A CBC-approach accounting to screening from both sides

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Abstract:

In the literature on consumer behaviour, a two-stage decision process in choice situations is often assumed, whereas in choice-based conjoint analysis (CBC) a linear utility function - which mirrors a compensatory decision rule - is regularly applied. Gilbride and Allenby (2004) introduced a model, wherein individuals first screen out alternatives that do not meet minimum values for every attribute, followed by a choice between the remaining ones using a compensatory rule. We extend this approach by considering not only minimum values in the screening step, but also maximum values. Using three real-world data sets of CBC, we compare this extension with the model proposed by Gilbride and Allenby, as well as the basic compensatory model.

The results indicate that the two-sided screening is applied especially to prices. Both screening rules, while showing almost identical performance, improve on the linear compensatory model on fit and predictive validity.

Keywords: *conjunctive screening rule, two-sided screening, two-step decision process*

Track: *Consumer Behaviour*

1. Introduction

It is commonly accepted that customers use decision heuristics during their decision process (Hauser, 2014). One widespread assumption is that individuals follow a two-step decision process when choosing an alternative from a wide range of products. In a first step, individuals screen out some alternatives applying non-compensatory rules. From the remaining they then choose one final option in a second step. (Hauser, 2014)

Conjoint analysis, in particular choice-based conjoint analysis (CBC), is frequently applied to uncover consumers' preferences (Orme, 2006). Researches usually presume a compensatory utility function when using CBC and, therefore, disregard the possibility of a two-stage decision process. Gilbride and Allenby (2004) presented multiple methods for modelling a two-stage decision process with data gathered via a CBC. They assume respondents to use, among others, a conjunctive rule in the first step. The respondent compares each attribute value to an individual minimal threshold and screens out alternatives which do not exceed all threshold values. In the second step, one alternative from the alternatives passing the screening is chosen in a compensatory comparison process using the linear additive rule. We hereafter refer to this model as *one-sided (conjunctive) screening rule*.

The literature provides several indications that consumers may also use maximum thresholds in the screening phase. Price can be seen as an indicator of quality (Shapiro, 1973). Therefore, consumers might not only screen on high price values but also on low values, thereby screening from both sides. Offering too many features can lead to a feature overload (Karr-Wisniewski & Li, 2010). That's why individuals might screen out alternatives offering an - according to their view - unnecessary feature. Another indicator is the possibility that a certain feature violates the self-concept of some consumers (Simonson, Carmon & O'Curry, 1994) and therefore is unwanted. In addition, the literature contains further indications for screening from both sides.

In this paper we extend the model of Gilbride and Allenby (2004) to allow for both minimum and maximum threshold values. The extended model is referred to as the *two-sided (conjunctive) screening rule*. We aim to investigate whether individuals use two-sided screening in the first step of their decision process, and to evaluate the performance of the two-sided screening rule in comparison to the one-sided rule proposed by Gilbride and Allenby as well as the classical linear model without screening. We investigate the model performance by estimating three real-world data sets of CBC (one of which is the camera data set used by Gilbride and Allenby (2004)).

The paper is structured as follows: First the two-sided conjunctive screening rule is briefly introduced. Next, the real-world data sets are described and the results of the estimations are illustrated. The paper concludes with a short summary and a discussion in the last chapter.

2. A choice-based conjoint model considering two-sided screening

In this section, we outline a choice-based conjoint model accounting for screening from two sides. As mentioned above, we extend the model suggested by Gilbride and Allenby (2004) to allow for two-sided screening in the first step of the decision process. Transferred to a CBC with I choice sets of J alternatives with M attributes, only alternatives which fulfil the following condition for individual h are taken into account for the second step:

$$\Sigma_{m=1}^{M}\left[\mathbb{I}_{\{x_{hkim} > \gamma_{low_{hm}}\}} + \mathbb{I}_{\{x_{hkim} < \gamma_{up_{hm}}\}}\right] = 2 \cdot M \tag{1}$$

$\mathbb{I}$ is an indicator function which takes the value 1 if the condition is met and 0 otherwise, γ_{low} is the individual specific minimum threshold and γ_{up} is the maximum bound for the attribute levels. x_{hikm} reflects the attribute value of the m-th attribute of alternative k in the i-th choice set for person h. From the alternatives which have passed the screening on the first stage, the individual chooses the one with the highest utility value in the second step. Therefore, in the CBC the alternative with the greatest value of

$$U_{hji} = \sum_{m=1}^{M-1}\sum_{l=1}^{L}\beta_{hml} \cdot \mathbf{1}_{x_{hjim},l} + \beta_{h,price} \cdot f(price) + \varepsilon_{hji} \tag{2}$$

is chosen. (Gilbride & Allenby, 2004) Here the indicator function takes the value 1, if the j-th alternative of the i-th choice set has level l in the m-th attribute and β represent the part-worth utilities. The M-th attribute is the price. The function *f* is applied to the price variable to transform the price into an increasing variable (e.g. –ln(price)). Therefore, upper screening here results in screening out alternatives with low prices. If we assume the error term ε to be normally distributed, the multinomial probit model results. (Gilbride & Allenby, 2004; Train, 2009)

Considering the first (1) and the second step (*2*) together, the probability of choosing alternative j in a certain choice set i is:

$$\mathbb{P}(j)_{hi} = \mathbb{P}(U_{hji} > U_{hki} \forall k \in \{1, \dots, J\} \setminus j$$
$$\text{such that } \Sigma_{m=1}^{M}\left[\mathbb{I}_{\{x_{hkim} > \gamma_{low_{hm}}\}} + \mathbb{I}_{\{x_{hkim} < \gamma_{up_{hm}}\}}\right] = 2 \cdot M) \tag{3}$$

Gilbride and Allenby (2004) assumed the following distributions for individual specific part worth utilities β_h and the lower thresholds γ_{low}:

$$\beta_h \sim MVN(\bar{\beta}, \Sigma_\beta)$$

$$\gamma_{low_{h,m}} \sim \text{Multinomial}\ (\theta_{m1}, \dots, \theta_{mn}) \text{ for discrete attributes } \gamma_{low_1}, \dots, \gamma_{low_{M-1}} \quad (4)$$

$$\gamma_{low_M} \sim \text{Normal}\ \left(\bar{\gamma}_{low}, \sigma^2_{gamma_{low}}\right) \text{ for } \gamma_M \text{ (continuously scaled attribute)}$$

In this paper, we also assume multinomial distributions for the upper thresholds γ_{up} used to account for upper screening on discrete attributes and a normal distribution for γ_{up_M} for upper screening on the continuously scaled attribute price.

$$\gamma_{up_{h,m}} \sim \text{Multinomial}\ (\theta_{m1}, \dots, \theta_{mn}) \text{ for discrete attributes } \gamma_{up_1}, \dots, \gamma_{up_{M-1}}$$

$$\gamma_{up_M} \sim \text{Normal}\ \left(\bar{\gamma}_{up}, \sigma^2_{gamma_{up}}\right) \text{ for } \gamma_M \text{ (continuously scaled attribute)} \quad (5)$$

Gilbride and Allenby (2004) presented the appropriate prior distributions for the hyperparameters and the detailed algorithm to draw from the posterior distributions in the appendix of their paper. We add further steps to this procedure to draw from the distributions for γ_{up} and modify other steps to account for alternatives screened out by upper screening[1].

The one-sided conjunctive screening rule forms a special case of the two-sided conjunctive screening rule with the parameter γ_{up} set to the maximum possible value plus 1 for every attribute. Thus, the condition $x_{hkim} < \gamma_{up_{hm}}$ is met for all attributes.

Another special case of the two-sided conjunctive screening rule (and as well of the one-sided rule) forms the linear model in which the individual chooses directly (without any screening) the alternative with the highest utility value. In this case, the lower and upper bounds are set to values resulting in acceptance of every alternative in the first step.

To investigate if the model is able to recover screening behavior, we used one simulated data set. Fit and predictive validity as well as parameter recovery are improved when the two-sided rule is applied for estimation as compared to the other modelling approaches. The results therefore indicate that the model and estimation approach are appropriate if respondents do apply screening from both sides.

3. Real-world data sets

Data collected by means of conjoint experiments in three product categories (cameras, printers and smartphones) are used here to investigate the performance and the application of the two-sided conjunctive screening rule.

[1] A detailed description is available from the authors on request.

3.1. Data

Conjoint data collected by Gilbride and Allenby for their 2004 paper build the first data set. 302 participants chose in 12 choice sets (+2 holdouts) which camera out of 6 they would like to purchase or if they would not choose any (no-choice option). The cameras were described by 8 attributes, which are outlined in detail in Gilbride and Allenby (2004) and Rossi, Allenby and McCulloch (2005), and are presented in Table 1.

For the second data set 121 students of a German university participated in a choice-based conjoint study on printers. Participants evaluated 12 choice situations (+2 holdouts) where they could choose one of four printers or the no-choice option. The printers were characterized by 7 attributes (Table 1).

The third data set contains choice decisions on smartphones. 148 students took part in choosing one out of three alternatives for 10 choice sets (+2 holdouts), which were defined by 5 characteristics (Table 1). They also had the possibility to select none of the three devices (no-choice option).

	choice sets	alternatives	attributes
camera	12+2	6+1	1. body style 2. mid roll – change 3. annotations (4 different features) 4. operation feedback 5. zoom lens 6. viewfinder 7. settings feedback 8. price
printer	12+2	4+1	1. double-sided printing 2. scan function 3. Eco-modus 4. costs per page 5. staple and punch function 6. star rating 7. price
smart-phone	10+2	3+1	1. battery life 2. megapixel camera 3. memory 4. eco-label 5. price

Table 1: Descriptions of the real-world data sets.

3.2. Results

The fit and predictive validity of the different models are presented in Table 2.[2] In the training sample the two-sided screening rule outperforms the one-sided rule, which in turn has a better performance than estimating the data with the linear model. This observation isn’t surprising, as the one-sided rule and the linear model form special cases of the two-sided screening rule (see chapter 2). The log-likelihood cannot be determined in the holdout sample, because in some holdout choice sets alternatives that were predicted to be screened out may be chosen, resulting in a likelihood of 0. Therefore, like Gilbride and Allenby (2004), we report the average probability predicted for the observed choices (hit probability) alongside the hit rate. The linear model achieves the worst performance regarding the holdout sets. Both

[2] Every method was estimated five times with 100 000 iterations (out of which 90 000 form a burn-in phase). From the remaining values we used every 10th for the evaluations.

screening rules achieve almost identical predictive validity. Prediction is slightly improved when the two-sided rule is applied to the smartphone data set as compared to the one-sided rule. This also applies to the camera data set with regard to hit probability.

	estimated rule	log-like-lihood	hit rate training	hit rate holdout	hit proba-bility
smartphone	**two-sided**	-511.71	0.865	0.622	0.6090
	one-sided	-535.34	0.858	0.620	0.6064
	linear	-666.88	0.824	0.582	0.5613
printer	**two-sided**	-552.08	0.785	0.581	0.5654
	one-sided	-563.07	0.782	0.585	0.5681
	linear	-658.4	0.758	0.563	0.5421
camera	**two-sided**	-2779.96	0.689	0.452	0.4231
	one-sided	-2993.56	0.668	0.456	0.4222
	linear	-3459.55	0.624	0.442	0.3997

Table 2: Fit and predictive validity.

Table 3 presents the number of attributes used by respondents to screen out alternatives. It should be noted that the respective rule is only applied by a respondent if the number of screening attributes is at least 1. Using 0 characteristics for screening is equivalent to using a linear rule without screening. The models applying one and two-sided screening rules show almost similar proportions of respondents using lower bounds.

number of screening attributes			**0**	**1**	**2**	**3**	**4**	**5**	**>5**
smart-phone	**two-sided**	**min. threshold**	17.6%	44.7%	30.8%	6.0%	0.8%	0	
		max. threshold	94.7%	4.6%	0.8%	0	0	0	
	one-sided	**min. threshold**	17.6%	44.5%	31.6%	5.7%	0.5%	0	
printer	**two-sided**	**min. threshold**	30.9%	35.4%	22.9%	9.3%	1.6%	0	0
		max. threshold	97.0%	2.1%	0.7%	0.3%	0	0	0
	one-sided	**min. threshold**	32.0%	36.4%	22.7%	7.5%	1.3%	0	0
camera	**two-sided**	**min. threshold**	28.3%	44.1%	22.0%	5.0%	0.6%	0	0
		max. threshold	15.8%	48.1%	27.2%	7.6%	1.2%	0.1%	0
	one-sided	**min. threshold**	27.8%	46.0%	20.8%	4.8%	0.6%	0	0

Table 3: Number of attributes used for screening.

While in the smartphone and printer data set only 5.3%, respectively 3.0%, of the individuals use a maximum limit (Table 3) the proportion of respondents screening out alternatives which exceed upper thresholds is considerably higher (84.2%) in the camera data set. A closer look at the screening attributes of this data set (Table 4) shows that 67.46% of the respondents screened out alternatives with low prices. This indicates that they associated a low price with poor quality in this data set.

camera data				
estimated rule	**two-sided**			**one-sided**
attribute	screened by γ_{low}	screened by γ_{up}	screened by γ_{low} and γ_{up}	used for screening
1 (body style)	30.22%	3.37%	0.60%	25.26%
2 (mid roll change)	1.72%	0.00%	0.00%	1.77%
3 (annotation 1)	0.41%	0.54%	0.00%	0.40%
4 (annotation 2)	0.13%	0.00%	0.00%	0.21%
5 (annotation 3)	0.08%	2.81%	0.00%	0.18%
6 (annotation 4)	0.14%	0.00%	0.00%	0.21%
7 (operation feedback)	1.55%	1.71%	0.00%	1.64%
8 (zoom lens)	13.86%	2.61%	0.28%	12.49%
9 (viewfinder)	0.08%	3.94%	0.00%	0.17%
10 (settings feedback)	13.36%	1.04%	0.10%	13.30%
11 (price)	37.70%	67.46%	25.25%	41.98%

Table 4: Relative frequency of screening for every attribute (camera data).

In the second step of the estimations part worth utilities are determined. Considering the values of the smartphone and printer data sets, the posterior means of the utilities follow an ascending order (i.e. for higher levels of attributes higher part worths are estimated). Furthermore, the posterior mean of the part worth utilities estimated by the different models (two-sided and one-sided conjunctive screening rule, linear rule without screening) are almost identical. Therefore, we do not discuss these results in more detail here. Estimating the camera data all model estimations show a non-ascending order of the posterior means for some of the attributes (see, among others, body style in Table 5). The negative coefficient of price in the model applying the one-sided screening rule indicates that respondents use price as a quality indicator. As this effect is not observed in the linear model, screening out alternatives with huge prices results in a positive correlation between price and perceived quality among the remaining alternatives. Price is thus used as a quality indicator, but prices that are too high (above the threshold) are rejected. Using the two-sided screening rule, 67% of the respondents screen out alternatives with very low prices, even though price has a negative effect on utility concerning the part worth estimate. Taken together, the results indicate that in the camera market a price-quality effect exists, but this effect does not apply to the entire range of prices. Several respondents screen out low prices because of quality doubts, but also reject alternatives with prices that are too high.

estimated rule	two-sided	one-sided	linear model
body style	2.571	-0.801	0.075
	3.534	0.412	2.745
	3.045	-0.232	2.121
mid roll change	0.195	0.246	0.145
	0.355	0.167	0.178
annotation 1	0.339	0.313	0.353
	0.669	0.640	0.670
annotation 2	0.493	-0.497	-1.128
annotation 3	0.790	0.686	0.759
annotation 4	-0.048	-0.483	-1.069
operation feedback	0.486	0.414	0.339
zoom lens	0.917	0.893	1.117
	1.387	1.295	1.474
viewfinder	-0.044	-0.152	-0.131
settings feedback	0.505	0.571	0.824
	0.525	0.571	0.824
	0.685	0.718	0.972
-ln(price)	0.388	-0.138	0.693

Table 5: Posterior means of the part-worth estimates of the camera data.

To sum up, the two-sided conjunctive screening rule provides a better fit than the other two rules in the training sample. In the holdout sets there is partly a marginal improvement over the one-sided rule and the hit rate outperforms the one of the linear model without screening for all three data sets. Moreover, it is worth noting that only approximately 5% of the individuals used a maximum threshold with the exception of the attribute price in the camera data set, where this variable appears to be used as a quality indicator.

4. Discussion

In this paper we extend a model proposed by Gilbride and Allenby (2004). Our approach considers that respondents in a CBC Study may screen out alternatives with values of attributes that are too high or too low. A simulation study confirmed the ability of our approach to model this kind of behaviour.

To analyse the real usage of lower and upper thresholds, three real-world data sets were used. We compare our model to the model by Gilbride and Allenby (2004), which considers lower threshold values to allow for screening of alternatives with values that are too low. The linear model presuming compensatory behaviour serves as a standard of comparison for both models. In the training sample the fit of the two-sided conjunctive screening rule exceeds the ones of the one-sided rule or the rule without screening. This result was to be expected, as the model without screening forms a special case of the one-sided rule and the one-sided rule is a specific case of the two-sided conjunctive screening rule.

Regarding the holdout sample, the linear model without screening performs worst. Both screening rules predict the data in the holdout set approximately equally in the respective data set. An upper threshold is rarely used except for the camera data set, where the attribute price is used by two-thirds of the individuals for an upper screening (i.e. screening out alternatives with prices that are too low). The different screening behaviour might be reasoned in the different survey conditions. In the camera data more attributes were used to describe the objects than in the other two data sets, which could lead to more screening in general. Furthermore, in the printer and smartphone data the participants were university students, whereas in the camera survey (partly experienced) camera users were the respondents.

Considering the indications of two-sided screening the wide usage of an upper threshold for the price attribute in the camera data indicates that low prices are perceived to be an indicator of inferior quality. Only a small proportion of respondents used upper screening for non-price attributes. Potential reasons for rejecting values that are too high as mentioned in section 1 might have been not strong enough to show this kind of behaviour or the attribute values used in the studies did not exceed upper thresholds of most respondents.

Usually in (choice-based) conjoint analysis attribute levels are set in a way that the range is reasonable and acceptable by the respondents. A compensatory relationship is assumed for attribute values and k.o. criteria should be avoided (Huber, Herrmann, & Gustafsson, 2007). In order to ensure this, pretests are carried out. This could contribute to the observation that the respondents use moderate screening strategies, as more extreme attribute values are excluded in advance. Therefore, the availability of screening methods can provide the option to use a higher range of attribute levels in (choice-based) conjoint analysis. In this way a company can investigate if some consumers are willing to pay a very high price, which forms a k.o. criteria for other customers. This would violate the aforementioned condition of non-existence of k.o. criteria. The availability of screening methods can therefore open up new applications for conjoint-analysis.

In this paper electronic devices were used in the real world data sets. Further research is needed to extend the results to other product categories. Moreover, the results of the smartphone and printer survey were almost equal, but differed from the ones of the camera data. Potential reasons for this differences might be the different product categories or the participants (non-students vs. students). To more precisely pinpoint the cause for this, further research is needed.

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