Chapter 3

Understanding the Value of Conjoint Analysis

Market researchers face two main challenges as they provide market intelligence for managers: to meet managers' objectives with useful, valid results and to communicate those results effectively. Failure on either of these points is fatal. Conjoint analysis provides useful results that, when presented well, are easy for managers to embrace and understand. It is no wonder that conjoint analysis is one of the most widely used market research techniques today. This chapter discusses the benefits of conjoint analysis and finishes by highlighting a dangerous pitfall to avoid when presenting market simulators.

3.1 Realism Begets Better Data

Even though conjoint analysis involves sophisticated survey design and statistical analysis, and more effort by respondents, simpler approaches can be unrealistic, even useless. Suppose we were conducting a study about laptop computers, and using a survey like the one in exhibit 3.1. Respondents can answer importance survey questions with an average time per response of five seconds (Orme 2003). Most respondents answer with high ratings, while the bottom half of the scale is largely ignored. This results in sub-par data for statistical analysis: skewed distributions, with typically little differentiation between attributes. Such self-explicated importances reveal little about how to build a better laptop. How much battery life will buyers trade off for a given increase in processor speed? Further, stated importances often do not reflect true values. It may be socially desirable to say price is unimportant—after all, respondents do not want to appear cheap. Yet in real-world laptop purchases, price may become a critical factor.

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When purchasing a laptop computer, how important is . . .

(Circle one number per item)

	Not Important								*Very Important*
Brand	1	2	3	4	5	6	7	8	9
Hard drive	1	2	3	4	5	6	7	8	9
Battery life	1	2	3	4	5	6	7	8	9
Display size	1	2	3	4	5	6	7	8	9
Price	1	2	3	4	5	6	7	8	9

Exhibit 3.1. Importance survey questions

Even though it is much easier on respondents to ask them to complete a grid such as shown in exhibit 3.1, these importance questions are not very meaningful. Buyers cannot always get the best of everything in the real world. They must make difficult trade-offs and concessions. When survey respondents (just like buyers) are forced to make difficult trade-offs, we learn the true value of product alternatives. And rather than ask respondents to react to generic terms like "battery life," we ask them to react to specific, realistic product specifications. The results are both meaningful and managerially actionable.

Conjoint analysis aims for greater realism, grounds attributes in concrete descriptions, and results in better discrimination among attribute importances. Conjoint analysis creates a more appropriate context for research. Consider a pairwise trade-off question featuring laptop computers. See exhibit 3.2.

Of course, conjoint questions can also be asked one product profile at a time, as in a traditional card sort. The rationale behind pairwise comparisons is this: People can make finer distinctions when they directly compare objects. For example, if someone hands you a four-pound rock, takes it away, and then hands you a five-pound rock, chances are you will not be able to tell which is heavier. But if you hold one rock in each hand, you will have a much better chance of guessing which weighs more. Despite the probable benefits of pairwise comparisons, we conducted a research study and found virtually no difference in the results for one-profile versus pairwise traditional conjoint analysis (Orme and King 1998).

Another flavor of conjoint analysis offers even greater realism and extends the idea of side-by-side comparisons: choice-based conjoint (Louviere and Woodworth 1983; Sawtooth Software 1993). For a choice-based conjoint question about laptop computers, see exhibit 3.3.

Which laptop computer would you rather purchase?	
2,000 GB hard drive 10 hour battery life $1,199	1,000 GB hard drive 7 hour battery life $599

1	2	3	4	5	6	7	8	9
Strongly prefer left				Indifferent				Strongly prefer right

Exhibit 3.2. Pairwise trade-off question

If you were in the market to purchase a laptop PC today, and if these were your only alternatives, which would you choose?

Dell 2,000 GB hard drive 15 hour battery life 14-inch display $1,199	Acer 1,000 GB hard drive 10 hour battery life 14-inch display $899	HP 1,000 GB hard drive 7 hour battery life 11-inch display $599	None: If these were my only choices, I'd defer my purchase.

Exhibit 3.3. Choice-based conjoint question

Choice-based conjoint questions closely mimic what buyers do in the real world—choose among available offerings. Including *none* as an option enhances the realism, and allows those respondents who are not likely to purchase to express their disinterest. Choice-based data reflect choices, not just preferences that respondents have attempted to translate onto a ratings scale. If we agree that the ultimate goal of market simulators is to predict choice, then it is only natural that we would value choice-based data.

Some managers do not have the training in statistics to grasp the concept of orthogonal designs, main effects assumptions, or part-worth utility estimation. More technical folks, utilizing specialized software, can manage these details. Whether statisticians or otherwise, almost everyone can grasp the idea that realistic models should result from realistic questioning methods, and they can be comforted that conjoint analysis is a reliable, time-proven method.

3.2 Brand Equity

Conjoint analysis provides useful results for product development, pricing research, competitive positioning, and market segmentation. It can also measure brand equity, which is an especially critical issue for many managers.

Brand equity encompasses the intangible forces in the market that allow a product with a brand name to be worth more to buyers than one without. High-equity brands command higher prices and are less price elastic. Because brand equity goes directly to the bottom line, it is no surprise that managers are focused on it.

Choice-based conjoint offers a reliable way to measure brand equity. Choice-based conjoint presents respondents with varying product configurations and asks which they would purchase or choose. Each brand is presented at various prices throughout the interview. The percentage of times respondents choose each brand at each price point reveals preference and price sensitivity for the brands. Compelling demand curves result when we plot the probability of choice by price and connect the points with smooth lines. See figure 3.1 for hypothetical demand curves for three brands of pain reliever: Renew, Balmex, and PainFree.

If the brand manager for Renew wants to quantify the price premium it commands over the other brands, choice-based conjoint analysis reveals the answer. We can use the demand curves from figure 3.1 as a starting point: We draw a horizontal line through points A, B, and C representing a level of equal relative demand or preference. If Renew is priced at \$3.90 and Balmex at \$3.50, respondents on average will be indifferent (have the same preference) between the two. This forty-cent difference (point C price minus point B price or \$3.90 minus \$3.50) represents the premium or brand equity that Renew commands over Balmex. Similarly, Renew commands a sixty-cent premium over PainFree (point C price minus point A price). See figure 3.2.

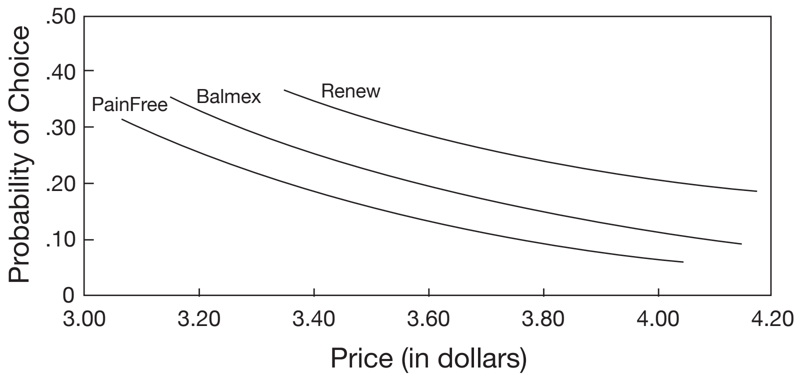

Figure 3.1. Choice-based conjoint demand curves

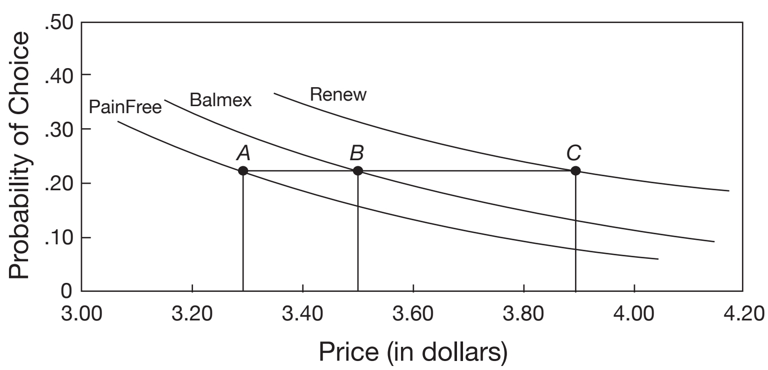

Figure 3.2. Estimating brand equity using points of equal relative demand

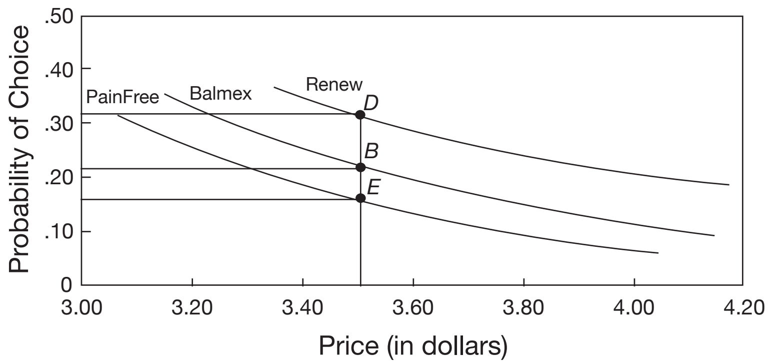

Figure 3.3. Estimating brand equity using points of equal price

Another approach to assessing brand equity results from comparing preferences with all brands offered at the same price. Imagine that we continue drawing the vertical line from \$3.50 through point B until it intersects Renew's demand curve. That point represents a relative preference or choice probability of 0.32. At \$3.50, Balmex and PainFree have choice probabilities of 0.22 and 0.16, respectively. See figure 3.3 with labeled points D, B, and E for Renew, Balmex, and PainFree, respectively, at the selected price point of \$3.50. Brand equity may be estimated by using ratios of choice probabilities or percentages. At the selected price point of \$3.50, Renew is preferred to Balmex by a ratio of $\frac{32}{22}$, or it has 45 percent higher preference than Balmex. Similarly, Renew is preferred to PainFree by a ratio of $\frac{32}{16}$ or 100 percent over PainFree.

3.3 Strategic Pricing Research

In an ideal world, researchers could accurately measure price sensitivity by manipulating prices in test markets and measuring changes in demand. While scanner technology and online shopping data have made this sort of analysis more feasible than ever before for many categories of consumer goods, these real-world experiments often face significant hurdles. Markets do not remain constant for the duration of the experiment. Macroeconomic forces can alter demand. Competitors can change their prices and/or promotions. Buyers can stock up to take advantage of lower prices. And new products may be introduced. While conjoint pricing experiments are not as realistic as the real-world event, conjoint experiments hold market forces constant. They can test price ranges or new products outside of current offerings.

In the demand curve example, Renew holds the enviable position of being preferred to Balmex and PainFree at all price levels. Notice also that the demand curves in exhibits 3.1 through 3.3 are not parallel. Renew's preference declines at a slower rate than the other brands' as price increases. Respondents are less price sensitive toward Renew than the other brands. The ability to more directly measure unique price sensitivities by brand is an advantage choice-based conjoint enjoys over traditional main-effects-only conjoint analysis. While it is true that differential price sensitivities can be observed through sensitivity simulations from traditional full-profile conjoint analysis, most researchers believe that choice-based conjoint captures more accurate information about price sensitivity.

Demand curves provide strategic information for pricing decisions. Suppose Renew is the market leader. Renew's manager is considering initiating a price cut, and her past experience suggests that the discount brands will react with similar price cuts. She could learn a great deal using conjoint data—enough to avoid a mistake. The slopes of the demand curves show that, if prices were lowered, Renew would gain share at a slower rate than Balmex or PainFree. So if she lowers the price and the other brands follow, Renew's market share and profits would decrease.

Price elasticity can be quantified for each brand by examining the ratio of preference at the highest price versus preference at the lowest price. Alternatively, the price elasticity of demand (defined as percentage change in quantity demanded divided by percentage change in price) can be easily calculated for each brand in a choice-based conjoint study.

Some managers have been so pleased with this approach to strategic pricing research that they have funded wave after wave of conjoint tracking studies. They compare demand curves across time periods to quantify changes in brand equity, to gauge the results of previous pricing or other marketing mix changes, and to formulate future strategy.

Choice-based conjoint analysis has proven very useful and generally accurate for pricing decisions, especially when it comes to fast moving consumer goods. As an example, price sensitivity measurements by conjoint analysis for various Procter & Gamble products were shown to match well (on average) the price sensitivities calculated from econometric models applied to actual sales data (Renkin, Rogers, and Huber 2004).

3.4 Preference, Not Market Share

In the mid 1990s, we were involved in a choice-based conjoint study for a manufacturer of personal computers. Our main contact was the pricing manager whose objectives were to measure market awareness, preference, and price sensitivity for his sub-brands and major competitors. We conducted the study and were soon delivering top-line conjoint results.

Our client was skeptical when he saw that the conjoint analysis reported that one of the company's newly released brands, call it FastPC, was preferred to its well-established brands. The client insisted that this could not be right and that we check the data. We did—somewhat nervously, we might add—but found no errors. In the meantime, he called his sales department for a sanity check. Sales reported that FastPC was flying off the shelf. FastPC had exceeded all expectations.

While this happy-ending story warms us inside, it also illustrates a limitation of conjoint analysis. Conjoint analysis predicts preference, not market share. While the newly released FastPC was selling above expectations, its market share at that point fell short of established brands. Given enough time, adequate promotion, and distribution, we would expect FastPC's market share to align more closely with conjoint results.

Conjoint models do not predict market share due to a variety of reasons, including the following:

- Conjoint analysis assumes perfect information. In the conjoint interview, respondents are educated about available brands and features. In the real world, obscure brands have less chance of being purchased. Conjoint analysis cannot fully account for differences in awareness developed through advertising and promotion.
- Conjoint analysis assumes that all products are equally available. One brand is as conveniently selected as another in a conjoint interview.
- Respondents might not accurately reflect potential buyers. Many will not have the interest, authority, or ability to purchase.
- Results from conjoint analysis reflect the potential market acceptance of products and services, given proper promotion, distribution, and time.

Many researchers quantify factors that conjoint analysis cannot account for and build them back into the model using external effect adjustments. While this practice typically brings conjoint results more closely in line with actual market share, it draws us into a troublesome paradox. As more factors are accounted for and as we more accurately tune the conjoint model to market share, we start to believe that we have actually developed a valid market share predictor.

Believing that we have an accurate predictor of market share can lead us to misuse a model. That said, conjoint models are excellent directional indicators. Conjoint analysis can reveal product modifications that can increase market share, but it will probably not reveal how much actual market share will increase. Conjoint analysis can tell us that the market is more price sensitive for Brand A than Brand B, but we probably do not know the exact price sensitivity of either one. Conjoint analysis can identify which market segment will be most likely to purchase your client's product, but probably not the exact number of units that will be purchased.

The market simulator is usually the most anticipated deliverable for managers. Do not let this enthusiasm get out of hand. Conjoint simulators are directional indicators that can provide a great deal of information about relative feature importances and preferences for product configurations. While conjoint simulators are excellent tools for revealing strategic moves that can improve the success of a product, they are not infallible market share predictors. Many other factors, such as awareness, distribution, advertising, and product life cycles, drive market share in the real world. Conjoint models can be fine-tuned to account partially for these elements, but we must avoid thinking that adjusted conjoint models can consistently and accurately predict volumetric absolutes such as market share. The only exception to this rule follows from careful validation based on real sales data, establishing a clear link between the calibrated conjoint model and sales volume for the specific product category and market in question.

Conjoint analysis increases the return on research dollars by providing managers with useful, valid information. Its realism leads to more accurate results and provides a strategic tool for quantifying brand equity and relative price sensitivity. To ensure success, researchers must carefully set management expectations regarding what conjoint analysis can and cannot do.