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ARTICLE INFO	Christoph Breidert, Michael Hahsler and Thomas Reutterer (2006). A Review of Methods for Measuring Willingness-to-Pay. *Innovative Marketing* , *2*(4)
RELEASED ON	Monday, 11 December 2006
JOURNAL	"Innovative Marketing "
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
0	0	0

A REVIEW OF METHODS FOR MEASURING WILLINGNESS-TO-PAY

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Abstract

Knowledge about a product's willingness-to-pay on behalf of its (potential) customers plays a crucial role in many areas of marketing management like pricing decisions or new product development. Numerous approaches to measure willingness-to-pay with differential conceptual foundations and methodological implications have been presented in the relevant literature so far. This article provides the reader with a systematic overview of the relevant literature on these competing approaches and associated schools of thought, recognizes their respective merits and discusses obstacles and issues regarding their adoption to measuring willingness-to-pay. Because of its practical relevance, special focus will be put on indirect surveying techniques and, in particular, conjoint-based applications will be discussed in more detail. The strengths and limitations of the individual approaches are discussed and evaluated from a managerial point of view.

Key words: Willingness-to-pay, pricing, surveying techniques, conjoint measurement.

Introduction

Despite considerable advances in both academic and applied pricing research over the past decades, many companies still make their pricing decisions without a profound understanding of the likely response of (potential) buyers and competitors to alternative prices quotations. As a result of missing adequate knowledge of the customer's willingness-to-pay (WTP) for their products, these companies fail to pursue a pricing strategy that is suitably customized to their marketing environment and thus also risk ignoring valuable sources for increasing profitability of the products offered. Different practical studies have shown that minor variations of prices and the corresponding consumer behavior can have notable effects on revenues and profits (Marn et al., 2003).

Companies often adopt some business rules and follow a strategy that could be denoted as "intuitive" pricing. Remarkably, such a behavior is not limited to retailing or service industries only, where mark-up-pricing is still representing the predominant practice (cf. Levy et al., 2004; Berman and Evans, 2001, p. 555 ff.; Monroe, 2003, p. 257). Several recent studies indicate that only 8 to 15% of all companies develop pricing strategies based on likely buyer response behavior (Monroe and Cox, 2001). In contrast to what seems to be common practice, managers consider the knowledge of customers' responses to different prices as a cornerstone of marketing strategies, particularly in the areas of product development, brand management, value audits, and competitive strategy (Anderson et al., 1993).

Researchers agree with managers on the importance of valid WTP estimates. Balderjahn (2003, p. 387) considers valid estimates of WTP essential for developing an optimal pricing strategy. Similar arguments about the importance of WTP and perceptions of value by customers can also be found by many other authors (cf. Monroe, 2003, pp. 11-12; Nagle and Holden, 2002, p. 7 and pp. 104-105; and Simon, 1992, p. 365 ff.). Such estimates can be used to forecast market response to price changes and for modeling demand functions. Furthermore, various approaches to measure brand equity (cf. e.g., Farquhar, 1989; Srivastava and Shocker, 1991; Park and Srinivasan, 1994) emphasize customers' WTP in terms of the (monetary) added value endowed by a brand to a specific product vis-à-vis its competitors or an unbranded baseline product, respectively. Good over-

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views on contemporary approaches to brand equity measurement are presented by Sattler (1995) or Ailawadi et al. (2003).

As our literature review will show, a huge variety of competing approaches and corresponding analytical techniques for measuring WTP has been added to the realm of marketing literature in the past. Equally, evidence on the relative empirical performance is scattered across a number of comparative studies of selected measurement approaches. Despite that fact, today the research area is rather fragmented and there has been relatively little attention paid to attempts towards an in-depth and comprehensive synopsis of the various existing approaches as well as what is known from empirical research regarding their effectiveness and efficiency to measure WTP. The purpose of this paper is to provide some insights into this direction. Moreover, we conceptualize a general evaluation framework that aims to be helpful for managers when it comes to select a particular measurement approach in practical applications. Against this managerial background, it is important to balance the specific merits and obstacles of the available approaches.

Specifically, the remainder of this paper is organized as follows: First, we provide a review of methods for measuring WTP and the corresponding data collection techniques. For the sake of clarity, we start with a classification of the various methods, thereafter we provide references to related substantial theoretical and empirical work, and discuss advantages and drawbacks for each method. Finally, we consolidate the most important results to provide guidance for managers who plan to measure WTP and provide ideas how to enhance indirect surveying techniques.

Classification of Methods

Several authors proposed different hierarchical classification frameworks to organize existing methods to WTP estimation. Marbeau (1987) distinguishes the estimation methods on the highest level, whether they are monadic tests or competitive tests. In the former, price information is elicited without considering a competitive context. In the latter, a competitive context is present. Balderjahn (2003) distinguishes estimation methods on the highest level, whether they elicit price information at the individual level or at the aggregate level. Nagle and Holden (2002) classify techniques for measuring price sensitivity at the highest level into uncontrolled and experimentally controlled measurement of the variables. Furthermore, they classify the techniques based on the variable measurement into measurement of purchase behavior and measurement of purchase intention.

To guide the reader through this paper, we use the classification framework based on data collection methods as presented in Figure 1. On the highest level, methods can be distinguished whether they utilize surveying techniques or whether they are based on actual or simulated price-response data. Taking a closer look at response data, market observations can be used or data can be generated by performing experiments. Experiments can further be divided into field experiments and laboratory experiments. Since auctions are a very important form of laboratory experiment, we included them as an extra method in the classification framework. Results obtained from price-responses are often referred to as *revealed preference* data. Looking at survey-based techniques for estimation of WTP, there exist direct and indirect surveys for collecting the relevant data. In contrast to revealed preferences, preference data derived from surveys are frequently referred to as *stated preferences* (cf. Louviere et al., 2000, p. 20 ff.).

With direct surveys, respondents (e.g., selected customers) are asked to state how much they would be willing to pay for some product. In indirect surveys some sort of rating or ranking procedure for different products is applied in order to estimate a preference structure from which WTP can be derived. Conjoint analysis and discrete choice analysis are examples of indirect surveying methods.

In practice, selecting a feasible method for measuring WTP is often restricted, for example, by time or monetary constraints. Data collection determines to a great extent the time and the costs of the method. Therefore, this framework provides a useful guideline for choosing an appropriate method and it was used to structure this paper.

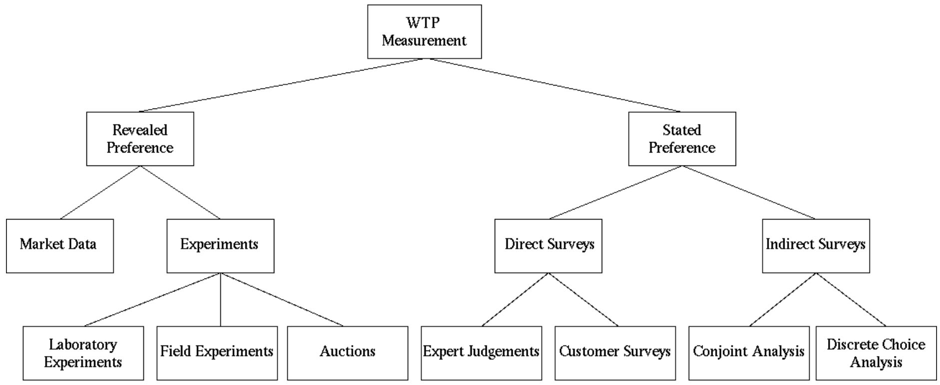

Fig. 1. Classification framework for methods to measure willingness-to-pay

Analysis of Market Data

Analyzing observed market data (i.e., sales data) is often used to estimate price-response functions. Depending on their data sources, sales data suitable for WTP estimation can be roughly subdivided into the following two subtypes: (1) *panel data* – individual purchase data reported by members of a customer panel, and (2) *store scanner data* – sales records from retail outlets. Using historical market data is based on the assumption that past demands can be used to predict future market behavior. This implies that the product for which future demand is estimated has only been exposed to minor variations in the product profile. A problem of the method arises if the historical data do not contain the necessary price variations to cover the desired spectrum of WTPs. Indeed, small ranges of observed price variations often appear to be a pitfall when analyzing historical sales data. For this reason Sattler and Nitschke (2003) even classify WTP estimation based on market data as infeasible. Demand curves based upon sales data are usually modeled with regression techniques. A restriction is that this is only possible if the requirements of the independent variables are met (cf. Balderjahn, 2003, p. 399; Nessim and Dodge, 1995, p. 72).

Note that sales data are often available at the aggregate level only. The data are aggregated over time and different stores are combined. In such cases derivation of individual customer level estimates is infeasible. This is different with panel data where the actual prices paid for products are observed at the individual level. The drawbacks are that running a customer panel entails high operating costs. Furthermore, it is often questionable, whether the customer panel adequately represents the market (Nagle and Holden, 2002, p. 335).

Conventional scanner data provided by commercial market research companies are usually not aggregated over time but aggregated at the store level. Scanner data are useful for observing response to short time price variations. But because of store level aggregation, individual level repeated purchase behavior cannot be extracted from such sources of scanner data. Parallel to the diffusion of point-of-sale (POS) scanning technologies combined with customer ID cards, however, customer specific reactions to items' price variations are accessible at least for purchase transactions realized with a specific retailer (cf. Kahn and McAllister, 1997, p. 106 ff.). Inclusion of price variations across competing stores is warranted by POS-ID scanner panels (cf. e.g., Simon et al., 1982; and Erichson, 1992).

In general, using market data has the advantage that real purchases, which include information about competing products, are used instead of, for example, only stated purchase intentions. Limitations are that the price variations in the data are normally very limited and that it is not possible to estimate WTP for entirely new products where no data are available (yet). Empirical applications are provided by Kamakura and Russell (1993) or Leeflang and Wittink (1992).

Experiments

Generally, experiments can be divided into laboratory experiments and field experiments (e.g., Malhotra, 2004). Both types can be applied in pricing studies including WTP estimation.

Laboratory Experiments

In laboratory experiments, purchase behavior is typically simulated by giving the subjects an amount of money and asking them to spend the money on a specific selection of goods. The goods and prices are varied systematically. Methods for accessing price response of this form have been applied by Silk and Urban (1978) in their well-known ASSESSOR procedure. In laboratory experiments the results are obtained quickly. Due to the non-biotic context of investigation, a major drawback is that the subjects are aware of the experimental situation. This might lead to subjects becoming more rational of their purchase behavior compared to their normal shopping behavior which can lead to low external validity (Nessim and Dodge, 1995, p.74). Another source of bias might be the artificial setup as described above, in which the subjects either do not take real possession of the "purchased" goods, or do not use their own money (Nagle and Holden, 2002, p. 341).

Field Experiments

Field experiments or in-store purchase experiments do not suffer from the problem of the artificial setup because they are performed in a real-world shopping environment. Depending on the experimental conditions, the respondents are aware of participating in an experiment or not. Field experiments are often conducted in form of so-called test markets. In different test markets the prices are systematically varied and the consumers' responses are analyzed. A crucial issue in test market analysis is to select small scaled market environments that are representative for the target market under investigation. An overview of institutional test market simulations in Germany is provided by Gaul et al. (1996). Compared to laboratory experiments, considerably higher expenditures and the longer time intervals entailed by monitoring market responses to price changes are reported as main drawbacks of test markets as well as other forms of field and in-store experiments (Nagle and Holden 2002 p. 341; Sattler and Nitschke, 2003; and Urban and Hauser, 1993, p. 495 ff.).

Auctions

A special application of experiments are auctions which can be carried out as laboratory or field experiments. In laboratory settings auctions have been intensively employed for WTP elicitation. If the true monetary evaluation of a product as perceived by the customer(s) were known, there would be no need for an auction. The offering party would simply sell the good to the bidder with the highest valuation at a price close or equal to that valuation. If the seller is uncertain about customers' valuations, however, an auction can provide valuable insights to sell the item at a fair price. Therefore, an auction is useful to gain knowledge of consumers' evaluations of a product or brand and can therefore be used to reveal consumers' valuations to facilitate future pricing decisions.

According to Wertenbroch and Skiera incentives to reveal true WTP can be provided with Vickrey auctions: "Vickrey suggests that incentive compatibility is ensured if a given bid determines only whether the bidder has the right to buy the good that is auctioned off" (Wertenbroch and Skiera, 2002). The Vickery auction takes place in sealed form, and the purchase price is determined by the second highest bid. A participant in the auction submits a bid containing how much he or she would be willing to pay in sealed form, for example in a closed envelope. If the participant has the highest bid, he or she wins the auction. However, the participant only has to pay the price of the second highest bid. With this mechanism the participants are provided an incentive to reveal their true valuation, because they must buy the good if their bid wins the auction (Vickrey, 1961).

Skiera and Revenstorff (1999) investigate the ability of Vickrey auctions to reveal consumers' WTP. The mechanism of the auction was described to the students, and the optimal bidding strategy was explained (which is bidding the true valuation) and different phone contracts were offered in a Vickrey auction. Based on a questionnaire the subjects seemed to have a good understanding of the mechanism of the auction. But the optimal bidding strategy (bid the true valuation) was less clear to the subjects which might be a problem for the method.

In a different experiment Sattler and Nitschke (2003) find that the Vickrey auctions in addition to the first-price auctions (auction where the highest bid wins) both tend to overestimate consumers' WTP. The authors suppose that this effect is due to the overbidding phenomenon. The overbidding phenomenon occurs when bidders strategically place bids above their true WTP to increase their chance of winning (Kagel et al., 1987).

Another incentive compatible auction form is the well-known BDM procedure introduced by the authors Becker, DeGroot and Marshak (cf. Becker et al., 1964). In BDM every participant simultaneously submits an offer price to purchase a product. A sale price is randomly drawn from a distribution of prices. The possible prices cover an interval from zero to a price greater than the anticipated maximum price, which any bidder would submit. The bidders whose bids are greater than the sale price receive a unit of the good and pay an amount equal to the sale price. The mechanism is incentive compatible for the same reason as the Vickrey auction: A given bid determines only whether the bidder has the right to buy the good that is auctioned off. The price is set by some mechanism and is below the participants bid.

The BDM procedure was tested by a number of researchers for its ability to forecast WTP. Wertenbroch and Skiera (2002) tested it together with a Vickrey auction in a field experiment with a purchase obligation for the participants. The participants of the experiment easily understood the BDM method and hardly any of the approached individuals refused to participate. Validity was determined by relating the estimated WTPs to data from an additional questionnaire asking the respondents to rate their desire of the tested products. After the experiment the participants rated how satisfied they were with their purchase. The buyers as well as the non-buyers were extremely satisfied with the outcome of the BDM experiment. This result indicates that BDM does not suffer from the overbidding bias, which is found in some Vickrey auctions.

In a study published by Noussair et al. (2004) the Vickrey auction is compared with the BDM mechanism, with the aim to test which method converges towards the optimal bidding strategy (bidding the true valuation) more rapidly. The authors found that under the Vickrey auction the bias from the true valuation is more rapidly reduced and the dispersion of bids is narrowed down more rapidly. That is, the subjects learn the best bidding strategy more quickly. The authors argue that the reason for this difference lies in the fact that a deviation from the optimal strategy is more costly under the Vickrey auction than under the BDM mechanism. With respect to these results Noussair et al. (2004) conclude that Vickrey auctions are superior to the BDM procedure for elicitation of WTP towards private goods.

Applied research using experimental auctions in laboratory settings for estimating products' WTP is rather limited. However, auctions are applied as sales mechanisms in practice as for example by EBAY and can deliver useful information for understanding buyer's likely response behavior to different prices.

Another approach to estimate WTP with an auction-like procedure is the so-called reverse-pricing or name-your-own-price mechanism (e.g., Chernev, 2003; and Spann et al., 2004). In this mechanism each buyer names a price he or she is willing to pay for a certain product. Based upon a price threshold set by the seller but unkown to the buyers, the buyers who have the right to purchase the product are determined. Each buyer pays the price which he or she named. Unlike the Vickrey auction and the BDM mechanism, reverse-pricing is not incentive compatible. In the latter each buyer has the incentive to name a lower price than the true valuation in order to get a better deal. However, it is argued that the named prices will be determined by the WTP and if each buyer can submit several bids, WTP can be estimated. In contrast to more conventional auction procedures, numerous applications of reverse-pricing can be found in practice. A well-known example is priceline.com, a US-based retailer operating since 1998, whose primary focus is on sales of flights, rental cars, and vacation packages.

Direct Surveys

In the previous sections, we discussed methods for measuring WTP based on revealed preference data. It is not always possible for a marketing analyst to obtain such data in order to estimate price-response functions. For example, new or differentiated products would have to be designed and manufactured before they can be tested experimentally. Typically the number of possible differentiated products is large and not all candidates can be tested under justifiable budget and time restrictions. In this case specific surveying techniques that render respondents' statements with respect to their price preferences are better suited.

In the next sections, an overview of various surveying and related data analytical techniques with relevance to WTP estimation will be given. The most important methods, namely conjoint analysis and discrete choice analysis, are discussed in more detail. According to the classification provided above, direct surveys can be further divided into expert judgments and customer surveys. Reflecting their relative suitability to deliver accurate WTP estimates, we only review expert judgments briefly while focusing on customer surveys.

Expert Judgments

As a heuristic to assess customers' WTP as well as to provide rough estimates of expected demand in response to different price levels, expert judgments are quite popular in marketing practice. They can be collected more time and cost efficient as compared to interviewing customers.

Usually sales or marketing managers serve as experts in projecting customers' WTP. Since sales representatives work directly in the market and in close connection with the consumers, they are aware of the competitive structure in the market and are sensitive to trends in consumer needs. Therefore, interviewing sales people can provide an important source of information for demand estimates. Nevertheless, the opinion of sales people might be biased because of conflicting objectives of the marketer and the sales force. For example, if the sales force's rewarding system is tied to sales volume, intentionally or unintentionally overstated or understated expert judgments might result in biased estimates (Nessim and Dodge, 1995, p. 70).

Conversely, marketing experts' estimates of product demand under different price schedules might suffer from the distance to the market and the consumers. In contrast to judgments provided by sales people there are no incentives to over- or understate the true estimates. Usually, there are less marketing executives in a company than sales force people and the opinions of few marketing managers might lead to poor forecasts of future demand.

In general, expert judgments seem to be best applicable in a market environment with only small numbers of customers. In such an environment the customers are known well enough to adequately approximate their WTP. With a larger and more heterogeneous customer base, the availability of this knowledge becomes a critical issue.

Authors are divided on the usefulness of using exclusively expert judgments. For example, Nessim and Dodge (1995, p. 70) argue that expert judgments are an important source of information because an educated guess is better than a random selection of a presumably adequate price from a number of price possibilities. Other authors, for example Balderjahn (2003, p. 391), label expert judgments as a poor measurement instrument with low validity and discourage from its use.

Customer Surveys

If one attempts to forecast consumer behavior in response to different prices, the evident way is to directly ask the customers. One of the first applications of direct surveys was a psychologically motivated method for estimating WTP developed by Stoetzel (1954). Stoetzel's idea was that there is a maximum and minimum price for each product which can be elicited by directly asking the customers. Studies based on this idea consist of the following two questions formulated by Marbeau (1987):

1. "Above which price would you definitely not buy the product, because you can't afford it or because you didn't think it was worth the money?

2. Below which price would you say you would not buy the product because you would start to suspect the quality?"

Directly asking respondents to indicate acceptable prices is referred to as a *direct approach* to measure WTP. Other researchers continued to build upon this idea and research in this area became quite popular (e.g., Abrams, 1964; Gabor et al., 1970; and Stout, 1969). Van Westendorp (1976) introduced a price sensitivity meter which included two additional questions on a reasonable cheap price and a reasonable expensive price of the product under consideration. Applications of this approach can be still found in commercial applications (for example, the pan-european market research company GfK utilizes the procedure to attain critical price ranges for new or relaunched products).

Recently, several other procedures based on direct customer surveying have been established. An example is the commercial tool BASES Price Advisor by ACNielsen. The tool's procedure presents the subjects with several typical product profiles. The products can be in an early conceptual phase or already marketable. The subjects are then asked to name prices at which they consider a product to have a very good value, an average value, and a somewhat poor value. From the responses, purchase probabilities for different prices are derived. According to Balderjahn (2003, p. 392) the price for "a somewhat poor" value could be interpreted as reflecting a respondent's WTP.

Quite obviously, directly surveying customers has some flaws:

1. By directly asking the customers for a price, there is an unnatural focus on price which can displace the importance of a product's other attributes.
2. Customers do not necessarily have an incentive to reveal their true WTP. They might overstate prices because of prestige effects or understate prices because of consumer collaboration effects. Nessim and Dodge (1995, p. 72) suppose that "buyers in direct responding may also attempt to quote artificially lower prices, since many of them perceive their role as conscientious buyers as that of helping to keep prices down". Nagle and Holden (2002, p. 344) observe the opposite behavior. To not appear stingy to the researcher respondents could also overstate their WTP.
3. Even if customers reveal their true valuations of a good, this valuation does not necessarily translate intro real purchasing behavior (Nessim and Dodge, 1995, p. 72).
4. Directly asking for WTPs especially for complex and unfamiliar goods is a cognitively challenging task for respondents (Brown et al., 1996). While it remains unclear whether this leads to over- or understating of true valuations a bias is likely to occur. Note, that this effect also occurs in the Vickrey auction and the BDM mechanism which were introduced in the previous section about experiments.
5. The perceived valuation of a product is not necessarily stable. Buyers often misjudge the price of a product, especially if it is not a high frequency purchase or an indispensable good (Marbeau, 1987). This can lead to an abrupt WTP change once the customer learns the market price of the product.

An empirical comparison between a field experiment, a laboratory experiment, and a personal interview was carried out by Stout (1969). In this experiment the prices for different products were varied and the changes in demand were measured. The results showed significant quantity changes on systematic price changes in the field experiment. As expected, the demand for the products decreased as the prices were raised and vice versa. For the other two methods, no significant changes in demand for the products could be measured caused by raised and lowered prices. The personal interview even contained reversals. For some respondents the demand increased when the prices were raised.

Overall, directly asking customers' WTP for different products seems not to be a reliable method. Balderjahn (2003, p. 402) explicitly alludes to the distortional effects of direct surveys and pleads against its use. Nagle and Holden (2002, p. 345) even state that "the results of such studies are at best useless and are potentially highly misleading".

Indirect Surveys

Brown et al. (1996) argue that for a respondent it is cognitively easier to decide whether a specific price for a product is acceptable than to directly assign a price. When the respondent is presented competing product alternatives and their prices, he or she can be asked to apply a preference rating, preference ordering or select his most preferred choice.

In contrast to directly asking respondents for their WTP, customers are presented product profiles with systematically varied prices and are asked to indicate whether they would purchase the good at that price or not. This measurement approach is denoted to as indirect survey (cf. Marbeau, 1987).

In an approach proposed by Camron and James (1987), the authors suggest to present to a random sample of respondents product profiles with randomly assigned prices. Camron and James (1987) explain their technique as follows: "Across the selection of product scenarios, the investigator is free to vary not only the proposed price, but also the levels of all other product attributes. Each consumer's willingness or unwillingness to purchase the specific product at the designated price is recorded. If the experimental design includes variability in the levels of prices, product attributes, and consumer characteristics, the researcher will be able to use the statistical techniques [...] to calibrate the demand function."

Methods based on this idea are discussed in the following sections.

Conjoint Analysis

Generally speaking, conjoint analysis is a technique for measuring individuals' preference structures via systematical variations of product attributes in an experimental design. A product's attribute is considered as a set of possible realizations, which are referred to as the attribute's levels. The respondent is presented a number of product profiles consisting of realizations of the product's attributes and arranges them according to her or his perceived preference, e.g., by indicating a rank order with respect to the degree of preference. These overall preference evaluations are used to make inferences of the relative contributions of the different attribute levels. The latter are called part-worths and the evaluation of a full product stimulus is referred to as the product's utility. In a conjoint study part-worths are estimated for all attribute levels. That is, each level is assigned a number, such that the respondents' preference structure based on the attributes and levels is represented. The measurement focusing on the different attributes is called importance. The importance of one attribute is based on the level's part-worths and simply describes the range of the part-worths from the least preferred to the most preferred level. Overview articles on the development of conjoint analysis can be found in Carroll and Green (1995), Green and Srinivasan (1978, 1990), Gustafsson et al. (2000), Louviere (1994), and Rao and Hauser (2004).

The conjoint methods considered here follow the assumption of an *additive compensatory decision rule* that governs respondents' information processing (cf. Young, 1973; Lilien et al., 1992 p. 93 ff.; and Johnson, 2001). This assumption on utility formation is quite common in the marketing literature (cf. Lilien et al., 1992, p. 93 ff.). Hence, the utility of product *c* is calculated as the sum of the part-worths of the levels of all attributes as follows:

$$y_c = \sum_{a=1}^{A} \sum_{l=1}^{L_a} \beta_{al} \cdot x_{al}$$

with

y_c: Rank of product card *c*

β_{al}: Unknown part-worth of level *l* and attribute *a*

x_{al} =1 if product card *c* has level *l* of attribute *a* and 0 otherwise.

Green and Rao (1971) were among the first who introduced conjoint measurement into the marketing literature. Since then, the methodology experienced many extensions and refinements and today represents an important technique of the modern marketing analyst's toolbox (see e.g., Wittink and Cattin, 1989; Wittink and Burhenne, 1994; Voeth, 1999; Hartmann and Sattler, 2002a, 2002b).

The classic approach to conjoint measurement is *full profile conjoint analysis* (Green and Rao, 1971). In full profile conjoint analysis the subjects are presented sequences of product profiles that are described as a combination of the levels of all attributes. These full profile stimuli are presented on cards with textual and/or graphical descriptions of the product profiles. The respondent's task is to evaluate each of these profiles. In the classical case, preference rankings of the product cards are provided and the parameters β_{al} of the respondent's preference structure need to be fitted. If the rankings of the respondent are treated using an ordinal scale, typically MONANOVA (Kruskal, 1965) is applied. If the rankings are assumed to be equidistant, they can be treated using an interval scale and OLS regression or ANOVA can be applied. However, various studies have shown that different estimation procedures do not lead to significantly different results (e.g., Cattin and Wittink, 1976; Carmone et al., 1978; and Wittink and Cattin, 1981).

Once the part-worths are fitted, a utility score for any stimulus composed from the attributes and levels can be predicted using the additive composition rule. Note that the utility can also be calculated for products that were not actually presented to the respondent during the study as long as they are constructed only from attribute level which were part of the analysis.

Naturally, apart from rankings other answer formats for measuring preferences in conjoint experiments can be employed as well (see, e.g., Otter, 2001, p. 64 ff. for an overview and a comparative empirical evaluation). For example, the respondents can be instructed to rate the product profiles on a 1-7 attractiveness scale (Huber, 1997) or a 0-100 purchase likelihood scale (Mahajan et al., 1982). Such rating-based approaches are also frequently denoted as metric conjoint analysis (Louviere, 1988). The recovery of part-worths is accomplished in the same way as the estimation procedure for ranking data as described above. Furthermore, the use of choices as an answer format in conjoint studies converges to the methodology of discrete choice analysis, which is further discussed below.

Apart from full profile there exist other conjoint approaches. So-called *trade-off methods* confront the respondent with only two attributes at a time (Johnson, 1974). This is done for all attribute pairs. The intention of using partial profiles instead of full profiles is to avoid information overload tendencies that are likely to occur when all possible attributes are present in a product stimulus (Green and Srinivasan, 1978). However, the drawback with trade-off matrices is that by decomposing the factors into two-at-a-time partial profiles, there is a sacrifice of realism to the respondent who is confronted with incomplete products (Green and Srinivasan, 1978). In this sense full profiles can be considered as more realistic and trade-off method is rarely used in practice (Wittink and Cattin, 1989).

There exist conjoint methods that use self-explicated data to elaborate the estimation of each respondent's utility function. Self-explicated data are elicited directly by asking the respondent to rate the different attributes levels. Such a procedure typically entails the following steps (cf. Fishbein, 1967; and Green and Krieger, 1996).

1. The decision maker rates the desirability of each of a set of possible levels of each of a set of attributes on, e.g., a 0-10 scale.
2. Following this, the decision maker rates the importance of each attribute on, e.g., a 0-10 scale. In this model, a part-worth is defined as the product of the attribute's importance times the associated level's desirability.

In *hybrid conjoint analysis* self-explicated data are used to obtain preliminary part-worths for each respondent. After this, a limited number of full-profile cards is presented for evaluation. Thus, the number of profiles and, as a consequence, information overload tendencies can be reduced. The profiles are chosen and presented to all respondents in such a way that each profile is at least rated once. The evaluations are pooled and group level part-worths are estimated by dummy variable regression (Green et al., 1981). The part-worths at the individual level are then fitted with data from the group level estimates of the full profile task by multiple regression analysis. Several empirical studies have shown that cross-validity of hybrid models is better than self-explicated data alone. However, full-profile models appear to be superior of hybrid models (Green and Krieger, 1996). In newer hybrid models, part-worths from a self-explicated task are fitted with individual level estimates from full-profile conjoint. If the number of full profiles is reasonable and an orthogonal design can be applied, individual level part-worth estimates can be calculated for all attributes and levels. This can increase the internal validity measured on holdout scores of hybrid models (Green and Krieger, 1996).

Adaptive conjoint analysis (ACA) also uses self-explicated data as preliminary input. Instead of combining the data with full product profiles partial profiles are used. ACA was developed in the beginning of the 1980's when the technological possibility arose to perform computer-administered interviews (Johnson, 1987). Based upon the self-explicated data, the respondent has to evaluate a sequence of pairs of partial profiles. The method is called adaptive because the selection of the subsequent partial profiles is adapted based on the respondent's preference indications. Using ACA studies with more attributes and levels can be performed than with full profile conjoint analysis. ACA has successfully been implemented in many conjoint studies and was the most frequently chosen method in Europe (Wittink and Burhenne, 1994) and the USA in the 1990s (Orme, 2003). The advantage of ACA over other conjoint methods is that it is a combined presentation and estimation computer package. With a web-front end it can be also used for online surveying.

Using Conjoint Measurement in Pricing Studies

According to the literature, pricing studies are one of the most important applications of conjoint analysis (e.g., Gustafsson et al., 2000, pp. 6-7). In a study on conjoint applications in the US in the years 1981-1985 Wittink and Cattin (1989) surveyed 59 companies who carried out 1062 conjoint studies. 38% of the identified studies were pricing studies. In a similar study on the application of conjoint analysis in the European market in the years 1986-1991 Wittink and Burhenne (1994) surveyed 66 companies and reported a total of 956 conjoint studies. Out of these 46% were pricing studies. Baier (1999) carried out a smaller study in the German market. 8 companies were interviewed and 382 conjoint studies were identified, of which 62% were pricing studies. Hartmann and Sattler (2002a,b) surveyed 54 marketing research institutes in Germany, Austria, and Switzerland in the year 2001. These institutes performed a total of 304 studies regarding preference measurement. 121 studies were documented in greater detail by the marketing research institutes, showing that 48% were pricing studies.

Not only overview articles on the usage of conjoint analysis show its importance in pricing research. Also, publications of the application of conjoint analysis in scientific journals illustrate its importance. In a broad review Voeth (1999) summarizes the publications on conjoint analysis in German between the years 1976-1998. Most of the identified 150 studies were published in the 1990s of which 31 studies explicitly focused on pricing.

Some of the best examples from the literature regarding pricing studies performed by conjoint analysis in important German and English scientific journals are Currim et al. (1981), Mahajan et al. (1982), Goldberg et al. (1984), Green and Krieger (1990), Hanson and Martin (1990), Balderjahn (1991), Green and Krieger (1992), Eppen et al. (1991), Venkatesh and Mahajan (1993), Balderjahn (1994), Eggenberger and Christof (1996), and Green et al. (1997). As can be seen from practical applications and journal publications, pricing studies are an important field of conjoint analysis. Apparently, conjoint analysis is a method which is well suited for pricing studies (cf. Diller, 2000, p. 202).

The commonly used approach in pricing studies by conjoint analysis is incorporating the price in the study as an additional attribute (e.g., Green and Srinivasan, 1990; Orme, 2001). The levels of the attribute price are then assigned part-worths like the other attributes. For different part-worths of price points, interpolation heuristics are applied to obtain the part-worth for any intermediate level which was not part of the conjoint analysis.

Kohli and Mahajan (1991) published the first article explicitly focusing on WTP estimation within a conjoint analytical framework. The authors define WTP as follows: "We assume that a consumer's reservation price for a new product is determined by his or her (estimated) utility for the product in relationship to the price and utility for his or her most preferred product among all product offerings in his or her evoked set." An evoked set consists of all products that are accessible to an individual consumer and perceived as potential consumption alternatives, of which one, and only one, can and will be purchased. Formally, Kohli and Mahajan model WTP estimation based on conjoint data as follows:

$$u_{it|\sim p} + u_i(p) \geq u_i^* + \varepsilon.$$

In this notation individual i prefers product t over some status quo product with utility u_i. The status quo product has the highest estimated utility of any currently available product in consumer i's evoked set. Product t is preferred if the sum of the part-worths of the non-price attributes $u_{it|\sim p}$ and the part-worth due to price $u_i(p)$ is higher than the utility of the status quo product plus some arbitrarily small number ε.

In the remainder of their work the authors assume that the WTP observations are drawn from a normal distribution. They estimate this distribution and describe shares of preference for different products at different prices based upon the distribution's density function.

In an empirical application study, Kohli and Mahajan tested different apartment concepts among MBA students. The preference structure for the concepts is estimated for each individual via conjoint analysis. Price is included as an attribute and modelled as a continuous linear variable in the multi-attribute preference function. A status quo apartment is assumed to be given at a fixed price. This status quo apartment is the same for every respondent. Against this apartment the prices for all other concepts at which the respondents would switch away are calculated. These prices are representing the participants' WTPs.

Note that the prerequisite for a correct forecast of a respondent's WTP is that he or she perceives the status quo apartment the best alternative in his or her evoked set. Furthermore, every respondent must be willing to purchase the status quo product at the current price. Notice this approach rests on the critical assumption that all respondents are willing to purchase the status quo product, otherwise, conjoint data only poorly reflect realistic market behaviour (cf. Balderjahn, 1993; Weiber and Rosendahl, 1997).

Another problem is respondents' heterogeneity with respect to status quo products: Different participants might consider different products their best alternative. Hence, using the same status quo product for all participants might not yield correct WTP predictions. Researchers reacted to this problem by letting every respondent indicate his or her own status quo product. Voeth and Hahn (1998) let the subjects arrange the product profiles in a rank order and then insert a so-called limit-card. Up to the position of the card, the respondent would be willing to purchase the product profile at the indicated price, below the card the respondent would not purchase the product. The product at the position of the limit-card is used as the status quo product. This approach was picked up by other researchers. A somewhat different approach was used by Sattler and Nitschke (2003) where the subjects order different product profiles with prices and then indicate those which they would actually purchase. The stimulus with the lowest overall part-worth is then used as the status quo product.

A crucial design question for conjoint interviews with price is to set appropriate price levels. Usually the attribute price is set so that it covers the range of usual market prices. This is problematic for respondents whose WTP is far above or below the average market price. These respondents rate or rank a large number of profiles with prices assigned that are far displaced from their WTP. It can happen that the relevant product stimuli are only presented in very few conjoint questions and therefore only few relevant data-points are elicited. Furthermore, using a fixed range of market prices does not allow the estimation of market expansion or contraction effects, if the prices for the products were set outside of the range of usual market prices.

Jedidi and Zhang (2002) question that the assumption of unconditional category purchase holds when new products are introduced that attract consumers, who did not buy in that category before. Therefore, the authors depart from the approach by Kohli and Mahajan (1991) by estimating an origin of zero utility for each respondent individually. With this, the authors dismiss the assumption that every respondent would accept a status quo product and allow the estimation of market expansion and contraction effects caused by consumers who switch to and from the category. In their approach a consumer's WTP is the price at which the consumer is indifferent between buying and not buying the product, given all consumption alternatives available to the consumer (e.g., products in other categories). Formally, Jedidi and Zhang present the condition for WTP $r_i(P)$ that some individual i has for some product P as:

$$U_i\left(P, \frac{m_i - r_i(P)}{p_i^y}\right) - U_i\left(0, \frac{m_i}{p_i^y}\right) \equiv 0.$$

As in economic theory each individual has a utility function $U_i(P, y_i)$ for the consumption of the product P and the consumption of some amount of the composite product y_i. The amount of the composite product consumed by the individual is expressed in terms of a budget constraint $m_i = p_i^y y_i + p$ and the price p for product P. Based upon the assumption that WTP solely depends on the alternative purchase opportunities, Jedidi and Zhang interpolate between the levels of the attributes in the conjoint study and extrapolate to zero. The derived utility for the absence of the attribute is assigned zero monetary value. This is assumed to be the origin of utility for that attribute. Offset to this part-worth, the exchange rate between utility and price is used to calculate the WTPs.

Table 1

Example of attributes price and hard drive with assigned levels and estimated part-worths

Hard Drive	Part-Worth
100 GB	10
200 GB	15

Price	Part-Worth
500 €	10
200 €	50

To illustrate the approach, we give a brief example for the two attributes price and size of hard drive shown in Table 1. The part-worths of the attribute levels are estimated by conjoint analysis. The linear extrapolation of the size of hard drive to 0 GB leads to 5 utility units (calculated from the numbers in the upper part of Table 1). Since 5 utility units is equivalent to the absence of hard drive, the authors derive that the respondent would pay no money for 5 utility units. The exchange rate between utility and price in this example calculates to 10 € per utility unit ((500 € -100 €) / (50 -10) = 10 €). Using the exchange rate between utility and price and subtracting the utility for which the respondent would pay no money the authors calculate an individual's WTP for the levels of hard disc. For 100 GB hard drive the WTP of the individual would be 50 € (calculated by (10 -5)·10 € = 50 €).

Jedidi and Zhang present an empirical study carried out amongst MBA students at a major U.S. university. The students participated in a conjoint analysis for notebooks consisting of the attributes price, brand, memory, speed, and hard drive with either two or three levels. The data were collected with a traditional conjoint measurement method. The authors simulate market shares and profits at different prices for the new notebook and show that their estimation yields different results compared to a conventional approach with a status quo product. In the conventional approach the market is simply divided between the offered products. In order to test the validity of their model Jedidi and Zhang compute the correlation between self-stated WTPs and estimated WTPs for the new product and find a positive correlation between the two values across the consumer population.

Jediddi and Zhang's approach does not require status quo products and is able to estimate the share of non-buyers which reflects real market behavior with market expansion and contraction phenomena more adequately. This is accomplished by using an augmented set of conjoint data with assumed choices via interpolation heuristics. However, since actual choice data are not explicitly collected, validation of the interpolation results remains an open issue.

Limitations of Existing Conjoint-Based Approaches

In all approaches presented in the previous section price was incorporated in conjoint designs as an additional attribute in order to provide WTP estimates. This practice, however, has some severe shortcomings which will be discussed in the remainder of this chapter. By doing so, we distinguish the following three types of problems encountered with the inclusion of price attributes in conjoint experiments:

1. ***Theoretical Problem:*** By treating price as an attribute in a conjoint study, part-worth utilities are estimated for the presented price levels. By definition price does not have a utility, rather it reflects an exchange rate between different utility scales, implying, the price of goods do not influence the goods' utility. Rather, it denotes how much of alternative consumption (with the associated utility) has to be given up to consume the good.
2. ***Practical Problem:*** The occurrence of interactions between price and other attributes are likely to occur in a conjoint study. When this happens the additive-compensatory model is violated. Furthermore, crucial effects are the price effect, the range effect, and the number-of-levels effect that occur when price is included as an attribute. Last but not least, problems calculating the interpolation heuristics between utility and price can occur, when more than two price levels are used.
3. ***Estimation Problem:*** Traditional conjoint analysis does not incorporate a decision rule. That is, only preference structure is estimated and not choices for or against different products. When the objective is to estimate WTP, researchers need choice information. This information is usually added to the data by assuming or explicitly asking the respondents for a status quo product with an associated WTP. Estimating the WTPs for all products of the conjoint study based on one data-point (the status quo product) only might not be sufficient for accurate estimations.

Let us first address the **theoretical problems** raised: In neoclassical economic theory of consumer behavior price is treated as an exogenous variable. It bears no more information to a customer besides how many units of different goods he or she may consume before the budget is exhausted. This treatment of price permits the construction of choice behavior and indifference curves as well as demand functions. In these neoclassical approaches price enters any model solely through a budget constraint (cf. Varian 2003, chap. 5-6)[1].

[1] Nevertheless, besides an allocative function of the budget constraint, price can bear information for the customer. Price can provide evidence of quality, as was first documented by Scitovsky (1945). On this topic a great number of empirical studies have been carried out, an overview is given in Rao (1993) and recent publications include Sattler and Rao (1997) and Brooks et al. (2000). These studies indicate a mixed relationship between quality and price. A very low price might be perceived as an indicator of low quality, and vice versa a very high price might be perceived as an indicator for high

By assigning part-worth utilities to the price levels of the study, price is treated fundamentally different than in neoclassical economic theory. As emphasized by Rao and Gautschi (1982) this approach is data-based rather than theory-based. The conjoint analyst would simply treat price as another attribute in the multi-attribute utility function because it makes estimation of response behavior simple. Srinivasan (1982) responded to the argumentation of Rao and Gautschi (1982) that the distinct treatment of price is not so great after all and should not cause theoretical problems. If a consumer's WTP for a product solely depends on the consumer's budget constraint and the consumption alternatives given elsewhere, the utility function of two goods, the good of interest and the composite good, can be re-arranged into a utility function of only the good of interest with price included as an attribute that attaches value to the product (cf. Ratchford, 1979; and Srinivasan, 1982).

However, we believe that in real purchase situations WTP does not only depend on the composite product and a budget constraint but also on alternative product offerings, so-called reference products. Therefore, the theoretical problem of including price as an attribute in conjoint analysis still remains unresolved.

Practical Problems: When the participant of a conjoint analysis with randomly assigned profiles is presented a ranking or rating task, it is possible that some of the presented profiles have an unfairly high price to some respondents or appear to be an extremely good deal. When this happens, the respondents fail to compare the current profile with other profiles and this would lead to a non consistent ranking or rating. These profiles would be rated artificially low or high. If this happens, the additive-compensatory model is violated and interactions between certain price levels with other attribute levels have occurred. This is likely to happen in a conjoint study with price as an attribute (Weiber and Rosendahl, 1997). Attempts to relax the restrictive assumptions of compensatory decision models are numerous in the psychometric literaterature (cf., e.g., Tversky, 1972; Tversky et al., 1988) as well as in marketing. A general discussion as well as advanced more flexible modeling approaches towards this direction are provided by Gilbride and Allenby (2004), Jedidi and Kohli (2004), Yee et al. (2005).

The price effect occurs when the number of attributes becomes large. In conjoint studies with many attributes of which one is price the importance of price tends to be artificially understated, and the degree of understatement increases as the number of attributes increases (Orme 2003). Practitioners attempt to overcome this problem by calibrating the importance of price in a post process by re-scaling the importance of the attribute price.

The range effect is a well studied effect in psychophysics (e.g., Parducci, 1974). If the physical range of attribute levels in an experiment is altered, the range of the stimuli responses is also altered (Verlegh et al., 2002). This is important for price, because price does not have a natural upper or lower limit. In a traditional price study using conjoint analysis determining the range of acceptable prices is crucial. Choosing a price range that is very wide, covering all possible prices will result in a larger importance of the attribute price, than if a narrower range was chosen.

Another important effect in conjoint analysis is the number-of-levels effect. This effect has been studied by many authors (e.g., Wittink et al., 1989; Steenkamp and Wittink, 1994). Increasing the number of levels of an attribute increases the attribute's importance significantly (Green and Srinivasan, 1990). The number-of-levels effect is even stronger than the range effect (Verlegh et al., 2002). Again, since price does not have a natural number of levels, the conjoint analyst must decide how many levels to use. In many cases, certain price levels are of special interest to a re-

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quality. There also exist goods for which the allocative effect of price is reversed. For these products preference for buying increases as a direct function of price. They are called Veblen goods, examples are expensive wines and perfumes. Decreasing their prices decreases consumers' preferences for buying them because they are no longer perceived as exclusive or high status products (Leibenstein, 1950). However, in this work we focus on "normal" products and do not wish to separate the allocational and informational effect of price. Instead, we are generally interested in WTP estimation which contains both effects.

searcher which confronts the researcher with the dilemma that inserting the intermediate levels of interest, artificially increases the importance of price.

The price effect, the range effect, and the number-of-levels effect cannot be avoided for price, when it is included as an attribute in a conjoint study.

Another problem occurs by using more than two price levels. The estimation procedure for attribute level parameters is usually not constrained to support a natural ordering of the levels. But price has a natural ordering: A higher price level should have a lower part-worth than a lower price level. In unconstrained estimation it is possible and sometimes expected that the natural ordering of part-worths of price levels contains reversals (Orme, 2001). Practitioners get around these problems by using as few levels as possible (Orme, 2002). Another problem that occurs if more than two price levels are used is to decide how interpolation heuristics should be applied to estimate an exchange rate between utility and price. Possible heuristics are piecewise linear interpolation between the price levels, least squares fitting, or using the highest and lowest price level for linear interpolation only. Depending on the interpolation heuristics different WTPs are estimated for the products of the conjoint study.

Estimation Problems: Traditional conjoint analysis does not include a way to estimate choice behavior. In particular, the respondent cannot indicate that he or she would refuse to accept a product at a certain price level, even though he or she would prefer that product offering over others which are even less desirable. Indication of refusal to accept is only explicitly present in discrete choice analysis which is discussed in the next section. Forecasting choice behavior based on conjoint data can only hypothesize that a respondent would actually purchase some of the product stimuli at certain price levels. Calculating the WTPs of an individual is usually done by offsetting the products prices to a status quo product. However, the estimation of the exchange rate between utility and price for all product stimuli and the assumption that all possible prices only rely on just one indicated status quo product and its price seems not very robust. We believe that it would be better to elicit more data points in order to fit the exchange rate between utility and price.

Discrete Choice Analysis

In discrete choice analysis the respondents choose between alternative product profiles (Ben-Akiva and Lerman, 1985; and McFadden, 1980, 1986). In a conjoint measurement context this is also referred to as choice-based conjoint analysis (cf. Louviere and Woodworth, 1983). The connection to conjoint analysis lies in the ability of both methods to decompose products into attribute levels and estimate part-worths for these levels. The difference lies in the underlying estimation methods (for a detailed discussion see, e.g. Louviere et al., 2000). Albeit, as further outlined below, recent developments allow individual level estimates as well, conventional discrete choice analysis tries to estimate a latent utility structure on the aggregate or segment level (see, e.g. mixture models as outlined in Wedel and Kamakura, 2000).

The utility structure is estimated based on a choice set, which is typically (but not necessarily) fixed across all respondents. Every choice can be fully described in terms of its attributes. The respondents are presented different alternatives and indicate which one they would actually choose. Often the respondents are provided a no-choice alternative, to indicate that they would not choose any of the presented product profiles (cf. DeSarbo et al., 1995; and Haaijer et al., 2001).

A latent preference for every choice in the evoked set is assumed to exist at the aggregate (or segment) level. The evoked set refers to the set of possible products or brands the respondent is currently considering in the decision process. This latent preference is estimated based on choices between different product profiles the participants make during the analysis. For every participant the utility value for a choice is modeled consisting of a deterministic component, that represents the latent preference structure at the aggregate level, and a random component. The random component is due to fluctuations in perceptions, attitudes, or other unmeasured factors (McFadden, 1986). Depending on whether the random component is normally or logarithmically distributed, the model is referred to as a probit-model or a logit-model. The more common model is the logit model.

Based upon random utility theory, the utility that an individual i assigns to some alternative can be described as

$$U_i = V_i + \varepsilon_i .$$

In this notation U_i is the unobservable, but true utility of alternative i. V_i is the observable or systematic component of utility and ε_i is the random component.

Price is included as an attribute of the product profiles and the levels cover the range of the possible and meaningful prices. The probability for the choice for a specific alternative i from a specific choice set can be described by the multinomial logit model

$$P_C(i) = EXP(V_i) / \sum_{j \in C} EXP(V_j).$$

"In this model, $C = \{1, 2, ..., M\}$ denotes a set of available alternatives, indexed from 1 to M, and P is the probability that an individual when presented with this set will choose alternative i" (McFadden, 1986). Note that V does not depend on the individual. This parameter describes the latent preference structure of the population. The unknown parameters V_j for all alternatives $j \in C$ are typically estimated from the data by the maximum likelihood procedure. The probability for a product P_C is used as a market-forecast and can be viewed as the potential market share.

Since part-worths for different prices are estimated, a change in price can be expressed in terms of change in utility and exchange rate between utility and price can be calculated. Given this exchange rate, the WTP for any product profile relative to the most preferred choice in an individual's evoked set can be calculated. An example of an empirical study using this approach can be found in Balderjahn (1991). A comparison between ratings-based conjoint analysis and discrete choice analysis can be found in Elrod and Louviere (1992). The authors find little difference between the two methods with respect to predictive validity on holdouts.

From the estimation procedure described above we see that discrete choice modeling aims at estimating preference structure at the aggregate level. In this approach it is not possible to directly estimate part-worths at the individual level because usually too few data points are elicited for each respondent. This is due to the fact that the observation of a choice out of an evoked set only contains information about the chosen product and not about the remaining products. This is different in conjoint analysis in which a ranking or rating of all products is provided by the respondent.

However, recent improvements of powerful Markov Chain Monte Carlo simulation methodologies have been shown to successfully alleviate the estimation problems of individual level part-worths (and hence also WTP) in a number of discrete choice type studies (cf., e.g., Allenby and Ginter, 1995; Lenk et al., 1996).

Comparison of Methods

Many authors have compared competing approaches to WTP measurement. A brief summary of their findings is reported in the following. An early comparison between direct surveys eliciting WTP, conjoint analysis using ranking, and conjoint analysis using rating was performed by Kalish and Nelson (1991). The experiment was conducted among undergraduate and first year graduate students of different business classes. The authors tested the three approaches in terms of their predictive validity on holdout products. The products of the experiment were airline tickets described by the non-price attributes service level, seating room, and non-stop. In the direct survey the respondents were asked to state their WTP for different product configurations. WTP was explained to the students as the amount of money that would make them indifferent between purchasing the ticket and keeping the money. For the two conjoint approaches prices covering the usual range of typical prices in the market were used. For the ranking the students were asked to bring the products into a preference order, for the rating the students were asked to distribute a number of rating points over the presented products. The main goal of Kalish and Nelson's experiment was to test for internal validity by predicting holdout products. At the end of every survey the participants were presented four product profiles (so-called holdouts) with assigned prices and were asked to indicate their preferred choice. The predicted choices derived from the data of the three surveys were compared to the actual choices of the respondents. The predictive validity of the conjoint models based on rankings as well as the model based on ratings clearly outperform the model fit from the directly elicited WTPs. 62% of the first choices were correctly predicted in the two conjoint approaches compared to only 46% for the direct survey. The authors find that directly surveying WTP "is not as robust to respondent involvement as are ranks or ratings" (Kalish and Nelson, 1991).

More recently, researchers tested different approaches to WTP estimation for external validity. Sattler and Nitschke (2003) performed an empirical comparison of the methods direct survey, conjoint analysis, first-price auction, and Vickrey auction. The authors elicited WTP for different prepaid telephone cards among students. Each of the students was exposed to all four instruments in random order. Based upon the WTP estimates derived from the four instruments, Sattler and Nitschke systematically tested for differences. Furthermore, they tested for external validity by requiring a sub-sample of respondents for each instrument to actually purchase the telephone card at the indicated WTP. All approaches except the two auction mechanisms show significant pairwise differences in estimated WTPs. The results of the study indicate that WTP is systematically higher in hypothetical settings where the subjects do not have to make a purchase at the end. In real settings, with a purchase at the end, the estimated WTPs are systematically lower. These findings are consistent with other studies, for example by Harrison and Rutström (2004) and Wertenbroch and Skiera (2002). Sattler and Nitschke discover this bias for the methods conjoint analysis, ascending auction, and Vickrey auction. Also in the setting with the real purchase at the end, the estimated WTPs exhibit significant pairwise differences between the four methods. The authors draw the conclusion that one cannot decide which method mimics real market best and thus should be advised for use.

In a different study Backhaus and Brzoska (2004) used a Vickrey auction to test external validity of WTPs estimated by a conjoint procedure and by discrete choice analysis. The authors assume that the Vickrey auction is feasible to elicit true product valuations and therefore can be used to test hypothetical procedures for external validity. For the conjoint procedure a Limit-card (as described above) was used. The object of their study is a selection of four different DVD players for which the subjects could place bids in a Vickrey auction after completing one of the two interviews. Backhaus and Brzoska constructed a price-response curve for each player from the observed bidding data as well as from the data elicited by conjoint analysis and by discrete choice analysis. A comparison showed that the two hypothetical procedures substantially overestimated the WTP for the participants of the experiment. At the aggregate level the overestimation by the conjoint approach was smaller than the overestimation by discrete choice analysis. However, at the individual level underestimations of WTPs also occurred which lessens the overestimation at the aggregate level. In a recent comparative study of a broad range of alternative approaches to WTP estimation conducted by Völckner (2005) significant and substantial differences between the derived WTP are reported depending on whether respondents had to pay the stated prices or not (revealed versus stated preferences in our classification system).

Conclusions and Managerial Implications

In the present paper different methods to estimate consumers' WTP have been discussed. The methods were classified into four groups: Analysis of market data, experiments, direct surveys, and indirect surveys. As discussed, all methods have specific theoretical as well as practical advantages and drawbacks, which we summarize in Table 2.

Market data represent customers' purchase behavior. Depending on whether the data are already available and on the size of the data set this can be a cost effective and time efficient method to estimate consumer's WTP. Since WTP estimates are derived from actual demand data, they are generally very reliable and reflect highly external valid results. In many practical situations, however, usage of market data is not appropriate for WTP estimation. In particular, for new or hypothetical products that are not yet available in the market there is no market data available. Equally, market prices frequently do not contain sufficient price variations to estimate demand at different price levels.

Table 2

Comparative evaluation of competing methods for measuring willingness-to-pay

	Market data	Experiments	Direct Surveys	Indirect Surveys	
				Conjoint Analysis	Discrete Choice Analysis (CBC)
Cost effective	+/-	--	++	+	+
Time efficient	+/-	--	++	+	+
Flexibility to include new price/product combinations	--	++	+/-	++	++
Validity of estimations	++	+/-	--	+	+
Real purchase behavior	++	+/-	--	--	--
Observed choice behavior	++	+	--	--	+
Individual level estimations	+/-	+/-	++	++	+

+ (++) = (strong) advantage
- (--) = (strong) disadvantage
+/- = no clear advantage or disadvantage
(depending on data-collection and/or estimation method)

By using experiments the above mentioned problems encountered with new products or insufficient price variations can be overcome. In this approach, WTP for different products is also estimated by observing purchase behavior, but in an experiment the products and prices are easily adaptable such that the participants are opposed with the necessary price variations. Depending on the setup, the participants are more or less aware that they are participating in an experiment which might result in biased estimates and loss of external validity (cf. Völckner, 2006). Practical disadvantages related to experiments are the associated expenditures and time needed which makes them less suitable for many practical application contexts.

In general, surveying techniques will be the preferred methodological approach when the manager is facing monetary and/or time constraints. This can be the case when consumer reactions need to be collected as repeated measurements or the results are required to be available quickly. Surveys are also very flexible when product features need to be varied and when a larger set of possible prices need to be tested. In surveys the respondents state their choice or desire for a number of products. Since, in general, real purchase behavior remains unobserved WTP estimates derived from survey data can be typically considered to exhibit a lower degree of validity as compared to, e.g., WTP estimated from market data. Direct surveys require the respondents to (directly) state how much he or she is willing to pay for a specific product or bundle of attributes. Naturally, this approach has a number of possible biases. For example, it is often difficult to state a WTP for an unfamiliar product. WTP also tends to be sometimes overstated because of prestige effects or understated due to consumer collaborations effects to keep the prices low.

In many real-world applications, indirect survey approaches turn out to be the method of choice for WTP estimation, because they usually exhibit both higher internal and external validity. Using indirect approaches the respondents are confronted with a number of different products (or attribute combinations) with assigned prices and have to choose the most preferred one or are involved in a task to rank or rate the offered combinations of products and prices. Based upon the choices the respondents make (or the applied rank order) WTPs for the different products can be estimated by statistical techniques.

Among indirect surveys, two groups of approaches, namely conjoint analysis and discrete choice analysis (also referred to as choice based conjoint), are available for marketing analysts to estimate WTP. Most of the available methods for conjoint analysis typically are capable to estimate WTP for the respondents at the individual level based on every respondent's data. Generally, WTP estimation at the individual level is particularly important if the price-sensitivity in the market under study is assumed to be heterogeneous. In discrete choice analysis WTP is traditionally estimated at the segment or sample level. Notice, however, that with the diffusion of advanced empirical Bayesian estimation techniques, individual level estimates becomes feasible also in a choice-based conjoint context. Using commonly available statistical software, WTP estimation based on data collected within a discrete choice task currently remains to be more expertise demanding and therefore also more time-consuming than estimations based on ordinary conjoint data.

In conjoint analysis, individual level WTP is estimated based on each respondent's data only. But in contrast to the no-purchase option in discrete choice analysis, in the classical conjoint analysis approach the respondent typically is not asked whether he or she would actually buy a product. With respect to the presentation technique to the respondent, this is regarded as the main disadvantage of conjoint analysis compared to discrete choice analysis. Letting the respondent choose rather than rate or rank mimics real purchase behavior more closely.

To estimate product choice probabilities at different prices based on conjoint data marketers usually assume the existence of a (preferred) status quo product. Furthermore, the respondents of the interview are a priori assumed to buy this product. The WTP for a competing product is then estimated as the price at which the respondent would switch away from the status quo product. With this set of assumptions, WTP cannot be estimated for customers who would actually not buy the status quo product in the first place or have a different (unknown) status quo product. To circumvent this problem, respondents can be allowed to select their individual status quo product themselves.

The gray area in Table 2 (above) shows that the two indirect surveying methods have complementary strengths. In discrete choice analysis, product choice probabilities are estimated the aggregate level and with HB individual level choices can be regained. In conjoint analysis, the preference structure is estimated for each respondent individually but choice behavior is not elicited and price only enters as an additional attribute.

A modified approach that combines the relative strengths of both methods in a two-step interview approach can proceed as follows:

1. A regular conjoint analysis using non-price attributes only is performed to estimate the respondent's individual utility structure. This avoids the above discussed issues with using price as an attribute while exploiting the methodological strength of easily estimating individual utility structures.
2. WTP for product profiles is estimated in a choice-based interview scene (including a no-purchase option). The respondent is presented a sequence of dynamically selected product profiles with associated prices based on the previously determined utility structure. With a suitable search algorithm, one can find several (at least 2) points in the utility-price space where the respondent is indifferent between buying and not buying the presented product. Based upon these datapoints, a model can be estimated (for example a simple linear model by least-squares fitting) that maps the utility of each product profile on a price scale, which represents the individual's WTP for the product.

This new hybrid approach eliminates the shortcomings while combining the strengths of the currently mostly used conjoint and choice based methods. A first implementation of such a hybrid approach is discussed in Breidert et al. (2005).

Our previous discussion revealed that, in general, each method has its specific merits and limitations. Choosing a suitable method depends on the managerial task underlying the estimation of WTP and is influenced by both conceptual considerations (e.g., if individual estimates are required or not) and practical restrictions (e.g., time and budget availability). With a particular emphasis on conjoint-based methods this article provides a thorough review of available approaches for measuring WTP, evaluates their strengths and limitations and therefore provides marketing managers with a basis for selecting an appropriate method.

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