Simple Models for Multiattribute Choice with Many Alternatives: When It Does and Does Not Pay to Face Trade-offs with Binary Attributes

Robin M. Hogarth

ICREA and Universitat Pompeu Fabra, DEE 08005 Barcelona, Spain, robin.hogarth@upf.edu

Natalia Karelaia

HEC (Ecole des Hautes Études Commerciales), Université de Lausanne, Internef, 1015 Lausanne-Dorigny, Switzerland, natalia.karelaia@unil.ch

Given the difficulties people experience in making trade-offs, what are the consequences of using simple models that avoid trade-offs? We examine choices by such models in environments where “true” preferences are linear and attributes are characterized by binary attributes. A deterministic elimination-by-aspects (DEBA) model is highly effective over a range of conditions. When preferences are quite compensatory, however, a modified equal weighting (EW) model that uses DEBA to resolve ties is more effective. We explore the sensitivity of results to errors in using DEBA, to different distributions of alternatives, and to error in “true” preferences. Under the conditions examined here, the outcomes of these “boundedly rational” models are highly consistent with “rational” models that explicitly confront trade-offs. We emphasize the importance of binary attributes in reaching these conclusions.

Key words: decision making; bounded rationality; lexicographic rules; choice theory

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Introduction

There is much evidence that people do not like to face trade-offs and that they use choice strategies that avoid them (see, e.g., Payne et al. 1992). Two reasons are typically advanced. One is cognitive: trade-offs are difficult to execute. The other is emotional: People don't like to face trade-offs explicitly (Hogarth 1987, Luce et al. 1997). Given these difficulties, it is important to understand when avoiding trade-offs does and does not lead to negative outcomes.

Preferences are commonly represented by linear multiattribute functions (see, e.g., Keeney and Raiffa 1993). Thus, the utility of a choice object $X_i = x_{i1}, x_{i2}, \dots, x_{ik}$ is determined by the function

$$U(X_i) = \sum_{j=1}^k w_j u(x_{ij}), \quad (1)$$

where the w_j are weighting parameters subject to the constraint that $\sum_{j=1}^k w_j = 1$.

Since the weighting parameters reflect trade-offs between attributes, it is appropriate to ask when choice is and is not sensitive to their specification. As a starting point, consider choosing between two options, X_a and X_b , with two attributes. Clearly, X_a

will be preferred to X_b if

$$w_1 \{u(x_{1a}) - u(x_{1b})\} > w_2 \{u(x_{2b}) - u(x_{2a})\}. \quad (2)$$

Knowledge of the weighting parameters (w_1 and w_2) is required to make a decision. However, the precision of this knowledge depends on how the utilities of the attributes are measured. In particular, if these are binary variables (i.e., 0/1), both $\{u(x_{1a}) - u(x_{1b})\}$ and $\{u(x_{2b}) - u(x_{2a})\}$ are limited to taking values of $-1, 0$, or 1 . In this case, one needs to know only the relative sizes of w_1 and w_2 to choose according to Equation (1). On the other hand, if the variables are continuous, both $\{u(x_{1a}) - u(x_{1b})\}$ and $\{u(x_{2b}) - u(x_{2a})\}$ are unconstrained, and more precise knowledge of the weighting parameters is required.

This example suggests that specifying trade-offs is less important with binary than with continuous variables and thus, as a consequence, may indicate situations where strategies that avoid trade-offs are relatively effective. We therefore restrict our attention in this work to linear preference functions and binary attributes. In these environments, we assume that the “true” utility for any object, X_i , can be modeled by

$$V(X_i) = \sum_{j=1}^k \beta_j x_{ij}, \quad (3)$$

where x_{ij} takes the values of 0 or 1, the utility of each attribute is identical to x_{ij} , and the β_j 's are weighting parameters subject to the constraint that $\sum_{j=1}^k \beta_j = 1$.

The goal of this paper is to illuminate the conditions under which trade-off-avoiding choice strategies are effective. In doing so, we follow Brunswik (1952) and Simon (1956), who emphasized the importance of understanding the *joint* effects of environments and behavior (modeled here by simple decision rules) in producing outcomes. Specifically, using Equation (3) as the model of “true” preferences, we investigate the performance of several trade-off-avoiding decision rules across different environments.

Of particular relevance is work by Thorngate (1980), who demonstrated (through simulation) the surprising efficiency of simple decision rules in choosing the best of several gambles using expected value as the criterion. More extensive simulations were conducted by Johnson and Payne (1985) (see also Payne et al. 1993). Like Thorngate, these investigators only considered continuous variables, but, in addition to performance, they calculated estimates of the hypothetical cognitive effort their models used to make choices. They thus also provided interesting perspectives on possible trade-offs between accuracy and effort. More recently, Gigerenzer and his colleagues have investigated the effectiveness of simple models for binary inferences based on binary cues (cf. attributes) within a more general research program on “bounded rationality” (Gigerenzer and Goldstein 1996, Gigerenzer et al. 1999). In addition, Fasolo et al. (in press) have examined the effects of simplifying decisions by restricting the number of attributes used in multiattribute choice.

This paper is organized as follows. We first specify the models we examine. Second, we analyze the effectiveness of these models in choosing the “correct” alternative from sets of three, four, and five alternatives when using three and four binary attributes.¹ Third, we examine what happens when people err in executing their own preferences. Fourth, we demonstrate how different environments affect results. In this analysis, we also include the role of random error in preferences. Finally, we discuss results, assumptions, and implications.

Overall, we show that the outcomes of simple models (specified below) are often as good as explicitly using Equation (3). However, their performance is affected by joint characteristics of the decision maker's “true” preferences and the environments in which they operate, specifically, the proportion of choices involving dominated alternatives and identical attribute profiles as well as particular distributions of attribute profiles.

¹ The five-attribute case is presented in the appendix that is available in an online supplement (available at <http://mansci.pubs.informs.org/ecompanion.html>).

The Models

We now describe the models we consider. In doing so, we assume that the data have been ordered so that overall value or utility, that is, $V(X_i)$, is increasing in x_{ij} , $j = 1, \dots, k$.

Deterministic Elimination By Aspects (DEBA)

This is an adaptation of the elimination-by-aspects (EBA) model originally proposed by Tversky (1972). First, the relative sizes of the β parameters associated with the different attributes are assumed to be known (i.e., the attributes can be ordered in terms of relative importance). Second, the model follows a multistage process that involves examining alternatives sequentially by attributes.

At the first stage, the decision maker examines the attribute associated with the largest β parameter for all choice alternatives. If all alternatives have a value of 0, the attribute with the next largest β parameter is considered. Otherwise, alternatives with 0 values are eliminated. If a single alternative remains (i.e., with a value of 1), it is chosen. If two or more alternatives have values of 1, selection between them involves the same procedure, but using the attribute associated with the second largest β parameter. If this second stage leaves more than one alternative, the procedure is repeated using the attribute associated with the third largest β parameter, and so on. If, after the last attribute is examined, two or more alternatives remain, the choice between them is determined at random.

DEBA differs from EBA (Tversky 1972) in that the attributes (or aspects) used to eliminate alternatives at each stage of the process are selected by a deterministic rather than probabilistic procedure (hence the name *deterministic* EBA). We also note that DEBA generalizes—to more than two alternatives—the lexicographic binary-choice model take-the-best (TTB) proposed by Gigerenzer and Goldstein (1996). In the discussion section, we consider the psychological plausibility of the DEBA model.

Equal Weighting (EW)

This model assigns equal weight to attributes such that the value of an alternative is the sum of its attribute values. The choice rule is to select the alternative with the largest sum. If there is a tie, choice is made at random.

Strictly speaking, EW implies trade-offs. However, the EW assumption is not demanding from a cognitive viewpoint. On the other hand, EW does require looking at *all* information *by* alternative, determining the sums associated with each alternative, and then comparing the sums. It is therefore both more systematic and cognitively demanding to execute (particularly as the number of alternatives increases).

DEBA/EW Hybrids

Evidence suggests that people sometimes first eliminate one or two alternatives and then examine those remaining in greater depth (see, e.g., Payne et al. 1993, Rieskamp and Hoffrage 2002). We model this as follows. The decision maker starts the process as if using DEBA. If, after examining the first attribute, the decision maker eliminates all but one alternative, the noneliminated alternative is chosen. If, however, two alternatives remain, choice between these alternatives is made using EW. If three or more alternatives remain, the decision maker starts the process over again by examining the second attribute, and so on.

EW/DEBA Hybrids

With binary attributes EW can lead to ties between many alternatives. However, if the decision maker has even limited knowledge about the relative importance of attributes, it makes little sense to choose between ties at random.

We therefore propose a model where attempts are first made to choose by EW. If this results in a tie, DEBA is used to resolve the tie. We call this model EW/DEBA. It generalizes the EW/TTB model proposed for binary choice (Hogarth and Karelaia 2003). Like EW/TTB, the EW calculation in EW/DEBA can be made on a subset of attributes, for example, the three most important attributes in four-attribute models. In this case, the decision maker need not examine all attributes for all alternatives.

DOMRAN

Several researchers have suggested that decision makers do and should exploit dominance in choice (cf., Montgomery 1983, Keeney and Raiffa 1993). We therefore propose a model, DOMRAN, that first examines all alternatives on all attributes to see whether any alternative is dominated by at least one other. If this happens, dominated alternatives are eliminated from consideration. Choice is then made, at random, from the remaining nondominated alternatives. Thus, the DOMRAN strategy requires examining all information (all attributes on all alternatives) and making many comparisons. However, it does not require prior knowledge about the relative importance of variables nor any calculations (see Hogarth and Karelaia 2003, concerning DOMRAN for binary choice).

Assessing Model Performance

To assess model performance, we need to specify both types of “true” preferences and characteristics of environments in which choices are made. Ideally, the joint distribution of types of preferences and task environments in people’s natural ecologies should also be specified. However, lacking the ability to do this,

Table 1 Attribute Profiles for Three-Attribute Models

	x_1	x_2	x_3	Sum	Dominates “ x ” other profiles	Is dominated by “ x ” other profiles
A	1	1	1	3	7	0
B	1	1	0	2	3	1
C	1	0	1	2	3	1
D	1	0	0	1	1	3
E	0	1	1	2	3	1
F	0	1	0	1	1	3
G	0	0	1	1	1	3
H	0	0	0	0	0	7

we adopt the following strategy. First, we define distinct types of preferences. Second, we analyze environments consisting of three and four attributes using as a baseline populations of complete, distinctive attribute profiles. Third, we examine the effects of error in the use of models (i.e., using weights incorrectly). Fourth, we assess the sensitivity of “baseline” conclusions by varying characteristics of the environments in which choices are made. Fifth, we examine the effects of error in “true” preferences.

Noncompensatory and Compensatory Preferences

We classify preferences by considering different distributions of the β parameters of Equation (3). In particular, following Martignon and Hoffrage (1999, 2002), we distinguish between noncompensatory and compensatory preferences. Specifically, noncompensatory preferences have the property that, when weights are ordered from largest to smallest, each weight is larger than the sum of all weights that are smaller than it, that is,

$$\beta_j > \sum_i \beta_i, \quad \text{for any } i > j, j = 1, \dots, k-1. \quad (4)$$

All other preferences are *compensatory*. Thus, for three attributes, $\beta_1 > (\beta_2 + \beta_3)$ defines noncompensatory preferences, whereas $\beta_1 \leq (\beta_2 + \beta_3)$ defines compensatory preferences (assuming $\beta_1 > \beta_2 > \beta_3$). For expository purposes, we discuss the cases involving three and four attributes separately.²

Environments with Three Attributes

We examine choices between three, four, and five alternatives in populations of complete, distinctive attribute profiles.³ With three attributes, there are eight distinctive attribute profiles (illustrated in Table 1), 56 different combinations of attribute profiles

² The simulations conducted by Payne et al. (1993) used continuous variables and thus did not refer to noncompensatory and compensatory functions per se. However, they did investigate a similar issue by examining the effects of probability distributions (or “weights”) that varied in dispersion.

³ Before looking at results, we encourage readers to forecast what these might be. In conducting this work, we implicitly made such forecasts and were quite surprised by what we found. In addi-

Table 2 Probabilities of Correct Choices by Different Models for Noncompensatory and Compensatory Preferences (Best of Three)

Combinations of attribute profile types			Probability of correct choice								
			Noncompensatory preferences				Compensatory preferences				
			DEBA	EW	DEBA/EW	EW/DEBA	DEBA	EW	DEBA/EW	EW/DEBA	DOMRAN
A	B	C	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
A	B	D	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
A	B	E	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
*...	...	...	...	...	...	...	...	...	...	...	...
A	G	H	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
B	C	D	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
B	C	E	1.00	<u>0.33</u>	<u>0.50</u>	1.00	1.00	<u>0.33</u>	<u>0.50</u>	1.00	<u>0.33</u>
B	C	F	1.00	<u>0.50</u>	<u>0.50</u>	1.00	1.00	<u>0.50</u>	<u>0.50</u>	1.00	<u>0.50</u>
B	C	G	1.00	<u>0.50</u>	<u>0.50</u>	1.00	1.00	<u>0.50</u>	<u>0.50</u>	1.00	<u>0.50</u>
B	C	H	1.00	<u>0.50</u>	<u>0.50</u>	1.00	1.00	<u>0.50</u>	<u>0.50</u>	1.00	<u>0.50</u>
B	D	E	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
B	D	F	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
B	D	G	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	<u>0.50</u>
B	D	H	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
B	E	F	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
B	E	G	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
B	E	H	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
B	F	G	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	<u>0.50</u>
B	F	H	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
B	G	H	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	<u>0.50</u>
C	D	E	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
C	D	F	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	<u>0.50</u>
C	D	G	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
C	D	H	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
C	E	F	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
C	E	G	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
C	E	H	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
C	F	G	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	<u>0.50</u>
C	F	H	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	<u>0.50</u>
C	G	H	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
D	E	F	1.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	<u>0.50</u>
D	E	G	1.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	<u>0.50</u>
D	E	H	1.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	<u>0.50</u>
D	F	G	1.00	<u>0.33</u>	1.00	1.00	1.00	<u>0.33</u>	1.00	1.00	<u>0.33</u>
D	F	H	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
D	G	H	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
E	F	G	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
E	F	H	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
E	G	H	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
F	G	H	1.00	<u>0.50</u>	1.00	1.00	1.00	<u>0.50</u>	1.00	1.00	<u>0.50</u>
Correct (%)			<u>100</u>	<u>79</u>	<u>96</u>	<u>95</u>	<u>95</u>	<u>84</u>	<u>91</u>	<u>100</u>	<u>76</u>

Notes. Probabilities of 0.00 are bold, e.g., **0.00**. Probabilities of 0.33 and 0.50 are underlined, e.g., 0.33, 0.50.

*We do not show all results for combinations beginning with attribute profile A because this always dominates all other attribute profiles.

for three alternatives, 70 for four alternatives, and 56 for five alternatives.

Assuming that Equation (3) represents the decision maker's true preferences, we first distinguish between noncompensatory and compensatory preferences, except that we only consider strict inequalities. Thus, noncompensatory preferences are defined by

$\beta_1 > (\beta_2 + \beta_3)$ and compensatory preferences by $\beta_1 < (\beta_2 + \beta_3)$. Using the restriction that $\beta_1 > \beta_2 > \beta_3$, we calculate the probabilities that each model will make the "correct" decision for each of the 56 combinations of attribute profiles involving three alternatives (see Table 2).⁴

tion, we conducted a small survey at the 2004 BDRM conference in which several leading researchers were asked to predict some of our results. Their responses indicated that our results are not "obvious."

⁴ By "correct" we mean choices that are consistent with the specification of preferences as being noncompensatory or compensatory, as appropriate. By calculation we mean complete enumeration of all cases. When choices are made at random, we assume probabili-

Table 3 Percentages of Correct Choices by Different Models for Noncompensatory and Compensatory Preferences (Three-Attribute Models)

Three-attribute models	Noncompensatory preferences				Compensatory preferences				DOMRAN
	DEBA	EW	DEBA/EW	EW/DEBA	DEBA	EW	DEBA/EW	EW/DEBA	
Best of three (56 distinct choice sets)	100	79	96	95	95	84	91	100	76
Best of four (70 distinct choice sets)	100	78	91	96	96	82	87	100	76
Best of five (56 distinct choice sets)	100	80	91	98	98	82	89	100	79

Note. Bold figures indicate the largest figures within specific comparisons.

The left-most columns in Table 2 list the different possible combinations of attribute profiles using the same labels as Table 1 (i.e., A, B, C, etc.). To simplify, we do not show all combinations starting with profile A, because all the models respect dominance and A dominates all other profiles. Table 2 shows separate results for noncompensatory and compensatory preferences. Only one column is shown for DOMRAN (at the right of the table) because its performance is unaffected by whether preferences are noncompensatory or compensatory.

At the foot of Table 2, we show the expected percentage correct responses across the complete set of 56 distinct combinations of attribute profiles. For noncompensatory preferences, DEBA is 100% correct; for compensatory preferences, EW/DEBA is 100% correct. The former result is consistent with a theorem by Martignon and Hoffrage (1999, 2002) that shows that, within the class of linear functions of binary variables, a lexicographic model will always choose the better of two options (see also Katsikopoulos and Fasolo in press). More intuitively, if—when differences between attributes are examined in a sequential manner—the weight of a discriminating attribute is greater than the sum of the weights of the attributes that have not been considered, the outcome cannot be affected by the latter.

To appreciate the effectiveness of EW/DEBA in the compensatory case, compare the performance of the separate DEBA and EW models. Here, DEBA makes three errors by selecting D from the sets (D, E, F), (D, E, G), and (D, E, H). (Errors are in boldface type in Table 2.) EW does not make these errors. On the other hand, there are 17 cases where EW is forced to choose at random, that is, with success probabilities of 0.33 or 0.50 (underlined for emphasis in Table 2). Since DEBA's choices for these 17 cases are always correct, EW/DEBA's expected overall performance is 100% correct for the sets of three distinctive attribute profiles.

The DEBA/EW and EW/DEBA comparison is intriguing because, although both have the same components, one (DEBA/EW) involves less information

processing than the other (EW/DEBA). For noncompensatory functions, DEBA/EW is marginally more effective than EW/DEBA (96%–95%). The former makes no explicit errors but chooses at random in four cases; the latter makes three errors. For compensatory functions, however, EW/DEBA dominates DEBA/EW.

The DEBA and DEBA/EW comparison is noteworthy in that DEBA dominates the more complicated model for *both* noncompensatory and compensatory preferences. This occurs because there are four choices that DEBA/EW is forced to resolve at random whereas DEBA alone would have made the correct choice. Paradoxically, by switching from DEBA to EW to conduct a more thorough analysis, more errors are made.

DOMRAN is the most ineffective model. However, its performance of 76% is probably higher than most would have guessed.

For four and five alternatives, there are, respectively, 70 and 56 possible sets of choices characterized by distinctive attribute profiles. The expected percentage correct choices are shown in Table 3. Results (percentage correct) are almost identical to those when choice is made from three alternatives (also shown in Table 3). The only exception is that EW/DEBA is more effective than DEBA/EW for both noncompensatory and compensatory weighting functions.

Finally, we stress that the above results are conditional on a population of a complete set of distinctive choices. Thus, for example, if the number of dominated alternatives were reduced, model performance would generally not be so high. On the other hand, DEBA would always be optimal for noncompensatory preferences, and EW/DEBA would be optimal for compensatory preferences. Later we consider the impact of varying distributions of alternatives with different attribute profiles.

Environments with Four Attributes

Whereas the operational definitions of compensatory and noncompensatory preferences are straightforward for three attributes, this is not the case for four attributes (see also Hogarth and Karelaia 2003). Here, defining compensatory preferences by violations of

ties of 0.50 and 0.33 for cases involving two and three (remaining) alternatives, respectively.

Figure 1 Classification of Compensatory (CF) and Noncompensatory Functions (Non-CF) for the Four-Attribute Case

the condition for noncompensatory preferences leads to several distinct classes of the former. Specifically, if—for four attributes—we define noncompensatory by the conditions that first $\beta_j > \sum_i \beta_i$, for any $i > j$, $j = 1, \dots, k-1$, and second that $\beta_1 > \beta_2 > \beta_3 > \beta_4$, there are several compensatory functions that violate the first condition to different extents. For instance, if we specify that $\beta_1 < \beta_2 + \beta_3$ (which in turn implies that $\beta_1 < \beta_2 + \beta_3 + \beta_4$), this can be accompanied by either $\beta_2 < \beta_3 + \beta_4$ or $\beta_2 > \beta_3 + \beta_4$. In fact, there are five different classes of functions that span the parameter space of compensatory preferences—see Figure 1. As in the three-attribute case, we only consider strict inequalities.

The left-hand side of Table 4 illustrates parameter values for the different classes of preferences going from noncompensatory (non-CF) and the least compensatory (CF1) to the most compensatory (CF5). We illustrate CF5 with two sets of parameters because the range of values it can accommodate is relatively large. The table shows expected percentages of correct choices from sets of distinctive combinations of attribute profiles for three, four, and five alternatives.⁵ (There are 560 possible choices with three alternatives; 1,820 choices with four alternatives; and 4,368 choices with five alternatives).

The results mirror the three-attribute case. With noncompensatory preferences, DEBA is optimal within this linear world. However, of particular interest is the fact that DEBA is also most effective for CF1, CF2, and CF3 (we use **bold** to highlight the largest expected performance per function). As preferences become more compensatory, however, the advantage passes to EW/DEBA and EW-3/DEBA.⁶ The comparison between DEBA/EW and EW/DEBA also matches the three-attribute case. When the choice is among three

alternatives, DEBA/EW outperforms EW/DEBA for noncompensatory preferences, but this advantage reverses itself as preferences become progressively more compensatory. When choice is from four and five alternatives, the performance of EW/DEBA is always better than that of DEBA/EW. Also, once again, DEBA dominates DEBA/EW.

Brief Summary

For linear preference functions with binary attributes, simple models exhibit remarkably high levels of performance. In particular, DEBA is optimal for noncompensatory preferences and also performs well when preferences are compensatory. With three attributes, however, EW/DEBA is optimal for compensatory preferences and also has the best performance with four attributes when preferences are most compensatory. With binary attributes, the performance of EW is limited because it predicts many ties (resolved at random). Comparing the hybrid models, EW/DEBA requires more information and calculations than DEBA/EW and generally has better performance. On the other hand, the less-demanding DEBA model dominates DEBA/EW. Finally, the performance of DOMRAN is well below that of the other models. The appendix in the online supplement shows that these general conclusions are also valid for five binary attributes.

Effects of Errors in “Vague” Preferences

Only DEBA (and DEBA hybrids) require the decision maker to allocate different weights to attributes. What happens, therefore, if the decision maker errs and uses weights that do not reflect their “true” importance?

In Table 5, we illustrate, for the three-attribute case, how model choices vary if attributes enter the DEBA models in different orders for a population of complete, distinctive attribute profiles. With three attributes, there are six possible orderings and we show results for choosing the best out of three, four, and five alternatives. First, note that neither EW nor DOMRAN is affected by the order in which variables enter the models (as must be the case). Second, DEBA is generally the best model in the noncompensatory case, provided the most important variable enters the model in first or second position. Exceptions occur

⁵ The entries in Table 4 are calculated using the specific parameter values indicated. However, it should be emphasized that any set of parameter values that meets the specifications of non-CF (see Figure 1) results in identical choices. This is also true for CF1, CF2, and CF3. For CF4 and CF5, however, there are three and five cases (respectively) out of 120 where choices depend on specific parameter values within the constraints implied by CF4 and CF5 (see Hogarth and Karelaia 2003, and the appendix).

⁶ In EW-3/DEBA, EW is used on the *three* most important attributes, with ties being resolved by DEBA.

Table 4 Percentages of Correct Choices by Different Models for Noncompensatory and Compensatory Preferences (Four-Attribute Models)

					Expected correct (%)										DOMRAN
					Noncompensatory preferences					Compensatory preferences					
					DEBA	EW	DEBA/ EW	EW/ DEBA	EW-3/ DEBA	DEBA	EW	DEBA/ EW	EW/ DEBA	EW-3/ DEBA	
β_1	β_2	β_3	β_4												
Best of three (560 distinct choice sets)															
Non-CF*	0.53	0.24	0.13	0.10	100	73	94	89	95						67
CF1*	0.57	0.19	0.14	0.10						98	75	94	92	93	
CF2*	0.48	0.28	0.14	0.10						99	74	92	91	96	
CF3*	0.48	0.22	0.17	0.13						96	77	93	93	94	
CF4	0.42	0.31	0.15	0.12						94	79	88	95	96	
CF5	0.40	0.25	0.20	0.15						93	79	89	95	95	
CF5	0.29	0.26	0.24	0.21						89	84	85	99	91	
Best of four (1,820 distinct choice sets)															
Non-CF*	0.53	0.24	0.13	0.10	100	70	87	89	96						63
CF1*	0.57	0.19	0.14	0.10						97	73	86	92	93	
CF2*	0.48	0.28	0.14	0.10						99	71	86	90	97	
CF3*	0.48	0.22	0.17	0.13						96	74	85	93	94	
CF4	0.42	0.31	0.15	0.12						95	75	82	94	96	
CF5	0.40	0.25	0.20	0.15						93	76	83	94	95	
CF5	0.29	0.26	0.24	0.21						90	81	79	98	91	
Best of five (4,368 distinct choice sets)															
Non-CF*	0.53	0.24	0.13	0.10	100	69	85	90	97						62
CF1*	0.57	0.19	0.14	0.10						96	72	84	92	94	
CF2*	0.48	0.28	0.14	0.10						99	70	84	91	98	
CF3*	0.48	0.22	0.17	0.13						95	73	83	93	94	
CF4	0.42	0.31	0.15	0.12						97	73	82	94	97	
CF5	0.40	0.25	0.20	0.15						94	74	81	94	95	
CF5	0.29	0.26	0.24	0.21						92	79	79	98	92	

Note. Bold figures indicate the largest figures within specific comparisons.

*Any set of specific parameter values meeting the constraints specified in Figure 1 implies exactly the same outcomes.

when choices are from sets of three alternatives but differences between DEBA and the best strategies are small. When the most important variable enters the model in third position, EW has the best performance. Third, for compensatory functions, EW/DEBA has the best performance for the first three orders (1–3). EW is best for the latter three orders (4–6), except for choices from sets of four and five alternatives, where DEBA performs best in the fifth order (x_3 , x_1 , x_2). Overall, significant differences from results with the appropriate order of variables only occur when the most important variable enters the model in last (i.e., third) position.

Table 6 provides analogous data for the four-attribute case, although we only illustrate results for choosing the best of three alternatives and not for all compensatory preferences. Although qualitatively similar, results are not as simple as in the three-attribute case. For noncompensatory preferences, DEBA-based models perform well when the most important variable enters the model first. However, when the third or fourth most important attribute enters the model first, EW is generally most effective. As preferences move from noncompensatory to compensatory, this situation changes in

the direction of the results for the most compensatory case. Here, EW/DEBA is highly effective, provided the first or second most important variable enters the model first. Otherwise, EW has better performance.

Effects of Different Choice Sets

The above results all assume complete distributions of distinctive attribute profiles. We now investigate effects of different distributions. We consider three situations based on the extent to which distributions contain (1) dominating attribute profiles (cf., Payne et al. 1993, Fasolo et al. in press), (2) repeated attribute profiles, and (3) attribute profiles that are “friendly” or “unfriendly” to specific models (cf., Shanteau and Thomas 2000). We illustrate these factors using three-attribute models.

On the right side of Table 1 we indicate how often different attribute profiles dominate and are dominated by others. Thus, profile A dominates all other seven profiles; profile B dominates three others but is dominated by one (A), and so on. All our models respect dominance. Therefore, holding all other factors constant, distributions that have more

Table 5 Percentages of Correct Choices by Different Models for Noncompensatory and Compensatory Preferences when Attributes Are Used in Different Orders (Three-Attribute Models)

				Expected correct (%)								
Orders	1st	2nd	3rd	Noncompensatory preferences				Compensatory preferences				DOMRAN
				DEBA	EW	DEBA/EW	EW/DEBA	DEBA	EW	DEBA/EW	EW/DEBA	
Best of three (56 distinct choice sets)												
1	x_1	x_2	x_3	100	79	96	95	95	84	91	100	76
2	x_1	x_3	x_2	89	79	93	84	84	84	88	89	76
3	x_2	x_1	x_3	82	79	79	84	86	84	82	89	76
4	x_2	x_3	x_1	71	79	75	73	75	84	79	79	76
5	x_3	x_1	x_2	75	79	71	75	79	84	75	80	76
6	x_3	x_2	x_1	64	79	68	64	68	84	71	70	76
Means				80	79	80	79	81	84	81	85	76
Best of four (70 distinct choice sets)												
1	x_1	x_2	x_3	100	78	91	96	96	82	87	100	76
2	x_1	x_3	x_2	86	78	86	81	81	82	81	86	76
3	x_2	x_1	x_3	89	78	80	87	90	82	81	91	76
4	x_2	x_3	x_1	74	78	74	73	76	82	76	77	76
5	x_3	x_1	x_2	84	78	76	80	86	82	77	84	76
6	x_3	x_2	x_1	70	78	70	66	71	82	71	70	76
Means				84	78	80	81	83	82	79	85	76
Best of five (56 distinct choice sets)												
1	x_1	x_2	x_3	100	80	91	98	98	82	89	100	79
2	x_1	x_3	x_2	82	80	80	80	80	82	79	82	79
3	x_2	x_1	x_3	96	80	88	95	96	82	88	96	79
4	x_2	x_3	x_1	79	80	77	77	79	82	77	79	79
5	x_3	x_1	x_2	95	80	86	91	95	82	86	93	79
6	x_3	x_2	x_1	77	80	75	73	77	82	75	75	79
Means				88	80	83	86	88	82	82	88	79

Note. Bold figures indicate the largest figures within specific comparisons.

dominating alternatives will show higher levels of correct choices than distributions with fewer such alternatives. For example, consider two distributions that have equal numbers of alternatives: [4, 2, 1, 1, 1, 1, 3] and [0, 1, 2, 4, 4, 2, 1, 0]. (The first element in each vector denotes the number of alternatives with attribute profile A, the second, those with profile B, and so on.) Dominance plays a more important role in the first than in the second distribution.

The second factor is the number of identical attribute profiles (“repeats”). There are two ways of interpreting repeats, between which all models choose at random. One is that it does not matter which alternative is selected. Thus, repeats increase the percentage of correct choices. The other is that choices between repeats can only be correct on a probabilistic basis (e.g., 0.50 between two alternatives). Thus, repeats decrease the percentage of correct choices. We adopt the second interpretation on the grounds that preferences are not strictly deterministic.

The third factor is the extent to which distributions are “friendly” or “unfriendly” to different models (cf. Hogarth and Karelaia 2003). To illustrate, consider Table 1 and the column labeled “Sum.” This reveals two factors. First, in pairwise choices between alter-

natives, the EW model predicts ties between choices involving B, C, and E (sums equal to 2) and D, F, and G (sums equal to 1) such that choices between any two profiles in both groups are made at random. Thus, when a distribution of alternatives contains many such attribute profiles (relative to a comparable uniform distribution), it is “EW unfriendly.” Conversely, if it contains fewer, it is “EW friendly.”

Second, consider how DEBA chooses between profiles D and E with a compensatory weighting function. Here, DEBA errs by choosing D. (Examine the implications of the profiles, [1, 0, 0] and [0, 1, 1]). Thus, conditional on compensatory preferences, a distribution of alternatives is “DEBA unfriendly” (“DEBA friendly”) when it contains more (fewer) D and E profiles than would be expected in a comparable uniform distribution.

These concepts are illustrated in the upper panel of Table 7. Here we have calculated model choices for three distributions for noncompensatory and compensatory preferences. The distributions (listed at the foot of Table 7) are (1) all *distinctive* profiles, (2) DEBA *friendly* (no possible D-E pairs), and (3) DEBA *unfriendly* (12 D-E pairs).

Table 6 Percentages of Correct Choices by Different Models for Noncompensatory and Compensatory Preferences when Attributes Are Used in Different Orders (Some Four-Attribute Models)

Best of three (560 distinct choice sets)					Expected correct (%)											
					Noncompensatory preferences				CF3				CF5*			
					DEBA	DEBA/ EW	EW/ DEBA	EW-3/ DEBA	DEBA	DEBA/ EW	EW/ DEBA	EW-3/ DEBA	DEBA	DEBA/ EW	EW/ DEBA	EW-3/ DEBA
Orders	1st	2nd	3rd	4th												
1	x_1	x_2	x_3	x_4	100	94	89	95	96	93	93	96	89	85	99	91
2	x_1	x_2	x_4	x_3	95	93	84	91	91	92	88	92	84	84	94	86
3	x_1	x_3	x_2	x_4	91	90	84	86	92	91	88	87	84	83	94	87
4	x_1	x_3	x_4	x_2	86	89	79	81	87	90	83	83	79	83	89	81
5	x_1	x_4	x_2	x_3	86	89	80	81	87	89	83	83	80	82	89	81
6	x_1	x_4	x_3	x_2	81	88	75	77	82	89	78	78	75	81	84	76
7	x_2	x_1	x_3	x_4	84	78	82	86	83	77	86	87	84	81	93	87
8	x_2	x_1	x_4	x_3	79	77	77	81	78	76	81	83	79	80	88	81
9	x_2	x_3	x_1	x_4	75	74	77	77	74	73	81	78	79	79	88	82
10	x_2	x_3	x_4	x_1	70	74	72	66	69	73	76	67	74	78	83	76
11	x_2	x_4	x_1	x_3	71	73	73	72	70	72	76	73	75	77	83	76
12	x_2	x_4	x_3	x_1	66	72	68	61	65	71	71	63	70	77	78	71
13	x_3	x_1	x_2	x_4	78	71	78	78	80	74	81	79	81	77	88	83
14	x_3	x_1	x_4	x_2	73	71	73	73	75	73	76	74	76	76	83	77
15	x_3	x_2	x_1	x_4	69	68	73	69	71	70	76	70	76	75	83	78
16	x_3	x_2	x_4	x_1	64	67	68	62	66	69	71	63	71	75	78	72
17	x_3	x_4	x_1	x_2	64	66	68	63	66	69	72	64	72	74	79	72
18	x_3	x_4	x_2	x_1	59	66	63	57	61	68	67	58	67	73	74	67
19	x_4	x_1	x_2	x_3	75	69	74	74	77	71	77	75	77	73	83	77
20	x_4	x_1	x_3	x_2	70	68	69	69	72	70	72	70	72	73	78	73
21	x_4	x_2	x_1	x_3	66	65	69	64	68	67	72	65	72	72	78	72
22	x_4	x_2	x_3	x_1	61	64	64	58	63	66	67	59	67	71	73	68
23	x_4	x_3	x_1	x_2	61	64	64	59	64	66	68	60	68	70	74	68
24	x_4	x_3	x_2	x_1	56	63	59	53	59	65	63	54	63	69	69	63
Means					74	75	73	72	75	76	77	73	76	77	83	77
EW					73	73	73	73	77	77	77	77	84	84	84	84
DOMRAN					67	67	67	67	67	67	67	67	67	67	67	67

Note. Bold figures indicate the largest figures within specific comparisons. If there is no bold figure, EW is best.

*Based on parameters 0.29, 0.26, 0.24, and 0.21.

First, note that the predictions for the distinctive distribution are the same as in the first line of Table 3. Second, observe that the unfriendly distribution has relatively few dominating alternatives (e.g., no As) and many repeat cases. Both factors imply that the performance of all models will be lower than with the distinctive distribution. Third, note how performance of the models for the friendly distribution dominates that of the distinctive. In particular, the lack of a D-E pairing allows EW/DEBA to achieve 100% for the noncompensatory functions and DEBA to achieve 100% for the compensatory functions. Finally, to emphasize that the unfriendly distribution affects DEBA with compensatory preferences, note that its performance here surpasses only that of DOMRAN (58%). Indeed, for this distribution EW performs marginally better than DEBA (69% vs. 68%).

In short, these calculations demonstrate how characteristics of distributions of attribute profiles impact model performance. Overall, this is affected positively by the presence of dominating profiles and nega-

tively by repeats. The performance of specific models (e.g., EW and DEBA) can be affected (positively or negatively) when distributions are “friendly” or “unfriendly” to those models (conditional on the type of preferences). Although we have only demonstrated these concepts here for choices made from sets of three alternatives based on three attributes, we have also examined choices from sets of four and five, alternatives, as well as for alternatives involving four attributes (involving three, four, and five alternatives). However, because all results are qualitatively similar, they are not reported here.

The Role of Error

Within a linear, binary attribute framework of preferences, choices made by simple trade-off-avoiding strategies are often surprisingly consistent with “true” trade-off-confronting preferences. However, if “true” preferences were subject to error, how would this affect model performance?

Table 7 Percentage Correct Choices for Different Models (Choosing Best of Three Alternatives) for Different Distributions and Under Different Error Conditions

	Noncompensatory preferences						Compensatory preferences					
	DEBA	EW	DEBA/EW	EW/DEBA	DOMRAN	“True”	DEBA	EW	DEBA/EW	EW/DEBA	DOMRAN	“True”
Distribution ¹												
Distinctive	100	79	96	95	76	×	95	84	91	100	76	×
Friendly	100	88	96	100	80	×	100	88	96	100	80	×
Unfriendly	86	55	86	70	58	×	68	69	68	84	58	×
Error ² , $\sigma = 0.1$												
Distribution ¹												
Distinctive	88	70	86	83	68	88	90	82	89	92	75	92
Friendly	87	78	84	87	70	87	92	87	91	92	78	92
Unfriendly	83	53	83	68	55	83	69	65	69	78	57	78
Error ² , $\sigma = 0.3$												
Distribution ¹												
Distinctive	73	60	71	70	59	72	73	68	73	72	64	71
Friendly	72	66	70	72	60	71	73	70	73	72	66	72
Unfriendly	71	47	71	60	49	71	58	56	58	61	52	60
Error ² , $\sigma = 0.5$												
Distribution ¹												
Distinctive	64	54	64	62	54	63	61	58	61	60	56	58
Friendly	63	59	62	62	55	61	63	60	63	61	59	60
Unfriendly	62	45	62	55	46	62	50	49	50	52	48	50

Note. Bold figures indicate the largest figures within specific comparisons.

¹Distributions of profiles

Distinctive [1, 1, 1, 1, 1, 1, 1]

Friendly [1, 1, 1, 1, 0, 1, 1]

Unfriendly [0, 2, 0, 2, 6, 0, 3]

²The data in the upper panel were created by calculations (cf. Tables 2 and 3). Data in the three lower panels are mean figures based on simulations involving 100 trials.

Error can be modeled in several ways. For simplicity, we have modified Equation (3) so that “true” utility is expressed by

$$V(X_i) = \sum_{j=1}^k \beta_j x_{ij} + \varepsilon_i, \quad (5)$$

where ε_i is normally distributed with constant variance, $\varepsilon_i \sim N(0, \sigma^2)$.

Using Equation (5), we simulated data for the three distributions of attribute profiles discussed above (i.e., distinctive, friendly, and unfriendly), each with three levels of error, small ($\sigma = 0.1$), medium ($\sigma = 0.3$) and large ($\sigma = 0.5$). For all nine cases we calculated the correct choices made by each of the models in selecting the best from all possible combinations of three alternatives. This process was repeated 100 times; the average results are reported in the three lower panels of Table 7.

The results show consistent patterns. First, the optimal models for the noncompensatory and compensatory preferences (i.e., DEBA and EW/DEBA, respectively) perform at the same level as the “true” model, that is, the linear model with parameters specified in Equation (5). Second, differences between performances of the models due to the different distributions decrease as the size of the error variance

increases. For example, for DEBA with noncompensatory preferences, the difference between the distinctive and unfriendly distributions is 14% with no error (i.e., 100%–86%). With $\sigma = 0.5$, the analogous difference is 2% (i.e., 64%–62%). Similarly, assuming compensatory preferences for EW/DEBA, the difference is 16% with no error and 8% when $\sigma = 0.5$. Third, as error increases, performance of all models degrades systematically. Fourth, within different levels of error, results for the distinctive and friendly distributions are similar for all models except EW.

In summary, error diminishes differences in model performance as well as differences due to characteristics of choice sets. Overall, the presence of error in “true” preferences emphasizes the relative efficacy of trade-off-avoiding models.

Discussion

Summary

Faced with choosing between multiattribute alternatives where attributes are both binary in nature and appropriately scaled, simple trade-off-avoiding models produce choices that are remarkably consistent with hypothetical sets of “true” preferences. In particular, the DEBA model has optimal performance if

“true” preferences are noncompensatory, and it still performs well over a range of compensatory preferences. When preferences are compensatory (with three attributes) or the most compensatory (with four and five attributes), the composite EW/DEBA model has optimal performance. Interestingly, the DEBA/EW model is not as effective as EW/DEBA across all types of functions and is inferior to DEBA alone. The EW model is generally not as effective as models that allow some differential weighting of variables, and DOMRAN is the least effective of the models we examined.

In reaching these conclusions, we assumed that (1) people know the relative importance of attributes, (2) distributions of alternatives are comprised of complete and distinctive sets of attribute profiles, and (3) there are no errors in “true” preferences. Investigating these assumptions, we found first that results generally held, provided the decision maker identified the most important attribute. Second, results depend on characteristics of distributions of alternatives. Specifically, the frequencies of dominating (repeat) profiles increase (decrease) levels of performance. More importantly, the presence or absence of particular attribute profiles affects the performance of specific models, conditional on classes of preference functions. For example, EW can perform as well as or better than DEBA in a “DEBA-unfriendly” environment involving compensatory preferences. Third, the presence of error in “true” preferences reinforces the relative efficacy of trade-off-avoiding models such as DEBA. Overall, error reduces differences between models as well as differences due to characteristics of alternatives.

Our results are important because we have identified circumstances in which simple trade-off-avoiding strategies are remarkably consistent with “true” preferences. In other words, in many cases it is impossible to distinguish whether people’s choices are in agreement with a “rational” or “boundedly rational” model of behavior (Chater et al. 2003, Gigerenzer et al. 1999).

Limiting Conditions

Our results are conditional on “true” preferences being in the form of Equation (3) and using percentage correct choices as the criterion for model performance. We now discuss these assumptions.

We believe that the linear form of Equation (3) is reasonable in that nonlinear functions can be well approximated by linear functions, particularly when the former are conditionally monotonic with respect to the criterion (Dawes and Corrigan 1974). The presence of error or “noise” also makes linear approximations more “optimal.”

Both Equation (2) and our results as a whole emphasize the importance of binary variables as

attributes. Indeed, in related work we have analyzed the performance of some simple models for *binary* choice using continuous variables with a percentage correct criterion (Hogarth and Karelaia 2005). This analysis suggests that, in a relative sense, continuous variables favor EW but hurt DOMRAN. In short, EW predicts few ties with continuous variables (thus avoiding chance-level outcomes), and there are fewer cases involving dominance.⁷ (Continuous variables also imply fewer “repeats,” thereby increasing the probability of correct choices above chance for all models.)

It is intriguing to compare our results with those of Payne et al. (1993), who examined a somewhat different set of models with attributes that were continuous variables and used an accuracy measure as the criterion. They investigated choices between multioutcome gambles and distinguished first between environments where dominance was and was not possible and, second, probabilities (analogous to weighting parameters in our work) that had low and high dispersion (similar to compensatory and noncompensatory, respectively). Their best performing model was a lexicographic strategy in the high-dispersion conditions, but this did not have “perfect” performance. Interestingly, EW was shown to be the best model in the low-dispersion condition when dominance was possible (see previous comments).

The work of Gigerenzer and his colleagues relates directly to ours in that it deals with binary attributes (Gigerenzer et al. 1999). That work demonstrates remarkable predictive performance of the TTB model in binary choice (for theoretical analyses, see Martignon and Hoffrage 1999, 2002; Hogarth and Karelaia 2003; Katsikopoulos and Martignon, in press). The parallel is that TTB is the same model as DEBA when there are only two alternatives.

Our results are conditional on using percentage correct choices as a criterion; that is, in evaluating relative performance we do not differentiate between large and small errors (in terms of utility). In adopting this criterion, we followed precedence in the literature involving binary attributes or cues (e.g., see Gigerenzer et al. 1999). Clearly, other loss functions should be investigated. However, two reasons suggest that many conclusions might be robust. One is that all models we examined respect dominance such that differences between models only occur in cases where dominance is not a factor (see, e.g., the details in Table 2. In addition, all models have the same performance levels with repeats). The second—and more

⁷ As documented elsewhere, EW can also perform well in specified conditions, compared to “optimal” regression models (Einhorn and Hogarth 1975).

important—reason is that the better performing models are optimal or close to optimal, that is, 100% or close to 100% correct (see Tables 3 and 4). Thus, conclusions as to which model(s) perform best under which circumstances cannot be sensitive to how performance is measured. Indeed, recent work calculating upper bounds on the expected loss of using DEBA supports these assertions (Baucells et al. 2005). On the other hand, if errors are made in determining the relative importance of weighting parameters, models that use DEBA could be sensitive to specification of the loss function (Tables 5 and 6).

We restricted our analysis to, at most, five attributes on the grounds that people are limited in their ability to process information.⁸ As the number of attributes increases, DEBA must continue to be optimal for non-compensatory preferences. Based on work in binary choice, Martignon and Hoffrage (1999, 2002) show that EW becomes relatively more effective as the number of attributes increases (it is better able to discriminate between alternatives). This may be true but the trend cannot be detected in our calculations across the three-, four-, and five-attribute cases. Finally, the performance of DOMRAN will clearly decrease systematically as the number of attributes increases.

By the present analysis, we are not arguing that people should always avoid trade-offs in choice. For example, DEBA performs relatively poorly in DEBA-unfriendly environments when the weighting function is compensatory (see, e.g., the top panel of Table 7). Nor do we advocate the use of DOMRAN, even though this can be surprisingly effective for binary choice in noisy environments (Hogarth and Karelaia 2003). If people do not face trade-offs when these are important, they stand to make unsatisfactory choices.

Descriptive Considerations

Do people use DEBA-like strategies, and to what extent are choices based on binary variables? Several experimental studies have investigated the first issue (see, e.g., Rieskamp and Hoffrage 1999, 2002; Bröder 2000, 2003; Bröder and Schiffer 2003; Newell and Shanks 2003; Newell et al. 2003). The general finding is that people do use such strategies but not all the time. The principal deviation is that they seek more information, that is, consider more attribute or cue values than the models. On the other hand, such models are preferred under task conditions that limit information search (e.g., time pressure (Payne et al. 1993, Rieskamp and Hoffrage 2002)).

⁸ We also did not include an analysis of the two-attribute case. We believe that, qualitatively, this is quite different in that in choosing people are forced to consider one variable more important than the other and, in this sense, face a trade-off even though they may not need to do so precisely (see, e.g., Equation (2)).

Of particular interest to the present investigation is the finding that people do not require many trials to learn the relative validities of cues or, in our terms, the relative sizes of β weights (Rakow et al. 2004). When these differ, people can discriminate. Moreover, as our theoretical findings showed, it is generally only the identification of the attribute with the largest β weight that is important.

Clearly we cannot say how often people's choices involve exclusively binary attributes; however, we believe the occurrence is substantial. First, many attributes are qualitative and naturally encoded in binary fashion (e.g., color vs. black and white, presence vs. absence, bitter vs. sweet, and so on). Second, although such attributes can also take continuous forms (e.g., *how* bitter), what matters is how they are viewed in the set of alternatives under consideration. Third, whether attributes are perceived as binary or continuous could also depend on substantive expertise. Lacking expertise, decision makers might well conceive of only two levels of attributes (e.g., good vs. bad). On the other hand, experts might also simplify complex tasks by treating continuous variables in binary fashion. And fourth, evidence supports the notion that, in the presence of affect, people treat variables in categorical—and often binary—fashion (Hsee and Rottenstreich 2004).

Our analysis has implications for the learning of preferences through experience. Specifically, if people can successfully use simple, trade-off-avoiding strategies, what incentives or possibilities exist for them to learn to express trade-offs with greater precision? Moreover, if feedback is deficient (Einhorn and Hogarth 1978, Hogarth in press), what do people really learn when they make choices using these simple strategies?

Finally, the fact that outcomes of the simple models are so consistent with more complex rational models is also important for descriptive research. It means that tests of whether people use particular models must focus on those few cases where choices differ (for a good example, see Newell and Shanks 2003).

Conclusion

When attribute values are binary variables, simple trade-off-avoiding strategies are remarkably effective in yielding the same choices as linear multiattribute models. We have clearly identified situations where people can avoid trade-offs with relative impunity. Our work, however, is but a first step in this direction, and reaching a complete picture poses considerable challenges. In particular, it will be important to extend this kind of theoretical investigation to multiattribute choices involving continuous variables with different loss functions and more complete analyses of the role of error.

An online supplement to this paper is available on the *Management Science* website (<http://mansci.pubs.informs.org/ecompanion.html>).

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References

- Baucells, M., J. A. Carrasco, R. M. Hogarth. 2005. Cumulative dominance and heuristic performance in binary multiattribute choice. DEE working paper 895, Universitat Pompeu Fabra, Barcelona, Spain.
- Bröder, A. 2000. Assessing the empirical validity of the take-the-best heuristic as a model of human probabilistic inference. *J. Experiment. Psych.: Learning, Memory, Cognition* **26**(5) 1332–1346.
- Bröder, A. 2003. Decision making with the “adaptive toolbox”: Influence of environmental structure, intelligence, and working memory load. *J. Experiment. Psych.: Learning, Memory, Cognition* **29**(4) 611–625.
- Bröder, A., S. Schiffer. 2003. Take the best versus simultaneous feature matching: Probabilistic inferences from memory and effects of representation format. *J. Experiment. Psych.: General* **132**(2) 277–293.
- Brunswik, E. 1952. *Conceptual Framework of Psychology*. The University of Chicago Press, Chicago, IL.
- Chater, N., M. Oaksford, R. Nakisa, M. Redington. 2003. Fast, frugal, and rational: How rational norms explain behavior. *Organ. Behavior Human Decision Processes* **90** 63–86.
- Dawes, R. M., B. Corrigan. 1974. Linear models in decision making. *Psych. Bull.* **81** 95–106.
- Einhorn, H. J., R. M. Hogarth. 1975. Unit weighting schemes for decision making. *Organ. Behavior Human Performance* **13** 171–192.
- Einhorn, H. J., R. M. Hogarth. 1978. Confidence in judgment: Persistence of the illusion of validity. *Psych. Rev.* **85** 395–416.
- Fasolo, B., G. H. McClelland, P. M. Todd. In press. Escaping the tyranny of choice: When fewer attributes make choice easier. *Marketing Theory*.
- Gigerenzer, G., D. Goldstein. 1996. Reasoning the fast and frugal way: Models of bounded rationality. *Psych. Rev.* **103** 650–669.
- Gigerenzer, G., P. M. Todd, the ABC Research Group. 1999. *Simple Heuristics That Make Us Smart*. Oxford University Press, New York.
- Hogarth, R. M. 1987. *Judgement and Choice*, 2nd ed. John Wiley and Sons, New York.
- Hogarth, R. M. In press. Is confidence in decisions related to feedback? Evidence—and lack of evidence—from random samples of real-world behavior. K. Fiedler, P. Juslin, eds. *In the Beginning There is a Sample: Information Sampling as a Key to Understand Adaptive Cognition*. Cambridge University Press, Cambridge, UK.
- Hogarth, R. M., N. Karelaia. 2003. “Take-the-Best” and Other Simple Strategies: Why and When They Work “Well” in Binary Choice. DEE Working Paper 709, Universitat Pompeu Fabra, Barcelona, Spain.
- Hogarth, R. M., N. Karelaia. 2005. Ignoring information in binary choice with continuous variables: When is less “more”? *J. Math. Psych.* **49** 115–124.
- Hsee, C. K., Y. Rottenstreich. 2004. Music, pandas, and muggers: On the affective psychology of value. *J. Experiment. Psych.: General* **133**(1) 23–30.
- Johnson, E. J., J. W. Payne. 1985. Effort and accuracy in choice. *Management Sci.* **31**(4) 395–414.
- Katsikopoulos, K., L. Martignon. In press. Naïve heuristics for paired comparisons: Some results on their relative accuracy. *J. Math. Psych.*. Forthcoming.
- Katsikopoulos, K., B. Fasolo. In press. New tools for decision analysts. *IEEE Trans. Systems, Man, Cybernetics: Systems Humans*.
- Keeney, R. L., H. Raiffa. 1993. *Decisions With Multiple Objectives: Preferences and Value Trade-Offs*. Cambridge University Press, Cambridge, NY.
- Luce, M. F., J. R. Bettman, J. W. Payne. 1997. Choice processing in emotionally difficult decisions. *J. Experiment. Psych.: Learning, Memory, Cognition* **23**(2) 384–405.
- Martignon, L., U. Hoffrage. 1999. Why does one-reason decision making work? A case study in ecological rationality. G. Gigerenzer, P. M. Todd, the ABC Research Group, eds. *Simple Heuristics That Make Us Smart*. Oxford University Press, New York, 119–140.
- Martignon, L., U. Hoffrage. 2002. Fast, frugal, and fit: Simple heuristics for paired comparison. *Theory Decision* **52** 29–71.
- Montgomery, H. 1983. Decision rules and the search for a dominance structure: Towards a process model of decision making. P. Humphreys, O. Svenson, A. Vari, eds. *Analysing and Aiding Decision Processes*. North Holland, Amsterdam, 343–369.
- Newell, B. R., D. R. Shanks. 2003. Take the best or look at the rest? Factors influencing “one-reason” decision making. *J. Experiment. Psych.: Learning, Memory, Cognition* **29**(1) 53–65.
- Newell, B. R., N. J. Weston, D. R. Shanks. 2003. Empirical tests of a fast-and-frugal heuristic: Not everyone “takes-the-best.” *Organ. Behavior Human Decision Processes* **91** 82–96.
- Payne, J. W., J. R. Bettman, E. J. Johnson. 1992. Behavioral decision research: A constructive processing perspective. *Ann. Rev. Psych.* **43** 87–131.
- Payne, J. W., J. R. Bettman, E. J. Johnson. 1993. *The Adaptive Decision Maker*. Cambridge University Press, New York.
- Rakow, T., N. Hinvest, E. Jackson, M. Palmer. 2004. Simple heuristics from the adaptive toolbox: Can we perform the requisite learning? *Thinking Reasoning* **10**(1) 1–29.
- Rieskamp, J., U. Hoffrage. 1999. When do people use simple heuristics, and how can we tell? G. Gigerenzer, P. M. Todd, the ABC Research Group, eds. *Simple Heuristics That Make Us Smart*. Oxford University Press, New York, 141–167.
- Rieskamp, J., U. Hoffrage. 2002. The use of simple heuristics: Inferences and preferences under time pressure. Working paper, Max Planck Institute for Human Development, Berlin, Germany.
- Shanteau, J., P. P. Thomas. 2000. Fast and frugal heuristics: What about unfriendly environments? *Behavioral Brain Sci.* **23** 762–763.
- Simon, H. A. 1956. Rational choice and the structure of environments. *Psych. Rev.* **63** 129–138.
- Thorngate, W. 1980. Efficient decision heuristics. *Behavioral Sci.* **25** 219–225.
- Tversky, A. 1972. Elimination by aspects: A theory of choice. *Psych. Rev.* **79** 281–299.

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