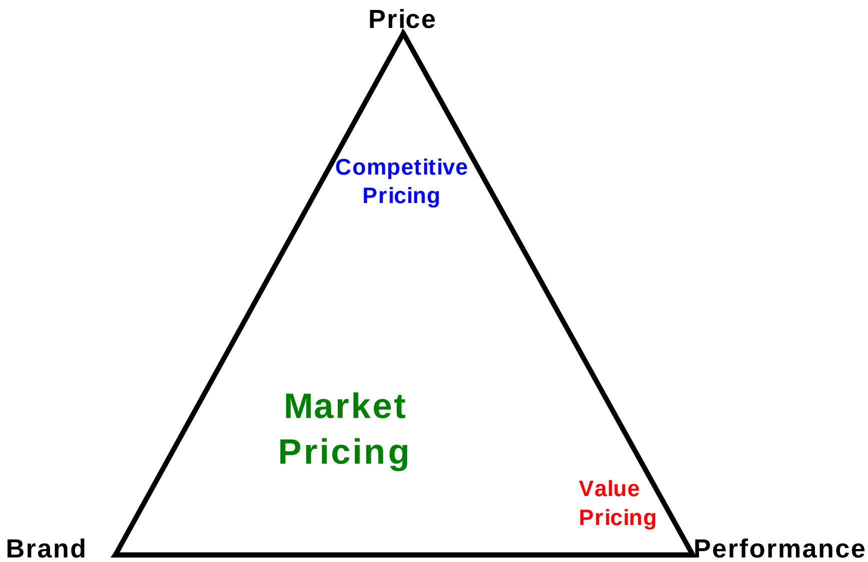
5. PRICING RESEARCH METHODS

Table of Contents

Page

5.1. PRICING STRATEGIES

There is a broad range of marketing conditions that would dictate different pricing strategies. However, it is useful to think of three approaches to pricing depending on the importance of the key product attributes of: (1) price, (2) brand and services, and (3) uniqueness of product performance in the buying process. The “marketing triangle” shown below indicates possible regions and the preferred pricing strategies.



- For true commodities, pricing tends to be purely competitive and linked directly to cost. This is often referred to as “cost based pricing” but in reality, it is directly linked to the competitive price. However, it should be noted, that this is an unusual situation and is best thought of as a characteristic of effective auctions. Unfortunately, many large manufacturing firms use cost based pricing as a simple vehicle to generate target prices.

- When the product is truly unique and fully customized then value based pricing may be appropriate. Value pricing requires that each customer or group of customers is isolated from the rest of the market. Under this condition, prices are negotiated with the objective of obtaining a major portion of the total product value. Economic and perceived value marketing research tools are used to assess the product value. These are discussed in detail in other chapters of these notes.

- However, in most cases the market or at least segments of the market must be considered as a whole. Individual customers can not be isolated to allow for value-based pricing. A market pricing policy must be used. Price under these conditions should be based on the “demand curve.” It is this type of policy that the quantitative marketing research tools discussed in this chapter are appropriate.

5.1.1. MARKET PRICING POLICING

Pricing policies, while strongly dependent on customer reactions, cannot be totally determined by the market. There are a number of critical factors beyond that captured by pricing research that need to be considered, including:

- Limited Control of the Market Price -- Usually only the resellers (distributors and dealers) have actual market pricing control. Typically manufacturers who generally conduct this type of pricing research can set the wholesale price but they can only **influence** the final market price of their products. As such, the influences of the distribution channel have to be more than just considered, they need to be integrated into the pricing policy.

- The Total Deal -- Often credit/payment terms, discounts and promotional programs are handled separately from the product pricing. However, such programs influence the ultimate customer costs and need to be considered.

- Competitive Reaction -- Pricing is not done in isolation, competitors are likely to react to price changes often with significant time delays. This can create an oscillating or “run away” price effect where each set of competitors’ reactions generating the next set. This has been known to drive prices to unacceptable low levels and make whole industries unprofitable. It is, therefore, critical to consider potential competitive reaction.

- Capacity Limitations -- Manufacturing capacity may be highly limited. It may be inadvisable to encourage product growth if capacity is unavailable.

- Mill Costs -- While it is typically assumed that “variable” or marginal mill costs are independent of sales volume, in reality they are not. Many ventures are based on meeting specific capacity utilization or minimum volumes. Below those levels mill costs rise sharply. If these effects are critical they need to be considered in setting pricing policies.
- Product Position and Long Term Earnings -- Price carries information regarding the nature of the product and as such it is a product feature. In some classes of products (expensive consumer products and pharmaceuticals) price is a primary factor in setting the perceived use and “quality” position of the product. As such, setting the price also may change the characteristics of the product and its market.
- Non-isolated Market Segments -- Market segments are not necessarily isolated. Pricing in one segment effects other segments. In many cases, the same channel may serve multiple segments making independent pricing infeasible.

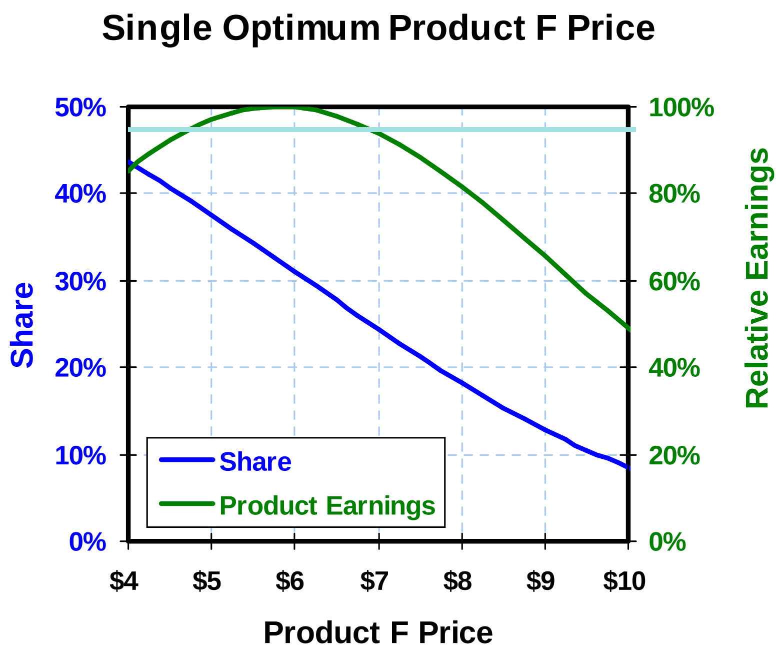
Beyond these external factors, lies the uncertainties associated with the pricing market data. As we have previously discussed, there are many sources of imprecision and inaccuracy associated with measurement of market price sensitivity. While many of these errors can be considered “random,” some are systematic and need to be taken under consideration.

5.1.2. Degrees of Uncertainty

Not all pricing situations show the same degree of uncertainty. In many cases we can consider the competitive market to be fairly stable. While prices may vary somewhat, the range is fairly tight. Changes in market prices can at least be anticipated and scenarios developed.

However, there are occasions when such analysis is not feasible, and competitive prices are either totally unknown or are considered to exist within a broad range or can be estimates as a probability distribution. These situations are covered by the “stochastic models” discussed in a later section. Unfortunately, most product and brand managers find that analysis both difficult to understand and utilize. In most cases, we have found that these managers would still prefer to consider the market stable and use a larger number of scenarios rather than dealing with the uncertainty analytically.

For stable competitive markets we generally use plots of relative earnings and share against price based on market data, as discussed earlier in this chapter. Below is a typical chart. Indicated on this chart is a range of prices that is expected to deliver at least 95% of the maximum earnings. We consider this range to giving a “satisfactory” return.



In almost all real business situations, earnings information is not precisely known and therefore, this range is probably within the accuracy of available data. We identify the lower price end of the range as the "Low Price Point" and the upper price end as the "High Price Point." The maximum point is referred to as the "Optimum Price." However, it must be understood that this "optimum" does not represent the best price to charge. It only represents the highest earnings that would be obtained based on perfect data and no outside effects. This is our basic tool for examining pricing strategies. The choice is between the three possible positions.

There are two basic situations that we consider for setting pricing policies: (1) repricing existing products and (2) pricing new products. These have very different conditions associated with them and need to be handled separately.

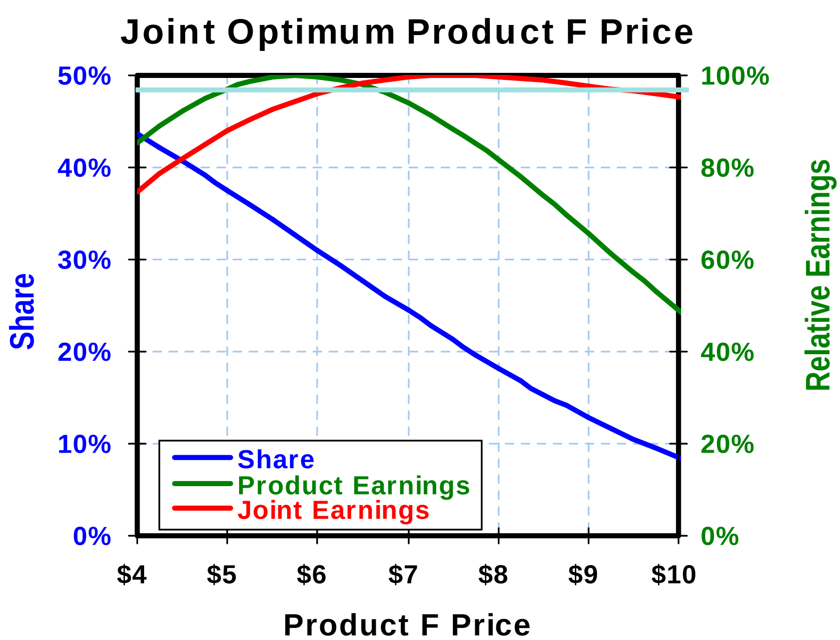
5.1.3. REPRICING EXISTING PRODUCTS

With repricing, it can be assumed that the respondents are familiar with the competing products. If there are new product entries that are not well known to the market, the situation reverts to a new product pricing problem even though it may involve someone else's new products. However, new combinations or packages of existing products can be considered to be basically repricing since all offerings are well known. The basic problem with repricing, however, is with multiple offerings and potential competitive reaction.

Multiple offerings may be separate products or, in the case of consumer package goods, bundled products. Both Choice Modeling and Concept Testing data are used for this analysis. However, Choice Modeling data is clearly preferred if there is relatively small and consistent competitive consideration set, since it allows exploring competitive reaction. As noted earlier in this chapter, Concept Testing allows for testing of multiple product offerings within tight constraints. In general, Concept Testing is preferred for new product introductions.

We have found that it is critical to view the setting of a new price in terms of the change from the current price. Typically, one does not wish to disturb the market and induce competitive reaction. As such, it is usually preferred to produce the minimum price movement. It is assumed that the likelihood of an adverse competitive reaction will be proportional to the size of the price change. This usually sets the “best” price at one of the price points on either side of the optimum price closest to the current price. On the other hand, pricing can be used to induce a desired competitive reaction. It is often, particularly with industrial product, to try to induce a general price rise. Repricing offers an opportunity to indicate the desirability for such a move.

With only two products being offered, a bivariant plot can be used to select “best” prices. This allows for optimum prices and regions of acceptable prices to be identified. However, in many cases there are three of more products making this type of visualization infeasible. Typically we use an iterative approach using a similar chart as shown above but including the total or joint earnings as well as those from the individual product, as shown below. This type of graph is used with joint optimum calculations to start the iterative process exploring the impact of alternative prices.



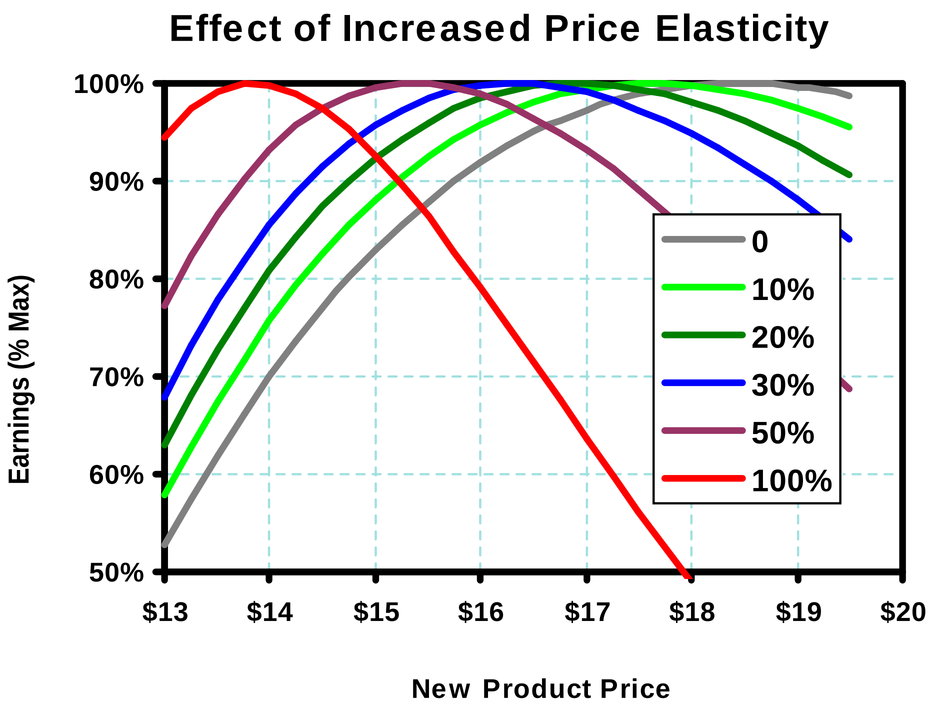
5.1.4. Pricing New Products

New products introduce unique problems in estimating the initial “best” price. Accuracy of new product marketing research data is problematic. The only source of information on the product is coming from the description that is part of the survey instrument. As such, the respondent is “primed” for a positive perspective. Furthermore, there is generally no way to hide the objective of the study. Therefore, we face the inherent effect of respondents wishing to "please" the interview by producing favorable, but unrealistic, results. These potential errors are combined with uncertainty as to costs and manufacturing capacity to produce a very uncertain decision making environment. We typically consider two archetypes of new products as means of handling these uncertainties.

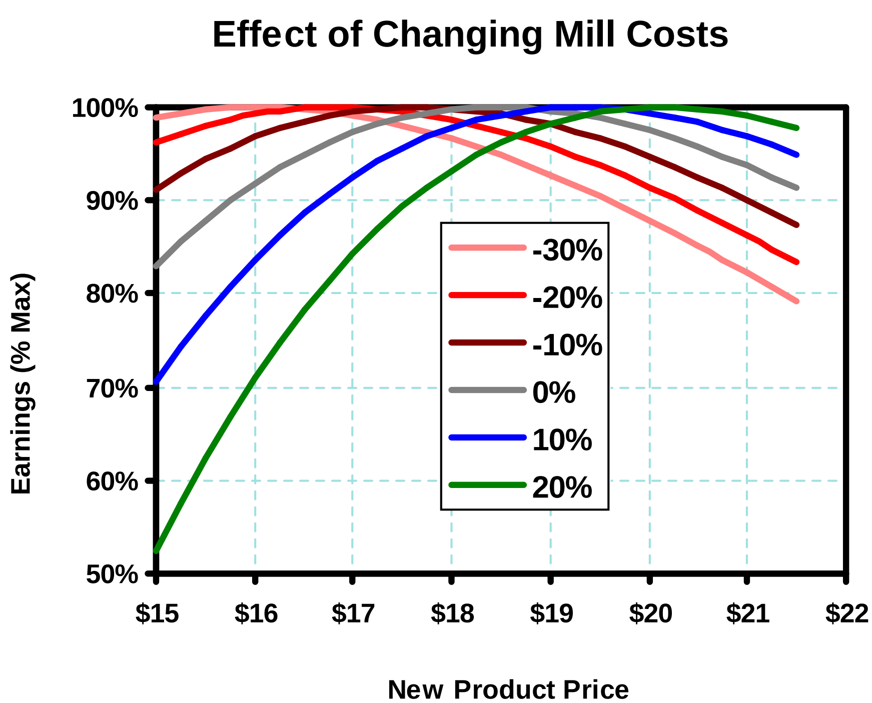
Industrial Type New Product	**High Value-in-Use New Product**
• Price sensitivity is usually underestimated due to measurement error.	• Price sensitivity is usually overestimated due to "sticker" shock.
• Manufacturing mill costs are typically overestimated due to start-up conditions.	• Capacity is often limited due to low initial yields and short experience.
• It is desirable to establish a competitive price position to induce trial and evaluation.	• High price conveys a desirable "quality" and status position.
• It is desired not to produce strong competitive reaction to either increase or decrease prices.	• It is usually desirable for a competitive increase in prices.
• It is desired to capture as large a market share as feasible to overcome slow penetration due to the qualification process.	• It is desired to "cream" the market by capturing the most valued customers first and then expand the market by decreasing price.

We often recommend the low price point for the industrial type new products while the high price point is usually preferred for the high value-in-use products. A typical chart for a new industrial product is shown below. Notice that in this case we have almost a 25% price range that can be considered. This is not unusual for industrial type new products with a low apparent price elasticity.

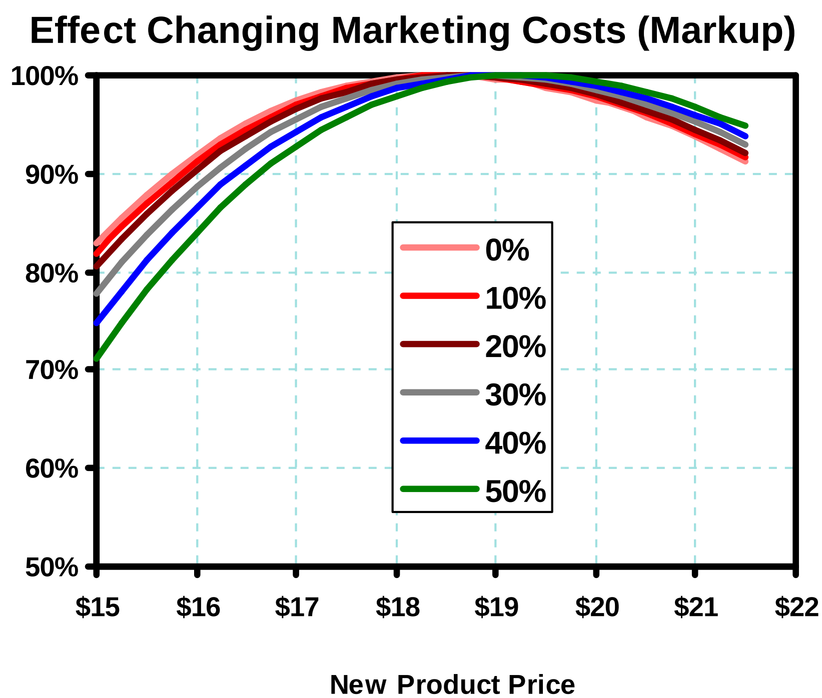
Increases in price elasticity will act to decrease the estimated optimum price as shown in the curves below. It is often useful to generate these sensitivity curves to illustrate the problem with actual data. Notice that with a 100% increase in elasticity there is almost a 30% decrease in the optimum price. While this is extreme, it clearly illustrates the problem.

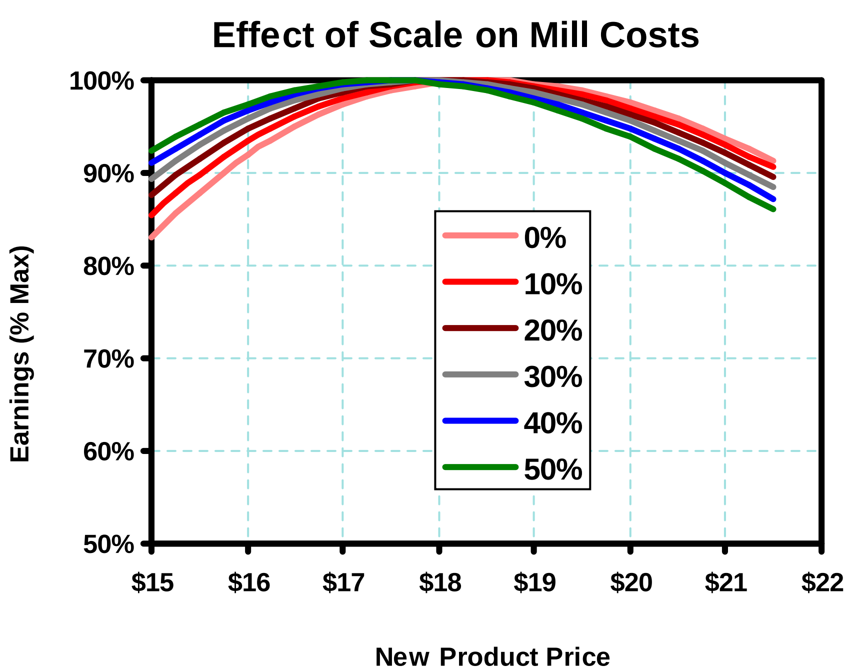


Similarly, a decrease in mill costs produces a major drop in the optimum price as shown below.

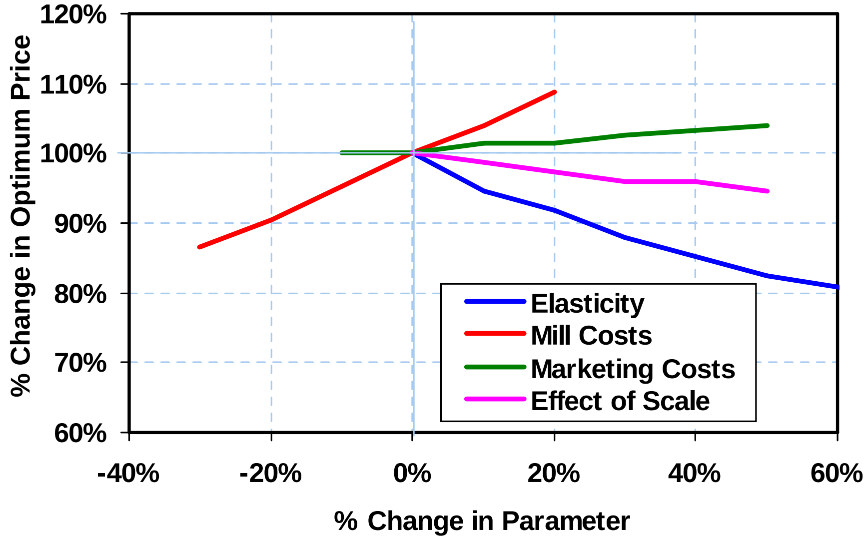


However, not all factors have similar impact. Changes in the marketing costs (product mark-up) and introducing of a scaling factor to account for the decrease in mill costs with sales volume do not change the optimum price significantly.





Below is a chart showing these effects. Notice that changes in price elasticity and mill costs have about the same general effect, while the other factors are significantly weaker.



These factors of overestimated mill costs and underestimated of elasticity act in the same direction to give a significantly lower optimum price. While we usually are unable to estimate these uncertainties, we can expect them. Therefore, to compensate, we generally select the low price point for conditions when they are expected. As shown on the table, in some cases the reverse is also true, where we expect overestimates of elasticity and underestimates of prices, these naturally lead us to the high price point. However, it should be noted that other factors need to be considered.

5.1.5. Price Premium

An alternative view of price sensitivity is to consider the price premium that a product can command over its competition. This is particularly important with the replacement of new products for older versions. In this case, the question is should the new product be introduced at a higher price. Price premium is also used as a direct measure of customer loyalty. The more that a customer is willing to differentially pay for a product, the higher is his meaningful loyalty. This approach allows for a distinction between “liking” a product or supplier and his willingness to put his money there.

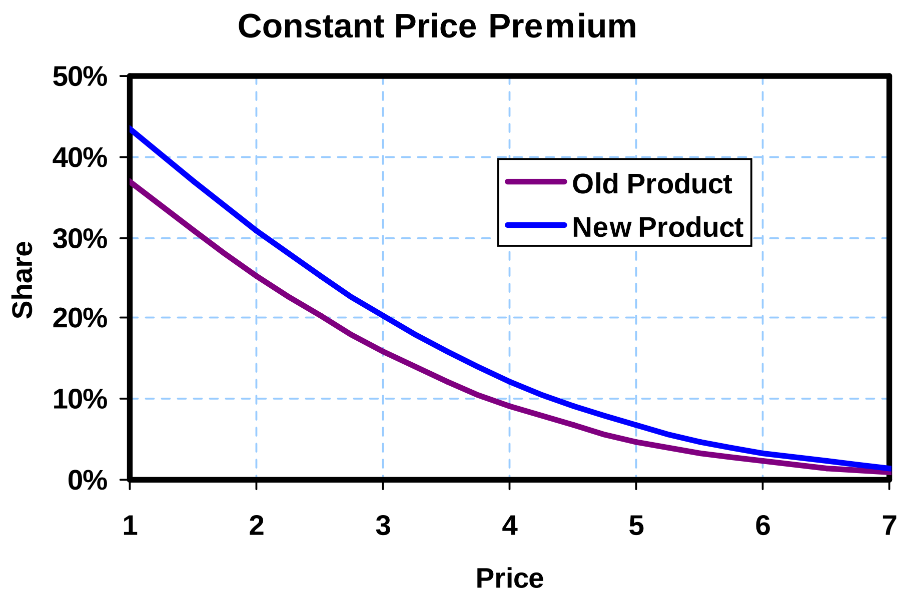
From a consumer behavior perspective, the price premium is the additional money that a customer is willing to pay to purchase one product over another[1]. Under this perspective, price premium is a distributed value among the population of customers. However, from a marketing perspective, the price premium is derived from the difference between the

[1] This presupposes that the process involves a series of single item purchases.

demand or price sensitivity curves for a product and its competition. Here the price premium is defined at each price or share point[2]as the difference between the curves.

5.1.5.1. Constant Price Premium

The traditional assumption is that the price premium is constant along the demand curve. The resulting typical demand curves with constant price premium are shown below.



It should be noted that the demand curve is expected to be upward turning or convex[3] in the lower portion of the demand curve. This is partially due to the asymptotic approach to zero share and high prices. The effect is to give an apparent tightening of the curves. However, in reality the horizontal difference between the curves remains constant.

5.1.5.2. Constant Proportional Price Premium

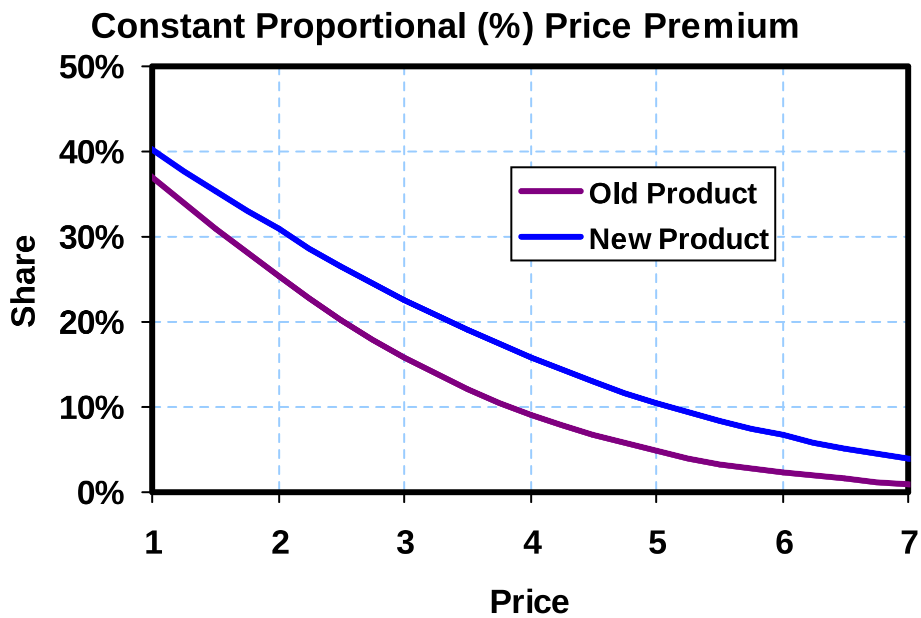
Alternatively, it is sometimes assumed that there will be a constant proportional price premium. That is, that there is a constant percentage premium that is maintained over the price range[4]. This situation is shown below.

---

[2] This definition is effective for both single, partial and multiple purchases, since it reflects the total market behavior.

[3] This indicates a positive second derivative of the curve (∂^2Share/∂Price^2)>0

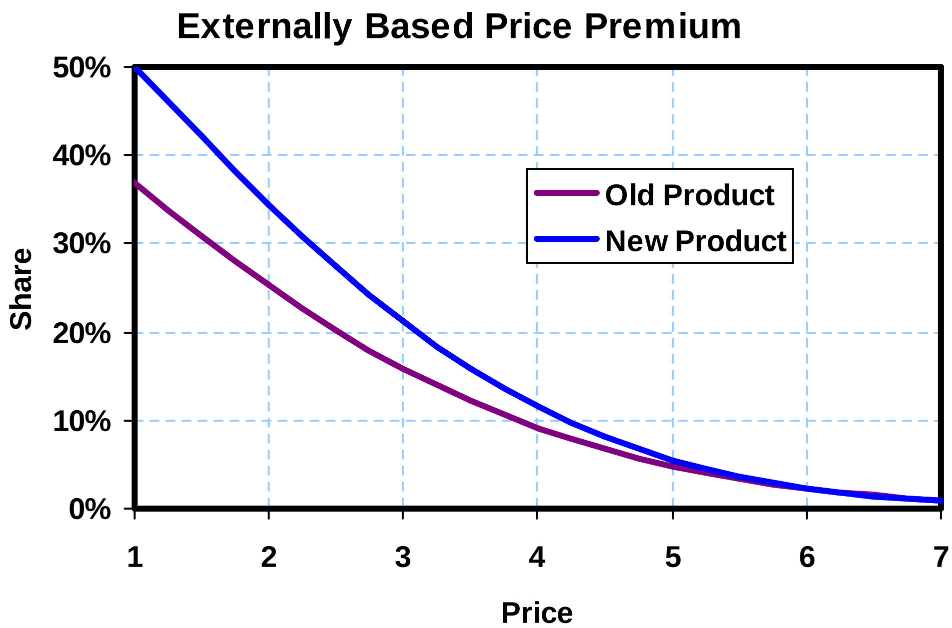
[4] This corresponds to a price premium that maintains a constant % or logarithm price differential. This type of process is motivated by the "Weber's" law of perception which relates response to the logarithm of stimuli.



This results in an increasing price premium with the increased selling price and decreasing price premium with increased share. This implies an increased willing to purchase the new product from the more “select” purchasers.

5.1.5.3. Externally Referenced Price Premium

However, in some cases, we find the opposite effect of decreasing price premium with higher prices. This may be due to the effect of alternative products, The price premium can be consider to be split into two parts, one related to the difference between the new and old version of the product, and a premium of both compared to other products in the market. It should be noted that the demand curves assume constant prices of alternative products. As such, the relative price premium captures the competitiveness against other products as well as between the alternative noted. At higher prices, much of the price premium of both products has been surpassed. As such, the differences between the products become increasing similar. The resulting demands in this case are shown below.



5.2. MARKET PRICE TESTING

The purpose of market or business testing is to determine the acceptability of a product in the marketplace. As a pricing research tool the procedure is carried out at a number of different price points. This type of activity is usually associated with the product launch and not typically considered a part of the standard marketing research activity. However, it is still one of the most powerful measurement procedures and is included here for completeness.

5.2.1. Introduction

Multiple price market tests have historically been a complex and involved process. The inception of the World Wide Web, however, has greatly improved the feasibility of market price testing directly into the market. Recently *amazon.com* had undertaken a pricing test using randomly changed prices on a limited set of products. Unfortunately, the implementation produced adverse customer reaction since it resulted in erratic multiple prices being offered to the same individual at different times. However, this is probably an implementation problem and not fundamental to the methodology.

5.2.2. Procedures

The procedures of market testing are aimed at reducing the outside influences and not disturbing the market. This usually involved carefully experimental designs. However, due to the expense involved only very simple designs are usually permitted. Historically price testing has been done in specifically characterized regions. This is designed to allow for almost simultaneous execution of the price tests. These regions have been selected mainly for advertising testing rather than pricing. But in general they are used interchangeably. The product is typically offered through the standard channel and accompanied by the expected promotional and advertising campaigns but at differing prices.

5.2.3. Unique Advantage

Market testing is the only behavior based experimental method of determining price sensitivity. As such, it is the best method to determine the actual demand for a product at various prices.

5.2.4. Limitations of Analysis

The conditions under which the market test is carried out are set. No effort is undertaken to determine the influence of factors other than product price. Forecasts of sales can be done only under identical conditions. This greatly limits the scope of the analysis. As such, market tests are usually carried out only immediately prior to full scale market launch or repricing actions.

5.2.5. Problems and Difficulties

This type of research tends to be extremely expensive (with the potential exception of the Internet situation) and is susceptible to several unique problems and sources of error:

- No two areas are identical nor are time periods and therefore, the results of pricing tests are often not clear. No matter how much effort is undertaken to assure identical conditions, they are not. While calibration does help, it does not provide sufficient assistance to remove this problem.
- Because of the cost and the lack of sufficient numbers of areas, fully structured experimental designs with adequate controls are usually not feasible.
- Competitors have been known to take actions designed to confound the results of price testing. The testing experiments usually require long preparation, which often signals competitors. Competitors then will undertake local promotional campaigns that destroy the validity of the experiments.
- The introduction of price points to the market sets expectations. Therefore, it is usually unwise to offer prices significantly outside of the foreseen price range. This greatly limits the use of the data and requires a high degree of extrapolation, in many cases to optimize prices.
- Using different prices in regions typically is disquieting to both the salesforce and marketing management. It is often uncomfortable to prevent a salesman from offering the lowest available price to his customers particularly if those customers become aware of the lower prices. This is particularly a problem with industrial products where geographic barriers are low.

5.2.6. RECOMMENDATIONS

Market tests are mainly undertaken for consumer packaged goods. The difficulty and expense associated with the technique limits its applicability. On-line research, however, may change the situation. Care will, of course, be needed to prevent the problems experienced by *amazon.com*. In any event, the procedure is only applicable to existing products with sufficient resources to undertake this type of research.

5.3. CONCEPT TESTING

The term “Concept Testing” is used in marketing research to cover the exploration of the feasibility of a board range of product and promotional materials. However, in the context of product development, “Concept Testing" refers to the testing of the price that customers are willing to pay for a new product against all other competition. We focus on the new product as either a unique product or one that can be considered to be offered in isolation. In this context it is considered to be one of the two major price research tools along with competitive or Choice Modeling.

5.3.1. INTRODUCTION

Similar to the goal of Concept Testing is to capture the price sensitivity of the product within a market segment. As the name implies the product does not have to exist. It is usually in a development stage. However, the product concept must be at a stage at which it can be fully described. The process consists of presenting a concept (or a series of concepts) to the potential customers and solicit their intent to purchase based on various price scenarios. The effectiveness of the procedure rests on the validity of this estimate to capture what the market is actually willing to do.

5.3.1.1. Commercialization Decision

Concept Testing is often used for new and unique products or when the direct marketing procedures are planned. However, because of its simplicity and flexibility it is also used to test new ideas prior to detailed development. In this regard, it is similar to other testing procedures, providing insight into the market behavior.

5.3.1.1.1. The Intent to Purchase[5]

While many products will attract interest, that interest does not assure purchases. The concept tests tries to capture the extent of interest to purchase. As such, the concept of likelihood of purchase and the extent of future purchases is critical.

5.3.1.1.2. Pricing

The focus of Concept Testing is on pricing. It is an issue of price where interest translates into action. Price is the reality of commitment to purchase. What is the correct price is critical.

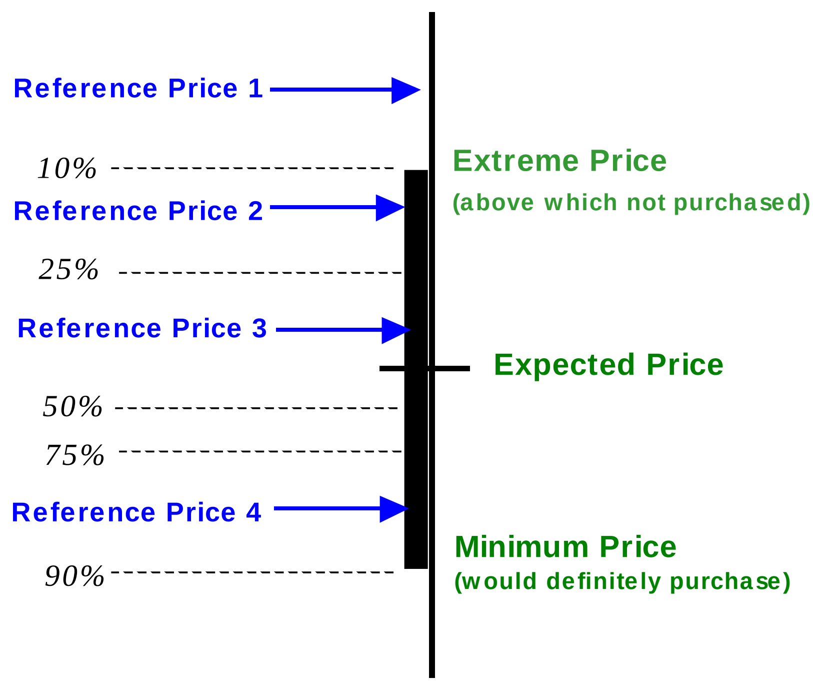
[5] It should be noted that intent to purchase is taken in a broad sense to mean intent to do the appropriate action.. For the case of physicians selecting pharmaceuticals, we can substitute purchase to writing prescriptions; or for hospitals it would be the likelihood to approve.

5.3.1.1.3. The Pricing Decision

The purpose of the exploratory market price model (based on Concept Testing) is to estimate the price sensitivity of new products or groups of new products.. While there are other factors including competitive prices and the believability of new product features that effects the market potential for the new product, these are not usually included for exploratory purposes. In addition to excluding factors, there is inherent uncertainty in all market models but particularly those involving new product concepts. These sources of uncertainty require us to recognize limitations in using relying solely on market models to set pricing policy. The purpose of the market models must be to provide insight into price sensitivity rather than the determination of specific prices.

Decision analysis based on Concept Testing involves identifying and testing a number of price points with the respondents. The underlying principal is that there exists a range of prices for which the respondent may purchase the product. This range varies from an Extreme Price where the product is viewed as too expensive to a Minimum Price representing the highest price that the respondent "would surely buy the product." The Expected Price represents a "standard or main reference" price of what the respondent is expecting in the market. That price may or may not be the center of the price range.

Alternatively, we can view the decision process to be inherently uncertain. As such, the price range represents a likelihood scale with the highest prices being most unlikely to purchase and the lowest the highest likelihood. Typically for Concept Testing both types of estimates are solicited from the respondents. That is, we ask the values of Extreme, Expected and Minimum Prices and we ask the likelihood of purchase against a number of reference prices.



It should be noted, that market models based on Concept Testing data can be applied to any product choice situation. This includes approving, specifying, reseller carrying, and writing of prescriptions as well as end-use purchasing.

5.3.1.2. Advantages and disadvantages

Perceived Attribute Value Analysis and Choice Modeling are the principal alternatives to Concept Testing for obtaining market-pricing information. Estimating optimum price with Perceived Attribute Value is notoriously inaccurate. It is based on the assumption that the value of a product is the sum of the values of its attributes. Choice modeling, on the other hand, is a viable approach for developing market simulators. There some key advantages of Concept Testing.

5.3.1.2.1. Simplicity and Fault Tolerance

Concept Testing is among the simplest methods to collect pricing information. For well defined product concepts, it can be added to other types of studies. This has allowed pricing information to be gathered during early development market research. The simplicity makes it particularly attractive for qualitative research where the interviews are already fairly lengthy.

5.3.1.2.2. Fault Tolerance

It is also fault tolerant in that it is difficult to “mess-up” the execution procedures or misinterpret the results[6]. This makes the procedure particularly attractive for international studies.

5.3.1.2.3. Telephone Executable

Unlike Choice Modeling and Perceive Value techniques, Concept Testing can often be executed as part of a simple telephone surveys. This makes the technique among the least expensive to field.

5.3.1.2.4. Multiple Offerings

While Perceived Value techniques and Concept Testing allow for the modeling of different situations, Choice Modeling does not, without heroic assumptions. This is particularly useful when multiple product concepts may be offered concurrently.

[6] However, it is not impossible to mess-up these studies. There is always something that can go wrong. In one study, the interviewer substituted an incorrect measure of use. In another, the interviewer used incorrect levels. In any case, the method is far simpler than Choice Modeling and where appropriate is preferred.

5.3.1.2.5. Lack of Competitive Action

However, Concept Testing has some limitations. Since only one product is shown at a time, there is no measure of the impact of competitive reaction.

5.3.1.2.6. Unrealistic Conditions

Concept Testing requires the presentation of a single product to the respondents. Unless this is inherent in the purchase process, this is typically an unrealistic condition.

5.3.1.3. Issues of Measurement: The Buying Situation

The key to all quality marketing research is asking the right questions to the right individuals in an appropriate fashion. These are the major issues in Concept Testing. There are two key questions:

1. Can the individuals that we interview tell us how they intend to react to a new offering in isolation of the other information?

2. Will these responses predict what the "market" will do?

5.3.1.3.1. Issues of Influence

Most major purchase decisions require the influence of multiple individuals; each performing a different role. Furthermore, the same individual may play different roles. This produces a problem in soliciting responses on individuals since they do not make the decisions total themselves. The standard purchase model consists of two phases: (1) specification and selection of the "consideration set" and (2) the selection of vendor. This covers both consumer products as well as industrial. For consumer products such as package goods, the first stage for the customer is the selection of outlet or retailer and the second phase is the selection of the product. For industrial products, engineers and users usually set the specifications and the buyers or agents select vendors and purchase the products. While we try through sample selection to get at the most important individuals in this process, it is usually unclear how successful we have been.

5.3.1.3.2. The Value Chain (Distribution)

The ultimate purchase of product usually requires multiple transactions down a supply or value chain. As such, the product will be purchased and sold several times. Pricing policies usually is only fully effective with the direct customers. Rare is complete control of pricing down the value chain achievable. As such, optimum pricing can only be approximate. Furthermore, research needs to be undertaken along the value chain to identify any points where the pricing policies will be ineffective.

5.3.1.3.3. The Consideration Set

Each group of purchasers considers a number of potential competitive products for "consideration". While Choice Modeling requires the specification of these competitive products, this is not the case in Concept Testing. Any set of "other" products are likely to be in the minds of the respondents. While this simplifies the design of the pricing exercise, it makes interpretation problematic.

5.3.1.4. Simulating the Buying Process

The key in selecting the procedure is its ability to simulate the buying process. The closer the pricing exercise resembles the purchasing conditions, the more reliable the results will be.

5.3.1.4.1. The Buying Situation

Concept Testing by its nature, resembles a "take it or leave it" buying process or the "negotiated price" situation with a single offering. This is not a choice situation where the respondent can choose among offerings. Nor does it resemble a custom contract or product situation where the buyer may choose among features. Because most industrial applications are more similar to the other situations, the results of Concept Testing should be considered limited. However, due to the typical timing between Concept Testing and commercialization, this problem is usually viewed as minimum.

5.3.1.4.2. Describing the Offering

The single most critical factor in Concept Testing is describing the product or offering to the respondent. This is the most difficult and most problematic part of the process. Often the features of the eventual offering are not fully defined during early marketing research. Furthermore, the position as indicated by the future advertising and promotion is usually not established yet. This provides additional uncertainty in the results. Typically, new concept features are over-estimated which results in an overly optimistic market response.

5.3.1.4.3. Describing the Application

As critical as it is to describe the concept, it is also important to describe the application or use of the product. Respondents often can conceive of multiple applications for the product. Each of these applications may rest on different features and values. Eventually, multiple offerings may be launched for different applications at different prices. Therefore, it is important to differentiate the applications for the concept.

5.3.1.4.4. Monadic Measures

Because of order effects and to better simulate a single offer buying situation, it is sometime useful to test only one price point for each respondent. This is referred to as monadic measures. The problem is that the sample must be split to accommodate all of the test points[7]. If there are four points needed, this means that you need four times the sample to yield the same precision. Its value lies in high face validity in cases where a single price will be offered. Typically, if monadic measures are to be used, other estimates of price will be executed after the monadic test.

5.3.1.5. Measuring Price

There are two methods of soliciting price sensitivity explicitly: (1) asking the respondent for a price or (2) requesting a measure of confidence or frequency of intent to purchase.

5.3.1.5.1. Price Self Explication

Asking the respondents to give a price is often considered very problematic in that it is soliciting a number that is not based on any comparison. Typically, we ask for at least three estimates:

1. Expected Price indicating what the respondent expects such a product to cost;

2. The Extreme or Maximum Price, indicating the upper limit of an acceptable price; and

3. The Minimum Price, indicating the price that the respondent would surely purchase the product.

The perceived problems with self-explication surround the potential of signaling on the part of the respondent. There are two directions of thought in this manner. First, since it is likely to be in the interest of the respondent to express a low price value in the hope of its effect on eventual pricing, the respondent is likely to give lower values. On the other hand, since the respondent is likely to wish you to continue development and commercialization of the product, he may indicate a higher than actual value. In either case the values are suspect. As noted below, we normally use both methods of measurement and normally find them consistent.

5.3.1.5.2. Likelihood of Purchase

The second method surrounds the concept of the likelihood of purchase. This is an estimate by the respondent of his confidence to make a future purchase. If multiple purchases are feasible with the product, the estimated frequency of future purchases or use can be used. However, likelihood of purchase tends to be preferred. It should be noted that likelihood of purchase is a measure of confidence not an occurrence rate. We tend not to use it as a probability measure and estimating the total market. We generally assume that it is a consistent ordinal measure of purchase intent.

---

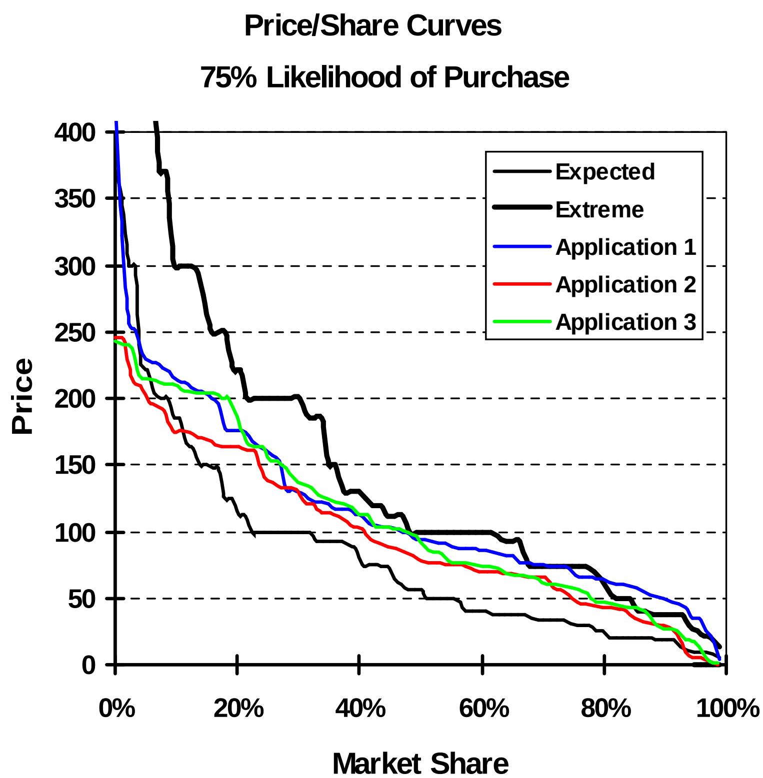
[7] This is similar to the problem of using split samples for full profile conjoint.

5.3.1.5.3. Market Profiles

The simplest method of viewing the data is in the form of profiles that give the share of the respondents that had indicated a price value or less. This is shown on the chart below. Note that this is by definition a monotonically decreasing function that starts at zero share at high prices and asymptotically approaches 100% share at low prices.

5.3.1.5.4. Multiple Measures and Multiple Applications (Segments)

The figure below shows typical data for the Expected and Extreme Prices along with the "reasonable value" prices for three applications. The range between the expected price and the extreme price indicates the acceptable price range[8]. Note in this example that the specific applications are similar to the expected curve at high prices and the Extreme Price curve at low prices. This reflects insensitivity to price at the lower price range.



It must be recognized that vertical (share) positions do not represent the same respondent. A respondent may be in the lower 10% of Minimum value and within the upper 10% in the Extreme Price. This would indicate a much larger range than for most respondents; however, it is not infeasible and does happen. The curves or profiles represent the price distribution and a measure of respondents' demand.

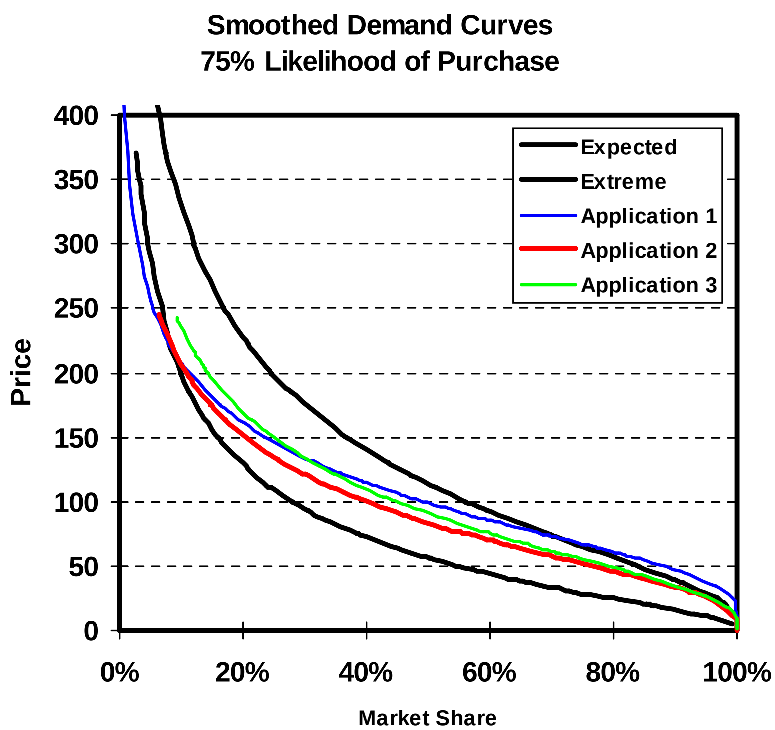
[8] Note in this example that the specific applications is similar to the expected curve at high prices and the extreme price curve at low prices. This reflects insensitivity to price at the lower price range which is typical of pharmaceutical products described in this example.

5.3.1.6. Smoothing the Data

The chart above shows the "raw" data taken directly from the responses of the survey. By its nature, this type of data is "noisy"; indicating sharp changes. This is particularly a problem with small sample sizes or when there are large "preferred or quantized" price points. It is useful to smooth the data by fitting it to a number of possible demand models including:

- Exponential distribution;
- Gaussian (Normal) distribution;
- Log-Normal distribution; and
- Logistic distribution[9]

Typically an exponential or log-normal distribution is used (generally it is the log-normal distribution)[10]. The resulting demand curves are more easily interpreted as shown below.



[9] The logistics is a "S-shaped" or sigmoidal distribution which is very similar to a Gaussian normal distribution but with a simpler mathematical form. This allows its use in a particular form of nonlinear regression (*Logit Regression*)

[10] The exponential and the logistics distributions can be fit using a pseudo-linear regression (linear regression on transformed variables). The Gaussian and log-normal require a nonlinear regression. Both types of regression can be done on *EXCEL*; linear using standard formulas and the nonlinear using *SOLVER*. Alternatively, smoothing can be done within a statistical package (*SYSTAT, SAS, or SPSS*)

5.3.1.7. Quantized "Preferred" price points

A major disadvantage to smoothing is the loss of the preferred price points. These are points where the market expects transitions. These are sometimes referred to as "Quantized" price points since prices tend to exist on these discrete levels. The problem with smoothing is the loss of that information. It is critical to review the distribution for that information and to not rely solely on smoothed curves.

5.3.1.8. Question of Quality and Position

High prices can confer an image of high quality and similarly low prices can confer a "low quality" position. This can happen irrespective of the performance or consistency of the actual offering. Under these conditions, low price may not result in higher sales. In fact, it is generally expected for product categories (functions such as apparel) to have a skewed price-point distribution with low share at both extremes. Low share at low price reflects poor quality and low share at high prices reflects price sensitivity.

5.3.1.9. The Price Point Consideration Sets

The price point may effect more than the perception of the product. Some products such as pharmaceuticals may be used either as routine (first line) or as backup treatment. Similarly, products may be excluded from the consideration set because the prices are perceived to be out of range.

5.3.1.10. The Van Westendorp Method [11]

Peter Van Westendorp, during the 1970's, has proposed a methodology to explore the problems of quality driven purchases. As an economist, he took a value distribution approach consisting of the analysis of Concept Testing questions. The Van Westendorp method is design primarily for consumer products where the price is a major measure of quality available to the purchaser.

5.3.1.10.1. Questions

The following are the traditional questions used in this method. It should be noted, however, that they can and should be modified to reflect the nature of the product, its use, the purchasers and the applications.

1. At what price would you consider the product to be so expensive that you would not consider buying it?

2. At what price would you consider the product to be priced so low that you would feel that quality cannot be very good?

---

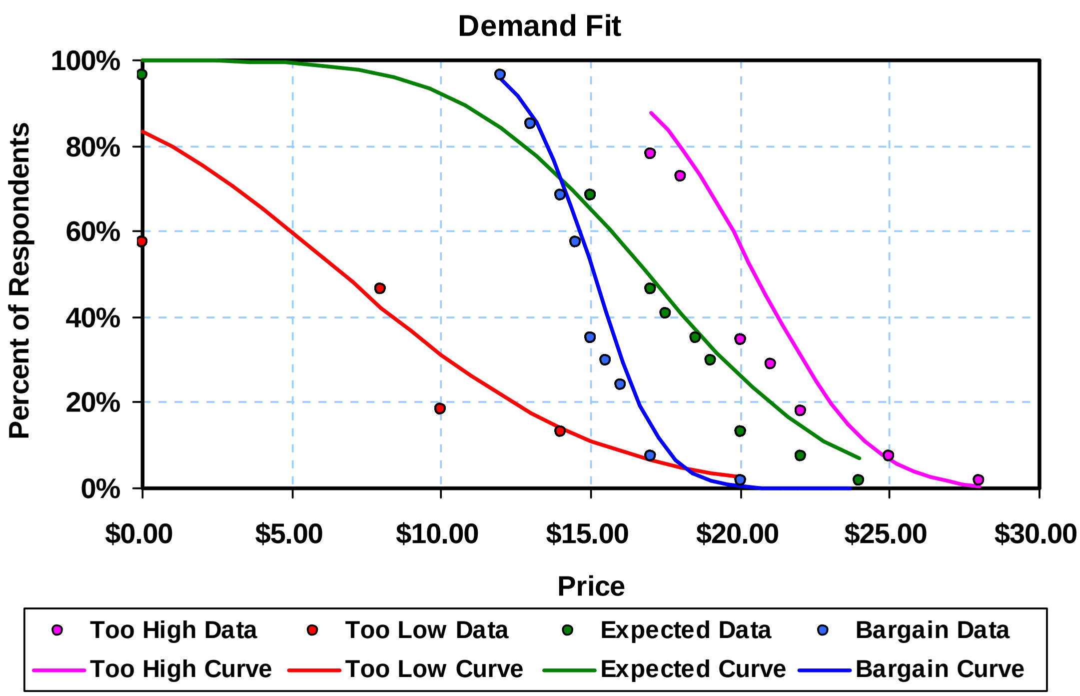
[11] Based on a description of the Van Westendorp Model by Pulse Analytics Incorporated, who advocates using it with the full profile conjoint method of perceived value measurement.

3. At what price would you consider the product starting to get expensive, so that it is not out of the question, but you would have to give some thought to buying it?

4. At what price would you consider the product to be a bargain - a great buy for the money?

5.3.1.10.2. Response Profiles

The response distributions are computed from the survey data. Usually this involves samples of at least 40 respondents and sometime several thousand, if many segments must be covered. In some case very few respondents may be used. This does however introduce significant error. he cumulative frequency distributions are computed and may be smoothed as discussed earlier.. These response profiles represent the fraction of the respondents that indicated a price or higher for one of the questions, as shown below.



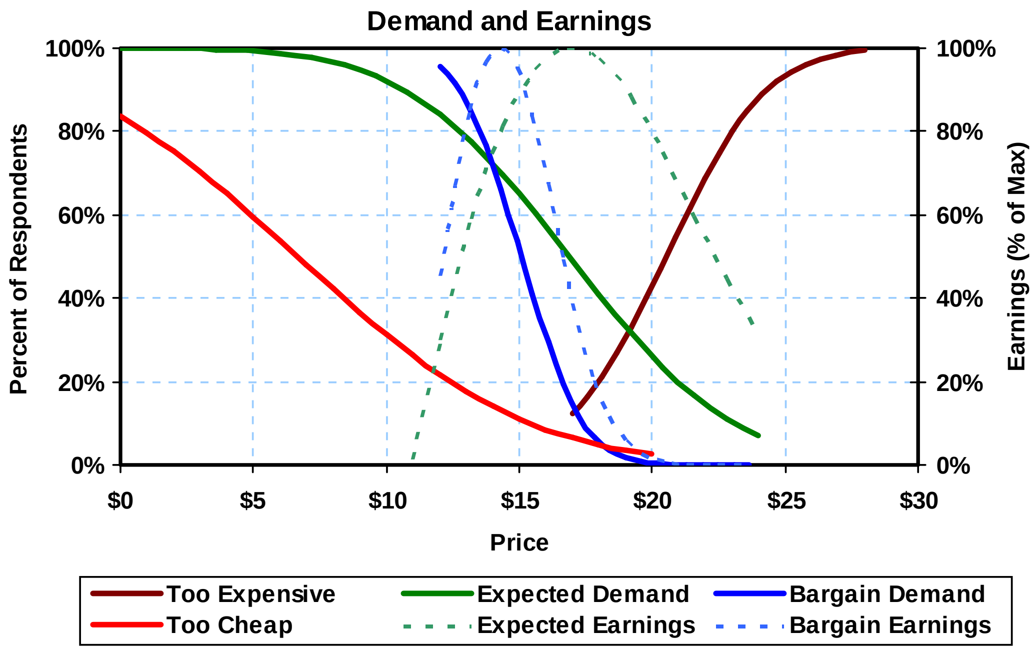
5.3.1.10.3. Analysis and Complementary Response Profiles

The range of prices indicated by the demand curves for each situation can be used to identify acceptable prices of the concept, as shown below. The furthest range is that bounded by the prices that are too low and that which is too high. A complementary profile[12] of the distribution of those that considered prices too expensive is used to show those individuals that would not pay the price or higher. The standard profile shows the percent of respondent willing to buy at a price or less. These curves are the light and dark red lines. The too high line is of particular interest in that it represents the "Price

[12] The complementary profile is equal to one minus the standard values.

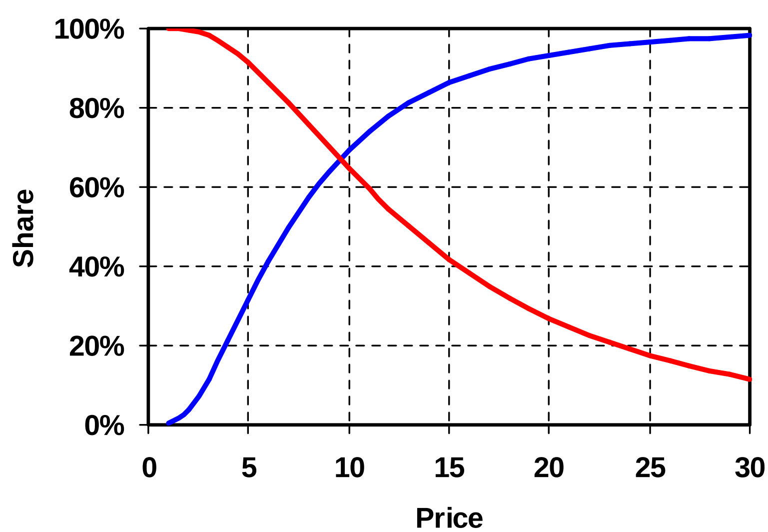
Shock" point for the respondents. Typically we do not want the "list price" to exceed this range since is would be a turn-off even before exploring potential discounts and promotional adjustments being offered.

Along with the extreme range are the expected and the bargain price ranges. These are shown as the blue and green curves. Earnings curves are also give assuming a cost structure usually the Cost of Goods Sold (COGS) and some marketing charges.



5.3.1.10.4. Events (The Salient Points)

The classic Van Westendorp method is based on identify the intersection of selected response and complementary response profiles. These profiles are based on cumulative distributions and are, therefore, either monotonically increasing or decreasing. Under these conditions there exists only one intersection point for each analysis.



The following are the traditional “Salient Points” based on the intersection of profiles.

- The Point of Marginal Cheapness (PMC) is defined as the price point where more sales would be lost because quality is questionable than would be gained from “bargain hunters.”

- The Point of Marginal Expansiveness (PME) is defined as the price point above which cost is a serious concern, where it is felt that the product is too expensive for the value derived from it.

- Optimum Price Point (OOP) is the point at which the same percentage of customers feel the product is too expensive as those who feel that the price is so low that the quality is questionable.

- Indifference Price Point (IDP) is the point at which the same percentage of customers feel that the product is getting too expensive as those who feel that price is at a bargain level. This is the point at which the most customers are indifferent to the price.

As we will discuss later there is a problem in this analysis dealing with cumulative distributions.

5.3.1.10.5. Price Ranges

Similarly, the traditional analysis identifies price ranges and issues based on the “Salient Points”. These include:

- Range of Acceptable Pricing (RAI) will be defined as the difference between the Point of Marginal Cheapness (PMC) and the Point of Marginal Expansiveness (PME)

- Level of Price Stress (LPS) occurs when the Optimum Price Point (OOP) is lower than the Indifference Price Point (IDP). Customers experience “Sticker Shock” with significant separation between these two points; they start to believe that the normal price is too high. This occurs most frequently for recent significant price increases. Under this circumstance, customers will seek alternative products or abandon the product altogether.

5.3.1.11. The Modified Process

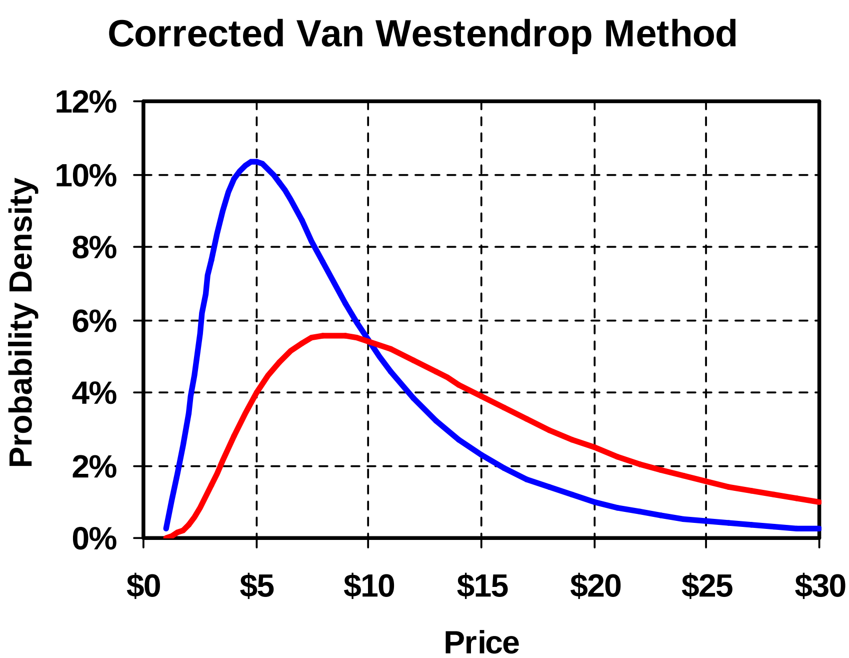
The philosophic basis for the Van Westendorp method is economic equilibrium. That is, that an optimum value results in the balance of two counteracting processes and exists where the marginal loss of one is balanced by the marginal gain of another. While the method is purported to follow this procedure, in reality is doesn’t since it uses cumulative responses rather than the density functions.

The cumulative responses give the total fraction of respondents who had indicated a specific price. There is no reason to believe that when the totals of two processes are the same; their marginal effects will be balanced.

5.3.1.11.1. Using the Intensity Profile

In order to obtain the actual marginal balance, one needs to consider marginal or intensity profiles. These profiles show the marginal increase or decrease in purchasers at each price. The intersection of these profiles will give the proper event that the general Van Westendorp method is seeking.

It should be noted from the chart below, that there maybe at least three such intersecting points[13]. However, two are trivial, the origin and at extremely high prices. Both of these points can be excluded.



5.3.1.11.2. Smoothing the Data

It should be noted that it is critical to smooth the data before computing the intensity profiles. Smoothing is best done using the cumulative profiles. The intensity profiles are then computed from the smoothed cumulative functions.

[13] There may be as many as four such points but that is very unusual with smoothed data.

5.3.1.11.3. Limits of Use

It should be noted, that the Van Westendorp method relies heavily on the importance of the implied quality value information of price. For industrial products, this tends to be less an issue and therefore, the method is not recommended.

5.3.2. SOURCES OF ERROR

Before developing the market simulators based on this type of data, it is important to review the sources of error around the market estimates. Note that the total error is the combination of all of these sources. This point is particularly critical when considering sample size. Traditionally, only precision, due to sample size, is considered in the evaluation of the statistical error. This is due to the fact that sample precision is the only error measure that can be statistically (quantitatively) estimated. However, it is rarely the overwhelming source of error.

5.3.2.1. Appropriateness

The most critical issue is the appropriateness of this procedure to estimate price sensitivity in regards to the buying situation. Concept Testing is often selected for its simplicity and flexibility not for its appropriateness to the buying situation. Typically, the buyer sees a number of competing products rather than a “take it or leave it” choice made by Concept Testing. This difference can be a significant source of error.

In general, we try to minimize this error by capturing the decision process during discussions with the respondents. Concept Testing is typically conducted as part of an in-depth interview. The interviewing process usually gives time to explore the decision process and to evaluate the appropriateness of the pricing exercise.

5.3.2.2. Accuracy

Accuracy is the general term for all types of instrument and fielding errors. It captures the difference between what we think we are measuring and what we get. This could be a huge difference.

5.3.2.2.1. Concept Description

Since the only knowledge of the product is often the concept description given to the respondent, that description is critical to the pricing exercise. Inflated estimates of properties, features and resulting benefits can exaggerate value and price sensitivity. Usually the product description is presented in written form to minimize inconsistencies. However, that description still may not agree with the actual presentation of the product at launch.

5.3.2.2.2. Order Bias

How the prices and options are presented to the respondents can effect the results. Typically highest prices are given first followed by lower prices. Alternatively, the exercise may be rotated to reduce this problem.

5.3.2.2.3. Interviewing Bias

One the problems in this type of pricing research is the potential for the respondents to give “adjusted” answers. It is sometimes assumed that if the respondents can “figure-out” the exercise they can either give lower priced results or alternative the results that they think the interviewer wants. In this case, it produces a biased result. While we have not found this to be a major problem, it does greatly affect the “Face Validity” of the procedure.

5.3.2.2.4. Measurement Error

Even if the respondents understand the exercise and are not affected by the various forms of bias, there are likely to give only approximate values. This is an inherent error due to the inability of the respondent to be more “precise” in their estimates.

5.3.2.2.5. Execution Error

The processes of transmitting information and collecting results are open to error. Interviewers may not be consistent with their product descriptions and respondent (or interviewers) may make errors in transcribing responses. This becomes particularly difficult when the interviewer is required to rotate the responses.

Some of these problems can be caught during the “cleaning” of the data. Inconsistencies of responses are often very apparent. It is usually recommended where feasible to observe at least some of the interviews to assure consistency.

5.3.2.3. Reliability

Reliability is a timing issue. Would the results of the survey change by the time the product is launched? Alternatively, would we obtain the same results with the same respondents at another point in time? Usually, this is a major problem when there is a long lead time between the research and the product launch. Since, Concept Testing is often done early in the product development cycle, this is a major problem. Typically, pricing research is undertaken several times during the product development process. Concept Testing is often used throughout the process and Choice Modeling used just prior to launch.

5.3.2.4. Precision

Precision is the statistical error due to sampling. There are two general sources of imprecision: (1) grouping of the respondents and applications, and (2) sample size.

5.3.2.4.1. Segmentation

The population of potential customers is almost never uniform and consistent. There is generally several applications and groups of customers. Typically, we group them as market segments. These segments can include the value chain and influencers in the buying process. Miss defining or excluding a critical segment can greatly affect the usefulness and precision of the results.

It should be noted that it is often desirable to use a quota or stratified sample (sampling by segment) to get a reasonable view of the market. This requires the use of weights in describing the market and developing the models and simulators.

5.3.2.4.2. Sample Size

Sample size determines "statistical" error or statistical precision. The larger the sample the better the resulting average would correspond to the total for the market. This error is usually estimated by a confidence interval over the results.

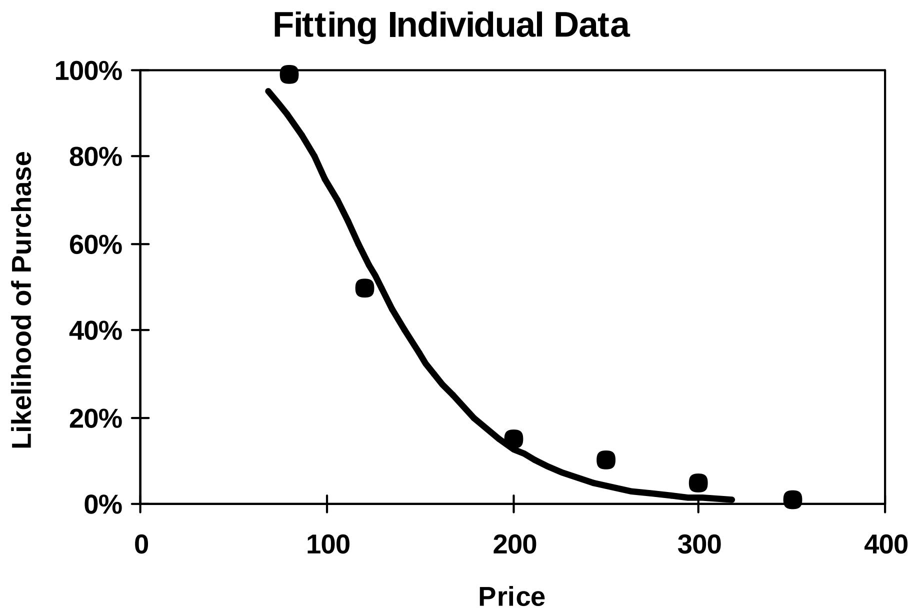
5.3.3. MARKET MODEL AND SIMULATIONS

Market models are developed from the total database. These market models provide forecasts based on a general smoothing of the total data set. Market simulators, on the other hand, are based on individual models whose results are aggregated to forecast market behavior. Because of the complexity of the market, in general, simulators tend to be more successful and allow greater flexibility.

5.3.3.1. Individual Modeling

Both market models and simulators are based on estimating procedures for "likelihood of purchase" on the individual basis. This usually requires development of a data smoothing response model. Typically, the respondent has given reaction to four price points. To increase the individuals' data available, we often assume that the Extreme Price is at 5% or 10% likelihood of purchase and the Minimum Price is at 90% or 95% likelihood of purchase. The Expected Price may or may not be included. Note that this data can also be obtained using the Van Westendorp method by assuming that the purchase price situations represent given levels of likelihood to purchase. For example we would assume that the expected price would represent 50% likelihood to purchase, while the bargain price would be 90%.

The individual respondents' data is used to fit a demand function as shown below. As previously noted, the likelihood of purchase is a measure of confidence not an estimate of occurrence. As such, the theory underlying the choice of the appropriate distribution is weak. There are five functions that are typically used:



5.3.3.1.1. Log Normal Distribution[14]

The log-normal is the traditional distribution for fitting price point data. The underlying thought is that the purchase phenomenon is Gaussian (Normally) distributed against the value and value goes geometrically (logarithmically) with price. The resulting distribution is generally in good agreement with data.

5.3.3.1.2. Linear Models

A truncated linear, straight line, function can be used. It is limited between 0% and 100%. However, this is usually not considered an adequate model.

5.3.3.1.3. Exponential Distribution

The exponential model can be fit using a modified regression procedure as mentioned earlier. However, it also does not do as well as the log-normal

5.3.3.1.4. Gaussian (Normal) and the Logistics Distributions

[14] While nonlinear regression procedures can be used to fit these models, it is feasible to convert both the share and the price attribute and use linear regression. This is a pseudo-linear regression procedure. The only difficulty is in the interpretation of the “goodness-of-fit”, the R-Square. That measure is on the converted coordinates.

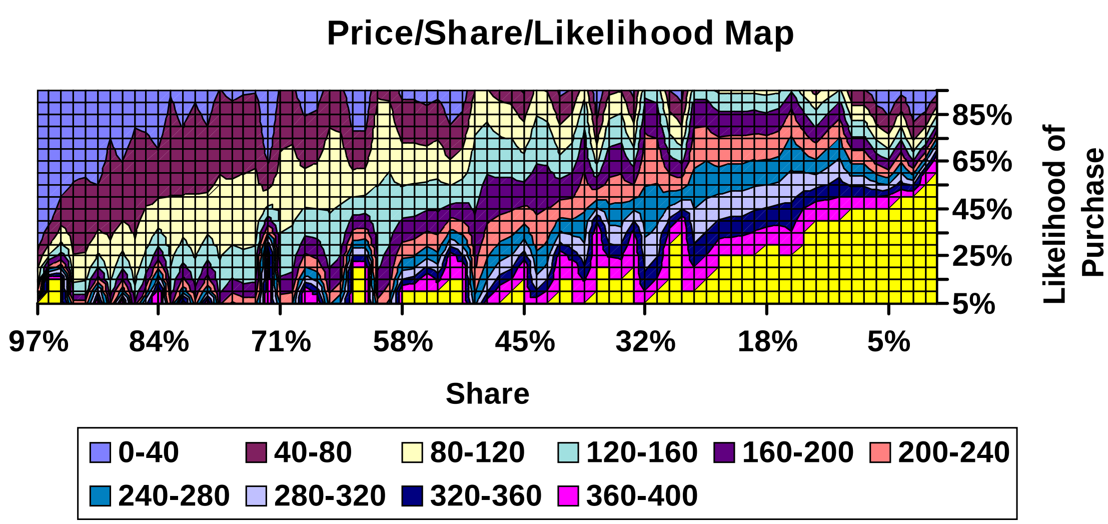
Standard “S-Shaped” curves including both the Gaussian and the Logistics distributions have been used. However, once again, they tend not to as well as the log-normal distribution.

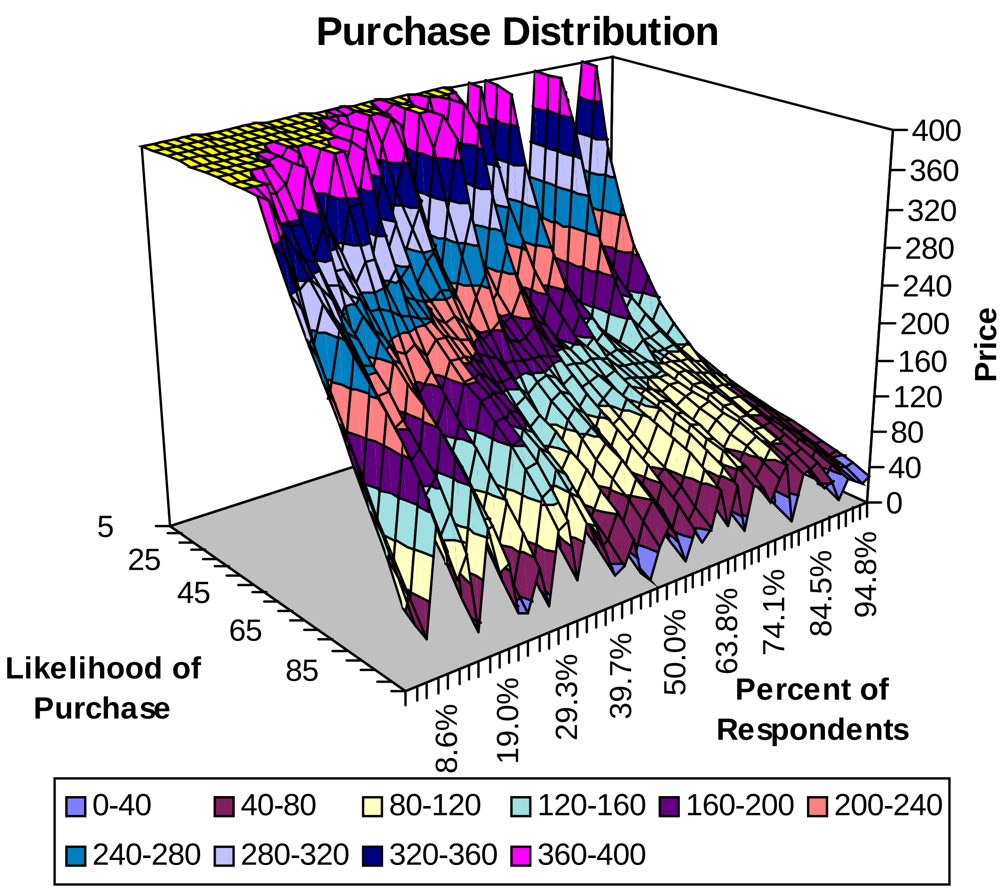
5.3.3.2. Missing Data

Occasionally, the test price points are beyond the range of acceptable prices. Under this condition the likelihood of purchase is either zero or 100% for all test prices. Under this condition, these respondents can be aggregated as sub-groups and handled separately. However, that would remove the respondents for consideration of multiple products. Alternatively, the Extreme, Minimum and Expected prices can be used to “guesstimate” the demand function.

5.3.3.3. Constructing Aggregated Market Models

In order to construct the market model the individual responses have to be merged to produce the aggregated model. This is shown on the two following charts. They represent the distribution of the responses that have been sorted by the Expected Price. These are three dimensional plots displaying the share as a function of the likelihood of purchase and price. The chart below is a contour map, which is the traditional way of displaying this data. The following chart is the same data displayed as a three dimensional perspective plot.

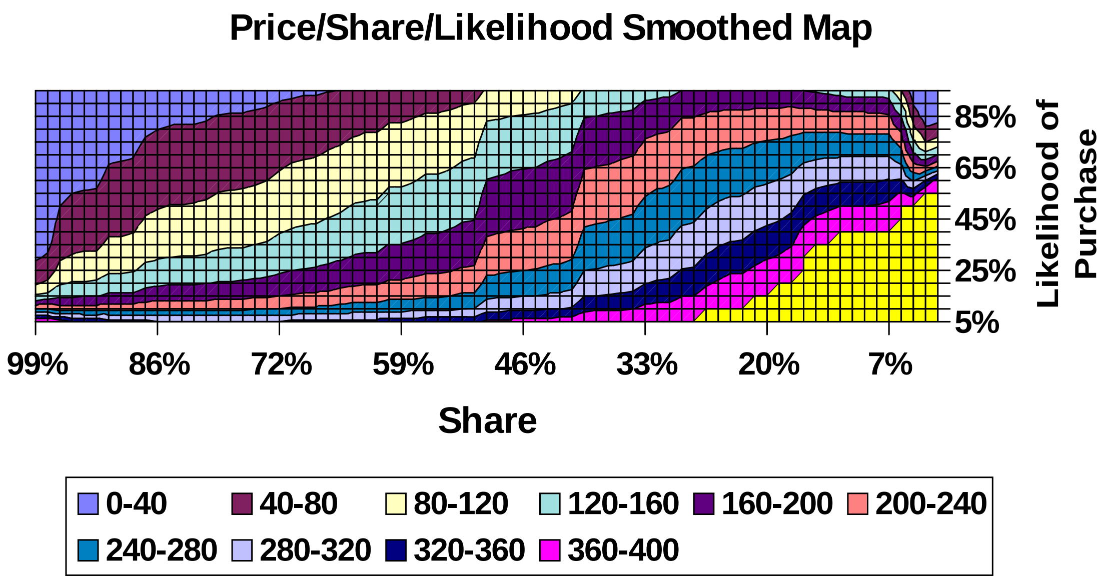




`

5.3.3.3.1. Smoothing Data

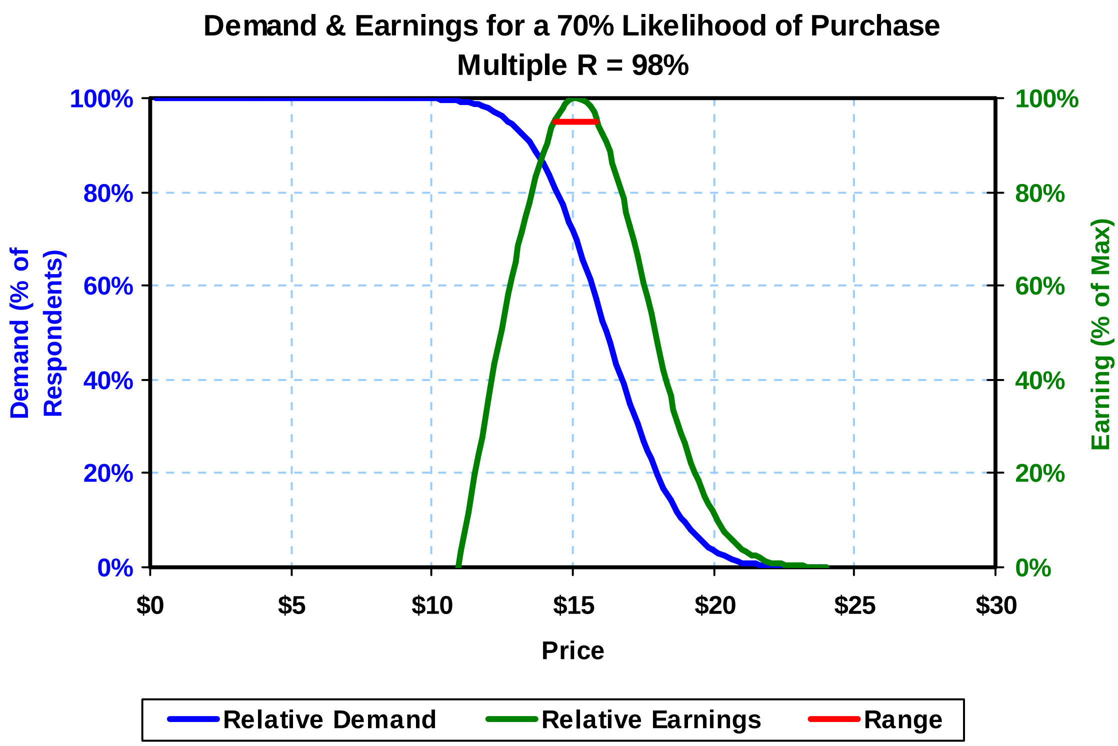
Unfortunately, the highly irregular function does not easily allow forecasting consistent market behavior. To construct an effective market model, these curves are usually smoothed again to give consistently changing values of share, price and likelihood of purchase. This is done by constructing a smooth relationship between the spread of the individual demand distribution and their mean value. The results are shown on the figure below.



As noted, this approach to building market models requires the introduction of a number of assumptions that are not needed in the development of market simulators. As such, market simulation approach is usually preferred to building market models.

5.3.3.3.2. The Aggregated Concept Pricing Model

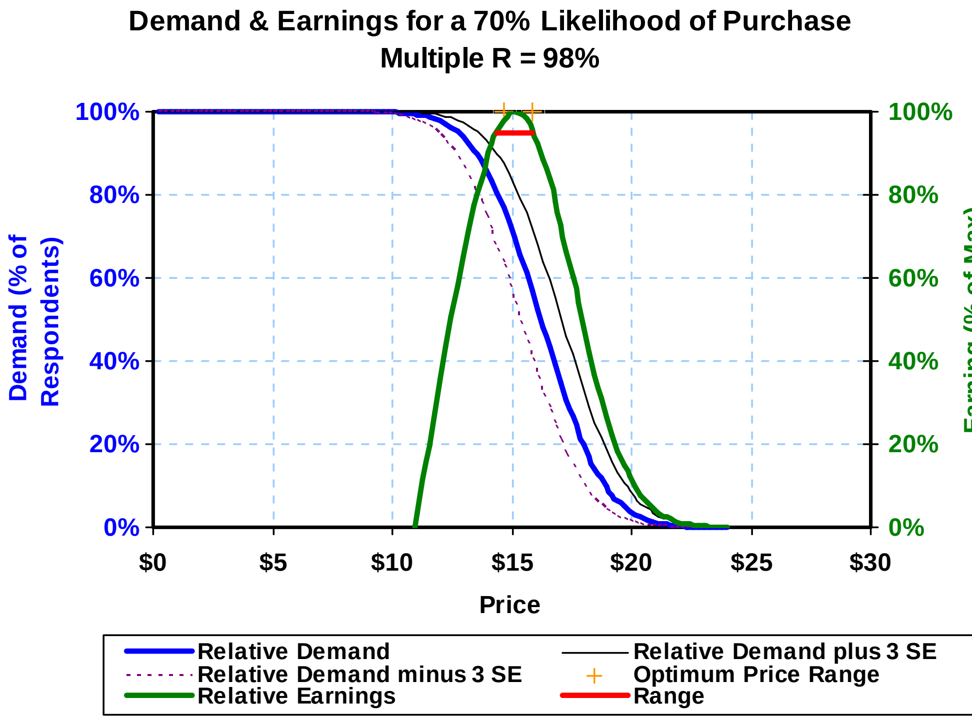
An aggregated concept pricing model can be constructed by combining the projected prices for each individual respondent given a assumed likelihood of purchase. This represents the demand for the product for the group of respondents. Based on this demand the projected earning is also computed given assumed costs as shown below for the case of a 70% likelihood of purchase. The optimum price is the maximum of the earnings and the range is set at some fraction of the maximum earnings. The indicated fit (Multiple R) is between the data and the smoothed normal distribution. This sane general form is used with choice modeling data as well as discussed in section 5.4.6.3.



5.3.3.3.3. The Confidence Bounds around Demand

A confidence range can be computed around the demand and the optimum price as shown below. The range of demand curves has been computed by assuming a number of standard errors from the mean. The effect on the standard deviation can also be included[15]. The range of optimum prices is shown as the orange crosses around the maximum earnings point.

[15] We assume that the standard error around the standard deviation is equal to the standard deviation divided by the square root of 2 times the number of respondents.



5.3.3.4. Multiple Offerings

While most Concept Tests involve a single product, in some cases it is desirable to test a number of products for the same application. In these cases, the client may wish to offer any number of the possible products in combination. It is the combination issue where Concept Testing offers significant advantage over competitive (Choice based) modeling. The market simulator provides a measure of likelihood of purchase. As such we can estimate the share based on those likelihood estimates. The consideration set can be changed in the simulator. This involves simply including various items in the comparison.

5.3.3.4.1. Multiple Purchasing Market Models

There are a number of ways of estimating share based on the likelihood estimates. The most common are: (1) Winner-takes-All and (2) Stochastic Value. Both of these methods are used with Attribute Evaluation and Perceived Value Modeling. In both of these methods the market is estimated by aggregating the estimated behavior of the individual respondents.

5.3.3.4.1.1 Winner-Takes-All

With the Winner-Takes-All assignment the respondent is assumed to select exclusively the product that has the highest significant likelihood of purchase. It is an all or nothing rule[16]. In most cases Winner-Takes-All is the preferred assignment method using Concept Testing data unless the sample size is extremely small.

5.3.3.4.1.2 Stochastic (Distributed Value)

With one of the Stochastic or Distributed Value models the purchases are assumed to be distributed among the products with a significant likelihood of purchase. That distribution may be based on a function of the likelihood of purchase or the product ranking.

5.3.3.5. Threshold and the No-Buy Option

One needs always to consider the No-Buy option. It is a rare occasion where the buyer is forced to purchase one of a limited set of options. If the likelihood to purchase is low, it is unlikely that the respondent will ever purchase the product. As such, a threshold is used to identify those cases where the respondent will not purchase. The choice of the threshold level will depend on the nature of the market and products. The typical simulator usually contains an option to set the threshold level.

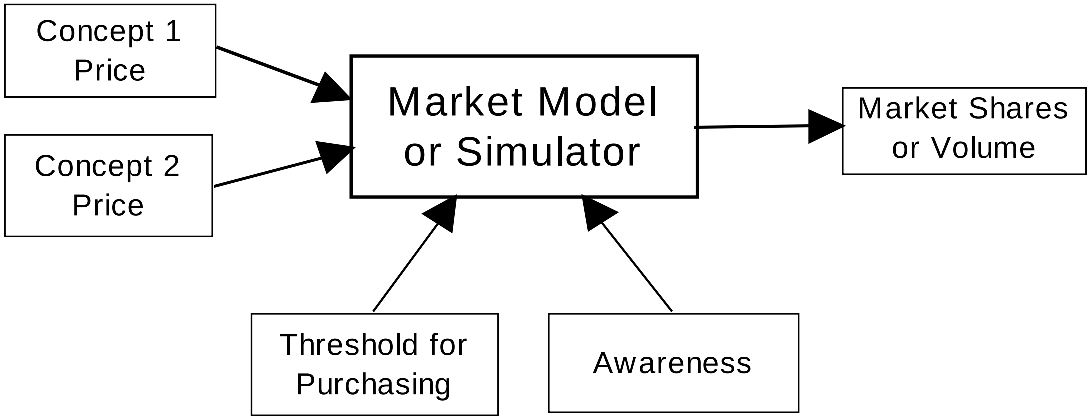
5.3.3.6. Awareness

Concept Testing is generally undertaken for new products and offerings. As such, only a limited portion of the market will be aware of the offerings. Where this is an issue, the market simulator has an option to adjust the share with awareness. It should be noted, that awareness level depends on the promotional effort.

5.3.4. MARKET SIMULATORS

The market simulators predict product share given competitive prices. For each product in each market segment we compute an estimate of its market share. This is a simple "black" box process:

[16] Ties are usually handled by splitting the purchase.



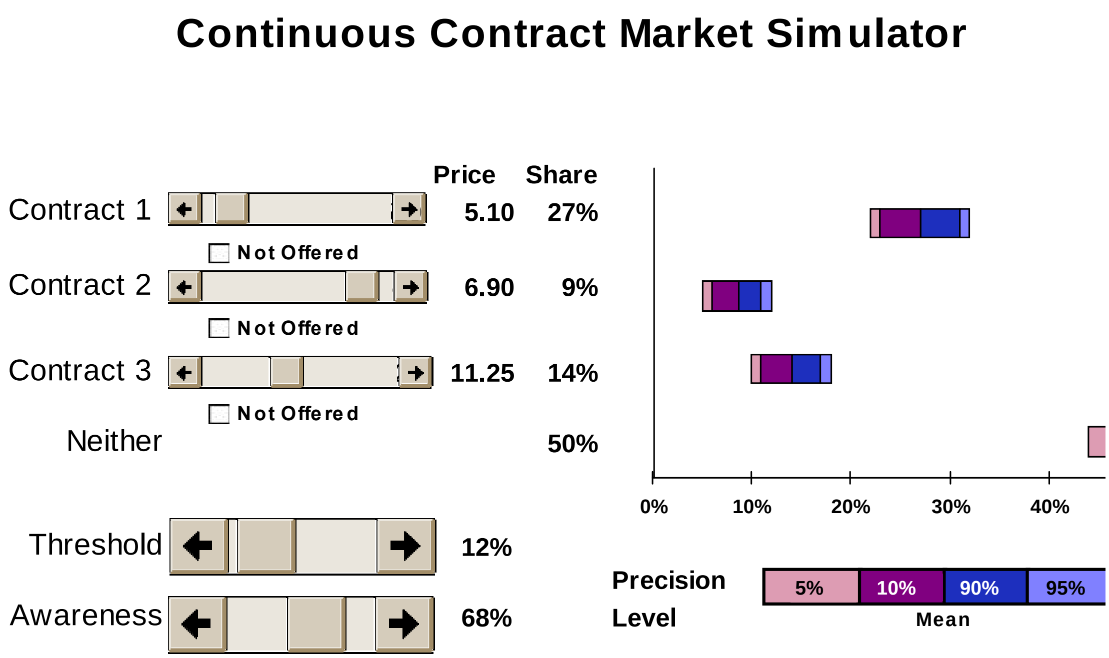
Concept prices, the threshold level, and the awareness level are entered into the simulator. The results are market share estimates for the concepts along with measures of revenue and potentially the earnings.

5.3.4.1. Discrete Models

The simplest of the simulators and the most conservative is based on discrete prices. These are the prices that have been tested in the survey. Entered prices are limited to only those that have been tested. Shares are computed usually with a Winner-Take-All rule, but other alternatives can be used. A typical user interface for an *EXCEL* spreadsheet is shown below. Prices are entered by choosing the appropriate buttons. Threshold levels and awareness can be changed by the slide bar. Note that products, or in the example below, contracts are excluded by selecting the N/A button.

5.3.4.2. Continuous Models

The continuous model allows for a broader range of possibilities. These include prices that are not only interpolated between measured values but also can be extrapolated beyond the tested price range. However, the simulator user interface does allow for constraining prices to within the tested range. A corresponding example of the continuous simulator is shown below.



5.3.4.2.1. Error Bounds (Precision)

It is often useful, particularly with small sample sizes to should the expected error around the share estimates. This error or precision range can be estimated from the binomial distribution. The following formula is used to compute the bounds in *Microsoft EXCEL*[17].

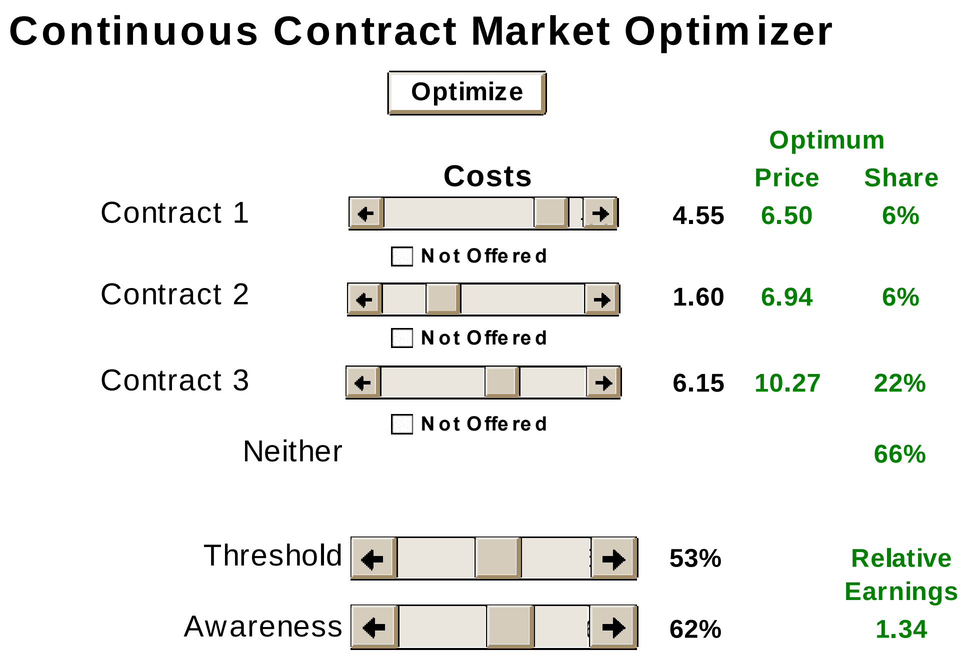
Error Bound = BETAINV(Level,[P õ N],[N - (P õ N)+1],0,N)/N

where **P** is the share of the market expected to choice the product, **N** is the sample size, and **Level** is the probability level. Typically we use 90 and 95% confidence intervals as indicated on the figure above.

[17] This formula uses the beta distribution that is a continuous version of the binomial and allows inversion.

5.3.4.3. Optimization

Optimum prices can also be computed. Optimum prices are based either on maximizing revenue or earnings. If earnings are used, estimates of the costs must be included. Optimization can be done with the *SOLVER* capability in *EXCEL*. In the case of this simulator shown below, the optimization has been put into a *MACRO* attached to the spreadsheet. This allows the optimization of multiple products. Alternatively, for a single product concept the earnings, revenue, and share can be plotted out to show the effect of various prices.



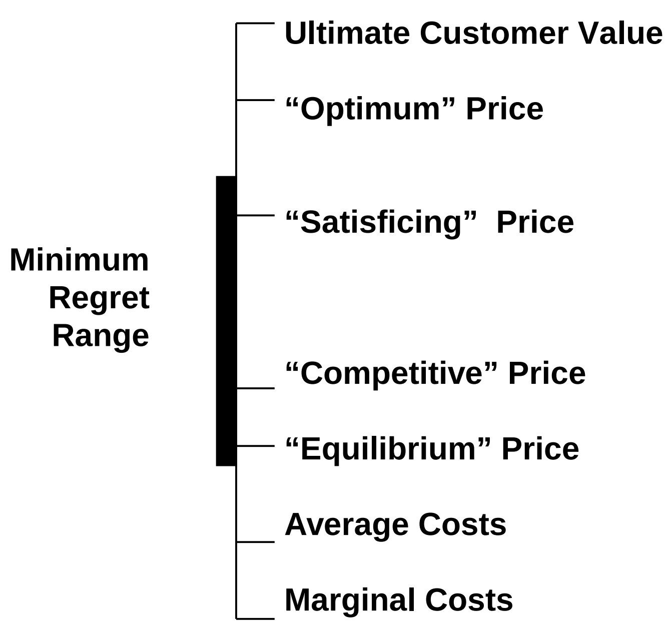
5.4. CHOICE MODELING

In this section, we examine market modeling using competitive pricing data. The experimental procedure referred to as "choice modeling" is the preferred marketing research technique when the key issue is brands selection among active competitors. If we can assume that competitors' prices will not change over time and that there will be no competitive reaction to the prices of the targeted products then we can use concept testing. Other methods are used when attributes and features are important in determining price.

5.4.1.1. The Pricing Decision

The purpose of the market price model is to capture the impact of pricing on the purchase decision. It must be recognized that they are potential factors other than the purchaser that will effect optimum price; these include: competitive reaction, costs, and the impact of the distribution channels. In addition to these factors, there is an inherent uncertainty in all market models. These sources of uncertainty require us to recognize limitations in using relying solely on market models to set pricing policy. The purpose of the market models must be to provide insight into price sensitivity rather than the determination of specific prices.

Effective price selection can be viewed as a decision along a range from the ultimate customer value down to the marginal cost of production. Along this range we can imagine a number of "sign posts" which indicate effective prices based on different assumptions. The purpose of market model is to obtain quantitative estimates of these measures from which we hope to gain insight into what the price of the product should be.



The methods to determine these "sign posts" are shown in the sections on Price Analysis Section.5.4.

5.4.1.2. Purchase Decision

The method of data collection as well as market modeling is based on understanding the purchase decision process. By initially selecting "choice modeling" as the basis of building the market model we have assumed that the fundamental unit of purchase is "brand" or clearly identified products. Furthermore, we have assumed that there are a small number of competing products.

5.4.1.2.1. Two Staged Process

In general, purchase decisions are thought of as taking place in two stages: (1) qualification, and (2) selection. For industrial type (business to business) and government type purchases this usually involves different decision-makers. Engineers and manufacturing personnel qualify a product or set specifications and purchasing agents determine the specific products. For consumer products as well as agricultural chemicals it is usually a single purchaser. In some cases, it is a complex mix of influences.

However, in all cases we consider the process to be two stages, first a selection of a "consideration set" of possible products, followed by its selection. Market price modeling only covers the second stage of this process. Usually, selection of the consideration set involves tangible and intangible features of the products. Measurement of perceived values of these products are handled using other methods and procedures.

5.4.1.2.2. The Consideration Set

The user of "Choice Modeling" assumes a relatively small set of potential competitors in the consideration set. A key design issue is the consistency of the consideration set among the targeted market. Do all potential customers consider the same products? If they do, and if the set is relatively small (less than eight products) that the design of the task is straightforward. Problems arise if we must consider individualized experiments with each respondent using a different consideration set. This is discussed in Section 5.2.3.2. A fundamental source of experimental error in this type of research is the incorrect identification of the competitive set of products. One can easily become "blind sighted."

5.4.1.2.3. Decision Makers Selection

As previously noted, there are often a number of individuals that influence the decisions. This is not only regarding the two staged purchase decision process, but also within each stage. Our concern is the selection of brands from the considerations set. Here too, there are likely to be a number of participants in the purchase decision. Normally, during measurement, we consider only a single individual. The key problem is to assure that the individual, which is identified as the decision maker, does, in fact, make the decision. Voluntary identification of influence is usually unreliable. However, it is often the only method available. Here again, incorrect selection of decision makers is a key source of fundamental error in measuring market price sensitivity.

5.4.1.2.4. Simulating the Decision Process

If the measurement process is viewed as a hypothetical exercise by the respondent, it is unlikely to reflect his actual behavior. A key objective is, therefore, to make the experimental process appear to be as close to the purchasing decision as feasible and still obtain sufficient information to build the model. This involves a number of considerations:

- Face Validity – The task that the respondent is asked to perform should look like the purchase decision, otherwise it would be viewed as hypothetical.

- Limited Exposure – The number of products and scenarios that the respondent is asked to consider should be kept to a minimum. Large complex tasks tend to tire the respondent producing unreliable results. Some researchers seek to reduce the exposure to only one scenario. This is referred to as a monadic test.

- Realistic Scenarios – If the prices or the selection of products (brands) are not within reason, the exercise is likely to be viewed as hypothetical. This may greatly effect the ranges and acceptability of designs.

- Simplicity – Purchasers abhor complex decisions. In general, purchasers seek buying situations that they feel in control. If the experimental procedure is excessively complex, it will be viewed as hypothetical.

5.4.2. PRICE MARKET MODELING

The price market model predicts a volume of products sold given the its price and the prices of the competing products. The potential buying process can be viewed as extremely complex and the resulting modeling tasks infeasible unless simplifying assumptions are made. The process of developing the market models is one of introducing appropriate simplifying assumptions. The process of development starts with the general model. This is shown in the following relationship.

$$\mathbf{Volume_j = Function\ (P_i \mid i = all\ products)}$$

An even more general form would be a function of volume of a product being predicted by a function of price. Several kinds of functions are used to predict sales; however, the simplest is the linear (or straight line) relationship shown below.

$$\mathbf{Volume_j = S_j \times P_j + T_j + \sum_i X_{ji} \times P_i}$$

where $\mathbf{S_j}$ is the price sensitivity of the product **j**, that is it represents how the volume of product **j** changes with changes in its price $\mathbf{P_j}$. $\mathbf{X_{ji}}$ is the cross sensitivities representing how the volume of product **j** changes with changes in the price of the competitive products and $\mathbf{T_j}$ is "intercept" which represents the volume of product **j** if prices were equal to zero. This type of model is often displayed as a matrix in the following from:

	Product A	**Product B**	**Product C**	**Product D**
Intercept	$\mathbf{T_a}$	$\mathbf{T_b}$	$\mathbf{T_c}$	$\mathbf{T_d}$
Product A	$\mathbf{S_a}$	X_{ba}	X_{ca}	X_{da}
Product B	X_{ab}	$\mathbf{S_b}$	X_{cb}	X_{db}
Product C	X_{ac}	X_{bc}	$\mathbf{S_c}$	X_{dc}
Product D	X_{ad}	X_{bd}	X_{cd}	$\mathbf{S_d}$

The intercepts are the first row values, the price sensitivities are the diagonal values, and the cross sensitivities are the off-diagonal values. With a standard linear model of this type the sum of the cross sensitivities down a column is equal to the value of the product price sensitivity. This is simply a volume balance where the loss of volume from one product must be obtained by the product causing that loss.

5.4.2.1. Volume Models (Growth)

Volume models forecast the actual volume of product sold. It captures the potential changes in the total volume of the market with decreasing prices. There is usually significant uncertainty as to the size of the total market and therefore, these models are usually tied to some standard size or they are calibrated to give "reasonable" results. Methods of calibration are discussed later. In this approach the total forecasted volume is not considered to be constant. It will vary with price.

$$\sum_{j} \mathbf{Volume_j} \neq \mathbf{Constant}$$

Problems and Difficulties

The major difficulty in using volume models is that distinguishing between errors in market estimation by respondents and actual decisions to change the purchase rates. Even when respondents are asked to give share values, their total often do not equals 100%. Furthermore, there are often other factors that influence market growth.

5.4.2.2. Share Model (Normalized)

Because of the broad range of external factors that will influence the total market as well as inconsistencies inherent in price modeling[18], usually a share model is constructed. Under this condition the volume is associated with the market share and, therefore the sum of these sales volumes equals one hundred percent.

$$\mathbf{Volume_j = Share_j}$$

$$\sum_{j} \mathbf{Volume_j = Constant = 1}$$

5.4.2.3. Price Change Designs (Standardized)

Prices in models can be given either as specific monetary values or as changes from standard prices. We refer to cases where the prices are given as premiums and discounts as standardized designs or price change designs. The most important issue is how price is presented to the respondents. If monetary values are presented, analysis may be done either in terms of prices or in terms of price change. This, then, is only an analytical issue. However, if the data is presented as price changes, then analysis must be done consistent with standardized prices.

The underlying issue is how the respondents view price. Do they react to absolute price changes or percent changes? The problem lies in the variation in prices that the respondent sees in the market. If he responds to absolute price changes, these variations will effect those decisions. If, on the other hand, the response is to percent change then the presentation of price should have little effect on the buying decision. Typically, absolute price changes are presented to the respondent. Models, however, are constructed in both ways.

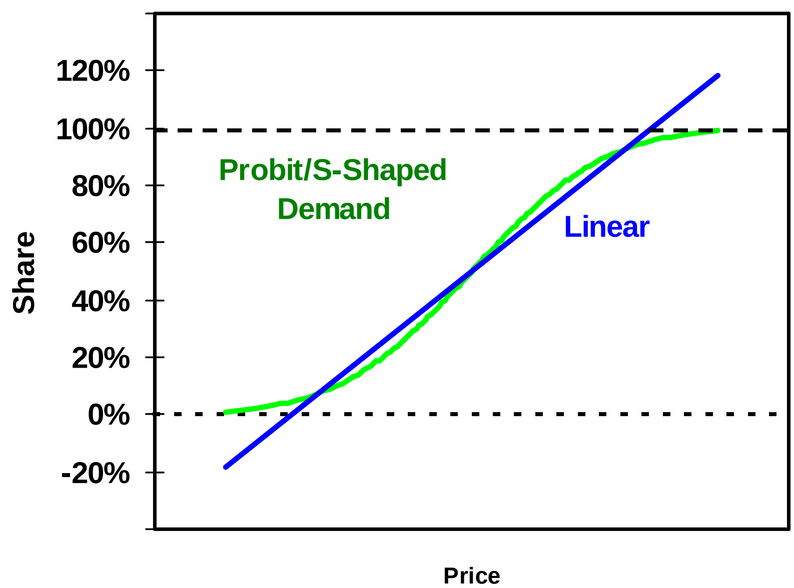
5.4.2.4. Non-linear (Probabilistic/Stochastic) Models

A key problem using linear models is that predicted share can exceed 100% or be below 0%. While this is less of a problem with volume models it is an unfortunate in share models. Furthermore, the linear model predicts a constant difficulty in increase market share throughout the range. This is unrealistic. One could expect increasing difficulty in pushing products out of the market or increasing share to 100%. Stochastic models impose a distribution effect where the share asymptotically approaches these limits. This is shown below using the normal Gaussian or Probit distribution.

---

[18] The overall pricing model consists of a number of separate and independently constructed models, one for each product. Each of these models contains their own uncertainty. In order to handle this "noise", the results are generally renormallized.

Linear and Stochastic Models



Several types of distributions can be used. However, in general symmetric probability distributions are typically used[19]. These include the Gaussian and the Logistics distributions[20]. Typically we use the Gaussian or traditional bell-shaped (S-Shaped) distribution for stochastic market modeling.

Problems and Difficulties

While the stochastic models have some advantages they also provide some difficulties in computation and the developing of effective decision support tools. Typically, both linear and stochastic models are developed. The difficulties include:

- While the Probit models typically give better "goodness of fit" (R-Square) measures, particularly for low share products, the differences over simple linear models is small and probably not statistically significant.
- The interpretations of the R-Square measures are difficult, since the regression is done with a transformed variable. This is particularly the case if Logit is used since it involves both a transformation of variables and a different (maximum likelihood) measure of fit.

---

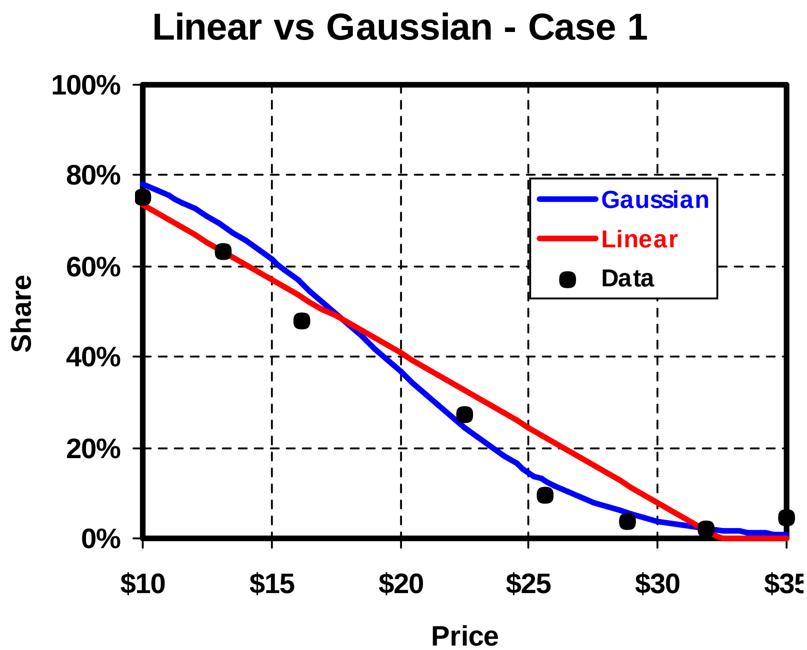
[19] Other distributions include Log-normal, Beta, and Gamma distributions. These are skewed distributions that capture different underlying decision mechanisms. The major difference between these distribution models for this application from the Gaussian is their asymmetry. However, usually, we are concerned with only the lower limit and therefore symmetry is not a problem.

[20] These two distributions are extremely similar though the logistics is of a much simpler analytical form. It is used mainly for "Logit" or logistics regression when the analytical form helps simplify the non-linear regression process.

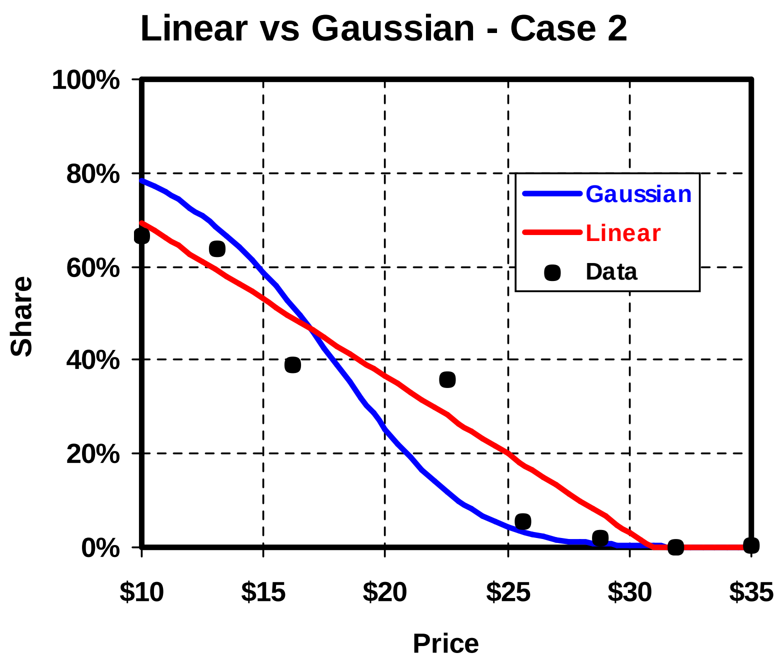
- Unlike the linear case, the coefficients in the Probit model are not readily interpreted. They do not represent changes in share but changes in Z scores.
- It may be difficult to explain the procedure to clients and may not be intuitive

5.4.2.4.1. Model Agreement

Ultimately, the best decision model must agree with the survey data. While it would be convenient that all situations should better agreement with the Gaussian (Probit) model than the linear, it is not always the case. Below are two examples of sub-sets of a similar population with the same product. Notice in the case below the data closely tracts the s-shaped curve.



However, this is not the situation in the next case. Here the linear model is in better structural agreement. This was particularly critical since the greatest deviation was over the most important pricing region of the curve.



This analysis is based on averaged values at given prices for the scenarios[21]. It should be noted that the actual model consists of a large number of additional terms that captured in these charts. As such, the agreement should be viewed only qualitatively.

The goodness of fit (R-Square) is less revealing. For the first case both curves had a very good fit with the linear indicating 98% of the variance explain compared to 97% for the Gaussian. For the second set, once again 98% of the variance was explain by the linear model but only 91% for the Gaussian. While there is appreciable difference between these last values, it would not be sufficient to indicate the degree of discrepancy.

5.4.2.4.2. Continuous (Volumetric) versus Discrete Choice

There are many ways to solicit data from the respondents that can be used to simulate the buying process. If there are multiple purchases or if multiple products will be purchase, the respondent would be asked to indicate what that distribution of future purchases would be for various pricing scenarios. However, in some cases, particularly with consumers, the purchase is a single choice action. This is referred to as a discrete choice process[22]. Analysis of the data is done either collectively as a market model or individually using a non-linear regression process[23]. If the analysis is done collectively,

[21] The number of available points depends on the experimental design. For the 16 scenario design, up to eight points are available. However, for the typical 12 scenario design only four points are computed. However, the increased number of point reduces its degeneracy. The values, therefore, not as well averaged over the prices of the other products.

[22] There are several variants on this theme involving choosing a first and second choice rather than only one.

[23] Logit regression is usually used. This involves using a logistics demand model and a maximum likelihood loss factor. This is discussed later.

the process is the same as using continuous decision data.

Problems and Difficulties

The major difficulty in using Discrete Choice is the larger sample size needed. The yes or no response tends to give a much higher standard error than does the continuous response[24]. Furthermore, with consumer exercises it is often necessary to collect the data monadically, that is testing only a single scenario per respondent. This greatly increases the sample size required.

5.4.2.4.3. Asymmetric Price Sensitivities

The standard linear pricing models provide for price sensitivity coefficients that are constants and therefore the same above and below the present or reference price. This assumes a "symmetric" response to price changes. Alternatively, we can assume that price sensitivity will be different for price increases and discounts. This introduces an additional term in the regression model. Because of the increased complexity, usually only the standard (symmetric) form is used. While the form of the pricing model is linear, asymmetric price sensitivities capture some of the non-linear price behavior.

The procedure can be extended to give two sets of all parameters depending on the price level. However, there may be insufficient data for that extensive a modification[25]. The regression results would fill the following table:

	Product A	**Product B**	**Product C**	**Product D**
Intercept	$\mathbf{T_a}$	$\mathbf{T_b}$	$\mathbf{T_c}$	$\mathbf{T_d}$
Product A	$\mathbf{S_{+a}, S_{-a}}$	X_{ba}	X_{ca}	X_{da}
Product B	X_{ab}	$\mathbf{S_{+b}, S_{-b}}$	X_{cb}	X_{db}
Product C	X_{ac}	X_{bc}	$\mathbf{S_{+c}, S_{-c}}$	X_{dc}
Product D	X_{ad}	X_{bd}	X_{cd}	$\mathbf{S_{+d}, S_{-d}}$

The pricing model is of the following form:

$$\mathbf{Share_a = S_{+a} \times Z_{+a} \times P_a + S_{-a} \times Z_{-a} \times P_a + T_a + \sum_i X_{ai} \times P_i}$$

$$(\mathbf{Z_{+a}} \text{ is 1 and } \mathbf{Z_{-a}} = 0 \text{ when } \mathbf{P_a} \geq \text{ Standard Price})$$

Problems and Difficulties

---

24 This is discussed in the section on Percent versus Standard Error

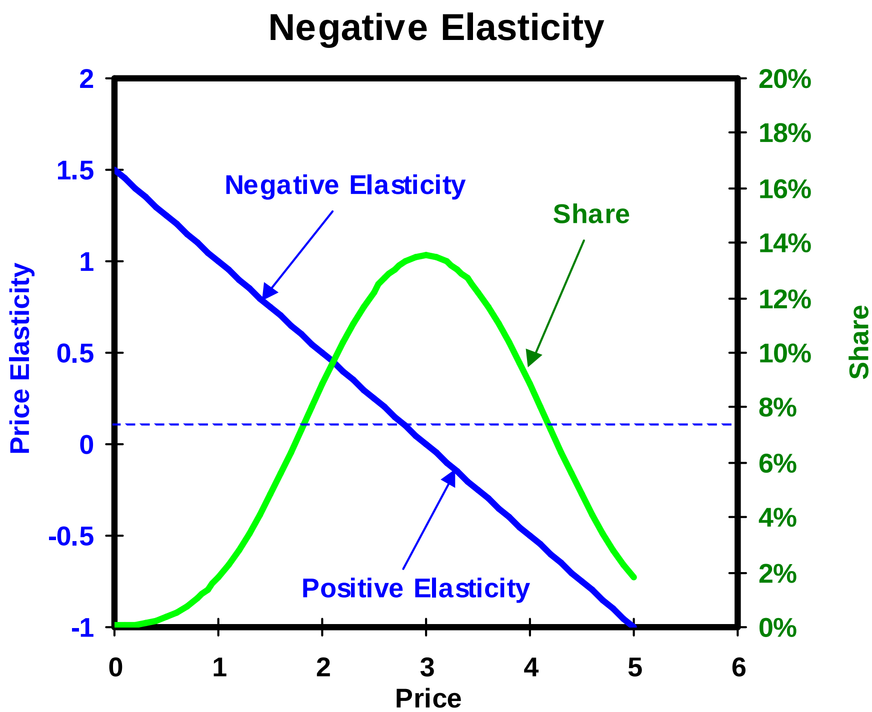
25 Typically we would like to have at least twice as many data points as the parameters being estimated. For a five product set, the single parameter model has six parameters, for the full asymmetric model would have 11 parameters that would require at least 22 scenarios.

While some marketing research firms have popularized asymmetric models, they have a number of problems, which greatly limit the appropriateness of their application:

- The transition point is arbitrary. If it is a natural point based on “street price” estimation may not be difficult. But usually, various parts of the market see different prices making the reference price problematic.
- Most price measurement designs do not have the adequate number of point above and below the reference for a reliable estimate of both price sensitivities.
- The non-linear, Probit, model tends to already capture the asymmetry of the demand curve. Asymmetric parameters merely add to the complexity not the accuracy.
- It is a difficult to interpret values and explain results to clients.

5.4.2.4.4. Negative Price Sensitivities

While it is unusual for industrial products to show negative price sensitivity where the sales volume increases with increased price, it is possible and fairly common among consumer products. This is often associated with price being the major source of quality information. When negative price sensitivities (positive price elasticities) appear, they do so only over a range of price, typically not over the total range. This results in a complicated, non-linear and non-monotonic share curve even if the changes in elasticity are simple. The following graph shows the linearly changing elasticity and the resulting market share. Note that when the elasticity is positive share increases with price while when the elasticity is negative share decreases.



Standard choice modeling is not well suited to handle this situation. Typically, only a single estimate of price elasticity is estimated as previously noted. Measurement of asymmetric price sensitivity can indicate this situation but only if the choice of price division is fortunate. Estimating multiple price points is an alternative but is difficult and has design problems. Typically "Concept Testing" is used in these cases. This allows for price point evaluation on the respondent basis as well as probing the effect of price on quality properties.

5.4.2.4.5. Price Point Estimates

While asymmetric elasticity estimation captures two points, it is feasible to capture a number of values. Typically three or four points are used. The procedure is similar to "Full Profile Conjoint" analysis in that the experiment is designed based on a few set discrete levels of price[26]. Because of the number of parameters being estimated, usually point estimations are done only on the price elasticities; cross elasticities are assumed to be constant[27]. The resulting elasticity matrix is shown below.

---

[26] The 12 scenario design in the Appendix is a fixed price point design where four price points are used for each of the products. This allows for each to show up three times. A 16 scenario design would allow balancing of the design where each variation of product price is compared with each of the other products.

[27] It is feasible to do point estimates on all elasticities and cross elasticities but these require a large number of scenarios.

	Product A	Product B	Product C	Product D
Intercept	T_a	T_b	T_c	T_d
Product A	S_{a1}, S_{a2}, S_{a3}, S_{a4}	X_{ba}	X_{ca}	X_{da}
Product B	X_{ab}	S_{b1}, S_{b2}, S_{b3}, S_{b4}	X_{cb}	X_{db}
Product C	X_{ac}	X_{bc}	S_{c1}, S_{c2}, S_{c3}, S_{c4}	X_{dc}
Product D	X_{ad}	X_{bd}	X_{cd}	S_{d1}, S_{d2}, S_{d3}, S_{d4}

Parameters are estimated using a Mixed Dummy Variable Regression where each price elasticity value is a discrete parameter [0,1] in the regression model while the cross elasticities are continuous variables.

Problems and Difficulties

While point elasticity estimation is sometimes done, the procedure has a number of problems that makes it not usually worthwhile and greatly limits its application, including:

- Reduced measurement precision. Few data points are actually used in the estimation of elasticities. For the 12 scenario design using four price points, this corresponds to only three data points.
- The prior selected transition points are arbitrary. It is necessary to select the price points at which the elasticities will be estimated, prior to the analysis. Unfortunately, that is often the most important information. This produces the dilemma of having only one or no points in the region of interest.
- The resulting model is ill-designed. The values of the elasticities point estimates are effected by assuming that the cross elasticities is the same in each price region. It is unreasonable to assume that this will be the situation.

5.4.3. Designing the Exercise

Designing the pricing exercises can be somewhat complex. There is need to reduce the number of price varying products and to accommodate constraints and conditions. The number of scenarios in the exercise is ideally proportional to the number varying priced products or parameters[28]. Fortunately, there are number of situations where the number of price varying products can be reduced.

5.4.3.1. None Price Varying Products

Occasionally it is useful to introduce products whose prices are assumed to be constant. The prices of these products are usually expected to have little impact on the share of other competing products. Basically, it is assumed that the volumes of the competing products will not depend on the prices of these "other" (none price varying) products and that the shares of these "other" products depend only on the prices of those products whose price vary in the design.

This is usually a convenience to handle "all other" products where there is little data. Local products and distributors repackaged goods can confound the experimental design. Often the best approach is to introduce these as "other" products. The regression matrix takes the following form where the "Other" product represents one of these none priced items.

	Product A	**Product B**	**Product C**	**Other**
Intercept	$\mathbf{T_a}$	$\mathbf{T_b}$	$\mathbf{T_c}$	$\mathbf{T_d}$
Product A	$\mathbf{S_a}$	X_{ba}	X_{ca}	X_{da}
Product B	X_{ab}	$\mathbf{S_b}$	X_{cb}	X_{db}
Product C	X_{ac}	X_{bc}	$\mathbf{S_c}$	X_{dc}
Product D	**0**	**0**	**0**	**0**

This situation can be modeled linearly, in a stochastic (Probit) form or even using asymmetric price sensitivities.

Problems and Difficulties

The major problem of using these independent products is that their prices do not affect share. The very purpose of the choice modeling exercise is to capture interactive price sensitivities. These products normally enter the markets because of a "competitive price window". These are usually thought of as commodity products. Yet, by modeling them as independent products, we lose the very information we seek. In general, it is not desirable to include these options if feasible.

---

[28] Typically we would want to have at least 2 times the number of parameters + one. The additional one covers the intercept in the regression model. However, as the number of parameter increases, we generally are unable to accommodate that increase number of scenario. Typically we set the limit at 16 scenarios with less than 11 parameters without resorting to splitting the sample.

5.4.3.2. Interactive Products

In some cases product prices are linked. This is particular the case in packaged goods where offerings may be different sizes of the same product or combinations of products. Under this condition, the prices of interest may include premium or discounts for selected products rather than the total prices. For example, product C is a combination of product A and product B. The price of product C would equal:

$$\mathbf{Price_c = Price_a + Price_b + Discount}$$

The price of product C may be designed never to be greater than the prices of product A plus product B. The statistical (experimental) design will not be the same as the respondents' scenarios. While the respondent will see each of the three prices for A, B. and C. The statistical design will be **$Price_a$, $Price_b$** and the **Discount**. This is not a particularly difficult modification of the standard procedures but adds additional complexity to the analysis.

5.4.3.3. Price Constraints

In many cases, particularly when the client offers multiple products, there is a "natural" ordering of the prices among these products. For example, if two sizes of the same product are being offered, the price of the larger package is always expected to be higher than the smaller one. Under these constraints there are two commonly used methods of response: (1) use percentages among these products, and (2) adjust cases where conflicts exist.

The simplest approach is to impose a percentage between the product prices. That percentage is allowed to vary sufficiently to cover the desired price ranges. But since the percentages are not allowed to exceed 100% typically, it will prevent the conflict. For example, generic or house branded products are almost always priced below those of branded products. In addition in some cases, where there are multiple product offerings by single suppliers it is often useful to set prices proportional to each other. The price for product B would be some discount on the price of product A.

$$\mathbf{Price_b = Discount}\ õ\ \mathbf{Price_a}$$

Product B will always be less than product A. This is similar to the size example mentioned above but these relationships can be much more complex and relate to a number of other products. It should be noted that the orthogonal design is based on the percentages not on the actual prices that the respondent will see. As such, the analysis is done in a different context than what was observed in the market. Generally, this has not been a problem in the analysis. However, it can make interpretation more difficult.

It should be noted that in some cases this is insufficient to assure that price relationships and constraints will be maintained. Price ranges may also be adjusted to eliminate cases where the constraints are violated. In a final effort to remove these problems, specific values are sometimes adjusted. Note that in this final action the intercorrelation and balance of the design may be compromised.

5.4.3.4. Price Schedules

When a product is offered on some type of installment or subscription payment, the corresponding fee can be included in the consideration set. It should be noted that the fee is some proportion of the underlying price. While this does not produce a conceptual problem, it can produce a difficult modeling issue. This factor must be introduced into the statistical model as a linear form in order to assure the ability to optimize prices. This is a distinction between the levers or measures of the model and the price values seen by the respondent. For example, it is often useful to use payback period for subscription prices. While this may be traditional for the respondent and useful in analysis, it would enter as a quotient in the analysis model and not yield a finite optimum value. Typically, an equivalent price is used in the design and converted to the payback period for presentation to the respondent.

5.4.3.5. Sweet Points

Markets often use prices in particular forms. These include rounding large prices to only two or three significant digit for capital products. Also it is often desired to use only "sweet points,", that is rounding to nearest 9 dollars or ending with a 95 cents with consumer products. This is a “rounding” process which forces values into these constraints. However, this process of forcing the values increases the intercorrelation. In many cases, this increase is relatively small. However, in some cases it can be significant. This difference is due to the size of the pricing value. Where the adjustment is a significant contribution to the total value, the effect is going to be large. It should be noted, here that if the pricing structure is different than the orthogonal design, as mentioned above, the new design needs to be recomputed and intercorrelations rechecked.

5.4.4. Regression Issues

The market pricing models are constructed by fitting the model parameters to the data. This is referred to as “Regression” analysis. There are a number of different approaches, models, and techniques that can be used. In this section, the issues underlying the statistical procedures are discussed.

5.4.4.1. Simulators and Market Models

Simulators are based on combining the forecasts from the individual respondents. On the other hand, market models consist of direct estimates of the market behavior. Functionally, market models are constructed by merging the respondent data to provide a database of market decision behavior. This is then used to statistically estimate the underlying model. To construct a market simulator, separate decision models are constructed for each respondent usually by regression analysis. The market behavior is then estimated based on merging the results of how each respondent is forecasted to behave.

There are several advantages for market models:

- Better Model Fit – In general, the fit of data to the model improves significantly when the data is aggregated. This is partially due the discrete nature of the decision process. The pricing models are based on incremental changes in sales with corresponding incremental changes in price. Individual behavior tends to be far more abrupt. Aggregating the data provides a softening of the response and a far improved fit.

- More Sophisticated Models – Since the modeling has to be done only once, more complex models are more readily used. Furthermore, due to the better fit between the models and the data, improvements in modeling can be more readily observed.

- Simpler Regression Forms – The aggregation of the data allows for use of Quasi-linear approaches rather than having to use non-linear techniques such as Logit regression.

- More Efficient Decision Support Systems – Because only one model is being used, the resulting decision support system is far faster and more compact than using a market simulator. This allows far more sophisticated computations with the data including a broad range of price analyses.

However, there are advantages to the market simulator:

- More Details of Market Behavior – Because the analysis is done on an individual basis, outlier (peculiar) behavior can be identified. This allows the analysis of exceptions.

- Simpler "Live Segmentation" – Often it is desirable to look at segments of the market based on demographic information in the database. While this type of "live" analysis is feasible with market models it is far simpler to construct with market simulators.

Because of the advantages of market models they are usually preferred over simulators.

5.4.4.2. Levers and Predictors

In the last section of these notes, model parameters were presented that were discounts or factors and not prices. That is the underlying model that forecasted volume and share were not prices but underlying measures. These measures are referred to as levers of the model. They are the adjustments that drive share. However, typically when a price-market model is developed it is desired to have share driven by price. Competitive prices are then referred to as the predictors. Note that in simple pricing models the predictors, prices, are also the levers of the models. Measures of sensitivity in these cases can be obtained directly from the computed regression models (coefficients). However, when this is not the case, and the levers and not the predictors are included in the regression models, other computations are necessary to provide the price-market model. In fact, the apparent examination of the underlying regression model coefficients may be misleading. They may show for example a positive relationship between the levers and share while after computing in the structural effects, a proper negative relationship will emerge. It is important to recognize that the exercise design and the regression model are constructed to allow for a proper estimation of the coefficients based on the levers. It is the lever values that are designed to be orthogonal and balanced, not necessarily the predictors.

5.4.4.3. Types of Regression

There are three groups of regression procedures that are used to fit the model parameters to the data.

- Multi-linear Regression – This is the traditional statistical method to fit data to linear pricing models including asymmetric models. It is based on finding the parameters to the model that minimizes the sum of the squared difference between predicted and given values.

- Quasi-Linear Regression – It is useful to consider a non-linear response of volume to price. One method of handling this is to convert the share values to normal "S-Shaped" curve ("Z") values. Price is assumed to be a linear function of this transformed share. Standard multi-linear regression is then used to fit the parameters[29]. This is typically used for estimating Probit or "S-Shaped" market models.

- General Non-linear Regression – In general, any reasonable and acceptable model can be fit to the data using non-linear regression. This is a family of curve fitting techniques where a non-linear model and any "loss" function can be used.

- Stochastic Regression (Logit) –This non-linear regression procedure is design to give an S-Shaped response from individual discrete choice data.[30] The results of this type of analysis are an estimate of the likelihood of a set of responses to the price model.

Computing non-linear regression is fairly complex and time consuming. Methods to

[29] This is referred to as Quasi-linear regression because the actual loss term used is based on a transformed least square factor.

[30] "Logit" regression is a form of non-linear regression where inverse S-Shaped function of a linear relationship is fit to data based on a logarithmic type loss term (Maximum Likelihood).

handle linear and quasi-linear regression are very well established. As such, these methods are generally preferred where feasible over non-linear methods.

5.4.4.4. Goodness of Fit

The degree to which the model fits the data reflects its internal consistency. The quality of the fit would reflect the ability of the model to explain the data. Unfortunately, we can not attribute all lack of fit to the quality of the model. Marketing research data is always suspect. Furthermore, not all decision process can be expected to be internally consistent. People behave in inconsistent fashions.

The traditional measure of "Goodness of Fit" is the fraction of the variance explained by the model (R-Square). It is a natural measure of fit for multi-linear regression. The linear regression process naturally maximizes the R-Squared. Other regression procedures may not. However, experience has indicated that in general, the R-Square is a good measure of fit. It is used with almost all models. As a general rule of thumb we prefer to have R-Squares above 80% for use.

5.4.4.5. Degrees of Freedom (Number of Scenarios)

A key issue is the number of scenarios that is needed to estimate the model parameters. Statisticians refer to this as the degrees of freedom as the difference between the scenarios and the number of parameters. While some statisticians wish as much as 5 and 10 to one, we have found it acceptable to have as little as 2 to one. However, we dare not go below this limit.

5.4.4.6. Respondent Considerations

The nature of the purchasing decision can greatly effect the way the data is collected. This effects the way the prices are presented, the choice and number of competing products and the number of scenarios.

5.4.4.6.1. Individual Street Prices

It is preferred to present each respondent with the same sets of competitive prices. This allows for a straight forward formulation of the prices, a common execution instrument and a simple means of merging data for computing a market model. Unfortunately, this is not always consistent with the customers' situation. Particularly, with industrial products where there are different levels of use or where group purchasing is done, each respondent may see a different set of market or street prices. For agricultural chemicals this may be due to differences in practice, infestation, or conditions. In pharmaceuticals, difference may arise from contractual conditions with hospitals and buying groups.

In these cases it may be necessary to present the scenarios in terms of the present perceived market prices. These are usually conducted as phone-mail (fax or E-mail) - phone studies. During the initial interview, street prices are solicited. These prices are then used in developing the scenarios. Typically, a standardized price design is used with the street prices substituted for the present price. Analysis is done as the price standardized form where share changes are computed based on premiums and discounts from the present street price.

Problems and Difficulties

There are a number of difficulties in using street prices including:

- Respondent estimates of street prices are very unreliable. Usually the only reliable estimates are regarding products that were used.
- It is difficult to execute due to the customization for each respondent and prone to error. Unfortunately, the errors in reproduction may result in incorrect design and non-useable results.
- While the pricing exercise is conducted based on specific prices, the analysis assumes that the specific price level does not effect share. Only the relative price is assumed to effect share. This may give an incorrect picture of the respondents' behavior.

5.4.4.6.2. The Individual Consideration Sets

Often there is a large number of potential competitors. However, respondents only consider a small number in the relevant buying decisions. This is due to local brands, limited distribution, and specific needs. Under this condition while nationally, we may wish to consider 20 or more offerings each respondent only considers 6 or 7 at most. If the consideration sets are limited and predictable, separate studies can be undertaken. If, many of these potential products are small local brands or minor products they can be handled as independent products.

However, in some cases the number of important products and consideration sets are too large to be handled simply. In these cases, each respondent is allowed to set the competing products to be considered. This means that each respondent results need to be analyzed separately. Usually, if this is undertaken we either use standardized prices, or street prices. Street prices if used tend to greatly increase the complexity of the study. The resulting market model is constructed either by simulation or by merging the linear coefficients[31].

[31] Building a market simulator involves predicting individual responses to price changes and then merging results. This greatly increases the computation complexity if a non-linear model is used. Alternatively, if a linear model is used, the coefficients of the individual model can be merged into an overall market model. For the linear case, the results of the simulator and market model are the same.

Problems and Difficulties

Using individual consideration sets greatly increases the complexity and expense as well as introducing sources of increased error. Fortunately, it is rarely used. The problems include:

- It is very difficult to execute and analyze. Since each respondent's consideration set is different with potentially different ranges in prices, analysis has to be done separately. This often involves thousands of regression analyzes.
- As noted, with individually designed experiments the potential for errors in design, printing and analysis is much higher than the normal design.
- The final model is very complex. For example a 30 product model will have 930 coefficients. With limited sample size, very small numbers of respondents count for many of the products.
- These market simulators tend to be limited only to linear models.

5.4.4.6.3. Split Samples

The number of scenarios necessary to collect adequate data often run between 12 to 25 sets depending on the need for price coverage and the number of products. For industrial products (including agricultural biocides and pharmaceuticals) respondents tend to be able to complete these tasks. However, for consumer products it is often doubtful if the respondents can reasonably complete the task. The process becomes increasingly artificial and therefore the results become less reliable. Under these conditions, smaller numbers of tasks are usually requested with the sample split to cover the needed data. The extreme case is monadic execution where respondents only see one case.

Problems and Difficulties

While the reliability of using split samples may increase the accuracy of the data, the difficulty in cost and in merging the data makes it less favorable. The difficulties include:

- There is no measure of individual behavior. The data can not be used to segment the market nor to obtain any consumer distribution information[32]. Therefore, only prior defined market models results are possible.
- It is critical that the sample be fully random or stratified prior to the execution. Once the data is collected it is difficult to reassign groups for segment analysis.
- The use of split samples decreases the effective sample size.

[32] Sawtooth Software claims that they have methods to estimate individual preference based on "Choice Based Conjoint" procedures. These are based on latent class and Logit regression analysis procedures. However, latent class segmentation procedures do not produce unique solutions and may be unreliable.

5.4.4.6.4. Handling Sub-Sets of Products

The experimental design should reflect the actual decision situation that the buyer is expected to see. As we have discussed, the consideration set of the buyer may differ from that which concerns the seller. This is particularly the case with new product introductions where the seller is considering a number of feasible new products targeted to a market segment. If three new products are being considered, there are seven possible sets of new product offerings (3 of each product by itself, 3 combinations of 2 products, and the case of all three being offered). This would require 7 sets of probably 16 scenarios to cover the total situation.

This situation can be handled by concept testing where any number of combinations can be tested, but assuming that there is no interaction with competitive prices. However, it is rare if there is no effective competition and therefore, interaction is usually a dominant market characteristic. Choice modeling can be used in this situation. As previously mentioned, several sets of exercises can be used to cover the range of conditions. However, this is usually expensive and only applicable to large highly potentially profitable markets. If a discrete choice exercise is applicable, a hierarchical approach can be used based on a single exercise. Otherwise, products can be excluded from a final model, but this is only an approximation to the actual market behavior or intention.

5.4.4.7. Reducing Products from the Model

It is feasible to approximate the effect of excluding a product from the consideration set. There are two sets of methods that can be used. The first is based on the measurement of multiple options using Hierarchical Discrete Designs. This relies on the ability of respondents to choose multiple options. The second set of methods are approximations and should be viewed as artificial in that we are estimating the choice model of a situation that the respondent has not seen. There are three approaches in this group removing products from overall pricing models. Each of these procedures is based on fundamental assumptions regarding expected respondent behavior.

5.4.4.7.1. Hierarchical Discrete Choice

Discrete choice pricing exercises involve respondents selecting a single option from the list of products and given prices for each scenario. In this regard, the data for each scenario consists of a list of zeros with one single chosen item, which is assigned a value of one. In partial or volumetric choice pricing exercises the respondents are allowed to distribute partial purchases across the products. These partial values represent a number of purchases, share, or likelihood of purchase. The choice of which technique is used depends on the nature of the purchase and the purchase process. However, if discrete choice is used, a modification of the procedure can provide sufficient information to allow the removal of products from the results.

Hierarchical discrete choice involves having the respondent give additional choices. The respondent would therefore give, for example, first, second and possibly a third choice of desired products for each scenario of prices. This is, of course, a forced selection and typically the list of products includes a rejection option, of none. With this data, it is feasible to remove a number of products from the data set and recompute the standard discrete choice structure by assigning the most favored option remaining. For example, if a respondent considered the following scenario of prices and gave the indicated results:

Scenario	Product A	Product B	Product C	Product D	Product E	Product F	None
G	$1.50	$2.25	$2.00	$1.95	$2.75	$1.25	
Choices	**0**	**0**	**1**	**2**	**0**	**0**	**3**

In this case the respondent chose Product C as his first choice, Product D for the second and none for the third. If one just wished to consider this result for a standard discrete choice the resulting data would include only the first chosen selection, with the values of the second and third choices set to zero.

Scenario	Product A	Product B	Product C	Product D	Product E	Product F	None
G	$1.50	$2.25	$2.00	$1.95	$2.75	$1.25	
Choices	**0**	**0**	**1**	**0**	**0**	**0**	**0**

However, if it was desired to remove Product C from consideration then the first choice no longer exists for this scenario and the next highest choice is Product D and the third choice set a zero.

Scenario	Product A	Product B	Product D	Product E	Product F	None
G	$1.50	$2.25	$1.95	$2.75	$1.25	
Choices	**0**	**0**	**1**	**0**	**0**	**0**

Similarly, if it was desired to remove both Product C and Product D then the third choice becomes relevant and the results become:

Scenario	Product A	Product B	Product E	Product F	None
G	$1.50	$2.25	$2.75	$1.25	
Choices	**0**	**0**	**0**	**0**	**1**

Notice that using this approach one could remove any number of products and still produce a workable data set for modeling. Typically, however, no more than three choices are used due to the difficulty of the task and a tendency of driving respondents to the "none" option.

Design Issues

It should be noted that if a product is removed from consideration, the design may have to be changed. That is if the removed products are inherently a part of the levers in the design, those levers may need to be modified or removed. For example, in a simple pricing design where each product has an independent price, the removal of the product from consideration would require the removal of it from the design. Otherwise, any change in the price of the removed products would influence the shares of the other products even though the removed products were excluded. This can become fairly complicated with more complex designs, where targeted product prices are linked.

Automated designs can allow for the removal of any combination of products from the exercise. However, this requires both the adjustment of the responses as indicated above and the modification of the underlying pricing design.

Problems and Difficulties

This process is feasible and recommended when appropriate. However, there are limitations:

- The hierarchical approach is only applicable to discrete choice.
- The exercise is somewhat artificial in that rarely does purchase conditions consists of a hierarchical choice.
- There is a tendency of respondents to move to the "none" option for follow-up choices.
- It can be complicated to design and particularly to automate as a simulation and decision support tool.

5.4.4.7.2. By Price Selection

For Volumetric Choice Models, however, this method can not be used. Here we need to either force the share of the unwanted variable to zero or to “fix” the resulting matrix. The first method is to introduce sufficiently high prices into the model to result in zero values of the excluded products. The process is straight forward though heuristic in that it is desirable to select the smallest price that produces the desired result. This is intended to reduce the impact on the other product prices.

Problems and Difficulties

This process while feasible is strongly not recommended. Among the problems are:

- The resulting model does not reflect the reactions of the respondents.

- The high prices are typically beyond the scope of the measured values and therefore, the resulting impact on the volumes of other products can be very unreliable

- Potential loss of overall volume due to the increased price of the excluded products.

5.4.4.7.3. By Exclusion

The second and simplest method is just ignoring the excluded products. This involves removing both the product columns and the rows. This is a simplified version of the the next procedure but assuming that the interactions and impact of the removed products is small. It is usually acceptable when the computation is based on shares, which are typically normalized, and the volumes of the excluded products are relatively small. As in the first case, this can be applied to both linear and non-linear models (S-Shaped)

Problems and Difficulties

This process is fairly straightforward and while highly useful it is not fully recommended. Typically it is used only in cases where the excluded products have a relatively small volume. The problems include:

- Once again the resulting model does not reflect the reactions of the respondents. This is critical since the existence of options can affect the choices.

- An apparent reduction in the overall expected volume since there is no compensation for the lost volume with the additional products.

- A fundamental problem with this method is that the fundamental structure of the model is not maintained. This shows up as imbalances in the share estimates.

5.4.4.7.4. By Adjustment

The third approach is more complicated in that it preserves the fundamental structure of the matrix, but compensates for the potential loss of overall volume and the effect on other products. Note that this process applies to only linear models. That is a linear model generating the market shares. It is formed either using a discrete structure or by normalizing the resulting average selected choices. This process excludes the product from the model in two steps: (1) adjusting the intercept or based line price, and (2) readjustment of the effective elasticity. Let us apply this process to the linear case where we wish to remove product D.

	Product A	Product B	Product C	Product D
Intercept	$\mathbf{T_a}$	$\mathbf{T_b}$	$\mathbf{T_c}$	$\mathbf{T_d}$
Product A	$\mathbf{S_a}$	X_{ba}	X_{ca}	X_{da}
Product B	X_{ab}	$\mathbf{S_b}$	X_{cb}	X_{db}
Product C	X_{ac}	X_{bc}	$\mathbf{S_c}$	X_{dc}
Product D	X_{ad}	X_{bd}	X_{cd}	$\mathbf{S_d}$

Step 1 involves redefining a price of Product D as a linear function of the previous prices such that the Intercept $\mathbf{T_d}$ is zero[33], this in effect cancels out the influence on base price by adjusting the intercept based on the .

$$\mathbf{T_i' = T_i - T_d \bullet X_{id}/S_d}$$

Where the new intercepts are $\mathbf{T'_i}$. As such, we remove the effect of the cross sensitivity for Product D, $\mathbf{X_{id}}$. The result is:

	Product A	Product B	Product C	Product D
Intercept	$\mathbf{T'_a}$	$\mathbf{T'_b}$	$\mathbf{T'_c}$	
Product A	$\mathbf{S_a}$	X_{ba}	X_{ca}	X_{da}
Product B	X_{ab}	$\mathbf{S_b}$	X_{cb}	X_{db}
Product C	X_{ac}	X_{bc}	$\mathbf{S_c}$	X_{dc}
Product D				

It should be noted that for the linear model based on shares (normalized):

$$\mathbf{S_j} = -\sum_{i} \mathbf{X_{ji}}$$

This is now used to adjust the product sensitivities to drop the other cross terms. Step 2 involves subtracting the corresponding cross coefficients $\mathbf{X_{di}}$ to the primary sensitivities, resulting in:

	Product A	Product B	Product C
Intercept	$\mathbf{T'_a}$	$\mathbf{T'_b}$	$\mathbf{T'_c}$
Product A	$\mathbf{S'_a} - X'_{ad}$	X_{ba}	X_{ca}
Product B	X_{ab}	$\mathbf{S'_b} - X'_{bd}$	X_{cb}
Product C	X_{ac}	X_{bc}	$\mathbf{S'_c} - X'_{cd}$

[33] The same procedure can be applied to the S-shaped demand model if the redefinition of price drives the $\mathbf{T_d}$ term to a large negative value.

The process may be applied repeatedly to remove multiple products. However, errors will accumulate with additional removals.

Problems and Difficulties

While this process is feasible it is no recommended. Among the problems are:

- The resulting model does not reflect the reactions of the respondents. This is critical since the existence of options can affect the choices.
- Error in the coefficients of Product D will now affect the other products shares. This is also critical since new product price coefficients are often among the most uncertain.
- Error in the model parameters can become magnified in this process. For example low negative valued primary sensitivities can become positive with this modification, resulting in (economically) irrational responses.

5.4.4.8. Adjusting for Intent (A Bayesian Approach)

The choice exercise approach to price-market modeling rely on potential buyers indicating their intention to purchase products at given prices. Through a number of scenarios sufficient information is collected to estimate the respondents' price sensitivity if their intentions are translated into real actions. That is, of course, a major problem with all causal marketing research approaches. All such methods rely on the ability of respondents to indicate what they would do under the experimental conditions. With multiple purchase situations such as for retailers, distributors, or frequent industrial buyers, this is not believed to be a major problem. However, for the less frequent purchases or complex purchasing processes, such as with consumers, or less frequent industrial, or for agricultural protection products, the difference between intention and behavior may be significant.

We could expect that buyers would be conservative in that their final behavior will be some combination of their intentions and their previous behavior. That is, they would most likely have a tendency to repeat previous purchases in addition to the new intentions. This can be viewed as a type of risk aversion. From a statistical perspective, this is referred to as a "Bayesian" approach in that the future or posterior results depend on both the prior actions and the indications of future behavior.

This type of Bayesian estimate is easily computed from the aggregated choice pricing exercise. The pricing data is normally aggregated as an intended market use rates or shares by product for each of the several scenarios. The pricing model is obtained by regression analysis of these results against a statistically designed set of price stimuli. To impose the Bayesian conditions, a weighted average of the aggregated previous market behavior and the indicated intentions is used.

The main issue is the size of the weights to be used. The extreme cases are, of course, trivial. In one extreme, no effect of the past is included. The result is the original pricing model based solely on the intention to purchase. The other extreme is only using the past behavior. The result is a totally inelastic solution, where there is no variation in behavior due to price. Between these extremes, the additional of past behavior should decrease the apparent elasticity and increase the optimum price.

This will be particularly apparent with some very low use products, where small changes in price produce large proportional changes in volume. This tends to result in an overly sensitive pricing situation, which also tends to be unstable. That is small changes of the situation, produces large changes in the optimum price. The addition of even a small (20 to 30%) Bayesian effect tends to stabilize this situation. In other cases, however, the influence of the small amount of past purchase behavior tends to be marginal with some lowering of the elasticity and rising optimum price estimates.

Problems and Difficulties

The real issue is what is the correct balance between intention and past behavior. This should ideally be determined by tests of the models against actual behavior. In general, however, the weights are included to produce a better match down the distribution channel. Typical estimates of prices are produced on the buyer, dealer, influencer, and sometimes on the wholesale levels. These produce multiple estimates of price elasticity and optimum retail price. Bayesian weights can be applied to the buyer level to bring buyer estimates more closely aligned with the distribution channel.

5.4.4.9. Calibration and Validation

Analytical model validation is a comparison of the model against actual market behavior. There is very little in this type of analytical validation. However, there are a number of other measures that people have used as a surrogate for analytical validation. Unfortunately none of these are really substitutes for an effective test. These include:

- Procedural Face Validity – This is the appearance of the total procedure to model the buying process.

- Model Face Validity – This is the ability of a model to behave "as expected." This involves both reasonable behavior and the ability to reproduce expected values. This is tied to calibration of the model and unfortunately is often confused with calibration. True analytical validation must be based on comparison of the model against data that was not used in its construction.

- Internal Consistency – This is basically a statistical measure of the fit of the model against data. Normally R-Squares are reported as measures of consistency and therefore validity.

- Reliability – Occasionally multiple studies are done in an area often over a number of years. The ability to reproduce estimates is used as a measure of reliability and also as a surrogate of validity.

5.4.4.9.1. Model Calibration

Fundamentally, market models reflect the data from which they are developed. In most cases, there is a deviation between the model forecasts of current conditions and the data and perception of the business describing the present situation. This is due to inaccuracies and imprecision in all data, inherent assumptions, and the distinction between the current situation and a future forecast. Calibration is a process of readjusting models to appear to fit the current data. Validation, however, is a test of the model against actual market reaction and should not be confused. In general, we prefer not to calibrate models since it tends to distort the results and furthermore there is no overwhelmingly preferred method.

5.4.4.9.2. Segmentation and Weighing

The general method of calibration pricing model is through market segmentation and weighing. Markets are often segmented based on preferred product use or equivalently by characteristics that favor specific products. By weighing these segments in the market model, one can often approximate a given distribution under constrained conditions. This is typically used to calibrate the model. It must be noted that this effects how the model will react to other conditions.

5.4.4.10. Collective Decision Making

A major problem of market modeling is that several individuals may influence the purchase of products, including: wholesalers, dealers, consultants as well as members of the purchasing organization. In some cases, such as pharmaceuticals, additional factors may also effect purchases including buying groups, health care providers as well as the more direct decision makers the physicians and the patients. The problem, therefore, is how to merge the results from several sources into an overall model.

Typically, this is handled by segmentation, averaging effects, or linking. The first two methods are straightforward where we either combine the groups or display them separately. Often these methods are used together. Weighted averages can also be used if there is a natural way to identify the markets they represent. For example, hospital practices can be separated from private medical practices in some cases.

5.4.4.10.1. Linking Models

The more difficult problem is when the decision-making segments are linked. Developing linked models, however, requires careful planning and design. For example, in pharmaceuticals there is a decision process to allow a drug to be used and another by the physician to select it. Typically these are linked through selection of the measure of results. In this case, the decision process to allow the drug use is measured as a likelihood of approval. The physicians' are then asked the likelihood of prescribing given that the drug is approved. These models can then be merged as a conditional probability. Unfortunately, the problems of linkage are often identified after the execution of the study. This makes it difficult if not impossible to link the results. Typically, segmentation and averaging are used.

5.4.4.11. Experimental Design

These market price models are based on experimental data. As previously noted the data is collected from respondents as reactions to a series of scenarios. Designing these experiments is not simple and generally consists of compromises of various principles.

5.4.4.11.1. Conditions of Design

Each scenario consists of a series of prices on products. The following are key design considerations the set of scenarios.

- Non-Intercorrelation – In order to have unique values of the parameters it is critical that the prices of the products are not intercorrelated. In regression we refer to the prices as "independent variables." They really must be independent or orthogonal. The correlation should be as low as possible[34].

- Number of Products – The number of products or brands sets the minimum number of scenarios we need to deal with. It also effects the intercorrelation. Typically we prefer to have less than six in the experiment, though we have use up to eight. This is discussed later.

- Range – The range of prices that will be considered is a critical element in the design. Too large a range produces unrealistic scenarios. Too small a range will not cover the possibilities that one wishes to simulate.

- Balance – Consists of the frequency of comparison of prices of various products. This is less of a problem in choice modeling than in full profile conjoint where the levels correspond to different features.

- Discrimination – This covers the differences in prices within scenarios. If this difference is consistently too high it bias the results to high price sensitivity. If it is consistently too low it will bias it in the other direction.

[34] While we would like them to be less than .1 we have used designs with values slightly less than .2. There are some statistical procedures to handle modest levels of intercorrelation, Ridge Regression. However, these are heroic methods and their use is more of an art form than a well-established statistical procedure. We do not recommend their use unless critically necessary.

- Number of Scenarios – This is generally determined by the number of products, the range of values and the intercorrelation.

5.4.4.11.2. Testing Designs

Usually the two issues that we are most concerned in choice model designs are intercorrelation and discrimination. Intercorrelation is particular troublesome. A highly intercorrelated design is worthless. This happens when the prices of two or more products are interrelated. The resulting parameter values are uncertain and therefore, we cannot forecast results. It should be noted that some conjoint designs are highly sensitive. Several of them show little intercorrelation with one set of prices substituted for features, but show high intercorrelations under other conditions. We find it critical to test all designs as they will be used and not rely on either published analyses or analyses based on the conjoint design.

Discrimination is the second most troublesome issue since it can greatly bias results. Here again we test designs based on how they will be used.

5.4.4.11.3. Standard Designs

Unfortunately we have found very few designs that meet our requirements. Therefore, we have typically used standard designs for choice modeling experiments. Since we prefer not to use split populations, we have found in necessary to restrict our designs to 12 to 16 scenarios. This is led us to very few acceptable designs for cases of more than five products.

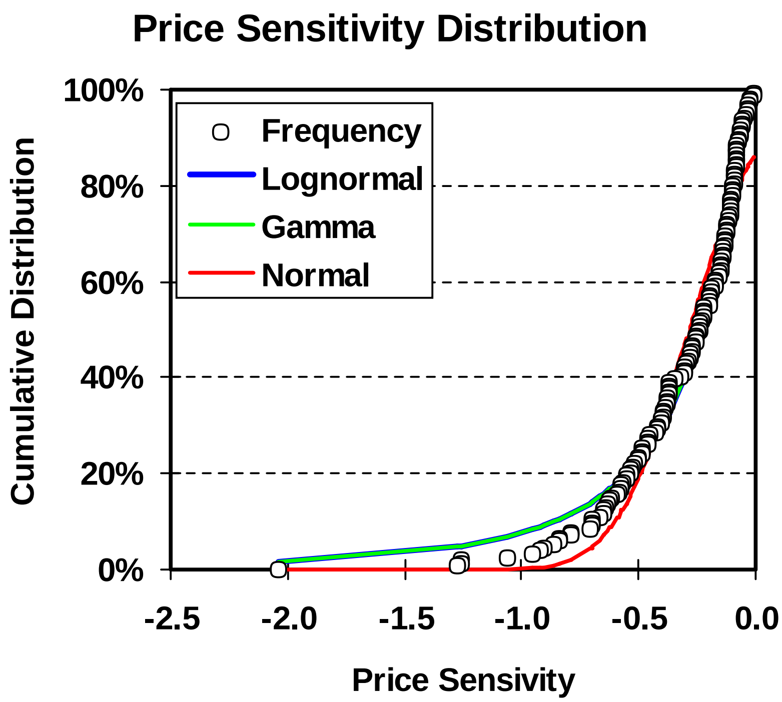
5.4.5. Expected Distributions and Error

In this section we will discuss the results from a fairly large number of studies. While the results are limited to the study investigated, we believe the results are generally applicable to all industrial type choice model exercises and probably the best first estimate for other markets.

5.4.5.1. Expected Price Sensitivity Distributions

Price sensitivity is the key parameter in pricing models. The chart below shows distribution of price sensitivity from a number of studies. While these studies reflect a number of unique markets they are all in the same industry. As you can note the cumulative distribution is fairly smooth and appears to form a “S-Shaped” curve. Not surprisingly the distribution appears to be most closely fit by a log-normal distribution[35].

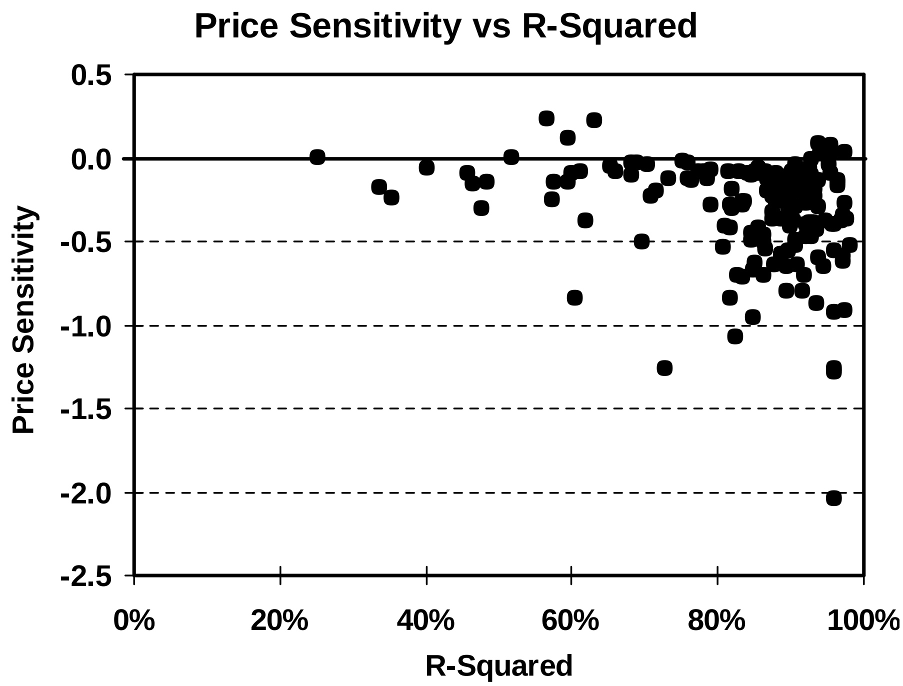
[35] The log-normal and the gamma distributions are almost identical. An exponential distribution would also fit this data.



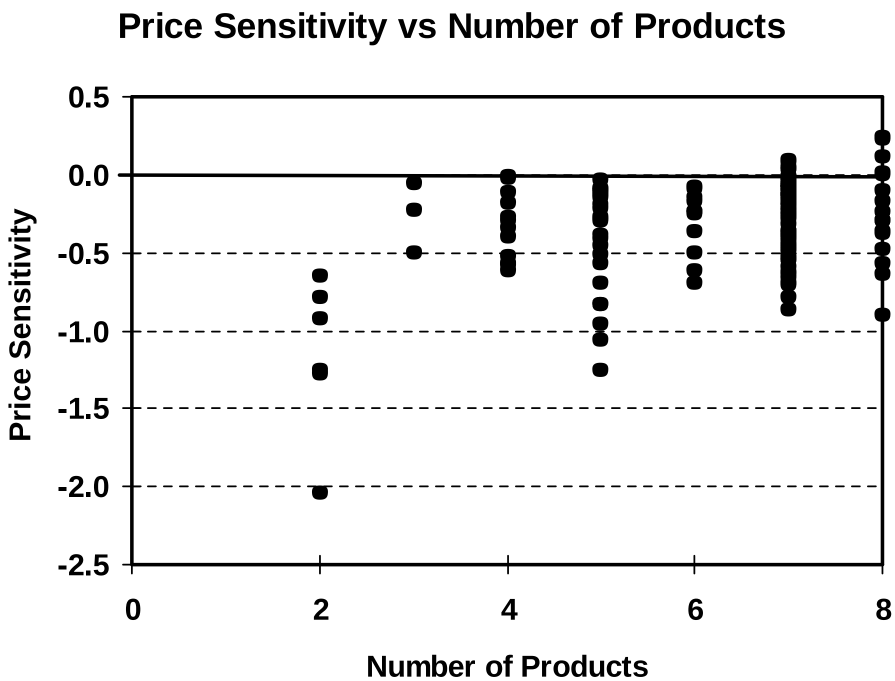
This chart and the rest in this section are based on standardized prices. That is the price is set as a change in the current or average price. This distribution gives us a measure of the likelihood of various price sensitivities. Based on this distribution, there is less than a 20% chance that any product in this category chosen at random will show greater than a 10% increase in sales from a 20% decrease in price.

5.4.5.2. Variance of Price Sensitivity

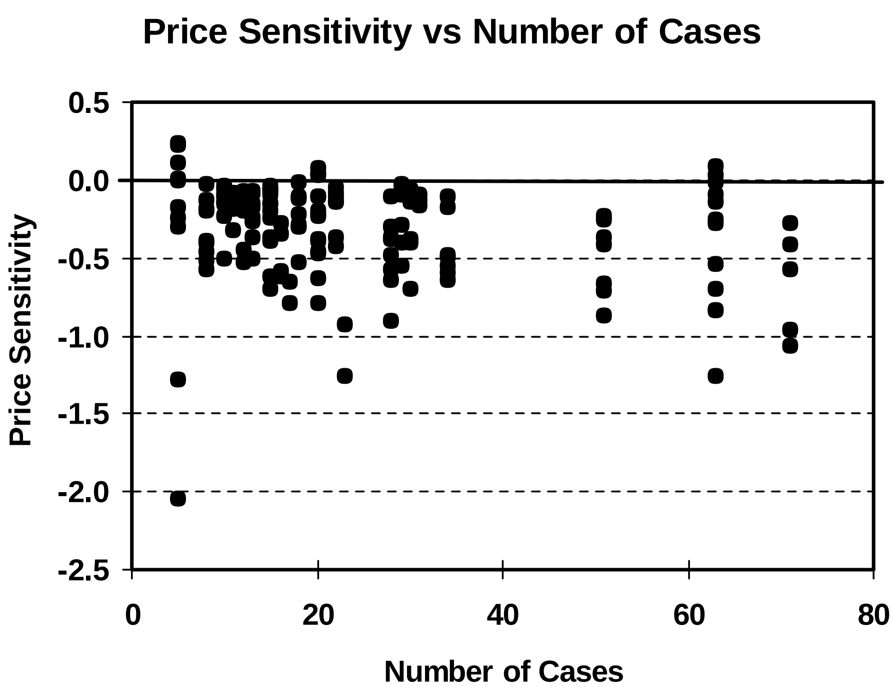
The following four charts show the variability of price sensitivity with fit and design characteristics. It should be noted that a positive price sensitivity is probably a poor measurement. We normally expect all price sensitivities to be negative; that is we expect sales volume to increase with decreasing price. Notice on the following chart of price sensitivity and internal consistency (R-Square) that the worst cases of positive price sensitivities come with inconsistent models, those with R-Squares below 0.7. The cases with high R-Square are probably statistical noise and we should consider them to be measures of precision.



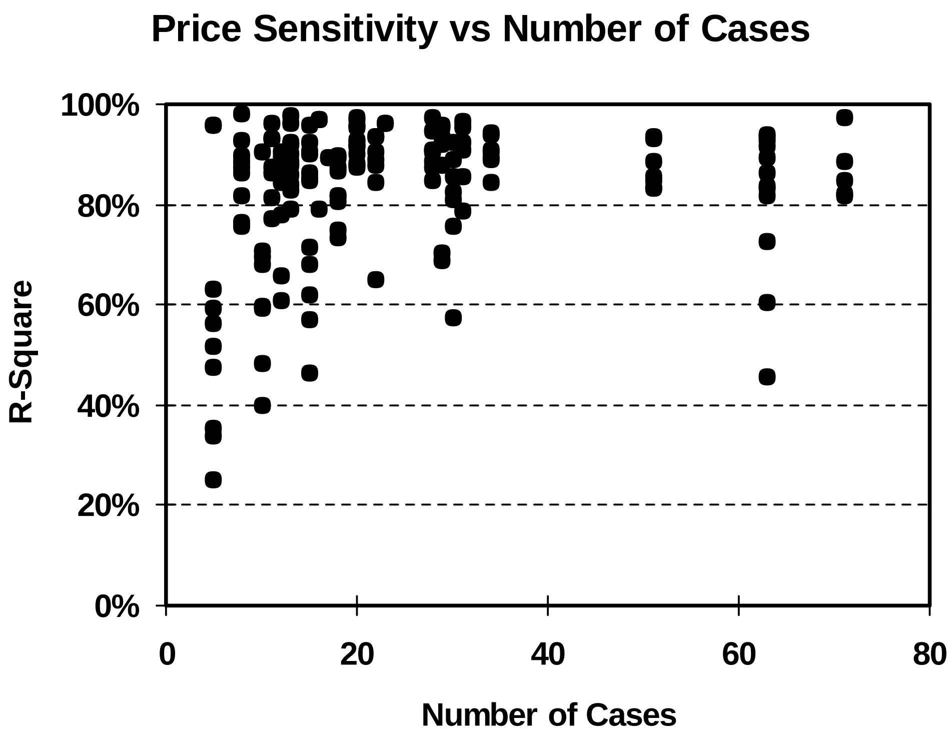
In the following chart the price sensitivity is shown against the number of products tested. Positive price sensitivities exist only with greater than six products. This is not unexpected since the task of selecting among seven and eight products is fairly complex. Furthermore, these experimental designs are less “clean” than those of fewer products. It appears clear that the fewer products the better.



For comparison the following chart shows the price sensitivity against the number of respondents. Notice no particular relationship. The number of respondents within the range tested did not seem to increase the likelihood of inconsistent results.



Similarly, the number of respondents did not seem to effect the internal consistency. This is an interesting observation and somewhat unexpected. We generally assume that individual models are more likely to be inconsistent that the aggregated market model. This would lead one to expect a significant improvement in R-Squared with the size of the sample. This is not seen consistently. However, the extreme cases do show that trend. That is, the poorest R-Square appears to decrease with the size of the sample.



5.4.5.3. Sample Size Error

This brings us naturally to the estimate of sample error. This is the traditional problem of estimate the precision of the model parameters due to the relatively small sample size. It should be noted here that the sample size (degrees of freedom) used to measure of goodness of fit, the R-Square, is based on the design not on the number of respondents. It measures the quality of fit between the model and the data, but says nothing about the precision of the results. Nor, can we rely on the traditional measures of parameter precision since once again, it is based on the number of items in the design not the number of respondents. Because of the complexity of the computation, traditional statistical methods are not applicable.

However, random simulation, Monte Carlo, can be used. This involves obtaining a number of alternative samples of the population randomly, and estimating the resulting parameters from the distribution of the parameters and the precision estimated. The trick is then, how to obtain these alternative samples. Two general approaches have been used: Data Enhancement and "Bootstrapping."

Data Enhancement

Data Enhancement involves generating a large set of new estimates, which maintains the original data structure. That is, the population of new or synthetic estimates has the same cluster structure, intercorrelations and distributions as the original data. The process is fairly involved and operates under a number of constraints. It is occasionally used for building market and business simulators where only limited data exists. The details of the process are discussed in the chapter on decision support systems and market models.

Bootstrapping

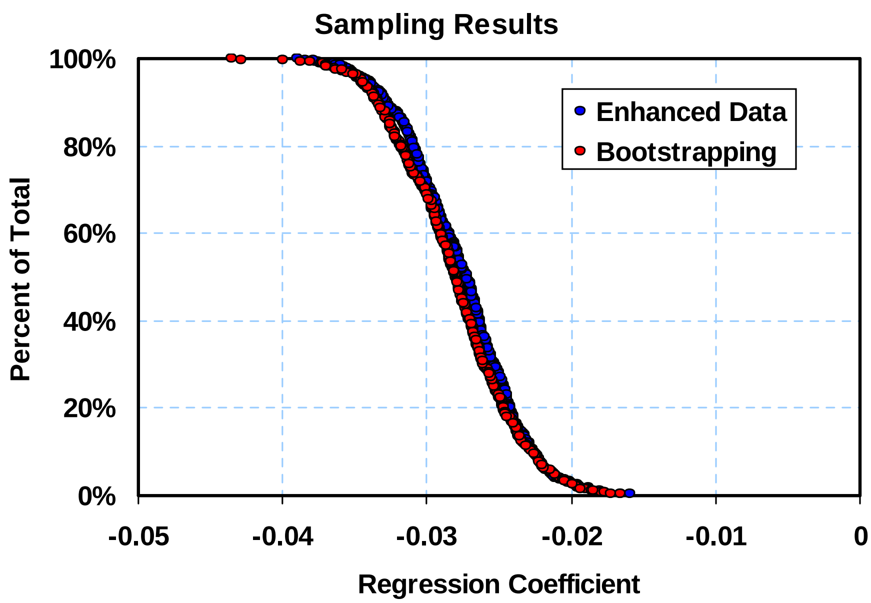
Bootstrapping is a relatively new procedure for estimating alternative sample distributions. It involves resampling the original data with replacement. That is, we consider the original data to be the population and then sample it as often as we had originally, but in this case we do not remove respondents after selection. This produces a series of samples each with the same number of respondents as the original but with multiple duplications. This is a fairly straightforward process and fair simpler to execute than Data Enhancement Monte Carlo.

Comparison of Results

Below are the results of a pricing choice model measurement using both Data Enhancement Monte Carlo and Bootstrapping.

	Enhanced Data	Bootstrapping	% Difference
Average	-0.02761	-0.02816	-2%
Std. Dev.	0.00397	0.00417	-5%

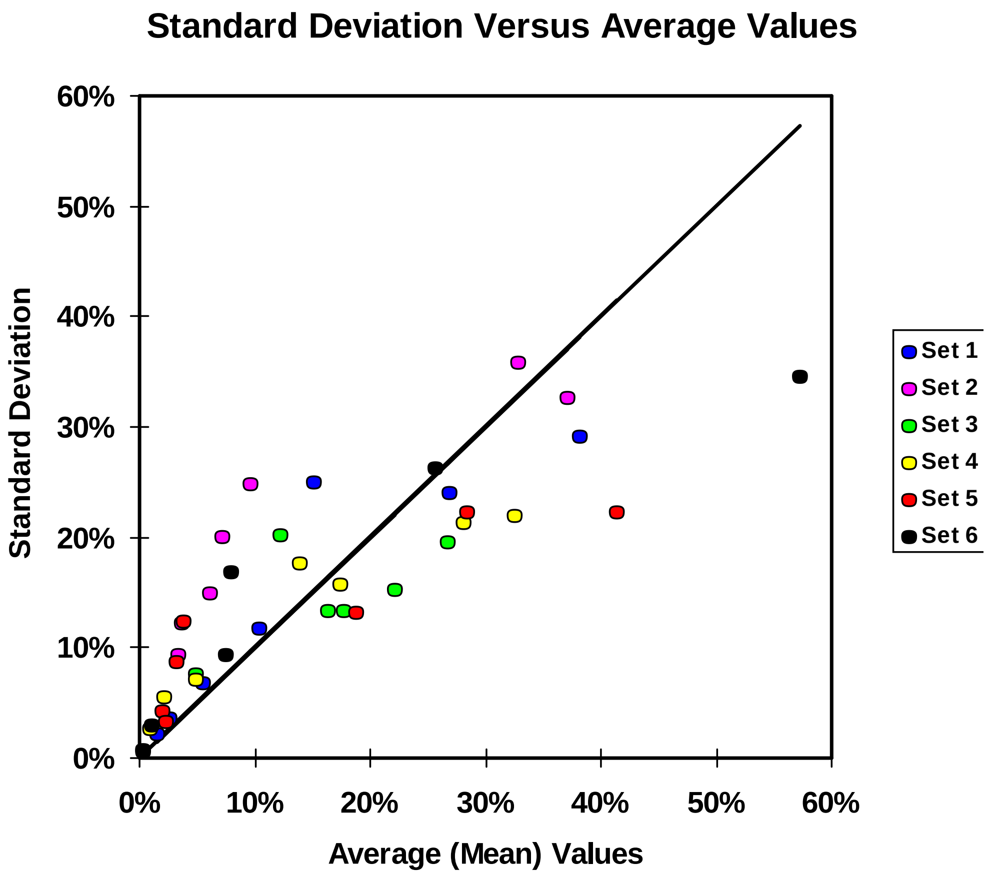
Notice that there is very little difference between the methods. The distributions of the results are almost identical as shown below.



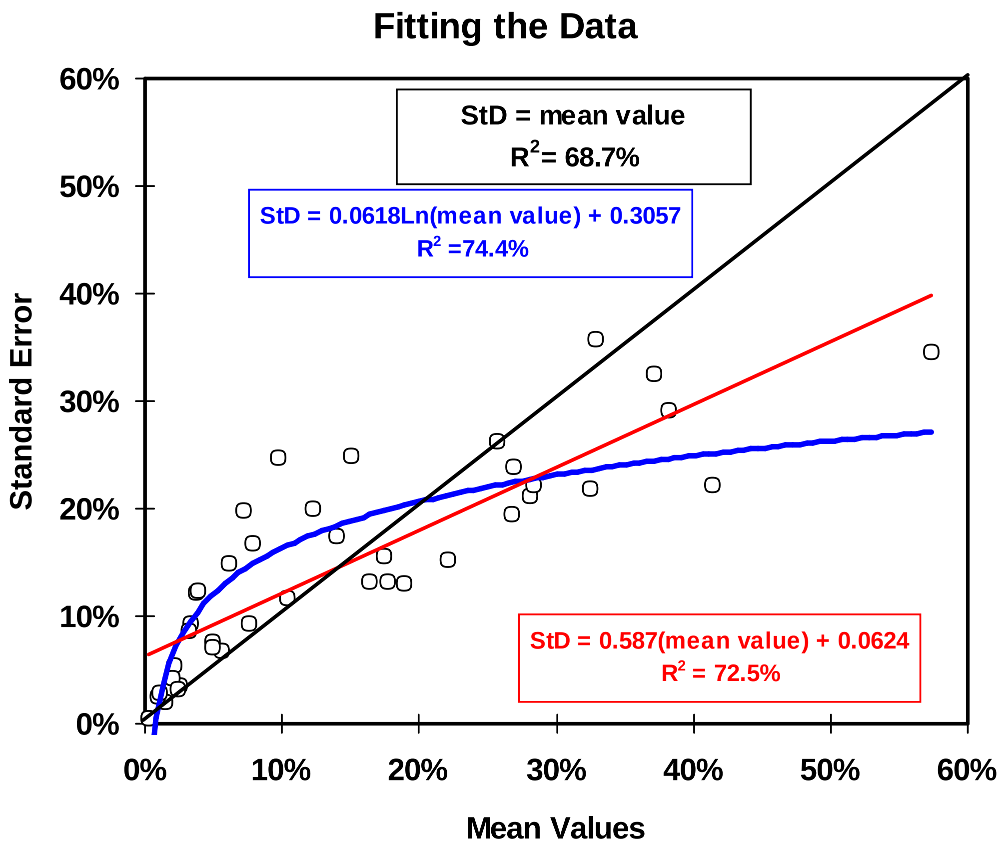
Since bootstrapping is much simpler to execute than the data enhancement procedure, it is should be used as the first choice if analytical estimates of precision are required.

5.4.5.4. Distribution Analysis

In this section we example the distribution of share estimates and price sensitivity on the individual basis. While we typically use market models for estimating sales, the simulator is a better model for estimating precision. In this case, we developed individual respondent models and examined the distribution of values. In the following chart shows the average share from a number of studies against the standard deviation. There is approximately a simple linear relationship between the two.

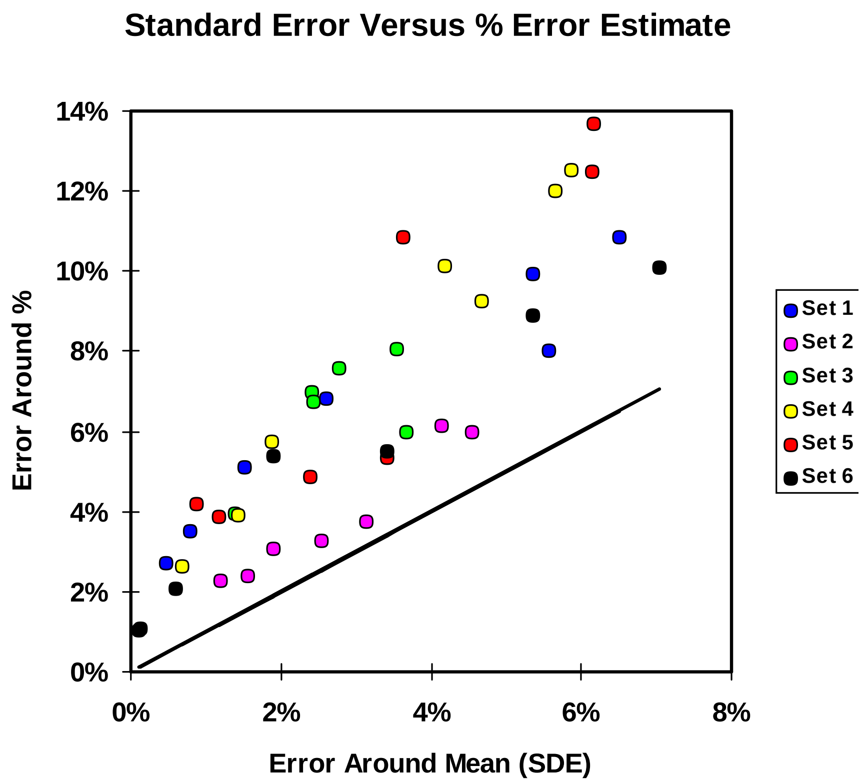


The following chart tests the results with a number of other curves, both linear and logarithmic. Notice that the simple equal value rule is almost as effective as the more complex relationships.



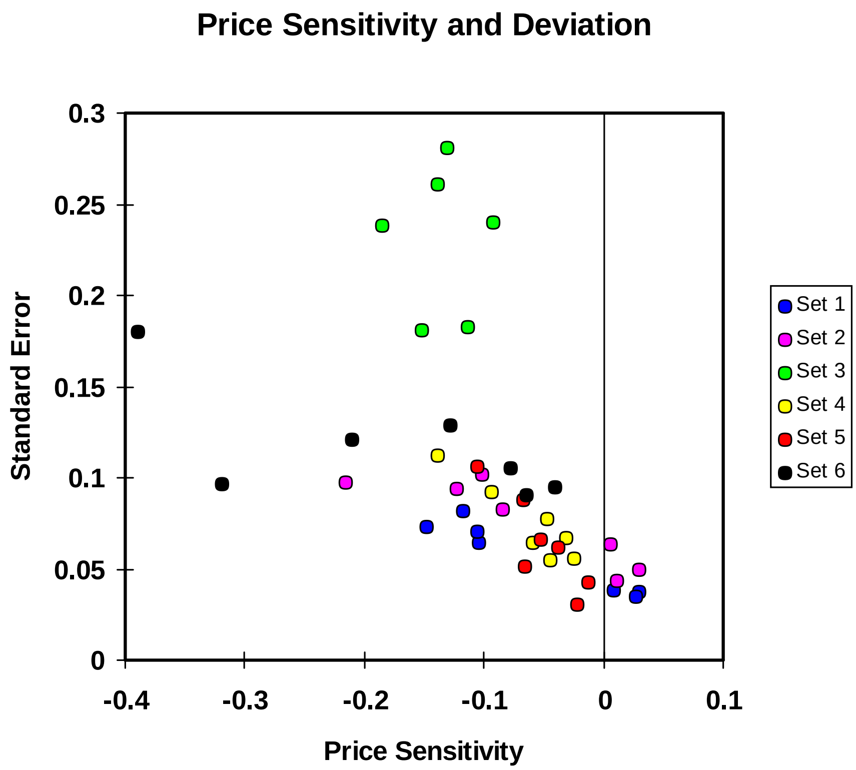
Ratio Error and Standard Error

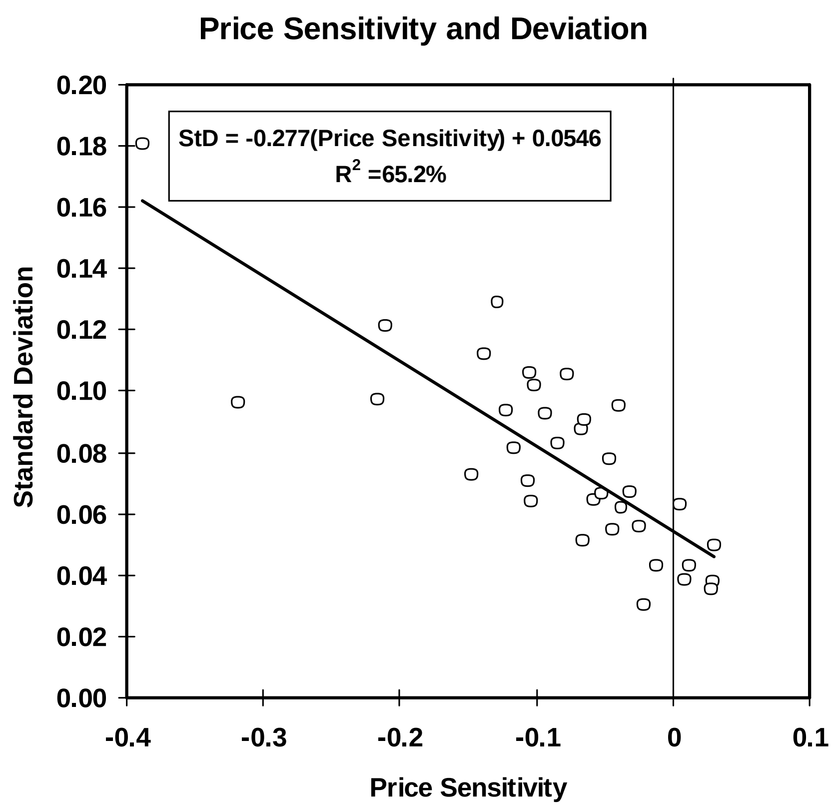
The alternative approach is to assume that the share estimates are based on a binomial distribution. The following chart compares the results. The straight line indicates the expected error around a 10% share based on the equality rule discussed above, the point represent the values based on the binomial distribution. As can be seen the error estimate based on the standard deviation is significantly lower than that of the percent expected error. This indicates that smaller sample sizes could be used than would normally have been expected.



Price Sensitivity

The following charts show estimated price sensitivity against its standard deviation. Notice the wide range of values. This is mainly due to one study. If we remove that study, as we have in the second chart, the relationship appears to be linear. That is the standard error appears to be linear with the estimates of price sensitivity. Once again we can use this relationship to estimate the error due to sample size.


Price Sensitivity and Deviation
Standard Error
Price Sensitivity
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.4
-0.3
-0.2
-0.1
0
0.1
Set 1
Set 2
Set 3
Set 4
Set 5
Set 6


Price Sensitivity and Deviation
StD = -0.277(Price Sensitivity) + 0.0546
R2 =65.2%
Standard Deviation
Price Sensitivity
0.20
0.18
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
-0.4
-0.3
-0.2
-0.1
0
0.1

5.4.6. STANDARD PRICE ANALYSIS

The purpose of the market analysis is to provide insight into appropriate product pricing. The selection of "Choice Modeling" as the means to obtain that insight implies three dominate conditions in the customer product selection: (1) the existence of recognized competitors; (2) the relative invariance in these competing products and (3) the critical importance of competitive price. The business client is usually faced with the dilemma of selecting a price under the uncertainty of competitive prices and the potential competitive reaction while using uncertain market data. The objective of the price analysis is to provide insight into:

- The direction of price above or below that presently contemplated;
- Measures of a desirable price level for the product or products;
- Estimates of an acceptable range of prices; and
- Insight what the long range competitive situation may become.

5.4.6.1. Actual Behavior and Intentions

As indicated previously, the choice exercise generates a measure of the intended behavior of respondents. While this is often a good indicator of future behavior, some cases it tends to be overly active. Buyers often overestimate their reaction of prices. As such, it may be useful to factor in prior behavior. The "Bayesian Approach" to this correction is to use a weighted average of the intended data and prior behavior. This is done before further analysis. Within the simulator this modification can be done either on all of the data prior to analysis or dynamically to give the user an option as to the level of weighting.

5.4.6.2. "Economic" Price and Cross Elasticities

Definitions

The traditional economic measure of price sensitivity is the elasticity of demand or price elasticity. It is defined as the negative ratio of the % change in volume of a product to the corresponding % change in its price. The influence of competing products is given by the "cross elasticities", which are the ratios of the % change in volume of a product to the % change in the prices of the competitive products. Each product will have a measure of price elasticity and several cross elasticities.

A price elasticity of zero means that sales volume does not change with price. The product is considered to be inelastic. A price elasticity of 1 or unity means that the percentage change in volume equals the negative percentage change in price. Price elasticities greater than 1 indicates that revenue will increase with decreased price. Under this condition, the economists refer to the market as elastic.

While price elasticity and cross elasticities can be computed on an individual basis, if sufficient data is collected, they are usually viewed as market segment properties. Therefore calculations are normally done only on market or market segment data. Elasticity in a broad sense is a function that is expected to change over the price range. However, typically it is computed around the presently anticipated price.

Calculations

The price elasticity and the corresponding cross elasticities can be computed from the standardized linear pricing market model. The model is computed based on scenarios redefined as percentage changes from the reference price. Typically the reference price is either the historical or anticipated prices for existing products or the target price for new product concepts. The price sensitivity measures are computed based on average share values of the responses. The linear statistical model results in the following price sensitivity matrix:

	Product A	Product B	Product C	Product D
R-Square	$\%_a$	$\%_b$	$\%_c$	$\%_d$
Intercept	$\mathbf{T_a}$	$\mathbf{T_b}$	$\mathbf{T_c}$	$\mathbf{T_d}$
Product A	$\mathbf{S_a}$	X_{ba}	X_{ca}	X_{da}
Product B	X_{ab}	$\mathbf{S_b}$	X_{cb}	X_{db}
Product C	X_{ac}	X_{bc}	$\mathbf{S_c}$	X_{dc}
Product D	X_{ad}	X_{bd}	X_{cd}	$\mathbf{S_d}$

The price elasticity is computed as the negative ratio of the price sensitivity, $\mathbf{S_i}$, divided by its intercept $\mathbf{T_i}$. In the above example the price elasticity for product A is:

$$£_a = -1 \text{ õ } S_a/T_a$$

and the cross elasticity for product A by product B is:

$$£_{ab} = -1 \text{ õ } X_{ab}/T_a$$

Problems in Its Use

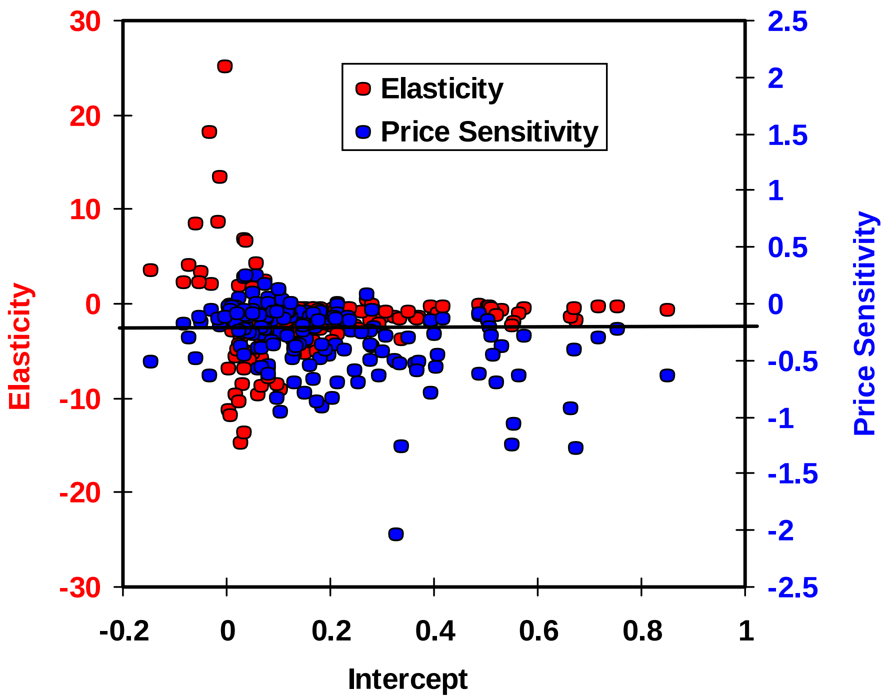
Though economic price elasticity is widely considered in the academic literature, there are key difficulties in its calculation and its meaning. It is typically not very useful for strategic or tactical pricing decisions. The problems include:

- Economic price elasticity analysis focuses on revenue rather than on earnings gain.
- Elasticity measurements rely on the existence of a common historical or anticipated price. This is required in order to standardize the design. The

results can be highly sensitive to those estimates. Unfortunately, reliable standard prices are often in question.

- Elasticity is a ratio of two uncertain parameters. In particular, the intercept can be very uncertain when it is close to zero. As such, the ratio has even more error than either of its parameters[36]. The result is a highly uncertain measure of price sensitivity. This is particularly the case when using small market samples.

- Because of the uncertainty introduced by the computation of the price elasticity, it has a much higher variation than does the price sensitivity, S_i. In fact, price sensitivity tends to be fairly constrained. The variation is shown on the graph below covering several different studies.

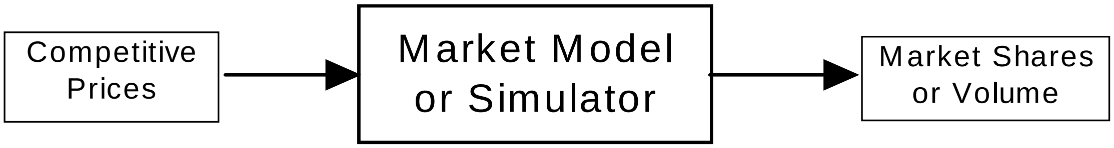


5.4.6.3. Market Simulation: Share and Earnings

Definitions

The market models predict product share given competitive prices. For each product in each market segment we compute an estimate of its market share. This is a simple “black” box process:

[36] Ratios of distributed uncertain values are among the standard numerical methods to generate random numbers.



Share Calculations

Usually a market model procedure is used with choice modeling data both for ease of computation and for accuracy. This involves merging the raw data either as complete data sets or as sub-sets of a split population[37]. Segmentation is usually done prior to analysis, though it is possible to due the computation "live", where the data is compiled based on user entered segmentation criteria[38]. In either case, the first step in the process is developing a number of data matrices with the results indicating the market response to each of the scenarios. Typically this data is normalized to represent market shares. However, in some cases where market growth is needed to be computed, sales volume is estimated. The requirement to estimate sales volume will limit the use of some statistical models. The resulting models are obtained from the market data by multi-linear regression[39]. This results in a matrix of demand and cross price sensitivities.

For the stochastic, Probit, S-Shaped, model, the share values have to be converted into a Gaussian or "normal-bell-shaped" distribution parameter or Z scores. Unfortunately, Z scores can not be computed for zero and one hundred percent share values. These values are first limited between 0.01% and 99.99% and then converted to the appropriate Z scores.

Computation of shares is done by matrix multiplication of the prices and the regression results matrix.

	Product A	**Product B**	**Product C**	**Product D**	**Prices**
Intercept	$\mathbf{T_a}$	$\mathbf{T_b}$	$\mathbf{T_c}$	$\mathbf{T_d}$	**1.0**
Product A	$\mathbf{S_a}$	X_{ba}	X_{ca}	X_{da}	$\mathbf{P_a}$
Product B	X_{ab}	$\mathbf{S_b}$	X_{cb}	X_{db}	$\mathbf{P_b}$
Product C	X_{ac}	X_{bc}	$\mathbf{S_c}$	X_{dc}	$\mathbf{P_c}$
Product D	X_{ad}	X_{bd}	X_{cd}	$\mathbf{S_d}$	$\mathbf{P_d}$

---

[37] Discrete choice using highly split samples may require Logit regression. However, if a small set of scenarios is used, the process of analysis is similar to standard choice modeling. The raw data results are compiled into an overall data matrix indicating market share for each scenario condition.

[38] If Logit (logistics) regression is to be used on the raw data, segmentation must be done prior to developing the model.

[39] This is Ordinary Least Squares Regression that can be done either using a separate statistical package, or using the **Regression** option in the **Data Analysis** menu option in the **Tools** menu in *EXCEL*. Alternative the regression can be done using *EXCEL*'s matrix functions. This is used to construct "live" segmentation models.

The intercept of the model represents the zero priced share. For the linear model the matrix product of the prices and the price sensitivities is the market shares. For the stochastic models it is the Z-scores of the share. In this stochastic case, the values have to be converted back to share values. For the linear models, share may vary below zero percent and above 100%. In order to prevent this, unless the model is design for it, results are bound by these limits.

Note that the share estimates are based on a number of independent regression equations. There is no constraint that the resulting shares should or will sum to one hundred percent. It is typically necessary to renormalize the results. Finally, it is feasible to calibrate the share results by weighing a number of segments. However, this is usually not done, as discussed earlier.

Earnings

It is also useful to compute the potential earnings for the products of interest. This is “relative” earnings based on share. Our interest is in the earnings contribution and therefore the costs reflect the marginal or variable costs of selling the product. This is not to say the fixed costs are not important. Unless the product is profitable on a full cost basis, it is not making money ill-respective to its “contribution.”

The Relative Contribution Earnings are given as:

$$\mathbf{Earnings_a = (Price_a - Cost_a) \times Share_a}$$

Marginal costs, $\mathbf{Cost_a}$, can be a function of share or price, $\mathbf{Share_a}$ if there is a large economy of scale[40]. However, the range of share and price is often considered small enough that marginal cost is considered a constant.

An alternative example with considering mill and marketing cost where mill costs are constant but marketing costs are proportional to the market price.

$$\mathbf{Earnings_a = (Price_a - (Mill\ Cost_a + Mktg\ Cost_a \times Price_a) \times Share_a}$$

Decision Support Systems

The table below shows the typical decision support system for the market simulator. In this case, contribution earnings are computed individually for two products and collectively or as joint earnings. This situation, of multiple product offerings, has become a typical where a firm has two or more products competing in the same market. A column labeled either current or expected share represents the share based on “standard

[40] For long term dynamic models Costs are often presented as a “power-law” function of $Cost = \phi \bullet Volume^{\eta}$. Typically $\eta = -0.4$ for what is referred to as the “6/10th rule”

prices." These are either historical or anticipated prices. They are shown to allow the visual assessment of changes in share.

In this case both the linear and the Probit, S-shaped, demand, estimates are shown. If additional segments are important, they are typically given as additional columns. However, if there are many segments to be considered, the two types of estimates (Linear and Probit) may be placed in separate tables or one not included.

	New Price	S-Shaped		Linear		1998 Average	Standard Price
		Estimate	Current '98	Estimate	Current '98		
Product A	$24.00	7.4%	7.4%	6.8%	6.8%	0.0%	$24.00
Product B	$20.00	0.7%	0.7%	1.1%	1.1%	0.0%	$20.00
Product C	$9.00	38.7%	38.7%	39.4%	39.4%	37.9%	$9.00
Product D	$20.00	0.8%	0.8%	0.5%	0.5%	0.6%	$20.00
Product E	$13.00	9.3%	9.3%	9.6%	9.6%	13.6%	$13.00
Product F	$7.00	28.5%	28.5%	28.0%	28.0%	28.8%	$7.00
Product G	$19.00	14.5%	14.5%	14.6%	14.6%	19.1%	$19.00

		Earnings	
	Cost	S-Shaped	Linear
Product A	$6.85	1.27	1.16
Product E	$5.00	0.74	0.77
Total		2.01	1.93

5.4.6.3.1. Segmented Data

It is often useful to present shares based on groups of customers, referred to as segments. These are predetermined groups of customers of interest. Simulator construction involves developing separate models for each segment. Prices may be linked or independent depending on the nature of the segments. Geographic segments often have independent pricing. Segmentation is done two ways: (1) prior and (2) live. Prior segmentation focuses on pre-set definition of segments. In this case any type of definition is feasible. This may involve both data that are held in the database and other information. Live segmentation involves the user defining segments on-line. This requires a set of criteria that is included in the database.

Problems in Its Use

Segmentation is widely used in simulations though live segmentation is more rare. However, there are problems with their use including:

- The precision of the results depends on the sample size. Segmentation can grossly reduce the effective sample size and thereby increase the error. This is particularly a problem with choice modeling since sample sizes are typically small to start off with.

- Live segmentation typically requires the total data set to be included in the simulator. The total database can be quite large and the resulting simulator slow. However, this is becoming less of a problem with newer high speed PC's.

- The simulator is fairly complex and the screen made more complicated. This is particularly the case for live segmentation where both the segmenting criteria and the result are included on the same screen.

5.4.6.3.2. Estimated Share Error Bounds

Error bounds reflect the precision of the share estimates. This is only a measure of the impact of sampling on the average values, not accuracy of the estimates or the reliability of the model. For convenience and flexibility we tend to use the binomial distributed error around a percentage value as a measure of the precision. As noted previously in the section on sample size error, this measure can be expected to be significantly more conservative than the error based on standard deviation. The percentage is used for three reasons:

- It provides a natural limit of error restricted to zero and one hundred percent;
- It is a conservative measure that should exceed any other measure; and
- It allows for direct measure of the impact of size for small samples.

In order to compensate for the conservative nature of the estimate a lower value of the probability level is typically used such as 75% or 85% rather than the more typical 90% and 95%.

Using *EXCEL* the following formula is used to compute the error bound:

Error Bound = BETAINV(Level,[P õ N],[N - (P õ N)+1],0,N)/N

where **P** is the share, **N** is the sample size, and **Level** is the probability level[41].

5.4.6.3.3. Error Bounds with Weighed Data

Weighting of the data allows for adjustment for the varying importance of respondents. However, weighting the data reduces the effective sample size as discussed in the section on Attribute Analysis. This is a balancing problem. The greater the effect of weighting reflects an increased importance of the weights but the greater the impact on sample size. This is obviously a critical problem with small samples. An estimate of the effective sample size can be obtained from the normalized weights:

[41] The formula uses the beta distribution, which is a continuous version of the binomial and allows inversion.

$$\textbf{Effective Sample Size} = 1/\sum_{i=1}^{N} W_i^2$$

Where $\mathbf{W_i}$ is the normalized weight and **N** is the actual sample size.

5.4.6.4. Optimum Pricing

Definition

The optimum price represents that price that gives the maximum earnings against a scenario of competitive prices. Since share roughly goes with price, the earnings tend to be approximately quadratic. That is, earnings form a “hump” shaped curve with price. Therefore, typically, there exists a price that will maximize earnings.

EXCEL makes it relatively simple to compute optimum values using the **Solver** built-in capability with the market simulator[42]. As noted above, the earnings based on Probit (S-Shaped Demand) and Linear models are be computed in the market simulator. These earning estimates are based on all competitive prices and selected product marginal costs. They represent the relative contribution earnings from the products or group of products.

5.4.6.4.1. Singular Product Optimum Price

The singular product optimum price reflects the maximum earnings for the product given that the other prices remain constant. Referring to the simulator, there are two estimates of earnings, one for each of the two market models (S-Shaped Demand and Linear). In general, the Probit or S-Shaped Demand estimate is usually considered more accurate. The optimum was computed as noted above using the **Solver** capability in *EXCEL*.

The optimum price is not limited by the range of data collected. However, the market model itself may not be valid over the total range of possible prices. As such, it is often necessary to impose constraints on the range of possible optimum prices.

5.4.6.4.2. Joint (Product Line) Optimum Prices

Often there is more than one product being offered to the market by the client. This may be either in form of multiple packages of the same product or different products such as different pesticide chemistries. Under this condition, the optimum prices of all the client products are being sought. It is not unusual on these conditions that groups of customers uniquely prefer a subset of products. This may result in some degree of product cannibalization. The optimum prices of the products may not (and usually does not) agree with the optima for each product separately.

---

[42] **Solver** seeks numerically a condition where a cell is maximized, minimized or set equal to a value, by changing the values in a number of cells under a set of conditions. The process is a “non-linear” optimization based on the classic Newton-Raphson Approximation.

The joint optimum is obtained in a similar fashion as the separate optima but using a collective earnings and adjusting the prices of the relevant products. If there is a high interaction between the products being optimized, optimum prices can be driven well beyond reasonable ranges. This is due to the effect of driving the less profitable product out of the market so that the remaining product can be sold at a high price. Unfortunately, this drives all prices beyond reason. Under this condition, we constrain optimum prices within reasonable limits.

Problems and Issues

Optimum prices should be used only as references in the direction of price changes rather than a specific recommendation for the future price. This is due to several inherent assumptions in their calculations.

- Optimum prices often extend beyond the scope of the underlying market pricing models.
- Optimum prices are based on constant competitive prices that are unlikely.
- Furthermore, it is assumed that the competition will not react to even extremely large changes in prices and subsequently large changes in share.
- Earnings often change slowly around the optimum. Therefore, it is unlikely that the client would be able to see a significant difference in earnings while pushing prices much higher than necessary.
- Market prices are neither as uniform nor as controllable as would be needed for the fine-tuning of optimum pricing.

5.4.6.5. Minimum Action Pricing - Sufficiency

Definition

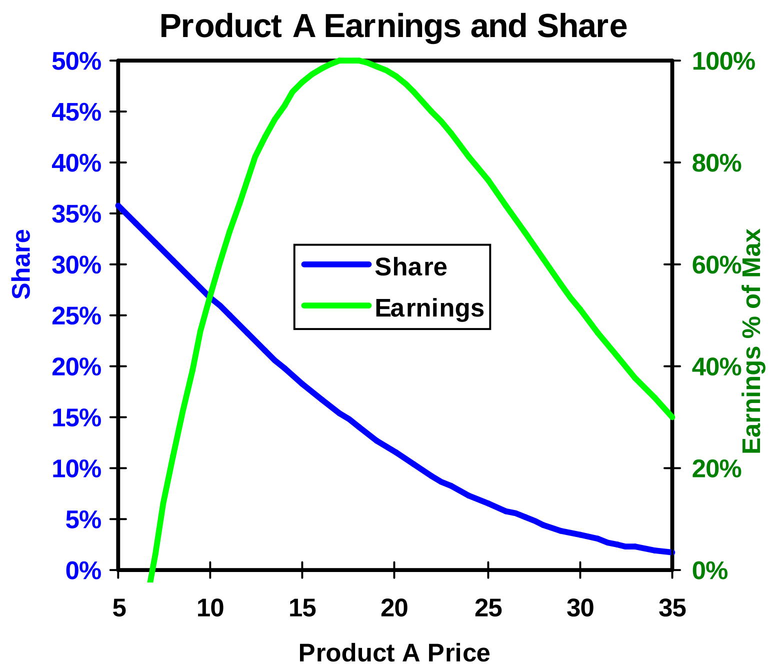
The "best" price might be one that satisfies the client's earnings needs, captures a satisfactory share and that does not incite competitive reaction. This is a balancing game, under the assumptions that competitive prices will remain constant. In order to identify this condition, the trace of earnings against price is generated. Fortunately, *EXCEL* allows for the dynamic plotting of data[43]. This allows assumptions to be tested and the results of scenarios evaluated graphically.

5.4.6.5.1. Singular Products

The graph below shows the typical trace for a single product. Changes in competitive prices will automatically change the curves. As such, this analysis is handled on a scenario basis. The client can make changes in competitive prices and marginal costs and then examine their impact.

[43] This is done using the **TABLE** Option (**DATA** Menu) coupled with the plotting options in *EXCEL*.

Notice that the earnings curve has a maximum. We assume that the client would be satisfied (sufficiency) at say 90% of the maximum earnings. This would cover a range, in this example, of $15 to $25 with the optimum at approximately $20. If the present price is at $27, the client could reduce prices to $25 and still be satisfied. He would not have to reduce price to $20 that would likely generate a significant competitive reaction.

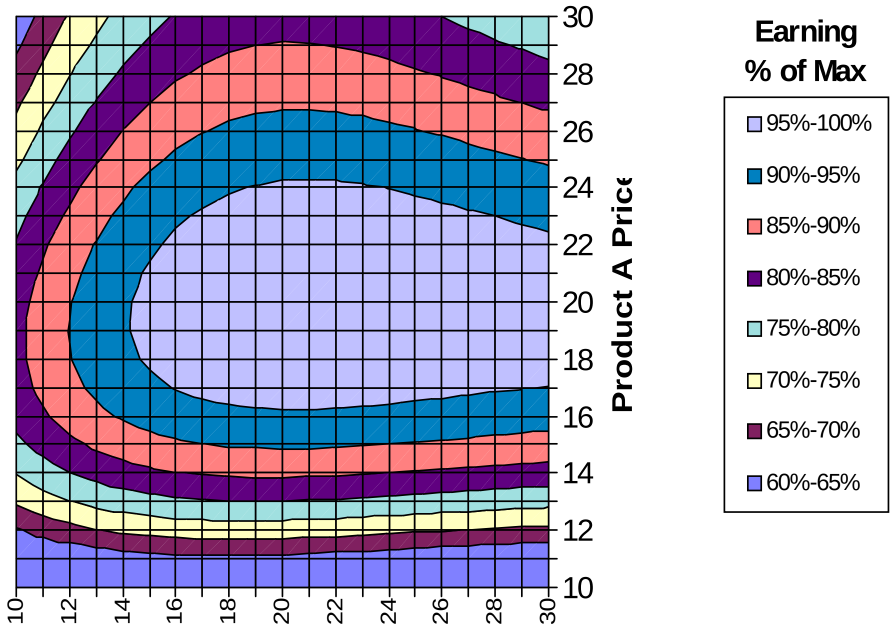


5.4.6.5.2. Joint Products

As would be expected, joint products produce a more complex situation. Typically, we handle only two products at a time[44] and do not show the share values. A density map of earnings for two products is shown on the following graph. The center region represents 95% of the maximum earnings. Pricing within this, and probably the next lower concentric region would yield satisfactory earnings for the client.

Similar to the single product trace, this joint earnings contour map automatically readjusts with changes in competitive prices and with marginal costs. Here again, this graph acts as a decision support tool to examine potential changes in the market and business conditions.

[44] It is feasible to produce a dynamic system that allows examining a third product. However, this requires a fast computer system (450 MHz Pentium II).



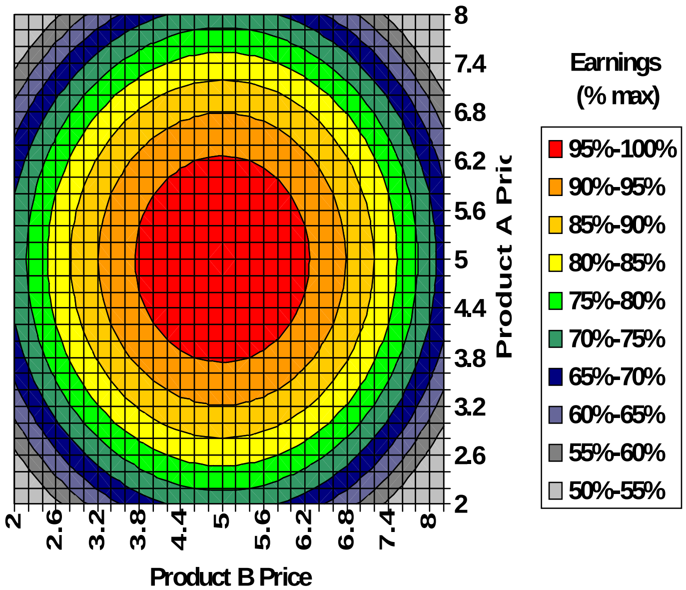
Problems and Issues

Similar to optimum pricing, sufficient, minimum action, pricing should be used as references in the direction of price changes rather than a specific recommendation for the future price. Note several problems with this analysis.

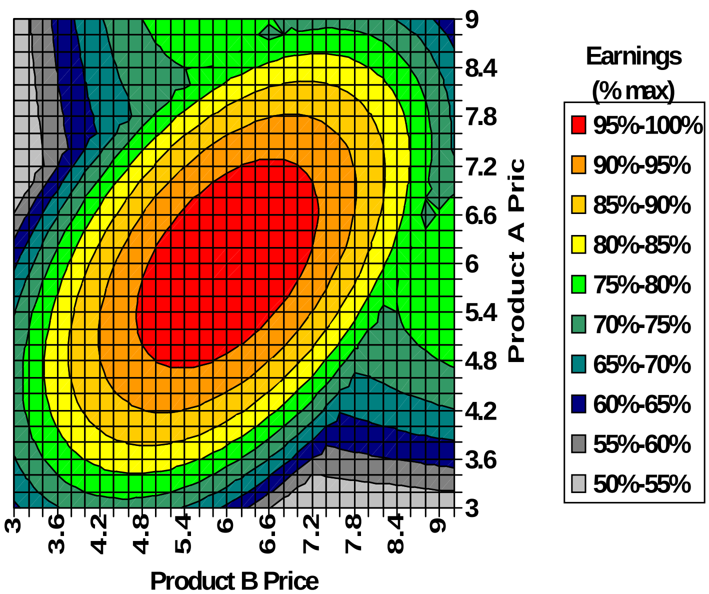
- Sufficient prices may also extend beyond the scope of the underlying market pricing models.
- Sufficient prices are based on constant competitive prices.
- And of course, market prices are neither as uniform nor as controllable as would be needed for the fine-tuning of sufficient pricing.

5.4.6.5.3. Interaction among Joint Products

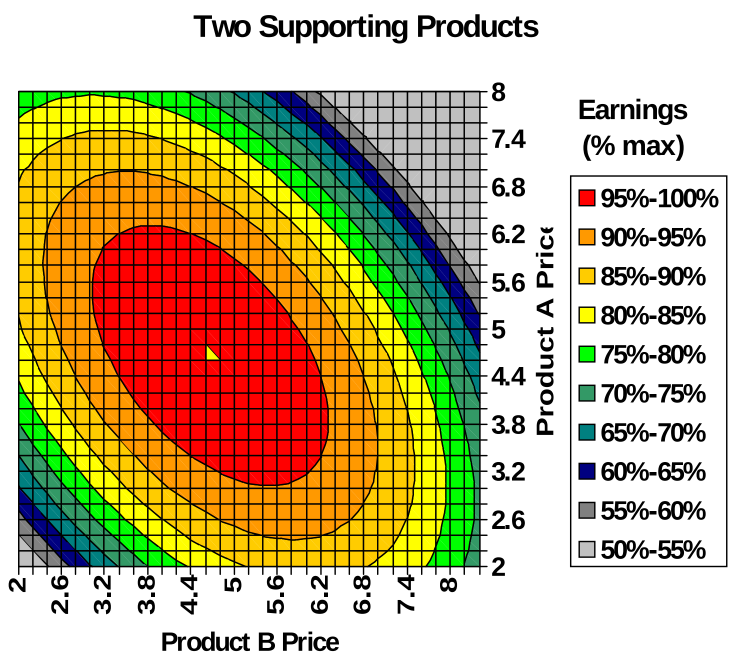
The shape of the earnings map indicates the interdependence between the two products. If the map is radially symmetric as in the figure below the products are independent. Under this condition the separate optimum and the joint optimum should be similar.



When products compete against each other the earnings map will be slanted upwards as shown below. This indicates that much of the gain of one product comes from another. The pricing chore under this cannibalization condition will depend on relative profitability of the two products.



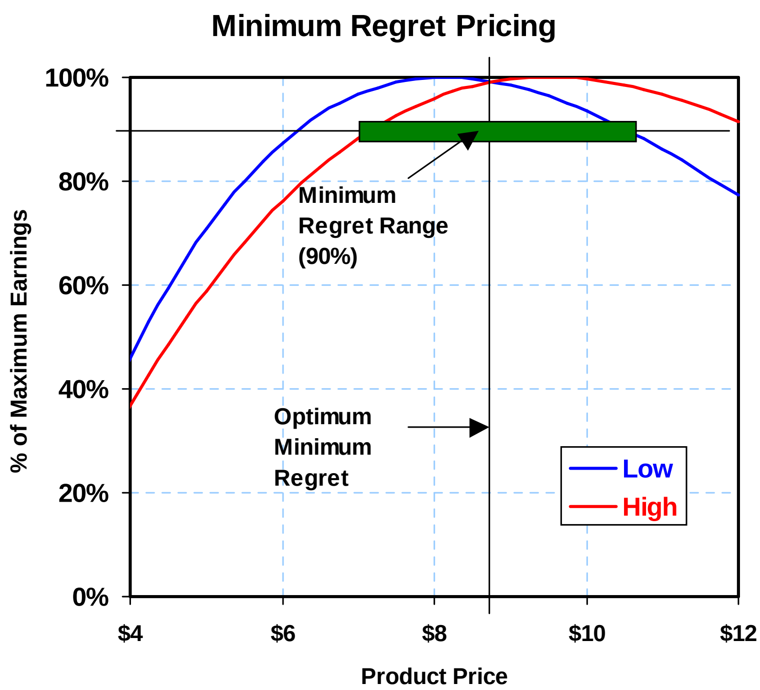
Finally, there are conditions where the sale of one product is tied to another. This is the mutually supporting situation as indicated on the following map.



5.4.6.6. Minimum Regret Pricing: Handling Uncertainty

The concept of minimum regret comes from game theory under maximum uncertainty. This concept is to find a solution or range of solutions such that the decision-maker will almost always be satisfied. In this case, we seek a range of prices under extreme potential changes in competitive prices that should satisfy the decision-maker. We assume that the decision-maker would be satisfied at some level of earnings below the optimum, such as 90% of the best achievable. The trick is then to find a range where earnings will equal or exceed that condition against vastly different competitive price scenarios. Note, however, that the actual earnings obtained at 90% of the optimum under a high priced competitive situation is different than at the more competitive low priced scenario.

The simplest approach is to generate the earnings curves for the two extreme cases as shown below. The "low" scenario is for the case where all competitive product prices are significantly below those that are presently expected. The "high" scenario is the opposite cases. It is assumed, which is reasonable, that intermediate scenarios will have earnings curves between these extremes. The point at which the two curve cross represents the highest common percent earnings for the two cases and the optimum minimum regret price. The acceptable range is considered to be that range in common at an acceptable percent. In this case, we have chosen 90% of the earnings. However, that is arbitrary.

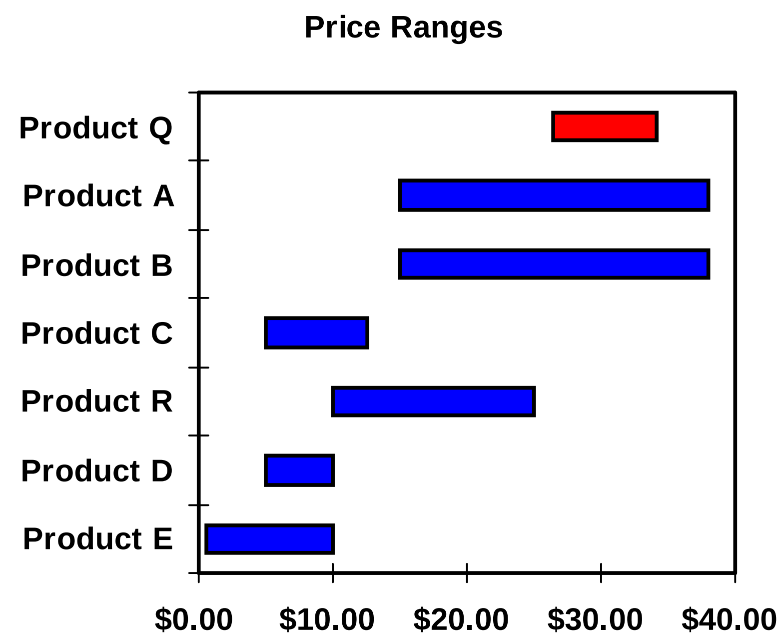


5.4.6.6.1. Decision Support System

Below is an alternative approach using a decision support system for developing an estimate of the resulting minimum regret range for Product Q where the potential price ranges of the other products are as shown. Optimum and equilibrium pricing levels may fall within that range confirming those as potential targets or they may for outside that range indicating alternative approaches.

The inputs for these estimates are the potential competitive prices, marginal costs and the level at which the decision maker would be satisfied. If the satisfaction level is too high there will not be a range. The range requires sufficient latitude for an overlap in the range of acceptable prices for the two scenarios. As the scenarios become more extreme the required satisfaction level will tend to decline.

In order for the graphical decision support system to be dynamic with changes in the competitive price ranges, an analytical model was used. This required relying on the linear price market model rather than the stochastic models used in the other analyses. Below is the derivation of the analytical model.



5.4.6.6.2. Optimum Minimum Regret

The minimum regret range is determined by the targeted level of satisfactory earnings, i.e. 90% of the "optimum" earnings. This is a range of values. It is feasible to determine the maximum value of percent of "optimum earnings". This represents the greatest percentage of the optimum earnings that is obtainable satisfying a reasonable pricing against the two extreme scenarios. This is computed by using the **Solver** yielding the highest level of earnings where a minimum regret solution exists.

5.4.6.6.3. The Minimum Regret Range

As noted, there are two prices that will yield the targeted earnings for each competitive scenario. In order to cover the range of possibilities we examine two extreme conditions: (1) a high competitive price situation and (2) a low competitive priced scenario[45]. These results in four prices, a high and low price estimate for each of the two competitive price levels. The operating range is those values that are included for both scenarios. That are between the high value of the low price points and the low value of the high prices. This corresponds to the min-max solution.

Problems and Error

The minimum regret price range can only be considered approximate and is for general guidance rather than a prediction of results. There are several sources of error that should be considered:

---

[45] Since in most cases, cross elasticities are positive, that is an increase in a competitive price will increase the sales of the product being examined, the collective effect of high and low price scenarios covers the range of collective risk.

- It is based on the linear model.
- It is assumed that the parameters are well structured (negative price sensitivities and positive cross sensitivities). and
- Known and realistic estimates of the competitive ranges.

5.4.6.7. Equilibrium Pricing - Long Range Insight

Equilibrium pricing probes long-term market viability. Markets tend to go to an "equilibrium" competitive share distribution where share is only dependent on the number of competitors and their competitive ranking. The distribution that tends to most agree with this long-term behavior is referred to as the "broken stick rule." It is based on a theoretical random process where rank order is maintained[46]. Below are the distribution results for up to five competing products.

Competitor Rank	2	3	4	5
1	75.00%	61.11%	52.08%	45.67%
2	25.00%	27.78%	27.08%	25.67%
3		11.11%	14.58%	15.67%
4			6.25%	9.00%
5				4.00%

Equilibrium Share

The equilibrium shares can be computed with the market simulator and are shown below in the last column. This is computed based on the ranking of the shares and uses a lookup table for the values. Equilibrium share is typically used for dynamic analysis to identify prices that might lead to advantageous long term positioning.

	New Price	Share Estimates S- Shape	Share Estimates Linear	1998 Average	Standard Price	Equilibrium Shares
Product A	$24.00	7.4%	6.8%	0.0%	$24.00	7.3%
Product B	$20.00	0.7%	1.1%	0.0%	$20.00	2.0%
Product C	$9.00	38.7%	39.4%	37.9%	$9.00	37.0%
Product D	$20.00	0.8%	0.5%	0.6%	$20.00	4.4%
Product E	$13.00	9.3%	9.6%	13.6%	$13.00	10.9%
Product F	$7.00	28.5%	28.0%	28.8%	$7.00	22.8%
Product G	$19.00	14.5%	14.6%	19.1%	$19.00	15.6%

[46] This is a linear ergotic stochastic order process. There are a number of other processes that yield different distributions. However, this process of linear confined measures appears to be a good metaphor for established businesses where price adjusts for differences in performance. Furthermore, the distribution is particularly good at describing competitive markets.

Equilibrium Price

The equilibrium prices for the products represent the prices necessary to produce the equilibrium shares. This is under the constraint that the average prices remain constant. Underlying this analysis is the assumption that there will be no changes in the perception and price sensitivity in the market. The predicted prices, therefore, highlight changes that are likely to take place in the market. Prices that are predicted to be unrealistically low would indicate products that will be or are under pressure to exit the market or change their marketing strategy. Products with lower than equilibrium prices can be viewed as being destabilizing. This may be due to their management being unaware of the product value or following an aggressive strategy to restructure the market.

Below is the decision support screen showing the equilibrium prices. The equilibrium prices are obtained by numerical optimization (minimizing the squared difference between shares and the theoretical values) under the constraint that the average prices remain constant. This is computed using the **Solver** capability in *EXCEL* in the same manner as for optimum price computations. Usually we use the stochastic, Probit, price market model.

	Equilibrium Prices	S-Shaped Share	1998 Average	Standard Price	Equilibrium Shares
Product A	$21.17	7.3%	0.0%	$24.00	7.3%
Product B	$6.76	2.0%	0.0%	$20.00	2.0%
Product C	$8.81	37.0%	37.9%	$9.00	37.0%
Product D	$4.24	4.4%	0.6%	$20.00	4.4%
Product E	$12.21	10.9%	13.6%	$13.00	10.9%
Product F	$11.34	22.8%	28.8%	$7.00	22.8%
Product G	$15.98	15.6%	19.1%	$19.00	15.6%

Problems and Issues

There are some issues and concerns in this computation:

- Computation is usually long, though with the new generation of computers, it does not take more than a few minutes.
- It is required to assume some stable overall price condition. Equilibrium price is based on share not volume. Equilibrium shares can be approximated therefore at any overall price point. But some constraint must be imposed. However, this constraint limits the interpretation of the results.
- It is sometimes necessary to constrain the price range to prevent unrealistic prices. Both extremely high prices, as with optimization, and even negative values can be computed unless constrained out.

5.4.6.8. Stochastic Pricing (Monte Carlo Modeling)

Minimum Regret Pricing assumes that we know little about the nature of the uncertainty in competitive prices[47]. If we allow ourselves the ability to estimate the nature and range of future prices, we can simulate the results. The price simulator is modified to allow random sampling of price values[48]. In the case below we are using normal distributed competitive prices with 10% standard deviations[49]. Usually, pricing scenarios of the target product is explored while the competitive price distributions are assumed static. The results of the stochastic simulation are obtained using a **DATA TABLE**. The simulation is recomputed for every row of the table[50]. The figure below shows the decision support entry screen.

Variability	10%

Normal Distribution: Mean	Std/Mean		Price	Expected	1998 Average	Standard Price
		Product A	$20.00	7.4%	0.0%	$24.00
$20.00	10.0%	Product B	$21.55	0.7%	0.0%	$20.00
$9.00	10.0%	Product C	$8.32	38.7%	37.9%	$9.00
$20.00	10.0%	Product D	$23.56	0.8%	0.6%	$20.00
$13.00	10.0%	Product E	$10.70	9.3%	13.6%	$13.00
$7.00	10.0%	Product F	$7.49	28.5%	28.8%	$7.00
$19.00	10.0%	Product G	$22.48	14.5%	19.1%	$19.00

	Cost	Optimum	Likelihood of Earnings <	1.2	1.9%
Product A	$6.85	$17.53	Likelihood of Share <	10%	9.2%

The most critical values from the simulation are the likelihood that earnings and share goal will not be reached. With Monte Carlo simulation this computed directly from the results. On the lower part of the entry screen are the results of that computation. The levels can be changed to examine goal sensitivity.

The results of the simulations are presented as probability distributions of the results. For pricing simulations, these are usually normally earnings and share. Below are the resulting graphs from the simulation. The bi-variant distribution shows the probability of an event within a range of earnings and share[51]. The marginal distributions of earnings and share are shown as the bar charts. These are dynamic graphs. The graphs are recomputed each time the simulation is rerun.

---

[47] There is some fundamental questions about the reliability of subjective estimates of future probabilities. Doubt about the ability to estimate the probability distribution of future events has led to the recommendation of Minimum Regret approaches from a game theoretic perspective.

[48] There are several add-on packages that facilitate the development of Monte Carlo models. These include *Crystal Ball* and *@Risk*. However, in order to develop a live decision support system, we selected to do the process totally in *EXCEL*.

[49] This is computed as **NORMINV**(**RAND(),mean, std.dev**).

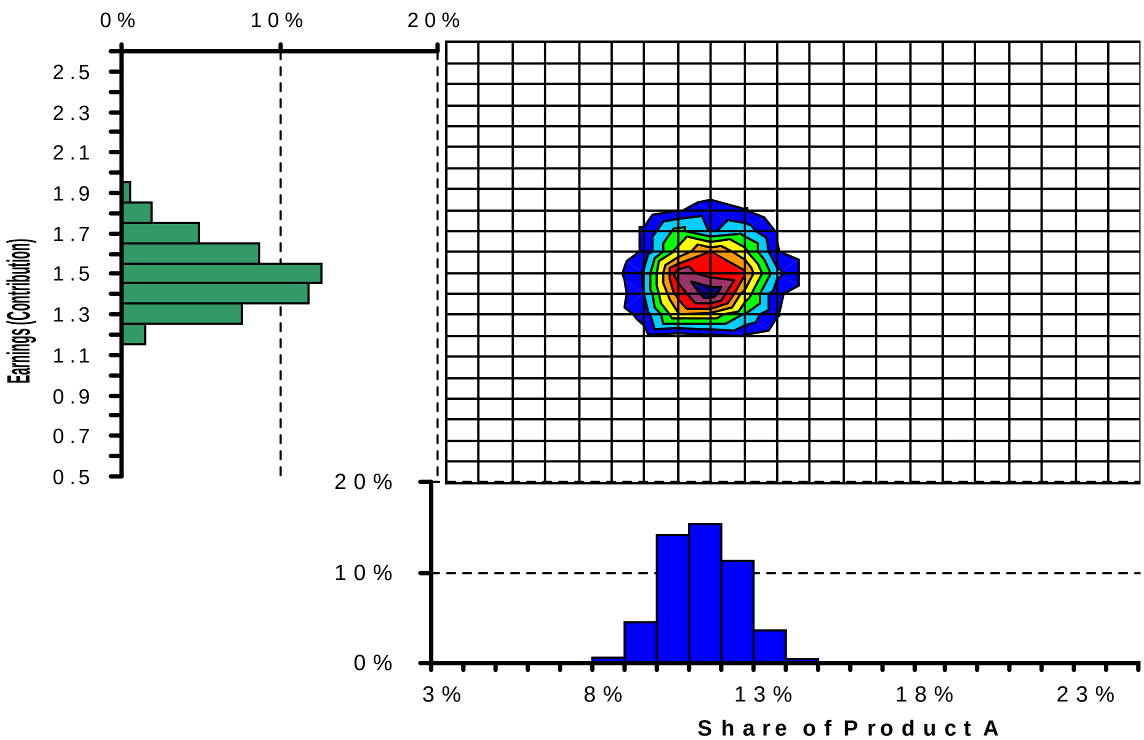
[50] In this case almost 1500 scenarios were generated.

[51] The bivariate density plots is obtained by way of a density matrix generated from the data.

Problems and Issues

There are some significant issues using stochastic simulation:

- The simulation can be extremely slow. Even on a modern high speed system, there is a noticeable delay in the computation.
- The stochastic simulator is not easily built. Several of the components such as bi-variant density distributions are not available directly in *EXCEL* nor the add-in packages.
- As previously noted, the simulation is based on subjective estimates of future probabilities with all of the reliability issues that that estimate implies.
- Generally, we assume independence of the prices. Assuming joint probabilities can be handled but introduces complexity in estimation.



5.4.6.9. Minimum Risk Pricing

As previously discussed, Monte Carlo analysis gives estimates of the likelihood of exceeding or not exceeding some goal. The goal may be either an earnings level or a market share measure. If an earnings goal is at issue, an estimate of a minimum risk "optimum" price can be obtained. This is done by tracing the likelihood of meeting that goal against price and identifying the point of maximum likelihood, as shown below. Once the Monte Carlo simulator is developed, this analysis is straight-forward but computationally intensive.

Problems and Issues

There are several concerns in using this technique.

- It must be noted that these estimates are based only on uncertainty of market prices not in total demand due to external factors. In many cases, those external factors can far exceed the importance of price variations on the earnings uncertainty. However, they usually do not influence the choice of the best price.
- The minimum risk price depends on the goal selected. Different goals can, and probably will, result in different price levels.

5.4.6.10. Dynamic Policy Pricing

A potential use of the simulator is to dynamically test pricing policies assuming competitive reaction. This usually involves setting up the simulator to focus on a number of competitors. A dynamic process is set up by allowing the results of one simulation to drive the following periods'. Generally, this is handled manually to allow for competitive optimization of price or similar strategies. Because of its complexity and the lack of knowledge of competitive reaction, we have tended not to do this type of simulation on pricing. However, it has been used for industrial capacity modeling.

Problems and Issues

There are some issues and concerns in this computation:

- It can be very complex;
- Based on uncertain assumptions of competitive behavior; and
- Usually focuses on a time frame beyond the scope of the pricing decision.

5.4.7. METRICS OF PRICING STRATEGY

Maximizing current earnings is not the only objective of pricing. Ultimately, the pricing and for that matter the business strategy should provide for the long term benefit for the business. There are additional issues that affect “best” pricing strategy. These include price premium, brand loyalty, reseller decisions, user share and substituted value. Information on all of these can be obtained with choice modeling.

5.4.7.1. Price Premium Estimation

Price premium represents the difference in prices that the market is willing to pay for one product or brand over another. It is a measure of the “good-will” of the brand as captured by its perceived value. The concept is developed around an idealized customer who chooses between two products. Unfortunately, markets are diverse groups of customers with differing degrees of product loyalty and willingness to pay. From a market perspective, we define price premium as the difference in prices that can be sustained at given share distributions.

Typically, the equilibrium share distributions are used. As such, the equilibrium price estimate is used as the basis of price premium. Alternatively other share distributions can be used including, minimum sustained entry and equal share distributions. The minimum sustained entry is based on assuming some lower limit of penetration is needed for a competitor to remain in the market. This lower limit is used as the competing product shares. This is used in a defensive analysis against new entries. The equal share distribution comes closest to the idealized concept of measuring the dollar value of the brand under equal conditions. However, it is rarely used since it represents an unrealistic and unstable situation.

It should also be noted that a constraint must be imposed on the prices to obtain unique solutions. While for equilibrium pricing, a constant expected average price is imposed, for price premium calculations, a given price of the primary product is typically used.

Problems and Issues

There are some issues and concerns in this computation:

- It must be reemphasize that the price premium calculations are dependent on the standard share distribution used and the imposed pricing constraint. As such, the values must be viewed as relative to the market situation.
- Because of the complexity and difficulty of the computation, price premium calculations are generally only done on a market or segment basis. As such, it is difficult to use the procedure to understand drivers of value.

5.4.7.2. Channel Based Optimum Pricing

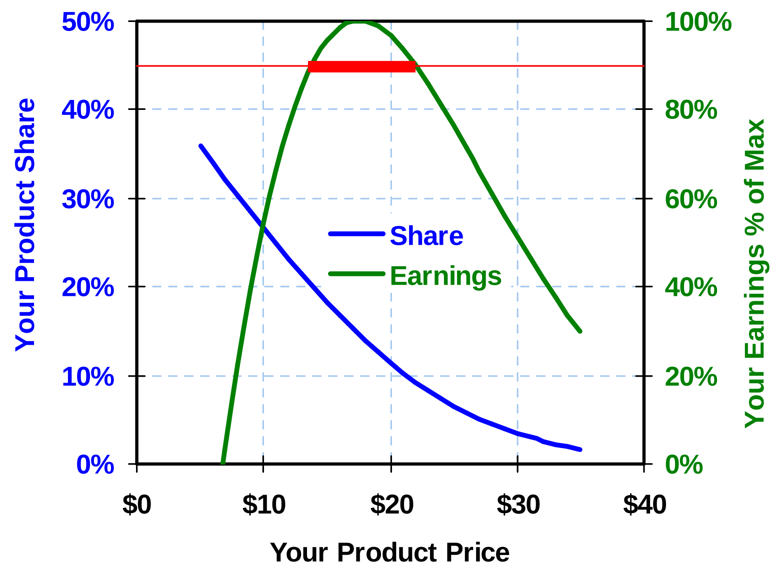
Products are typically sold through some kind of reseller or distribution channel or network. The channel connects the manufacturer or OEM with the customer. These channels contain all forms of resellers including distributors and dealers. The members of the channel may or may not own the product or take physical possession of it. From a strategic pricing perspective, what is more important, the manufacturer may or may not have control of the sales price. This is the key problem. Customer demand for a product is defined in terms of the price that he or she sees in the marketplace. The only price that the manufacturer will usually have control over is the price into the distribution channel. That is the price that he can charge the reseller.

There are a number of methods to measure consumer demand. Among the best is the *Complete Choice Analysis* method. This approach allows for the estimation of the customer demand function, which provides forecast of the sales of various products within the consideration set based on the prices of all of the products. It is a multivariate approach, which captures the interaction among product prices. The resulting demand functions can then be used to estimate the earnings to the manufacture based on a cost relationship. And from the earnings one then can estimate the customer price that would maximize earnings, the "optimum price.

The cost relationship captures both the cost of goods sold by the manufacturer and the marketing costs based on the "resellers’ margin". And here we see the issue of market control, which dictates the resellers' margin. There are three conditions: (1) the margin is assumed to be known and constant, (2) the market price is controlled by the manufacturer, and (3) both the reseller sets the price to maximize his earnings. This can results in very different optimum prices.

- ***Standard Price Optimum with Fixed Reseller Margins***

As previously discussed the standard approach to price optimization is to include marketing costs into the overall cost relationship. Furthermore the resellers' margin is assumed to be constant irrespective of the product's price. This is a traditional approach where the distribution channel uses a standard markup for final pricing. Optimum pricing using this cost relationship is fairly straightforward and shown graphically below for a single product. However, it can be more complex when dealing with multiple products.



In this case we are using a "S-Shaped" (Gaussian) demand curve. The red line represents a reasonable price range (at 90% of the maximum earnings). Once again, this approach assumes both constant cost of goods sold and margin.

- ***Pareto Optimum***

An alternative is if the manufacturer controlled the customer price. This is equivalent to maximizing the total of the earnings and resellers revenue. It is the total "pie". The way that this total is split between the manufacturer and the resellers is indeterminate. What we are looking for is the maximum return. This is referred to the "*Pareto*" or the "Potential Pareto" optimum in that all parties should be potentially best off. This optimum is computed similarly to the standard approach but with a zero resellers' margin.

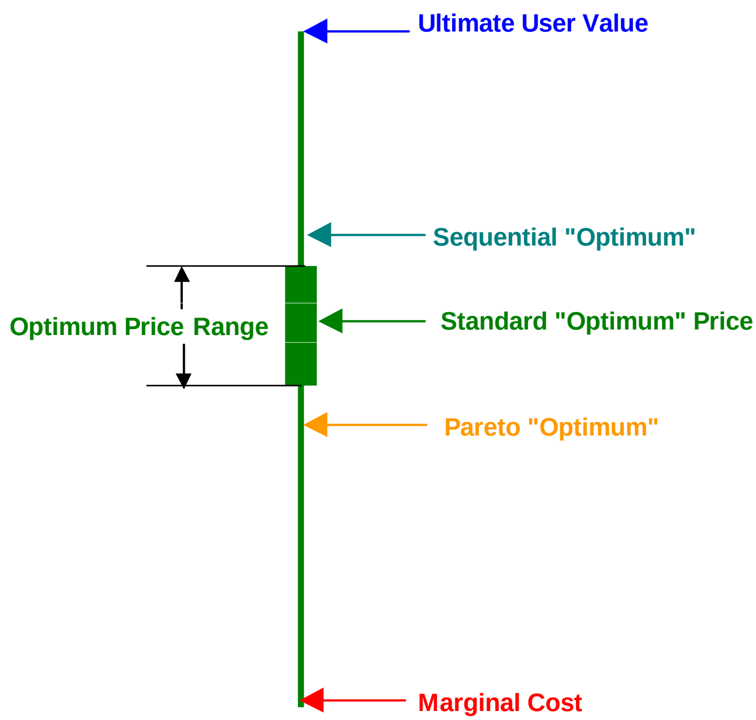
- ***Sequential (or Nested) Optimum***

The third approach is more complex in that we assume that the resellers and the manufacturer will both wish to maximize their returns. That is we seek the optimum manufacturer's price given that the resellers will maximize their earnings. It is a two-step process. The resellers will maximize their earnings given a price from the manufacturer. Then the manufacturer will choose the price of the series that maximizes his earnings. Note that the resellers' margin is likely to change with the manufacturer's price. Typically, the reseller can command a higher margin, in many cases, at lower manufacturer's price.

Since margin is included in the costs, the resulting optimum price will be higher than that for the *Pareto Optimum* but may or may not be above that for the *Standard Optimum* based on the assumed resellers' margin. This is interesting in that the "free" market approach, where the resellers have total discretion to set price, results in a higher price for the customer than the manufacturer controlled case.[52] The equations describing this nested optimum pricing process for linear demand functions are derived in Appendix 5.10.4

- ***Comparing Optimum Prices***

Below is a diagram showing the three optimum prices along with the optimum price range. The *Sequential* and *Pareto Optima* may or may not exist within the standard price range. Note that each optimum reflects different underlying assumptions. Furthermore those assumptions capture different pricing and marketing strategies based on the control of the marketplace.



- ***Resellers' Programs and Negotiated Prices***

The *Pareto Optimum* case provides a difficulty, however, since the mechanism of splitting the total return is not specified. This is important since the resellers, "the market", needs to be persuaded to price the products in-line with that specified. It should be noted that the reseller will always obtain a higher return if they were allowed to optimize the price given any manufacturer's price. This would result in less than optimum earnings for the manufacturer. However, the reseller should obtain higher earnings with *the Pareto Optimum* solution with a "reasonable" split than he would receive based on the *Sequential Optimum* that the manufacturer would otherwise follow. The net result is that reseller must be convinced to accept a margin below what he would

[52] This has "social welfare" and government policy implications.

have desired by either inducement (reseller programs) or by fear of a much higher manufacturer's price.

Note that this is not the only reason to pursue reseller programs buy it is probably the most well-reasoned for an economics perspective. There are at least two other general reasons: (1) differential pricing and (2) added value through the sales and support effort. The first is somewhat problematic. It is always uncertain if the reseller will pass on any savings. It is usually preferred to use some direct incentive such as customer programs, rebates, and coupons. Regarding the value added proposition. This is also problematic due to the commonality of competitive programs and the inability to monitor results.

- ***Market Equilibrium (or Collective Optimum) Pricing***

Taking a collective approach, we could attempt to compute optimum competitive market prices. That is, if each competitor offered their products at the price that would maximize their earning considering that the other competitors did the same. This is motivated by the idea of a “Nash Equilibrium” for the market with each competitor acting both independently but accepting expected competitive behavior. Ideally this approach could generate “equilibrium” prices for all competing products. However, that is not usually feasible. Either the demand function is limited to only a set of driving variables, prices, or the “equilibrium” relationship of only a few competing products are of interest.

As such, the equilibrium prices are considered conditional other “fixed” competitive prices. Though this is a limitation in using market equilibrium pricing, it has an advantage in focusing on specific issues. For example, we can use this approach to examine relative pricing of branded and generic products where we consider only single pairs. For some types of the demand functions, (linear) an analytical solution can be found. This is shown in the Appendix 5.10.5.

Problems in Its Use

There are some issues and concerns in using the Market Equilibrium Pricing:

- Acceptable solutions may not exist. Basically, there is no assurance that the “Nash Equilibrium” exists for market pricing. That is, that the solutions may include negative price values or extremely high prices which would call for negative volumes (linear case). Neither of which would be acceptable.
- The price solutions depend on the form of the demand function. That is the solutions may be different depending on the form of the function, linear, exponential or “S-Shaped” (Gaussian).

5.4.7.3. Brand Loyalty

Ultimately the goal of price premium is to understand why and how much do customers prefer one brand over another. As previously noted, it is usually not feasible to compute the price premium estimates on a respondent level. Alternatively, a measure of brand loyalty is used. This is estimated based on the average share by brand across all scenarios. Typically, these are divided into categories such as loyal, neutral and non-loyal customers. Key drivers can then be identified using statistical modeling methods[53].

Problems and Issues

There are basic underlying concerns in this analysis:

* The definitions of loyal customers depend on the structure of the pricing scenarios. This may lead to arbitrariness in the definitions. However, typically the separation of loyal from non-loyal customers is based on median rather than an absolute level. This reduces the arbitrariness of the definition.
* Effective customer loyalty key driver analysis depends on the collection of adequate additional customer characteristics. Pricing studies are usually limited to the pricing exercises and marketing information rather than detailed characterization of customers. This greatly limits the effectiveness of the analysis. This is one of the advantages of using established respondent panels where additional characteristics are available.

5.4.7.4. Price Sensitivity Segmentation

Occasionally it is useful to try to segment the market based on price sensitivity as well as with other data. With concept testing and perceived value data this is not a problem. Typically hierarchical clustering can be used after the normalization across the respondents' results with this data. Hierarchical and other methods of statistical clustering for deriving market segments are discussed in the section on Attribute Analysis.

However, Choice Modeling data is more difficult to use since the results are not explicit measures of willingness to purchase. At least, two approaches have been used: (1) derive individual pricing models and (2) develop surrogate measures for price sensitivity. While it is feasible, particularly, with volumetric data, to develop individual pricing models, it is extremely difficult with large sample sizes. It is usually preferred to use surrogate measures. These typical involve measures of overall price sensitivity with volumetric data and the willingness to change brands, or mode of purchase with both volumetric and discrete data. For example with volumetric data, the ratio of the maximum to minimum purchases across the scenarios would be a measure of price sensitivity. Similarly, the sum of the maximum purchases by products across scenarios would measure the willingness of respondent to change brands. These estimates can be obtained directly from the raw data and then used with other information such as the product purchases for a specific scenario to provide the basis for price sensitivity and loyalty segmentation.

---

[53] Because the customer loyalty is usually a discrete variable Discriminate Analysis and Logit Regression are the preferred methods to identify key drivers.

5.4.7.5. User Share and Average User Rates

The shares developed with discrete choice pricing exercises reflect both the share of the market and the share of the users or purchasers. Note that in this case the respondents choose the products that they would purchase. This may be a single product or multiple ones. In volumetric choice, the respondents indicate how much of each of the consideration set of products they would purchase. Here market share and user share may be different. Purchases may be tied together.

A user share model can be computed from the volumetric data by transforming the volumetric data into a discrete form. That is any purchases or those above a threshold point will be considered a discrete purchase. This results in a database of zeros and ones. The user share model is then computed in a similar fashion as the demand share model[54], and the results are shown in a table as indicated below.

	Price	Share	% Base	Users	Use Rate	Standard Price
Product 1	$12.00	24.4%	201.4%	99%	203%	$16.00
Product 2	$15.00	6.6%	54.2%	52%	105%	$15.00
Product 3	$8.00	10.9%	89.9%	66%	137%	$8.00
Product 4	$12.00	9.1%	75.2%	68%	111%	$12.00
Product 5	$17.00	1.0%	8.6%	17%	51%	$24.00
Product 6	$13.00	6.4%	52.5%	52%	101%	$10.00
Product 7	$16.00	3.6%	29.9%	42%	71%	$20.00
Product 8	$15.00	9.7%	79.9%	52%	154%	$20.00
Product 9	$22.00	7.2%	59.2%	48%	124%	$22.00
Product 10	$22.00	10.9%	90.0%	67%	135%	$40.00
Product 11	$22.00	5.0%	40.9%	37%	111%	$22.00
Other	$14.76	5.3%	43.7%	28%	159%	

Demand and User Share values are computed, as with the demand model, by using estimates of the product prices. The Average User Rate can also be computed by dividing the Total Demand by the User Share. This provides an estimate of the average use rate by those respondents selecting the product.

Strategically this is useful to determine both the penetration of the product as well as the demand and share. This is particularly interesting when the database is cut across segments.

5.4.7.6. Average Substituted Value

Substituted value is based on the value of the alternative products selected compared to a targeted product. In most cases, we are interested in the price position of a number of

54 There is a difference in the calculations of user share compared to that of the demand in that we do not normalize the Gaussian model values. Data is computed based on the raw data producing a stochastic (Gaussian) model predicting the user share for each product given the selected prices in the model.

new concepts. The substituted value represents the value of products that would have been used instead of a particular product. For example, with pesticides, a new product would substitute for the use of a number of other products.

The substituted value can be computed from the choice exercise pricing model[55]. It is based computed the weighted sum of the other products. This represents the total alternative value of products selected. The substituted value is computed as the incremental difference in a series of values at differing demand rates. This is obtained from a table indicating differing prices of the targeted product and computing both the demand and the value of alternative products. From the differences along the table, the incremental substituted value as a value/unit of targeted product is calculated[56].

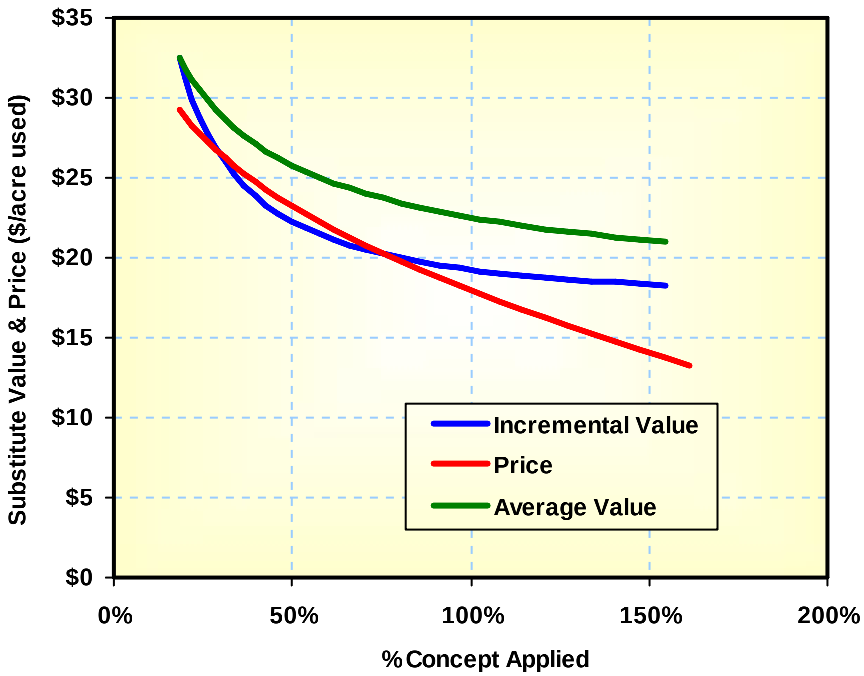
The incremental substituted value represents the marginal change in value between points along the demand for the product. An estimate of the average value can be computed by using a weighted average[57] which compensates for the differences in increments[58]. These are shown on the following graph.

[55] Often the “Other” option is included in the consideration set, but it is not priced. For the use in the calculation of alternative value, the weighted average price is used for “other”.

[56] At very low demand rates the incremental values can go to extremely high or negative values. This is associated with values beyond those tested by the original data. The underlying model may be only marginally valid under these conditions. Typically, incremental values at low demand are set equal to zero to stabilize the results.

[57] With Excel the weighted average is taken as the **SUMPRODUCT(Price$_i$ ● Demand$_i$)/SUM(Demand$_i$)** across all alternative products.

[58] Without corrected incremental values, the average value could produce erroneous results. Lower demand values tend to be carried across into the weighted average values. As such, it is critical to check that the lower values do not dominate these averages.


$35
$30
$25
$20
$15
$10
$5
$0
Substitute Value & Price ($/acre used)
0%
50%
100%
150%
200%
% Concept Applied
Incremental Value
Price
Average Value

5.5. PERCEIVED VALUE METHODS FOR PRICING

The pricing methods discussed in this chapter are designed to capture the value of fairly well defined products and services. However, there are cases where the product concept is only available as a combination of features and attributes. Under these conditions perceived value techniques may be the only methods available to provide pricing policy information. Perceived value marketing research methods are designed to determine monetary value of product features. There is a broad range of techniques that are used for this complex research activity. These methods are discussed in a separate chapter in these notes. This section will only review some the issues as they apply to the pricing of final products.

5.5.1. INTRODUCTION

The objective of perceived value research methods is to obtain the relative value of attributes of products to the purpose of designing optimum offerings. Products are considered, for the purposes of this type of research, to be linear combinations of features; and their value to be the sum of the partial feature values. While there is some ability to handle interaction among features, this is rarely used and is considered a major complication. The methods, in general, either forecast the preferred mix of features or give utilities of the features that can then be scaled to a monetary value.

5.5.2. LIMITATIONS AND ADVANTAGES

The key limitation as well as the strength of these methods is that products are constructed based on recombinations of features. This allows a wide range of possibilities to be compared. However, the products are synthetic and, therefore, the respondents have not reacted to the actual offerings. Furthermore, the procedures are highly hypothetical exercises that usually do not reflect the buying process. These factors tend to create biases toward higher prices compared with those measured otherwise or seen in the marketplace.

5.5.3. PROBLEMS AND DIFFICULTIES

There a host of perceived value methods and while some are better for some purposes than others, they all have common problems and difficulties including:

* The consideration set of features are limited and restricted to those easily defined.
* Monetary values are derived by scaling feature utilities against price levels or discounts. This greatly limits the price range and sensitivity.
* The execution is a hypothetical exercise, which has little resemblance to the buying process.
* The analysis is fairly complex and somewhat arbitrary in that multiple analytical models are feasible.

* Many of the procedures are very “fault intolerant” in that errors in the design can make the results meaningless.

5.5.4. Modifying Concept Testing and Choice Modeling

There are cases where perceived value methods either alone or in combination with other pricing research methods are the preferred procedure. These usually involve situations where the product is defined by a set of components that are varied. These situations include contracts, deals, services and bundled products. In most of these cases multiple offerings will be available.

The objective of combining perceived value and complete choice models is to be able to modify the products in the choice model. That is we wish to develop a modified situation where the products in the choice model have been changed by introducing some new benefit or feature. In traditional complete choice modeling, only the predetermine set of products are considered. The resulting price-demand model captures the market sensitivity to changes in prices among those products. Changes in products are not inherently allowed.

Now if all we wanted to know was value of new features to potential customers, we could measure them using perceived value or conjoint methods. These allow for the measurement of monetary value of features or benefits and to be able compute collective value of multiple features. This can, by itself, be used to estimate the value or price of a brand new offering or product concept. However, it tells you very little regarding how an improved existing products will behave let alone the effect of price. To do that, we will need to combine both the competitive choice price modeling with perceived value data.

What we would like to have is illustrated in the table below, where we can add features to the existing products as well as change prices. The check boxes are used to select the new features and prices can be entered into the white boxes. The volume or share is then calculated by the collective model.

Feature Selection

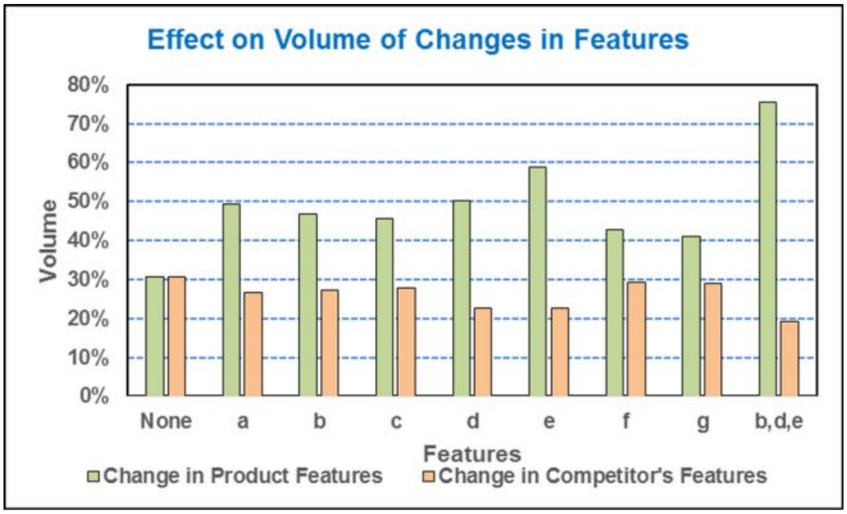
New Features	Competitive Products B	C	D
a	☐	☐	☐
b	☐	☐	☐
c	☐	☐	☐
d	☐	☐	☐
e	☐	☐	☐
f	☐	☐	☐
g	☐	☐	☐

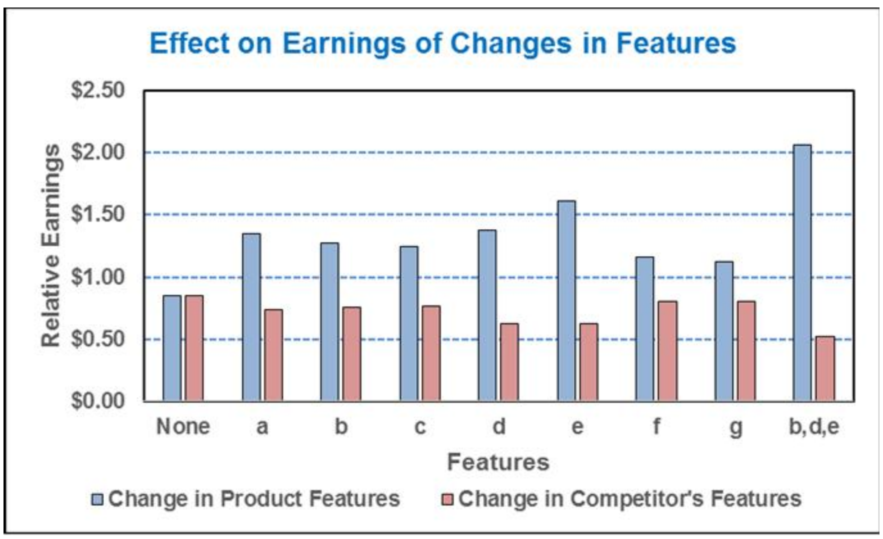
Competitive Pricing Model

Product	Price	Volume	Standard Price
A	$5.00	66%	$5.00
B	$5.00	**31%**	$5.00
C	$5.00	76%	$5.00
D	$5.00	111%	$5.00
Other		15%	

The relative earnings and an estimate of the optimum price could also be obtained. For a specific product of interest these results can be shown as demand and earnings curves. The choice model is based on sets of prices referred to as the "design". For each scenario, there is a set of prices. Respondents react to those prices by considering which or how much of each product will be purchased.

The maximum point in the earnings curve represents the optimum price, or the price at which the earnings would be maximized. We should also examine the impact on the sales and earnings of the target product with changes in the offered features at a standard price. Alternatively, we can examine the impact on a specific product when the competitive products offered those features while the targeted product did not. Below is an example of the profile for the inclusion or exclusion of one of seven features along with a bundle of three features on sales volume and on relative earnings.





The first entry on the left represents the case in which there has been no new features added to either the target product or its competition. Notice the large change in the last entry; this represents three features being added to either the target product or its competition.

5.5.4.1. Using Averaged Values

Averaged perceived feature value can be used to modify specific product prices where the new benefit is being introduced. This is done by using a percent change in the price based on the average perceived value measurements. For example, if a new feature would increase the value of a product by say 10% as measured, estimated using a conjoint exercise, then, we can increase the price of that product in the design by 10%. This assumes that the respondent would react to the higher price with the feature as he would have at the lower price without it.

This, however, is very simplistic in that it ignores the distribution of feature values. In the above approach only the average value of the feature or bundle of features is considered. In reality, the value is usually highly varied with either a normal or exponential distribution. To provide a handle for this, the analysis can be done in pieces. For example, the distribution of value can be divided into thirds: with a high, medium and low range. The values of each range can be set at its average value and the participants or segment members in each range are identified. Three price models can then be generated based on those identified participants, with corresponding modified pricing designs. The final model would then merge the results of the three sub-models.

Note, that further refinement could be made using larger numbers of ranges. Unfortunately, there is a down side, in that the precision of the pricing model depends on the sample size. The more divisions used, the poorer will be the fitted models used. This then becomes a balancing issue, the greater the number of divisions, the better the feature value is captured but the poorer the modeling fit.

5.5.4.2. Modeling Individual Responses

In the previous approach we used the averaged perceived values as a means of computed the average demand function. The demand function in this case can be of any form, linear or S-Shaped. It is basically a regression model. This is a collective approach. However it can also be done on a respondent basis. It can be constructed either on a respondent basis or collectively. That is we can either construct a separate model for each respondent and average the results or we can construct the model based on the average responses as previously mentioned. For strictly linear or straight-line economic demand models, we get the same results using either approach[59].

For the standard application, without new features, we use a common scenario price design. However when we consider new features, we will modify the pricing design for each respondent. The perceived feature value tools that we use give individual or respondent level percent value estimates for each feature[60]. From these estimates the value of feature bundles can be computed. What we then compute is the composite value for the selected features for each product, for each of the individual respondents.

As we select features in the first figure, using the checkboxes, the added value is computed for each of the products. For each individual, the scenario pricing design is then modified by inclusion of the additional value associated with the selected features by product. The individual demand model is then generated using this new scenario pricing

[59] If we use a non-linear function such as an "S" Shaped (Gaussian or Normal) demand, the results are different using the average of the individual demand models than developing the composite model with the average responses.

[60] This requires complete respondent level value measurement. We have typically used the either compositional conjoint which is the simplest and most straight-forward method or full-profile conjoint.

design and the individual's responses. The collective model is based on the average values[61].

With modern computers and the newest version of Microsoft® Excel® these calculations are fairly efficient and allows for easy exploration of alternative futures. Variation in both the feature bundles and prices can be readily explored.

5.5.5. Estimating Demand and Optimum Price

The distribution of perceived value can be used as an estimate of the demand curve. These distributions can be estimated either using an agency approach, where the measured sample is considered the market or using market simulation, Monte Carlo. In both cases the total perceived product value is considered to be equal to the target price. It should be noted that this becomes a dynamic model in that various products can be assumed based on the unique combination of features whose value had been captured by perceived value measurement tools. An underlying assumption in this analysis is that the estimated value is equal to what the market would command, the target price.

With a demand curve one can then construct the earnings curve from which an optimal price and price range can be estimated in a similar fashion as done with pricing data. In addition and elasticity can be estimated over the range of values. The analysis that follows in a similar fashion as what showed earlier.

[61] Note that there is no requirement for the use of all of the data. Sub-samples, groups and segments can be used. This requires only that the averaging be done over the sub-set of respondents.

5.6. ECONOMIC VALUE METHOD FOR PRICING

Economic models can also be used to construct the demand curves. These are based on projected value of products. They capture all of the economic benefits and cost savings that could be associated with the use of a new product or service. These models go by a number of different identifications including value-in-use, application economics, and economic evaluation. The development of economic value models is covered in another chapter in these notes.

Note that these models are normative, in that they reflect what should be the value of the product rather than what is the perceived value. To a very great extent the economic models must be considered hypothetical. They bring together a great many assumptions and beliefs about the market and about the applications of the products.

5.6.1. Limitations and Advantages

More than almost any other technique of pricing, the use of economic evaluation rests upon the need to use heroic assumptions. The term heroic here refers to assumptions that are both critical and cannot be independently tested. The use of these assumptions are both its strengths and its great limitations. As a strength it allows consideration of yet to be determined features and benefits. As a limitation the results could be highly hypothetical.

A key assumption in using economic value for pricing is the willingness of the potential buyers to surrender a portion of their value to the seller. This is always an “iffy” proposition. There is little theoretical basis for choosing a percentage of value that the market would surrender. However it is still a critical factor to be considered typically this assumption is estimated based on a comparison of value and prices of expected products in the marketplace. The biggest problem with these estimates is that this can be highly dynamic. With unique products for which there is no direct competition this may be stable and long-term. However with the introduction of competition this value tends to erode drastically.

5.6.2. Problems and Difficulties

While there is a host of procedures to estimate economic value, the end results are usually the same; that is, a measure of economic value to a user from the application of a product. Distributions are then generated from which pricing analysis is done. Most of the problems and difficulties using this method are derived from the hypothetical nature of economic evaluation. These include:

- The benefits that can be considered are restricted to those which can be economically evaluated. This excludes any number of benefits which are not “tangible”. These would include the reduction of risk and nonmonetary benefits.
- The performance of the product, the improvement in benefits, are assumed. There is no direct connection between perception by potential buyers and this assumed performance.
- There are a number of inherent, critical, untestable assumptions relating the estimated economic value to the target price.

- The analysis and construction of these economic models are complicated and somewhat arbitrary in that there are many different models and approaches that can be used.
- The resulting demand curves are both normative and hypothetical. That is they represent what should be the value in the marketplace but may not be.

5.7. UTILITY VALUE APPROACH FOR PRICING

Utility is a modeling procedure for estimating product value; and is based on the combination of attributes. It is taken as the sum of the product of the perceived performance of attributes times their importance. The calculation and use of utility is discussed in a separate chapter of these notes on value. Note, however, that utility does not have a monetary value. To use it as an influence on pricing it needs to be scaled. This can be done based on the evaluation of multiple competitive products in the marketplace. This is referred to as a value map, also discussed in the chapter on value. It must be noted that the method of scaling can be arbitrary. And as such, the values using utility should only be viewed as approximate.

5.7.1. LIMITATIONS AND ADVANTAGES

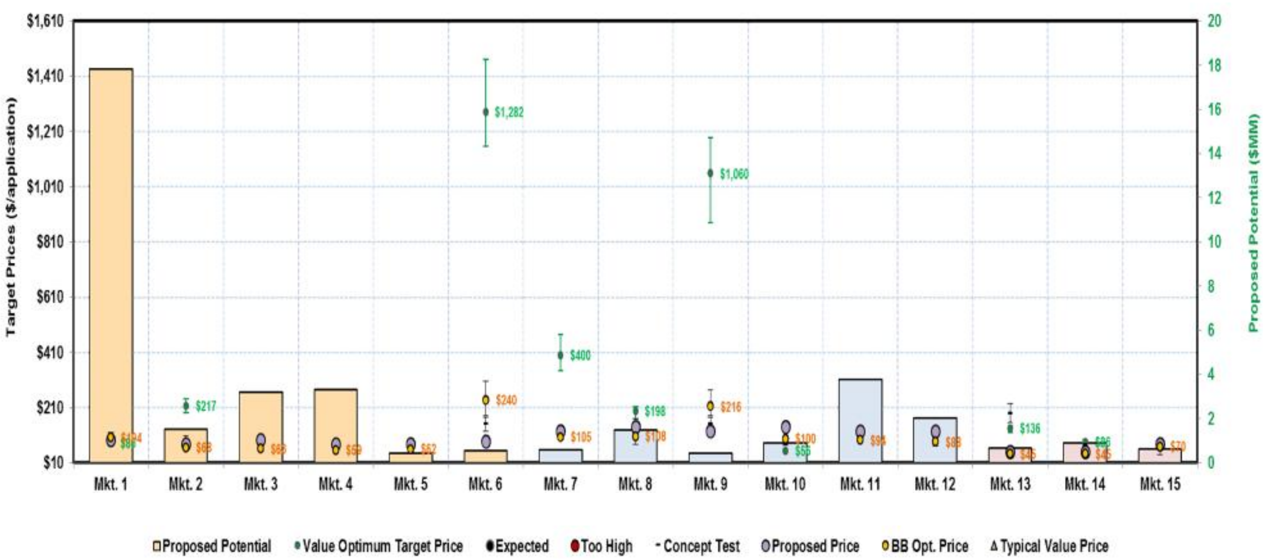
Utility, value mapping, is a comparative and strategic tool. It provides a view of the competitive situation indicating the approximate position of product value and prices. As such it provides a measure of consistency in pricing strategy. However this should not be viewed as a normative tool. There may not be an inherent strategic reason why a product’s price needs to be aligned with competitive value. Though such a position should imply and strategic condition. Typically we have found it useful to combine value mapping with other estimates of optimum pricing to provide an overview of the strategic pricing situation.

5.8. APPENDIX: CROSS MARKET PRICING ANALYSIS

The pricing analysis covered in this chapter dealt with a single market or segment. However, often the selling and marketing situation is much more complicated. Multiple markets and segments often need to be addressed together. A common pricing strategy often needs to be applied cross multiple markets. The trick is to adjust a pricing strategy that will provide the best solution of course the multiplicity of issues and concerns. In this regard we need to look at the metrics of pricing across the multiple markets as well is to examine the attractiveness and issues within each of the markets and in comparison.

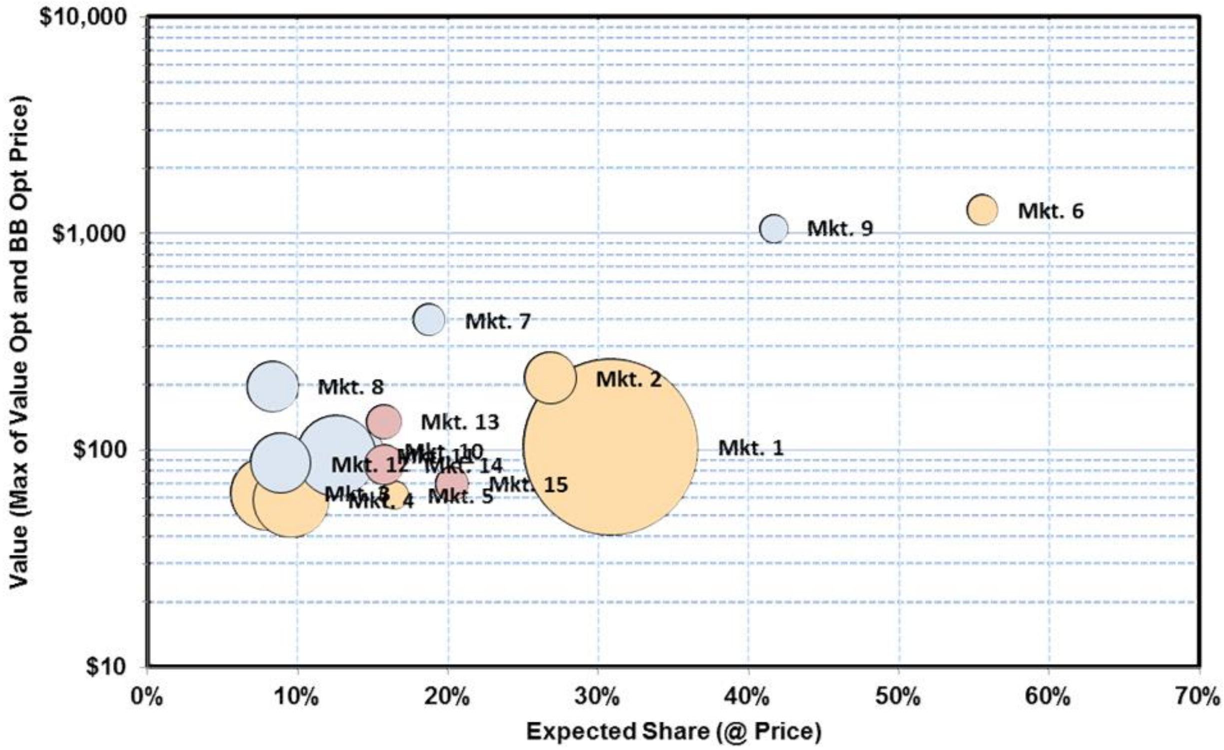
5.8.1. CROSS-MARKET PRICING CHART

Below is shown a Cross-Market Pricing chart. This displays a number of pricing metrics including a number of estimates of optimum price and price range for a product sold into 14 markets and segments. Along with estimates of the pricing metrics are measures of the market potential at various target prices. In this example the proposed price may differ slightly depending on markets. This is due to external costs and factors. The trick is to select a proposed price across the markets that would provide a satisfactory earnings and not overly exclude some markets. Particularly for new products this is always a balancing game.



5.8.2. MARKET POSITION AND PROPOSED PRICE

The pricing decisions results in changes in the earnings potential for each market and the shares that can be expected. These are shown in the bubble chart below. This is dynamic in that changes in the proposed prices will change the relative positions of the various markets. In this description the value however does not change with the proposed price. The vertical position therefore remains constant. However the sizes of the bubbles and that position horizontally does change with price. Along with these calculations on the chart, is typically a summary chart indicating the overall benefits of the pricing decision.



5.9. APPENDIX: REFERENCE MARKET (EQUILIBRIUM) PRICING

A product's price is likely to be affected by changes in competitive products' prices. Concept testing including using the Van Westendorp method, ignores market affects. These methods assume that the key product's demand curve takes into account the start of an expected competitive prices. However, when we do market pricing, using Choice Modeling, we capture the demand functions for competing products. These demand functions allow us to test competitive prices. The problem is that we do not have actual knowledge of what the competitive prices are going to be. The best we can do is try to understand the current situation and even this is offered uncertain.

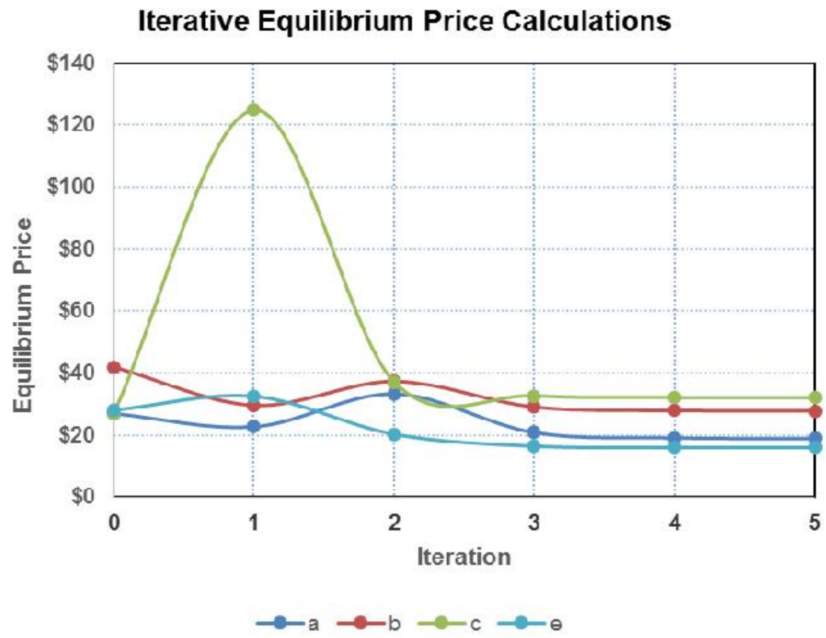
What we actually use could be referred to as competitive reference prices. These are prices that we would consider to be those that might be expected in the marketplace. The simplest of these are based on published prices. However an alternative can be developed based on "game theory". Based on this type of economic theory, one should expect that a "rational" market would behave in such a way that all competitors would adjust price as to seek their optimum returns, maximum earnings. This represents what is referred to as a Nash Equilibrium. It is a point in which no competitor could do better by changing its prices.

5.9.1. ITERATIVE EQUILIBRIUM MARKET PRICES

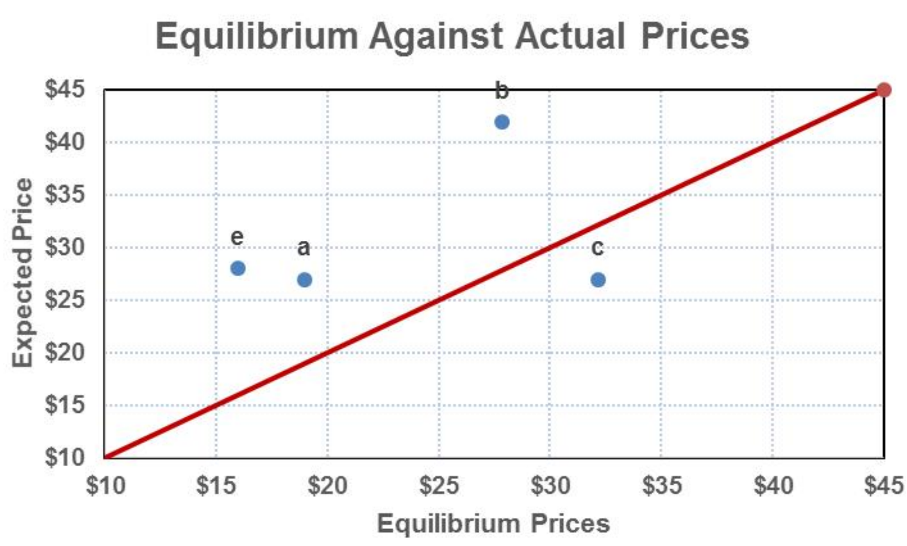
Analytically obtaining this Nash Equilibrium solution for linear demand functions is discussed in another section. As mentioned in that section using the linear demand functions can produce problems in estimating the Nash equilibrium. This is an idiosyncrasy of the linear demand function. However, the Nash equilibrium can also be obtained using nonlinear demand functions; but this is somewhat more difficult and needs to be done iteratively.

Basically the Nash Equilibrium solution can be obtained through iterative optimization. That is, that is to sequentially compute the optimum for each product consecutively. And then to we do the optimizations until the Nash Equilibrium solution converges. The result of that iterative process is shown below. Note that these trajectories can vary widely; however, convergence is usually fairly quick.

The



Equilibrium prices on not necessarily aligned with the current expected published prices. In fact equilibrium prices may be consistently higher than the current estimates, as shown below. This is in the nature of the equilibrium prices where all market participants are trying to maximize earnings.



5.9.2. Alternative Market Reference

The Nash equilibrium reference represents a natural market reference in that it indicates projective expectation for the market assuming that all competitors sees the same economic situation. However it is not the only market reference that can be constructed given the economic demand function. Another alternative market reference could be based on cooperative behavior for the marketplace whereby all competitors try to optimize the collective earnings while maintaining their current earnings limited by some ceiling level on prices. In other words, we see prices that would maximize the collective earnings from the products throughout the market. Unlike the Nash equilibrium, this involves a collective optimization and is easy to compute. That is that it is not an iterative calculation irrespective of the form of the demand curves. Below is an example of the three alternative references for a single situation: Current Market Prices, “Nash Equilibrium” representing an independent “free” market, and the Cooperative Scenario representing a collective optimization.

Product	Market Price	"Nash Equilibrium"	"Cooperative Scenario"
a	$13.00	$16.65	$14.08
b	$40.00	$40.43	$43.80
c	$18.00	$29.79	$18.13
d	$90.00	$79.85	$112.44
e	$30.00	$46.27	$43.42

5.10. APPENDIX: LINEAR DEMAND OPTIMA

As previously noted the various measures optimum price (individual optimum, Equilibrium or Pareto optimum, the sequential optimum, the minimum regret range and the stochastic optimum) can be obtained numerically based on any reasonable demand function. However, this can be highly tedious and would not lend itself to a decision support system since it would require a multiplicity of optimizations and complex calculations. An alternative is developing analytic expressions for these optimum prices.

5.10.1. SINGLE PRODUCT OPTIMA

The following analysis provides the analytic expressions for the single product optimum, Pareto optimum and minimum regret range based on the linear price model. The linear model for product A is of the following form as previously discussed:

$$\textbf{Share} = S_a \text{ õ } P_a + T_a + \underset{i}{\text{ĝ}} \; X_{ai} \text{ õ } P_i \qquad \textbf{(1)}$$

The expression $\left[T_a + \underset{i}{\text{ĝ}} \; X_{ai} \text{ õ } P_i\right]$ represents the impact of the prices of all

competing products. For simplicity we will use the symbol ¸ for this term. With simpler demand curves, it represents the constant. Simple earnings can be then computed by assuming that the costs are constant[62]. Earnings are then expressed in the form:

$$\textbf{Earnings} = (P_a - C_a) \text{ õ } \textbf{Share} \qquad \textbf{(2)}$$

$$= S_a \text{õ} P_a^2 + \left[\text{¸} - C_a \text{õ} S_a\right] \text{ õ } P_a - C_a \text{õ ¸} \qquad \textbf{(3)}$$

This is a quadrant equation on the price of product a of the form:

$$\textbf{Earnings} = \; \sim P_a^2 + \quad P_a + \text{¶} \qquad \textbf{(4)}$$

Where:

$$\sim \; = S_a$$

$$= \; \text{¸} - C_a \text{õ} S_a$$

$$\text{¶} = C_a \text{õ ¸}$$

[62] An alternative earnings model is developed if the marketing costs are assumed to be proportional to price. This introduces another term which is complicates the ~ term but otherwise does not effect the solution.

The optimum price can be computed by setting the derivative of the earnings equal to zero.

$$d\,Earnings_a/d\,P_a = 2 \sim P_a' + \quad = 0$$

$$P_a' = - \quad /2\sim \qquad (5)$$

We can verify that this is a maximum value by showing that the second derivative of earnings at this point is negative:

$$d^2Earnings_a/d\,P_a^2 = 2 \sim$$

It should be noted that ~ is the price sensitivity that is almost always negative. The optimum earnings can be computed by substituting P_a into equations 4.

5.10.2. Price Range Yielding Sufficient Earnings

Because the equation describing earnings is quadratic, equation 4, there are two prices that could yield any value of earnings below the optimum. These prices represent a price range that would yield at least the selected sub-optimum earnings, for example 90%. That range is obtained by solving equation 2 using the classical quadratic relationship:

$$\hat{P}_a = \frac{- \quad \text{ï Ë} \quad \overline{\quad ^2 - 4\sim\text{õ}(\text{¶} - E)}}{2\sim} \qquad (6)$$

Where E represents the sub-optimum earnings.

5.10.3. Using Percentage Levers

In some cases we set a price of a product to be a percentage of another competing product. This is often happens when considering a product line or alternative offerings where prices are constrained to be above or below those of other products. The resulting demand models then contain percentage values rather than actual prices. Under this condition equation 1 is still valid, but equation 2 has to be modified as well as the definition of ~ and . Equation 2, ~ and become:

$$Earnings = (P_r \text{ õ } P_a - C_a) \text{ õ } Share$$

$$\sim = P_r \text{ õ } S_a$$

$$= P_r \text{ õ } \text{¸} - C_a \text{õ } S_a$$

Where P_r is the reference price for the price P_a which would then be expressed as a percentage of P_r.

5.10.4. Pareto and Sequential (Nested) Optima

The Pareto Optimum price is obtained using equation 4 but with the costs C_a set equal to the cost of manufacture without any consideration of marketing costs. Similarly the optimum prices for the reseller can also be obtained using equation 4 given that the costs now represent the cost to the reseller for the product or the supplier's price. The objective of the sequential or nested optimum is now to find the optimum supplier's price given that the reseller will optimize his price. Under this condition the earnings to the supplier is:

$$\mathbf{Earnings} = (\mathbf{C_a} - \mathbf{C_d})\ \text{õ}\ \mathbf{Share}$$

Where C_a represents the supplier's price and C_d is the supplier's costs. The share then is:

$$\mathbf{Share} = \mathbf{S_a}\ \text{õ}\ \mathbf{P_a}' + \text{¸}$$

P_a' is the optimum price for the reseller for his cost of C_a based on the more general form.

$$\mathbf{P_a}' = (\mathbf{P_r}\ \text{õ}\ \text{¸}\ - \mathbf{C_a}\text{õ}\ \mathbf{S_a})/(-2\ \mathbf{P_r}\ \text{õ}\ \mathbf{S_a})$$

And then supplier's earnings becomes:

$$\mathbf{Earnings} = (\mathbf{C_a} - \mathbf{C_d})\ \text{õ}\ (\mathbf{S_a}\ \text{õ}\ \{(\mathbf{P_r}\ \text{õ}\ \text{¸}\ - \mathbf{C_a}\text{õ}\ \mathbf{S_a})/(-2\ \mathbf{P_r}\ \text{õ}\ \mathbf{S_a})\} + \text{¸}) \qquad (7)$$

This is a quadratic form of the same type as equation 4. The optimum in respect supplier's price is then equal to:

$$\mathbf{C_a}' = - \quad /2\sim \qquad (8)$$

Where now:

$$\sim = \mathbf{S_a} /2\ \mathbf{P_r}$$

$$= \quad \text{¸}/2\ - \mathbf{C_d}\text{õ}\ \mathbf{S_a}/2\ \mathbf{P_r}$$

The solution for the sequential optimum is then obtained evaluating equation 7 for the optimum supplier's price given the supplier's cost and then evaluating equation 5 to evaluate the reseller's price or market price given their costs then supplier's price. It should be noted that this results in a situation where the manufacturer’s price equals the Pareto price.

5.10.5. EQUILIBRIUM (COLLECTIVE OPTIMA) PRICING

The Equilibrium prices represent the optimum price for each product given that the competitive prices are also optimum. Basically what needs to be constructed is a set of simultaneous equations for the optimum prices where each row represents the conditions for price optimization. Each row the simultaneous equation represents the Pareto Optimum price for one product. This is basically derived starting with equation 4. Using our previous notation for the linear demand function model we get the following for product a:

$$\mathbf{Earnings_a = S_a \bullet N_a \bullet P_a^2 + [(T_a + \rho_{i \neq a} X_{ai} \bullet P_i) \bullet N_a - C_a \bullet S_a] \bullet Pa - Ca \bullet [(T_a + \rho_{i \neq a} X_{ai} \bullet P_i)]}$$

Where $\mathbf{N_a}$ is 1 minus the market margin for product a. This represents percent of the price returning to the manufacturer. Of course, if sales are direct, this is 100%. Ca is the cost of goods sold for product a. The rest of the parameters comes out of the demand function shown below:

	Product A	**Product B**	**Product C**	**Product D**
Intercept	$\mathbf{T_a}$	$\mathbf{T_b}$	$\mathbf{T_c}$	$\mathbf{T_d}$
Product A	$\mathbf{S_a}$	X_{ba}	X_{ca}	X_{da}
Product B	X_{ab}	$\mathbf{S_b}$	X_{cb}	X_{db}
Product C	X_{ac}	X_{bc}	$\mathbf{S_c}$	X_{dc}
Product D	X_{ad}	X_{bd}	X_{cd}	$\mathbf{S_d}$

The optimum price requires that the first derivative of the earnings in respect to the specific product price is equal to zero. The derivative is shown below. Note that for this derivative on the specific product, the prices of the other products are considered constant.

$$\mathbf{d[Earnings_a]/dP_a = 2S_a \bullet N_a \bullet P_a + [T_a + \rho_{i \neq a} X_{ai} \bullet P_i] \bullet N_a - C_a \bullet S_a = 0} \qquad \mathbf{(9)}$$

This represents the optimization of one of the products. We can then put these together to form a set of simultaneous equations. For convenience we will define a number of arrays.

[T] = array of model constants including $\mathbf{T_a}$

[N] = array of one minus the market margins including $\mathbf{N_a}$

[C] = array of costs of goods sold including $\mathbf{C_a}$

[S] = array of price sensitivities including $\mathbf{S_a}$

[P’] = the array of equilibrium prices

{E} = matrix of demand coefficients with the diagonal squared

	Product A	Product B	Product C	Product D
Product A	$2 \cdot S_a$	X_{ba}	X_{ca}	X_{da}
Product B	X_{ab}	$2 \cdot S_b$	X_{cb}	X_{db}
Product C	X_{ac}	X_{bc}	$2 \cdot S_c$	X_{dc}
Product D	X_{ad}	X_{bd}	X_{cd}	$2 \cdot S_d$

With this notation the equation 9 becomes:

$$[N] \cdot [T] + [N] \cdot \{E\} \times [P'] - [C] \cdot [S] = 0$$

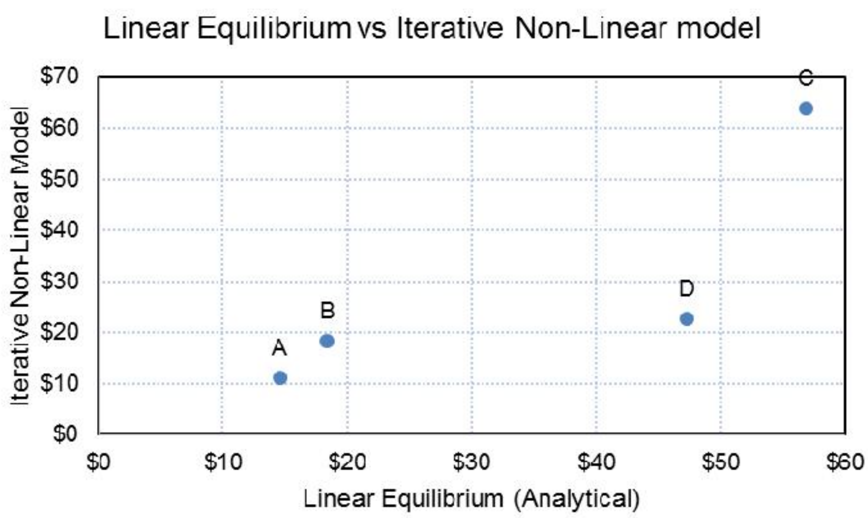
With the x referring to matrix cross multiplication and • is the simple cell multiplication. With the solution of:

$$[P'] = \{E\}^{-1} \times (-[T] + [C] \cdot [S]) / [N]) \qquad (10)$$

Where the notation of the notation $\{\}^{-1}$ refers to the matrix inverse. Note that equation 10 is directly computable from the linear demand function and the sales costs.

5.10.5.1. Comparison with the Iterative Equilibrium Calculations

The linear demand model has some idiosyncrasies. For example, these demand curves can predict negative sales volumes for high prices, and very high volumes for negative prices. Sigmoidal, S-shaped, demand curves avoids these problems. However, computing equilibrium prices is far more difficult using these nonlinear models. The problem really arises with specific products with low price sensitivities. In these cases, you can get wildly different values of equilibrium prices than shown with the iterative estimation procedure with nonlinear models, as is shown below.



Typically the linear demand functions are modified to remove price insensitive products and to reduce the likelihood of extreme values. `

5.11. APPENDIX: COMPLETE CHOICE PRICING DESIGNS

5.11.1. DESIGNS

The original[63] price choice models were based on "Conjoint" study designs. These used discrete levels of price and allowed the computing of the price elasticity at each price point. Furthermore, this allowed for testing of alternative demand models. Unfortunately, because of the specific number of number of price points selected, these designed usually required a large number of scenarios. In the designs that we have developed, price is considered a continuous variable and therefore, there are as many different prices as there are scenarios. This resulted in a less constrained problem and required fewer scenarios.

5.11.1.1. Eleven Products (16 Scenario) Designs

The following designs allow for up to 11 products. There are four desired conditions on these designs: (1) the range set between extreme values, (2) centralized in that the average values of each product prices are the same, (3) symmetric or "balance" in that the number of points above the average equals those below, and (4) minimum intercorrelation (orthogonal). It is the non-existence of significant intercorrelation, however, that is critical. The lack intercorrelation or collinearity that makes the parameters of the resulting model uniquely associated with one product.

The issue of balance covers a number of key issues. For simple regression considerations the set of values as previously noted should be symmetric to avoid weighing values above or below the mean. However, there may be also value in concentrating values at the mean[64] or spreading out the values when extrapolation may be critical. Typically we try to obtain values that well spread out and to avoid duplications of values. This is intended to assure a quality solution which will allow extrapolation to both larger and smaller values beyond those measured.

In the published design below there is significant intercorrelation among the prices and it is inadvisable to use all 11 products[65]. This is a centralized symmetric design but suffers from fairly high intercorrelation. Using less than nine products gives maximum intercorrelation of less than 20%, which is still very high. We recommend using intercorrelations of 10% or less. However we have used this design with large number of products.

---

[63] Though they may be earlier uses of the discrete pricing designs for choice modeling, the earliest that I have found is by Paul Green (1982). This method was referred to as "Elasticon". That term is still retained by some business methods dictionary to refer to the use of "Conjoint" designs for pricing studies.

[64] This is similar to the use of Numerical Quadrature values to increase precision.

[65] This design was given to me by Lynn Bacon, who indicated that he had obtained it from a published source.

Max	73%	73%	73%	73%	73%	73%	73%	73%	73%	73%	73%
Min	127%	127%	127%	127%	127%	127%	127%	127%	127%	127%	127%
Average	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Median	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Abs. Max Cor	**1.7%**	**1.7%**	**4.2%**	**6.7%**	**10.1%**	**17.7%**	**18.5%**	**19.3%**	**21.0%**	**23.5%**	**28.6%**
Set/Product	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	73%	73%	73%	80%	87%	87%	87%	87%	80%	73%	80%
2	87%	120%	80%	73%	120%	127%	73%	80%	113%	120%	127%
3	80%	87%	87%	127%	113%	120%	127%	120%	87%	113%	73%
4	73%	127%	113%	87%	73%	113%	120%	127%	127%	80%	87%
5	87%	113%	127%	113%	80%	73%	80%	113%	73%	127%	113%
6	80%	80%	120%	120%	127%	80%	113%	73%	120%	87%	120%
7	113%	120%	73%	127%	87%	87%	127%	87%	113%	120%	80%
8	120%	73%	80%	113%	73%	127%	87%	120%	127%	73%	127%
9	127%	127%	87%	80%	120%	73%	120%	127%	80%	80%	113%
10	113%	113%	113%	120%	113%	120%	73%	80%	87%	87%	73%
11	120%	87%	127%	73%	80%	113%	113%	73%	73%	113%	120%
12	127%	80%	120%	87%	127%	80%	80%	113%	120%	127%	87%
13	93%	93%	100%	93%	107%	107%	100%	107%	107%	93%	93%
14	107%	100%	93%	100%	100%	93%	93%	93%	100%	107%	100%
15	100%	107%	107%	107%	93%	100%	107%	100%	93%	100%	107%
16	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

We have developed a number of alternative designs that can give lower inter-correlations. In the following design, a fairly low intercorrelation exists using all 11 products. However, this design is neither centralized nor symmetric. The lack of symmetry can be seen in the difference in the average and median values. The series are placed in order of the asymmetry of the values. However, in many cases the symmetry issue is less important than intercorrelation and this design has been used.

Max	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Min	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Average	**45%**	**51%**	**53%**	**47%**	**42%**	**48%**	**45%**	**58%**	**43%**	**45%**	**62%**
Median	**49%**	**51%**	**56%**	**41%**	**39%**	**39%**	**38%**	**65%**	**35%**	**33%**	**75%**
Abs. Max Cor	**0.00%**	**0.00%**	**4.60%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**3.75%**	**0.00%**
Set/Product	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	39%	19%	0%	0%	0%	86%	31%	75%	37%	46%	0%
2	14%	100%	1%	69%	42%	28%	16%	52%	30%	100%	82%
3	62%	66%	0%	42%	62%	40%	36%	2%	21%	0%	53%
4	82%	77%	20%	49%	65%	70%	68%	80%	32%	33%	100%
5	33%	16%	24%	38%	54%	25%	71%	50%	30%	32%	93%
6	76%	60%	42%	23%	37%	38%	100%	83%	91%	33%	82%
7	50%	36%	39%	100%	25%	16%	70%	46%	100%	77%	19%
8	54%	0%	50%	80%	22%	0%	9%	81%	21%	27%	87%
9	4%	24%	63%	30%	100%	92%	35%	63%	69%	83%	78%
10	1%	25%	67%	92%	45%	86%	39%	75%	48%	0%	72%
11	8%	99%	78%	7%	13%	12%	26%	100%	49%	31%	70%
12	47%	74%	98%	40%	10%	72%	13%	0%	90%	24%	83%
13	100%	42%	85%	26%	97%	20%	0%	66%	50%	55%	28%
14	91%	83%	80%	90%	23%	100%	45%	79%	10%	59%	48%
15	54%	18%	96%	19%	10%	48%	73%	24%	0%	91%	87%
16	0%	78%	100%	53%	69%	29%	89%	47%	9%	31%	7%

The design shown above has been centralized (normalization) and the resulting design is shown below. Note that the intercorrelation is much higher. But it is still significantly lower than the first design and captures but the desired restrictions on range and centralized values.

Max	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Min	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Average	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**
Median	**44%**	**41%**	**42%**	**50%**	**37%**	**53%**	**55%**	**41%**	**56%**	**59%**	**48%**
Abs. Max Cor	**0.35%**	**0.35%**	**0.93%**	**1.45%**	**2.85%**	**5.44%**	**5.55%**	**5.77%**	**8.95%**	**10.19%**	**10.28%**
Set/Product	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	0%	91%	35%	19%	52%	0%	64%	44%	45%	0%	0%
2	73%	30%	18%	100%	100%	1%	45%	36%	15%	64%	51%
3	45%	42%	41%	64%	0%	0%	2%	28%	70%	42%	76%
4	52%	74%	77%	75%	38%	19%	68%	38%	93%	100%	79%
5	40%	26%	80%	15%	36%	23%	42%	36%	37%	74%	66%
6	24%	40%	100%	59%	37%	40%	70%	98%	86%	65%	45%
7	100%	17%	79%	35%	87%	37%	39%	100%	57%	15%	30%
8	85%	0%	11%	0%	30%	47%	69%	25%	62%	68%	26%
9	32%	97%	39%	24%	93%	59%	54%	82%	5%	62%	100%
10	97%	91%	44%	25%	0%	63%	63%	57%	6%	57%	55%
11	7%	13%	30%	96%	35%	74%	100%	58%	9%	55%	26%
12	43%	76%	15%	72%	27%	92%	0%	98%	54%	66%	24%
13	28%	21%	0%	41%	62%	80%	56%	59%	100%	22%	98%
14	96%	100%	50%	81%	71%	76%	67%	16%	98%	38%	28%
15	20%	50%	82%	18%	98%	90%	20%	0%	61%	69%	12%
16	57%	31%	100%	76%	35%	100%	40%	23%	0%	5%	84%

Finally, the design can be both centralized and equalized to give a normalized balanced design similar to the first design. Notice that the intercorrelation is approximately the same as the first case, as would be expected. The maximum correlation is lower at 23% compared to almost 29%. If necessary, this would be a preferred design. Both designs have unacceptable high intercorrelation. We recommend using the unbalanced designs for large sets of products.

Max	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Min	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Average	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**
Median	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**
Abs. Max Cor	**1.2%**	**1.2%**	**5.3%**	**6.5%**	**9.1%**	**11.7%**	**12.4%**	**17.6%**	**21.8%**	**22.1%**	**22.6%**
Set/Product	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	13%	100%	93%	100%	40%	47%	33%	60%	100%	67%	80%
2	67%	47%	87%	40%	0%	60%	60%	73%	27%	80%	0%
3	47%	27%	100%	67%	93%	73%	93%	27%	47%	53%	40%
4	33%	20%	80%	0%	47%	53%	20%	13%	40%	33%	27%
5	73%	33%	73%	7%	60%	67%	67%	67%	60%	20%	93%
6	53%	53%	60%	33%	53%	7%	7%	20%	80%	7%	47%
7	87%	60%	67%	87%	20%	0%	80%	47%	0%	27%	60%
8	100%	73%	53%	20%	80%	80%	13%	33%	20%	93%	100%
9	7%	0%	47%	47%	13%	20%	53%	93%	67%	60%	73%
10	20%	40%	40%	53%	100%	40%	40%	87%	7%	47%	67%
11	93%	80%	33%	60%	67%	33%	0%	80%	93%	73%	7%
12	27%	87%	7%	27%	87%	7%	100%	53%	53%	87%	33%
13	80%	7%	20%	80%	33%	27%	47%	0%	73%	100%	53%
14	0%	67%	27%	73%	27%	93%	27%	7%	13%	40%	13%
15	40%	93%	13%	13%	7%	100%	87%	40%	87%	13%	87%
16	60%	13%	0%	93%	73%	87%	73%	100%	33%	0%	20%

5.11.1.2. Five Items on Four Price Levels (12 Scenario) Design

The following is a design to allow for up to 5 products on four price levels. While the design is a classic orthogonal form, it does not allow all price values to be used. If the prices are equally spaced and in a corresponding order, there is no intercorrelation. However, variations of either spacing or order can produce sharp and surprising intercorrelations. It is critical to test the resulting design prior to use.

12 Scenario 5 Product Design

Products	1	2	3	4	5
1	0	0	0	0	0
2	0	0	1	3	3
3	0	3	2	0	3
4	1	1	2	3	0
5	1	2	3	1	1
6	1	3	1	2	2
7	2	3	0	3	1
8	2	2	3	2	0
9	2	1	3	1	2
10	3	2	0	1	2
11	3	1	1	0	1
12	3	0	2	2	3

5.11.1.3. Smaller Designs

In some cases it is desired to reduce the number of scenarios to a minimum. For analysis reasons it is usually not desirable to reduce the number of scenarios below two times the number of parameters that will be estimated. In the case of choice modeling that is two times the number of products plus one. The additional parameter is the intercept of the models.

5.11.1.3.1. Two Products (6 Scenario) Designs

For two products, six scenarios should be the minimum necessary to fully define the model.

Max	100%	100%
Min	0%	0%
Average	50%	50%
Median	50%	48%
Abs Max Cor	0.00	0.00
Set/Product	**1**	**2**
1	60%	0%
2	0%	44%
3	20%	44%
4	80%	51%
5	100%	60%
6	40%	100%

5.11.1.3.2. Three Products (8 Scenario) Designs

Similarly for three products, eight scenarios should be the minimum necessary.

Max	100%	100%	100%
Min	0%	0%	0%
Average	50%	50%	50%
Median	50%	49%	55%
Abs Max Cor	0.00	0.00	0.00
Set/Product	**1**	**2**	**3**
1	10%	30%	74%
2	90%	32%	0%
3	25%	45%	42%
4	65%	53%	42%
5	100%	100%	68%
6	35%	64%	100%
7	0%	76%	5%
8	75%	0%	68%

5.11.1.3.3. Four Products (10 Scenario) Designs

And for four products, ten scenarios are needed.

Max	100%	100%	100%	100%
Min	0%	0%	0%	0%
Average	50%	50%	50%	50%
Median	50%	50%	49%	39%
Abs Max Cor	0%	0%	4%	0%
Set/Product	**1**	**2**	**3**	**4**
1	22%	0%	100%	0%
2	67%	15%	49%	100%
3	100%	25%	60%	93%
4	11%	35%	30%	47%
5	56%	45%	17%	25%
6	78%	55%	0%	22%
7	44%	65%	29%	32%
8	33%	75%	49%	57%
9	0%	85%	66%	100%
10	89%	100%	100%	23%

5.12. APPENDIX: MATRIX REGRESSION

Multilinear regression can be done in *Microsoft EXCEL* either using their Analysis Package programs or by applying matrix operations. Using matrix operations have two advantages: (1) it allows for simple computations on a respondent level, and (2) it allows for live recomputation of segment model values. The derivation of doing multilinear regression with matrix operations is covered in any advanced statistical text. The form is based on the design matrix that includes an identity value for the intercept:

X =

	Scenario	**Z**	**Product A**	**Product B**	**Product C**
	1	1	A_1	B_1	C_1
X =	**2**	1	A_2	B_2	C_2
	3	1	A_3	B_3	C_3
	4	1	A_4	B_4	C_4

The coefficients are obtained by the matrix operations:

$$\mathbf{Coefficients = (X^tX)'X^t\ Y}$$

where $\mathbf{X^t}$ is the transpose of the design matrix, **X**, **Y** is the response vector capturing the respondents decisions for a product and ' refers to the matrix inverse. In terms of *EXCEL* matrix functions this is:

Coefficient Array = ª =

MMULT(MMULT(MINVERSE(TRANSPOSE(X),X),TRANSPOSE(X)),Y)

R-Squared Calculations

The generally accepted measure of goodness of fit is the R-Squared that represents the fraction of the variance explained by the regression line. This is a scalar value for each product model. It is computed by measuring the squared variation between the data and the projected values. In terms of *EXCEL* functions it is

R-Squared =1- SUMSQ(Y-MMULT(ª,X))/((COUNT(Y)-1)*VAR(Y))

5.13. APPENDIX: PRICING RESEARCH METHODOLOGIES COMPARED

	Concept Testing **(Van Westendorp)**	**Choice Modeling**	**Perceived Value** **(Conjoint & Profiling)**	**Market Testing**
Task	Acceptable pricing levels or likelihood to purchase at given pricing for on hypothetical offerings.	Expected purchase behavior to multiple scenarios of competitive prices against specific consideration set.	Ranking of hypothetical products from which the value of features is derived.	Capture purchases from offering and different prices.
Principal Objective	Acceptable price range of multiple new offerings against unknown competition.	Market model to estimate optimum prices against a potential changing market.	Value of the features of products within the competitive set.	Optimum market price
Product Pricing Accuracy	Good within its context	Very Good	Poor	Excellent
Typically Use	Market testing closely timed to launch	Longer term market testing	Research & Development	Pre-launch test
Key Pricing Variables	Multiple offerings and "Price Inferred Quality" in the **perceived** competitive environment**.**	Multiple products and changing competitive prices.	Product design	Product price in the **existing** competitive environment.
Purchase Conditions	Single product purchase.	Single (discrete) or multiple product purchases	Single product purchase	Single or multiple product purchases.

Fault Tolerance	Highly fault tolerant	Dependent on selection of consideration set and statistical design. Fault Intolerant	Highly dependent on the design and presentation of features. Fault Intolerant	Dependent on external controls. Very fault intolerant
Degree of Difficulty	Simple to execute and analyze.	Simple to execute, more complex in analysis	Simple to execute, more complex in analysis	Extremely difficult and expensive
Types of Analysis:				
Simple Demand Curve	Yes	Yes	Yes	Yes
Conditional Multiple Offering Models	Yes	Little	No	No
Multiple Product Pricing	No	Yes	No	No
Competitive Market Pricing	No	Yes	Yes	No
Market Uncertainty Analysis	Yes	Yes	Possibly	No
Strategic Modeling	No	Yes	Possibly	No

Product Design Conditions	Little	No	Yes	No
Quality Considerations	Yes	No	Yes	No
Typical Products	Contracts and Services and consumer products.	Industrial multiple purchased products.	"Deals" and customized products (industrial & consumer)	Packaged goods