2

Assessing Value Using Surveys

Synopsis

Value is measured and defined in different ways depending upon the domain. In product planning, the value of a product, is an aggregate measure of worth that can be used with price to forecast the product's demand as it competes within a specified market segment. Social scientists have developed experimental techniques to estimate the relative importance of the attributes in the value functions and techniques to assess the validity of the results. Marketing research strives to understand the behaviors and preferences of consumers in a market-based economy. Surveys are one of the primary tools employed by market researchers to gain insight and provide important information for product planning decisions. The steps in a survey project are introduced and discussed to help the practitioner avoid common pit-falls.

2.1 Background

In highly competitive markets, managers continually make decisions about what ideas to incorporate into their products and services as they strive to innovate to increase their competitiveness. If a new idea reduces cost without affecting performance, it is clear the idea should be incorporated. Likewise, if a new idea improves the performance without affecting cost, the idea will easily gain support from management. The challenge to the product planner comes when a new idea improves performance and increases cost. Often, costs are estimated and those responsible for product planning must rely on their instincts as to whether the innovative idea can garner additional profits. When making these decisions, managers often place too much attention on cost at the detriment of improved performance because it is frequently the only quantified financial metric upon which the decision can be made. This is the driving force for a value metric that rigorously converts performance changes into willingness to pay for a comparison against cost.

Value can take on several meanings depending on context. Value engineers define value as functional worth divided by cost (Fowler 1990). Alternatively, Taguchi's "Cost of Inferior Quality" (CIQ) is a measure of value lost due to a specification being off from its ideal point (Taguchi and Wu, 1980). Utility, which incorporates a decision maker's risk attitude, is often used as a measure of value when comparing two or more uncertain prospects (von Neumann and Morgenstern, 1947). In economics, utility takes on a different meaning as it is a proxy for satisfaction derived from quantities or combinations of commodities (Henderson and Quandt, 1980). Although each of these measures of value has demonstrated to be useful within each of their respective domains, these measures of value are not useful in product planning because they can not be used to provide insight into how changes in product performance will affect consumer behavior or the firm's financial performance.

2.2 Value and Value Functions

During product planning, the value V_i of a product i, is an aggregate measure of worth to the customer. This can be used with the price of the product P_i to forecast the product's demand as it competes within a specified market segment. For a value metric to be useful in making product planning decisions, it must therefore possess the following properties: (1) it must have the same units as price; (2) the willingness to pay for the good must decrease as price approaches value; and (3) if a product change creates an increase in demand while holding price constant, value has been increased.

All models that strive to forecast consumer behavior are founded upon the concept of a value function. A value function yields a real number that possesses the three properties listed above and is based upon a vector of Critical-To-Value (CTV) attributes, z, that are used to define abstractly each alternative—more of a good attribute increases V_i. This postulate is consistent with the view that consumers derive their satisfaction from a product's bundle of attributes rather than satisfaction from mere ownership (Lancaster 1966, 1971). Value functions can be classified as either linear or non-linear, where the choice of functional form is dictated by the research design.[1]

Economic choice theory has been used by econometricians, decision scientists, and marketing researchers to parameterize value functions used to create descriptive models of consumer behavior for decades (McFadden, 1986; Ben-Akiva and Lerman, 1985; Train, 1985). These models, whose parameters can be estimated from historical purchase data (revealed choice) or psychometric market research surveys (stated choice), have well-defined statistical properties, several software packages to ease the computation burden, and a legacy of successful applications in industry.

---

[1] Louviere, *et al.* (2000) devote a chapter to choosing amongst choice models.

If the tickets of Chapter 1 were for a real lottery and were offered for sale to different groups at different prices (each group being randomly selected from the same large population) their actual purchases would constitute a revealed choice survey. Asking buyers to reveal the brand and price for a recent vehicle purchase is another example of a revealed choice survey. The choice models parameterized using revealed methods have high external validity because the input data comes from real transaction data. There are a few downsides of revealed methods however. Because prices in the real-world vary within small ranges, the results of a revealed study are not useful for predicting behavior for prices outside those ranges (Ben-Akiva, *et al.* 1994). Moreover, it is impossible for revealed models to estimate value parameters for product attributes that are not yet available in the market place. Therefore, revealed models are limited to forecasting consumer behavior for new products that are priced within the same small range as existing products with the same CTV attributes.

The revealed choice study of the automobile market performed by Boyd and Mellman (1980) illustrates a few other important principles to consider when using choice models. First, the paper illustrated how important it is to compare parameter estimates with a priori beliefs. Indeed, their value estimates appeared to be higher than was expected, which later led to the conclusion that the impact of price was too small. Secondly, if multiple segments are to be investigated, a price coefficient should be calculated for each segment. Because the authors used a single price coefficient for all segments, the simulation yielded valuations that were generally too low for the luxury segments and valuations that were too high for the compact and sub-compact segments. Lastly, the study points out how the researcher must search for possible unobserved, yet correlated attributes that may ultimately be responsible for value differences between product alternatives. In the auto market, for example, very often the larger cars are more luxurious, have desirable styling, acceleration performance, passenger space and cargo volume. When conducting a revealed discrete choice study, the research must make sure that chosen attributes are not confounded by unintended correlated attributes.

Demand-Price (DP) Analysis (described in Appendix A) is an alternative methodology for gleaning value information from phenomenological purchase data. Rather than try to link purchase behavior directly to product attributes, as with choice models, DP analysis uses a game theoretic model to estimate the total values of products based on each good's historical price and demand.

Stated techniques, on the other hand, can be used to build models of consumer behavior that span larger price ranges and new innovative product attributes. Stated research methods are usually classified as being based upon either conjoint analysis (Green and Srinivasan, 1990) or contingent valuation (Cameron and James, 1987; Mitchell and Carson, 1989). Conjoint analysis models are used to measure trade-off elasticities between attributes. Alternatively, the contingent valuation techniques have a respondent write-in threshold prices or state if they would purchase at certain prices. The values of the two lottery tickets determined in Chapter 1 were based upon the respondents' stated willingness to pay for the prospect of winning the prizes and is therefore a good example of a contingent valuation stated choice survey. The results of contingent valuation and conjoint analysis surveys often differ (Backhaus, *et al.* 2005), but they also might be used to cross-validate each other. Each method is subject to bias and has supporters and critics.[2]

As explained by Little (1970), models for decision making should be simple, robust, easy to control, adaptive, as complete as possible, and easy to communicate with. To date, even though choice models have gained widespread acceptance among market researchers and econometricians, product planners have found it difficult to utilize the models in their decision making for several reasons. First, the mathematical functions of the choice models are often very complex and require special software to translate survey data into function parameters. Second, the theory behind the choice models is very difficult to explain to laymen, which makes it hard to garner the trust and acceptance of decision makers. Third, it is very cumbersome to adapt the model as new information becomes available and therefore requires researchers to execute large studies rather than multiple focused studies. Fourth, it is very difficult to understand how uncertainty in parameters might influence the attractiveness of prospects to decision makers.

The guiding rationale for the methods and tools advocated by this book is to balance simplicity and rigor through the use of analytical models that are phenomenological in nature. Simplicity is needed so that the models can parameterized with limited resources and the underlying techniques can be communicated and understood by management. Rigor, on the other hand, is needed so that the outputs of the model are trusted and used. While the steps in analyzing the data and obtaining results are indeed important, it is important that data being fed into the methodology is free of confounding and biases. The remainder of this chapter describes the steps for designing stated choice surveys for maximum effectiveness.

2.3 Causal Research of Value

As mentioned earlier, multiple attributes are used to describe a product's value because purchase decisions are rarely based upon a single criterion. Although the respective attribute preference weights are probabilistic and a researcher can never prove causality definitively, social scientists have developed experimental techniques to estimate the relative importance of the attributes in the value functions. The resulting value functions are said to be internally valid if the attributes demonstrate causality within a testing context. The results of an experiment have external validity if the results can be generalized to the real market environment.

While the results of a revealed analysis are by definition externally valid, it is very difficult for stated techniques to demonstrate external validity. Indeed, a survey experiment must be carefully designed and executed just to earn the distinction of internal validity, which is only possible if the parameter estimates are free of experimental and cognitive biases. Biased estimators are those that for

[2] The interested reader is referred to Louviere, *et al.* (2000) for an overall view of traditional stated choice methods and discrete choice literature.

some reason over- or underestimate, on average, the measure being estimated. An experimental bias occurs when extraneous variables confound the parameter estimates. Alternatively, the question format within a survey can introduce cognitive biases into the parameter estimates. Because obtaining an unbiased estimate of value functions is so important, much research has been carried out to develop rigorous techniques that mitigate cognitive biases stemming from survey design.

There are three ways to limit confounding in an experiment: replication, randomization, and blocking. Replication allows the experimenter to estimate experimental error and to obtain a more precise estimate of a factor's effect on value. Randomization mixes up the order in which trials of an experiment are performed, which helps to "average out" the effects of extraneous factors that may be present. Lastly, blocking is used to reduce variability stemming from nuisance factors, which are factors that could influence the value measurement but are not of particular interest.

One of the predominant tools used in the cognitive sciences to increase the fidelity and efficiency of experiments is the statistical design of experiments (DOE).[3] A DOE enables an experimenter to analyze and control causal variables in a way that allows several basic experiments to be conducted simultaneously and employ the three methods to limit confounding, concurrently. The specific advantages of using DOE's are: (1) the experimenter can efficiently determine the effect of more than one independent variable; (2) confounding variables can be statistically controlled; and (3) some designs allow interactions between independent variables to be measured. For these reasons, using a carefully thought out and executed DOE is the most effective way to guard against experimental biases.

When a DOE investigates more than one attribute, a design matrix is often used to designate the level setting for each attribute of a trial. When there are only two levels for a factor, they are often termed "low" and "high" and denoted as "-" and "+", respectively. The low/high distinction can be used to describe both continuous factors (temperature, speed, *etc.*) and discrete factors (material, color, *etc.*). Alternatively, a code is often assigned to the low/high settings such as 0/1 or -1/1. When the factor under investigation is continuous, the researcher is often able to use results of an experiment to forecast the response of the system for levels between the high and low code using interpolation.

2.4 Survey Project Design and Execution

Marketing research is a common form of applied sociology that strives to understand the behaviors and preferences of consumers in a market based economy. Surveys are one of the primary tools employed by market researchers to gain insight and provide important information for product planning decisions.

[3] Experimental designs based upon orthogonal arrays (OAs) are described in Appendix F.

The goal of a survey project is to obtain information to aid decision making, which gives a clear indication (bias-free) of how the group under study will make choices based upon changes in product design. Researchers using these techniques have long known that the way questions are asked within a survey can bias the results and that the results of a survey are strongly influenced by who completes the survey.

To ensure that the survey project meets the research goals, the project must pass through seven stages, regardless if it is quantitative or qualitative:

1. Objective—Determine what you want to learn
2. Respondent Selection—Determine the source of your respondents
3. Methodology—Determine the method of administering the survey
4. Questionnaire Design—Determine what and how to ask
5. Pre-test—Determine if the questionnaire can be improved
6. Collect Data—Distribute and conduct the survey
7. Data Preparation and Analysis—Enter the data and draw conclusions

The remainder of this section further describes each stage with a focus on quantitative surveys and lists some important considerations during each step to reduce systemic biases that may develop, which might reduce the fidelity of the results and the ability to make effective policy decisions.

2.4.1 Stage 1: Determine Objectives

In all cases, a survey project should only be executed after a management problem has been clearly expounded and management buys-in to the survey process and presumed results (Jones, 1985; Curren, *et al.* 1992). Some typical objectives of management that drive marketing research activities include concept testing, market segmentation, market positioning, brand name valuation, demand and sales forecasting, price elasticity determination, and understanding customer satisfaction. The methodology laid out in future chapters enables the researcher to address each one of these objectives in turn and, as will become clear later, not all objectives require the completion of a survey project.

2.4.2 Stage 2: Respondent Selection

The respondent target population consists of all individuals about whom conclusions are to be made and is derived directly from the objective of the study. An imprecisely defined target population can lead to misleading results. For example, if the objective of the study is to determine how a change in the design of a semi-truck will affect the value of a brand name, the target population would likely include those who purchase semi-trucks and not include those who only purchase vehicles for personal transportation. Once the target population's characteristics are defined by the researcher, a sampling strategy must be developed.

A sampling strategy describes how a subgroup of the population will be chosen to participate in the study. A poor sampling strategy can lead to selection bias, which results when the sample of respondents does not represent the target population in a statistical sense. There are at least four types of selection biases: confirmation bias, exclusion bias, self-selection bias, and non-response bias. Confirmation bias describes the tendency of the researcher to seek out respondents that are likely to confirm the researcher's preconceived notions of what is true. Exclusion bias may result if the sample of respondents systematically excludes individuals from the target population. Alternatively, if respondents are informed of the purpose of the study and given the option to participate, the results may suffer from self-selection bias because the respondent choices to take part in the study may be correlated to traits that affect the study result. Lastly, when individuals of the target population are unable or unwilling to participate, the study may suffer from non-response bias. There are several ways to reduce non-response bias, including giving the respondent sufficient notification of event (Yu and Cooper, 1983), motivating the respondent (Fern, *et al.* 1986), providing honorariums, good questionnaire design, and survey personalization (Greer and Lohtia, 1994). Although one can not determine that the sample is unrepresentative from low response rates alone, a low response rate does increase the probability of non-response bias (Leslie, 1971).

There are several prevailing sampling strategies (listed in Tables 2.1 and 2.2), which are classified as either non-probabilistic (Table 2.1) or probabilistic (Table 2.2) (Malhotra, 1996). Non-probabilistic sampling allows the researcher to use his/her personal judgment about whether to include or exclude a potential respondent. With probabilistic sampling, each potential respondent in the target population has a fixed chance of being selected for the sample. Because respondents are selected by chance, the researcher is able to calculate confidence intervals about the true population value for a given level of certainty. Ultimately, the best sampling strategy is the one that effectively balances the cost of obtaining respondents from the target population against the risk associated with selection biases that may be introduced from an unrepresentative sample.

There are both qualitative and quantitative considerations for determining sample size. Important qualitative considerations include (Malhotra, 1996): (1) the importance of the decision, (2) the nature of the research, (3) the number of variables, (4) the nature of the analysis, (5) sample sizes used in similar studies, (6) incidence rates, (7) completion rates, and (8) resource constraints. In commercial marketing studies, it is often the resource constraints (financial analyst availability and timeline) that drive the research design and ultimately the sample size. Nevertheless, sample size influences the strength of a finding through statistical inference—the precision goes up as sample size increases. Kramer and Thiemann (1988) and Frankel (1983) both describe quantitative methods for determining sample size requirements based upon the necessary statistical precision when using random sampling. One shortcoming of the purely statistical calculations of sample sizes is that they do not consider the sampling cost. Kish (1965) and Sudman (1976) describe techniques to include cost considerations into sample size determination.

Table 2.1. Non-probability Based Strategic Sampling Techniques

Type	Definition	Positives	Negatives
Convenience	Respondents are often selected because they are readily available.	It is the least expensive and time-consuming of all techniques.	Not representative of any population and therefore can not be used to make reliable inferences.
Judgmental	Respondents are chosen based upon judgment of researchers.	Inexpensive and not time-consuming.	Subject to many types of sampling biases.
Quota	Quotas are established based on respondent characteristics and then convenience and/or judgmental sampling is used to fulfill the quota.	Once the quotas are defined there is considerable freedom in selecting respondents. It is possible to obtain results close to those for probability sampling.	If a characteristic is overlooked, the quota sample will not be representative of the target population.
Snowball	An initial group is selected randomly and subsequent respondents are selected based upon referrals.	The process is carried out in waves and often leads to a snowballing effect.	Even though probability sampling may be used to identify the initial group, the final sample is nonprobabilistic.

Table 2.2. Probability Based Strategic Sampling Techniques

Type	Definition	Positives	Negatives
Simple Random	Each element in the population has a known and equal probability of selection as in a lottery.	Easily understood and results can be projected upon population.	Samples may be spread out geographically, which increases cost. Possibility that sample may not represent population. Lower precision and larger standard error than other random sampling techniques.
Systematic	From a list of the population, every i^{th} element is chosen.	If the list is ordered with respect to a characteristic under investigation, a representative sample should result with lower sampling error.	Sometimes it may be hard to find the "right" characteristic to order the list.
Stratified	Two step process: (1) population is partitioned into subpopulations (strata) based upon a stratification variable; (2) elements are selected from each strata using simple random selection.	Increased precision without increased cost.	Stratification variable may be hard to measure and/or apply.
Cluster	Two step process: (1) population is divided into mutually exclusive and collectively exhaustive subpopulations; (2) sample selected using random selection of clusters.	Can reduce administrative costs such as travel.	Cluster sampling can increase the variability of sample estimates above that of simple random sampling based on how the clusters differ between themselves when compared to the within-cluster variation.

2.4.3 Stage 3: Methodology for Administering Survey

The objectives, respondent selection strategy, and resource constraints often dictate the survey methodology. Nevertheless, there are four broad categories for administering surveys in order of popularity: through the internet, over the telephone, person-to-person ,or through the mail. Administering surveys through the internet can be quite convenient, as the respondent can guide themselves to the survey web-site and enter the data themselves. Moreover, the internet allows the survey to include multi-media, such as video and sound; input screens can be used to ensure responses meet the data field requirements; and personal information can be retained in the system to expedite future correspondences.

Although surveys administered by phone require additional resources, sometimes they are necessary to help respondents resolve and clarify ambiguities. A downside is that the respondent loses the visual cues that can aid working memory such as videos, pictures, and lists. Surveys administered person-to-person share the benefits of both internet and telephone based methodologies, but are much more expensive because they require respondents and the administrators to be in physical proximity. In spite of this disadvantage, person-to-person administration allows researchers to include smell, taste, and feel attributes, which would be impossible using any of the other methods. With the advent of the internet, mail surveys have become even less popular than in the past. Mail surveys are still useful, however, in cases when resources are not available to create a web-based application and when there is a high confidence that the targeted respondent will indeed respond.

2.4.4 Stage 4: Questionnaire Design

Questionnaire design must match the administration methodology chosen, such that the information transfer from survey to respondent and back is feasible. For example, choosing from a list may cause excessive cognitive stress if the survey is administered over the telephone. Likewise, it is impossible to ask the respondent about sound, taste, or feel attributes via a mail survey.

Conjoint analysis techniques allow the researcher to vary several attributes at a time to create different design alternatives for the respondent to evaluate. The attributes in a conjoint analysis survey are often varied according to an experimental design (the benefits of DOEs were discussed earlier in this chapter), which allows the researcher to control extraneous variables and deliver importance weightings that can be used to rank attribute importance. When too many attributes are varied within a single experiment, the cognitive demands of the respondents can compromise choice consistency (DeShazo and Fermo, 2002).

Indeed, long and complex surveys have been shown to increase cognitive stress, which in turn increases the variability of the results. There are five principle dimensions for measuring questionnaire complexity: number of design instantiations to be considered throughout the survey, number of attributes used to define those designs, number of levels for each of the attributes, range of attribute levels and the number of times a respondent must make a choice. Research into the influence of these five dimensions on experimental results demonstrated that the two most critical dimensions are number of attributes and number of alternatives (Caussade, *et al.* 2005). Increasing the number of attributes and having more or less than four alternatives decreased choice consistency. The results also suggested that having 9-10 choice situations and keeping the number and range of levels relatively small maximizes consistency. All of the aforementioned results confirm the adage that surveys should be kept short and simple. One of the simplest designs is the Direct Value (DV) survey discussed in Chapter 3.

Biases can also be introduced by the way questions are asked. There are five principle biases that stem from questionnaire design: Type I hypothetical bias, Type II hypothetical bias, framing bias, response bias, and the endowment effect. Type I hypothetical bias can manifest when respondents are asked to imagine a situation or product that they have never experienced before. Type II hypothetical bias refers to when the consequences of a respondent's choice are hypothetical. Examples of Type II hypothetical bias include the studies conducted by Horowitz (1991) and Neill, *et al.* (1994), which indicated that subjects behaved as if cash payment requirements were hypothetical even when they were instructed to consider the situations as real. Framing bias manifests if the question is asked in a way that it might direct respondents to choose alternatives in an inconsistent way. Similarly, when the respondents answer the questions the way they think the researcher want them to rather than according to their true beliefs, it is called response bias. Lastly, since people typically place a higher value on the objects they own relative to objects they do not, the researcher must be aware of the endowment effect because willingness-to-pay will likely be different to willingness-to-accept.

2.4.5 Stage 5: Pretest the Survey

Pretesting a survey is a necessary safeguard to identify and eliminate potential problems that may lead to unreliable or misrepresentative data (Hunt, *et al.* 1982). The pretest should include the entire questionnaire and the respondents should be members of the target population (Diamantopoulos, *et al.* 1994). The pretesting can be performed by conducting a one-on-one interview with the respondents to gain more direct feedback into clarity and perceptions. In protocol analysis, respondents are asked to "think aloud" as they move through the survey. Alternatively, debriefing involves interviewing the respondent after the survey has been completed. The data obtained from the pretest should be analyzed to ensure it will be useful in fulfilling the objectives (Reynolds, 1993).

2.4.6 Stage 6: Collect Data

One of the greatest concerns while administering surveys is the possibility of experimenter effects (Rosenthal, 1976; Coulter, 1982; Singer, *et al.* 1983), which may occur if a researcher expects a given result and unconsciously manipulates an experiment or misinterprets the data in a way that affects the experimental conclusion. Some examples of experimenter effects include field worker personal or social attributes that may alter the way the question is answered by the respondent. Another example is the experimenter expectancy effect, where the respondent perceives cues from the field worker about how to answer. Lastly, Cottrell (1972) described evaluation apprehension as a phenomenon that an individual will behave differently in situations when there is an audience present. Experimenter effects can be controlled by using a double-blind methodology.

Using direct computer data collection has been shown to provide results that are at least as accurate as personal interviews and self-administered surveys (Klein and Sobol, 1996). The study indicated that one trade-off of using computer-only administration is that the response rates on list-type questions were lower than person-to-person interviews. Moreover, the study reported that three out of ten questions had "significantly more omissions" when the survey was administered by a computer. It is clear that each method of administering surveys has its own idiosyncrasies that might introduce bias into the results and therefore the risks of each method should be considered and methods to mitigate those risks should be identified.

2.4.7 Stage 7: Data Preparation and Analysis

After all the surveys have been administered and the sample size criterion has been satisfied, the next step is to prepare the data and proceed with analysis. Checking the data is a necessary step because some questions may have been left unanswered, responses my be illegible, the pattern of responses may indicate that one or more of the questions were misunderstood by the respondent, or the responses are "too consistent," which might indicate the respondent may not have given a good-faith effort.

If responses are deemed unsatisfactory, there are three basic remedies: return the survey to the respondent, assign missing values, or discard the respondent's entire data set. Since returning the survey is not always possible and discarding an entire data set is unsatisfactory, assigning missing values may sometimes be a desirable solution. Assigning missing values is permissible when: (1) the number of respondents with unsatisfactory responses is small compared to overall sample size, (2) the ratio of unsatisfactory responses for each of the respondents is small, and (3) the variables with unsatisfactory responses are not the key variables (Malhotra, 1987; 1996).

Often, respondent data must be coded so that it can be efficiently tabulated and stored in a computer file. For example, responses to a Yes/No question may be coded as a 1 and 2, respectively. This technique works well for closed-end questions with predefined responses. Open-ended question coding is much more complex and requires a code to be developed after the survey has been administered, where the code list is mutually exclusive and collectively exhaustive.

2.5 Summary

- Consumers value a product because of its attributes.
- Historical purchase information can be used to reveal how consumer's value features and technologies currently in the marketplace.
- Surveys can be used to understand how consumer's value new features and technologies not currently in the marketplace.
- Surveys should use DOE methods and tools to minimize bias and correlation between factors.
- Seven stages of development were identified for developing a survey: (1) Objective Identification, (2) Selection of Respondents, (3) Methodology, (4) Design, (5) Pre-test, (6) Collection of Data, (7) Data Preparation and Analysis.

- The designer of the survey should strive to minimize cognitive stress on the respondents by not making the survey complex and lengthy.

2.6 Supporting Case Studies

Case Study 2: Simulated Survey of Boston to Los Angeles Flights
Case Study 3: Analysis of a Multinomial Stated Choice Survey
Case Study 5: Revealed Values: Minivan Trends
Case Study 7: Value of Interior Noise in a Luxury Automobile
Case Study 9: Value of Mustang Options
Case Study 11: Assessing Relative Brand Value

2.7 Exercises

2.1 Write the definition of value or utility for each domain as indicated.

	Domain	**Metric**
a)	Economics	Value
b)	Economics	Utility
c)	Decision Analysis	Utility
d)	Value Engineering	Value
e)	Taguchi	Value
f)	Product Planning	Value

2.2 What are the three properties of a value metric that make it useful for product planning?

2.3 Explain the concept of purchasing a bundle of attributes versus purchasing a physical product. Why should product planners focus on Critical-To-Value (CTV) attributes and not all the attributes of a product?

2.4 What's the difference between internal validity and external validity? Give an example.

2.5 List the three ways to limit confounding.

2.6 List and define four types of sampling biases.

2.7 List five dimensions that can be used to define questionnaire complexity.

2.8 List and define the five biases that stem from questionnaire design.

2.8 References

Backhaus K, Wilken R, Voeth M, and Sichtmann C (2005) An empirical comparison of methods to measure willingness to pay by examining the hypothetical bias. International Journal of Marketing Research 47:543-62

Ben-Akiva M and Lerman S (1985) Discrete choice analysis. MIT Press, Cambridge

Ben-Akiva M, Bradley M, Morikawa T, Benjamin J, Novak TP, Thomas P, Oppewal H, and Rao V (1994) Combining revealed and stated preference data. Marketing Letters 5:335-50

Cameron TA and James MD (1987) Estimating willingness to pay from survey data: an alternative pre-test market evaluation procedure. Journal of Marketing Research 24:389-95

Caussade S, Ortuzar JD, Rizzi LI, and Hensher DA (2005) Assessing the influence of design dimensions on stated choice experiment estimates. Transportation Research Part B 39:621-40

Cottrell, NB (1972) Social facilitation. In McClintock C (ed.) Experimental social psychology. Holt, Rinehart & Winston: New York, NY, pp. 185-236

Coulter PB (1982) Race of interviewer effects on telephone interviews. Public Opinion Quarterly 46:278-84

Curren MT, Folkes VS, and Steckel JH (1992). Explanations for successful and unsuccessful marketing decisions: the decision maker’s perspective. Journal of Marketing 56:18-31

DeShazo JR and Fermo G (2002) Designing choice sets for stated preference methods: the effects of complexity on choice consistency. Journal of Environmental Economics and Management 44:123-143

Diamantopoulos A, Schlegelmilch BB, and Reynolds N (1994) Pretesting in questionnaire design: the impact of respondent characteristics on error detection. Journal of Market Research Society 36:295-314

Fern EF, Monroe KB, and Avila RA (1986) Effectiveness of multiple request strategies: a synthesis of research results. Journal of Marketing Research 23:144-53

Fowler TC (1990) Value analysis in design. Van Nostrand Reinhold, New York

Frankel M (1983) Sampling theory, in Rossi PH, Wright JD and Anderson AB (eds.) Handbook of Survey Research. Academic Press, New York, pp 21-67

Green PE and Srinivasan V (1990) Conjoint analysis in marketing: new developments with implications for research and practice. Journal of Marketing 54:3-19

Greer TV and Lohtia R (1994) Effects of source and paper color on response rates in mail surveys. Industrial Marketing Management 23:47-54

Henderson JM and Quandt RE (1980) Microeconomic theory—a mathematical approach. McGraw-Hill, New York

Horowitz JK (1991) Discounting money payoffs: an experimental analysis. Handbook of behavioral economics. JAI Press, Inc., Greenwich

Hunt SD, Sparkman RD Jr, and Wilcox J (1982) The pretest in survey research: issues and preliminary findings. Journal of Marketing Research May: 269-73

Jones S (1985) Problem-definition in marketing research: facilitating between clients and researchers. Psychology and Marketing 2:83-93

Kish L (1965) Survey sampling. Wiley, New York

Klein G and MG Sobol (1996) Bias in computer-assisted surveys. IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans 26:566-571

Kraemer HC and S Thiemann (1988) How many subjects? Sage Publications, Newbury Park

Lancaster K (1966) A new approach to consumer theory. Journal of Political Economy 74:132-57

Lancaster K (1971) Consumer demand: a new approach. Columbia University Press, New York

Leslie L (1971) Are high response rates essential to valid surveys? Social Science Research Sept:332-34

Louviere JJ, Hensher DA, and Swait JD (2000) Stated choice methods: analysis and application. Cambridge University Press, Cambridge, UK

Malhotra NK (1987) Analyzing marketing research data with incomplete information on the dependent variable. Journal of Marketing Research 4:74-84

Malhotra NK (1996) Marketing research: an applied orientation, 2nd edn. Prentice Hall, Upper Saddle River

McFadden D (1986) The choice theory approach to market research. Marketing Science 5:275-97

Mitchell RC and Carson RT (1989) Using surveys to value public goods: the contingent valuation method. John Hopkins University Press, Baltimore

Neill HR Cummings RG, Ganderton PT, Harrison GW, and McGuckin T (1994) Hypothetical surveys, provision rules and real economic commitments. Land Economics 70:145-54

Reynolds N, Diamantopoulos A, and Schlegelmilch BB (1993) Pretesting in questionnaire design: a review of the literature and suggestions for further research. Journal of the Market Research Society 35:171-82

Rosenthal R (1976) Experimenter effects in behavioral research, expanded edn. Irvington Publishers, New York

Singer E, Frankel MR and Glassman MB (1983) The effect of interviewer characteristics and expectations on response. Public Opinion Quarterly 47:68-83

Sudman S (1976) Applied sampling. Academic Press, New York

Taguchi G and Wu Y (1980) Introduction to off-line quality control. Central Japan Quality Control Association, Nagoya

Train K (1985) Qualitative choice analysis. MIT Press, Cambridge

von Neumann J and Morgenstern O (1947) Theory of games and economic behavior, 2nd edn. Cambridge University Press, Cambridge, UK

Yu J and Cooper H (1983) A quantitative review of research design effects on response rates to questionnaires. Journal of Marketing Research 20:36-44

http://www.springer.com/978-1-84628-964-4

Value Driven Product Planning and Systems Engineering
Cook, H.E.; Wissmann, L.A.
2007, XVIII, 213 p. 60 illus. With online files/update., Hardcover
ISBN: 978-1-84628-964-4