CHAPTER 12

Measurement of Price Sensitivity

Research Techniques to Supplement Judgment

Quantitative estimates of customer price sensitivity and willingness-to-pay can substantially improve both price setting and price segmentation. Indeed, some estimate of price sensitivity, whether it be quantitative or qualitative, is required for the price setting process described in Chapter 6. Sometimes research can provide very specific estimates of the impact of prices on sales volume. Other times estimates provide only a rough indication of a customer's willingness-to-pay given a set of circumstances. At their worst, estimates of price sensitivity fail to reflect the real nature of the buying decision, misleading management into making ineffective pricing decisions. This is often the case when a research design causes respondents to pay much more attention to price than real customers would. In almost all cases, it is possible to develop an estimate of price sensitivity somehow. The key to using the estimate to make a better decision is to recognize that even a very precise estimate is not necessary very accurate or unbiased. It is only an approximation of the actual value or price sensitivity. We always need to consider how differences between a real purchase situation in the future and an experiment in the present or past can change the impact of price on choice.

There are numerous procedures for measuring and estimating price sensitivity. Each procedure offers particular advantages over the others in terms of accuracy, cost, and applicability, so the choice is not arbitrary. One must think carefully about the appropriate procedure for any particular product before beginning research. In no case should a manager use a particular technique just because it is cheap, convenient, or fast. Instead, managers need to carefully assess their needs and adopt techniques that are most appropriate for the given situation. Even if the cost for those techniques is high, the benefit is often sufficiently large to justify the expense.

TYPES OF MEASUREMENT PROCEDURES

Procedures for estimating price sensitivity differ on two major dimensions: the conditions of measurement and the variable being measured. Exhibit 12-1 classifies the various procedures according to these two dimensions. The conditions of measurement range from a completely uncontrolled to a highly controlled research environment. When making uncontrolled measurements, researchers are only observers. They measure what people actually do, or say they would do, in a situation not of the researcher's making. For example, marketing researchers might collect data on consumer purchases of laundry detergent in a grocery store, but the prices and other variables that influence those purchases are beyond their control. This is often the case when analyzing historical sale data.

In contrast, when making controlled measurements, researchers manipulate the important variables that influence consumer behavior to more precisely observe their effect. Researchers conducting an experimentally controlled study of price sensitivity for a laundry detergent could select the prices as well as the advertising and shelf placement of various brands in order to make the data more useful. They might attempt to gain even more control by conducting a laboratory experiment in a simulated store, carefully selecting the individuals whose purchases would be recorded. Participants for the experiment could be chosen to represent various demographic variables (such as race, gender, income, and family size) in proportions equal to those of the product's actual market or to represent a particular group (such as mothers with children) to whom the product was intended to appeal. Generally, controlled research produces more accurate estimates of the effects of the controlled variables on price sensitivity, but depending on the level of realism, it is often costly to implement in a "real-world" setting. A laboratory setting is often used

EXHIBIT 12-1 Techniques for Measuring Price Sensitivity

	Conditions of Measurement	
Variable Measured	**Uncontrolled**	**Experimentally Controlled**
Actual purchases	• Historical sales data • Panel data • Store scanner data	• In-store experiments • Laboratory purchase experiments
Preferences and intentions	• Direct questioning • Buy-response survey • In-depth interview	• Simulated purchase experiments • Trade-off (conjoint) analysis

to better control other factors that may affect price sensitivity as well as to reduce costs, but these improvements come at the expense of realism.

The dependent variable for estimating price sensitivity is either actual purchases or purchase preferences and intentions. Actual-purchase studies measure behavior, whereas preference-intention studies measure the intended choices that people claim they would make in a hypothetical purchase situation. Since the ultimate goal of the research is to estimate how people respond to price changes in actual-purchase situations, research that measures actual behavior is generally more desirable, but it is also more costly, time-consuming, and sometimes impractical, given the need to move products to market quickly. The following discussion summarizes these research techniques and some of the trade-offs of choosing one method over another.

Uncontrolled Studies of Actual Purchases

One way to estimate price sensitivity is to analyze past sales data. Naturally, one would expect this to work well in assessing the price sensitivity of customers for existing products in which consumers have prior-use experience. Given the increased use of scanners in supermarkets and mass merchandisers, and the databases maintained on their most frequent customers by hotels, airlines, and websites, analysis of historical data is becoming an increasingly important source of information to model customer sensitivity to prices and price deals. Still, changes in (1) the number of brands on the market, (2) how recently competitors offered price promotions, (3) the amount and effectiveness of advertising by each brand, (4) increased price sensitivity of more-educated consumers, and (5) general economic conditions can undermine the ability of historical data analysis to diagnose the true effects of a price change.

There are three types of past sales data from which a marketing researcher might attempt to estimate price sensitivity: (1) historical sales data—sales reports from a company's own records or from a sales-monitoring service, (2) panel data—individual purchase reports from members of a consumer panel, and (3) store scanner data—sales data for an individual retail outlet.

HISTORICAL SALES DATA Sales data collected as part of a company's regular operation are cheap and available for all products that have prior sales histories. Given the ability to actually track data on a daily or even real-time basis, marketers are able to analyze trends and project future movement of product sales. One needs to be careful in recognizing that sales data only allow for the estimation of price elasticity of the next level in the channel. For example, in a retail environment, unless a manufacturer sells directly to the end-user, its sales data reflect shipments to retailers, not actual retail sales during the period. Retailers may stockpile products purchased at promotional prices with no intention of passing the savings on to the consumer, or in anticipation of increases in demand on the part of consumer in a later period. Understanding this, some marketers have direct links with the inventory movement of their retail outlets, combined with up-to-date retail price data. While this is generally part of the inventory-management system to facilitate timely replacement of stock, it also provides the marketer with instant data that can be analyzed for important trends in demand.

In the past, using historical data for any product not sold directly to the end consumer was problematic. Sales data was usually available only at an aggregated level for a long period of time—say a week. In any given week, some stores will charge higher prices than others. Over time, the same store will put the product on sale for a week and then return its price to the regular level. These price variations influenced sales but were masked by the aggregation. Now, however, nearly all retailers use scanners to track sales and most sell their data to manufacturers. Since sales can be observed within short time frames, and loyalty cards can even enable tracking changes in an individual shopper's behavior over time, researchers can now readily track the impact of regular and promotional price differences. Unfortunately, data that aggregate sales for all stores over a number of weeks conceal these individual price differences. Given the aggregation in the data, the researcher is forced to explain sales variations by looking at only the average retail price across stores and throughout the time period. Since average prices have less variation and fewer observations than actual prices at individual stores in particular weeks, the data have less statistical power than data on individual purchase prices. In addition, some stores serve segments that are substantially more price responsive than others; aggregated sales data will mask these differences and will lead to price elasticity estimates that may, on average, be correct, but do not really apply to any single store setting.

PANEL DATA A number of marketing research companies collect individual purchase data from panels of a few thousand households. Each household keeps a daily record of all brands purchased and price paid or uses a special credit card that tracks purchases. Since products are purchased daily, the data for each household must be aggregated to produce a series on weekly or biweekly purchases. Such data have a number of advantages:

1. One can accumulate observations more quickly with weekly panel data than with bimonthly or quarterly sales data, reducing the problem that other factors may change and reduce the comparability of the data.
2. One can observe the actual price paid, rather than an average of the retail prices that different stores charge, and one can identify sales that were made with coupons or promotions that alter the price actually paid.[1] This captures more price variation in the data, making the effects of price changes easier to detect.
3. One can get data on the sales and prices of competing products (provided someone in the panel bought them), as well as on sales of one's own product.
4. One can correlate price sensitivity with various demographic classifications of consumers and possibly identify opportunities for segmentation.[2]

One potential drawback is that panel data may not be adequately representative of the market as a whole. Of all households invited to join a panel, fewer than 5 percent accept the offer and accurately record their purchases. There is reason to suspect, therefore, that panel members are a biased sample of the population. Moreover, the fact that panel members must record their purchases tends to make them more price aware, and thus more price sensitive. This problem increases the longer a household participates in a panel. Fortunately, technological advances have enabled research companies to develop panels that do not require consumers to record most their purchases.[3] Instead, in-store scanners record purchases automatically whenever panel members identify themselves in the store's checkout line. This vastly simplifies panel membership, increasing the panel participation rate to more than 70 percent and attenuating the problem of heightened price awareness. Further, the data tend to be more representative of real purchasing behavior of consumers without the bias that has been problematic in the past.

A second potential drawback to panel data is that typically only one member of the household agrees to participate in the panel, yet in most households multiple people perform shopping duties. As a result, it is easy to miss purchase data from the nonparticipating member(s) of the household who often have very different criteria for making purchase decisions. For example, if the nonparticipating family member joins Costco and purchases cereal by the bushel, the family is essentially out of the cereal market for a while, no matter how substantial a discount is offered to the participating panel member. Given the ever-widening use of scanners and the ability to link scanner data with panel data, increasing numbers of consumer products can be analyzed using this type of analysis. The superiority of panel data estimates over those from aggregate sales data is due to the availability of more observations from a shorter and more comparable time period. With the availability of advertising and other promotional data, researchers are able to estimate price sensitivities for different customer groups with a reasonable degree of reliability (Box 12-1). Since multiple companies share the cost of the same ongoing research, estimates based on panel data are also less expensive than estimates based on an equal number of observations from proprietary research.

STORE SCANNER DATA An alternate source of actual sales comes from auditing price transactions and sales at individual retail stores. Modern technologies have made accurate daily sales and price data available at reasonable cost. Retailers generate such data as part of their normal operations. The high frequency of scanner data makes it vastly superior to aggregate sales data, providing marketers with almost immediate information on the movement of their product. And although scanner data lacks the balanced and complete demographics of consumer panel data, loyalty programs have made it possible to infer demographics and to track purchases over time. Scanner data also costs a lot less than panel data. When store

BOX 12-1

Using Panel Data to Measure the Impact of Promotion on Choice

The authors of a recent study asked two important questions: whether consumers are getting more price sensitive and whether the group of price-sensitive consumers is growing. To evaluate these and other questions, they examined more than eight years of usage data from a panel of consumers and were able to compare those data with quarterly advertising data from producers within a household nonfood product category. They were able to evaluate three different types of price promotions: temporary price reduction, price feature of the product, or the offering of a coupon. For their analysis, they used a multinomial logit model to evaluate the impact of the promotional (price and nonprice) activities on the consumer's choice of a product. Further, they were able to segment users into loyal and non-loyal segments and compare the price sensitivities of the two groups. The summarized results indicated the following:

Consumer's Sensitivities to:	Average Price Sensitivities	Sensitivity Changes Over Time
1. Loyal segment		
Price	−.28	Increase
Price promotion	.02	Increase
Nonprice promotion	.03	Decrease*
2. Non-loyal segment		
Price	−1.70	Increase
Price promotion	.04	Increase
Nonprice promotion	.09	Decrease*
Non-loyal segment size		Increase*

*Indicates significant at $p < .05$, all else $p < .001$.

The price sensitivities are shown across all of the periods analyzed. Based on the elasticities, the loyal segment showed little price sensitivity, but it did increase over time. The non-loyal, price-oriented segment showed higher price sensitivities that increased over time as well. The study authors did note that the size of the non-loyal segment increased over time, indicating that "an increasing proportion of consumers have become more price and promotion sensitive over time."

Source: Carl F. Mela, Sunil Gupta, and Donald R. Lehmann, "The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice," *Journal of Marketing Research* (May 1997): 248–261.

scanner data can be combined with panel data that track the demographic and broader behavioral characteristics of consumers, researchers often get huge insights into shoppers' price sensitivity and purchasing behaviors. Scanner data have become a major source of information on the price sensitivity of consumer-packaged goods.[4]

While sales data—in the form of panels and scanner data—are quite prevalent in the consumer packaged goods industry, in many business-to-business markets there are simply too few transactions and market oversight to develop similar data sets. However, not all is lost. We recently spoke with a firm that created a competitive sales database. Specifically, the firm (a tractor manufacturer) created an internal database in which its sales force would register any competitive bid information. Over time the company built a database of competitive price information, which, combined with the record of its own bid outcome history, allows the firm to estimate the price sensitivity of customers, by segment if necessary, as well as to estimate the incremental value its tractors offered over the competition. For this project, the total investment for this multi-billion-dollar firm was on the order of $50,000.

There is some level of bias in the data that one needs to be aware of—the competitive quotes are being obtained from customers who have an incentive to provide low prices. One thus needs to adjust the distribution to reflect the bias; the level of bias can be estimated if one can confirm actual quotes for a sample of transactions and measure the actual level of bias. One also needs to be careful to "normalize" competitive quotes so that equivalent comparisons are being made. Are after-sale services, special financing terms, or training included, for example?

Further, when the quote history is overlaid with actual sales success data, it is possible to estimate the probability at which a sale is imminently likely, as well as the decline in the probability in a sale as price increases—a form of estimating price sensitivity as well as a way to estimate the amount of "money left on the table" in successful bids.

Finally, as firms update their pricing capabilities, many are discovering new opportunities to study responses to pricing actions. For example, as companies invest in technologies that allow for rapid and frequent price changes, they can look to yield management techniques that allow for the study of demand changes in response to pricing actions. Motel 6 for example, has the ability to post prices electronically on its billboards and can change these prices—at nearly no cost—by the hour. In only a short span of time, this company can study the price responsiveness of its customers by location, by day of week, and indeed even by time of day. As companies add to their ability to set and manage prices, new opportunities will become available to create "natural experiments" to allow for the study of price reactions at relatively low cost.

ANALYZING HISTORICAL DATA Analysis of historical sales data often involves application of linear regression analysis. This statistical technique attempts to show how much of the historical variation in a product's sales can be explained by each of the explanatory variables, including price, that the researcher includes in the analysis. One should not expect, however, that the researcher will necessarily succeed in identifying the effect of price with such an analysis. If there has been little historical variation in a product's price, then no statistical technique applied to its sales data can reveal the effect of price changes. Moreover, if every time price was changed and some other variable—such as advertising—was also changed, the best one can do is discover the joint effect of such a simultaneous change on sales. Fortunately, the use of more sophisticated multivariate techniques such as time series analysis or structural equations modeling can often provide estimates of their cross-impacts on demand.

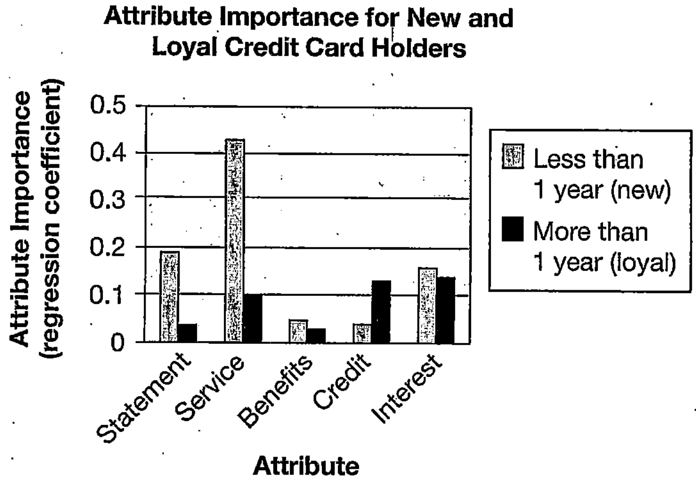
In any case, one must be careful to recognize the limits of a successful analysis of historical data. To estimate any equation, the researcher must develop a mathematical form for the relationship between price and sales. To the extent that the assumed form incorrectly specifies the relationship, estimates of price sensitivity may be misleading. Moreover, the researcher's estimate of price sensitivity is valid only over the range of price and advertising levels used to estimate it. There is no reason to believe that the same relationship would necessarily apply to price changes outside that range. One also needs to be careful to recognize that it is not enough to consider just a point estimate of price sensitivity; one needs to also look at the size of the corresponding error terms to understand the quality and accuracy of the estimate. Finally, regardless of how well an estimated equation fits past data, its value in predicting the effect of future price changes rests on the assumption that the future is like the past. The more other factors change, the less the past can predict the future. Despite these limitations, if a researcher has a lot of historical data with enough price variation in it, useful estimates of price sensitivity are possible.[5] For multiproduct companies, an understanding of price responsiveness can be used to help optimize demand flow across a product line. Specifically, prices can be adjusted to direct demand to specific products to better manage inventories, obtain better leverage with suppliers, and yet at the same time allow a wide product selection for customers who require specific items.

Exhibit 12-2 shows the results of research that utilized regression analysis to evaluate the importance of various product attributes to two groups of credit card holders: those who are loyal (more than one year of ownership) and those who are new (less than one year). The categorization of customers as new or loyal was based on input from the managers of the credit-card company who found that people who used their card for at least one year tended to stay users for an extended period of time. Of interest is the marginal increase in price sensitivity as measured by sensitivity to interest rates, for non-loyal customers (attribute importance of 0.16 compared to 0.14 for loyal customers) and the very large difference in needs for service. The researchers were also able to run regression equations for different time periods and determine how attribute importance was changing over time.

Experimentally Controlled Studies of Actual Purchases

A researcher might attempt to estimate price sensitivity by generating experimental purchase data. Such data may come from pricing experiments

EXHIBIT 12-2 Use of Regression Analysis



Source: Vikas Mittal and Jerome M. Katrichis, "Distinctions Between New and Loyal Customers," *Marketing Research* (Spring 2000): 27–32.

conducted in a store without the buyers' knowledge or from pricing experiments conducted in a laboratory. Since the researcher controls the experiment, price variations can be created as desired to generate results while holding constant other marketing variables, such as advertising levels and in-store displays, which often change with price variations in uncontrolled sales data. The researcher can examine the effect of a number of different prices quickly and either (1) exclude many unwanted external effects in the laboratory experiment or (2) establish a control for the in-store experiment that will take account of them. Moreover, all this can be done while still providing buyers with purchase decisions that are comparable to those they make under normal conditions. As a result, to the degree that the experimental setting reflects the actual purchase environment, experimental research provides fairly reliable estimates of price sensitivity.

IN-STORE PURCHASE EXPERIMENTS An in-store purchase experiment relies on actual purchase data collected when buyers are unaware that they are participating in an experiment. Although the term "in-store" reflects the fact that most such experiments are conducted in stores, the principles of in-store experimentation are equally applicable to any natural purchase environment. Such experiments are often easier to conduct for products sold through more controlled direct-retail methods, such as mail-order catalogs, than for those sold in traditional retail stores. For example, the researcher can select a subset of the mailing list to receive catalogs with experimental prices that differ from those in the regular catalog. Even in direct sales to business, one can sometimes select a representative sample of customers from one sales area, offer them an experimental price, and monitor the difference between sales to those buyers and to those in other regions where sales are made at the regular price.

The simplest design for an in-store pricing experiment involves monitoring sales at the historical price to obtain a base level of sales and then initiating a price change to see how sales change from that base level. In practice, this is a very common experimental design that can yield useful information; however, it fails to exploit one of the major advantages of experimentation: the ability to control for external factors. Without such control, the researcher is forced to make the tenuous assumption that any sales change from the base level resulted from the price change alone, not from changes in other factors. Fortunately, the addition of an experimental control store (or mail sample or sales territory) can reduce this problem substantially. To establish such a control, the researcher finds a second store in which sales tend to vary over the base period in the same way that they vary in the first store, indicating that factors other than price influence both stores' sales in the same way. The researcher then changes price only in the first store, but continues to monitor sales in both stores. Any change in sales in the control store indicates to the researcher that some factor other than price is also causing a change in sales. To adjust the results, the researcher subtracts from the sales in the experimental store an amount equal to the change in sales in the control store before determining the effect of the price change alone.[6]

One of the greatest benefits of in-store experimentation is the ability to test for interactions between price and other marketing variables that, in historical data, tend to change together. Unfortunately, the cost of such experimentation is very high because each additional factor studied requires the inclusion of more stores. The experimental design with the greatest amount of information, called a full factorial design, would require enough stores to match every level tested for each marketing variable with every level of the other variables. Usually, the researcher is forced to use a less-than-perfect experiment, called a fractional factorial design, that sacrifices some precision (generally by assuming away interaction effects) in order to reduce the number of stores required.[7]

Although many articles illustrate the successful application of in-store experimentation to estimate price sensitivity, the greatest impediment to using in-store experiments is the high cost of monitoring sales, analyzing the data, and securing the cooperation of retailers.[8] Although in theory this is an inexpensive experiment because as few as two stores for one week could constitute a test, accurate tests require many stores and last for months. A large number of stores are necessary to reduce the problem of an external factor influencing just one store and to obtain a representative sample of consumers whose behavior can reasonably be generalized to the market as a whole. It is often necessary to set a long time period for an in-store test in order to get past the short-run inventory effect on price sensitivity that initially masks the long-term effect. Consequently, a good in-store experiment is very expensive. When, for example, Quaker Oats conducted an in-store experiment that focused on the effect of price alone, the study required 120 stores and ran for three months. Such a study can easily cost several million dollars.[9]

In addition to the financial and time cost of in-store experiments, there are other drawbacks. There is the potential loss of consumer goodwill when some buyers are charged higher prices than others. On the other hand, charging prices below normal can become too costly when the product is a large-expenditure durable good such as a car or a piece of industrial equipment. An in-store test also involves the very real risk of being discovered by a competitor. If the product is new, a company may not wish to give its competitors an advance look. Moreover, when competitors find out about a test market, they often take steps, such as special promotions or advertising in selected areas, to contaminate the results.[10] Thus, although in-store experiments have the potential for yielding very high-quality estimates, market researchers are more often forced to use alternatives. The closest of those alternatives is a laboratory purchase experiment.

LABORATORY PURCHASE EXPERIMENTS Laboratory purchase experiments attempt to duplicate the realism of in-store experimentation without the high cost or the possible exposure to competitors. A typical laboratory experiment takes place in a research facility at a shopping mall. Interviewers intercept potential participants who are walking by and screen them to select only those who are users of the product category being researched. Based on information from a short pretest questionnaire, the researchers can control the proportion of participants in each demographic classification (for example, gender, age, race, income, or family size) to ensure that the experimental population is representative of the actual population of buyers, a technique known as proportionate sampling. If members of some demographic categories cannot be found in adequate numbers in the mall, telephone interviews may be used to contact such people and offer them an incentive to come and participate in the experiment.

The laboratory researcher can control who participates and can quickly manipulate prices and other elements in the purchase environment (such as shelf location and point-of-purchase displays), all at a single location. Moreover, the researcher can almost entirely eliminate external factors such as changes in competitors' prices, stock-outs of competing products, or differences among stores that may contaminate the results of an in-store test. Participants exposed to different prices see exactly the same display at the same location in the laboratory experiment. Even effects associated with the time of day can be controlled by constantly changing prices for each new participant in the experiment. Thus, if testing three different price levels, approximately one third of the consumers who take the test at any hour can be exposed to each price level. This ability to control the experiment so closely enables the researcher to draw inferences from far fewer purchases in much less time than would be possible with an in-store experiment.

Laboratory research facilities vary greatly depending on the sophistication of the research organization and the budget of the client company. The simplest facilities may consist of an interviewing room with a display of products from a single product category. The price for each brand is clearly marked, and the participant is invited to make a purchase. In theory, since the consumer is actually making a purchase, or can choose not to buy at all, the purchase decision in a simple laboratory experiment is the same one that the consumer would make shopping in an actual retail store. In practice, however, that conclusion may not be true. The problem lies in the artificiality of a simple laboratory environment. First, a single display in a laboratory encourages the consumer to give the purchase decision much more attention than would be typical in an actual shopping situation. Research indicates that most grocery shoppers do not even look at most prices when actually shopping in a supermarket. In a laboratory, however, consumers do not want to appear careless. They are, therefore, much more likely to note and respond to price differences. Second, when consumers know they are being watched from behind one-way mirrors, they may act as they think they should rather than as they would in real life. Thus some consumers may buy the low-priced brand just to appear to be smart shoppers, or the high-priced brand so as not to appear stingy. They may also buy something from the category out of a feeling of obligation to the researcher who gave them the money, even though they would not buy from that category in a store.

To overcome these limitations, a few research companies offer highly sophisticated laboratory research facilities. The most elaborate facilities attempt to duplicate as closely as possible the actual conditions under which consumers buy the product. These facilities contain complete simulated stores the size of small convenience stores. Before entering the simulated store, consumers may view reruns of television programs within which are embedded television commercials for the research product, or they may read magazines within which are print advertisements for the product. When consumers finally enter the store, they are invited to do all their shopping, purchasing whatever they want, just as they would on a regular shopping trip.

The cost of even the most sophisticated laboratory experiment is only a small fraction of the cost of in-store testing. As a result, the leading marketers of consumer packaged goods and small appliances rely extensively on this research technique when making pricing decisions.[11] In the past decade, the number and frequency of laboratory purchase experiments for products sold via Internet web sites has boomed. The cost to design a realistic purchase environment, to control the promotional message, and to recruit respondents on the Internet is so low that it is possible to test more frequently, to get answers faster, and to employ much larger samples than marketers would usually have considered. Companies that design this type of research can solicit participants via pop-up ads on targeted websites. To reach buyers in very "thin" markets, such as purchasers of industrial equipment or adventure vacations, marketers can buy e-mail lists to solicit participants. Consequently, a realistic Internet purchase experiment can take as little as a week and cost one-tenth what similar research would cost in another purchase environment. Box 12-2 describes a laboratory experiment for a company considering entry into an existing Internet marketplace.

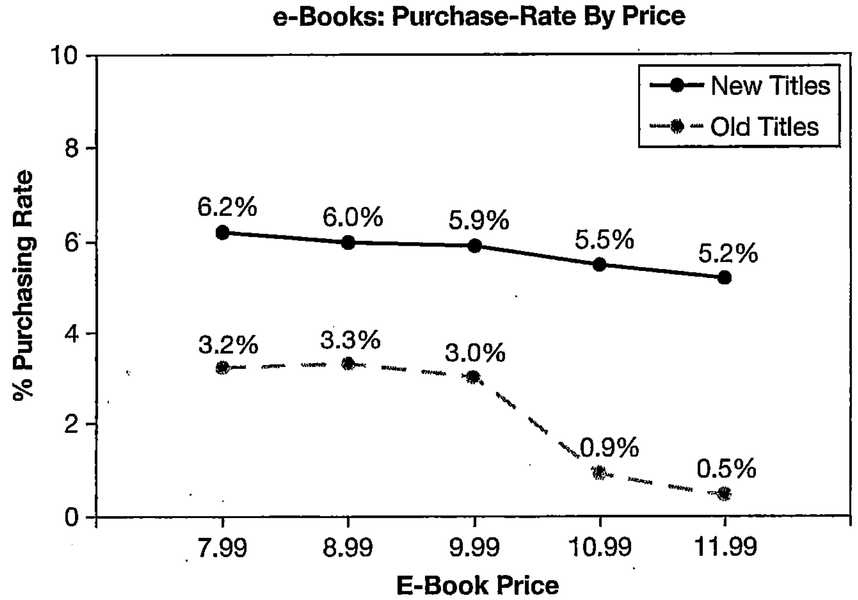
BOX 12-2

Measuring Price Sensitivity for e-Books

An online retailer wanted to test its ability to price some popular electronic book titles above the established level of $9.99 or less per download. The reason is that publishers were resisting e-book publishing for their latest and best publicized titles, fearing that e-books would cannibalize more profitable sales of newly released hardbacks. The retailer hoped to understand whether its customers would accept a segmented pricing model with higher prices for new, best-seller titles—particularly since bookstores generally price hard copies of newly released titles as loss leaders to draw store traffic. Such a model might use a lower e-book price for older tiles that had migrated to paperback while continuing to price e-book titles that are still in hard back at higher prices.

The company engaged Grail Research to design an online laboratory experiment, recruit 2,000 respondents, and analyze the results. To protect its reputation, the online laboratory store was given a name not associated with the retailer. The goal of the experiment was to understand the extent to which higher prices would affect consumers' e-book purchase behavior. The market research company spent one and a half weeks designing the experiment with the retailer and recruiting respondents from e-mail lists of electronic book purchasers. Respondents participating in the experiment were first asked their genre preferences, following which they were presented with several e-book options in each of their preferred genres. The e-books varied in price and time since publication. Some e-books were given prices above the standard $9.99 and some were priced at or below $9.99. The experiment was designed to replicate the actual experience a consumer would have purchasing a book online. Respondents were asked to add e-books to their shopping basket as if they were actually shopping on a website and they could monitor how much they had in their shopping cart. At the end of the experiment, respondents were presented with their total order and cost and given the opportunity to remove items from their shopping basket before confirming their order.

Only one and a half weeks after the launch online, more than 2,000 respondents had completed the experiment through confirming a purchase. After another week, the research company had completed its analysis of price sensitivity by demographic, type of book, and various other segmentations. The chart below shows the answer to the retailer's main research question. The online experiment demonstrated that e-book demand is relatively price inelastic for prices below $9.99 but very elastic for prices above $9.99 for titles generally available anywhere. However, respondents did show a willingness to purchase new titles, not generally available in paperback or in e-book format, at prices above $9.99. The experiment proved very insightful for the online book retailer. They learned that there was some upward flexibility in their prices for newer books, but a downward adjustment for older books would



not generate sufficient additional purchases to justify the drop in price. As a result of the experiment, the retailer decided to launch a segmented pricing model, offering publishers the chance to earn higher profits on e-book sales if they authorized them along with the hardback edition.

Source: Grail Research. Although this description is based on an actual study, some details have been changed to maintain client confidentiality.

Uncontrolled Studies of Preferences and Intentions

The most common research technique for directly estimating price sensitivity is the survey of brand preferences or purchase intentions. Companies prefer to measure preferences or intentions, rather than actual purchases, for a number of reasons:

1. Survey data costs much less to collect than purchase data.
2. Survey data can be measured for large durable goods, such as automobiles or photocopiers, for which in-store or laboratory experiments at various prices are impractical.
3. Survey data can be collected even before a product is designed, when the information is most valuable in directing product development.
4. The results can be collected quickly.

Unfortunately, the problem with survey research is that many consumers do not provide answers that are a reliable guide to their actual purchase behavior. The reasons are varied, but one of the main issues is that surveys require a level of abstraction that the respondent may or may not be able to perform. This is especially true of new products that are wholly unfamiliar or whose application is not readily apparent. As a result, determination of value delivered, or willingness-to-pay, is difficult to arrive at even for a committed respondent. In order to solve this problem, some research companies cross-validate the results of one survey with the results of another, often using slightly different methods of data collection and questioning. For example, a firm might collect data using personal interviews and validate the results by telephoning a different group of respondents and asking the same set of questions. The closer the results are from the two samples and methods, the more valid and accurate the final results.

DIRECT QUESTIONING Very early in the development of survey techniques for marketing, researchers learned that it was futile to ask consumers outright, "What is the most you would be willing to pay for this product?" Direct questioning sometimes elicits bargaining behavior, with consumers stating a lower price than they would actually pay. Other times, it elicits a desire to please the researcher or to not appear stingy, prompting consumers to state a higher price than they would actually pay. Frequently, it simply elicits a cursory answer that consumers would change were they to give the question the same thought as an actual purchase decision. Consequently, uncontrolled direct questioning as a research technique to estimate price sensitivity should never be accepted as a valid methodology. The results of such studies are at best useless and are potentially highly misleading.

BUY-RESPONSE SURVEYS A slight variant of the direct-question survey involves showing consumers a product at a preselected price and asking if they would purchase at that price. Surprisingly, although directly asking consumers what they would pay usually yields meaningless answers, asking them if they would buy at a preselected price yields answers that are at least plausible. When the answers given by different consumers for different price levels are aggregated, they produce what looks like a demand curve for market share, sometimes called a purchase probability curve (Box 12-3). Presumably, questioning willingness-to-buy generates better responses simply because it is structured more like an actual purchase decision than as an open-ended question about what the consumer would pay. Also, the consumer has no opportunity to bargain with the researcher.[12] Interestingly, there are a number of studies that have documented cultural differences that lead to large amounts of substantial and systematic variation in the accuracy of buy-response surveys across countries such as the United States, Germany, and Japan, among others.

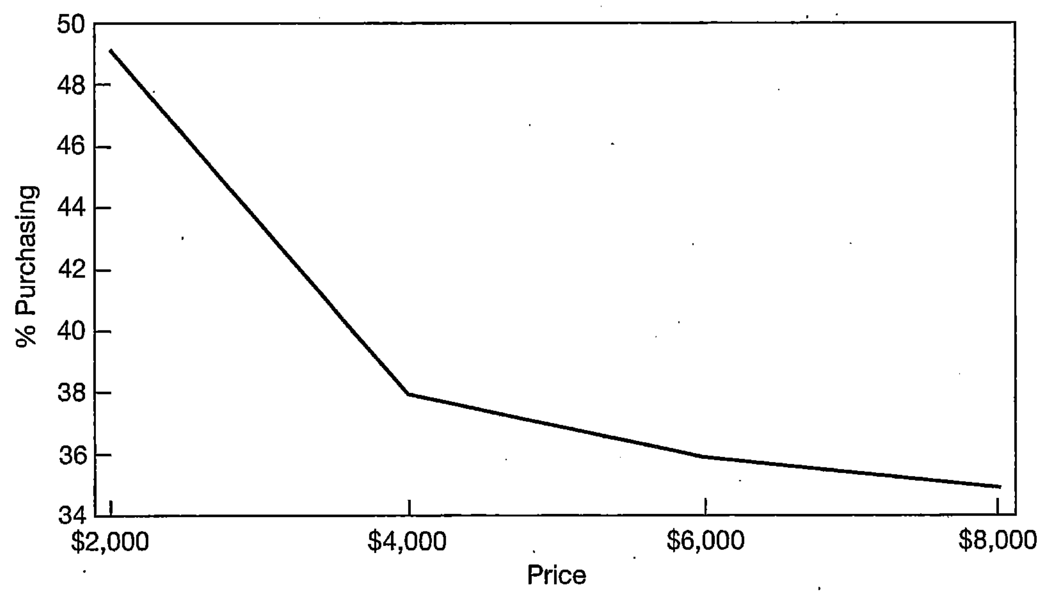
ATTRIBUTE RATING Another method for evaluating price sensitivity is to include price as one of the attributes describing a product or a purchase situation. Consumers rate the importance of each attribute using a variety of scaling techniques. Those scales can be a one to five or a one to 10 importance rating or simply an evaluation of the percent of respondents mentioning the attribute as being important.[13] This approach is problematic because responses tend to be offhand and overly positive, due to halo effects, where respondents tend to not carefully discriminate among listed attributes and give similar ratings or responses to many attributes, especially those adjacent to each other.

BOX 12-3

Purchase Probability Curves: A Simple Buy-Response Study—Opportunity for a Higher Price

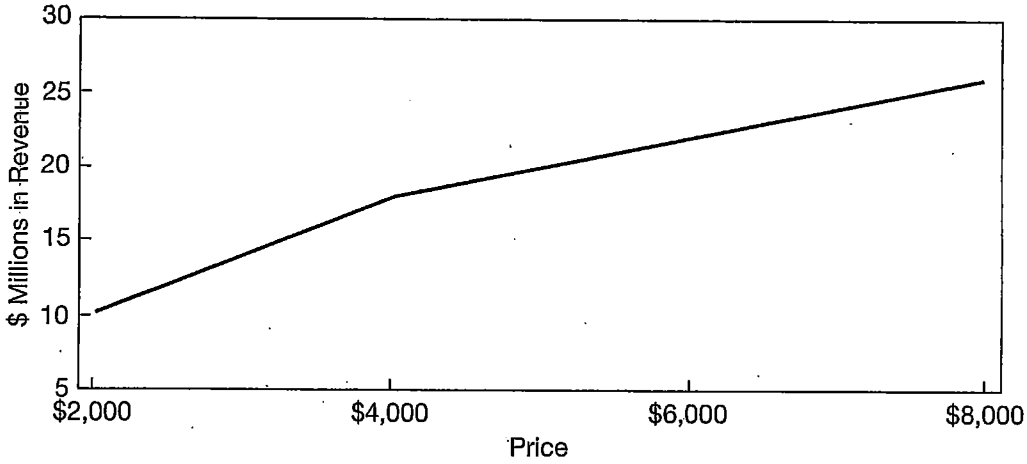
A software firm developed a product for law firms that would easily produce high-quality legal documents and would manage document storage and billing of time for both small and large offices. The original estimates of price were $500 per unit. Chadwick Martin Bailey, Inc. conducted a national study to measure price sensitivity for the product. It began the process by conducting extensive exploratory research, including focus groups and semistructured interviews. This phase of the research initially indicated that prices in the range of $6,000 might be perfectly acceptable to a large segment of attorneys. A random sample of 603 attorneys was contacted by telephone and asked the likelihood of purchase at $2,000, $4,000, $6,000, or $8,000, yielding about 150 responses per price point. Probability of purchase was measured using a 0–10 likelihood of purchase scale, and all responses in the 8–10 range were used as a basis for assessing price sensitivity. At $2,000, 49 percent of the firms would have bought the package. Demand was found to be very inelastic for higher prices, as shown in Figure A. Movement from $4,000 to $8,000 in price made little difference in the proportion of law firms willing to buy the product, but it produced large differences in revenue from sales, as shown in Figure B.

Figure A Purchase Probability Curve



Source: Chadwick Martin Bailey, Inc.

Figure B Total Revenue Estimates



Source: Chadwick Martin Bailey, Inc.

This study was provided by Chadwick Martin Bailey, Inc., a planning and market research firm located in Boston, Massachusetts.

One cannot, however, treat buy-response data as directly comparable to or directly predictive of the sales that would actually occur at the corresponding prices in a store. Most problematic is the fact that consumers' answers depend on their recollection of the actual prices of competing products. To the extent that they overestimate or underestimate competing prices, they will misjudge their willingness-to-buy. Even with this form of the question, some consumers will still want to please the researcher, or will fear appearing stingy, and so will falsely claim a willingness to buy the brand over competing brands regardless of the price.

Nevertheless, such research is useful (1) as a preliminary study to identify a range of acceptable prices for a new product and (2) to identify changes in price sensitivity at different points in time or place, assuming that the biases that affect these studies remain the same and so do not affect the observed change. For example, buy-response surveys for low-involvement consumer packaged goods often reveal little difference in consumers' willingness-to-buy at different prices before they try a new product, but a significant difference at different price points after they have tried it. In interpreting the study, one would not want to take the absolute percentage of consumers who claimed they would buy as an accurate prediction of the percentage of consumers who would actually buy at different prices. However, differences in the stated probability of purchase before and after trial may reliably predict the change in price sensitivity caused by the product trial.

Intention measurement is also sometimes used successfully to predict actual purchases when researchers have past experience that allows them to adjust for the bias in subjects' stated intentions. Typically, purchase intentions are measured by asking people to indicate which of the following best describes their likelihood of purchase:

Definitely would buy

Probably would buy

Might/might not buy

Probably would not buy

Definitely would not buy

The leading survey research firms have asked such questions of millions of buyers for thousands of products. Consequently, they are able to develop adjustments that reflect the average bias in these answers for various product classes. Thus, an experienced researcher might expect that only 80 percent of people answering "definitely would buy," 50 percent answering "probably would buy," 25 percent answering "might/might not buy," and 10 percent answering "probably would not buy" will actually purchase.

IN-DEPTH INTERVIEWS An in-depth interview is a "semistructured" method that is used to elicit responses from customers on how they use products and services, from which the research infers value rather than asking about value directly. The interview is often conducted one-on-one with a respondent and lasts for one to two hours. In a consumer environment, it is used to understand how individuals and families use products and how they might value different features or positioning approaches. In a business-to-business environment, the interviewers attempt to understand how businesses gain revenues or reduce costs by using a specific product or service; to do this successfully, one needs to have a deep understanding of the respondent's business. In-depth interviews in pricing research are useful in (1) understanding which product or service features and benefits are important to a customer, (2) assessing the monetary or psychological value of these features and benefits that a customer receives as a result of using the product or service, and (3) assessing roughly what a customer might be willing to pay to obtain these features and benefits. In-depth interviews are also used to develop economic-value models of how much a customer could gain in monetary terms from purchase of the product. The model then becomes part of a promotional campaign to increase customers' willingness-to-pay. Such models work well for business customers, where most benefits can be translated into additional revenues or costs saved. It also works well in consumer markets where the benefit is a cost saving (for example, the value of buying a more efficient refrigerator).

Like a focus group, an in-depth interview is relatively unstructured and is usually conducted by an experienced interviewer who has a specific interview guide and objective, such as to quantify the value of differentiating features. In-depth interviews are used less frequently in market research due to the need for highly specialized interviewers, the expense per interview, and the small sample size.[14] This is especially true for consumer pricing research for mass-market products and services. However, for more complex business-to-business pricing research, the interviews—in terms of the quality of information obtained with regard to customer value and willingness-to-pay—often yield much more fruitful insights and analysis. For example, in business markets, in-depth interviews enable the interviewer to probe customer needs, customer experiences, how they attempt to deal with problems, how the supplier's products or services could solve these problems, and the value to the customer of the consequent savings or gains they would realize from using the firm's products or services.

In-depth interviews do not ask customers directly how much they would be willing to pay. Instead, the interview focuses on the financial benefits to the customer that a product or service could influence. It is also possible to get a sense of perceived value by identifying other items that the customer buys to achieve the same benefit. For example, *evoked anchoring*, one method used successfully in business-to-business markets, asks respondents to identify items in their budget that they might consider a trade-off in order to obtain the value and benefits promised by a supplier's proposed product or service solution. For example, when helping a software client to price relationship–management software, we identified that one benefit was reduced customer turnover. By asking potential buyers of the software to identify the costs to acquire new customers, we could infer the value to retain them.

In-depth interviews enable marketers to understand not only what someone might perceive their product or service to be worth, but also why it is worth that much. The in-depth interview attempts to understand the needs that the product addresses and how the product or service addresses them. The process often uncovers ways that suppliers can enhance their current product or service offerings and, in doing so, provide the basis for creating more differentiated products that can be sold at higher prices. It also exposes who in the buying organization has goals that are likely to benefit from purchase of the product.[15]

The interview must be conducted outside the context of a selling opportunity or a negotiation, since customers are unlikely to reveal value at such times. However, the data garnered often form the basis of a value-based selling approach in which salespeople, armed with an understanding of how their products differ from those of competitors and how those differences create value for customers, can justify their pricing to the customer and to themselves. Companies often can use the information gained from in-depth interviews to develop "value case histories." These case histories describe the experience of a particular customer in using a firm's products and the specific value that the customer received. These case histories eventually become a sales support tool.[16]

The in-depth interview is an excellent method for developing a better understanding of how different product and service features create value for customers, especially customers in a business-to-business environment. It is especially useful in moving beyond the core product and understanding how different service and support elements can create incremental value for a user and provide insights into how a product might be priced to capture that value. It often identifies similar service and support characteristics that can successfully differentiate what are often thought of as commodity products.[17] A common concern is that customers won't provide the data. However, our experience is that most customers are quite willing to share insights and data that will help suppliers serve them better.

Experimentally Controlled Studies of Preferences and Intentions

To solve some of the problems of bias and extraneous factors when measuring preferences and intentions, researchers try to exercise some control over the purchase situation presented to respondents.

The questions must be designed to make the survey respondents consider the questions in the same way they would consider an actual purchase decision. The extent to which that can ever be fully accomplished is still an open question, but marketing researchers, recognizing the potential value of accurate survey information, are certainly trying.

SIMULATED PURCHASE EXPERIMENTS Many researchers believe that the best way to get consumers to think about a survey question and to respond as they would in a purchase situation is to simulate the purchase environment as closely as possible when asking the survey questions. With this type of research, the researcher asks the consumers to imagine that they are on a shopping trip and desire to make a purchase from a particular product class. Then the researcher shows the consumers pictorial representations, descriptions, or sometimes actual samples of brands along with prices and asks the consumers to choose among them, given various prices. Since actual products need not be used, this technique enables one to test pricing for new product concepts, as part of a general concept test, before the concepts are actually developed into products.

The primary difference between such a simulated purchase experiment and a laboratory purchase experiment is that participants only simulate the choice decision to purchase a product and so do not get to keep their choices.[18] The simulated purchase experiment is a widely used tool in pricing research that overcomes two important drawbacks of other types of surveys. If it is structured as a choice task among alternative brands, a consumer's thought process should more closely approximate the process actually used when making a purchase. Also, since consumers have no way of knowing which brand is the one of interest to the researcher, they cannot easily think of the choice as a bargaining position or as a way to please the researcher. Thus, simulated purchase experiments can sometimes predict price sensitivity reasonably well.[19]

While any type of research is prone to bias, the simulated purchase experiments can often be an acceptable method for gaining quick and low-cost information on the buying behavior of consumers. If, for example, a company wants to estimate the price sensitivity of a product sold nationally, the cost of hundreds of in-store experiments throughout the country would be prohibitive. If the company conducted both an in-store experiment and a simulated purchase experiment in a few locations and found them reasonably consistent, it could confidently use the latter to cover the remaining locations and to conduct future research on that product class. Even if the experiment showed a consistent tendency to be biased, simulated purchase experiments could still be used successfully after the results had been adjusted by the amount of that previously identified bias.

TRADE-OFF (CONJOINT) ANALYSIS An experimental technique, called trade-off (or conjoint) analysis, has become popular for measuring price sensitivity as well as sensitivity to other product attributes.[20] The particular strength of trade-off analysis is its ability to disaggregate a product's price into the values consumers attach to each attribute. Consequently, trade-off analysis can help a company identify the differentiation value of unique product attributes and, more important, design new products that include only those attributes that consumers are willing to pay for as well as how much they are likely to pay for the entire product and service package. Currently, trade-off analysis aids in the design of a range of products, from automobiles and office equipment to household cleaners and vacation packages.

The basic data for trade-off analysis are consumers' answers to questions that reveal not their directly stated purchase intentions, but rather the preferences that underlie those intentions. The researcher collects such data by asking respondents to make choices between pairs of fully described products or between different levels of just two product attributes. The product descriptions are designed to vary systematically in the levels of certain attributes that define the product as well as the price. When multiple levels of price are included in the study design, it is possible to assess not only the value assigned to certain product attributes but also to arrive at an estimate of price elasticity. The data are collected with a questionnaire or online.

After obtaining a consumer's preferences for a number of product or attribute pairs, the researcher then manipulates the data to impute the value (called utility) that each consumer attaches to each product attribute and the relative importance that each attribute plays in the consumer's purchase decision.[21] With these data, the researcher can predict at what prices the consumer would purchase products containing various combinations of attributes, including combinations that do not currently exist in the marketplace. The researcher can also estimate how much of one attribute the consumer is willing to trade off in order to obtain more of another attribute—for example, how much more price a consumer is willing to trade off in order to obtain more fuel efficiency in a new automobile.

With similar data from a number of consumers who are representative of a market, the researcher can develop a model to predict the share of a market segment that would prefer any particular brand to others at any particular price. Since the researcher has collected data that reveal underlying preferences, consumers' preferences can be predicted, or interpolated, even for levels of price and other attributes not specifically asked about in the questionnaire, provided the attributes are continuously measurable and bounded by the levels that were asked about in the survey. When the researcher knows independently the size of the market and market segments, it is possible to create a simulation model for testing different price-offer combinations. Box 12-4 provides an example of such a process. Readers should note how the basic features were varied along with price in order to develop a relationship between features and value, here termed "feature utility."

It is useful to contrast trade-off analysis with direct questioning methods. By having respondents evaluate a product in its entirety rather than in the more abstract form of individual attributes, responses are more likely to mimic actual choices. For example, in a study of recent MBA graduates, when asked about individual job attributes, the most important was the people and culture of the company. Salaries were rated low on the list of attributes under consideration. However, when the same students we asked to choose the job they would prefer among various job descriptions, analysis revealed that salary was the most important job attribute, followed by the region and location of job; people and workplace culture ranked only fourth.

Of all methods used to estimate price sensitivity from preferences or intentions, trade-off analysis promises the most useful information for strategy formulation. The researchers can do more than simply identify the price sensitivity of the market as a whole; they can identify customer segments with different price sensitivities and, to the extent that those differences result from differences in the economic value of product attributes, can also identify the specific product attributes that evoke the differences. Consequently, researchers can describe the combination of attributes that can most profitably skim or penetrate a market. The economic value of a product can also be identified even when the product is not yet developed by presenting consumers with different experimental product combinations in the form of pictorial and descriptive product concepts, or new product prototypes.

As a result of these promised advantages, the use of trade-off analysis by both market research firms and internal research departments has grown rapidly, but the performance of trade-off analysis is only as good as its ability to predict actual purchase behavior. There are, however, a number of reasons why a prudent manager might suspect the reliability of this technique for some markets. Trade-off analysis is an experimental procedure that introduces bias to the extent that it does not simulate the actual purchase environment. The respondent taking a conjoint test is encouraged to focus much more attention on price and price differences than may occur in a natural purchase environment. Thus, while trade-off analysis is still useful for studying nonprice trade-offs, it should not be trusted to predict choice for "low involvement" products for which there is little evidence that the purchasers carefully compare price and other attributes across brands when making a decision. It also is of little value where purchasers have much more difficulty obtaining and comparing price and product attributes in a real purchase situation. For

BOX 12-4

A Conjoint Study: Power Powder Ski

Conjoint Example: Power Powder Ski

A small sporting goods manufacturer designed a downhill ski that incorporated electronic vibration control, promising downhill skiers easier turning, reduced "chatter" on rough surfaces, and a general reduction in the physical effort of skiing. To commercialize the most financially lucrative offer, the company commissioned a market research study to address several questions that would inform the marketing strategy. Three of the research questions involved pricing:

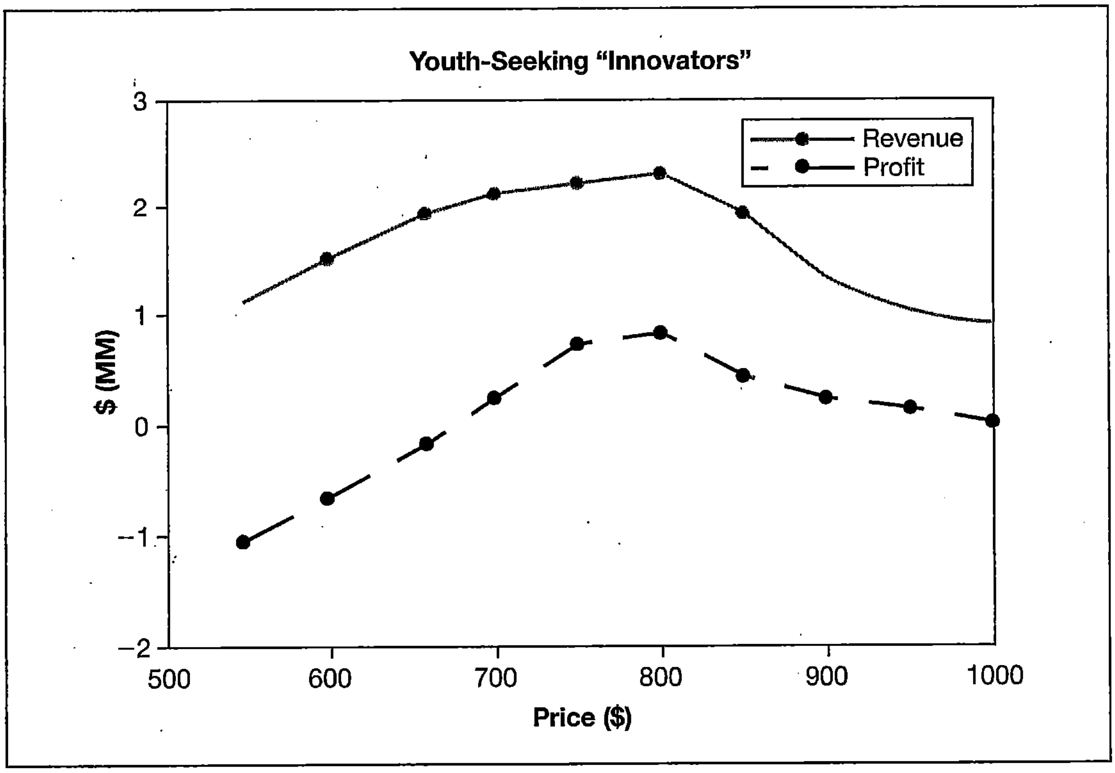
(i) What is the demand for the product, including the price-volume trade-off?
(ii) For what segment(s) of skiers could the offer be targeted most profitably?
(iii) Given the innovative technology, would it be financially worthwhile to offer a longer warranty than the standard 90 days?

To address these questions, a market survey was developed that collected information on skier demographics, ability levels, and willingness-to-pay for different types of benefits. The survey was administered to 1,200 skiers across North America. The survey revealed four major segments:

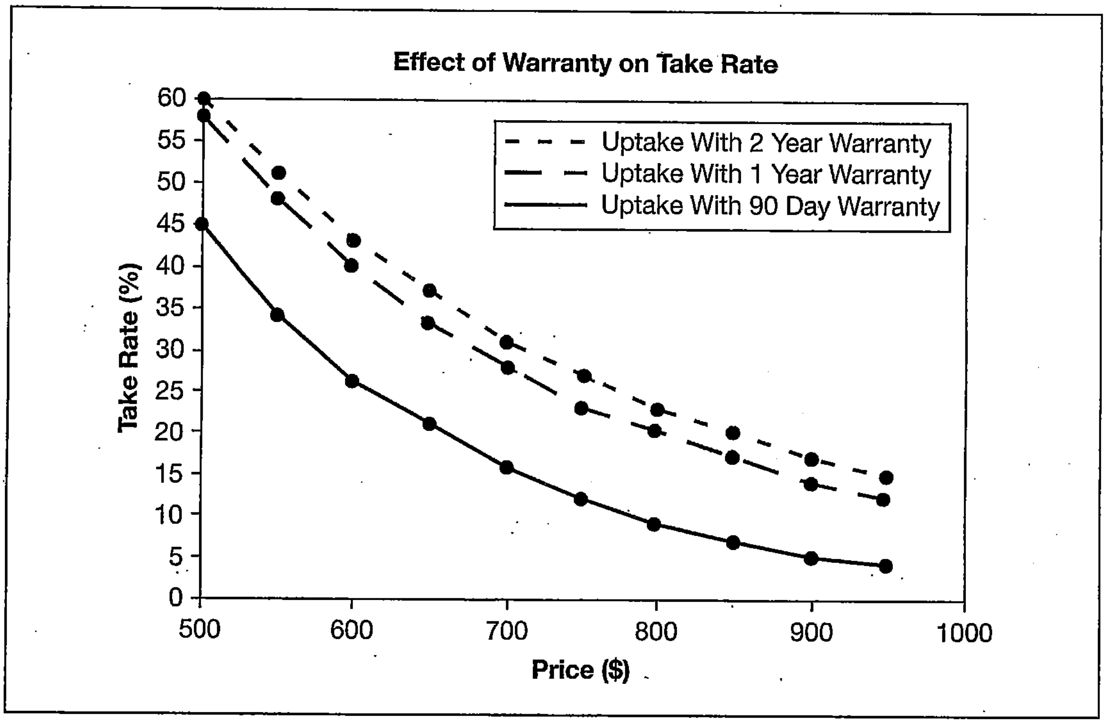
- **Budget shoppers** are generally beginner and intermediate skiers who make purchases only when old equipment is worn out or outgrown.
- **Value-seekers**, who range in ability from intermediate to expert, consider new purchases frequently, but they make careful price-value trade-offs before actually spending any money.
- **Innovators** are intermediate to expert skiers who readily buy new technology.
- **Elite skiers**, who actively participate in ski clubs and race competitively, test new equipment to find out what works best for them before purchasing it.

In addition to questions about personal demographics and past purchases, the survey included a conjoint-based simulated purchase exercise that asked respondents to evaluate several scenarios for their next potential ski purchase and indicate their most likely choice. Respondents were informed about the benefits of the new technology and then presented with several buying scenarios that included buying new skis with the electronic damping technology, buying well-known conventional skis, or keeping the skis they have and making no new purchase.

The early analysis of the survey generated disappointing findings: Overall the market was quite sensitive to price. Revenues were maximized at the $450 price point, but the Power Powder Ski captured a disappointingly small share with a rapid drop-off at still higher prices. Complicating matters, the company would incur a high variable cost due to cost of the additional technology and the royalty arrangement with the patent holder. Even at a profit-maximizing price for the overall market, the potential return was not worth the risk. Fortunately, one of the benefits of conjoint data is the ability to slice samples in various different ways. Analysis of just the "innovators" revealed that they did indeed have a higher "take rate" for the product and, importantly, the rate fell off much less rapidly at higher prices. Although only a small subset of the market, innovators could profitably support a price of $800. Furthermore, it turns out that it is much cheaper to sell to innovators because they actively seek out new products—as a result, advertising costs are significantly lower, and the manufacturer would not require an extensive distribution network. Apparently the higher take rate among the innovators reflected a demographic subset: 35- to 50-year-old men who had, in their youth, been very good skiers but were now feeling the effects of age in their knees. The promise of lower effort, reduced chatter, and easier turning were benefits for which this group was willing and able to pay a significant premium. This finding opened the possibility that there was also an opportunity to sequentially "skim" the market with a high initial price at launch.



Finally, conjoint analysis enabled the company to isolate and measure the impact of individual features on willingness-to-pay and overall purchase rates. The research revealed that moving form a 90-day to a one-year warranty more than doubled the take rate of the product by respondents in the target segment.



Source: Georg Muller, Monitor Company Group study. The product category and price levels have been changed to protect client confidentiality. Otherwise, the data outputs shown above are actual outputs from the research.

example, research companies have compared the predicted effects of price on physicians prescribing decisions with data on the actual price of the pharmaceuticals they prescribed. Conjoint tests invariably predict much higher price sensitivity among physicians than, in fact, is revealed by prescribing behavior. Also, if respondents have little experience with the product category, as is usually the case with innovative product categories, the technique poorly predicts the trade-offs that customers will make because of their inability to map differences in features into likely benefits.

Because trade-off analysis measures underlying preferences, researchers do have the ability to check if an individual consumer's responses are at least consistent. Consumers who are not taking the survey seriously, or who are basically irrational in their choice processes, are then easily identified and excluded from the sample. Even more comforting are three separate studies that show a high degree of consistency, or reliability, when subjects are asked to repeat a trade-off questionnaire a few days after having taken it initially.[22] Since the subjects are unlikely to remember exactly how they answered the questions in the earlier session, the consistency of the answers over time strongly suggests that they do accurately reflect true underlying preferences. More comforting still is the result of a study showing that the exclusion from the questionnaire of some product attributes a subject might consider important does not bias the subject's responses concerning the trade-offs among the attributes that are included.[23] Although trade-off analysis is more costly than a simple survey, it also provides much more information. Given its relatively low cost and the fact that it has met at least some tests of reliability, it certainly warrants consideration particularly to understand the value of features by segment when designing new products and offers.

USING MEASUREMENT TECHNIQUES APPROPRIATELY

Numerical estimates of price sensitivity can either benefit or harm the effectiveness of a pricing strategy, depending on how management uses them. This is especially true when respondents have considerable experience with the use and purchase of a product. If managers better understand their buyers and use that knowledge to formulate judgments about buyers' price sensitivity, as discussed in Chapter 6, an attempt to measure price sensitivity can be very useful. It can give managers new, objective information that can either increase their confidence in their prior judgments or indicate that perhaps they need to study their buyers further. An understanding of price sensitivity also provides a reference by which to judge proposed price changes—how will sales respond as we increase or decrease prices? Combined with variable cost data, it is possible to judge whether proposed changes in price will have a positive effect on profits.

Integrating soft managerial judgments about buyers and purchase behavior with numerical estimates based on hard data is fundamental to successful pricing. Managerial judgments of price sensitivity are necessarily imprecise while empirical estimates are precise numbers that management can use for profit projections and planning. However, precision doesn't necessarily mean accuracy. Numerical estimates of price sensitivity may be far off the mark of true price sensitivity. Accuracy is a virtue in formulating pricing strategy; precision is only a convenience.

No estimation technique can capture the full richness of the factors that enter a purchase decision. In fact, measurements of price sensitivity are precise specifically because they exclude all the factors that are not conveniently measurable. Some estimation techniques enable the researcher to calculate a confidence interval around a precise estimate, indicating a range within which we may have some degree of statistical certainty that the true estimate of price sensitivity lies. That range is frequently wider than the interval that a well-informed manager could specify with equal confidence simply from managerial judgment. Unfortunately, researchers often do not (or cannot) articulate such a range to indicate just how tenuous their estimates are. When they do, managers often ignore it. Consequently, managers deceive themselves into thinking that an estimate of price sensitivity based on hard data is accurate when in fact it is only a point estimate of something we can never predict with 100 percent accuracy. Fortunately, a manager does not have to make the choice between judgment and empirical estimation.

Used effectively, they are complementary, with the information from each improving the information that the other provides.

Using Judgment for Better Measurement

Any study of price sensitivity should begin with the collection of information about buyers—who they are, why they buy, and how they make their purchase decisions—since those are the essential inputs in the formulation of judgment. At the outset, this information should come from open-ended, qualitative, or exploratory research that enables managers to discover facts and formulate impressions other than those for which they may have been specifically looking.[24] In industrial markets, such research may consist of accompanying salespeople to observe the purchase process. After a sale, managers might follow up to ask how and why the purchase decision was made. One can also look at past bid histories to see the correlation between various price levels and the likelihood of winning the bid. In many cases, managers can interview important customers and intermediaries by telephone to gain their impressions about a variety of price and marketing issues.[25] In consumer markets, such research may consist of observing consumers discussing their purchase decisions in focus groups or in-depth interviews as previously discussed. Insights generated from such informal observation could then be confirmed with more formal research in the form of a survey administered to a larger number of buyers.

Having formed judgments about buyers based on qualitative impressions developed from observing them, a manager will often find it practical and cost-effective to expand this understanding through original primary research that attempts to measure certain aspects of buyer behavior, such as price sensitivity. That attempt is far more likely to produce useful results, to the extent that management already understands the way buyers make their purchase decisions and uses that information to help structure the attempt at measurement. There are a number of ways that managerial judgment can, and should, guide the measurement effort.

1. For experimentally controlled data estimation, managerial judgment should determine the focus of the research on certain target demographic groups and provide guidance for generalizing from those groups to the population as a whole.
   - Management may know that 80 percent of its product's buyers are women who are employed full-time. That information is important if the researcher plans to measure price sensitivity with an in-home survey or an experiment in a shopping center. On a typical day between 9:00 a.m. and 5:00 p.m., few of the experimental subjects at home or in the shopping center would be representative of that product's buyers. To get a representative sample, the researcher might need to conduct the in-home survey in the evenings or the experiment only during the lunch hour at locations near where many women work. He or she might also ask a prescreening question (Are you employed full-time?).

- If management also knows that different demographic groups buy the product in different quantities, that information can be used to scale the survey results differently for different subjects in the sample to reflect their relative impact on the product's actual sales.

2. For historical data estimations, the intervention of informed managerial judgment into the analysis is even more essential, since the lack of any experimental control invariably results in data that are full of potential statistical problems. Managerial judgment should be used to reduce random error and solve statistical problems.
   - The effect of price changes tends to get overwhelmed in historical purchase data by the amount of sales variation caused by other factors, which may not be obvious to the researcher but may be to managers who know their buyers. For example, a researcher analyzing many years' worth of data on the sales of a frozen seafood product could substantially improve the estimation of price sensitivity if management pointed out that many buyers purchase the product as part of their religious observance of Lent, a Christian holiday that shows up at a different time every year. That one bit of information about why consumers buy would enable the researcher to eliminate a substantial amount of random variation in the data that would otherwise yield a biased estimate of price sensitivity if it were not included.
   - The researcher using historical data is also often confounded by the problem called colinearity, where different explanatory variables change together. Perhaps, at the same time that a firm offers a promotional price deal, it always offers retailers a trade deal in return for a special product display. Without additional input from management, the researcher cannot sort out the effect of the price deal from that of the display. If, however, management knows that buyers of the product are like those of another product that is sometimes sold on special displays without a price deal, the researcher could use sales data from that other product to solve the colinearity problem with this one. Alternatively, if managers are confident in making a judgment about the effectiveness of special displays (for example, that they account for between one-third and one-half of the total sales change), that information can likewise help the researcher to narrow an estimate of the effect of price on sales.[26]
3. Managerial judgment should also be used to select the appropriate structure for an experiment or survey, and the appropriate specification of a statistical equation for analysis of historical data.
   - A manager who has studied buyers should know the length of the purchase cycle (time between purchases) and the extent of inventory holding, both of which will govern the necessary length of an experiment or the number of lagged variables to include when analyzing historical data. Failure to appropriately specify the purchase cycle could cause a researcher to grossly miscalculate price sensitivity by ignoring the longer-term effects of a price change.

- Management may have much experience indicating that an advertisement affects buyers differently when the advertisement focuses on price rather than on other product attributes. If so, the researcher should separate those types of advertising in an experiment or in historical data analysis. The researcher might also treat price advertising as having an effect that interacts with the level of price, and nonprice advertising as having an independent effect.

4. For survey research, managerial judgment should guide the preparation of product descriptions, to ensure that they include the variables relevant to buyers and that they describe them with the appropriate connotations.
   - For an automobile survey, management can point out that the amount of time required to accelerate to 65 mph is an important attribute to include when describing a sports car, but not when describing a family car.
   - For a survey on radios, managers can point out that the word "knob" in a description will carry a connotation much different from the word "control," which may influence buyers' perceptions about other attributes such as reliability and state-of-the-art technology.

The common failure to use this type of managerial input (or the failure of management to know buyers well enough to provide it) is no doubt one reason why research to measure price sensitivity is often disappointing.

When measurement embodies managerial judgment, it is much more likely to provide useful information, but even then the results should never be taken uncritically. The first question to ask after any marketing research is, "Why do the results look the way they do?" The measurement of price sensitivity is not an end result but a catalyst to learn more about one's buyers. If the results are inconsistent with prior expectations, one should consider how prior judgment might have been wrong. What factors may have been overlooked, or have been given too little weight, leading to the formulation of incorrect expectations about price sensitivity? One should also consider how bias might have been introduced into the measurement process. Perhaps the measurement technique heightened buyers' attention to price or the sample subjects were unrepresentative of the product's actual buyers. Regardless of the outcome of such an evaluation, one can learn more about the product's buyers and the factors that determine their price sensitivity. Even when one concludes that the measurement technique biased the results, the bias reveals information (for example, that the low level of price sensitivity that management expected is substantially due to buyers' low attention to price in the natural purchase environment, or that a segment of people who do not regularly buy the firm's product has a different sensitivity to price).

Using Internet-Based Techniques

Since the advent of the Internet, market researchers and their clients are increasingly using on-line surveys for gathering customer and market data.

Online research is often far less expensive and much faster than traditional research methods—for example, you avoid the costs of mailing or telephone staff. It tends to obtain better response rates because it is less intrusive and more convenient to simply click a "respond" button in an e-mail. However, online research may not be generalizable to an entire market because of sampling bias—online respondents are not necessarily representative of the broader target population. Minorities, lower-income households, rural residents, and older people, for example, are less likely to be represented among online samples. Nonetheless, online research can be particularly effective for identifying very specific or specialized subgroups to target for research. Esearch.com, for example, sends out qualifying questionnaires to many online respondents to find those with specific product or service needs, and then follows up with that smaller pool of respondents with more in-depth research. Eli Lilly, an Esearch.com client, used this online qualifying process to identify people with obscure ailments for which the company is developing treatments.[27]

Outside Sources of Data

In addition to performing experiments and evaluating available sales data, one should be aware of the many external sources of data that are available to shed light on price sensitivity. Public records such as those found at government institutions or industry trade groups contain vast sources of data and information on historical sales trends, industry actions, as well as a record of other factors that may affect the market of interest. Market research firms specialize in performing the types of experiments and analyses described in this chapter. The journals published by various academic and industry institutions offer lessons from the past that may apply to new products. The Society of Competitive Intelligence Professionals (SCIP) is an industry trade group that is devoted to the quest of finding competitive intelligence.[28]

Other secondary sources of data for industrial markets, including the Census of Manufacturers, the Survey of Industrial Buying Power, and numerous other governmental and private sources[29] can tell sellers the types of businesses their buyers engage in and the share of the total market each accounts for, the average size of their purchases in major product classes, and their growth rates. In consumer markets, consumer panel surveys are widely available to tell managers the demographics of their buyers (income, family size, education, use of coupons) as well as those of their closest competitors. Other companies develop complete psychographic profiles of buyers that go beyond just demographics to delve into the innermost psychological motivations for purchase. These are relatively inexpensive sources of data from which management can form judgments about price sensitivity.

Regardless of the method of intelligence gathering, recognize that the key aim of the marketer is to listen to the voice of the customer, understand how product attributes get translated into benefits, and how benefits are converted into a willingness to pay money to obtain a good.

Selecting the Appropriate Measurement Technique

The choice among measurement techniques is not arbitrary. Each is more appropriate than another under certain circumstances. Information about trade-offs between price and attributes is most valuable when a company is developing new products or improving old ones. Since one cannot use historical data or a purchase experiment to test undeveloped products, one must turn to research on preferences and intentions that require only product descriptions or experimental prototypes. Trade-off (Conjoint) analysis is a great choice at this point. But surveys of preferences, like conjoint analysis, often yield poor predictions of actual price sensitivity in real-world purchase situations because they create an artificial purchase environment in which price awareness and knowledge of substitutes is made easy. At the time of product development, however, those are not factors about which management need be concerned. Product development focuses on efforts to enhance the attractiveness of the product when customers are aware of differences. Even when survey research accurately measures only the effect of product attributes on price sensitivity, it is a useful tool for product development, although it may be inadequate for actually setting prices later on.

Once a product is developed, management would like to have measurements that capture as many of the different determinants of price sensitivity as possible. In-store or sophisticated laboratory purchase experiments are definitely the first choice for frequently purchased, low-cost products. With few exceptions, such products are bought by consumers who have low price awareness and give the purchase decision little attention. Consequently, surveys to estimate price sensitivity for such products focus much more attention on price in the purchase decision than would occur naturally, thus distorting the estimates. The cost of in-store experiments, however, may make them impractical for testing on a large scale. In that case, management might best do a few in-store experiments with matched simulated purchase surveys. If the amount of bias in the latter is stable, the survey could be used for further research and adjusted by the amount of the bias between the survey and the in-store experiments.

When the fully developed product is a high-cost durable good such as a TV set or a photocopier, an in-store experiment is impractical. A laboratory purchase experiment may be practical since experimental control permits inferences from fewer purchases but will be too costly for many products. Fortunately, high-value products are also products for which consumers naturally pay great attention to price. In fact, they may give all aspects of the purchase careful thought because it involves a large expenditure. Consequently, a simple laboratory experiment or a simulated purchase survey may be reasonably accurate in predicting price sensitivity for these types of products. Even a buy-response survey may be useful to identify the range of prices that potential customers might find acceptable for such products, although the exact estimates of sales at various prices should not be treated with much confidence.

Once a product has been on the market for a while, historical data become available. Such data are most useful when managers are willing to implement marketing decisions in ways that can increase the research value of the data. For example, sales data become more useful if price changes are sometimes accompanied by a change in advertising and other times not, enabling marketing researchers to isolate their separate effects. A log of unusual events that cause distortions in the actual sales data (for instance, a strike by a competitor's truckers may be causing stock-outs of the competitor's product and increased sales of yours) is also extremely useful when the time comes to adjust the historical data. Moreover, as managers talk with and observe buyers, they should keep questions in mind that would aid the researcher using historical data: What is the length of the purchase cycle? To what extent do buyers purchase extra for inventories when price is expected to rise in the future? Even if historical data are so filled with random variations that no conclusions can be drawn from them with confidence, they may still point toward possible relationships between price and sales or other marketing variables that would be worth examining with another research technique.

Summary

Numerical estimation of price sensitivity is no shortcut to knowing a product's buyers—who they are, how they buy, and why they make their purchase decisions. Numerical estimates are an important source of objective information that can supplement the more subjective observations that usually dominate managerial judgments about price sensitivity. As a supplement, they can substantially improve the accuracy of such judgments and the effectiveness of a firm's pricing.

Measurement techniques differ in the variables they measure and in the conditions of measurement. The variable measured may be either actual purchases or preferences and intentions. Since the ultimate goal of research is to predict customers' actual purchases, research based on actual purchase data is generally more reliable than research based on preferences and intentions. Unfortunately, collecting and analyzing actual-purchase data costs more, requires much more time, and is entirely impossible for products that are not yet fully developed and ready for sale. Consequently, most research on price sensitivity infers purchase behavior from questions potential customers answer about their preferences and intentions.

Pricing research studies range from those that are completely uncontrolled to those in which the experimenter controls almost completely the alternative products, their prices, and the information that customers receive. Although research techniques that permit a high degree of experimental control are more costly than uncontrolled research, the added cost is usually worth it. Uncontrolled data on actual purchases are plagued by too little variation in prices and too many variables changing at once. Uncontrolled data on preferences and intentions are biased by people's untruthful responses and by their inability to recall competitive prices. In contrast, controlled in-store experiments and sophisticated laboratory purchase experiments often predict actual price sensitivity well. Even experiments using preferences and intentions seem to warrant confidence when they are highly controlled. In particular, trade-off analysis is proving highly useful in predicting at least that portion of price sensitivity determined by the unique-value effect.

The appropriate technique for numerically estimating price sensitivity depends on the product's stage of development. When a product is still in the concept or prototype stage, research measuring preferences or intentions is the only option. Trade-off analysis is especially useful at this stage because it can identify the value of individual product attributes, thus helping to decide which combination of attributes will enable the firm to price the product most profitably. When a product is ready for the market, in-store or laboratory purchase experiments are more appropriate because they more realistically simulate the actual purchase environment. After a product has been on the market for a while, actual purchase data can be an inexpensive source of estimates, provided that management monitors sales frequently and makes some price changes independently of changes in other marketing variables. Even when actual purchase data cannot provide conclusive answers, they can suggest relationships that can then be measured more reliably with other techniques.

Regardless of the technique used to measure price sensitivity, it is important that managers not allow the estimate to become a substitute for managerial judgment. The low accuracy of many numerical estimates makes blind reliance on them very risky. One always needs to be aware of the range of values an elasticity estimate can take, the factors that can influence price sensitivity, and one must generally get an understanding of the range of values one can expect. They always should be compared with a manager's own expectations, based on his or her more general knowledge of buyers and their purchase motivations. When inconsistencies occur, the manager should reexamine both the measurement technique and the adequacy of his or her understanding of buyers. The quality of numerical estimates depends in large part on the quality of managerial judgment that guides the estimation process. Managers who know their buyers can get substantially better estimates of price sensitivity when they use that knowledge (1) to select a sample of consumers that accurately represents the product's market, (2) to identify and explain extraneous changes in sales that might camouflage an effect, (3) to provide information to sort out the effects of price from other variables that tend to change with it, (4) to identify an appropriate equation or experimental structure, and (5) to properly describe the product for survey research.

Notes

1. Actually, the researcher observes only the price that the consumer reports having paid. There is some risk of erroneous reporting, which weakens the data but does not bias it. Fortunately, this problem is being solved by technologies that enable consumers to avoid the task of reporting.
2. See Ronald E. Frank and William Massy, "Market Segmentation and the Effectiveness of a Brand's Dealing Policies," *Journal of Business* 38 (April 1965): 186–200; Terry Elrod and Russell S. Winer, "An Empirical Evaluation of Aggregation Approaches for Developing Market Segments," *Journal of Marketing* 46 (Fall 1982): 65–74.
3. The companies are Information Resources Inc. (headquarters in Chicago) and Burke Marketing Research (headquarters in Cincinnati, Ohio).

4. See, for example, David R. Bell, Joengwen Chiang, and V. Padmanabhan, "The Decomposition of Promotional Response: An Empirical Generalization," *Marketing Science* 18, no. 4 (1999): 504–526; Shuba Srinivasan, Peter T. L. Popkowki Leszczyc, and Frank M. Bass, "Market Share Response and Competitive Interaction: The Impact of Temporary, Evolving, and Structural Changes in Prices," *International Journal of Research in Marketing* 17 (2000): 281–305; and Koen Pauwels, Shuba Srinivasan, and Philip Hans Franses, "When Do Price Thresholds Matter in Retail Categories?" *Marketing Science* 26, no. 1 (January–February 2007): 83–100.
5. For a brief introduction to regression analysis, see Thomas C. Kinnear and James R. Taylor, *Marketing Research: An Applied Approach*, 4th ed. (New York: McGraw-Hill, 1991, 626–628); or Mark L. Bereson and David M. Levine, *Basic Business Statistics: Concepts and Application* (Upper Saddle River, NJ: Prentice Hall, 1992, Chapter 16).
6. In practice, of course, there are always some external factors that will affect only one store's sales, undermining the effectiveness of the control. For example, the control store may run out of a competing brand. One can reduce the distorting effect of such factors by increasing the number of both experimental and control stores, but at a corresponding increase in cost.
7. For guidance in the proper design of either a field or laboratory experiment, see Thomas Cook and Donald T. Campbell, "The Design and Conduct of Quasi-Experimental and True Experiments in Field Settings," in *Handbook of Industrial and Organizational Psychology*, ed. Marvin Dunnette (Chicago: Rand McNally, 1976, 223–235).
8. William Applebaum and Richard Spears, "Controlled Experimentation in Marketing Research," *Journal of Marketing* 14 (January 1950): 505–517; Edward Hawkins, "Methods of Estimating Demand," *Journal of Marketing* 21 (April 1957): 430–534; William D. Barclay, "Factorial Design in a Pricing Experiment," *Journal of Marketing Research* 6 (November 1969): 427–429; Sidney Bennet and I. B. Wilkinson, "Price-Quantity Relationship and Price Elasticity Under In-Store Experimentation," *Journal of Business Research* 2 (January 1974): 27–38; Gerald Eskin, "A Case for Test Marketing Experiments," *Journal of Advertising Research* 15 (April 1975): 27–33; Gerald Eskin and Penny Baron, "Effect of Price and Advertising in Test Market Experiments," *Journal of Marketing Research* 14 (November 1977): 499–508.
9. Barclay, "Factorial Design in a Pricing Experiment," p. 428.
10. Paul Solman and Thomas Friedman, *Life and Death in the Corporate Battlefield* (New York: Simon and Schuster, 1982, Chapter 24).
11. Several good discussions of the increased use and application of laboratory test markets (called Simulated Test Marketing by the authors) can be found in Kevin J. Clancy and Robert S. Shulman, "Simulated Test Marketing: A New Technology for Solving an Old Problem," in *A.N.A./The Advertiser* (Fall 1995): 28–33; and also in Kevin J. Clancy and Robert S. Shulman, "Test for Success: How Simulated Test Marketing Can Dramatically Improve the Forecasting of a New Product's Sales," *Sales and Marketing Management* (October 1995): 111–114.
12. One might well argue that buy-response surveys should be included with the experimentally controlled studies since the researcher does

exercise control over the price asked. That observation is correct. The reason that buy-response questioning is better than direct questioning is precisely because the researcher introduces a bit of control. Still, the amount of control that the researcher can exercise in these studies is slight. No attempt is made to control the respondents' perception of competitive prices, exposure to promotion, or demographics.

13. Henry Assael, *Consumer Behavior and Marketing Action*, 2nd ed. (Boston: Kent Publishing, 1983).
14. For a good discussion on the application of and difference between focus group and depth interviews as unstructured/uncontrolled data-collection techniques, see Thomas C. Kinnear and James R. Taylor, *Marketing Research: An Applied Approach*, 4th ed., (New York: McGraw-Hill, 1991).
15. Abbie Griffin and John R. Hauser, "The Voice of the Customer," *Marketing Science* 12, no. 1 (Winter 1993): 1–27.
16. F. James C. Anderson and James A. Narus, "Business Marketing: Understand What Customers Value," *Harvard Business Review* (November–December 1998): 53–65.
17. For an excellent discussion on the types of value drivers and how to uncover those value drivers in both consumer and business-to-business research, read Ian C. MacMillan and Rita Gunther McGrath, "Discovering New Points of Differentiation," *Harvard Business Review* (July–August 1997): 133–145.
18. D. Frank Jones, "A Survey Technique to Measure Demand Under Various Pricing Strategies," *Journal of Marketing*, 39 (July 1975), pp. 75–77.
19. John R. Nevin, "Laboratory Experiments for Estimating Consumer Demand," *Journal of Marketing Research* 11 (August 1974): 261–268.
20. The first article on trade-off analysis to appear in the marketing literature was Paul E. Green and Vithala R. Rao, "Conjoint Measurement for Quantifying Judgemental Data," *Journal of Marketing Research* 8 (August 1971): 355–363. For a nontechnical discussion of applications specifically to pricing, see Patrick J. Robinson, "Applications of Conjoint Analysis to Pricing Problems," in *Market Measurement and Analysis*, ed. David B. Montgomery and Dick R. Wittink (Cambridge, MA: Marketing Science Institute, 1980, 183–205).
21. The following articles describe data manipulation procedures for conjoint analysis: J. B. Kruskal, "Analysis of Factorial Experiments by Estimating Monotone Transformations of the Data," *Journal of the Royal Statistical Society*, Series B (1965): 251–263; Dove Peckelman and Subrata Sen, "Regression Versus Interpolation in Additive Conjoint Measurement," *Association for Consumer Research* (1976): 29–34; Philip Cattin and Dick Wittink, "Further Beyond Conjoint Measurement: Toward Comparison of Methods," *1976 Association for Consumer Research Proceedings* (1976): 41–45.
22. Franklin Acito, "An Investigation of Some Data Collection Issues in Conjoint Measurement," in *1977 Proceedings American Marketing Association*, ed. B. A. Greenberg and D. N. Bellenger (Chicago: American Marketing Association, 1977, 82–85); James McCullough and Roger Best, "Conjoint Measurement: Temporal Stability and Structural Reliability," *Journal of Marketing Research* 16 (February 1979): 26–31; Madhav N. Segal, "Reliability of Conjoint Analysis: Contrasting Data Collection Procedure," *Journal of Marketing Research* 19 (February 1982): 139–143.

23. McCullough and Best, "Conjoint Measurement," pp. 26–31.
24. Bobby J. Calder, "Focus Groups and the Nature of Qualitative Marketing Research," *Journal of Marketing Research* 14 (August 1977): 353–364.
25. Johnny K. Johansson and Ikujiro Nonaka, "Marketing Research the Japanese Way," *Harvard Business Review* (May/June 1987).
26. For the reader trained in classical statistics, these suggestions for adjusting the data with managerial judgment may seem unscientific. But it is important to keep in mind that the purpose of numerical measurement of price sensitivity is to derive useful estimates, not to objectively test a theory. If managers have strongly held beliefs, in light of which the historical record of sales could yield much better estimates, it is simply wasteful to ignore those beliefs simply because they may not be objective. See Edward E. Leamer, "Let's Take the Con Out of Econometrics," *American Economic Review* 73 (March 1983): 31–43.
27. "Survey Your Customers—Electronically," *Harvard Management Update* (April 2000): 3–4.
28. See, for example, http://www.scip.org.
29. The Census of Manufacturers is a publication of the U.S. Department of Commerce. For other federal sources, see the Commerce Department publication titled *A Guide to Federal Data Sources on Manufacturing*. The "Survey of Industrial Buying Power" is published annually as an issue of *Sales and Marketing Management* magazine. Other useful sources of information about the demographics and motivations of buying firms can be obtained from the buying firms' trade associations (such as the Rubber Manufacturers Association and the National Machine Tool Builders Association) and from privately operated industrial directory and research companies (for example, Predicasts, Inc., Dun & Bradstreet, Standard & Poor's).