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Optimal Effort in Consumer Choice: Theory and Experimental Analysis for Binary Choice

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Abstract

This paper develops a theoretical model of optimal effort in consumer choice. The model extends previous consumer choice models in that the consumer not only chooses a product, but also decides how much effort to apply to a given choice problem. The model yields a unique optimal level of effort, which depends on the consumer's cost of effort, the expected utility gain of a correct choice, and the complexity of the choice set. We show that the relationship between effort and cost of effort is negative, whereas the relationships between effort and product utility difference and choice task complexity are undetermined. To resolve this theoretical ambiguity and to explore our model empirically, we investigate the relationships between effort and cost of effort, product utility difference and choice task complexity using data from a conjoint choice study of two-alternative consumer restaurant choices. Response time is used as a proxy for effort and consumer involvement measures capture individual differences in (relative) cost of effort and perceived complexity. Effort is explained using the (estimated) utility difference between alternatives, the number of elementary information processes (EIP's) required to solve the choice problem optimally and respondent specific cost of effort and complexity perceptions. The predictions of the theoretical model are supported by our empirical findings. Response time increases with lower cost of effort and greater perceived complexity (i.e. higher involvement). We find that across the range of choice tasks in our survey, effort increases linearly with smaller product utility differences and greater choice task complexity.

1 Introduction

Economic models of choice traditionally assume that consumers are rational utility maximizers. This assumption has been popular because in the context of the random utility theory framework, it provides tractable models of consumer choice (McFadden 1986). In these models, observed inconsistencies in choice behavior, or ‘errors’, are typically taken to be the result of observational or modeling deficiencies on the part of the analyst (Ben-Akiva and Lerman 1985). The traditional model presumes that decision-makers are able to make all the complicated calculations required to find the optimal product in a choice set, with the implication that neither choice complexity nor consumer effort should play a role in the consumer decision.

More behaviorally oriented research on consumer decision-making on the other hand acknowledges that consumers do not always behave in a perfectly rational manner. In particular, consumers have been found to employ simplifying strategies to reduce cognitive requirements (Bettman et al. 1993) and to vary in the accuracy with which they make their choices (Haaijer et al. 2000) or provide preference evaluations (Fischer et al. 2000). Therefore it has been proposed that consumers should be modeled as boundedly rational (see Rubinstein 1998 for a review).

In this study we take an intermediate approach that recognizes the constraints on consumer decision processes arising from the limitations of human beings as problem solvers but embeds these constraints in a model of consumer rationality. In particular, we assume that consumers rationally take into account their cognitive effort when making their decisions (c.f. Tversky 1969, Johnson and Payne 1985). We develop a model in which effort is required to reduce the probability of a sub-optimal choice. This effort comes at a cost, and the consumer makes a trade-off between this cost and the expected utility gain of a higher probability of choosing the optimal product. The model explains how much effort consumers should put into choosing between two products if they rationally include the cost of effort in their objective function. We allow the choice of effort to depend on the expected payoff from a correct choice (the utility difference between the products), the complexity of the choice problem, and the cost of effort. We show that our model gives a unique optimal level of effort, which negatively depends on the cost of effort. On the other hand, the relationship between effort and product utility difference or complexity is undetermined.

We then explore the implications of the model in an empirical analysis. In a conjoint choice study of two-alternative consumer restaurant choices, response time was used as a proxy for the effort consumers put into their decision. Choice sets were varied in attribute composition to allow for an analysis of the impact of product utility differences and choice set task complexity on effort. Consumer involvement measures were taken as proxies for individuals' cost of effort and their perception of choice complexity. Least squares regressions were used to explain response time from product utility difference, choice task complexity, and consumer involvement measures. We find that across the fairly wide range of binary choice tasks in the survey (3,6 or 12 attributes with regular or large attribute level differences) effort increases linearly with task complexity and decreases with product utility difference. Thus we resolve in part empirically the theoretical ambiguity in the relationship between effort and choice set composition. In line with model predictions we find that response time increases with lower cost of effort (i.e., larger consumer involvement).

The remainder of the paper is organized as follows. Section 2 presents the components of the model compared to the existing literature. The economic model is discussed in section 3. Section 4 is about the empirical analysis. Section 5 concludes.

2 Effort and consumer choice

Previous studies have found that choice set and individual characteristics influence the effort consumers put into their decision process. These studies identify several determinants of response times, including choice set structure, choice task complexity, and situational and personal influences (Tyebjee 1979). Also recognized is the opportunity cost of processing time (Busemeyer and Townsend 1993, Payne et al. 1992). With the exception of situational influences (e.g. time pressure), we incorporate these components in our model.

The effect of relative cost of effort

When effort is costless the utility maximizing consumer will aim at choosing the best product no matter how much effort this requires. If effort is costly, however, choices may be based on limited information and personal characteristics may have an impact on the quality of the decision process. Consumers who are more interested in the product category may have lower cognitive costs per unit of effort, relative to the potential utility gains of choosing the optimal product.[1] As a consequence, they may spend more effort on their decision and reach a higher level of choice accuracy. For example, Mittal and Lee (1989) found that involved consumers use more information and go through more brand comparisons when choosing a product.

Product utility difference

[1] In terms of an overall utility function which increases with the utility of the chosen product in the category considered and decreases with effort spent on the choice, more involvement means that the weight of the former increases. This has the same effect as a fall in the marginal disutility of effort. See the formal model in section 3.

The effect of product utility difference on choice effort is twofold. First, the utility difference between two products affects the pay-off of consumer choice effort directly. Putting effort into choosing between an excellent alternative and a poor alternative has a higher pay-off than if two alternatives hardly differ in utility terms. This effect would lead to a positive relation between higher utility difference and effort. Second, product utility difference will typically also affect the probability of a correct choice. The greater the product utility difference, the lower the increase in the probability of making a correct choice with additional units of effort. This works in the opposite direction of the first effect and may explain the earlier findings that the time taken to choose between two goods is inversely related to the difference in utility (Bettman et al. 1993, Bockenholt et al. 1991, Tyebjee 1979). In other words, the closer alternatives are in terms of utility, the more conflict a choice evokes, and the more analysis is required by the decision-maker.[2]

Choice task complexity

Choice task complexity may affect the choice decision process in two ways (Bettman et al 1993, Bettman et al. 1990, Swait and Adamowicz 2000, Tyebjee 1979). First, as complexity varies, the individual may use the same decision strategy but vary the amount of effort spent on it. For example, as complexity increases, a consumer using a compensatory choice process might increase the amount of effort spent evaluating each attribute. Second, the decision-maker may switch to a different decision strategy altogether. For example, the consumer could use a compensatory choice process in

[2] As in most past research, conflict here refers to between-alternatives conflict, which results if competing alternatives have a small difference in utility terms (e.g., Shugan 1980). This differs from the approach of Fischer et al. (2000) where conflicts between and within alternatives are distinguished. The latter is more relevant for scenarios where single products are rated than for choice scenarios.

one choice environment and a lexicographic method in another. The use of such strategies may depend on both consumer and choice set characteristics.

Research in behavioral decision theory has suggested several aspects of choice sets that have the potential to increase the effort required for choosing the product with the highest utility (e.g. Bettman et al. 1993). The number of alternatives and the number of attributes describing the alternatives are found to be key drivers of this effort. One way to incorporate these is to count the number of elementary information processes (EIP's) required for performing the choice task. The idea of decomposing choice strategies into a set of components has been suggested for example by Huber (1980) and was implemented in a set of Monte Carlo experiments by Johnson and Payne (1985). These studies draw on ideas of Newell and Simon (1972), who suggested that heuristic strategies can be constructed from a small set of EIP's. Examples of EIP's suggested by Newell and Simon are 'READ' (read an alternative's value for a specific attribute), 'COMPARE' (compare two alternatives on an attribute), 'ADD' (add the utility values of different attributes), etc. By combining such EIP's different choice processes can be described. In previous research, it was emphasized that the number of EIP's depends on the nature of the choice problem as well as the decision strategy. For example, Johnson and Payne (1985) compared the number of EIP's required by different decision processes for a fixed choice task (i.e., keeping complexity constant) and found that more accurate decision strategies typically require a greater number of EIP's. In our study, we use EIP's as a measure of choice set complexity, for a given (fully compensatory) decision strategy. This measure will be a function of the number of alternatives in the choice set and the number of attributes of each alternative.

3 A Model for Optimal Effort

This section presents a model that describes the behavior of a utility maximizing consumer whose decision on how much effort to apply to a particular choice problem depends upon personal and choice set characteristics. We consider the choice between two alternatives that are not straightforward to compare. They can have many attributes or the attributes can be hard to evaluate, this is not made explicit. This case is complementary to the problem of searching the optimal product in a large set of alternatives addressed in the existing literature (Roberts and Lattin 1991 and Moorthy et al. 1997). We do not determine how many alternatives to evaluate, but focus on the effort applied to evaluating two products. The model is described in section 3.1. In section 3.2, we analyze how optimal effort changes with the relative cost of effort, with choice complexity, and with the utility difference. It appears that the theory does not determine the directions of the latter two effects. We therefore add an empirical analysis in section 4.

3.1 Model

The model explains two things: how much effort do consumers apply to acquire information relevant to the choice decision, and which choices do they make. In practice, these decisions will be intertwined: some effort is applied, some information is collected; this is used to decide whether or not more effort will be applied, etc. Such an iterative model would be hard to formalize and impossible to validate with existing data. We therefore work with a stylized non-iterative model in which effort is determined on the basis of a prior distribution of the utility difference, then products are evaluated and the choice is made.

The model considers a consumer faced with a choice between two products, say 0 and 1, with utilities U_0 and U_1. We model the consumer's decision process based on four decision components:

1) The consumer takes a first glance at the two alternatives. On the basis of this, he constructs some prior distribution of U_0 - U_1.

2) On the basis of the prior distribution, the complexity of the choice problem, and the cost of effort, the consumer chooses the optimal effort level for evaluating the two alternatives.

3) The consumer puts effort in evaluating the two alternatives, leading to proxies U_0* and U_1* of U_0 and U_1, respectively.

4) The consumer chooses on the basis of U_0* and U_1*: Product 0 is chosen if and only if $U_0^* > U_1^*$.

Constructing a prior distribution

First, the consumer considers the utility values of the two goods as random draws from some population of utilities (or goods). A global glance at the question gives the consumer some idea about the distribution of the values from which the utilities are drawn, such as its dispersion. In particular, we have choices in mind where each alternative is characterized by a large number of attributes, which are separately easy to evaluate. None of the alternatives dominates the other in all the attributes. Effort is required to weigh the positive and negative attribute differentials to come to a choice. The absolute attribute levels and the number of attributes give some indication on the expected absolute utility difference between the products, but since each product scores better on certain attributes, it is a priori completely unclear which product is better. While this may be a stylized view, we think it is a reasonable approximation, at least for the type of choice problem we consider in the empirical section.

Before making the choice, the consumer will then put effort in studying the two products more carefully. Thus before studying the alternatives in detail, the consumer has some (subjective) prior distribution in mind for the utility values U_0 and U_1. The consumer, *a priori*, has no idea which is better. Thus the prior satisfies

$$E\{U_1 - U_0\} = 0. \tag{1}$$

We define the *expected absolute difference in utility* between two goods D by

$$D = E\{|U_1 - U_0|\} = E\{U_{sup} - U_{inf}\}. \tag{2}$$

Here $U_{sup} = \max(U_0,U_1)$ and $U_{inf} = \min(U_0,U_1)$. If D increases, the expected payoff of correctly choosing the superior good over the inferior good will increase. If, for example, the respondent sees at first glance that all attributes are very similar for the two goods, D will be small.

The standardized prior for the consumer is given by:

$$Z = \frac{(U_1 - U_0)}{D},$$

Thus $E\{Z\} = 0$ and, by construction, $E\{|Z|\} = 1$. We assume that Z has a symmetric continuous distribution:

$$Z \text{ has density } g(z), \text{ with } g \text{ symmetric around } 0. \tag{3}$$

In the empirical analysis below, we assume that the distribution of Z is the same for all consumers and in choice situations, implying that D is a scale parameter of the prior distribution of $U_1 - U_0$.

Effort and utility proxies

Before making a choice, the respondent puts some effort in studying the two products and obtains proxies U_1* and U_0* of the utilities U_1 and U_0. The accuracy a of these depends on the *effort level E* and the *choice complexity C*:

$$U_j^* = U_j + \frac{e_j}{a(E;C)},\ j=0,1 \tag{4}$$

where

$$e_0, e_1 \text{ are iid with mean zero, independent of } U_0, U_1, Z, E \text{ and } C \tag{5}$$

$a(E;C)$ is a scale parameter of e_0, e_1 reflecting "accuracy." Its value determines the importance of the errors e_0 and e_1 in constructing the proxies U_1* and U_0*. Accuracy is inversely related to the variance of the errors. Thus if $a(E;C)$ increases, the proxies tend to be closer to the true utility values U_1 and U_0. We assume:

$$\frac{\partial a(E;C)}{\partial E} > 0 \text{ and } \frac{\partial a(E;C)}{\partial C} < 0\,. \tag{6}$$

The function $a(E;C)$ is where effort enters the analysis and is the core of the model. An increase in effort will lead to an increase in the accuracy of the utility proxies. As explained above, we do not specify which decision strategy the consumer uses; an increase in effort may mean that the consumer spends more time evaluating each attribute or that the consumer changes from a less effort-intensive to a more effort-intensive decision strategy. Johnson and Payne (1985) find a strong positive relationship between effort and expected accuracy across decision strategies, keeping complexity C constant, in line with the first inequality in (6).

The negative sign for the first derivative of $a(E;C)$ with respect to complexity implies that complexity increases the variance of the error terms, making it more difficult to distinguish the superior from the inferior good. As complexity increases the decision-maker's proxies for the true utilities U_1 and U_0 become less reliable. Thus in a more complex situation, more effort must be applied to achieve the same level of accuracy as in a less complex choice.

We assume that the accuracy function satisfies "non-increasing returns to effort:"

$$\frac{\partial^2 a(E;C)}{\partial E^2} \leq 0 \qquad \text{(NIRE)} \qquad (7)$$

We will need this condition to guarantee that the second order condition for optimality of effort is satisfied. It implies that the marginal increase in accuracy from an additional unit of effort falls with the level of effort.

Effort and expected utility

Given the proxies U_1* and U_0*, the choice between the two products will be based upon U_1*-U_0*. With the symmetric set up, the optimal choice rule will be:

Choose 1 if $U_1^* > U_0^*$; choose 0 otherwise

The expected pay-off is given by

$$\mathrm{E}\{1(U_1{*} > U_0{*})U_1 + 1(U_0{*} > U_1{*})U_0\}$$

Due to the law of iterated expectations, this can be rewritten as

$$\mathrm{E}\{P(U_1{*} > U_0{*} | U_0, U_1)U_1 + P(U_0{*} > U_1{*} | U_0, U_1)U_0\},$$

where the expectation is taken over U_0 and U_1. Working out the inner part of this for both $U_0 > U_1$ and $U_1 > U_0$ gives

$$\mathrm{E}\{P(\text{correct choice} | U_0, U_1)U_{\text{sup}} + P(\text{incorrect choice} | U_0, U_1)U_{\text{inf}}\}.$$

Due to symmetry of e_1 - e_0 and Z, this can be rewritten as

$$\mathrm{E}\{U_{\text{inf}}\} + \mathrm{E}\{P(e_1 - e_0 > U_0 - U_1 | U_0, U_1) \times | U_1 - U_0 | \,|\, U_1 > U_0\}$$

With $Z = \dfrac{(U_1 - U_0)}{D}$, this becomes:

$$\mathrm{E}\{U_{\text{inf}}\} + \mathrm{E}\{P(e_1 - e_0 > -D | Z | a(E;C) | Z) \times D | Z |\}$$

We thus have shown that the expected utility (R) is given by

$$R(a(E;C), D) = \mathrm{E}\{U_{\text{inf}}\} + \mathrm{E}\{P(e_1 - e_0 > -D | Z | a(E;C) | Z) \times D | Z |\} \qquad (8)$$

Defining $e = e_1 - e_0$, equation (8) becomes

$$R(a(E;C);D) = \mathrm{E}\{U_{\text{inf}}\} + \mathrm{E}\{P(e > -D | Z | a(E;C) | Z) \times D | Z |\}, \qquad (9)$$

The assumption that e_0 and e_1 are iid implies that e is symmetric around zero. In addition, it seems plausible to assume that e is unimodal, and thus has unique mode at 0. For convenience, we also assume that e has a continuous distribution with differentiable density f_e. These assumptions together thus imply.

$$f_e'(x) > 0 \text{ for } x < 0 \text{ and } f_e'(x) < 0 \text{ for } x > 0. \quad \text{(USYM)} \qquad (10)$$

Together with the non-increasing returns to effort assumption in (7), condition (10) will be sufficient to guarantee that the second-order condition for a unique maximum is satisfied (see (14) below).

Optimal effort

Equation (9) gives the expected utility, given the parameters D and C, and given the effort level E. As explained in section 2, we assume that effort comes at a cost. Cost of effort is introduced in the model as a fixed marginal disutility, g per unit of effort.

Thus, for a given choice question, the consumer has to decide on the effort level E, knowing g D, C, the distributions of Z and e, and the function $a(E;C)$. The choice of E will be based on the expected pay-off minus the disutility of effort, i.e., the consumer solves the problem

$$\mathrm{Max}_{E>0} \qquad R(a(E;C), D) - gE \qquad (11)$$

The term $\mathrm{E}\{U_{\mathrm{inf}}\}$ in (9) does not depend on E and can be removed, so that the maximization problem is equivalent to

$$\mathrm{Max}_{E>0} \qquad \mathrm{E}\left\{P\left(e > -D \mid Z \mid a(E;C) \mid Z\right) \times D \mid Z \mid\right\} - gE \qquad (12)$$

The optimal level of effort will satisfy the first order condition

$$g = \frac{d}{d\,E}\left[\mathrm{E}\left\{P\left(e > -D \mid Z \mid a(E;C) \mid Z\right) \times D \mid Z \mid\right\}\right] \qquad \text{(FOC)} \qquad (13)$$

This equation states that the individual equates the marginal benefits (in utility units) with the marginal cost (in utility units).

The second order condition guaranteeing that (13) gives a utility maximum is

$$\frac{d^2}{dE^2}\left[\mathrm{E}\{P(e > -D \mid Z \mid a(E;C) | Z) \times D \mid Z \mid \}\right] < 0 \quad \text{(SOC)} \tag{14}$$

This states that the marginal revenue of effort decreases with effort. A proof that (14) will hold if both (7) and (10) are satisfied is included in Appendix 1.

3.2 Comparative Statics

We examine how shifts in the model parameters affect the optimal level of effort. The first order condition (13) can be rewritten as

$$g = \mathrm{E}\left\{\frac{d}{dE}\left(P(e > -D \mid Z \mid a(E;C) \mid Z) \times D \mid Z \mid\right)\right\}$$

$$= \mathrm{E}\left\{f_e(-D \mid Z \mid a(E;C)) \times (D \mid Z \mid)^2 \times \frac{\partial a}{\partial E}\right\}$$

or, in other words,

$$g = \mathrm{E}\{f_e(-D \mid Z \mid a(E;C)) \times (D \mid Z \mid)^2\} \times \frac{\partial a}{\partial E} \tag{15}$$

The left-hand side gives marginal costs (MC) of effort (in utility units) and the right hand side gives the marginal revenues (MR).

Comparative statics with respect to g

An increase in g implies an increase in MC. To restore the equality, MR must rise as well. Due to SOC, this means that the effort level E will fall. Thus we have:

$$\frac{\partial E}{\partial g} < 0$$

An increase in the cost of effort leads to a fall in the optimal level of effort. This is in line with existing studies such as Moorthy et al. (1997).

Comparative statics with respect to C

The complexity of the choice problem affects MR in two ways:

C1 (*Effect of Accuracy on Probability of correct choice*) If complexity C increases, accuracy $a(E;C)$ will fall, and due to (10), $f_{\varepsilon}(-D|Z|a(E;C))$ will rise. This means that the marginal effect of a change in $a(E;C)$ on the probability of a correct choice will rise, so that the marginal impact of E on the probability of correct choice will rise. This increases MR and thus (due to SOC) increases the optimal E.

C2 (*Effect of Effort on Accuracy*) On the other hand, an increase in C will also affect the sensitivity of $a(E,C)$ for E, $\partial a/\partial E$. This effect will depend on sign of the cross derivative $\partial^2 a/(\partial E \partial C)$. Both signs are possible, so that we can make either of the following two assumptions.

Assumption REDC: $\frac{\partial^2 a}{\partial E \partial C} < 0$: returns to effort decrease with complexity.

Assumption REIC: $\frac{\partial^2 a}{\partial E \partial C} > 0$: returns to effort increase with complexity

In Appendix 2, we introduce a plausible functional form and show that it satisfies REDC (normally distributed error terms; $a(E;C)=E/C$). Under REDC an increase in C leads to a fall in $\partial a/\partial E$ and a fall in MR and the optimal effort level. Thus effects C1 and C2 have opposite signs and the net effect of complexity on MR and E is undetermined. If C1 dominates, E will increase with C; if C2 dominates, E will decrease with C. In general we cannot say which is the case:

$$\frac{\partial E}{\partial C} \quad \text{is not unambiguously determined under REDC.}$$

On the other hand, if REIC holds, the sign of C2 is the same as the sign of C1:

$$\frac{\partial E}{\partial C} > 0 \qquad \text{under REIC.}$$

Comparative statics with respect to D:

A change of *D* affects MR in two ways:

D1 (*Effect of Accuracy on Probability of correct choice*) if *D* increases, due to (10), $f_\varepsilon[-D|Z|\ a(E;C)]$ will fall. This reduces MR and thus *E* is reduced to restore the equality MR=MC (this is similar to C1 above).

D2 (*Direct effect*) if *D* increases, $(D|Z|)^2$ rises: there is more to be gained by changing the probability of correct choice, due to the larger expected utility difference. Thus MR increases and *E* increases.

Thus, the total effect of the expected utility difference on the optimal effort level is ambiguous.

A change in D versus a change in g

In order to understand how involvement affects the model parameters g *D* and *C* (section 4.3), the distinction between a fall in g and a rise in *D* should be emphasized. In our framework, a change in the expected utility difference *D* affects both the utility gain (leading to D2) and the probability of correct choice (leading to D1), keeping accuracy *a(E;C)* constant. A difference in preferences across consumers may have a direct effect (D2), without affecting the probability of correct choice (i.e. consumers' preferences may be different but their probability of making a correct choice may be identical). In our framework, this change would mean that *C* changes in so much that *a(E;C)* is reduced by the same factor with which *D* increases. Thus the probability of correct choice does not change and expected marginal revenues increase by the same proportion as *D* (see (8)). The effect of this on the optimal effort level is the same as the effect of a corresponding reduction of the cost of effort g since the scale of (dis-) utility is irrelevant. Thus increasing the expected utility difference keeping the probability of a correct choice constant will lead to a higher optimal effort level. Increasing *D* keeping *C* constant on the other hand, leads to the comparative statics for *D* discussed above, and the effect on the optimal effort level is undetermined.

4 Empirical analysis of the determinants of effort

The model suggests that the level of effort applied to a given choice task depends on the parameters g (the relative cost of effort), *D* (expected utility difference) and *C* (choice complexity). To provide external validity for the theoretical model and determine empirically the size and direction of these relationships, data from a conjoint choice study of consumers' two-alternative restaurant choices are used. We first discuss the nature of our data (section 4.1). Next, we explain how the model parameters g *D* and *C* are related to observable choice set characteristics and consumer involvement measures (sections 4.2 and 4.3). We then regress response time as a proxy for consumer choice effort on the choice set characteristics and involvement measures, and discuss the implications of the regression results for the validity of the economic model (section 4.4).

4.1 Data

To analyze the relationships between response time, consumer involvement measures, product utility differences and choice complexity, a conjoint choice experiment involving choices between restaurants was conducted. The preamble instructed respondents to imagine that they were on a short weekend break in a holiday home near an unfamiliar small town and were deciding on a restaurant to eat in on Saturday night. Respondents were asked to choose their preferred option in choice sets containing two restaurants. The survey was conducted amongst a representative consumer panel of households in The Netherlands. It was administered via modems and the Internet.[3] Of the 1320 respondents who were approached for this study, 1271 returned usable questionnaires.

For the purpose of the conjoint choice experiment, the sample was divided into 5 groups. All respondents in the same group received the same five (group 3) or nine (other groups) questions. Between groups, choices differed in the number of attributes (3, 6, 12) and the differences in attribute levels. The restaurants were described by up to 12 attributes (restaurant type, price, menu, style, number of guests, dessert menu, separate bar area, closing time, available methods of payment, distance from parking, available seating, and personnel). Table 1 presents the attributes and their levels. The different treatment conditions provide a range in the levels of product utility differences and complexity. A summary of the conditions that applied for each group is provided in Table 2.

Each attribute was presented at two levels in every group. Orthogonal fractional factorial designs were used to create hypothetical restaurant profiles (Green 1974, Louviere and Woodworth 1983). Each choice set contained one restaurant from the experimental design and one "base-alternative" which was a combination of

[3] To avoid selection bias, recruited respondents who did not own a PC received a PC from the panel organization.

attribute levels that was different from the alternatives in the experimental design and which was constant across all choice sets for each group. In addition to the chosen alternative, response times were recorded for all choice questions separately.

Table 1 Attributes and levels used in the experiment

Attribute	Base	Level 1	Level 2	Extra level*
Restaurant type	Small Restaurant	Restaurant	Hotel-Restaurant	Hotel-Restaurant
Average price of entrée	$ 8	$ 10	$ 15	$ 20
Menu	Basic Menu	Occasionally altered	Extensive	Very extensive
Style	Basic	Modern	Old-fashioned	Very old-fashioned
Number of guests	Reasonably busy	Quiet	Reasonably busy	Very busy
Dessert menu	Only Ice-cream	Occasionally altered	Extensive	Very extensive
Separate bar area	Yes	Yes	No	
Closing time	9 pm	10.30 pm	9 pm	-
Methods of Payment	Cash only	Cash, debit or credit card	Cash only	-
Parking	100 m away	In front of restaurant	300 m away	-
Seating available	Near entrance	Near window and inside		-
Personnel	Only the owner	A lot of personnel	Only a few personnel	-

* The extra level replaces level 2 for the first six attributes in experimental conditions 2 and 5 (see Table 2).

Table 2 Description of choice sets per group

	Number of choice sets	*Number of alternatives*	*Number of attributes*	*Level of attributes*	*Number of observations*	*EIP's*
Condition 1	9	2	6	Regular	314	35
Condition 2	9	2	6	Extra level	323	35
Condition 3	5	2	3	Regular	221	17
Condition 4	9	2	12	Regular	207	71
Condition 5	9	2	12	Extra level	206	71

To elicit information regarding differences in the respondents' cost of effort and perceived complexity, five specific measures of components of consumer involvement were constructed using the Consumer Involvement Profile (CIP) developed by Laurent and Kapferer (1985). In various studies, the CIP construct was found to be consistent and reliable across different applications and contexts (e.g., Mittal 1995, Rodgers and Schneider 1993). The CIP scale distinguishes interest in the product interest, pleasure derived from the product, the product's sign or symbolic value to the consumer, the importance the consumer assigns to making the wrong choice, and the probability the consumer assigns to making the wrong choice. Because of restrictions on the total number of questions in the survey, involvement questions could only be administered to 1052 respondents (see Appendix 3 for details). We found no evidence of separate effects of the CIP involvement factors interest and pleasure and therefore combined these two aspects into one factor. Thus the involvement analysis leads to four explanatory variables: *Interest/pleasure*, *Symbolic value*, *Risk importance*, and *Probability of mispurchase*.

The proxy most commonly used for choice effort in previous research is response time (e.g. Haaijer et al. 2000). We take consumers' response time per choice question as the dependent variable in our regressions. The explanatory variables are based on the (respondent specific) involvement measures, and choice question specific variables for utility difference and complexity. We also include a dummy for the first question, since this question generally takes more time to complete as respondents have to become familiar with the nature of the questions. Including additional dummies for questions other than the first did not change our results.

4.2 Product utility difference and complexity

To obtain measures of product utility differences between choice sets, a multinomial logit model was used to estimate consumer preferences for each attribute (Ben-Akiva and Lerman 1985). These estimates were then used to obtain predictions of the utility of each product in each choice set. The absolute values of the differences in these predicted utilities between the two products in each choice set were then calculated. These are taken as choice question specific proxies for variation in D.[4] The model in Section 3 leaves the sign of the relationship between D and the optimal level of effort undetermined. Previous research suggests that in many choice contexts effort will fall if product utility difference rises (Bockenholt et al. 1991).

As a measure of choice complexity across choice sets we use EIP's: the larger the number of EIP's, the more complex the choice problem. To calculate the number of EIP's, we assume that respondents evaluate all attributes of all alternatives, and compute the required number of cognitive steps for a fully compensatory choice process. Even if respondents do not use this decision strategy, this number of EIP's will serve as a reasonable proxy of choice complexity, since it is increasing in both the number of alternatives and the number of attributes describing each alternative.

[4] This ignores preference heterogeneity across respondents, but using the mean preference parameters in a mixed logit model with heterogeneous consumers gives almost identical results.

The theoretical model does not determine the sign of the effect of complexity on effort, i.e., the effect of EIP's on response time.

4.3 Involvement components, cost of effort, and perceived complexity

Individuals who find a product more interesting or receive more pleasure from it (*Interest/Pleasure component*) will find the choice task more relevant and enjoyable, and will therefore have lower relative opportunity costs of the processing time spent on the choice task. We do not expect a direct effect of *Interest/pleasure* on the probability of correct choice. In terms of the model, this means that *Interest/pleasure* is negatively associated with the relative cost of effort g(see the discussion at the end of section 3.2). Since the effect of $g$on E is negative (see section 3), we expect that response time will increase with *interest/pleasure*.

Similarly, we expect that the *symbolic or sign value* of the product is positively associated with the pay-off to a correct choice without affecting the probability of correct choice. In our framework this again means that symbolic value reduces g and we expect response time to increase with symbolic value.

The *risk importance* component measures how the consumer weighs the negative consequences of making the wrong choice. Higher risk importance means attaching more weight to the utility gain compared to the cost of effort. Risk importance has no direct effect on the probability of mispurchase. Thus, as in the previous case, a higher score on risk importance means a lower g and we expect that response time will rise with risk importance.

The consumer's evaluation of the probability of mispurchase can be regarded as a measure of the level of uncertainty the individual associates with purchases in the particular product class, and can be seen as a subjective measure of the respondent's perception of choice complexity. Thus the probability of mispurchase is positively related to *C*. The results in section 3 then imply that the sign of the relationship between response time and probability of mispurchase is not determined by the theoretical model. We can say, however, that the effect is expected to be of the same sign as the effect of EIP's, since both enter the model through their positive relation with complexity. If the effect of *C* on *E* is positive, both regressors should have a positive coefficient; if it is negative, both should be negative.

4.4 Results

Two OLS regressions were conducted. In the first, response time was explained from product utility differences and EIP's. In the second, response time was explained from the individual CIP consumer involvement measures.[5,6]

The results of the first regression are presented in Table 3. The estimates show that across choice tasks, consumer choice effort falls significantly with product utility difference and increases with higher task complexity. Allowing for non-linear effects (quadratic, cubic, log's; results not presented) showed that these effects retain the same sign over the range of utility differences and complexity covered by our data.

Table 4 presents the results of the second regression. Three of the four involvement components are significant at the 5% level, only the *Symbolic value* component is not. The signs for *Interest and pleasure*, *Risk importance,* and *Symbolic value* are as expected (see section 4.2). The positive sign of *Probability of*

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[5] One regression with both sets of regressors will give similar results since the sets of regressors are uncorrelated. We present separate regressions because more observations can be used in the first regression.

[6] The units of observation are all respondent/question combinations. Qualitatively similar results are obtained if, in the first regression, response times are averaged over respondents and each question is one unit of observation, or in the second regression, response times are averaged over questions and each respondent is one unit of observation. The same regressors are significant at the 5% level, though t-values become somewhat smaller.

mispurchase implies that effort increases with complexity. This is in line with the positive effect of complexity on effort observed in Table 3. Because Figures 2 and 3 suggest non-linear patterns, we tested if including squares of the involvement variables would improve the fit of the regressions. All squares were insignificant.

Table 3 Response time vs. expected utility difference *D* and EIP's*

Variable	Estimate	t-value
Constant	4.450	9.36
Question 1 dummy	21.784	45.61
Expected product utility difference (D)	-3.390	-9.97
Choice task complexity EIP (C)	0.365	42.01

* N =1271 observations, R^2 = 0.263

Table 4 Response time vs. involvement components*

Variable	Proxy for	Estimate	*t*-value
Constant		11.427	10.058
Interest/Pleasure	*g*	0.121	2.424
Symbolic	*g*	0.043	0.582
Risk Importance	*g*	0.267	2.369
Prob. Of Mispurchase	C	0.198	4.005

* N= 1052 observations, R^2 = 0.020

Summarizing, the empirical results are in line with the theoretical model. Where the theoretical model predicts an unambiguous sign, this sign is always found. In all cases but one (*symbolic value)*, it is also significant. Moreover, the signs of the two complexity measures (EIP's and *Probability of mispurchase*) are the same, which is also what the theoretical model predicts. With the variations in choice set composition in our set up (Table 2), we found no evidence of quadratic effects of cost of effort, product utility difference, (perceived) task complexity.

5. Conclusion and discussion

The purpose of this paper was to develop a theoretical model of consumer choice that relates the effort applied in a particular choice situation to consumers' relative cost of effort, choice set complexity and the expected utility difference between the products in a choice set. The proposed model is consistent with many observations in the existing literature on consumer choice and provides insight into what determines the effort involved in consumer decision processes. In particular, relationships are derived between the level of effort applied in a choice situation, cost of effort, and choice task variables such as choice complexity and product utility difference. The comparative statics of the model show that the relationship between effort and product utility difference and choice set complexity is ambiguous.[7]

Differences between consumers in terms of cost of effort, product utility and perceived complexity were analyzed using consumer involvement measures. It was discussed how various components of involvement determine the parameters of the model. An empirical application to restaurant choice provided insight in the validity and relevance of the components of the model. Increases in product utility difference and choice task complexity were found to lead to smaller and greater consumer effort respectively, with no evidence for possible non-linear effects. The effects of involvement were as expected.

[7] This not only holds in the general model but also for the plausible functional form presented in Appendix 2. There we find a hump shaped pattern of optimal effort as a function of both *D* and *C*.

Although these results are encouraging and suggest that the model is able to capture important aspects of consumer decisions, there are also some limitations. The model has only been developed for the case of a choice between two products. A valuable extension would be to augment the range of choice situations for which the model is applicable by allowing consideration of choices between multiple products. To which extent the results found here can be generalized to other product categories is also unknown.

From a managerial perspective our results may raise the question if, and if so, how the observed variations in effort affect consumer choice outcomes and the consistency of consumers' choices. Researchers using choice-based questionnaires may be interested in a similar issue, which is the optimal level of survey choice task complexity given the expected consumer choice effort and the desired accuracy of consumers' choice responses. We hope to address such questions in future research

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Appendix 1 - Proof that (NIRE) and (USYM) imply (SOC)

As seen in section three of the paper, the consumer faces the maximization problem

$$\mathrm{Max}_{E>0} \qquad \mathrm{E}\{P(e > -D \mid Z \mid a(E;C) \mid Z) \times D \mid Z \mid\} - gE \tag{12}$$

with first order condition

$$g = \mathrm{E}\left\{f_e\left(-D \mid Z \mid a(E;C)\right) \times \left(D \mid Z \mid\right)^2\right\} \times \frac{\partial a}{\partial E} \tag{15}$$

$$= \int_{-\infty}^{\infty} f_e\left(-D \mid Z \mid a(E;C)\right) \times \left(D \mid Z \mid\right)^2 f_Z(Z) dZ \times \frac{\partial a}{\partial E}$$

or, equivalently,

$$g = 2\int_0^{\infty} f_e\left(-DZa(E;C)\right) \times (DZ)^2 f_Z(Z) dZ \times \frac{\partial a}{\partial E} \ .$$

The second order condition requires

$$\frac{d}{dE}\left[2\int_0^{\infty} f_e\left(-DZa(E;C)\right) \times (DZ)^2 f_Z(Z) dZ \times \frac{\partial a}{\partial E}\right] \leq 0$$

Differentiating the expression in brackets yields:

$$2\int_0^{\infty}\left[\underbrace{-f_e'\left(-DZa(E;C)\right) \times \left(\frac{\partial a}{\partial E}\right)^2 DZ}_{\substack{\leq 0 \ for\ all\ Z \\ (USYM)}} + \underbrace{f_e\left(-DZa(E;C)\right) \times \frac{\partial^2 a}{\partial E^2}}_{\substack{\leq 0 \ for\ all\ Z \\ (NIRE)}}\right] \underbrace{(DZ)^2 f_Z(Z)}_{\geq 0\ all\ Z} dZ \leq 0$$

This shows that the (USYM) and and (NIRE) conditions are sufficient to ensure the second order condition holds.

Appendix 2 - A Parametric Specification of the Economic Model

The comparative statics derived in section 3 do not lead to unambiguous conclusions on how the expected utility difference and choice complexity affect the optimal level of effort. In this appendix, we analyze these relationships for more specific model assumptions, taking a plausible functional form for $a(E,C)$ and assuming normality of the random variables e_1-e_0 and Z. We assume[8]

$$e = e_1 - e_0 \sim \mathrm{N}(0,1), \text{ and } \; Z \sim \mathrm{N}(0, p/2).$$

The variance of $p/2$ is chosen so that Z satisfies the condition $\mathrm{E}\{|Z|\} = 1$ in (3). These assumptions imply (10), one of the conditions needed for the second order condition.

We specify the accuracy function $a(E;C)$ as[9]

$$a(E;C) = \frac{E}{C} \qquad \text{for } E, C > 0$$

This specification satisfies (6):

$$\frac{d\,a(E;C)}{d\,E} = \frac{1}{C} > 0 \quad \text{and} \quad \frac{d\,a(E;C)}{d\,C} = -\frac{E}{C^2} < 0\,.$$

It also satisfies (7), which (with (10)), is needed for the second order conditions:

$$\frac{d^2\,a(E;C)}{d\,E^2} = \frac{d}{d\,E}\left[\frac{1}{C}\right] = 0 \leq 0$$

Moreover, the choice of $a(E;C)$ implies that returns to effort fall with complexity:

$$\frac{\partial^2 a(E;C)}{\partial E\,\partial C} = -\frac{1}{C^2} < 0 \qquad \text{(REDC)}$$

With these assumptions, the optimization problem (12) can be solved numerically.

Comparative statics

The numerical solutions for the optimal level of effort can be used to derive the partial relationships between the optimal level of effort and the parameters g C, and D. The

[8] The qualitative results do not change if $e \sim \mathrm{N}(0, \sigma^2)$ with $\sigma^2 \neq 1$.
[9] The qualitative results do not change if $a(E,C) = k\,E^a/C^b$ for $k>0$, $0<a \,\#1$, $b>0$.

resulting functions, keeping two of the three parameters constant,[10] are depicted in Figures 1, 2, and 3, respectively.

Marginal cost of effort (g)

In Figure 1 the relationship between optimal effort and g the marginal cost of effort, is depicted. The curve is downward sloping indicating that effort falls with higher marginal costs, in line with the general comparative static results in section 3.2.

-INSERT FIGURE 1 ABOUT HERE-

Complexity (*C*)

In the previous section we saw that an increase in *C* may have two opposite effects on the optimal level of effort, leaving the sign of the relation undetermined. Figure 2 shows that for the chosen parametric specification, the pattern is in line with the suggestions from the literature discussed in section 2: an inverted U-shaped relationship between complexity and effort is found, as suggested for example by Swait and Adamowicz (2000).

- INSERT FIGURE 2 ABOUT HERE -

Utility difference (D)

The relationship between effort and *D* for our specification is shown in Figure 3. Effort is decreasing in *D* for high values of *D*. For low values of *D*, the direct effect (D1) dominates and the optimal effort level increases with *D*.

- INSERT FIGURE 3 ABOUT HERE-
-

[10] The chosen benchmark values are g= 0.152, D = 1 and C = 1. The basic shapes of the curves do not change with the benchmark values.

Appendix 3 – Consumer Involvement Profile

Involvement Construct

Respondents to the survey were asked 16 questions on their involvement with the product category ‘restaurants.’ Each question related to one of the five facets of involvement identified by Laurent and Kapferer (1985) and was drawn from the CIP measure developed by these authors. A principal component analysis was conducted reducing the measured responses into orthogonal components. The results are presented in Table A1. It can be seen that only four underlying components are found. It is not uncommon for the principal component analysis to identify fewer than all five separate facets of the CIP measure, due to the high level of correlation between the facets. Laurent and Kapferer also found that only four components were required as two facets loaded onto a single component. The table indicates the loadings of each question from each facet on each component. The most relevant loadings for the involvement constructs are shaded to provide a visual representation of the makeup of each component. Ideally, were the data to demonstrate “trait” validity, each facet should load onto only one component. Apart from the *Symbolic value* facet which has a significant loading on both components 1 and 3, the component generally exhibit trait validity. The discriminant validity of each component represents the degree to which each component can be considered as measuring different concepts. With all facets being related to the same concept of involvement it is likely that a significant amount of correlation exists between the facets reducing discriminant validity. Thus several facets may be found to load onto the one component. This is the case for the facets Interest and Pleasure and to a lesser extent the Symbolic value facet. The loading patterns indicate that all of these facets are significant determinants of component 1.

Although each facet loads on each component to some degree, considering only the more significant and the more discriminating loadings suggests that the four components relate mostly to the following four distinct facets:

Component 1: *Interest and Pleasure*

Component 2: *Probability of mispurchase*

Component 3: *Symbolic value*

Component 4: *Risk importance*

The first component is labeled as relating to only *Interest and Pleasure*, even though the *Symbolic value* facet also played a significant role in its calculation because the symbolic facet shows a high discriminant validity with component 3. Even though it lacks some trait validity through its strong association with component 1, component 1 is likely to pick up the part of the *Symbolic value* facet which is correlated to *Interest and Pleasure*. Due to the orthogonality of the components, only those dimensions of the *Symbolic value* facet which are independent *of Interest and Pleasure* are being picked up by component 3.

Table A1 Principal component analysis

		Component			
Question	*Facet*	1	2	3	4
1	Interest	.613	.085	.046	.089
2	Interest	.720	.166	.162	.030
3	Interest	.603	.281	.212	.038
4	Pleasure	.735	.264	.410	.115
5	Pleasure	.587	.026	.233	.030
6	Pleasure	.736	.268	.386	.052
7	Symbolic	.561	.257	.573	.139
8	Symbolic	.526	.311	.609	.103
9	Symbolic	.568	.249	.540	.013
10	Risk Importance	.053	.117	.113	.797
11	Risk Importance	.111	.347	.114	.410
12	Risk Importance	.187	.505	.060	.450
13	Prob of Mispurchase	.054	.679	.278	.111
14	Prob of Mispurchase	.017	.576	.299	.280
15	Prob of Mispurchase	.072	.746	.223	.026
16	Prob of Mispurchase	.079	.720	.303	.255

Figure 1 Optimal effort vs. marginal cost

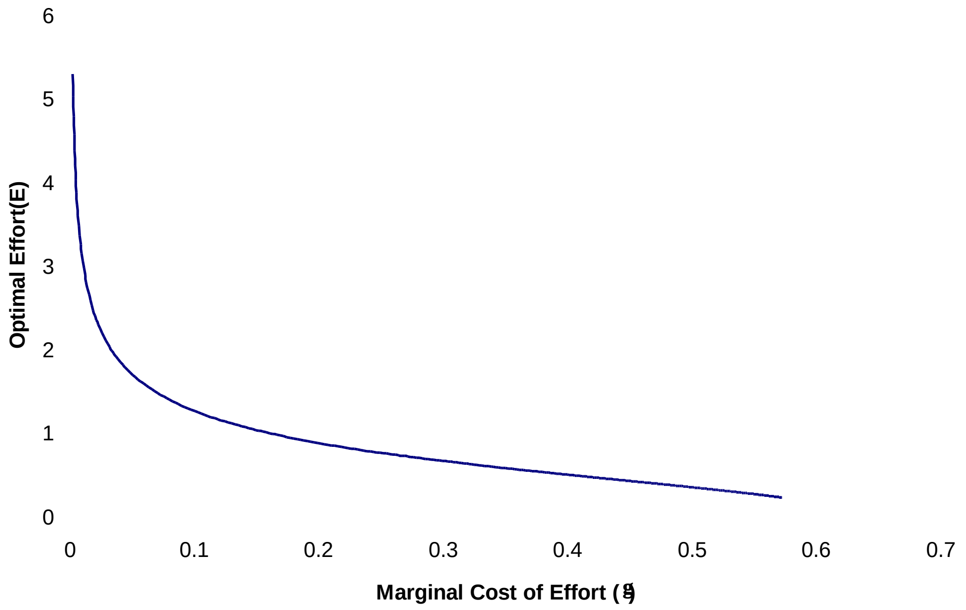

Figure 2 Optimal effort vs. complexity

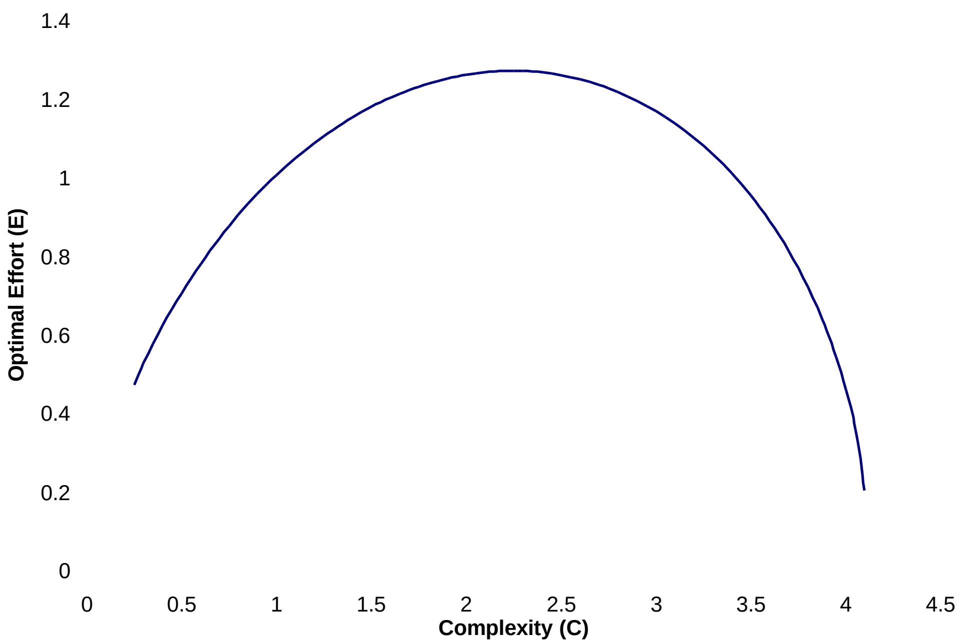

Figure 3 Optimal effort vs. expected absolute product utility difference