









Disimproving the European Energy Label's value for consumers?

Results of a consumer survey

Working Paper No. 5 within the project:
Soziale, ökologische und ökonomische
Dimensionen eines nachhaltigen Energiekonsums in Wohngebäuden
Funded under the BMBF Programme "Vom Wissen zum Han-

Funded under the BMBF Programme "Vom Wissen zum Handeln - Neue Wege zum nachhaltigen Konsum"

> Authors: Stefanie Heinzle (Uni St Gallen) Rolf Wüstenhagen (Uni St. Gallen)

> > St. Gallen February 2010

Disimproving the European Energy Label's value for consumers? Results of a consumer survey

Structure of the paper:

1.	Introduction			
2.	·		7	
3.			8	
	3.1.	Theoretical framework	8	
	3.2.	Choice experiments and discrete choice analysis	8	
	3.3.	Estimation of individual-level parameters	9	
	3.4.	Discrete choice design	12	
	3.5.	Respondent sample	14	
4.	Re	sults	15	
	4.1.	Results of the discrete choice model		
	4.2.	Relative attribute importances	16	
	4.3.	Willingness to pay	17	
	4.4.	Simulation of market response	18	
5.	Im	plications	21	
6.	Lis	st of tables	22	
7.	List of figures			
D.	forono	200	24	

The European Energy Label was introduced in the mid-nineties and since then has not kept up with the state of the art. After years of technological advancements and better know-how, an update of the scale became necessary because many products have reached the highest energy-efficiency class. For the product categories of refrigerators and washing machines, the scaling system was expanded in 2003 to include new energy efficiency categories on top of class A (A+ for washing machines, A+ and A++ for refrigerators and freezers). However, this scheme was regarded as an interim arrangement until a comprehensive revision of the energy labelling classes had taken place (OJ L 170/10, 2003). The EU commission has already worked for a couple of years on a revision of the label and the need for introducing a new system was published in the Energy Efficiency Action Plan in 2006 (COM 545, 2006):

"To increase the informational value of the EU labelling scheme, the Commission will revise, beginning in 2007, Framework Directive 92/75/EC to enlarge its scope, if this is shown to reinforce its effectiveness, to include other energy-using equipment, such as commercial refrigeration. The existing labelling classifications will be upgraded and re-scaled every 5 years or when new technological developments justify it, based on eco-design studies, with a view to reserve A-label status for the top 10- 20% best performing equipment."

Although the need for rescaling was explicitly mentioned in the 2006 action plan, in Spring 2009, the Commission - with the support of industry - proposed instead the introduction of new "A" classes such as A-20%, A-40% and A-60% on top of class A. The rationale behind this label was that no reclassification of products would be needed and that this system could easily be harmonised throughout all EU countries. However, in May 2009 the Parliament rejected the proposal to introduce these additional classes. This decision was also supported by an independent research study by Heinzle and Wüstenhagen (2009), which showed that a well-known A-G scheme has a greater impact on consumer decisions than an open-end scale with additional classes. Since the decision in May 2009, negotiations have continued and the European Parliament called on the Commission to withdraw the draft directive and to submit a new proposal to the committee by the end of September 2009. The Parliament fought to retain the closed "A to G" scale, provided that a dynamic system would be implemented to review the thresholds of the various classes every couple of years and a validity period would be introduced on the label. Although the well-known closed A-G scale has become familiar to most European consumers and is regarded by most consumer and environmental organizations as being clear, comprehensive, comparable and easy to understand (ANEC, 2008; Topten, 2009), industry and some member states insisted that their efficiency ratings should not be downgraded. The system proposed by the European Parliament would have resulted in a complex re-labelling re-

quirement for manufacturers and retailers and a transition period where old "A-G" labels would coexist with new, revised "A-G" labels. Industry mainly feared confusion in the market and claimed that these labels could no longer provide a clear ranking system that could communicate the improvements of an appliance (CECED, 2009). Industry has insisted on a label that goes "beyond A", allowing A rated appliances to remain A rated as newer, more efficient models enter the market and trigger the addition of new classes on top of the highest efficiency class. This industry position was also backed by a survey by the European Commission on graphic layouts for the Community Energy Label. The study showed difficulties during the transitional rescaling period during which old "A-G" labels would coexist with new "A-G" labels, showing that the validity period in form of annual figures initially could confuse consumers. The study found out that the closed A-G scale with rescaling was difficult for people to comprehend and concluded that an enlargement of the scale would actually be well understood by consumers (European Commission, 2009).

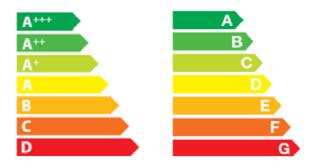
After months of negotiations, a compromise proposal from the Swedish Presidency of the Council finally came up. Members of the European Parliament and representatives from the European Commission and the EU Swedish Presidency finally reached an agreement that was also supported by manufacturers: the system would continue using letters A to G for classifications, but would expand the A categories into a maximum of three tiers (A+, A++ and A+++). Compared to the proposal of May 2009 which had additional classes A-20% etc., the new proposal limited the total number of classes to seven, unless more classes were still populated. Only the colour code of the highest class should always be dark green and only the red colour could be duplicated if there are more than seven classes. Another important pillar of this new proposal is that a review of the classification will take place when a significant proportion of products achieve the two highest energy efficiency classes. Such a review, which would also include the possibility of rescaling, should be carried out when there is a potential for additional significant energy savings. No later than 31 December 2014, the Commission shall review the effectiveness of this Directive and of its implementing measures and submit a report to the European Parliament and the Council (COD 2008/0222, 2009).

However, environmental and consumer groups criticise a "beyond A" scale and support the retention of a simple, closed A-G Energy Label, provided that a dynamic system would be implemented to review the thresholds of the various classes every couple of years (ANEC, 2008). They argue that the message "buy A" would keep the label simple and clear and would help consumers to buy more efficient household appliances. By introducing additional classes they fear that consumers would perceive the differences between the different A classes as minimal. They also point out that as a result of introducing the additional classes, an "A" class product would no longer necessarily be the best in class but might be even the worst.

The two environmental organisations, BUND¹ and DUH², support the concerns of consumer groups regarding the proposed introduction of the additional classes. These two organisations claim that consumers need to be assured that an A labelled device is actually the most efficient product on the market, and they believe that there is no alternative to a continuation of the established scale "A to G", provided that there is a dynamic system of reclassification in place. They demand that only a predefined percentage of about 20% of the available products on the market would be allowed to be labelled with an A class, and that all letters of the scale should be occupied (Bund/DUH, 2009). Regarding industry and Commission critiques of the co-existence of two different label versions, BUND and DUH recommend that the information regarding the time-frame of validity must be more comprehensive and clearly printed on the label. They mention that periods of validity have been established in other areas too, e.g. TUV labelling for consumers. They do not see the introduction of such validity periods as a barrier for the European Energy Label, provided that there is thorough communication of the system (BUND/DUH, 2009).

In addition, some member states, including the UK, have called for a simple rescaling of the A-G label. Research conducted by Ipsos MORI showed that the closed A-G label was understood and recognized throughout Europe (MORI 2008a, MORI 2008b).3 Additionally, a study conducted by Which? showed that consumers preferred the A-G design over A+++ style labels and found it easier to understand (Which?, 2009).

Figure 1: Illustration of energy efficiency classes of both label options



¹ The League for the environment and nature conservation, Germany (Bund für Umwelt und Naturschutz Deutschland e.V., BUND) is a non-governmental ecology group with the headquarters in Berlin and has more than 470,000 active members.

 $^{^2}$ The environmental and consumer protection NGO "Deutsche Umwelthilfe e.V." (DUH) offers a forum for environmental organizations, politicians and industry representatives and has more than 50,000 active members.

³ MORI research conducted for ANEC, BEUC, the UK National Consumer Council, the UK Energy Savings Trust and the UK Government Department for Environment, Food and Rural Affairs (May 2008) and for the UK Government, Sweden and the Netherlands (December 2008).

The compromise proposal agreed upon in November still has to be formally approved by the Council before Parliament as a whole gives its final endorsement. Once adopted and published in the EU Official Journal, Member States will have 12 months to adapt their national laws to the new EU rule.

2. Objective of this study

The goal of this study was to provide critical insight about the future energy efficiency label. It should provide evidence on the effect of both discussed labelling schemes on customer decisions for televisions and demonstrate the difference in magnitude of the effect of both schemes in realistic choice experiments in order to provide a valuable comparison of the options in terms of consumer perception.

The study aims to answer the question: "Which label is more effective in making energy efficiency a relevant attribute in customer decisions regarding new televisions?

3.1. Theoretical framework

An energy label helps consumers to rate the energy efficiency of a household product with the aim of providing credible and comparable information on the performance of the products. Therefore, the energy label aims to mitigate potential inefficiencies resulting from imperfect information distribution about energy use and is thus related to Akerlof's (1970) work on information asymmetry. Within information economics, a typology exists which distiguishes between search, experience and credence attributes. The distinction between search and experience attributes was defined by Nelson (1970) and was further developed by Darby and Karni (1973) adding the credence category for product characteristics which are generally unobservable qualities, even after purchasing (Darby and Karni, 1973). The term search attribute refers to those characteristics of a product (e.g. size or colour) about which the consumer can get information before he buys, whereas experience attributes refer to those attributes revealed only through use. Credence attributes, on the other hand, cannot be fully evaluated even after use. The key difference between the categories is the level of information customers possess or could cheaply acquire compared to sellers. The energy consumption of an appliance is therefore usually a credence attribute of a product which can lead to negative externalities of asymmetric information. As consumers are usually not able to identify the energy consumption level before their purchase decision, they have to trust the manufacturer. The risk of adverse selection can be overcome by the introduction of an energy label, where a third party certification process takes place and the credence attribute can be converted into a "quasi-search attribute". Compared to a search attribute, a quasi search attribute cannot be evaluated by consumers themselves, but only through a third party (Hüser and Mühlenkamp, 1992).

3.2. Choice experiments and discrete choice analysis

As the energy label has not been introduced for televisions yet, no market data is available about revealed preferences. Thus, it was not possible to observe people's actual purchase decisions. Accordingly, for the present study a market research technique was necessary to measure stated preferences. In contrast to the revealed preferences approach, which observes actual choices made by decision makers in real market circumstances, stated preferences are derived from preferred choices made under different hypothetical scenarios in experimental markets (Danielis and Rotaris, 1999). Particularly in the area of individual decision behaviour regarding new technologies, which have not reached extensive market penetration yet, and in the field of environmental behaviour analysis, the stated prefer-

ence approach using conjoint analyses is recommended (Train, 2003; Hensher et al., 2005).

Discrete choice experiments (DCE) belong to the family of conjoint analysis methods and are widely used in market research. Conjoint analysis is based on the work by Luce and Tukey (1964) and has been further developed in the last few decades into a method of preference studies which was not only drawn the attention of theoreticians, but also those who carry out field studies (Gustaffson, Hermann and Huber, 2003). Green and Rao (1971), McFadden (1974) and Green and Srinivasan (1978) introduced the method into marketing literature in the 1970s. The early conjoint analysis work highlighted modelling of behavioural processes in order to comprehend how consumers form preferences (Green and Rao, 1971; Norman and Louviere, 1974). Today it is largely used for marketing research and product design surveys; it has gained broader acceptance in the last decade with the technical advancement of personal computers which helped to simplify the application of the process (Hair et. al, 1995).

The basic idea of this method is that preferences for one specific stimulus are composed of separate contributions of different attributes. The underlying assumption of this method was subsumed by Lancaster (1966): "[t]he good, per se, does not give utility to the consumer; it possesses characteristics, and these characteristics give rise to utility." Therefore, the overall utility of a product or service is a summation of the utilities assigned to its separate attributes or part worth utilities. Conjoint analysis is a technique designed to analyse and predict consumers' responses by measuring the importance and degree of preference that individuals attach to each of these attributes. Consumers are asked to choose a set of criteria from numerous presented sets. Although the marketplace usually requires tradeoffs between different characteristics, consumers typically avoid the evaluation of conflicting attributes during market research. By forcing consumers to decide which characteristics are most important and by making tradeoffs between different levels of product attributes, it is possible to measure preferences in simulated quasi-realistic decision/purchasing situations since the decision making criteria are not presented separately, but simultaneously (Orme, 2006; Lilien, Rangaswamy and De Bruyn, 2007).

Furthermore, conjoint analysis usually selects only a reduced number of attributes on which to base the decision. The simplification in the conjoint analysis mirrors that in the market, as most decisions in the marketplace are also based only on remarkably few dimensions (Huber, 2005; Olshavsky and Grandbois, 1979).

3.3. Estimation of individual-level parameters

There are several possibilities to analyse discrete choice experiments. Briefly described, a discrete choice experiment considers a quasi-realistic buying situa-

tion, where consumers choose between one or more products from a restricted product set (evoked set). By choosing the most beneficial product from this restricted set, preferences of the respondents can be directly derived (McFadden, 1974). Discrete choice is actually a group-based analysis based on aggregation, and now, by using hierarchical Bayesian (HB) estimation, part worth utilities at the individual-level can be estimated (Allenby and Rossy, 2003). Hierarchical Bayesian analysis is regarded as being a state-of-the-art method for estimating utilities from Choice Based Conjoint Studies. Compared to traditional aggregate models (e.g. multinomial logit analysis) the Hierarchical Bayesian approach significantly improves the analysis of preferences. While earlier methods combined data for all individuals and were criticised for obscuring important aspects of the data, with a Bayesian framework, it is possible to analyse choice data at the individual level (see Allenby and Rossi, 2003; and Huber, 2001 for more detailed discussion of hierarchical modelling).

Discrete choice models are based on random utility theory. It is assumed that each respondent faces a choice among different alternatives in each choice situation and chooses the alternative with the highest utility (Huber and Train, 2000). The utility is assumed to be related to the valuation of specific attribute levels by the respondents, who are presumed to be heterogeneous in their preference for the attributes. If there is heterogeneity among individuals, hierarchical Bayes can significantly improve the analysis of preferences in comparison to traditional aggregate models. Within a Bayesian framework, the distribution of coefficients (part worths) across the population is estimated and combined with the information on individuals' choices to derive posterior or conditional estimates of the individual 's values. Therefore, hierarchical modelling can be used to link information about the distribution of coefficients across all respondents with information about the choices made by individuals to obtain estimates of individual values (Allenby and Rossi, 2003).

The hierarchical Bayes model is written as a series of hierarchical algebraic statements, where model parameters in one level of the hierarchy are explained in subsequent levels. The method thus involves combining aggregate and individual-level specification of parameters. At the higher level, individual 's part worths are described by a multivariate normal distribution. At a lower level, consumers' probabilities of choosing particular alternatives are governed by a multinomial logit model. Individual part worths are assumed to have the multivariate normal distribution,

 $\beta_i \sim Normal(\alpha, D)$

where:

 β_i = a vector of part worths for the ith individual

 α = a vector of means of the distribution of individuals' part worths

D = a matrix of variances and covariances of the distribution of part worths across individuals

The probability of the i^{th} individual choosing the k^{th} alternative in a particular task i is

$$p_{k} = \frac{\exp(x_{k}'\beta_{i})}{\in_{i} \exp(x_{i}'\beta_{i})}$$

where:

 p_k = the probability of an individual choosing the k^{th} in a particular choice task x_i = a vector of values describing the j^{th} alternative in that choice task

This equation describes that to estimate the probability of the i^{th} individual choosing the k^{th} alternative, part worths (elements of β_i) are added up for the attribute levels describing the k^{th} alternative to get the i^{th} individual utility for the k^{th} alternative, exponentiate that alternative's utility, perform the same operations for other alternatives in those choice tasks, and finally, obtain the percentage of the results for the k^{th} alternative by the sum of similar values for all alternatives (Sawtooth, 2009).

Under a Bayesian framework, a and D are considered to be stochastic and are estimated iteratively by conducting several thousand iterations by the iterative process called Gibbs Sampling. Another name for this procedure is a "Monte Carlo Markov Chain". By doing this, the multivariate normal mean vector, the covariance matrix and the set of part worths were each randomly updated conditional on the other current parameter estimates. To derive the final individual part-worth estimates, the last several thousand iterations are saved and the parameter estimates from these iterations are averaged. At the lower aggregate level, it is assumed that the probability a respondent will choose a particular alternative, given his individual part worths, is governed by a logit model.

A market simulator can be used to convert individual part worths from HB estimation into simulated market choices and to compute shares of preferences for competing products alternatives. Market simulation models are used to analyse consumer choices for a defined set of products and their specific product features. Share of preference can be defined as the percentage of respondents that would prefer one of the specified products. For our analysis, we applied a randomised first choice simulation method to estimate share of preference. A "maximum utility rule" is assumed, which predicts that respondents would choose the option with the highest composite utility, Randomised first choice simulations estimate then the choices of each participant, adding random error to the utility values at each of 100,000 iterations and averaging those predictions across iterations and respondents. See Huber et. al (1999) and Orme (2006) for more detailed discussions of the computation of randomised first choice simulations.

3.4. Discrete choice design

In this study, preferences for attributes of televisions were estimated in a choice-based-conjoint experiment in order to identify which label format has a stronger impact on consumer decisions. The choice tasks were randomly calculated with the software program Sawtooth and were full profile in the sense that all attributes were presented for each set of four television alternatives. Respondents thus had to choose between four product alternatives in each choice task. The recorded choices of each respondent for each of the twelve randomly generated choice tasks were analysed in a hierarchical Bayes estimation to calculate the respondents' utility functions across all attributes. The results were the input into a market simulation of competing product alternatives to determine preference shares of the respondents.

Respondents were split up into two different samples, which only differed with regard to the presentation format of the label. Technically, the set of attributes and levels for both subgroups was identical. Therefore, differences in the preference structure between two subgroups could be traced back to the different label version. Two assumptions were made. First, for the "A-G closed" scale format, we assumed that a dynamic system was in place for revising the thresholds of the categories every couple of years. In contrast, for label version 2 ("A+++" scale), we assumed that due to technical advancements, almost all TVs on the market had a grade higher than A. Therefore we could assume that the intervals which correspond to the amount of energy consumption between two label efficiency classes between the energy classes A, B, C and D in the label version "A-G closed" scale correspond to the same intervals between energy classes A+++, A++, A+ and A in the label version "A++++" scale.

All respondents received a series of 12 choice tasks involving comparisons of different televisions with varying levels of attributes. Each choice task presented four different television alternatives where respondents had to choose their preferred alternative. The attributes and the attribute levels that were presented in the choice tasks are listed in Table 1; a typical choice task is displayed in Figure 2.

Table 1: Attributes and attribute levels in the choice tasks

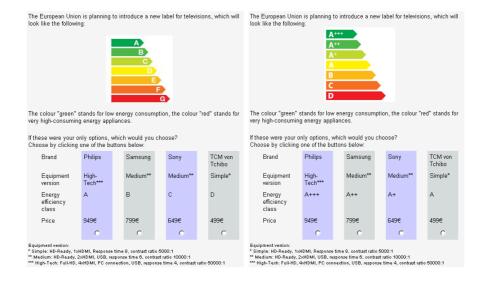
Attributes	Attribute levels			
	Sample 1	Sample 2		
	("A-G closed" scale)	("A+++" scale)		
Brand	Samsung	Samsung		
	Sony	Sony		
	Philips	Philips		
	TCM of Tchibo	TCM of Tchibo		
Equipment version	Simple*	Simple*		
• •	Medium**	Medium**		
	High-Tech***	High-Tech***		
Energy label	A	A+++		
	В	A++		
	C	A+		
	D	A		
Purchase price	499€	499€		
-	649€	649€		
	799€	799€		
	949€	949€		

Equipment version:

- * Simple: HD-Ready, 1x HDMI, Response time 8, contrast ratio 5000:1

 ** Medium: HD-Ready, 2x HDMI, USB, response time 6, contrast ratio 10000:1
- *** High-tech: Full-HD, 4x HDMI, PC connection, USB, response time 4, contrast ratio 50000:1

Figure 2: Sample choice task for both samples



3.5. Respondent sample

This study is based on 2244 choice observations in Germany, based on 12 choices each of 187 respondents. These respondents were recruited by a commercial marketing research company (GfK). Sample 1 (hereafter label version "A-G closed" scale) includes 1080 choice tasks, and sample 2 (hereafter label version "A++++" scale) is based on data for 1164 choice tasks. Looking at the sociodemographic characteristics of both samples, they are largely consistent with regard to gender, age, education and income.

4.1. Results of the discrete choice model

In this section we present the estimated coefficients for Sample 1 "A-G closed" scale and Sample 2 "A++++" scale and conduct hypothetical market simulations in order to answer our research question: "Which of the two labels is more effective in influencing customer choice for energy-efficient televisions?"

Table 2: Results of the discrete choice (Hierarchical Bayes) model for televisions

Attribute level	Sample 1 ("A-G closed" scale)			Sample 2 ("A++++" scale)		
	N=90			N=9	7	
	Coeff.	Std.	T-value	Coeff.	Std.	T-value
Brand						
Samsung	0.29	0.09	3.07**	0.07	0.10	0.69
Sony	0.27	0.09	3.04**	0.41	0.09	4.32**
Philips	0.36	0.09	4.02**	0.46	0.09	4.88**
TCM of Tchibo	-0.92	0.11	8.50**	-0.93	0.11	8.59**
Equipment version						
Simple*	-1.47	0.11	13.78**	-2.86	0.13	22.55**
Medium**	0.03	0.08	0.35	0.21	0.09	2.43*
High-Tech***	1.44	0.10	14.51**	2.65	0.12	23.06**
Energy label						
A/A+++/A-60%	3.18	0.13	24.90**	2.17	0.11	20.65**
B/A++/A-40%	1.36	0.11	12.85**	1.14	0.10	11.75**
C/A+/A-20%	-1.30	0.11	12.13**	-0.52	0.09	5.61**
D/A/A	-3.23	0.14	23.52**	-2.79	0.13	21.59**
Purchase price						
499€	3.13	0.14	23.17**	4.71	0.13	35.19**
649€	1.09	0.09	11.53**	1.37	0.11	12.74**
799€	-1.18	0.10	11.82**	-1.38	0.11	12.07**
949€	-3.04	0.14	21.17**	-4.70	0.16	29.81**
NONE	4.90	0.19	25.86**	4.07	0.16	25.23**

^{*} p < .1 ** p < .001

The coefficient shows the level of influence of a change of attribute level on the consumer's likelihood to choose the product. A positive value (e.g. a low price) increases the utility for a consumer, whereas a negative value (e.g. a high price) decreases the utility compared to the average level of a given attribute. The col-

umns next to the coefficient levels show different measures for the goodness of fit. The standard error indicates the exactness of estimating the coefficient whereas the ratio of the coefficient to the standard error (t-value) delivers a standardised value to estimate the exactness of the coefficient. T-values greater than 2.58 indicate a reliable estimate (within a 99% confidence interval). In our analysis, most coefficients are significant at the 99% level. Due to the arbitrary origin within each attribute, values between attributes cannot be directly compared. Even though when utilities within the same attribute are compared, it cannot be stated that one utility is x times preferred over another as interval data does not support ratio operations (Orme, 2010). By analyzing part-worths we are able to identify tendencies. However, we cannot test whether differences among the samples are significant because it is not possible to compare part worths between choice models of non-unique samples. To determine whether differences between two segments are significant or not, we conduct market simulations using individual-level part worth estimates to calculate share of preferences.

4.2. Relative attribute importances

In a second step, conjoint importances were computed. Importances describe how much influence each attribute has on the purchase decision. Conjoint importances are displayed in Table 3 and differences in relative attribute importances between both samples are displayed in Figure 3.

Table 3: Relative attribute importances derived from Hierarchical Bayes estimation of utilities

Attributes	Sample 1 closed" scale)	("A-G Sample 2 ("A+++" scale)
Brand	13.4%	10.9%
Equipment version	18.6%	23.6%
Energy label	33.6%	23.0%
Purchase price	34.5%	42.6%

In both samples the most important product attribute of a TV was the purchase price, followed by the energy label, the equipment version and the brand. However, there were differences in conjoint importances of the attribute energy label between Sample 1, with 33.6%, and Sample 2, with 23.0%. This analysis shows that an energy label with a "A-G closed" scale has over 10% more influence and

the price has over 8% less influence on the consumer decision than an energy label with an "A+++" scale.

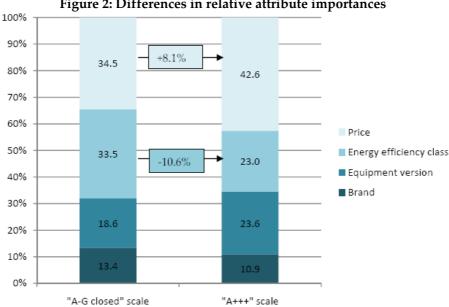


Figure 2: Differences in relative attribute importances

4.3. Willingness to pay

The results presented above can also be expressed in terms of implicit willingness to pay when the part worth utility coefficients are converted into monetary units. The results can be interpreted as an indication of the average consumer's willingness to pay for a change from a lower to a higher level of an attribute. This approach is often applied in pricing studies based on conjoint analysis (e.g. Green and Srinivasan, 1990; Orme, 2001).

In sample 1 ("A-G closed" scale) a utility difference of 6.17 of the attribute price (from the highest utility level of 3.13 for the lowest price to the lowest utility level of -3.04 for the highest price) reflects a 450€ change in price. Therefore, a 1€ change corresponds to 0.014 in utility change (6.17 utilities / 450€). It then follows that the highest energy efficiency level A, being worth 1.82 utility points more than the energy efficiency level B, is worth about 133€ more. An energy efficiency level B is worth about 194€ more than an energy efficiency level C and an energy efficiency level C is worth about 141€ more than an energy efficiency level D. In sample 2 ("A+++" scale) a utility difference of 9.41 of the attribute

price (from the highest utility level of 4.71 for the lowest price to the lowest utility level of - 4.70 for the highest price) also reflects a 450€ change in price. Therefore, a 1€ change in this sample corresponds to 0.021 in utility change (9.4 utilities / 450€). It then follows that the highest energy efficiency level A+++, being worth 1.03 utility points more than the energy efficiency level A++, is worth about 49€ more. An energy efficiency level A++ is worth about 79€ more than an energy efficiency level A+ and an energy efficiency level A+ is worth about 109€ more than an energy efficiency level A.

Table 4: Willingness to pay for a change from a lower to a higher efficiency class

Attributes	from the second highest to the high-	WTP for a change from the second low- est to the second highest efficiency class	change from the lowest to the
"A-G"	B → A:	C → B:	D → C:
closed scale	133€	194€	141€
"A+++"	A++ → A+++:	A+ → A++:	A → A+:
scale	49€	79€	109€

€ 200.00 € 150.00 € 50.00 A vs. B / A+++ vs. A++ B vs. C / A++ vs. A C vs. D / A+ vs. A

Figure 3: Differences in willingness to pay

4.4. Simulation of market response

Discrete choice provides a tool that can be used to simulate market response to different alternatives. For the purpose of this study, what-if analyses were con-

ducted to test the effect of the indication of the energy efficiency class. The estimated utilities (part worths) from the HB estimation method provided the basis for estimating share of preferences. Share of preference can be defined as the percentage of respondents that would prefer one of the specified products. By applying simulations, one can test whether differences among subgroups are significant. For our analysis, we applied a randomised first choice simulation method to estimate share of preference which assumes a "maximum utility rule".

In the following scenario, a realistic market situation was demonstrated by calculating the share of preference of four hypothetical products. Reflecting the real market situation, the price of the appliance varied according to the energy efficiency class (i.e. the most expensive television came with the highest energy efficiency class, whereas the cheapest television was labelled with the lowest energy efficiency class). The attributes brand and equipment were set at a constant level to allow testing of the isolated effect of the combination of energy efficiency class and price.

Table 5: Share of preference of four hypothetical products

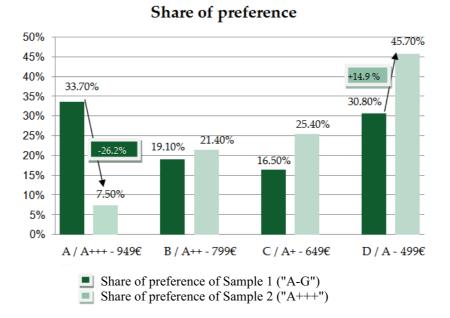
Attributes	Highest energy efficiency class & highest price	Second highest energy efficiency class & second highest price	•	Lowest energy efficiency class & lowest price
Sample	1 2	1 2	1 2	1 2
Brand	Samsung	Samsung	Samsung	Samsung
Equipment version	Medium	Medium	Medium	Medium
Energy la- bel	A A +++	B A ++	C A +	D A
Price	949€	799€	649€	499€
Share of Preference (in %)	33.7 7.5	19.1 21.4	16.5 25.4	30.8 45.7
Standard error	4.0 2.1	2.6 3.1	2.8 3.2	4.1 4.3

Note: Share of preference represents that percentage of the respondents who would prefer or choose each television, assuming these are the only four choices available. Shares of preference are ratio data.

Respondents in Sample 1 ("A-G closed" scale) were about 4.5 times more likely to choose the television with the highest energy efficiency class in combination with the highest price than respondents from Sample 2 ("A+++" scale) (33.7% vs. 7.5%). Respondents in Sample 1 were about 1.5 times less likely to choose the television with the lowest energy efficiency class in combination with

the lowest price than respondents from Sample 2 (30.8% vs. 45.7%). By changing the energy efficiency class from the lowest energy efficiency class in combination with the lowest price to a TV with the highest energy efficiency class in combination with the highest price, the preference share in Sample 1 increased by almost 2.9% whereas the preference share in Sample 2 decreased by more than 38.2%. We can therefore conclude that an increase from a D to an A labelled television produces enough utility for respondents in Sample 1 so that the shares of preference are more than equalised although the price goes up. In other words, respondents of Sample 1 are willing to put up with a high price if the energy efficiency class is high. Our analysis therefore proves once again that respondents from Sample 1 have a higher willingness-to-pay for energy efficient appliances than respondents from Sample 2. T statistics for the differences between shares of preferences of unique respondent groups in hypothetical product 1 and 4 have an absolute magnitude greater than 1.96 indicating a significant difference at the 95% confidence interval.

Figure 4: Illustration of share of preferences of four hypothetical products



5. Implications

The purpose of this study was to analyse the influence of two different label formats on consumer decisions. As conjoint analysis results provide much richer results than simple willingness to pay studies or direct inquiries into people's preferences, we were able to reduce the social desirability bias by asking consumers to face realistic trade-offs between different product attributes.

The survey shows that the well-known "A-G closed" scheme has a greater impact on consumer decisions than an "A+++" scale. The results clearly show that introducing the new label with its additional categories (A+, A++, A+++) weakens the effect of the label, resulting in lower consumer awareness about energy efficiency as an important attribute. Whereas with the old label, the energy efficienc rating was almost equally important to price, the importance of the energy label sharply dropped (from 33.6% to 23.0%) with the introduction of the new label, and consumers relied much more heavily on price (importance increasing from 34.5% to 42.6%). Hence, our results suggest that the confusion introduced by the new label categories makes consumers switch away from energy efficient products and shop for the cheapest TV instead. Differences between classes of the "A+++" scale (e.g. between an A+++ and an A++ efficiency class) are perceived as being much smaller than differences between classes of the "A-G closed" scheme (e.g. between an A and a B efficiency class). Therefore, we can conclude that the added categories would only have a limited impact. Therefore the results of the study suggest sticking to the established, straightforward and easily understood format of the A to G label.

With regard to marketing, the most important result of our analysis is that the impact of a "A-G closed" scale on consumers' decisions is much stronger and therefore consumers are more willing to pay a higher premium for the highest classes of the "A-G closed" scale than of the classes of the "A++++" scale. Not only would a watered-down scheme of ever more fine-grained variations of the A category confuse consumers and hence countervail European Union targets to cut energy consumption and carbon emissions, it would also not be in the best interest of industry. This strong willingness to pay for a labelled product should be encouraging for manufacturers to support the maintenance of the well-known A-G scheme in order to differentiate themselves based on energy-efficient products.

By reaping the benefit of this higher latent willingness to pay, manufactures might get a higher return on their investment in R&D with the "A-G closed" scheme. Manufacturers who are already producing energy efficient models would have a special international competitive advantage with a closed scale, whereas the introduction of new "A classes" would be a disadvantage.

6. List of tables

6. List of tables

Table 1: Attributes and attribute levels in the choice tasks	
Table 2: Results of the discrete choice (Hierarchical Bayes) model for telev	
Table 3: Relative attribute importances derived from Hierarchical Bayes estimation of utilities	
Table 4: Willingness to pay for a change from a lower to a higher efficiency	•
Table 5: Share of preference of four hypothetical products	

7. List of figures

7. List of figures

Figure 1: Illustration of energy efficiency classes of both label options	5
Figure 2: Differences in relative attribute importances	
Figure 3: Differences in willingness to pay	
Figure 4: Illustration of share of preferences of four hypothetical products	

References

- Akerlof, G. A. 1970. The Market for 'Lemons': Quality Uncertainty and the Market Mechanism. Quarterly Journal of Economics, 84(3): 488–500.
- Allenby, G. & Rossi, P. 2003. Bayesian Statistics and Marketing. Marketing Science, 22: 304 328.
- ANNEC. 2008. Consumers strongly in favour of keeping the A-G Energy Label. Press release by ANNEC-PR-2008-PRL-009. http://www.anec.eu/attachments/ANEC-PR-2008-PRL-009.pdf, January 28.
- BUND & DUH. 2009. Stellungnahme zur Neuggestaltung der EU-Energieverbrauchskennzeichnung. http://www.bund.net/fileadmin/bundnet/pdfs/klima_und_energie/20091111_e nergie label stellungnahme.pdf, January 28.
- CECED. 2009: Personal communication.
- COD 2008/0222. 2009. Proposal for a directive of the European Parliament and of the Council on the indication by labelling and standard product information of the consumption of energy and other resources by energy-related products. http://ec.europa.eu/prelex/detail_dossier_real.cfm?CL=fr&Dos Id=197621, January 28.
- COM 545. 2006. Communication from the commission. Action plan for energy efficiency: realising the potential. http://ec.europa.eu/energy/action_plan_energy_efficiency/doc/com_2006_054 5 en.pdf, January 28.
- Danielis, R. & Rotaris, L. 1999. Analysing freight transport demand using Stated Preference data: a survey. Transporti Europei, 13: 30-38.
- Darby, M. R. & Karni, E. 1973. Free Competition and the Optimal Amount of Fraud. Journal of Law and Economics, 16(1): 67-88.
- European Commission. 2009. Consumer survey on graphic layout for the community energy label. http://www.europarl.europa.eu/document/activities/cont/200910/20091001AT T61602/20091001ATT61602EN.pdf, January 28.
- Green, P.E. & Rao, V.R. 1971. Conjoint measurement for quantifying judgmental data. Journal of Marketing Research, 8: 355–363.
- Green, P.E., & V. Srinivasan. 1978. Conjoint Analysis In Consumer Research: Issues and Outlook. Journal of Consumer Research, 5: 103-23.
- Gustafson, A., Herrmann, A. & Huber, F. 2003. Conjoint measurement: methods and applications. Berlin: Springer.
- Hair, J., Anderson, R., Tatham, R. & Black, W. (1995): Multivariate data analysis. Englewood Cliffs: Prentice-Hall.
- Heinzle, S. & Wüstenhagen, R. 2009. Consumer survey on the new format of the European Energy Label for televisions Comparison of a "A-G closed" versus a "beyond A" scale format. Working paper, University of St. Gallen, Switzerland.
- Hensher, D. A., J.M. Rose & W.H. Greene. 2005. Applied Choice Analysis A primer. Cambridge: University Press.

- Huber, J. .2005. Conjoint Analysis: How we got there and where we are. Sawtooth Software, Research Paper series.
- Huber, J., Orme, B. K. & Miller, R. 1999. Dealing with Product Similarity in Conjoint Simulations. Sawtooth Software Conference Proceedings.
- Huber, J. & Train, K. 2001. On the similarity of classical and Bayesian estimates of individual mean partworths. Marketing Letters, 12: 259-269.
- Hüser, A. & Mühlenkamp, C. 1992: Werbung für ökologische Güter. Gestaltungsaspekte aus informationsökonomischer Sicht. Marketing ZFP, 3: 149-156.
- Kohli, R. & Mahajan, V. 1991. A Reservation-Price Model for Optimal Pricing of Multiattribute Products in Conjoint Analysis. Journal of Marketing Research, 28: 347–354.
- Lancaster, K. 1966. A new approach to consumer theory. Journal of Political Economy, 74: 132–157.
- Lilien, G. L., Rangaswamy, A. & A. De Bruyn. 2007. Principles of Marketing Engineering, Bloomington: Trafford.
- Luce, R. D., Tukey & John W. 1964. Simultaneous Conjoint Measurement: A new Type of Fundamental Measurement. Journal of Mathematical Psychology, 1: 1–27.
- McFadden, D. 1974: Conditional Logit Analysis of Qualitative Choice Behavior. In Zarembka, P. (Ed.), Frontiers in Econometrics: 105-142. New York: Academic Press.
- Miller, K. M. & Hofstetter, R. 2009. Measuring consumers' willingness to pay accurately. Norderstedt: Books on demand.
- MORI. 2008a. MORI research carried out for ANEC, BEUC, UK National Consumer Council (NCC), the UK Energy Savings Trust and the UK Department for Environment, Food and Rural Affairs in May 2008. http://www.anec.eu/attachments/ANEC-ENV-2008-G-040b.pdf, January 28.
- MORI .2008b. MORI research carried out for the UK Government, Sweden and The Netherlands in December 2008, http://www.mtprog.com/cms/library-publications/, January 28.
- Nelson, P. 1970. Information and Consumer Behavior. Journal of Political Economy, 78 (2): 311-329.
- Nitschke, T. & Sattler, H. 2005. Präferenzstrukturen und Zahlungsbereitschaften für Online-Medieninhalte: eine empirische Analyse am Beispiel von Online-Videoangeboten. Research Papers on Marketing and Retailing, Universität Hamburg.
- Nitschke, T. & Völckner, F. 2005. Präferenzmessung bei unsicheren Produkteigenschaften: Berücksichtigung von Risiko in Conjoint-Analysen. Research Papers on Marketing and Retailing, Universität Hamburg.
- Norman, K. L., & Louviere, J. J. 1974. Integration of attributes in bus transportation: Two modelling approaches. Journal of Applied Psychology, 59: 753-758.
- O JL 170/10. 2003. Commission directive 2003/66/EC of 3 July 2003 amending Directive 94/2/EC implementing Council Directive 92/75/EEC with regard to energy labelling of household electric refrigerators, freezers and their combinations. http://www.osram.by/osram_com/About_Us/ Society_and_the_Environment_Global_Care/EU_directives_and_promotion_oppo

References

- rtunities/EU_directives/Energy_Labeling/DIRECTIVE-2003_66_EC.pdf, January 28.
- Olshavsky, R.W. & D.H. Grandbois, D.H. 1979. Consumer decision making fact or fiction. Journal of Consumer Research, 6: 93-100.
- Orme, B. K. 2006: Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research. Madison: Research Publishers.
- Sawtooth Software. 2009. The CBC/HB system for Hierarchical Bayes Estimation Version 5.0 Technical paper. http://www.sawtoothsoftware.com/download/techpap/hbtech.pdf., January 28.
- Topten.info. 2009. Cold appliances: recommendations for policy design. http://www.topten.info/index. php?page=refrigerators_rg&fromid=144, January 28.
- Train, K. 2003. Discrete choice methods with simulation. Cambridge: Cambridge University Press.
- Which? 2009. Consumer research on energy labelling Review of the Energy Labelling Directive, http://www.which.co.uk/documents/pdf/consumer-research-on-energy-labelling---which---briefing-188489.pdf, January 28.
- WWF. 2009. Finally, an agreement for the EU Energy Labelling Directive for now.

http://www.panda.org/what_we_do/how_we_work/policy/wwf_europe_envir onment/news/?180942/Finally-an-Agreement-for-the-EU-Energy-Labelling-Directive---for-now, January 2