function Logit: practise of structuring tiered contractual agreements in accordance with the cost of transmitting the car traffic (e.g., offering a price break for regular traffic) can be inadequate, whereas separating contracts based on both traffic demand and the cost of carrying it into three or four layers yields located close profit for the The Demand Function Logit:.

3.2.1 Demand Functions that are Price-Dependent:

In this section, we evaluate and analyse price elasticity that have utilised in the research for deterministic price-sensitive demands integration pricing and strategic sourcing operating decision-making challenges. Table 3.1 is a summary of the related papers in this field. The majority of research in this area examines either as the linearity or the powers function.

A functional form is constantly distinguishable, rigorously decreasing, and has upper and lower bounds (Talluri and Van Ryzin, 2004). Let M represent the quantity produced and N represent the retail price, with M, N [0, + ∞).

A well linear functional form has the form M(p) = p, where, > 0 and p [0,], whereas the peak power function has the form M(N) = α-βN , where α, β> 0 andN $\in[0,\frac{\alpha}{\beta}]$, and is indeed the constant PED. Table 3.1 demonstrates that the linear model is the most preferred demand estimate functional, as it is the easiest and its variables are the easiest to calculate. As a result, it has become widely adopted by researchers. The peak power functional is the easiest nonlinear function created to represent the nonlinear relationship between the price and demand. In addition, the exponentially demand function, defined as M(N) = ϕ$eN^{-\mathcal{E}}$, where ϕ, > 0, Ɛ>0is utilised in a number of studies. Subsequently, the logit function has also been applied to the formula M(N) = N$e^{-\theta}N$, N > 0, θ> 0. In addition, many valuation customer behavior are included in many research articles. In their studies, Abad (1988) and Ray et al. (2005), for instance, evaluated all linear and logarithmic functions. The from this functions utilised by Pan et al. (2009) are the linear, power, and exponentially functions. Bernstein et al. (2016) utilised product attributes sales figures to fit a linear model and an exponentially quantity demanded. However, neither one of them adequately explains why a certain supply curve is chosen over others.

Table.1 A overview of price-dependent linear equations employed in pertinent publications:

Demand graph					
Paper	LogitA	LogitB	Exponential	Linear	Power
Our research		*			
Whitin (1955)				*	
Díaz - Mateus et. al. (2018)	*				
Thomas (1970)				*	
Bernstein et al. (2016)			*	*	
Schrage and Kunreuther (1971)			*		
Yaghin et al. (2014)	*				
Abad (1988)			*		*
Davoodi and Rezaei (2012)	*		*		
Lee and Kim (1998)					*
Pan et al. (2009)			*	*	*
Gilbert (1999)			*		
Biller et al. (2005)			*		

Ramesh and Bhattacharjee (2000)					*
Kim et al. (2011)			*		
Wang and Viswanathan (2003)			*		
Qi (2007)			*		
Ray et al. (2005)			*		*

Each of these production and supply are in line with the Law of Demand, which states that "as the price of a good increases (↑), the quantity demanded falls (); conversely, when the price of a good decreases (↓), the quantity demanded increases (↑)" (Nicholson and Snyder, 2011). According to Phillips (2005), however neither linear model nor the power functional appears to accurately capture customer behaviour. The linear pricing after several that price sensitivity approaches infinity even as retail price approach its maximum, whereas the powers function maintains a constant PED at all prices.In addition, as price approaches 0, the peak power function results in endless demand. Similarly, the exponentially demand function exhibits a considerably stronger demand at low prices. The benefits and drawbacks are also discussed in Oum (1989) and Huang et al (2013). When displaying the supply curve utilised by Bernstein et al. (2016) and Pan et al. (2009) in Figures 3.1 and 3.2, respectively, the location characteristics of each quantity demanded are readily apparent.

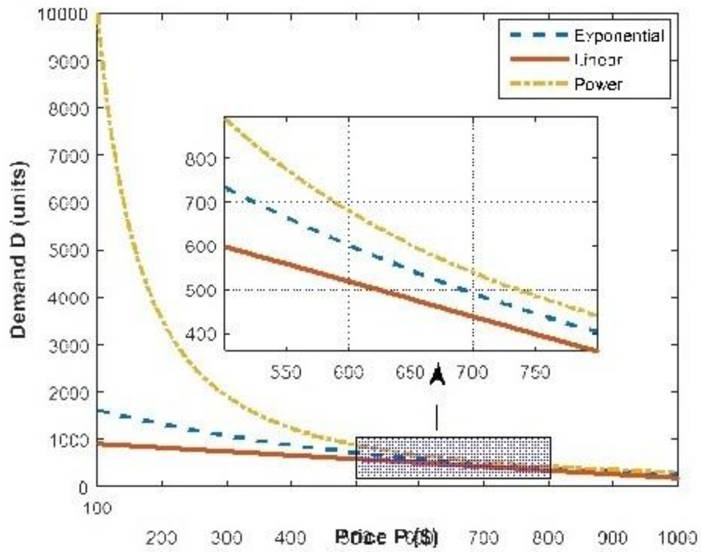


Figure 3.2. Demand curves from Pan et al. (2009)

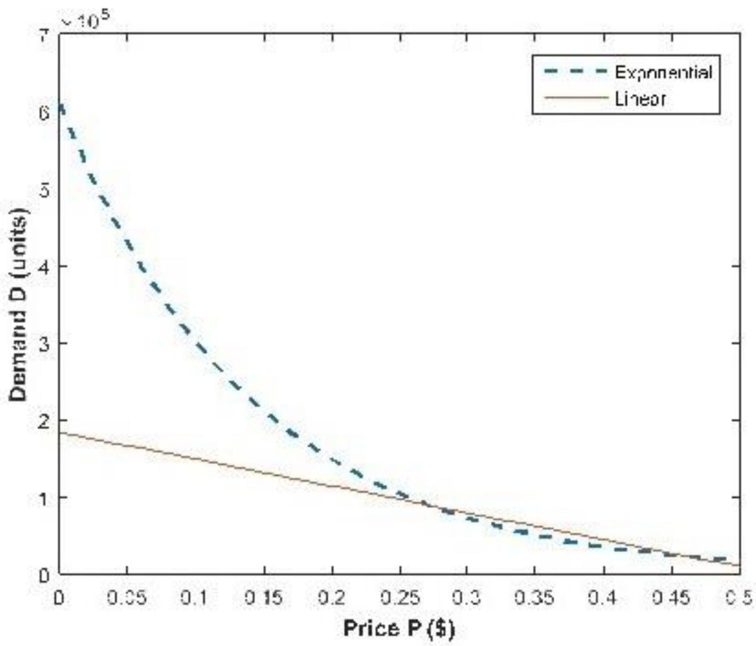
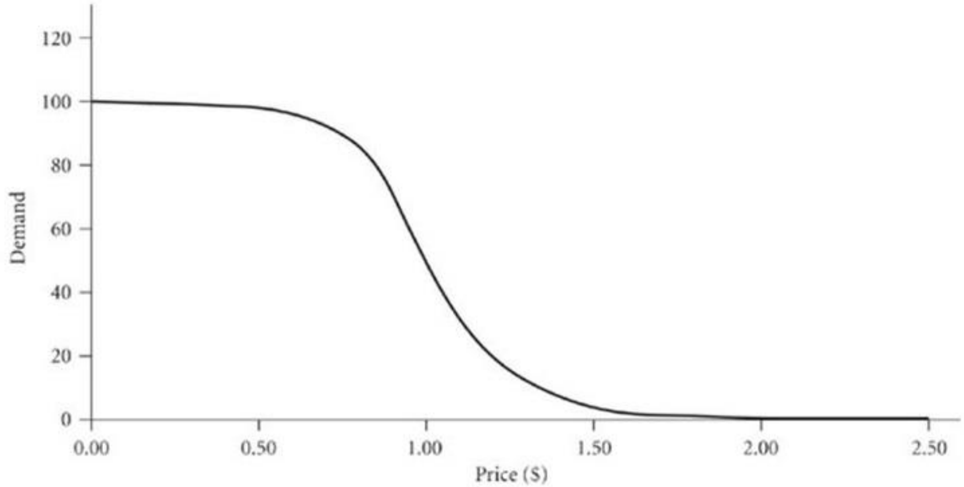


Figure 3.1. Demand curves from Bernstein et al. (2016)

In actuality, though, the market may be quite volatile when it reaches or near a given point. Within this range, small price adjustments might result in significant fluctuations in demand. As the price keeps rising, an increase in price will cause a slight decrease in demand. At certain instances in which the price is considerably higher, it is more common to notice customers who are no longer price sensitive. Conversely, if the price falls below a particular threshold, the demand increase will not be readily apparent. Consequently, product price is low in this circumstance. One may refer to Phillips (2005) for a car cost example and to Feuz for a beef pricing example (2009). Within those situations, neither a linear functional form nor a quasi required project, such as the power or exponentially required project, was capable of accommodating these characteristics. Therefore, the logit (reverse S-shaped) functional would provide a more accurate picture of real-world customer behaviour and a more honest portrayal of the relationship between price and demand. Scientists have previously suggested two kinds of logit linear equations. First, Phillips (2005) suggested the logistic regression price-response function M(N) =D$\frac{e^{-(C+DN)}}{1+e^{-(C+DN)}}$, C,D> 0, where D represents market size and C indicates pricing (Figure 3.3B). In addition, Chen and Simchi-Levi (2012) presented another form of logit price functional form as M(N) = N1. This is the combination of the market size N1 and the likelihood that a consumer with a coefficients of price elasticity a purchases at price N. (see Figure 3.3A). And though the logit function is more applicable than the linear and iso-elastic linear equations, few studies have used the logit cost function to distribution network optimization issues.

Using the logit A functional form, Yaghin et al. (2014) determined the optimal retail pricing for a co - marketing model in a two-tier supply chain. Recently, Daz - Mateus et al. (2018) also created a non - linear optimization model for a three separate supply chain with a provider and a vendor, including retail price, purchase order, and levels of inventory. In that study, the restricted multivariate regression logit model is employed to estimate demand, with the logit A functional form representing the demand of each socioeconomic class. Moreover, Fattahi et al. (2015) tackled a dynamic design of supply chain networks problem with a multiperiod horizon and price-sensitive client demand.

(A)



(B)

Figure 3.3 Logit demand curves derived from prior studies

After introducing a special case of the logit B price-response function, discrete price levels are utilised to price the products in the supply chain network. Considering that the logit A demand curve is quite close to the exponentially functional form, the focus of this study is on Phillips' logit B functional form (2005). For simplicity, we will refer to the logit B functional as the logit function for the remainder of this study. It is observed that no of the prior studies investigate the properties of the logit quantity demanded. Therefore, for the first time, we investigate the properties of the logit functional form and integrate it into an integrated strategic sourcing, stock control, and valuation problem with the objective of determining the best operational decisions regarding retail price, order number, and steadily over the years for the key suppliers.This research demonstrates that various widely-used stated preference models fulfill a parallel reverse aggregate demand property – alluded to as "parallel demands" in the following text. In particular, in response to an external alteration in the number of varieties in a market, inverted consumer spending curves shift vertically in parallel. This paper demonstrates that this property holds in stochastic frontier models with i.i.d. random utility shocks when the random utility impacts are dispersed in accordance with the Gumbel distribution, despite the fact that such a property of consumer spending curves appears to be a special case at first glance. In fact, we demonstrate that now the Gumbel distribution is a sufficient and required precondition for simultaneous demand in random utility models. According to our knowledge, this is a previously unrecognised property of this category of models; therefore, this article concentrates on theoretically characterising this estate and demonstrating how it can be utilized in an economic application to determine the shift in consumer behavior surplus associated with an extracellular shift in product variety.In explores a revealed preference model with symmetric prices and products and an outside alternative in order to enhance and enhance understanding. The first theorem demonstrates that the Gumbel distribution is both essential and sufficient for parallel requests. Next, we demonstrate that, for a diverse set of random benefit shock distribution, inverse aggregate demand curves are monotonically parallel; that is, money supply curves approach parallel demands as the number of varieties rises . When random utility shocks are independently distributed and identically distributed, the distribution of the greatest order statistics converges to a Gumbel distribution for a broad range of distributions. This indicates that assuming parallel demand may be a helpful approximation in many markets with a wide variety of products. Using numerical simulations, we demonstrate the accuracy of this estimate result and discover that convergence occurs rather quickly.In this, we expand the outcomes of in a variety of ways. First, we expand the baseline model to account for linked tastes, which permits differential substitutability within a market with product variety relative to the external choice. This addition permits us to include as a special case the usual Nested Logit model (McFadden 1978; Cardell 1997). We demonstrate that the Gumbel distribution is necessary and sufficient for parallel demands in this enlarged scenario (Proposition 1). Second, we extend our results to include asymmetric (or heterogeneous) products, as our baseline model assumes symmetric products and prices for simplicity's sake. This modification permits us to incorporate a random utility model with unobserved product heterogeneity (e.g., Berry 1994). In the symmetric products model, it is trivial to define the inverse aggregate demand curve. When prices are asymmetric, however, we rely on the distribution of the maximal willingness-to-pay for any of the available varieties rather than the aggregate demand curve, and we provide sufficient and necessary conditions for when this distribution shifts in parallel, just as the inverse aggregate demand curve shifted in parallel in our baseline model for symmetric products.

3.2.2 Logit Function Analysis:

Our research's logit function can be represented as $M(N) = D\frac{e^{-(C+DN)}}{1+e^{-(C+DN)}}$, where $D \leq 0, C \leq 2$. The maximum value of a denotes the breadth of the quantity demanded, whereas the perceived price parameter D indicates the demand curve's slope.

The study of the relationship with both binary or tuples feedback probability and explanatory variables has also been conducted using logistic regression. For bankruptcy prediction, the probability of a binary response is typically the standard probability, whereas a large number of independent variable may be employed. Maximum likelihood is typically used to fit linear logistic regression models for binary or datatype response variable (Hosmer and Lemeshow, 1989). Ohlson (1980) is one of the first authors to apply logit analysis to the context of financial anguish, accompanied by Zavgren (1985), to name a few references. Greene (1993) and Maddala also provide an excellent examination of various logistic models, prediction issues, and software (1983). Comparable to multiple regression, this method weights the different factors and designates a failure probability (PD) score (Y) to each sampled company.

3.2.2.1 Consequences of the Logit Function:

The second and first derivatives of M(N) are found and simplified in the following manner:

$$M'(N) = D\frac{e^{-(C+DN)}}{1+e^{-(C+DN)}} \leq 0 \tag{1}$$

$$M''(N) = D\frac{e^{-(C+DN)}}{1+e^{-(C+DN)}}\left[1-\frac{e^{-(C+DN)}}{1+e^{-(C+DN)}}\right] \tag{2}$$

Then, the following conclusions can be drawn:

- $M'(N)$ is negative, signifying the typical decline. Consequently, the logit demand function, like the linearity and power demand curves, fulfills the Law of Demand.
- a D is the price where $M''(N)$ equals zero (see Figure 3.4). As according Phillips (2005), this point indicates the median or market price, which in our research is designated by N^m. When $N < N^m$, $M''(N) \leq 0$, showing that M(N) is concave inside this price bracket. Nonetheless, M(N) becomes convex even as price exceeds N^m. Consequently, point N^m is a saddle point of the logit functional. Observe that all of these features are shown in Figure 3.4.
- The logit quantity demanded is symmetrical around point N^m. The desire approaches zero as the price approach $-\frac{2C}{D}$; hence, we set this price as the upper bound of the retail price, denoted by N^{max}, for the remainder of the chapter.

- The parameter a should be less than -2 for the pricing point- $\frac{C+2}{D}$ to be positive.

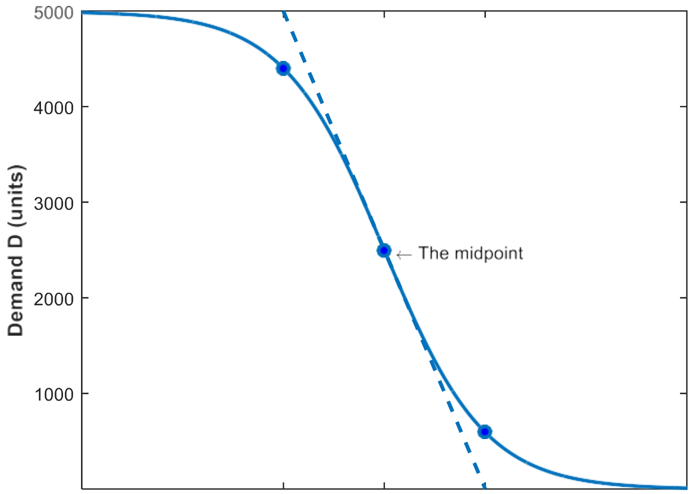


Figure 3.4 The Logit (reserved S curve) demand function was utilized in our study.

3.2.2.2. Price Elasticity of Demand (PED):

The price elasticity of demand (PED) quantifies the sensitivity of the amount requested of a commodity to a shift in its price. Specifically, it is the percent increase in quantity sought in relation to a one percent increase in the price, assuming all other demand factors remain constant. According to the laws of demand, the relation between demand and price for a product is inverse. Consequently, the PED factor is virtually invariably negative. However, analysts tend to disregard the symbol in daily use. Only non-conforming goods, such as Hegel and Giffen goods, have such a positive PED. The coefficient's values obtained could range from zero to infinity. In speaking, the desire for an item is relatively elastic (or relatively inelastic) when the price elasticity of demand (PED) is less than one (in exact amount): that is, changes in the cost have an influence on the amount of the good wanted that is less than proportionate. It is claimed that the demand for a good is elastic (or reasonably elastic) when its PED is bigger than one. In this instance, price changes have a greater than proportionate impact on the amount of a product demanded.A PED coefficient of one shows that demand is unit elastic; every price shift leads to a corresponding change in demand (e.g., a 2% decrease in demand would result in a 1% decrease in price). A PED coefficient of 0 shows demand that is perfectly inelastic. This suggests that pricing has no impact on the demand for a product.

In accounting, the PED has indeed been widely utilised to evaluate the responsiveness of demand variation to price. As according Phillips (2005), the PED of the logit curve at a particular location is computed as follows:

PED=$\frac{DN}{1+e^{-(C+DN)}}$

Perfectly Inelastic Demand: When demand is completely inelastic, there is no variation in the amount desired in response to a shift in price. When the PED coefficient equals infinity, demand is considered to be completely elastic. When demand is completely elastic, purchasers will not purchase at any other price. The demand is considered to be perfectly inelastic when there is no change in quantity demanded despite a change in the price of the good. Simply indicate no shift in demand for pricing changes. According to the laws of demand, the demand for products and services fluctuates in response to price fluctuations. However, the link between demand and price may not be the same under all market conditions; it may vary from product to product, time to time, and marketplace to marketplace. To comprehend the extent of the effect of price on demand, one must be familiar with the notions of price elasticity of demand.

The price elasticity of demand (PED) measures the sensitivity of the equilibrium quantity to variations in the good's price. This is in opposition to the cross-price elasticity of demand, that measures the sensitivity of a good's demand to a shift in the price of another good (a complement or substitute). Usually, the own-price elasticity of demand is referred to as the relative prices. There are few other essential considerations regarding the coefficient value produced by such a formula. First, the coefficient of elasticity is a pure number, meaning it has no related metric measurements. Second, the value of the coefficient can range between zero and positive infinity. Lastly, the answer obtained by the method will only be correct when quantity and price fluctuations are minimal. When the changes are significant, the outcome will be less precise.

When PED exceeds one, the demand is flexible. This might be viewed as consumers being extremely sensitive to changes in price: a 1% rise in price will result in a desire decrease of greater than 1%.

Inelastic demand occurs when PED is below one. This might be viewed as customers being sensitive to price changes: a 1% increase in price will result in less than a 1% decrease in quantity required.The effect of pricing adjustments on overall revenue PED could be crucial for companies looking to determine how to optimise revenue. For instance, if a company discovers that their PED is highly inelastic, it may decide to raise its prices, knowing that it can sell its items at a higher price without losing many customers. In contrast, if a company discovers that their PED is highly elastic, it may desire to reduce pricing. This would allow the company to significantly expand the amount of units sold without suffering a significant revenue loss per unit. There are two noteworthy instances of PED. The first condition is complete demand elasticity. A relatively elastic demand is graphically represented by a horizontal line. In this instance, any price rise will result in zero units being sought.

Perfectly Inelastic Demand:

The graph of completely quantity demanded is a vertical line. At all points along the demand curve, the PED quantity is constant. Since PED is calculated based on percentage price fluctuations, the nominal value and quantity mean that demands have varying elasticity at different points along the curve. Along a plain demand curve, the elasticity ranges from zero at the supply axis to infinity at the price axis. Below the midpoint of a plain demand curve, elasticity is below one, and the company wishes to raise prices in order to increase total revenue. Above the midpoint, elastic is greater than one, and the company desires to cut prices in order to boost total revenue. At the halfway point, E1, the elasticity is one, or unit elastic.

Determinants of Demand Price Elasticity:

The price elasticity of demand (PED) measures the extent to which a change in price affects the equilibrium quantity. A product's PED is determined by one or a mixture of the following variables:

- Availability of alternative products: The greater the elasticity, ever more possible alternatives there are for a particular commodity or service. When multiple close replacements are accessible, buyers were able to quickly change from one good to another, even if the price difference is minimal. In contrast, if there are no available substitutes for a product, its demand is more inclined to be inelastic.
- Percentage of the buyer's budget consumed by the product: Products that take a significant percentage of the purchaser's money are typically more elastic. The relatively high price of these items will prompt buyers to exercise caution and seek alternatives. In contrast, when a good constitutes a negligible fraction of the budget, demand would continue to be inelastic.
- Percentage of the buyer's budget consumed by the product: Products that take a significant percentage of the purchaser's money are typically more elastic. The relatively high price of these items will prompt buyers to exercise caution and consider alternatives. In comparison, when a product represents a negligible fraction of the budget, demand will likely to be inelastic.
- Degree of requirement: The more a product's requirement, the lower its flexibility. Consumers will strive to purchase essential things (such as life-saving pharmaceuticals such as insulin) regardless of price. Luxury goods, on the other hand hand, are typically more elastic. However, some originally low-necessity products are habit-forming and may turn into "basic needs" for users (e.g. coffee or cigarettes).
- Duration of price fluctuations: Long-term elasticity tends to be higher for non-durable items then short-term elasticity. In the short-term, it may be challenging for customers to locate alternatives in reaction to a price shift, but in the long-term, consumers are able to modify their behaviour. For instance, if there is sudden spike in the price of gasoline, customers may continue to fill their cars in the short-term, but they may switch to public transit, commute, or purchase more fuel-efficient automobiles in the long-term. Unfortunately, this trend does not hold true for durable goods. As consumers are required to replace durable goods (cars, for example) over time, their demand is typically less elastic.
- Breadth of a good's definition: The greater the breadth of a product's definition, the lesser its elasticity. For instance, potato chips have a rather high degree of demand elasticity due to the availability of numerous replacements. Food would have an incredibly low PED because there are no replacements.

3.3. Model Formulation:

In this part, we examine an integrated supplier selection and inventory replenishment model that takes into account numerous suppliers and a single retailer, where the price-dependent demand rate per time unit is determined by the logit demand function. The objective is to identify the retailer's optimal selections involving supplier selection, order amounts, and sale prices that yield the greatest profit per time unit. The shop receives a certain sort of product from vendors with capacity and safety limits. Using the Ahp, these prospective providers are chosen beforehand (Saaty, 2008). Here, we adhere to Mendoza and Ventura's (2008) conclusion that many orders may be placed with the specified providers over a recurring order cycle. During an order cycle, not only can different suppliers be selected, but also multiple orders can be placed with the selected source. The retailer must concurrently determine the selection of suppliers, related order volumes, and order frequency with respect to the selected suppliers. In addition, the retailer's demand rate is dependent on the selling price and is represented by the logit demand function in the form of $M(N) = D\frac{e^{-(C+DN)}}{1+e^{-(C+DN)}}$, as mentioned in Section 3. The merchant sets the pricing of the goods while determining the procurement strategy in order to earn the greatest profit per unit of time. We presume lead time to be insignificant, and the system does not permit shortages.

On the basis of these presumptions, the following parameters and decision variables are employed throughout this chapter:

3.4 Experiments:

In this part, we demonstrate the use of the logit function and the impact of different demand functions on optimum purchase decisions using experimental data. The very first experiment demonstrates the effectiveness of the recommended heuristics, while the second demonstrates the influence of the different Demand is dependent on issues and business. This experiment uses the global solver in LINGO 18.0 on a PC with such a 3.1 GHz INTEL® CoreTM2 Duo processor and 8 GB RAM.

3.5.1 Experiment 1

Let the company's demand rate for a particular product be valuation, defined by the inverted function D(p) = $D\frac{e^{-(C+DN)}}{1+e^{-(C+DN)}}$. The goal of the retailer's supplier evaluation, quantity of orders, purchase sizes, and sales price decisions is to maximise profit per month. The units inventories holding cost of the retailer is $5 per week, and the retailer's standard minimum quality level is 0.95. The pertinent parameters are shown in Table 3.2.

Table 3.2: Parameters provided by vendors

Price $\boldsymbol{ci}$ ($/unit)	Capacity rate $\boldsymbol{Fi}$ (units/month)	Quality level $\boldsymbol{q}$i	Setup $\boldsymbol{Ki}$ ($/order)	Supplier i
87	2200	.94	3000	3
93	2600	.95	3300	2
104	2100	.99	3600	1

First, let's determine the minimum acceptable sales price. As according Principle 3.3, the optimal retail price should exceed that price at which the PED exactly equals 1. In this instance, PED(p) = 1 and p = $312.9 Consequently, p > 312.9 is added to the list of constraints. In the meantime, p m = $400 and p max = $800.

Moreover, in order to acquire the ideal number of orders that maximises monthly profit, we first set m to a reasonably big value . Model M's optimum amount of orders per cycle is 23, that results in an extremely lengthy ordering process of 13,18 months. Since we require a shorter and much more realistic cycle time, you run Models M and Meq with m ranging from 2 to 16. Tables 3.3 and 3.4 display the detailed solutions. The largest monthly profit is attained when the total number of orders placed is m = 8. This is evident from Table 3.3. Furthermore, a single order for 3100.98 units is made with producers 2 and 4, whereas supplier 2 is liable for five orders totaling 3003. Please note that this ordering procedure will reduce the time duration to 5.61 months.

Table 3.4 displays the ability to incorporate when equal-sized order quantities from the selected suppliers are considered. In this instance, the best m value is 13 as well as the cycle period is 7.56 months.

Figure 3.8 depicts a look at the total monthly profit for Models M and Meq at various m values. Due to the adaptability of a order allocation mechanism, Model M often generates faster cycle times and better monthly profits than Model Meq.

Regardless of the value of m, supplier 2's capability has always been fully used because of its cost advantages and the needed quality level. Suppliers 1 and 3 are concurrently selected without sufficient capacity to meet the remainder request. The answer is uncomplicated. The desired quality cannot be met by picking only supplier 1, and selecting only vendor 3 results in greater costs. Consequently, the ideal procurement strategy reflects a compromise among quality and price. In this case, since suppliers 1 and 3 offer the same absolute deviation from the acceptable quality level, the optimal procurement strategy is to keep the same quantity of orders and amounts from both suppliers, hence satisfying the quantity restriction.

Table 3.3: Model solution characteristics (M):

Profit ($/month)	Cycle time (months)	J1	J2	J3	Retail Price ($/unit)	$\boldsymbol{Q}1$ (units/order)	$\boldsymbol{Q}2$(units/order)	$\boldsymbol{Q}3$(units/order)	m
761,485.3	0.68	0	0	0	400	0	0	0	0
811,234.3	1.68	1	1	1	359	1234.4	1234.4	1234.4	1
823,345.4	2.68	1	1	1	358	1235.4	1235.4	1235.4	2
833,456.4	2.34	1	1	1	357	1236.4	1236.4	1236.4	3
845,345.5	2.67	1	2	1	356	1237.4	1237.4	1237.4	4
856,765.8	2.78	1	2	1	355	1238.4	1238.4	1238.4	5
867,894.3	3.01	1	2	1	354	12310.4	12310.4	12310.4	6
873,456.4	3.02	1	2	2	353	1214.4	1214.4	1214.4	7
884,673.5	3.03	1	3	2	352	1224.4	1224.4	1224.4	8
894,678.4	3.04	1	3	2	351	1234.4	1234.4	1234.4	9
911,345.5	3.05	1	3	2	350	1244.4	1244.4	1244.4	10
921,345.5	3.06	1	3	2	349	1254.4	1254.4	1254.4	11
931,345.5	3.07	2	3	2	348	1264.4	1264.4	1264.4	12
941,345.5	3.08	2	4	2	347	1274.4	1274.4	1274.4	13
951,345.5	3.09	2	4	2	345	1284.4	1284.4	1284.4	14
961,345.5	3.10	2	4	2	344	1294.4	1294.4	1294.4	15

Table 3.4: Model Me solution features Meq:

Profit ($/month)	Cycle time (months)	J1	J2	J3	Retail Price ($/unit)	$Q1$ (units/order)	$Q2$(units/order)	$Q3$(units/order)	m
761,485.3	01.68	0	0	0	400	0	0	0	0
812,234.3	11.68	1	1	1	359	1234.4	1234.4	1234.4	1
823,345.4	21.68	1	1	1	358	1235.4	1235.4	1235.4	2
834,456.4	21.34	1	1	1	357	1236.4	1236.4	1236.4	3
845,345.5	21.67	1	2	1	356	1237.4	1237.4	1237.4	4
826,765.8	20.78	1	2	1	355	1238.4	1238.4	1238.4	5
866,894.3	31.01	1	2	1	354	12310.4	12310.4	12310.4	6
877,456.4	13.02	1	2	2	353	1214.4	1214.4	1214.4	7
888,673.5	31.03	1	3	2	352	1224.4	1224.4	1224.4	8
899,678.4	31.04	1	3	2	351	1234.4	1234.4	1234.4	9
911,345.5	30.05	1	4	2	350	1244.4	1244.4	1244.4	10
911,345.5	32.06	1	4	6	349	1254.4	1254.4	1254.4	11
921,345.5	32.07	2	4	6	348	1264.4	1264.4	1264.4	12
931,345.5	31.08	2	5	6	347	1274.4	1274.4	1274.4	13
941,345.5	31.09	2	5	7	345	1284.4	1284.4	1284.4	14
951,345.5	30.10	2	5	7	344	1294.4	1294.4	1294.4	15

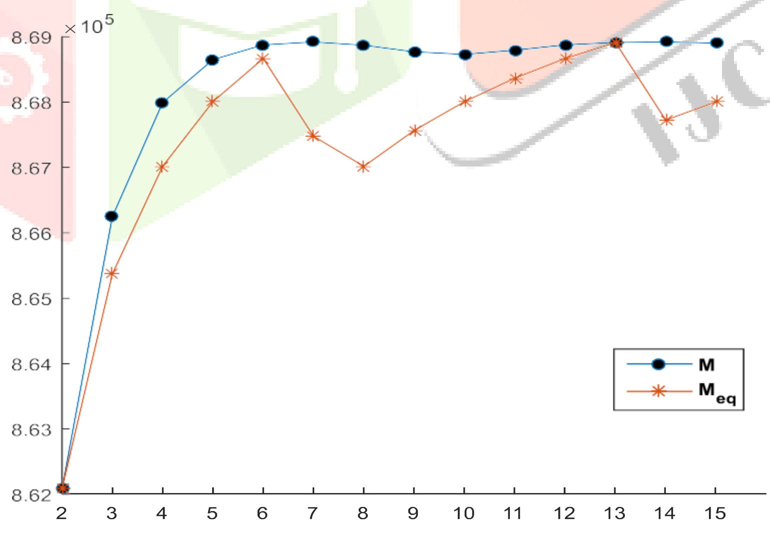


Figure 3.8. Comparison of M and Meq

3.6. Conclusions: Using the logit functional form, this chapter examines a joint pricing, supplier selection, and inventory replenishment problem for a single item in a two methods. To maximise the retailer's profit per unit of time, the selling price and procurement methods, including suppliers to be derived, the percentage of orders, and order quantity from every selected supplier, are determined and analyzed. The linear regression function reflects the predetermined nature of demand. Rather than selecting the functional form without sufficient justification, we focus on providing for the first time sufficient justification for selecting the logit function as well as a detailed examination of the proposed logit request function's characteristics. Then, we develop a mixed integer nonlinear programming model and demonstrate that the female's selling price has a lower bound. Given the computational complexity of the proposed model as the number of suppliers increases, we propose a two-stage PLA method and develop two heuristic algorithms to obtain near-optimal solutions for the problem. The proposed model and the corresponding heuristics are illustrated by means of a numerical example. Finally, we compare and demonstrate numerically the effects of different demand functions on pricing and procurement decisions. The logit demand function more accurately depicts the demand versus price trend in the real world.

References:

1. Woodruff, R.B. Customer value: The next source for competitive advantage. J. Acad. Mark. Sci. 1997, 25, 139–153. [CrossRef]

2. Guo, L.; Lotz, S.L.; Tang, C.; Gruen, T.W. The Role of Perceived Control in Customer Value Cocreation and Service Recovery Evaluation. J. Serv. Res. 2016, 19, 39–56. [CrossRef]

3. Mahmoud, M.A.; Hinson, R.; Anim, P.A. Service innovation and customer satisfaction: The role of customer value creation. Eur. J.Innov. Manag. 2018, 21, 402–422. [CrossRef]

4. Luo, Z.; Chen, X.; Kai, M. The effect of customer value and power structure on retail supply chain product choice and pricing decisions. Omega 2018, 77, 115–126. [CrossRef]

5. Forbes. A Visit to Hema in Beijing Changed My View of Grocery Shopping. Available online: https://www.forbes.com/sites/hendriklaubscher/2018/10/10/a-visit-to-hema-in-beijing-changed-my-view-of-grocery-shopping/?sh=44ea84ae3c54 (accessed on 6 November 2020).

6. Nash, J. The bargaining problem. Econometrica 1950, 18, 155–162. [CrossRef]

7. Gjerdrum, J.; Shah, N.; Papageorgiou, L.G. Fair transfer price and inventory holding policies in two-enterprise supply chains. Eur.J. Oper. Res. 2002, 143, 582–599. [CrossRef]

8. Wu, D.D. Bargaining in supply chain with price and promotional effort dependent demand. Math. Comput. Model. 2013, 58,1659–1669.

9. Kumar, V.; Reinartz, W. Creating Enduring Customer Value. J. Mark. 2016, 80, 36–68. [CrossRef]

10. Sanchezgutierrez, J.; Cabanelas, P.; Lampon, J.F.; Gonzalezalvarado, T.E. The impact on competitiveness of customer value creation through relationship capabilities and marketing innovation. J. Bus. Ind. Mark. 2019, 34, 618–627. [CrossRef].

11. Jaaskelainen, A.; Heikkila, J. Purchasing and supply management practices in customer value creation. Supply Chain Manag. 2019,

24, 317–333. [CrossRef]

12. Gilbert, S.M.; Cvsa, V. Strategic commitment to price to stimulate downstream innovation in a supply chain. Eur. J. Oper. Res.

2003, 150, 617–639. [CrossRef]

13. Nouri, Mmanufacturer's innovation and retailer's promotion and replenishment using a compensation-based wholesale price con; Hosseini-Motlagh, S.M.; Nematollahi, M.; Sarker, B.R. Coordinating tract. Int. J. Prod. Econ. 2018, 198, 11–24.

14. Zhou, X.; Yang, S.; Wang, G. Impacts of knowledge spillovers and cartelization on cooperative innovation decisions with uncertain technology efficiency. Comput. Ind. Eng. 2020, 143, 106395. [CrossRef]

15. Li, Z.; Ni, J. Dynamic product innovation and production decisions under quality authorization. Comput. Ind. Eng. 2018, 116, 13–21. [CrossRef]

16. Gurnani, H.; Erkoc, M.; Luo, Y. Impact of product pricing and timing of investment decisions on supply chain co-opetition. Eur. J.Oper. Res. 2007, 180, 228–248. [CrossRef]

17. Chenavaz, R. Dynamic pricing, product and process innovation. Eur. J. Oper. Res. 2012, 222, 553–557. [CrossRef]

18. Kim, B.C.; Ahmed, M. Price-Match Guarantees and Investment Incentives. Inf. Econ. Policy. 2020, 53, 100891. [CrossRef]

19. Yang, W.; Pan, Y.; Ma, J.; Yang, T.; Ke, X. Effects of allowance allocation ules on green technology investment and product pricing under the cap-and-trade mechanism. Energy Policy 2020, 139, 111333. [CrossRef]

20. Cachon, G.P.; Lariviere, M.A. Supply chain coordination with revenue-sharing contracts: Strengths and limitations. Manag. Sci. 2005, 51, 30–44. [CrossRef]

21. Cachon, G.P. Supply chain coordination with contracts. In Handbooks in Operations Research and Management Science; Elsevier: Amsterdam, The Netherlands, 2003; Volume 11, pp. 227–339.

22. Bart, N.; Chernonog, T.; Avinadav, T. Revenue-sharing contracts in supply chains: A comprehensive literature review. Int. J. Prod. Res. 2020, 1–26. [CrossRef]

23. Pan, K.; Lai, K.K.; Leung, S.C.; Xiao, D. Revenue-sharing versus wholesale price mechanisms under different channel power structures. Eur. J. Oper. Res. 2010, 203, 532–538. [CrossRef]

24. Chen, J.; Bell, P.C. Implementing market segmentation using full-refund and no-refund customer returns policies in a dual-channel supply chain structure. Int. J. Prod. Econ. 2012, 136, 56–66. [CrossRef]

25. Song, H.; Gao, X. Green supply chain game model and analysis under revenue-sharing contract. J. Clean. Prod. 2018, 170, 183–192.[CrossRef]

26. Panja, S.; Mondal, S.K. Exploring a two-layer green supply chain game theoretic model with credit linked demand and mark-up under revenue sharing contract. J. Clean. Prod. 2020, 250, 119491. [CrossRef]

27. Avinadav, T. The effect of decision rights allocation on a supply chain of perishable products under a revenue-sharing contract.Int. J. Prod. Econ. 2020, 225, 107587. [CrossRef]

28. Yao, Z.; Leung, S.C.; Lai, K.K. Manufacturer's revenue- sharing contract and retail competition. Eur. J. Oper. Res. 2008, 186,637–651. [CrossRef]

29. Linh, C.T.; Hong, Y. Channel coordination through a revenue sharing contract in a two-period newsboy problem. Eur. J. Oper. Res.2009, 198, 822–829. [CrossRef]

30. Wang, Y. Joint pricing-production decisions in supply chains of complementary products with uncertain demand. Oper. Res. 2006,54, 1110–1127. [CrossRef]

31. Avinadav, T.; Chernonog, T.; Perlman, Y. Consignment contract for mobile apps between a single retailer and competitive developers with different risk attitudes. Eur. J. Oper. Res. 2015, 246, 949–957. [CrossRef]

32. Chiang, W.Y.K.; Chhajed, D.; Hess, J.D. Direct marketing, indirect profits: A strategic analysis of dual-channel supply-chain design. Manag. Sci. 2003, 49, 1–20. [CrossRef].