

Attention to Risk and Return: Choice Experiment of the Stated and Inferred Use of Investment Attributes

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Received: September 5, 2016	Accepted: September 15, 2016	Available online: October 8, 2016
doi:10.11114/aef.v4i1.1858	URL: http://dx.doi.org/10.11114/aef.v4i1.	1858

Abstract

This paper applies a choice experiment method to analyze investors' attention to investment attributes. Prior research mainly in environmental, agricultural, and transport economics has observed that people actually use different attributes than which they say in choice experiment tasks. This research examines do people pay attention to all the given investment attributes, and if they do not, whether the self-reported attribute attendance corresponds to the behavior inferred from the choices. The experiment is conducted among a pool of 845 financially literate subjects, which enables a study of the factors affecting the investment decisions of informed individuals. The choice experiment puts the subjects in a decision making situation in which they are presented with hypothetical investment opportonities in the agricultural and food production sector. The investments are described with four attributes: voting right, return right, capital appreciation, and expect return. We use the equality-constrained latent class (ECLC) method to infer the choice patterns. The comparison of the stated attribute attendance patterns to the inferred attribute non-attendance patterns shows that the investors are prone to overstate the importance of expected return in their choices. The result indicates that individuals may not be fully aware of the factors affecting their investment decisions. Finding such behavioral bias among financial professionals implies that financially less knowledgeable people may be even more prone to uninformed investment decisions, be for example lured by the marketing of financial products with high returns.

Keywords: investments, decision making, finance professionals, attribute non-attendance

1. Introduction

Rational investors make allocation decisions based on risk and return. The assumption of the portfolio theory is, however, often violated as investors consider many other factors and fail to optimize risk and return. Individuals may even be unaware of the factors affecting their investment decisions. Research on responses to survey questions has revealed that the intended and the actual behavior may differ (e.g. Armitage & Conner, 2001). This is particularly true for complex decision making situations in which individuals try to avoid the cognitive burden by using simple decision rules, heuristics, e.g. in financial decisions. Choice modeling literature has increasingly focused on the phenomenon called attribute non-attendance, which increases understanding on the attribute processing strategies of the respondents by observing whether they ignore information given in choice tasks (Hensher, Rose, & Greene, 2005; Campbell, Hutchinson, & Scarpa, 2008); Scarpa, Gilbride, Campbell, & Hensher,(2009). There is a growing body of evidence on attribute non-attendance in environmental valuation and transport studies, but to our knowledge, evidence in the financial economics and investments is non-existing.

This paper utilizes data from a choice experiment conducted among 845 financial professionals to examine the use of investment attributes and whether there is a difference between what the investors say and how they actually behave. The attributes represent both currently available features of stock investments and hypothetical features regarding control right, return right, capital appreciation, and expected return and risk. The experiment is conducted as a web survey and it includes a set of decision making situations which describe investments in agricultural and food production sector. The sample consists of Finnish financial market professionals who hold the diploma for certified financial advisers. The sample forms a group of informed and financially literate individuals. Using this pool of respondents mitigates the common problems with experiments with student subjects (Harrison & List, 2004). The respondents are, however, advised to express their preferences as private investors instead of in their possible role of delegated portfolio managers.

The objective is to uncover which investment attributes the subjects state to use (i.e. are aware of using) and compare those statements to the attribute processing strategies inferred from the choices. After the choice tasks, the respondents were asked in the questionnaire, which attributes they attended to in making the hypothetical investment decisions. The self-reported attribute non-attendance is compared to the attribute non-attendance patterns which are obtained using the equality-constrained latent class (ECLC) model. The model divides the respondents to a number of classes so that the attribute preferences within a class are the same but they differ from the preferences of the members in other classes. The estimation of the latent class model results in class prababilities which indicate the proportion of respondents belonging to a particular class. If the class probabilities differ from the self-reported attribute non-attendance, we can conclude that respondents use simple rules in the choice tasks but are unware of it.

This research aims at increasing understanding in the finance literature regarding how aware individuals are of the factors affecting their investment decisions. A simple experimental setting enables uncovering whether investors overstate their focus on risk and return while in reality other factors drive the investment decision. The results show that this is the case in our sample of financial professionals. We observe in the data on self-reported attendance that expected return was the most attended attribute and less than 3% of the respondents stated to ignore it. Nevertheless, inferring the attribute non-attendance patterns from the choices with the ECLC model reveals that 15% of respondent ignored expected return. The random choice strategy, i.e. ignore all the investment attributes, is much more prevalent than what is observed from the stated decision strategies. As much as 12% of the respondents are inferred by the ECLC model to ignore all attributes. The majority relied on two attributes in their choices.

The contribution of this study to the existing literature is twofold. This is to our knowledge the first paper in the field of financial economics to utilize choice experiment method in the study of financial preferences. Methodologically, the results of this paper corroborate the findings of Kragt (2013) by showing the respondents' stated attribute usage patterns differ from the non-attendance inferred from the choices.

2. Literature

Choice experiments are frequently used in studies of consumer preferences (Swait & Adamowicz, 2001) in the fields of transport (Hensher & Rose, 2007), recreation (Train, 1998; Boxall and Adamowicz, 2002) and various environmental valuation contexts (Scarpa et al., 2009), health economics (Lagarde, 2013, Hole, Kolstad, & Gyrd-Hansen, 2013), and agricultural economics (Balcombe, Bitzios, Fraser, & Haddock-Fraser, 2011). The analytical framework is the economic theory of consumer behavior and random utility theory (Lancaster, 1966, McFadden, 1974). The implicit assumption in the behavioral model of random utility is that an individual pays attention to all attributes in the choice situations. In compensatory decision strategies an individual compensates with a higher value in terms of one attribute for a lower value of another. However, it is likely that respondents apply decision processing strategy that is partially compensatory, i.e. not consider all attributes in the trade-offs. In such simplifying decision processing model an individual does not compensate a change in an attribute with a change in another dimension (Caputo, Nayga, & Scarpa, 2013).

The recent literature on choice modelling literature has focused attention to the subjects' information processing strategies and the continuity of preferences. Preference discontinuity is studied in the contexts of environmental valuation (Campbell, Hensher, & Scarpa, 2011; Hensher, Rose, & Greene, 2012; Caputo et al., 2013; Kragt, 2013), transport (Hess & Hensher, 2010), and health economics (McIntosh & Ryan, 2002; Lagarde, 2013, Hole et al., 2013). Two approaches to identify preference discontinuity are typically used. The stated attribute attendance method relies on follow-up questions which request respondents to explicitly state if they ignored any attributes (e.g. Hensher et al., 2005; Campbell et al., 2008; Hole et al., 2013; Kehlbacher, Balcombe, & Bennett, 2013). Inferred methods typically rely on a latent class approach in which the attribute processing strategies are identified from the class probabilities (Scarpa et al., 2009; Campbell et al., 2011). The overall conclusion of the studies which compare the stated and inferred method is that the inferred strategies produce better model fit (Scarpa, Zanoli, Bruschi, & Naspetti, 2013; Hess & Hensher, 2010; Kragt, 2013).

3. Methodology

3.1 Experimental Data

The data consists of a questionnaire among Finnish financial market professionals. This represents a group of informed subjects. The sample is based on the register of persons who have completed the diploma for certified financial advisers during the period from January 2009 to June 2014. The financial industry has undergone such major structural changes in recent years that the contact information may be outdated if the sample were extended. The diplomas are administered by the Finnish Association of Securities Dealers' and Aalto Executive Education, which provided confidential access to the register. The subjects were briefed to respond to the questionnaire as private persons.

The Internet-based questionnaire was sent to 7,200 persons via email in October 2014. Approximately 1,200 email addresses returned a non-reception message and thus those persons were lost from the initial sample. After one

remainder, 845 individuals responded to the questionnaire yielding a response rate around 14%. The sample is slightly unbalanced in terms of gender as 540 (64%) responses are from female and 305 (36%) are male. However, this reflects the gender distribution in the financial sector in Finland as 70% of employees in banking were females in 2011 (Federation of Finnish Financial Services, 2013). The average age of all respondents is 41 years.

The majority of the respondents are employed in a bank or brokerage. The typical position is investment adviser, while about every fifth respondent is currently in a manager position. In line with the overall sector demographics, the bank management positions are male-dominated, and typical job titles of female employees are in customer service and service advisory. The final sample consists of rather experienced financial professionals as about a half has over 15 years work experience in the sector and 30% has over 25 years of experience.

3.2 Choice Experiment Design

In the choice experiment method subjects are presented with a number of choice sets that present several alternatives characterized by a set of attributes. Subjects are requested to choose the most preferred alternative in each choice task. The method is often used to test individuals' preferences in hypothetical situation, for example towards new products or policies, when revealed preference data is not available. The choice attributes of the investment instruments in this study are control right, return right, capital appreciation, and expected return (Table 1). The attributes are selected to capture the main components inherent in any stock investments. The attributes are kept simple to reduce the cognitive burden of the respondents but also to keep the focus on the key elements of an investment instrument. Each attribute has three qualitative levels.

Attribute	Description	Levels
Voting right	Voting rightThe entitlement to vote. In the first option, the control is exclusive restricted to the producers. In the other options, all investors are endowed with voting rights, but the control block held by the producers varies.Return rightThe form of the payment of the investment return.	 No voting right Voting right, ownership is dispersed Voting right, producers have
Return right		majority ownership 1. Dividend
		2. Preferred dividend
		3. Fixed interest return
Capital appreciation	The treatment of the invested capital. The value may fluctuate daily in a marketplace or the nominal may be safe and returned at nominal value or appreciates through bonus issues following the firm results.	1. Valued in a secondary market
		2. Capital is secured and is returned at nominal value
		3. Capital is secured and nominal is adjusted for the appreciation of firm value
Expected return	Annual rate of return.	1. 8%, high risk
		2. 5% moderate risk
		3. 2% low risk

Table 1. Attribute description and levels in the choice experiment

Note: Boldface text represents the reference level of an attribute.

The respondents were briefed that the choice situations represent equity claims in food chain companies in which agricultural producers are also owners themselves. Food production serves as a case sector for the study, and the choice experiment was part of a larger questionnaire. After the presentation of the attribute levels the respondents were instructed to weigh the choice tasks with regard to own surplus savings that could be allocated to investing and are not set aside for consumption. The standard cheap talk script was included in the instructions to mitigate the hypothetical bias which is a risk in stated preference studies (Landry and List, 2007; Hensher, 2010). The benefits of including a cheap talk script in choice experiment instructions are evidenced in Ladenburg et al. (2010).

To form the choice experiment tasks from the attributes, a fractional factorial design was generated with Ngene software. We used a D-efficient design with no prior information. A total of 36 choice sets was generated and split to six blocks to limit the number of tasks per respondent. Each respondent was presented with six choice sets that each offers three alternatives. A two-staged task was used: first, a forced choice included only two investment alternatives and subjects were asked to choose between those, after which an unforced choice incorporated also the third alternative, an opt-out.

The opt-out was defined as keeping the investment wealth in a bank account earning 1% return instead of allocating wealth to either of the new instruments. The interest level approximates the level offered by Finnish banks to retail customers' time deposits or savings accounts at the time when the questionnaire was conducted (Bank of Finland statistics). The two-staged task aimed at getting the respondents to concentrate on the attributes, but to mitigate the problems associated with forced choice tasks (Rose and Hess, 2010). The unforced task with an opt-out was the main data used for analysis.

The choice sets were organized in a random order to mitigate any effects on estimates from ordering of attributes. Six choice tasks followed by a question that requests the subject to state which attributes they paid attention to in making the choices. The question is intended for the analysis of serial stated attribute non-attendance.

3.3 Attribute Attendance

We analyze both stated and inferred attribute non-attendance models in order to examine the information processing strategies of investors. The comparison of the stated and inferred attendance patterns enables verifying which attributes investors attend to and how conscious investors are about their use of attributes. Several studies account for attribute non-attendance by asking the respondents to state explicitly whether they ignored an attribute or not (e.g. Hensher et al., 2005; Campbell et al., 2008). This is called stated attribute non-attendance. We elicited the serial non-attendance information by asking the respondents after completing the set of six choice tasks which of the attributes they attended to in the series of choice situations.

Another strategy to examine information processing strategies is to infer the attribute non-attandence from the choices. Inferred attribute non-attendance is typically analyzed with the latent class model in which the classes are formed based on the different attribute use patterns (Hensher & Greene, 2010; Scarpa et al., 2013; Campbell et al., 2011). The basic latent class model is described in Appendix 1. The equality-constrained latent class model (ECLC) infers the class membership from the observed choices and the discrete number of classes is determined endogenously (Kragt, 2013). The classes represent groups of respondents with different attribute non-attendance patterns, i.e. different decision strategies. The frequency of a certain predefined decision pattern is read from the class probabilities. The latent class structure can be estimated with fixed parameters for the choice attributes which implies homogeneous preferences across all classes (Scarpa et al, 2009; Hensher & Greene, 2010) and by accounting for heterogeneity by letting the parameters vary between the classes (Kragt, 2013).

We follow the stepwise estimation strategy of Kragt (2013) in inferring attribute processing rules from the observed choices of the financial professionals. With four attributes in our choice experiment, the number of possible decision strategies is 16. The possible patterns are: (1) full attendance in which all four attributes are attended to, (2) random preferences in which the individual ignores all attributes and makes choices randomly, (3) lexicographic preferences in which the individual uses only one attribute (four possible patterns), and (4) the possibilities to ignore one or two of the attributes (ten possible patterns). Following the method of Kragt (2013), the ECLC models are estimated so that in some of classes some attribute coefficients for the above mentioned sixteen decision patterns are restricted to zero. The estimation result is the class probabilities which describe the proportion of respondents which are inferred to use the particular attributed in their choices. The ECLC model is estimated using Nlogit 5.0.

4. Results

A minority of the respondents appear to attend to all attributes in the choice tasks. Table 2 shows the stated serial attribute attendance responses and that less than 4% of respondents stated they had used all of the attributes. The most frequent strategy was to make the choices based on two attributes and ignore two. The most attended attribute is expected return, and that holds in all possibilities of using one, two or three attributes. The attribute least attended to was voting in the responses stating lexicographic preferences but also it was the most ignored attribute in the combinations of two ignored attributes. Only two respondents did not indicate their attendance to any of the attributes so they are interpreted as random choosers.

Table 2. S	Stated Attribute	Non-Attendance
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	Number of respondents	Proportion of total, %
Full attendance	30	3.6
Ignore 1	135	16.0
ignore voting	84	9.9
ignore return	23	2.7
ignore capital	21	2.5
ignore expected return	7	0.8
Ignore 2	495	58.6
ignore voting and return	234	27.7
ignore voting and capital	157	18.6
ignore voting and expected return	38	4.5
ignore return and capital	38	4.5
ignore return and expected return	17	2.0
ignore capital and expected return	11	1.3
Lexicographic preferences	183	21.7
attention to voting only	6	0.7
attention to return only	15	1.8
attention to capital only	32	3.8
attention to expected return only	130	15.4
Random	2	0.2
Total	845	100%

To analyze the inferred attribute attendance, we estimate first the ECLC model using all the possible 16 combinations. These correspond to the stated attendance rules, and this allows the comparison to the stated attention. Relevant classes, whose probability is statistically significant, are kept for the iterated specifications. Insignificant classes are dropped stepwise accounting for the model fit statistics, and the final model includes only significant classes.

The ECLC model would produce classes and the associated class probabilities consistent with the stated attribute attendance frequencies if the stated information was a good predictor for the inferred strategies (Kragt, 2013). However, the specification search produced a nine-class ECLC model, in which the class probabilities are significant and the model fit is optimized. Table 3 presents the results for the model with parameters constrained the same across classes and the model allowing heterogeneous preferences between classes. Full attendance was dropped from the final model because its class probability was marginal and insignificant. The random choice strategy is much more prevalent than what is observed from the stated strategies as 12% of the respondents are inferred to ignore all attributes. The class probabilities of the lexicographic strategies were insignificant and they were consequently excluded from the final model.

Table 3. Estimates of Equality Constrained Latent Class Models for Attribute Attendance

Classes	ECLC 1 homogeneous preferences		ECLC 2	
			heterogeneous preferences	
	Coefficient	St.error	Coefficient	St.error
1. Random choice, igno	ore all attributes			
Class probability	0.12***	(0.04)	0.03***	(0.01)
Expected return	0.00	fixed	0.00	fixed
Voting	0.00	fixed	0.00	fixed
Return	0.00	fixed	0.00	fixed
Capital	0.00	fixed	0.00	fixed
Constant	-0.69**	(0.32)	-3.30***	(0.60)
2. Ignore expected retu	ırn			
Class probability	0.15***	(0.0)	0.17***	(0.03)
Expected return	0.00	fixed	0.00	fixed
Voting	1.75***	(0.13)	1.86***	(0.37)
Return	1.58***	(0.14)	1.70***	(0.36)
Capital	2.03***	(0.13)	1.82***	(0.38)
Constant	-0.69**	(0.32)	-0.69	(0.80)
3. Ignore return				
Class probability	0.07***	(0.03)	0.04***	(0.01)
Expected return	0.62***	(0.02)	4.92	(ne)
Voting	1.75***	(0.13)	-48.59	(ne)
Return	0.00	fixed	0.00	fixed
Capital	2.03***	(0.13)	32.40	(ne)
Constant	-0.69**	(0.32)	14.79	(ne)
4. Ignore voting and re	eturn			
Class probability	0.16***	(0.03)	0.05***	(0.02)
Expected return	0.62***	(0.02)	0.38*	(0.20)
Voting	0.00	fixed	0.00	fixed
Return	0.00	fixed	0.00	fixed
Capital	2.03***	(0.13)	4.01***	(1.40)
Constant	-0.69**	(0.32)	1.01	(5.30)
5. Ignore voting and capital				
Class probability	0.09***	(0.02)	0.09**	(0.04)
Expected return	0.62***	(0.02)	0.38***	(0.11)
Voting	0.00	fixed	0.00	fixed
Return	1.58***	(0.14)	-1.79**	(0.79)
Capital	0.00	fixed	0.00	fixed
Constant	-0.69**	(0.32)	22.03	(ne)

	ECLC 1		ECLC 2	
	homogeneous preferences		heterogeneous preferences	
6. Ignore voting and ex	spected return			
Class probability	0.10***	(0.02)	0.06***	(0.02)
Expected return	0.00	fixed	0.00	fixed
Voting	0.00	fixed	0.00	fixed
Return	1.58***	(0.14)	1.16***	(0.43)
Capital	2.03***	(0.13)	2.72***	(1.03)
Constant	-0.69**	(0.32)	-3.76***	(1.25)
7. Ignore return and ca	apital			
Class probability	0.19***	(0.03)	0.31***	(0.04)
Expected return	0.62***	(0.02)	0.58***	(0.07)
Voting	1.75***	(0.13)	0.37***	(0.14)
Return	0.00	fixed	0.00	fixed
Capital	0.00	fixed	0.00	fixed
Constant	-0.69**	(0.32)	1.25*	(0.66)
8. Ignore return and ex	spected return			
Class probability	0.05**	(0.03)	0.09***	(0.03)
Expected return	0.00	fixed	0.00	fixed
Voting	1.75***	(0.13)	0.41*	(0.23)
Return	0.00	fixed	0.00	fixed
Capital	2.03***	(0.13)	0.13	(0.29)
Constant	-0.69**	(0.32)	0.02	(0.51)
9. Ignore capital and e	xpected return			
Class probability	0.06**	(0.03)	0.17***	(0.04)
Expected return	0.00	fixed	0.00	fixed
Voting	1.75***	(0.13)	-0.01	(0.19)
Return	1.58***	(0.14)	0.04	(0.18)
Capital	0.00	fixed	0.00	fixed
Constant	-0.69**	(0.32)	27.57	(ne)
N of observations	5070		5070	
Log likelihood	-3822.01		-3682.78	
Pseudo R squared	0.31		0.34	
AIC	1.51		1.47	

Note: Attributes are dummy coded. *, **, and *** denote statistically significance at 10%, 5%, and 1% levels, respectively. 'ne' means that the standard errors for the attributes were inestimable and insignificant.

All in all, large discrepancies between stated and inferred attribute non-attendance are observed. The proportion of respondents ignoring expected return attribute is 15% whereas in the self-reported attendance that attribute was the most attended to. One can conclude that expected return is so inherent dimension of an investment instrument that the respondents perceive it as self-evident decision criteria and thus state to pay attention to it. However, the results of the ECLC estimations suggest the opposite and that the subjects rather concentrated on the other attributes. Extending the ECLC model by accounting for class-specific preference heterogeneity improves the model fit. The proportion of respondents ignoring all attributes falls to 3%. The largest share of respondents is inferred to have ignored return and capital (31%). The majority relied on two attributes in their choices.

5. Conclusions

This paper applies the choice experiment method in a novel setting in analyzing investor decision making. The analysis of attribute processing strategies suggests that stated attribute non-attendance may not be reliable and that investors may not be conscious of the factors affecting their investment choices. The comparison of the stated and inferred attribute non-attendance patterns provides evidence that investors are prone to overstate the importance of expected return in their choices. The inferred models produced more variety in the attribute processing strategies showing that choices were affected by attributes other than the expected return. One reason for the discrepancy may result from cognitive issues since expected return was the only attribute including numerical information.

Similar violations of the assumption of the continuity of preferences have been found in experimental studies in environmental, health, and transport economics (Campbell et al., 2008; Lagarde, 2013; Caputo et al., 2013; Hensher & Greene, 2010). Using the same methodology as Kragt (2013), our results confirm her findings that a considerable proportion of respondents in a choice experiment ignore attributes. Similar to previous studies that employ a latent class model in analyzing attribute non-attendance, we find a discrepance between self-reported and inferred behavior (Scarpa et al., 2009; Campbell et al., 2011; Kragt, 2013; Lagarde, 2013). While there is no prior evidence on individuals' attribute processing strategies in investment decisions in choice experiments, financial decision making situation may bear a resemblance to the decisions regarding health. Lagarde (2013) points out that health could be particularly prone to heuristics as in the presence of a strong attribute such as health outcomes respondents may overly focus on that attribute at the expense of the others. In financial decisions, risk and return are typically strong attributes so our result is in line with the prior evidence in health economics. If individuals ignore one or more attributes of an investment, changes in that attribute do not compensate for a utility change through another attribute.

The policy implications of the findings include that individuals may be lured by generous expected returns of an investment but the design of investment instruments should pay carefully attention to the other features as well. A priming of those other attributes may increase the salience of those other features and reduce the overrepresentation of expected return in investor behavior. While the results are observed in our sample of financially literate subjects, it is reasonable to expect that people with lower knowledge level regarding financial products are even more prone to behavioral biases in decision making.

Further research would be beneficial in increasing understanding on the individual-specific factors determining information processing strategies. Overall the results of this paper are useful in the marketing and design of financial instruments. The use of stated preference methods in financial economics is still in its infancy but our results provide promising evidence for how new features of investments can be tested.

Acknowledgements

I am grateful to Kyösti Arovuori and Suvi Rinta-Kiikka for insightful comments on the questionnaire design and the methodological discussions, Annika Hemmilä for the translation of the questionnaire to Swedish, Vaito Sauna-aho and Atso Andersen for facilitating access to financial adviser data on behalf of Aalto Executive Education, and Pörssis äätiö for financial support.

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Appendix I

In the basic latent class model, a consumer is assumed to choose the alternative *I*, described by a number of attributes A_k (k = 1, 2, ..., K) and a number of attribute levels A_{kl} (l = 1, 2, ..., L), which offers the greatest utility $U_I = V(A_{1b}, A_{2b}, ..., A_{kl}) + e_l$, where $V(A_{1b}, A_{2b}, ..., A_{kl})$ is the systematic part of utility and e_l is the random component (Carson et al., 1994). Parameter heterogeneity across individuals is modelled with a fixed set of classes, *C* (Greene, 2007). The membership of an individual in a class is latent, thus cannot be observed by the analyst, and is determined based on the preferences for the attributes. Each class is characterised by class specific parameter estimates.

In Greene's (2007) notation for latent class logit models, individual i makes a choice among J alternatives at choice situation t given that the individual is in class c that maximises her utility

$$U_{jit/c} = \beta_c \, x_{jit} + \varepsilon_{jit} \tag{1}$$

where U_{jit} = utility of alternative j to individual i in choice situation t

 x_{jit} = union of attributes in the utility functions

 ε_{iit} = unobserved heterogeneity for individual i and alternative j in choice situation t

 β_c = class specific parameter vector.

Within the class, choice probabilities are assumed to be generated by the multinomial logit model, when

$$P[y_{it} = j|c] = \frac{\exp(\beta_c' x_{jit})}{\sum_{j=1}^{j_i} \exp(\beta_c' x_{jit})}.$$
(2)

Class probabilities are determined by the multinomial

$$P[c] = Q_{ic} = \frac{\exp(\theta_c' z_i)}{\sum_{c=1}^{C} \exp(\theta_c' z_i)}, \theta_c = 0,$$
(3)

where z_i is a set of individual specific, situation invariant characteristics. The probabilities may be determined without the characteristics, as a function of only *C* parameters θ_c .

For a given individual, the probability of a specific choice is estimated as the expected value of the class specific probabilities, given by

$$P(y_{it} = j) = \sum_{c=1}^{c} P(c) \left[\frac{\exp(\beta'_{c} x_{jit})}{\sum_{j=1}^{J_{i}} (\beta'_{c} x_{jit})} \right]$$
(4)

The latent class model estimates the taste parameters βc within each class and the class probabilities θ_c .

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