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Using discrete choice experiments to estimate willingness-to-pay intervals

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Abstract Willingness-to-pay has always been conceptualized as a point estimate, frequently as the price that makes the consumer indifferent between buying and not buying the product. In contrast, this article estimates willingness-to-pay (WTP) as an interval based on discrete choice experiments and a scale-adjusted latent-class model. The middle value of this interval corresponds to the traditional WTP point estimate and depends on the deterministic utility; the range of the interval depends on price sensitivity and the utility's error variance (scale). With this conceptualization of WTP, we propose a new measure, the attractiveness index, which serves to identify attractive consumers by combining knowledge about their price sensitivities and error variances. An empirical study demonstrates that the attractiveness index identifies the most attractive consumers, who do not necessarily have the largest WTP point estimates. Furthermore, consumers with comparable preferences can differ in their purchase probability by an average of 16%, as reflected in differences in their WTP intervals, which yields implications for more customized target marketing.

Keywords Willingness-to-pay · Willingness-to-pay intervals · Discrete choice experiments · Scale heterogeneity

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1 Introduction

To set sensible prices, marketers require detailed knowledge about the willingness-to-pay (WTP) of their consumers. It is therefore not surprising that a lot of research has focused on WTP determinants and estimations (e.g., Jedidi and Zhang 2002; Miller et al. 2011; Wertenbroch and Skiera 2002), traditionally by regarding WTP as a point estimate that reflects the reservation price that makes consumers indifferent between buying and not buying a product (Eggers and Sattler 2009; Moorthy, Ratchford, and Talukdar 1997). Yet Wang, Venkatesh, and Chatterjee (2007) and Dost and Wilken (2012) have argued that WTP should be understood not as a single point but as an interval. Their idea is that consumers rarely know with certainty the amount they are willing to pay; instead, they draw from a distribution of WTP to make decisions. The authors therefore conclude that a definition of WTP should be linked to the consumer's probability of purchase, which implies that an interval estimate would more meaningfully and accurately represent WTP.

Wang, Venkatesh, and Chatterjee (2007) further propose to estimate WTP intervals using a procedure that directly asks consumers for three different kinds of WTP (reservation prices): the price at which he or she would buy with some certainty, which represents the lower end of the WTP interval (also called the floor reservation price); a price at which the consumer is indifferent between buying and not buying (indifference reservation price); and the price at which he or she would be rather certain to refuse to purchase the product, which represents the upper end of the WTP interval (ceiling reservation price). Similar methods that incorporate consumer uncertainty in WTP measures appear in environmental economics literature as closed-ended contingent valuations (for an overview, see Shaikh, Sun, and Cornelis van Kooten 2007).

Yet, these methods all focus on stated preferences, with additional questions asked during the data collection process. In particular, respondents must give probability statements about their purchase likelihoods (e.g., "Please reveal a price at which you are only 10% likely to buy the bar of chocolate"), which may be problematic, considering that prior research has shown that even highly educated people perform poorly when they must solve a basic probability problem or convert a percentage to a proportion (Lipkus, Samsa, and Rimer 2001). In addition, these approaches do not disentangle the size of the WTP intervals into separate effects of choice uncertainty versus price sensitivity. We show that such disentanglement enables marketing managers to decide which segmentation or communication strategy to use.

Accordingly, this article aims to (1) link WTP intervals to utility theory and choice models through a framework that disentangles preferences and choice uncertainty, (2) present an alternative approach to estimating WTP intervals that can be applied to stated and revealed preferences, and (3) develop an attractiveness index that combines knowledge about WTP point estimates and WTP interval estimates and helps identify the most attractive consumers in the market. Because we use a well-established discrete choice method, our results enable researchers to obtain WTP intervals directly, without having to modify the data collection process.

We organize the remainder of this article as follows: In Section 2, we motivate the consideration of WTP intervals with a stylized example. Section 3 outlines our approach for measuring WTP intervals and introduces the attractiveness index. We present an empirical study in Section 4 to demonstrate the value of using WTP intervals. Section 5 concludes.

2 Usefulness of WTP intervals

We describe a simple numerical example with two consumer segments to outline the usefulness of WTP intervals, as well as the insights that individual differences in consumers' choice uncertainty may provide. Assume that consumer segments A and B have a WTP of \$50 and \$52, respectively, and that segment B is four times more consistent in its choices (see Fig. 1a). A traditional interpretation of WTP would suggest that a marketing manager, who has restricted targeting capabilities and can only target one of the two segments, will choose segment B, with its higher WTP.

However, Fig. 1b reveals that a traditional understanding of WTP fails to capture differences in choice uncertainty between the segments. Segment B's purchase probability density function is much steeper than that of segment A, due to the higher consistency of segment B. Willingness-to-pay intervals, as illustrated in Fig. 1c, capture these differences in choice uncertainty. Segment B's WTP interval (i.e., prices at which the segment buys with purchase probabilities in the range [90%; 10%]) is four times smaller than that of segment A, which means that segment B is less likely to buy the product if its price exceeds, even by very small amounts, its average WTP. Figure 1d depicts the application of an attractiveness index *K* (defined in Section 3),

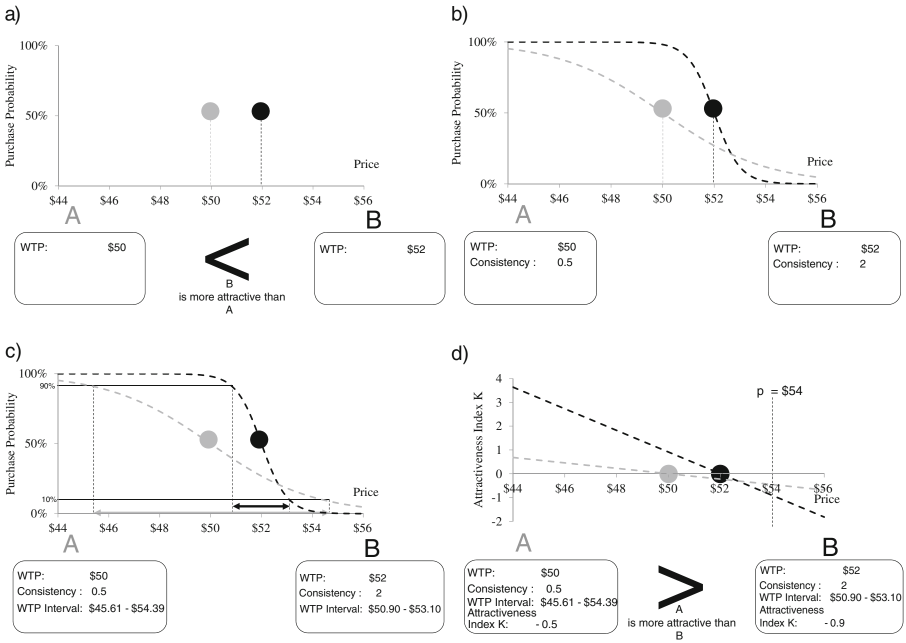

Fig. 1 Illustrative example of willingness-to-pay intervals

which combines the knowledge of WTP intervals and WTP point estimates.[1] With this attractiveness index, we can see that, at a price of $54, for example, segment A is actually more attractive as a target than is segment B.

The attractiveness index K also provides valuable insights for product managers who want to understand the relation between preferences and choice randomness and their effects on purchase probabilities. For high-preference consumers, the attractiveness index K is larger in the case of low randomness and thus should be preferred. In contrast, for low preference consumers, it is larger in the case of high randomness, because they are more likely to purchase, even though their WTP point estimate is below the asking price.

3 Method

Our proposed method is suitable for any type of choice data and can be applied to both stated preference data, e.g., obtained from online surveys, and revealed preference data, frequently offered by market research companies, for example, in form of household purchase histories. We illustrate our method using discrete choice experiments, in which consumers consider different choice sets in which they must choose among different choice alternatives as well as a no-purchase option.

3.1 Willingness-to-pay point estimator in the presence of scale heterogeneity

When analyzing discrete choice data, a researcher typically assumes that consumer h associates utility $u_{h,i}$ with product i and that the consumer has a budget Y_h. The consumer splits that budget between product i and $z_{h,i}$ units of another product that is not observed (i.e., outside good). The utility of product i is usually obtained by multiplying the design vector X_i by the vector of preferences β_h of consumer h. The utility of the outside good is assumed to be given by $\varpi_h \cdot z_{h,i}$, where ϖ_h can be interpreted as the price parameter. The direct utility function is then:

$$u_{h,i} = X_i \cdot \beta_h + \varpi_h \cdot z_{h,i}\,(\mathrm{h} \in \mathrm{H}, \mathrm{i} \in \mathrm{I}) \quad (1)$$

The budget Y_h can be spent on product i at a price p_i and on $z_{h,i}$ units of the outside good with a price normalized to 1. Assuming that a consumer fully spends this budget, the associated budget constraint is:

$$Y_h = p_i + z_{h,i}\,(\mathrm{h} \in \mathrm{H}, \mathrm{i} \in \mathrm{I}) \quad (2)$$

In addition, discrete choice modelers acknowledge the existence of an error term, added to the otherwise deterministic utility in Eq. 3 to capture the various, often unpredictable choices people make. Assuming Gumbel-distributed stochastic error terms ($\varepsilon_{h,i} \sim G \times (1/\lambda_h)$), we obtain a closed form solution for the choice probability $\Pr^a_{h,i}$. The scale (or error variance) λ_h of these Gumbel-distributed error terms reflects the uncertainty of individuals in their choices, where smaller variance implies lower choice uncertainty (Palma, Myers, and Papageorgiou 1994). Louviere et al. (2002) and Palma et al. (2008) note a

[1] For these illustrative purposes, it is sufficient to know that larger values of the index K indicate more attractive consumers. In this example, the attractiveness index is calculated on the basis of the choice probabilities for a particular product versus choosing not to purchase any product.

range of factors that could contribute to consumers' choice uncertainty; advances in choice modeling also propose different models to disentangle the impacts of preferences and error variances on choices (e.g., Fiebig et al. 2010; Magidson and Vermunt 2007). By considering this distinction between preferences and choice uncertainty, we derive the following choice probabilities in a choice set C_a of products:

$$\Pr^{a}_{h,i} = \frac{\exp(\lambda_h \cdot u_{h,i})}{\exp(\lambda_h \cdot u_{h,0}) + \sum_{i' \in C_a} \exp(\lambda_h \cdot u_{h,i'})} \quad (\mathrm{h} \in \mathrm{H}, \mathrm{i} \in \mathrm{I}) \tag{3}$$

The choice probability for a product i thus depends on the utility the product provides to consumer h, as well as the utilities of the competing products in the choice set. The estimation of WTP as a point estimate in discrete choice experiments builds on the ideas offered by Small and Rosen (1981), Moorthy, Ratchford, and Talukdar (1997), and Jedidi and Zhang (2002), namely, that WTP is the price at which a consumer is indifferent between buying and not buying a product. This equality implies that the utility of buying a product at a price equal to the consumer's WTP (or $\mathrm{WTP}_{\mathrm{h,i}}$) is as high as the utility of the no-purchase option, such that $u_{\mathrm{h,I}}=u_{\mathrm{h,0}}$. It also implies that the probability of a purchase at a price equal to the WTP is exactly 50%, and that the WTP point estimate can be expressed as:

$$WTP_{h,i} = \frac{X_i \cdot \beta_h}{\varpi_h} \quad (\mathrm{h} \in \mathrm{H}, \mathrm{i} \in \mathrm{I}) \tag{4}$$

which is independent of a respondent's error variance (or scale-parameter λ_{h}).

3.2 Willingness-to-pay intervals

In line with the preceding considerations, it is possible to derive WTP intervals instead of point estimates. The underlying idea for calculating WTP intervals is that choices take place with uncertainty and that consumer h is "rather certain" or "rather uncertain" about buying a particular product i at a given price (Wang, Venkatesh, and Chatterjee 2007). This level of uncertainty is represented by the probability with which a consumer chooses the product instead of the no-purchase option. Therefore, we can calculate the prices at which the consumer rather certainly starts or stops buying, as a function of the choice probability $WTP'_{h,i}(\Pr_{\mathrm{h,i}})$. The phrases "rather certain" and "rather uncertain" need further specification on the basis of concrete choice probabilities, such as, $\Pr^{\mathrm{UB}}=90\%$ and $\Pr^{\mathrm{LB}}=10\%$ (Wang, Venkatesh, and Chatterjee 2007), which then describe the upper and lower boundaries of the WTP interval:

$$WTP'_{h,i}[\Pr^{UB}; \Pr^{LB}] = \left[WTP_{h,i} - \frac{1}{\lambda_h \cdot \varpi_h} \ln\left(\frac{\Pr^{UB}}{1-\Pr^{UB}}\right); WTP_{h,i} - \frac{1}{\lambda_h \cdot \varpi_h} \ln\left(\frac{\Pr^{LB}}{1-\Pr^{LB}}\right) \right] \quad (\mathrm{h} \in \mathrm{H}, \mathrm{i} \in \mathrm{I}) \tag{5}$$

We provide details about the derivation of Eq. 5 in Appendix A. For our current discussion, we note that, if $\Pr^{\mathrm{LB}}<50\%$, the term $-\frac{1}{\lambda_h \cdot \varpi_h} \ln\left(\frac{\Pr^{LB}}{1-\Pr^{LB}}\right)$ is positive and represents the additional sum of money that a product may cost, beyond the WTP point estimate, such that it is purchased with a probability of $\Pr^{\mathrm{LB}}<50\%$. Similarly, given a choice probability $\Pr^{UB}>50\%$, the term $-\frac{1}{\lambda_h \cdot \varpi_h} \ln\left(\frac{\Pr^{UB}}{1-\Pr^{UB}}\right)$ becomes negative and reflects the discount necessary to obtain the choice probability $\Pr^{UB}>50\%$.

The midpoint of the WTP interval, which represents the WTP point estimate, depends on consumers' preferences, as well as their price parameter. The size of the WTP interval is determined by consumers' price parameter and the degree of consumer uncertainty. Greater choice uncertainty—that is, a lower scale λ_h—leads to larger WTP intervals, in theoretical support of the observation by Wang, Venkatesh, and Chatterjee (2007) that higher choice uncertainty increases WTP intervals. We finally note that the WTP interval has axial symmetry properties at the choice probability of 50%—a property also empirically observed in the direct WTP interval elicitation by Wang, Venkatesh, and Chatterjee (2007).

At this point, it is worth noting that our conceptualization of WTP intervals differs fundamentally from previous uses of the expression "WTP interval." In particular, we follow the conceptualization used by Wang, Venkatesh, and Chatterjee (2007), such that the boundaries of our WTP interval are defined according to different purchase probabilities for different prices. For example, a price of \$10 might be associated with a 90% purchase probability, a price of \$15 with a 50% purchase probability, and a price of \$20 with a 10% purchase probability. Therefore, the WTP [90%, 10%] interval for this particular product would be [\$10, \$20].

Our conceptualization differs from Bohm's (1984), Dubourg, Jones-Lee, and Loomes's (1994), or Park and MacLachlan's (2008). These authors suggest the use of different data sources (e.g., hypothetical and non-hypothetical decisions) to estimate consumers' WTP in different situations, and then recommend mixing those distributions. But different data sources rarely are available. Furthermore, our conceptualization differs from Swait and Erdem's (2007) effort to capture choice uncertainty using standard deviations of the estimated preference parameters. Their resulting WTP intervals come from sampling the prices at which the purchase probability equals 50% in the distributions of the preference parameters and calculating the standard deviations of these prices. We note that standard deviations may depend on the number of respondents or the number of observations per respondents though, such that the measured uncertainty mixes with the technical aspects of the data collection.

3.3 Attractiveness index

Our stylized example in Section 2 demonstrates the usefulness of WTP intervals for managerial decision making. However, that example cannot offer guidance about how companies should react to differences among WTP interval sizes and preferences. We introduce a new measure, the attractiveness index *K*, which outlines the attractiveness of individual consumers by summarizing the effects of differences in their utility assessments of competing products and differences in the WTP interval sizes (the formal derivation is in Appendix B).

We define the attractiveness index by the ratio Pr(A)/(Pr(A)+Pr(B)), which reflects the probability of choosing product A or B. Appendix B reveals that this probability is a continuous function of the attractiveness index $K_{AB,h}$, defined as:

$$K_{AB,h} = \frac{\left(CS_{h,A} - CS_{h,B}\right)}{Range_h} \quad (h \in H) \qquad (6)$$

where $CS_{h,A}=WTP_{h,A}-p_{h,A}$ and $CS_{h,B}=WTP_{h,B}-p_{h,B}$ are the consumer surpluses generated by products A and B, respectively. $Range_h$ denotes the size of the WTP interval and equals $WTP_{h,A}(Pr^{LB})-WTP_{h,A}(Pr^{UB})$. The numerator of Eq. 6 indicates monetary differences in the utility of both products (including price). This consumer-specific WTP interval size is defined by the consumer's price sensitivities and choice uncertainty.

The attractiveness index can prioritize targeting of individual consumers. The higher the consumer surplus for product A compared with product B, the higher is its probability of being chosen, that is, the more market share product A can gain. However, the attractiveness index $K_{AB,h}$ also points to another strategy that can lead to market share gains, namely purposefully influencing the consumer's uncertainty. Therefore, Eq. 6 offers a formal proof of the result we demonstrated numerically in Section 2: Because a larger attractiveness index $K_{AB,h}$ means higher market share for product A, we conclude that, for a positive numerator (i.e., product A is better than product B), the provider of product A should target consumers with a low WTP range (i.e., who are rather certain in their decisions or have a high price sensitivity). In contrast, if the consumer surplus of product A is less than product B and the numerator is negative, the provider of product A should target consumers with a rather high WTP range.

Beyond an enhanced understanding of available options in terms of a marketing strategy, the attractiveness index K can be exploited for targeting purposes. It provides a clear and simple decision rule to identify the most attractive consumers/segments, according to which ones have the highest index value (assuming equal purchase quantities across consumers).

4 Empirical study

In this empirical study, we demonstrate the managerial insights that can be gained from the use of WTP intervals and the attractiveness index. Relying only on WTP point estimates can be misleading for pricing decisions, and the concept of WTP intervals provides important insights for segmenting and targeting consumers.

4.1 Empirical study setup

The products considered in our study belong to the category of netbooks, which can be described by five attributes: brand (Acer, Samsung, and the fictitious Texxus), main memory (1 or 2 GB), display size (10.1 or 11.6 in.), hard drive (160 or 300 GB), and price (four levels, ranging from €229 to €399).

The questionnaire consisted of three sections: The first asked about the respondents' existing experience with computers and netbooks, their familiarity with netbooks, their knowledge about netbook prices, and their self-stated likelihood to purchase a netbook in the next 12 months, using seven-point Likert scales. The second section featured the discrete choice experiment, which used a D-efficient $(3 \cdot 2^3 \cdot 4)$–fractional factorial design with 13 choice sets. Each choice set included three netbooks and a no-purchase option, "I would not buy any of the three netbooks." We then asked respondents to rate the difficulty of the choice task on a semantic differential scale, as proposed by Bettman, John, and Scott (1986). Finally, in the third section, we asked for demographic information, such as gender and age. Using online survey software, we obtained 122 completed questionnaires, which is suitable for illustrating the benefits that WTP intervals and the attractiveness index provide.

4.2 Estimation

Without specific assumptions about the distribution of preferences or scales, we cannot identify the individual scale and can only estimate the products $\lambda_h \cdot \beta_h$ and $\lambda_h \cdot \omega_h$. However, as Swait and Louviere (1993), Swait and Andrews (2003), and Fiebig et al. (2010) argue, ignoring differences in the distributions of preferences versus error variances and assuming a normal mixing distribution, as is common in the mixed logit model, can lead to a seriously misspecified model. Louviere et al. (2002) propose estimating individual-level models to circumvent the need to specify a heterogeneity distribution for the product of the preferences and scale, though doing so poses stringent requirements on the data and cannot be used in every empirical setting. To overcome this limitation, Fiebig et al. (2010) introduce the generalized multinomial logit model (GMNL), which can estimate continuous consumer heterogeneity both for scale and preference parameters.

We use the scale-adjusted latent class (SALC) model proposed by Magidson and Vermunt (2007), a discrete version of the GMNL that offers an easier interpretation of parameter estimates by providing a segment solution. Covariates can link consumers to preference or scale segments, which in turn allows analysts to test the outcomes of different marketing strategies and then apply the most promising one. Both SALC model and GMNL can be applied to revealed and stated preference data, which enables calculations of WTP intervals in a wide range of contexts.

The SALC model assumes that the distributions of preferences and scales can be described by a finite number of preference classes L and a finite number of scale classes S, which together form L S classes. Different covariates, $v_h^{cov,pref}$ and $v_h^{cov,scale}$, explain membership in each class. The general probability density function associated with respondent h's choices across all A_h choice sets is given by

$$\Pr_h = \sum_{s \in S} \sum_{l \in L} \frac{\exp\left(\gamma_s \cdot v_h^{cov,scale}\right)}{\sum_{s'=1}^{S} \exp\left(\gamma_{s'} \cdot v_h^{cov,scale}\right)} \frac{\exp\left(\delta_l \cdot v_h^{cov,pref}\right)}{\sum_{l'=1}^{L} \exp\left(\delta_{l'} \cdot v_h^{cov,pref}\right)} \prod_{a \in A_h} \prod_{i \in C_a} \left(\Pr_{l,s,i}^{a}\right)^{d_{h,a,i}} (\mathrm{h} \in \mathrm{H}) \tag{7}$$

where $C_a = C_a^* \cup \{\text{no} - \text{purchaseoption}\}$ is choice set a that includes all alternatives (as well as the no-purchase option); $d_{h,a,i}$ is a binary variable that indicates whether alternative i was chosen by respondent h in choice set a; and the parameters γ_s and δ_l denote the multinomial logit parameters that drive scale and preference class membership, respectively.

4.3 Results

We estimate the SALC model with respondents' choices from 13 choice sets. All levels are effects coded, with the exception of the price, for which we assume a linear relationship. We allow for an influence of sociodemographic measures on consumers' choices and link preference class membership with respondents' ages and knowledge

Table 1 Comparison of different targeting approaches

	WTP Point Estimates	Rank (WTP Point Estimates)	Range of WTP Interval	Attractiveness Index K (price: 333.15 €)	Rank (Attractiveness Index)	Purchase Probability	
1L: Preference Class 1, low scale	369.49 €	5	248.27 €	0.15	6	66%	
1H: Preference Class 1, high scale	369.49 €	5	86.21 €	0.42	4	86%	+ 21%
2L: Preference Class 2, low scale	627.27 €	1	499.37 €	0.59	3	93%	
2H: Preference Class 2, high scale	627.27 €	1	173.39 €	1.70	1	100%	+ 7%
3L: Preference Class 3, low scale	380.79 €	3	216.48 €	0.22	5	72%	
3H: Preference Class 3, high scale	380.79 €	3	75.17 €	0.63	2	94%	+22%
4L: Preference Class 4, low scale	200.69 €	7	305.17 €	-0.43	7	13%	
4H:Preference Class 4, high scale	200.69 €	7	105.96 €	-1.25	8	0%	-13%

about netbooks' current market prices. The former covariate may affect the general preference structure; the latter can identify consumers who are more price-sensitive.

Swait and Adamowicz (2001) argue that perceived task difficulty influences choice consistency. We therefore test whether self-stated difficulty, respondents' familiarity with the category, or the time it takes to complete choice tasks may explain differences in respondents' choice uncertainty. Only the self-stated task difficulty is weakly significant ($p<0.1$), the latter two factors have no significant impacts ($p=0.27$, $p=0.71$) on scale class membership, so we refrain from reporting them. There might be other factors that influence scale and preference class membership; however, the sole purpose of our analysis is to demonstrate that WTP intervals can be used to segment and target consumers effectively.

We identify four preference classes (sizes, 49.85%, 24.57%, 13.16%, and 12.42%) and two scale classes (sizes, 54.52% and 45.48%) as the optimal solution, according to the Bayesian information criterion. Both scale classes vary substantially in their error variances, and the second, smaller scale class is almost three times as consistent as the first ($\lambda_2/\lambda_1 = 2.88$; detailed parameter estimates appear in Table 2 in Appendix C). The substantial differences in the sizes of the two scale parameters and the four preference classes, with their specific price sensitivities, lead to eight WTP intervals that vary substantially in size, from 75.17€ to 499.37€ (see Eq. B.3 and Table 1).

Covariates can partly explain both memberships in specific preference classes and in specific scale classes; respondents with high knowledge of market prices are more likely to belong to preference class 1, which also assigns the greatest importance to price among all attributes. Scale class membership can be predicted partly by the perceived difficulty of the task: The more difficult a respondent perceives the task to be, the more likely he or she belongs to the scale class with the high error variance (see Table 2 in Appendix C).

4.4 Managerial benefits of WTP intervals

We use these results to outline the usefulness of WTP intervals and the attractiveness index. In a simplified example, we consider a situation in which the manufacturer ACER might offer a netbook with 2 GB memory, 300 GB storage capacity, and a display size of 11.6″. We assume the variable costs are 100€. For simplicity and to reflect market realities, such as legal constraints or consumers' objections to price discrimination, we further assume that the company engages in no price discrimination and charges the profit-maximizing price of 333.15€ (see Appendix D). In Table 1, we report the WTP for each segment, the range of the WTP interval, and the attractiveness index K in this example. It also provides the best sequence for prioritizing consumers, using both a naive ranking that only considers WTP point estimates and the corrected ranking using the attractiveness index *K*.

As Table 1 illustrates, conflicting recommendations result from the differences in the WTP point estimates and the attractiveness index *K*. Targeting based on differences in WTPs would identify preference class 2 (2 L+2 H) as the most attractive, followed by preference class 3 (3 L+3 H) (see the third column of Table 1). Yet this targeting sequence fails to take into account the differences in the degree of choice uncertainty, as reflected in the size of the WTP intervals and the associated attractiveness index (see Fig. 1 in Section 2).

By taking those differences into account and thus balancing between price sensitivity and choice uncertainty, we obtain a different targeting sequence (sixth column of Table 1): Consumers with a high scale in preference class 2 (2 H) should be targeted first, then consumers with a high scale in preference class 3 (3 H), and so on. In addition to providing a full ranking of all preference/scale class combinations, the attractiveness index can identify more attractive consumers within each preference class. This identification increases purchase probabilities in preference class 1 by 21% (i.e., the increase in purchase probability by addressing 1 H instead of 1 L), in class 2 by 7%, and in class 3 by 22%, and in class 4 by 13%; with the average absolute increase in purchase probability equaling 16%.

5 Summary

Wang, Venkatesh, and Chatterjee (2007) and Dost and Wilken (2012) have recently argued that WTP intervals, rather than WTP point estimates, can better depict the uncertainty with which consumers make purchase decisions. The authors construct these WTP intervals using three questions to assess the prices at which respondents are almost certainly going to purchase the product, at which they are indifferent between buying and not buying, and at which they are almost certainly not going to purchase.

We show, for the first time, how discrete choice models enable estimates of WTP intervals. Our proposal provides a substantial advantage, in that respondents do not need to answer additional questions, and the approach is applicable for both stated and revealed preferences. Reviewing recent discussions on scale heterogeneity in choice modeling, we formally illustrate the impact of differences in consumers' error variances on the size of their WTP intervals.

We further derive an attractiveness index *K* that summarizes the attractiveness of each consumer as a single number, because we trade off between the strength of a product and the amount of choice uncertainty. The results of our empirical study suggest that this attractiveness index can easily identify the most attractive consumers, which increases purchase probability by an average of 16%.

The attractiveness index also shows that companies with products that, at the respective prices, are better than competitive offers should try to reduce consumers' uncertainty. To do so, they might rely on advertising campaigns that clearly outline the benefits of the product over competitive options. They also could strategically influence opinions about a product with a targeted product sample campaign in social networks (e.g., Marks and Kamins 1988). In contrast, if the product is associated with lower preferences, the company benefits from greater uncertainty. Nordgren and Dijksterhuis (2009) demonstrate that it is possible to purposely increase uncertainty by adding new, irrelevant information, which distracts consumers' attention from relevant information.

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Appendix

A. Derivation of willingness-to-pay intervals

The underlying idea for calculating WTP intervals is that choices are made with uncertainty and that a consumer h is "rather certain" or "rather uncertain" about buying a particular product i at a given price. In a logit model, this level of uncertainty is represented by the probability with which a consumer chooses the product over the no-purchase option. The choice probability $\mathrm{Pr}_{\mathrm{h,i}}$ can be derived analogously to Eq. 3 as follows:

$$\mathrm{Pr}_{h,i} = \frac{\exp\left(\lambda_h \cdot X_i \cdot \beta_h + \lambda_h \cdot \varpi_h \cdot \left(Y_h - p_{h,i}\right)\right)}{\exp(\lambda_h \cdot \varpi_h \cdot Y_h) + \exp\left(\lambda_h \cdot X_i \cdot \beta_h + \lambda_h \cdot \varpi_h \cdot \left(Y_h - p_{h,i}\right)\right)} \quad (\mathrm{h} \in \mathrm{H}, \mathrm{i} \in \mathrm{I}) \qquad (A.1)$$

Different levels of error variance in consumers' choices lead to more or less extreme choice probabilities. The insertion of Eq. 4 into Eq. A.1, solving for price $p_{\mathrm{h,i}}$, leads to:

$$p_{h,i} = WTP_{h,i} - \frac{1}{\lambda_h \cdot \varpi_h} \ln\left(\frac{\mathrm{Pr}_{h,i}}{1 - \mathrm{Pr}_{h,i}}\right) (\mathrm{h} \in \mathrm{H}, \mathrm{i} \in \mathrm{I}) \qquad (A.2)$$

To determine WTP intervals, we solve for prices that yield the corresponding choice probabilities of the interval boundaries. These choice probabilities denote the prices at which the consumer rather certainly starts or stops buying. The phrase "rather certainly" needs further specification with concrete choice probabilities, such as $\mathrm{Pr}^{\mathrm{UB}}$=90% and $\mathrm{Pr}^{\mathrm{LB}}$=10% (Wang, Venkatesh, and Chatterjee 2007). The price $p_{\mathrm{h,i}}$ is then a function of the choice probability $WTP'_{h,i}$ ($\mathrm{Pr}_{\mathrm{h,i}}$), and Eq. A.2 yields:

$$WTP'_{h,i}\left(\mathrm{Pr}_{h,i}\right) = p_{h,i} = WTP_{h,i} - \frac{1}{\lambda_h \cdot \varpi_h} \ln\left(\frac{\mathrm{Pr}_{h,i}}{1 - \mathrm{Pr}_{h,i}}\right) (\mathrm{h} \in \mathrm{H}, \mathrm{i} \in \mathrm{I}) \qquad (A.3)$$

From Eq. A.3, we can define a WTP interval as follows:

$$WTP'_{h,i}\left[\mathrm{Pr}^{UB}; \mathrm{Pr}^{UB}\right] = \left[WTP_{h,i} - \frac{1}{\lambda_h \cdot \varpi_h} \ln\left(\frac{\mathrm{Pr}^{UB}}{1 - \mathrm{Pr}^{UB}}\right); WTP_{h,i} - \frac{1}{\lambda_h \cdot \varpi_h} \ln\left(\frac{\mathrm{Pr}^{UB}}{1 - \mathrm{Pr}^{UB}}\right)\right] (\mathrm{h} \in \mathrm{H}, \mathrm{i} \in \mathrm{I}) \qquad (A.4)$$

where $\mathrm{Pr}^{\mathrm{UB(LB)}}$ is the probability for the upper (lower) limit of the WTP interval.

B. Derivation of the attractiveness index

We formally derive a new measure, the attractiveness index *K*, to depict the attractiveness of individual consumers by summarizing the effects of differences in the utility of competing products and different sizes of WTP intervals. Therefore, we consider the ratio Pr(A)/(Pr(A)+Pr(B)), which is the probability of choosing product A or B and rearrange it as:

$$\frac{\mathrm{Pr_h(A)}}{\mathrm{Pr_h(A)+Pr_h(B)}}=\frac{\exp\left(\lambda_h\times\omega_h\times\left(\mathrm{WTP_{h,A}}-\mathrm{WTP_{h,B}}\right)-\lambda_h\times\omega_h\times\left(\mathrm{p_{h,A}}-\mathrm{p_{h,B}}\right)\right)}{\exp\left(\lambda_h\times\omega_h\times\left(\mathrm{WTP_{h,A}}-\mathrm{WTP_{h,B}}\right)-\lambda_h\times\omega_h\times\left(\mathrm{p_{h,A}}-\mathrm{p_{h,B}}\right)\right)+1}\ (\mathrm{h}\in\mathrm{H}) \tag{B.1}$$

Given Eq. A.3 and the axial symmetry property, the range of the WTP interval for consumer h can be calculated as:

$$\mathrm{Range}_h=\frac{1}{\lambda_h\cdot\omega_h}\cdot\ln\left(\frac{\mathrm{Pr^{UB}}}{1-\mathrm{Pr^{UB}}}\right)-\frac{1}{\lambda_h\cdot\omega_h}\cdot\ln\left(\frac{\mathrm{Pr^{LB}}}{1-\mathrm{Pr^{LB}}}\right)(\mathrm{h}\in\mathrm{H}) \tag{B.2}$$

Using the axial symmetry property we discussed in Section 3.2, we also simplify this range:

$$\mathrm{Range_h}=\frac{2}{\lambda_h\cdot\omega_h}\cdot\ln\left(\frac{\mathrm{Pr^{UB}}}{1-\mathrm{Pr^{UB}}}\right)(\mathrm{h}\in\mathrm{H}) \tag{B.3}$$

If we then substitute Eq. B.3 into Eq. B.2, we obtain:

$$\frac{\mathrm{Pr_h(A)}}{\mathrm{Pr_h(A)+Pr_h(B)}}=1-\frac{1}{\exp\left(2\times\ln\left(\frac{\mathrm{Pr_h^{UB}}}{1-\mathrm{Pr_h^{UB}}}\right)\times\frac{\left(\mathrm{WTP_{h,A}}-\mathrm{WTP_{h,B}}\right)-\left(\mathrm{p_{h,A}}-\mathrm{p_{h,B}}\right)}{\mathrm{Range_h}}\right)+1}(\mathrm{h}\in\mathrm{H}) \tag{B.4}$$

The first term in the exponent of the denominator is constant for all consumers. Thus, the difference in probabilities between two products A and B is influenced only by the attractiveness index ($K_{\mathrm{AB,h}}$), such that a higher attractiveness index is associated with a higher purchase probability for product A:

$$K_{\mathrm{AB,h}}=\frac{\left(\mathrm{WTP_{h,A}}-\mathrm{WTP_{h,B}}\right)-\left(p_{\mathrm{h,A}}-p_{\mathrm{h,B}}\right)}{\mathrm{Range_h}}(\mathrm{h}\in\mathrm{H}) \tag{B.5}$$

C. Parameter results

We next report the details of the parameter estimates of the models. We identify four preference classes and two scale classes as the optimal solution, according to the Bayesian information criterion (BIC). The scale-extended version substantially improves the BIC from a value of 2,604 using the traditional finite mixture choice model to 2,567 with the SALC model. Table 2 reports the estimates of the SALC model.

Table 2 Results of scale-adjusted latent class (SALC) model

					Results			
	Scale class 1	Scale class 2			Wald	*p*-Wert	Wald(=)	*p*-Wert
Scale parameter	1.00	2.88***			63.77	0.00		
Covariates								
Constant	−0.51	0.51			1.58	0.21		
Difficulty	0.25*	–0.25*			2.66	0.10		
Segment size	54.52%	45.48%						
	Preference class 1	Preference class 2	Preference class 3	Preference class 4	Wald	*p*-Wert	Wald(=)	*p*-Wert
Constant	5.46***	3.48***	3.71***	1.03	120.37	0.00	14.08	0.00
Brand					54.60	0.00	40.01	0.00
Acer	0.10**	−0.05	−0.14	0.04				
Samsung	0.39***	−0.04	0.20	0.69**				
Texxus	−0.48***	0.08	−0.06	−0.73				
Main memory					113.57	0.00	48.77	0.00
1 GB	−0.33***	−1.26***	−1.94***	−0.53*				
2 GB	0.33***	1.26***	1.94***	0.53*				
Display size					47.47	0.00	48.77	0.00
10.1″	−0.35***	−0.04	−0.31	−0.84**				
11.6″	0.35***	0.04	0.31	0.84**				
Storage capacity					114.34	0.00	33.30	0.00
160 GB	−0.30***	−0.79***	−1.91***	−0.45**				
300 GB	0.30***	0.79***	1.91***	0.45**				
Price (per 100 €)	1.77***	0.88***	2.03***	1.44***	283.34	0.00	13.27	0.00
Covariates								
Constant	3.77***	−1.64	−0.36	−1.77	18.56	0.00		

Table 2 (continued)

Price knowledge	−0.62**	0.06	0.46*	0.10	12.09	0.01
Age	−0.03*	0.05***	−0.06*	0.03	10.83	0.01
Segment size	49.85%	24.57%	13.16%	12.42%		
Attribute importances						
Brand	18.27%	2.49%	3.10%	21.42%		
Main memory	13.82%	47.76%	35.64%	15.93%		
Display size	14.68%	1.56%	5.66%	25.21%		
Storage capacity	12.53%	29.80%	35.05%	13.63%		
Price (per 100 €)	40.70%	18.39%	20.55%	23.82%		

*$p<0.1$; **$p<0.05$;***$p<0.01$, with significance based on these z-values

D. Profit-maximizing price

Assuming no price discrimination across segments, the profit-maximizing price p_i* can be calculated as the price that maximizes the profit in each segment, multiplied by the segment *s*–specific probability $Pr_{s,i}$ of purchasing product i (see also Miller et al. 2011):

$$\max \pi_i = \sum_{s \in S} (p_i - c_v) \cdot \mathrm{Pr}_{s,i}(p_i) \ (\mathrm{i} \in \mathrm{I}) \quad \text{(D.1)}$$

Profit is the difference between the price and the variable costs, multiplied by the probability in each segment of purchasing at price p_i. Because $Pr_{s,i}$ contains all information inherent to the calculation of WTP point estimates, WTP intervals, and attractiveness indices, using the attractiveness index to determine the optimal price will not change the optimal price compared with previous approaches (e.g., Miller et al. 2011).

Equation D.1 also is consistent with random utility theory, but it differs from the model used in Jedidi and Zhang (2002). They state that a respondent will choose product A over product B if and only if the difference between his or her WTP for product A and its price is greater than that same difference for product B. With random utility theory, a purchase of product B would be allowed, but the probability of making the purchase would be less than 50%.

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