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1994

Faculteit der Economische Wetenschappen en Econometrie

Serie Research Memoranda

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Impacts of Project Attributes on Investment Preferences: an Empirical Cluster Analysis of Energy Conservation Investment Attitudes

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SUMMARY

investment attitude refers to the way managements of firms value attributes of investment proposals and weigh them in their final appraisal. It seems that among firms in the Netherlands an investment attiiude exists that hinders the implementation of energy conservation projects. Using paired comparison results from a survey on energy conservation, this paper evaluates investment preferences of firms by applying a Bradley-Terry model. The impact of project attributes on the investment preference is analysed in order to disclose the underlying investment attitude and to identify barriers to the advance of energy conservation technologies. A latent class approach is used to detect clusters of firms for which specific barners play a dominant role.

Keywords: BRADLEY-TERRY MODEL; CLUSTER ANALYSIS; ECONOMIC PROJECT APPRAISAL; ENERGY CONSERVATION; INVESTMENT ATTITUDE; PAIRED COMPARISONS

1. INTRODUCTION AND PROBLEM FORMULATION

The evaluation of the merits of proposed investment projects depends on a number of criteria such as type of project, amount of investment required, profitability and risk exposure. With investment attitude we mean the way managements of firms value these criteria and weigh them in their final appraisal. The investment attitude of the management of a firm will depend on its beliefs, values and goals (strategic relevance and societal/political acceptability of the projects), and the organisational culture.

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In this paper we examine investment attitudes to energy conservation projects. For the past decade many people and institutions all over the world have expressed great concern to the environment and its problems. Nowadays a great deal of attention is paid to the “Global Warming“ through what is known as the “Greenhouse effect”. As CO_2 is seen as the main contributor to this climate change, policies are developed to halt the climate change process by reducing the amount of CO_2 emissions. In the Netherlands the aim of the government is to stabilise the CO_2 emission level to 180 billion tons per year (the level in 1990) before the year 2000 (Energy Conservation Programme, 1989). This is equivalent to a yearly increase in energy conservation of 2%.

The major strategy to reduce CO_2 emissions is energy conservation. Many studies show that there are numerous opportunities to reduce energy consumption or to increase energy efficiency (see for the Dutch case Blok Worrell, 1990, Blok, 1991). Moreover, many technological opportunities for improving energy efficiency are economically attractive. Nevertheless the industry seems to overlook these profitable opportunities for energy efficiency improvement, as Werff and Opschoor (1992) show. Apparently a barrier raising investment attitude exists that hinders or even stops the advance of profitable energy conservation technologies (DeCanio, 1993). Gillissen (1994) provides a framework in which seemingly irrational investment behaviour is explained by a number of conceptual barriers to energy conservation technologies. Examples of such barriers are: Assignment of low priorities to cost cutting energy conservation projects, high initial investment costs in combination with low expectations of revenues, and a presumed high level of exposure to risk.

This situation hampers the achievement of the goals formulated in the 1989 Energy Conservation Programme. Therefore it is useful to explore the possible barriers that firms are facing when they consider implementing energy conservation technologies. It is also important to find out whether specific barriers play a dominant role in particular groups of firms. It is too simple to assume that each barrier affects the energy conservation projects of every firm alike. Even within industrial sectors substantially different investment attitudes may exist.

The object of this paper is to use a latent class Bradley-Terry paired comparison model to analyse investment preferences in order to find an answer to the following questions:

i) which attributes of an investment proposal have a negative impact on its acceptance, i.e. are barriers to a positive decision?

ii) Is it possible to cluster the firms in the sample adequately into homogeneous subgroups with respect to their predominant barriers?.

iii) What are the differences in investment attitude between these subgroups?

2. THE DATA

For our analysis we use a part of the results of a survey on energy conservation conducted during 1993 and the beginning of 1994. The Dutch National Research Programme on Global Change (1991) funded the survey and designed its questionnaire. More than 300 Dutch firms in 41 different **(sub)sectors** were questioned. It was not useful to examine all the Dutch sectors, because when energy use and technical potential are very low, little energy conservation is to be gained. The energy producing sectors were also not considered, as they are supposed to use already energy efficient equipment. The selection of sectors was largely induced by the sector digit code of the Dutch Central Bureau of Statistics and the sample can be regarded as representative.

To compare investment preferences among the various firms in different sectors under similar circumstances, eight "types" of investment projects were constructed, each type with four project attributes. These project types can be interpreted as possible real world situations, but are modelled on a meta-level. Dichotomous variables, which we will call covariates, represent the attributes. These covariates are specified in the following table.

TABLE 1

Specification of the covariates representing the project attributes

		Levels	
Covariate	Description	0	1
1	Type of investment	Energy conservation	Core business
2	Payback period	> 2 years	≤ 2 years
3	Size of investment	Small	Large
4	Riskiness	High risk	Low risk

The term core business refers to the elementary products, services and investment projects of a firm. For every firm core business projects may differ, but should be interpreted as an opposite to energy conservation investments. As energy producing firms are discarded, no conflict between core business and energy conservation activities will arise. As a profitability indicator the payback period is used. A payback penod of more than two years resembles a 5% return, while a payback period of two years or less matches a 20% return. Empirical evidence shows that' more than 80% of the Dutch firms use payback criteria to judge their investment projects and often use thereby a cut off point of two years (Werff, 1991). A large investment is defined as an investment which takes more than 10% of the total investment budget of a firm. Riskiness refers to what degree the cashflow of a project is prone to general economic and other uncertainties.

The attribute profiles of the projects were chosen by means of some kind of experimental design. A complete experimental design for four binary covariates would consist of sixteen projects. Experience with surveys has learned that many respondents find it difficult to assign priorities to various alternatives if their number becomes large or even moderately large. Then the chances of random choices become larger, which yields less reliable outcomes. A trade off between estimability and reliability resulted in a fractional design of eight alternative projects. Moreover, in order to make the investment decision realistic, some clearly dominant types of investment projects were discarded. This resulted in the following design matrix

TABLE 2

Design matrix

Project	Type of	PayBack	Size	Riskiness	*Code*
1	core	> 2 years	large	low	P1011
2	energy	≤ 2 years	small	low	P0101
3	core	≤ 2 years	small	high	P1100
4	core	≤ 2 years	large	high	P1110
5	energy	> 2 years	small	high	P0000
6	core	> 2 years	small	low	P1001
7	energy	> 2 years	large	high	P0010
6	*energy*	≤ 2 years	large	low	P0111

As a consequence of the choice of this design matrix some effects are **aliased** (see section6).

Respondents were asked to rank the eight investment types according to their preference. Unfortunately some firms were not able to rank the projects. They found it too diicult to assign priorities to eight projects on the basis of a combination of four project attributes. As a result 231 out of 313 cases remained available for our analysis, thus a non-response of **26%**. The sample of the 231 remaining firms showed a similar distribution by sector and size as the total sample and may still be regarded as representative. Other parts of the questionnaire were not affected by non-response.

The fact that 82 firms were unable to rank the projects indicates that firms do not base their ranks on a single attribute, but on a combination of attributes. Hence interaction effects may be just as relevant as main effects.

3. A LATENT CLASS BRADLEY-TERRY MODEL OF INVESTMENT PREFERENCE

3.1. fiomogeneous ***Choice behaviour***

As we have described above the respondents were asked to rank according to their preferences eight projects (the so-called “stimuli”), which have four distinct attributes. In fact these projects are rather types of investment opportunities than real investment proposals, but their combinations of attributes do correspond to those of realistic projects.

We assume that in ranking these stimuli the respondents compare each stimulus with every other one. Hence from each rank order of the s stimuli $S_1, S_2, \ldots S_s$

we can deduce $s(s-1)/2$ paired comparisons and the law of comparative judgement may be applied (Torgerson, 1958). Thus we assume that each of the r respondents $R_1, R_2, \ldots, R_r$ has expressed preferences between S_j and S_k ($j < k = 1, 2, \ldots$ s). In this way $n = rs(s-1)/2$ paired comparisons are obtained. Let the random binary variable y_{ijk} indicate the preference score of respondent R_i when comparing stimulus S_j with S_k, where $y_{ijk} = 1$ if S_j is preferred to S_k and $y_{ijk} = 0$ otherwise. Furthermore we assume independence for preference scores of the same pair by different respondents and for scores of different pairs by the same respondent.

In the case that the choice behaviour of the respondents is homogeneous (i.e. the respondents constitute a random sample from a population of respondents who have homogeneous preferences with respect to the s stimuli), Zermelo (1929), Bradley and Terry (1952), and Luce (1959) proposed the following scaling model to describe this situation.

Let $\mu_j > 0$ ($j = 1, 2, \ldots$ s) be the latent "true merit" of stimulus S_j measured on a ratio scale with an arbitrary scale factor. When stimulus S_j is compared with stimulus S_k the perceived merit ratio μ_j / μ_k may vary from respondent to respondent. As the choice behaviour is assumed to be homogeneous, it is described by a cumulative distribution function of the log-logistic form with $\ln(\mu_j / \mu_k)$ as location parameter and unity as scale factor. Hence the probability π_{jk} that stimulus S_j is preferred to stimulus S_k is given by

$$\pi_{jk} = \frac{1}{4}\int_{-\ln(\frac{\mu_j}{\mu_k})}^{\infty} \operatorname{sech}^2(\frac{z}{2})dz = \frac{1}{1+\exp[-\{\ln(\mu_j)-\ln(\mu_k)\}]} = \frac{\mu_j}{\mu_j+\mu_k}. \tag{1}$$

It is seen from the above equation that the merit scaling is unique except from a scale factor. Therefore the restriction

$$\sum_{j=1}^{s} \mu_j = 1 \tag{2}$$

is introduced, which makes the unique estimation of the μ_j possible.

If we make a logarithmic transformation of the merit ratings, thus

$$u_j = \ln(\mu_j) \qquad j = 1, 2, \cdots, s \tag{3}$$

then we obtain what appears to be a utility score on an interval scale. It is readily seen that

$$\pi_{jk} = \frac{1}{1+\exp\{-(u_j - u_k)\}} \tag{4}$$

and we have an alternative representation of the observed preference data, which is no better and no worse, but in our study more convenient.

Equation (4) can also be derived in an alternative way. Let $v_{ij} = u_j + \varepsilon_{ij}$ be the utility score of stimulus S_j as perceived by respondent R_i. Here ε_{ij} is a random error term, which is independently and identically distributed for all i and j according to the standard extreme value distribution

$$P(\varepsilon_{ij} < \varepsilon) = \exp\{-\exp(-\varepsilon)\} \quad (5)$$

Then it follows that for $j \neq k$

$$\pi_{ijk} = P(v_{ij} > v_{ik}) = P(\varepsilon_{ik} - \varepsilon_{ij} < u_j - u_k), \quad (6)$$

which can be shown to lead also to equation (4) (see for example Train, 1986).

By introducing dummy independent variables d_{il} we can write equation (4) as

$$\pi_{ijk} = \frac{1}{1 + \exp(-\sum_{l=1}^{s} u_l d_{il})}, \quad (7)$$

with

$$d_{il} = \begin{cases} 1 & \text{if } l = j \\ -1 & \text{if } l = k \quad \text{for all } i, \text{ and} \qquad j < k = 1, 2, \cdots, s. \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

The preference scores y_{ijk} have independent Bemouilli distributions with parameter π_{ijk} as specified by equation (4). This constitutes a Generalized Linear Model (GLM for short) with y_{ijk} as response variate, $rs(s-1)/2$ observations, the dummies d_{il} as covariates, a binomial error with index one and logit link, and linear predictor

$$\eta_{ijk} = \sum_{l=1}^{s} u_l d_{il}. \quad (9)$$

The utilities u_j, ($j = 1, 2, \ldots$ s) are readily estimated by GLIM4 (see for example Sinclair, 1982). Contrary to equation (2) the utilities are usually standardised in such a way that the smallest will have the value zero and the largest the value one. Note that the distribution of the deviance of the fitted model cannot be treated as approximately X^2 since the large sample theory does not apply here.

There is an alternative and more efficient way to estimate the utilities. Since the individual preference scores y_{ijk} are mutually independent and the respondents are supposed to have homogeneous preferences, we may use the aggregated preference scores instead

$$y_{\bullet jk} = \sum_{i=1}^{r} y_{ijk} \qquad j < k = 1, 2, \cdots, s, \tag{10}$$

which have a binomial distribution with parameter π_{jk} and index r. The GLM has now $y_{\bullet jk}$ as response variate, $s(s-1)/2$ observations, binomial error with index r and logit link. The dummy covariates and the link function are given by equations (8) and (9) from which the indices i are dropped. Both procedures will yield the same estimates of the utilities and their asymptotic covariance matrix. However, by using the aggregate preference scores we may treat the distribution of the deviance of the fitted model as approximately X^2 because r is sufficiently large. The direct estimation of the utilities on the basis of paired comparisons data is also referred to as internal analysis.

3.2. Heterogeneous choice behaviour

The assumption that the choice behaviour of the respondents is homogeneous is often not very realistic. Therefore we assume now that the respondents can be grouped into c latent classes $C_1, C_2, \ldots, C_c$, and that within each class the choice behaviour is homogeneous. Each respondent R_i belongs to one and only class C_m. The number of classes c and the actual classification is not known in advance. Wedel and DeSarbo (1992) have developed a probabilistic latent class model for the analysis of paired comparison data.

Let α_m represent the marginal probability that any respondent R_i belongs to class C_m, with

$$\sum_{m=1}^{c} \alpha_m = 1. \tag{11}$$

The likelihood $L_{i|m}$ for the paired comparisons data of respondent R_i conditional upon being in class C_m is given by

$$L_{i|m} = \prod_{j<k}^{s} \prod_{k=2}^{s} \pi_{jk|m}^{y_{ijk}} (1 - \pi_{jk|m})^{1-y_{ijk}} \tag{12}$$

where $\pi_{jk|m}$ is the probability that within class C_m stimulus S_j is preferred to stimulus Sk, with

$$\pi_{jk|m} = \frac{1}{1 + \exp\{-(u_{j|m} - u_{k|m})\}}, \tag{13}$$

and where $u_{j|m}$ is the latent utility of stimulus S_j within class Cm. The complete likelihood L of the paired comparisons data is given by

$$L = \prod_{i=1}^{r} \sum_{m=1}^{c} \alpha_m \prod_{j<k}^{s} \prod_{k=2}^{s} \pi_{jk|m}^{y_{ijk}} (1 - \pi_{jk|m})^{1-y_{ijk}}. \tag{14}$$

By maximizing the log-likelihood subject to the constraint given by equation (11) with respect to α_m and $\mu_{j|m}$ (m = 1, 2, . . ., c ; j = 1, 2, . .., s), thus by maximizing

$$\ln L = \sum_{i=1}^{r} \ln \sum_{m=1}^{c} \alpha_m \prod_{j<k}^{s} \prod_{k=2}^{s} \pi_{jk|m}^{y_{ijk}} (1 - \pi_{jk|m})^{1-y_{ijk}} + \lambda(\sum_{m=1}^{c} \alpha_m - 1), \tag{15}$$

where λ is a Lagrange multiplier, we can obtain simultaneously estimates of the marginal class membership probabilities and the utilities within the c latent classes of respondents. Once we have obtained these estimates, 'we can estimate the individual membership probability $\theta_m = P(R_i \in C_m)$ through Bayes' rule for each respondent R_i:

$$\theta_{im} = \frac{\alpha_m L_{i|m}}{\sum_{m=1}^{c} \alpha_m L_{i|m}}, \tag{16}$$

3.3. Numerical estimation procedure

Wedel and **DeSarbo** (1992) propose an EM-algorithm for computing estimates of α_m **and** $u_{j|m}$ ($m = 1, 2, \ldots c$; $j = 1, 2, \ldots$ s), which by making use of GLIM4 consists of the following steps:

Step 0. Define the number of classes c. Input row wise for every respondent the indices i, j and k, the preference score y_{ijk} and initial estimates of the individual membership probabilities $\theta_{im}^{(0)}$ (m = 1, 2, ... c). Compute the dummy covariates d_{jl} (l = 1, 2, ... s). Set the iteration counter t = 0.

Step 1. Given the $\theta_{im}^{(t)}$, compute the marginal membership probabilities α_m (m = 1, 2, ... c) according to the equation

$$\alpha_m^{(t)} = \frac{\sum_{i=1}^{r} \theta_{im}}{r}, \tag{17}$$

which follows from setting the derivative of equation (15) with respect to a,,, equal to zero. Estimates of $u_{j|m}$ are computed by running GLIM4 c times, each time with y_{ijk} as response variate, $\eta_{jk|m} = \sum_{l=1}^{s} u_{l|m} d_{jl}$ as linear predictor, binomial error with index one, **logit** link and weight $\theta_{im}^{(t)}$. This constitutes the M-step of the algorithm.

Step 3. Compute the individual membership probabilities $\theta_{im}^{(t+1)}$ according to equation (16). This constitutes the E-step of the algorithm.

Step 4. Test for convergence. Compute $\ln L^{(t+1)}$ and stop if $|\ln L^{(t+1)} - \ln L^{(t)}|$ is sufficiently small, else set $t = t+1$ and go to Step 1.

3.4. *Determining the appropriate number of classes*

As the actual number of latent classes c is unknown we apply a step wise procedure starting with c = 1 and use the Consistent Akaike Information Criterion (CAIC for short, Bozdogan, 1987) as a stopping criterion:

$$CAIC(c) = -2\ln L + n(c)[\ln\{r\,s(s-1)/2\} + 1], \tag{18}$$

where $n(c) = c(s-1)+c-1$ is the effective number of parameters to be estimated when the number of classes is equal to c. The CAIC penalises models that are overspecified. The value of c is selected which yields a minimum CAIC. We can only use the CAIC as a heuristic because the large sample theory does not apply here.

4. IMPACT OF PROJECT AT-TRIBUTES ON UTILITIES

In our study we are not only interested in the utilities of the stimuli, but also to which extent the project attributes can explain the expressed preferences of one stimulus to another.

Hence let the attributes $A_1, A_2, \ldots, A_a$ of the stimuli be described by the binary covariates x_{jl} ($j = 1, 2, \ldots, s$; $l = 1, 2, \ldots, a$). For the time being we assume that within class m ($m = 1, 2, \ldots, c$) a linear relationship exists between the utility u_{jm} of stimulus S_j and the binary covariates x_{jl}:

$$u_{j|m} = \beta_{0|m} + \sum_{l=1}^{a} \beta_{l|m} x_{jl}$$

in which the coefficients $\beta_{l|m}$ represent the impacts of the attributes on the utilities. in latent class m. Substituting the utilities in equation (4) by the right hand side of equation (19) yields

$$\pi_{jk|m} = \frac{1}{1+\exp\{-\sum_{l=1}^{a} \beta_{l|m}(x_{jl} - x_{kl})\}} \tag{20}$$

If we assume that a respondent's preference rating is also influenced by attractive combinations of two project attributes, we must augment equation (19) with first order interaction terms, thus

$$u_{j|m} = \beta_{0|m} + \sum_{l=1}^{a} \beta_{l|m} x_{jl} + \sum_{l=1}^{a}\sum_{n>l}^{a} \beta_{ln|m} x_{jl} x_{jn} \qquad j = 1, 2, \ldots, s. \tag{21}$$

For the corresponding augmented version of equation (20) we obtain

$$\pi_{jk|m} = \frac{1}{1+\exp[-\sum_{l=1}^{a}\{\beta_{l|m}(x_{jl} - x_{kl}) + \sum_{l=1}^{a}\sum_{n>l}^{a} \beta_{ln|m}(x_{jl} x_{jn} - x_{kl} x_{kn})\}]} \tag{22}$$

The coefficients β together with the marginal class membership probabilities and the individual class membership probabilities are readily estimated in a similar way by GLIM4 as described above for the direct estimation of the utilities, but now using the linear predictor

$$\eta_{jk|m} = \sum_{l=1}^{a} \beta_{l|m}(x_{jl} - x_{kl}) + \sum_{l=1}^{a}\sum_{n>l}^{a} \beta_{ln|m}(x_{jl} x_{jn} - x_{kl} x_{kn}). \tag{23}$$

The indirect estimation of the utilities on the basis of paired comparisons data by means of covariates describing the attributes of the stimuli is also referred to as external analysis. If the project attributes indeed adequately explain the expressed preferences of one stimulus to another, we may expect that the internal and external analysis will yield identical results with respect to the estimation of the marginal class membership probabilities and the individual class membership probabilities.

5. DATA ANALYSIS AND PARAMETER ESTIMATION

5.1. Analysis of aggregated *preference data*

The first step in our data analysis was to determine the degree of agreement among the 231 rankings by means of Kendall's coefficient of concordance W (Kendall, 1975), which is derived from the sums of ranks allotted by the respondents to the eight projects. These sums are denoted by Q_i (i = 1,2, . . ., 231) The mean value of these sums must be equal to 1039.5 and in general to $r(s+1)/2$. The sum of squares of the deviation of these sums from their mean value $\Sigma_i\{Q_i-r(s+1)/2\}^2$ would be given by $r^2(s^3-s)/12$ if all rankings were identical, i.e. perfect agreement. They are zero (or very close to zero) if there had been no agreement at all. Hence the degree of agreement among the r respondents is reflected by the degree of variance among the s sums of ranks. Kendall's coefficient of concordance

$$W = \frac{\sum_{i=1}^{r}\{Q_i - r(s+1)/2\}^2}{r^2(s^3-s)/12} \tag{24}$$

is a function of that degree of variance, which is equal to zero if there is no agreement at all and is equal to one if there is perfect agreement. If there is no agreement at all and s is larger than seven, the quantity

$$X^2 = r(s-1)W \tag{25}$$

is approximately distributed as Chi square with s-7 degrees of freedom.

For our 231 rankings of eight projects we found $W = 0.05$ and $X^2 = 85.958$ with 7 degrees of freedom, which is far beyond any common significance point ($P < 10^{-6}$). Thus the assumption of no agreement at all is rejected and we conclude that there is a slight but significant degree of agreement among the rankings of the 231 respondents.

In addition we have computed direct and indirect estimates of the utilities on the basis of the aggregated paired comparisons results deduced from the 231 rankings. The aggregated paired comparison results are listed in Table 3. An entry in row *i* and column *j* denotes the number of times that the project in row *i* is preferred to the project in column *j*.

TABLE 3

Preferences of 231 respondents for 8 investment projects

Project	PI011	PO101	P1100	P1110	PO000	P1001	PO010	P0111
P1011	—	90	96	95	96	loo	114	117
PO101	141	—	120	121	139	130	160	149
PI100	135	111	—	111	133	120	147	149
PI110	136	110	120	—	130	121	158	152
PO000	135	92	98	101	—	105	137	142
P1001	131	101	111	110	126	—	142	147
PO010	117	71	84	73	94	89	—	94
PO111	114	82	82	79	89	84	137	—

GLIM4 provided estimates of the utilities by means of the procedures described in section 3.1 The estimates are based on the upper triangular matrix of preferences given in Table 3 above. Table 4A below shows the results.

TABLE 4A

Estimated utilities on the basis of the aggregated preference data

	Projects							
Utilities	P1011	PO101	P1100	P1110	PO000	P1001	PO010	PO111
As estimated	0.101	0.660	0.539	0.586	0.327	0.475	-0.105	0
Standard error	0.067	0.068	0.067	0.067	0.067	0.067	0.067	Aliased
Standardised	0.269	1	0.842	0.903	0.564	0.757	0	0.137

Differencing the deviances obtained when fitting only a constant term, which is equivalent to assuming that there are no differences between the utilities, and when fitting the mutually different utilities leads to the following analysis of deviance table:

TABLE 4B

Analysis of deviance for testing the equality of the utilities

Model	Residual deviance	Degrees of freedom	Source	Deviance	Degrees of freedom
Constant term (equal utilities)	225.81	27			
Eight utilities	16.51	21	Different utilities	209.30	6

The deviance associated with the mutual differences between the eight utilities is approximately distributed as Chi square and is again far beyond any common significance point.

Subsequently we computed the impact of the project attribute values on the utilities. As a consequence of the chosen experimental design given in Table 2 the first order interactions between the covariates x_1, x_2 and x_4 are **aliased**. Furthermore, we have to assume that the effects of higher order interactions are immaterial. A model with only the main effects did not give a good fit as can be seen from the analysis of deviance in Table 5A below.

TABLE 5A

Analysis of deviance for testing the presence of first order interactions

Model	Residual deviance	Degrees of freedom	Source	Deviance	Degrees of freedom
$x_1 + x_2 + x_3 + x_4$	94.93	24			
$x_1 + x_2 + x_3 + x_4 + x_1x_3 + x_2x_3 + x_3x_4$	16.51	21	First order interactions	78.42	3

Therefore we have to include the estimable first order interactions as well. Table 5B below gives the estimated impacts of the covariates on the utilities.

TABLE 5B

Estimated impacts of the covariates on the utilities on the basis of the aggregated preference data

Covariate	Estimated impact	Standard error	Standardised impact
Constant term	—	—	0.564
Main effects			
x_1	0.013	0.047	0.017
x_2	0.199	0.047	0.260
x_3	-0.432	0.067	-0.564
x_4	0.135	0.047	0.176
Interaction effects			
x_1x_3	0.383	0.067	0.500
x_2x_3	0.096	0.067	0.125
x_3x_4	-0.325	0.067	-0.424

The utilities computed from the standardised impacts are exactly equal to the directly estimated standardised utilities given in Table 4, as they should be because the variation in seven independent utilities is explained by four covariates and three first order interaction effects. For example, the indirectly estimated utility of project PO600 is equal to the constant term in Table 4. The utility of project **P101** 1 is equal to 0.564 + 0.017 - 0.664 + 0.176 + 0.500 - 0.424 = 0.269. We should be cautious with the interpretation of the results in Table 4. Only if we assume that the effects of the first order interactions x_1x_2, x_1x_4 and x_2x_4 are immaterial, we can take the main effects x_1, x_2 and x_4 at their face value. Otherwise they are confounded with their mutual interaction effects.

5.2. Exploring clusters of homogeneous preferences

The degree of concordance among the 231 rankings was highly significant but very small. Hence our second step was to apply the procedure described in section 3.2 on the individual preference data in order to find clusters of more homogeneous preferences. The first problem was to obtain fair initial estimates of the individual membership probabilities θ_m (m=1, 2, . . ., c). For this we used the fuzzy clustering program FANNY written by Kaufman and Rousseeuw (1990). A fuzzy clustering method allows for some ambiguity in assigning respondents to various clusters by means of membership coefficients, that range from zero to one. We portray these membership coefficients as initial estimates of individual membership probabilities. We performed the fuzzy clustering on the basis of the rankings and used $(1-\rho)/2$ as a dissimilarity measure between any two rankings, where ρ is Spearman's rank correlation coefficient. We explored up to 15 clusters.

Figure 1 shows the values of -21nL and the CAIC obtained with the latent class Bradley-Terry model versus the number of clusters. Due to the used convergence criterion in our EM-algorithm and the possibility of arriving in a local maximum, the values of -21nL show a somewhat irregular behaviour. Therefore we have fitted a quadratic curve through the -21nL points From the smoothed values we recalculated the CAIC-values. The minimum value of the CAIC occurs when the number of clusters is equal to 11. Table 6A shows for each of the 11 clusters the frequency distribution of the 231 respondents by their individual membership probabilities. The vast majority of the individual membership probabilities is either close to zero or to one. This allows an almost definite grouping of the 231 respondents into the 11 clusters.

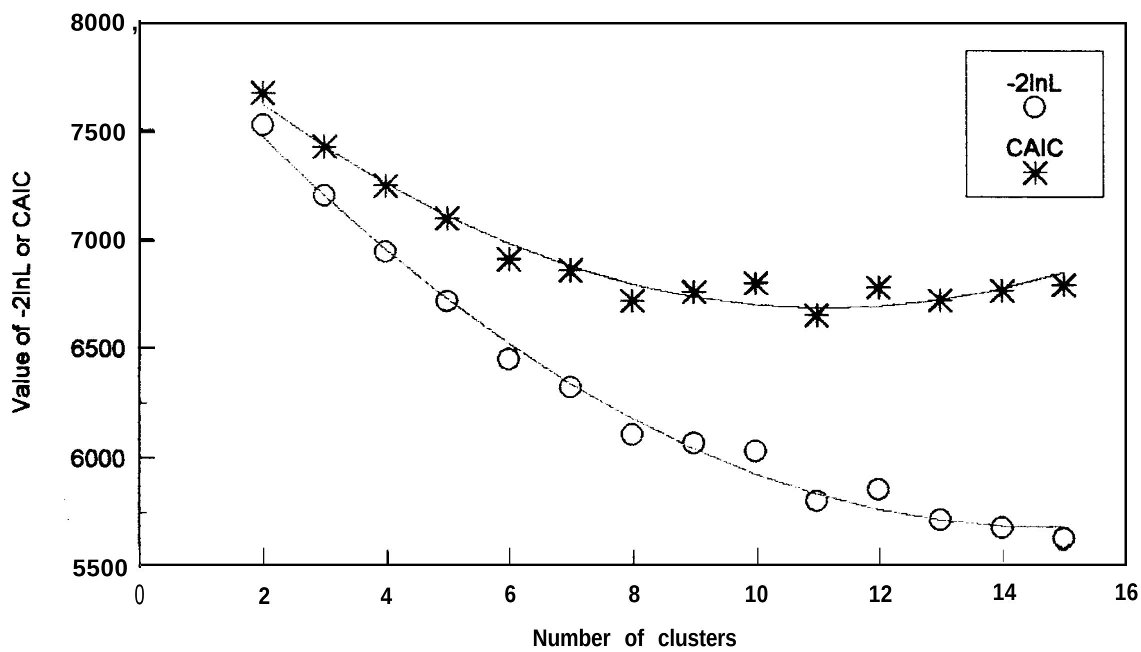

Fig. 1 Values of -2lnL and the CAIC versus the number of clusters

TABLE 6A

Frequency distributions of the 23 1 respondents by their individual membership ***probabilties*** *in the* ***1*** *1 clusters*

Membership probability	Cluster 1	2	3	4	5	6	7	8	9	10	11
20 - ≤ 0.05	186	188	205	205	208	214	217	217	217	221	221
> 0.05 - ≤ 0.10	1	0	0	0	1	0	0	0	0	0	1
> 0.10 - ≤ 0.25	0	2	0	1	1	1	0	0	0	0	0
> 0.25 - IO.50	0	1	0	2	0	0	0	0	0	0	0
> 0.50 - IO.75	0	1	1	0	0	0	0	0	1	0	0
> 0.75 - IO.90	1	1	0	2	1	0	0	1	0	0	0
> 0.90 - IO.95	0	0	0	0	0	1	0	0	0	1	0
> 0.95 - ≤ 1	43	38	25	21	20	15	14	13	13	9	9

Table 6B shows for each of these 11 clusters the size (i.e. number of respondents), the standardised utilities, the residual deviance (with 21 degrees of freedom) and the coefficient of concordance ***W*** among the respondents rankings within the cluster. Utilities and the residual deviance are computed from the aggregated preference data within each cluster. From this table it is seen that the clustering technique indeed managed to obtain clusters with substantial degrees of agreement. The coefficient of concordance between the clusters is equal to 0.10, which is fairly low.

TABLE 6B

Cluster size, standard&d utilities, residual deviance and the coefficient of concordance for the 11 clusters

		Standafdised utilities of project								Residual	
Cluster	Size	P1011	PO101	P1100	P1110	PO000	P1001	PO010	PO111	deviance	W
1	44	0.000	0.974	1.000	0.294	0.463	0.434	0.356	0.429	26.14	0.74
2	40	1.000	0.066	0.000	0.626	0.411	0.434	0.276	0.353	24.61	0.59
3	26	0.986	0.558	0.745	0.740	0.000	1.000	0.337	0.542	25.79	0.68
4	23	0.661	1.000	0.435	0.390	0.416	0.384	0.351	0.000	11.97	0.42
5	21	0.845	0.000	1.000	0.285	0.845	0.391	0.159	0.196	24.11	0.58
6	16	0.000	0.758	0.945	1.000	0.605	0.912	0.536	0.417	21.27	0.71
7	14	0.000	0.961	0.592	0.773	1.000	0.146	0.158	0.314	8.53	0.87
..8	14	0.335	0.855	0.000	1.000	0.809	0.502	0.396	0.493	16.54	0.72
9	14	**0.000**	**1.000**	**0.525**	**0.892**	**0.438**	**0.632**	**0.962**	**0.547**	14.59	0.71
10	10	**0.000**	**0.034**	1.000	0.773	0.756	0.598	0.841	1.000	20.45	0.57
11	9	0.000	1.000	0.301	0.359	0.415	1.000	0.434	0.880	13.86	0.64

There are highly significant differences **between** the clusters. This may be clear from the analysis of deviance table given below.

TABLE 6C

Analysis of deviance for testing the absence of ***differences*** *between* ***clusters***

Model	Residual deviance	Degrees of freedom	Source	Deviance	Degrees of freedom
Aggregate	3981	*301*			
11 Clusters	*212*	*231*	Between clusters	3769	*70*

The last step was to compute the impacts of the covariates on the utilities for each cluster. These impacts are listed in Table 7. An italic entry in this table indicates that the estimated effect is not significant at a level of **10%**.

TABLE 7

Impacts of the covariates on the project utilities within the clusters

Cluster	Impact of covariates on project utilities							
		Main effects				*Interaction effects*		
	Constant	x_1	x_2	x_3	x_4	x_1x_3	x_2x_3	x_3x_4
1	0.463	***-0.001***	0.538	-0.107	-0,028	-0.244	-0.355	-0.082
2	0.411	***-0.024***	-0.387	-0.133	0.046	0.521	0.237	0.180
3	0.000	0.594	0.152	0.337	0.406	-0.170	-0.172	-0.181
4	0.416	-0.298	0.318	-0.065	0.266	0.648	-0.629	-0.306
5	0.845	0.273	-0.118	-0.685	-0.727	0.774	-0.144	1.025
6	0.605	0.247	0.093	***-0.070***	0.060	-0.223	0.348	-0.619
7	1.000	-0.612	0.204	-0.842	-0.243	0.763	0.261	-0.066
8	0.808	-0.581	-0.228	-0.413	0.274	0.804	0.609	-0.559
9	0.438	-0.140	0.227	0.524	0.334	-0.168	0.077	-0.988
10	0.756	0.404	-0.160	0.085	-0.562	-0.938	0.626	0.256
11	0.415	-0.057	-0.057	0.079	0.642	-0.420	0.459	-0.598

6. INTERPRETATION

The obtained grouping of the 231 firms in 11 clusters reveals a clear heterogeneity among the 231 respondents with respect to their preferences for the eight project types. This is already a first step to a better understanding of the observed preference structure. The differences between some clusters are large. For example, a comparison of clusters 3 and 7 learns that three main and two interaction effects have opposite signs. The firms in cluster 3 have a strong preference for core business projects with a high return. Particularly, the combination of investment size and investment type has a substantial positive impact on the preferences (0.594+0.337-0.170=0.761 >>0). Firms in duster 7, however, strongly oppose to the combination of large core business projects (-0.612-0.842+0.763= -0.691<<0). Note that the degree of agreement within cluster 7 is rather high. Clusters 3 and 7 have fundamental different opinions about their preference structure.

Furthermore, there are firms that reveal similar underlying attitudes and nevertheless express very different preferences for specific projects. This can be illustrated by comparing clusters 1 and 2. The firms in both these clusters can be labelled as "risk-averse" (the underlying attitude), but differ in the way they work it out, which has large consequences for the rank order of the projects: Firms of duster 1 prefer small projects with a short payback period, while investment type and riskiness only play a minor role. Firms in cluster 2, however, prefer large core business projects with a low risk profile. Judging from Table 6B these clusters cannot be merged. In this respect we can say that the clustering analysis has given us a clear picture of firms that are very heterogeneous in their preferences and also in' their underlying attitudes.

In order to obtain a better understanding of the underlying attitudes of the observed preferences' structures, one has to examine both the main effects of the project attributes and the interaction effects. First we consider the main affects. Firms in the 11 clusters are rather consistent is evaluating payback period and riskiness. They prefer projects with short payback periods (6 positive, 1 neutral attitudes) and low risk (6 positive and 3 negative). There is a dislike for large investment projects (5 negative and 4 neutral). This is confirmed by looking at Table 6B: The only difference between the project types 2 and 8 is the investment size (where project 8 entails a large investment), but project 2 is more preferred than project 8, see Table 8. The same holds for project types 1 and 6, where project type 1 requires more capital.

The main impact of investment type (energy conservation vs. pore business) is not considered to be very important (3 neutral). It cannot be seen as the attribute that turned the scale (whereas investment size and payback period obviously are).

TABLE 8:

Frequency tables of preferred and disliked project types

Project	1	2	3	4	5	6	7	8
Like •	.	4	6	4	3	1	2	1	1
Dislike •	.	7	3	3	1	2	1	3	2

- 'Like' refers to the number of times that project *i* is among the 2 most preferred projects of a cluster; 'dislike' refers to the number of times that project *i* is among the 2 most disliked projects. The sum of 'like' must equal 2 times the number of clusters = 22; similarly for 'dislike"

The first order interaction effects play an important role. We have shown that by adding the three first order interaction effects to the main effects model the deviance is reduced with more than 78 points for only three degrees of freedom. In clusters 4 and 10 the interaction effects are even more important than the main effects. The implication of dominant interaction effects is that similar rank patterns can still have very different underlying investment attitudes. Thus, understanding the impacts of project attributes is more meaningful than observing preference ratings or rankings. Let us take for example cluster 10. Here the interaction effect of type x size is very negative (-0.938) and the interaction effect of payback period x size is strongly positive (0.626). Project 3 (code P1 100) is just as liked as project 8 (code PO1 1 1), while they differ in three out of four attributes. Equal utility ratings for different projects may originate from the impacts of the different project attributes.

It was not possible to estimate all the main and interaction effects due to the chosen particular experimental design. The main and interaction effects of the attributes type of investment, payback period and size of investment are confounded. This makes a straight forward interpretation complicated. However, our inferences with respect to the relevance of the underlying investment attitudes remain valid; only the absolute values of the impacts concerned should be interpreted with care.

This particular design was the result of a trade off between estimability and a set of realistic combinations of project attributes, in which no dominant investment projects were present. The latter aspect was important in order to avoid a bias in response.

7. DISCUSSION AND CONCLUSIONS

Our results indicate that investment attitudes of firms are more important than utility ratings or rank orders. Different underlying structures can produce equal utilities. Analysing barriers that hamper energy conservation investments means analysing which of the project attributes pose effective barriers. Our results suggest that there is a dislike for large investment projects. The type x size and size x risk interactions show that firms are not charmed by large investments. In other words, a barrier for investment is a large amount of capital required.

The investment preference is also negatively influenced by a long expected payback period and a high risk profile. These barriers are common to every investment project. In the case of energy conservation, the degree of risk is related to expected fluctuations in energy prices. Consequently high expected fluctuations in energy prices should be regarded as a barrier to investment in energy conservation technologies. The payback period too is largely determined by the energy price. Low expected energy prices lead (*ceteris paribus*) to a longer expected pay back period and may also pose such a barrier.

Type of investment does not seem to influence the preferences of firms. The often used argument of “too long a distance to core business activities” is less prominent than theory suggests. In other words, our results indicate that type of investment is not a main barrier to the implementation of energy conservation projects.

This analysis shows that there are large differences between the latent dusters of firms, and that within the dusters a substantial degree of agreement exists. Clusters which show more or less similar ranking patterns may have different underlying investment attitudes. The analysis of impacts of project attributes provides a better understanding of investment preferences than just the analysis of rank orders. Hence the model we propose is adequate to answer the questions we posed in the introduction with respect to homogeneity and the existence of potential barriers. It enables us to analyse in detail the impacts of both main effects and interaction effects of project attributes.

The results obtained with the model proposed here can be helpful for policy makers. They provide information on how different groups of firms react to “stimuli” and suggest that firms are sensitive to financial stimuli (e.g. payback period, required capital outlay) and risk. An implication could be that policy makers would focus on providing firms with financial stimuli. Eco-taxes combined with subsidies could prove to be effective to stimulate the advance of energy conservation technologies.

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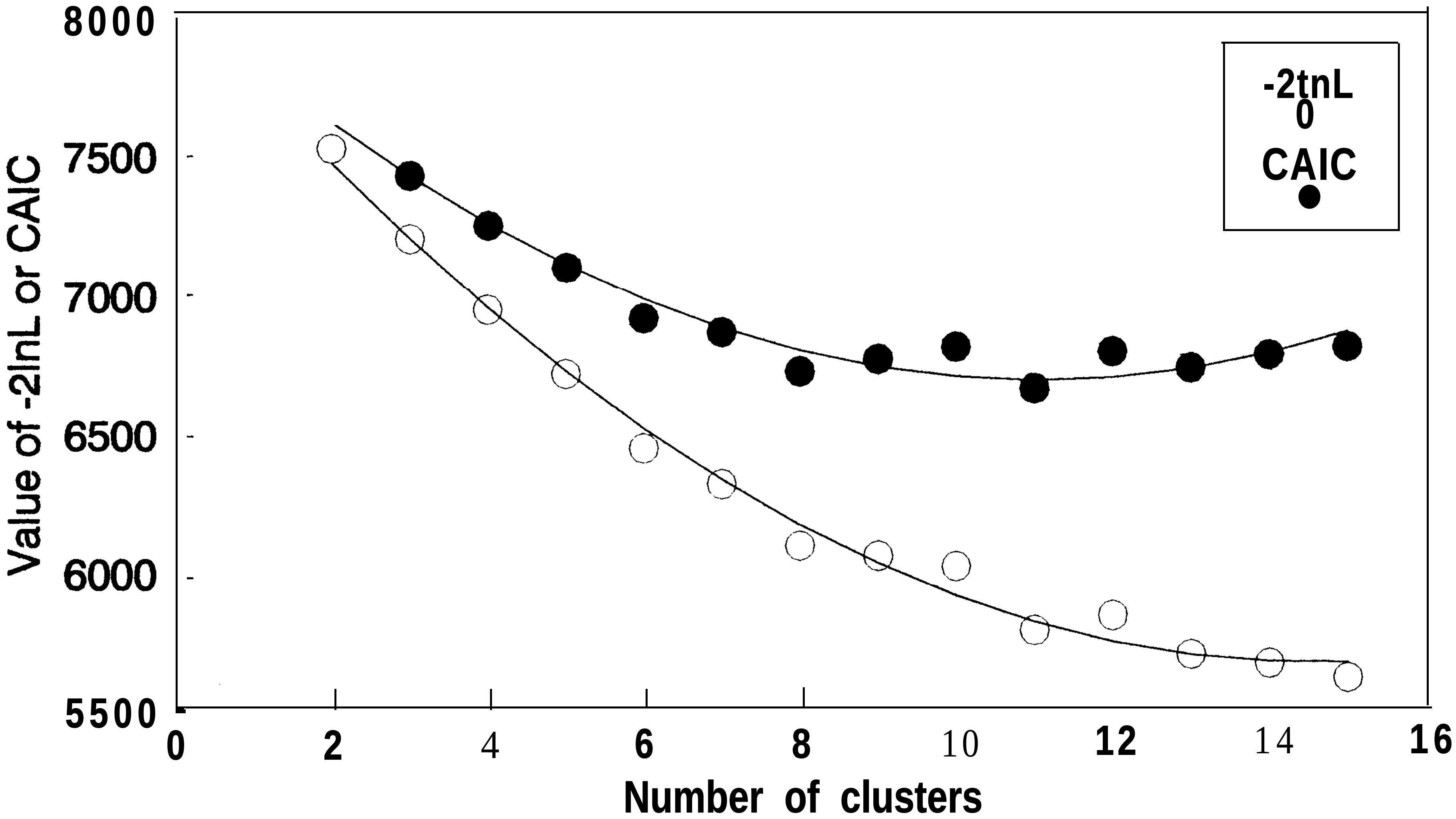

8000
7500
7000
6500
6000
5500
Value of -2lnL or CAIC
0
2
4
6
8
10
12
14
16
Number of clusters
-2tnL
0
CAIC

Fig. 1 Values of $-2\ln L$ and the CAIC versus the number of clusters