ABSTRACT. Analyses of preference for the timing of uncertainty resolution usually assumes all uncertainty to resolve in one point in time. More realistically, uncertainty should be modelled to resolve gradually over time. Kreps and Porteus (1978) have introduced an axiomatically based model of time preference which can explain preferences for gradual uncertainty resolution. This paper presents an experimental test of the Kreps-Porteus model. We derive implications of the model relating preferences for gradual and one-time resolving lotteries. Our data do not support the Kreps-Porteus model but show that some of the behaviour observed may be explained by similarity heuristics.

KEY WORDS: Temporal risk attitude, timing of uncertainty resolution.

Consider the choice problem shown in Figure 1. For lottery $E$, one will know in period 1 (now) whether in period 2 (e.g., next Christmas) one will receive either $z_{\text{max}} = \text{DM } 1000$ (Deutsch Marks) or $z_{\text{min}} = \text{DM } 0$. Choosing lottery $L$, one will not know the result of the lottery until next Christmas. Since the timing and the distribution of the consequences are the same in $E$ and $L$, neither discounting nor expected utility can discriminate between these two alternatives.

Yet, individuals may have reason not to be indifferent between $E$ and $L$ since they differ in the timing of uncertainty resolution. First, if intermediate decisions have to be made, early resolution might offer planning benefits; see Markowitz (1959), Mossin (1969), Machina (1984) and Spence and Zeckhauser (1972) for a discussion. Second, individuals may be averse to not knowing (or to knowing) about future consequences for purely psychological reasons such as hope or fear. Chew and Ho (1994) and Ahlbrecht (1996) showed that for small probabilities of large gains, people tend to prefer late resolution in order to prolong their hope of winning. Chew and Ho also found that people’s resolution preference is not correlated to their risk attitude. Wu (1992) has found that subjects have different attitudes to uncertainty resolution for the gain and loss domain.
Figure 1. Early and late resolution of uncertainty.

So far, research has focussed on preference for lotteries where all uncertainty resolves in one step. In $E$, all uncertainty is resolved in period 1, in $L$, all uncertainty is resolved in period 2. Nothing is known about people’s preferences if, more realistically, uncertainty is resolved gradually over time.

Investment project example: The success of an investment project does not become known by a single ‘toss of a coin’. Rather, before things finally turn out to be successful, responsible managers may, at an early stage, be able to exclude what once was their worst case scenario. A few weeks or months later, they may learn that the project will at least break even, but the exact profit will still not be known until the project has been completed. Here, uncertainty resolves in a way that allows better estimation of the final result as resolution progresses.
**Health test example:** Examples for gradual uncertainty resolution are not limited to the field of business administration. An individual who has himself tested for cancer may be told that he has some ulcer but that it need not necessarily be a malign one. An operation may confirm that the ulcer was malign, but since it is now removed, there remains the hope that no metastases have formed yet nor will form in the future. Further tests may be necessary, spread over the next years, with each result either sustaining or devastating the individual’s hope of final cure.

Decision makers may be influenced by the attractiveness or aversiveness of different uncertainty resolution patterns. Therefore, it is important to investigate the concept of gradual resolution of uncertainty.

Gradually resolving lotteries are intermediate between early and late resolution in the sense that with gradual resolution, some uncertainty resolves early and some uncertainty resolves late. In a certain sense (which we will explain in greater detail later) gradually resolving lotteries span a continuum between $E$ and $L$. Gradually resolving lotteries provide a richer set of alternatives allowing to ask questions like the following: how much uncertainty resolution needs to be shifted to period 1 in order to make one alternatives equally attractive as a given other alternative? This route may allow future research to define new concepts of resolution premia and compare it to existing concepts, e.g. the probabilistic premium suggested by Chew and Epstein (1989).

We are not aware of any study on preference for uncertainty resolution other than one-time resolution lotteries. As a first exploratory step, this study investigates individual preferences for gradual uncertainty resolution by comparing it to preferences for one-time uncertainty resolution. A way of formalizing gradual resolution of uncertainty is presented in Figure 2.

Consider the two lotteries shown in Figure 2. We will assume that $z_{\max} > z > z_{\min}$ ($z_{\max} < z < z_{\min}$ for losses) and compare the resolution process in $X$ and $Y$ for non-degenerate cases ($p > 0$ and $q > 0$):

- In $X$, period 1 resolution gives the decision maker the information that either the best or the worst outcome can be excluded. This is the case of the investment project example.
Figure 2. Two examples of gradual resolution.

– In $Y$, with a $q$ chance, period 1 resolution gives the decision maker the information that in period 2, he will face either the best or the worst consequence, i.e. an extreme lottery. With a $1-q$ chance, the stakes in period 2 are $z$, with $z \in (z_{\text{min}}, z_{\text{max}})$ and $z_{\text{max}} - z + z_{\text{min}}$, i.e. a less extreme lottery. For $z = (z_{\text{max}} - z_{\text{min}})/2$, in this case, period 1 resolution already determines period 2 consequence.

As for lotteries $E$ and $L$ in Figure 1, both $X$ and $Y$ in Figure 2 share the same distribution and timing of possible consequences. In other words, these lotteries do not differ except for their resolution process, which is why they seem worthwhile examples for our study. Clearly, many more resolution patterns are possible. However, we aimed to choose two lotteries preferences between which cannot be explained other than through their resolution process.
A theoretical basis for uncertainty resolution has been given by Kreps and Porteus (1978 and 1979, henceforth KP) who have introduced a model of intertemporal choice that allows for nonindifference to the timing of uncertainty resolution. It has become the basis for further work in modeling attitudes towards uncertainty resolution. Chew and Epstein (1989) have integrated non-EU axioms into the KP model. Epstein and Zin (1989) have extended it to an infinite time horizon and applied it to econometric studies of consumption-savings behavior in macroeconomics (1991), see also Weil (1990).

Although it constitutes the major theoretical contribution to the explanation of uncertainty resolution in event trees, the descriptive validity of the KP model has never been put to experimental test. The contribution of this paper is to provide such a test on an individual level in the light of gradual resolution of uncertainty.

The plan of the paper is as follows. In Section 2 we present a simplified version of the KP model, capable of explaining preferences between $E$ and $L$ as compared to $X$ and $Y$. Section 3 derives our hypotheses which are based on testable implications of the KP model and which relate preference for gradual and one-time resolution of uncertainty. Besides deriving implications of the KP model, we also discuss cases in which similarity heuristics may explain preferences between $X$ and $Y$, and we discuss how these heuristics compare to the KP implications. In Section 4 we present an empirical study which tests whether actual behavior is consistent with the hypotheses derived in Section 3.

1. THE KREPS-PORTEUS MODEL

For the sake of simplicity of the exposition, we only consider lotteries with finite support on $\mathbb{R}$ in a two-period setting. Also, since our objective is not to analyze how consequences in the two periods are evaluated against one another, we consider only consequences in period 2, as in the examples presented above. Period 1 serves only to resolve (part of) the uncertainty about period 2 consequences.

The outcome of period 1 resolution is a lottery over possible consequences in period 2. For a metric space $\Omega$, let $D(\Omega)$ denote the set of probability measures on $\Omega$. Then the set of possible outcomes of period 1 resolution is $D(\mathbb{R})$ and we consider the outcome
space $D(D(\mathbb{R}))$. KP have formulated axioms for preferences on the outcome space $D(D(\mathbb{R}))$. Like KP, we will call elements of the outcome space temporal lotteries. Three of KP’s axioms are closely related to the von Neumann-Morgenstern axioms of completeness, continuity and substitution. In addition, KP introduce a temporal consistency axiom. Suppose that, in period 1, an individual prefers $z$ to $z'$, where $z$ and $z'$ denote lotteries over consequences in period 2. Then, in period 2, he still prefers $z$ to $z'$.

Let $z_i (i \in \{1, \ldots, I\})$ denote the possible lotteries over consequences in period 2 that the decision maker may be faced with after period 1 uncertainty resolution. Let $p_i$ denote the probability with which $z_i$ occurs after period 1 resolution. Finally, let $\text{EU}(z_i)$ denote the expected utility of lottery $z_i$ subject to a utility function $u$ the decision maker will employ in period 2 in order to evaluate $z_i$.

KP prove that their axioms are necessary and sufficient for there to exist a continuous, real valued, strictly increasing function $h$ such that if $d, d'$ are temporal lotteries, a decision maker prefers $d \succeq d'$ if and only if $\text{KP}(d) \geq \text{KP}(d')$. Here, the KP utility $\text{KP}(d)$ of the temporal lottery $d$ is defined as the weighted sum of the transformed expected utilities,

$$\text{KP}(d) = \sum p_i \cdot h(\text{EU}(z_i)).$$ (1)

In (1), $h$ plays the role of a utility function since temporal lotteries are evaluated by the expectation of $h$. Contrary to the utility function $u$ which solely captures the decision maker’s risk preferences in period 2, $h$ also models the individual’s attitude towards uncertainty resolution. For illustration, reconsider Figure 1. Let $u(z_{\text{max}}) = 1$, $u(z_{\text{min}}) = 0$ and $h(x) = x^2$. Inserting into (1), we see that $\text{KP}(L)$ is equal to $p^2$. In contrast, in $E$, $h$ is applied to $u(z_{\text{max}}) = 1$ and $u(z_{\text{min}}) = 0$, yielding $\text{KP}(E) = p$. Thus for $0 < p < 1$ we have $\text{KP}(E) = p > p^2 = \text{KP}(L)$, a preference for early resolution.

We see that the KP model can allow for a preference for early or late resolution of uncertainty. For the general case, KP show that $h$ is convex (concave, linear) if and only if for all $p$, $z_{\text{max}}$ and $z_{\text{min}}$, the decision maker will always prefer $E$ over $L$ ($L$ over $E$, be indifferent between the two). In Section 3 we will apply the KP model to gradual resolution of uncertainty.
2. HYPOTHESES

For the special case $p = q = 0.5$ we will show that the KP model establishes a relation between preferences for gradual and one-time resolutions. This will allow us to test the descriptive validity of the KP model. Second, for extreme values of $p, q$ and $z$, we will show that $X$ and $Y$ are similar to $E$ or to $L$ (or to one another). Then one would expect preference for gradual and one-time resolution to be similar.

2.1. Implications of the Kreps-Porteus model

For a test of the descriptive validity of the Kreps-Porteus model for gradual resolution of uncertainty, logical implications of (1) are needed. For the case where the two probabilities in the temporal lotteries $X$ and $Y$ represent even 50–50 chances, such implications are provided by the following Theorem.

THEOREM. (i) Suppose the individual’s choice behaviour is described by (1) with $u$ either strictly increasing or strictly decreasing. Suppose both probabilities in the temporal lotteries $X$ and $Y$ are $p=0.5=q$. Then for all values $z \in (z_{\text{min}}, z_{\text{max}})$, if $h$ is strictly convex, the decision maker prefers $X \succ Y$; if $h$ is strictly concave, he prefers $X \prec Y$, and if $h$ is linear, he is indifferent, $X \sim Y$.

(ii) Define $X_E (X_L)$ the lottery which has the same consequences and probabilities as $X$ but all uncertainty is resolved in period 1 (period 2). If $h$ is strictly convex, the decision maker prefers $X_E \succ X \succ X_L$. Analogous results are true for $h$ being strictly concave.

Proof. See Appendix.

Since the curvature of $h$ is known to describe preference for one-time early or late resolution, the theorem links preference between $X$ and $Y$ with preference for one-time resolution: preference for complete early (late) resolution implies a certain preference for gradual resolution; we see that gradual resolution of uncertainty lies between early and late resolution and that KP give definite predictions about a decision maker’s preference with respect to different forms of gradual resolution of uncertainty. Note that the theorem is independent of the utility function $u$. This means that it gives a testable implication which does not require to elicit the utility function $u$. 
2.2. Similarity heuristics

For extreme values of $p$, $q$, and $z$, the gradually resolving lotteries $X$ and $Y$ degenerate into $E$ or $L$. The preferences between $X$ and $Y$ on the one hand and $E$ and $L$ on the other hand, should be similar.

2.2.1. Extreme values of $z$

Consider what happens to $X$ and $Y$ if $z$ approaches $z_{\text{max}}$. Then in $X$, there is no uncertainty left to be resolved in period 2 since the upper branch of $X$ degenerates into a certain $z_{\text{max}}$ and the lower branch into a certain $z_{\text{min}}$. Thus, $X$ degenerates into $E$. In turn, in $Y$, if $z = z_{\text{max}}$, the upper and the lower branch coincide, so period 1 resolution is irrelevant, see Figure 2. Thus, $Y$ degenerates into $L$. Therefore, for $z$-values sufficiently close to $z_{\text{max}}$, we would expect a decision maker who prefers $E$ to $L$ to also prefer $X$ to $Y$ (and vice versa).

As $z$ approaches $z_{\text{max}}$, the gradually resolving lotteries tend to one-time resolving lotteries. It is in this sense that they span a continuum between $E$ and $L$. We see that the concept of gradually resolving lotteries is not separate from one-time resolution, but it naturally extends the set of one-time resolving lotteries to a broader class of resolution patterns.

Consider the opposite case $z = z_{\text{min}}$. In both branches of both $X$ and $Y$, period 2 resolution determines whether $z_{\text{max}}$ or $z_{\text{min}}$ obtains. Period 1 resolution determines only the odds between $z_{\text{max}}$ and $z_{\text{min}}$, e.g., in the upper branch of $X$, $z_{\text{max}}$ obtains with probability $q$, in the lower branch with probability $1 - q$. The same holds for $Y$ and $p$. If $p = 0.5 = q$ and $z = z_{\text{min}}$, $X$ and $Y$ coincide. Consequently, we would expect subjects to state indifference between $X$ and $Y$ for sufficiently small values of $z$.

2.2.2. Extreme values of $p$

Finally, consider what happens if the probabilities are extreme. Clearly, if both $p$ and $q$ are either 0 or 1, both $X$ and $Y$ degenerate into certain consequences. As this situation is not of much interest, we fix $q = 0.5$. If $p = 1$ or $p = 0$, $X$ is a one-time late resolving lottery. Conversely, $Y$ is a one-time early resolving lottery. Thus for sufficiently small or large values of $p$ we would expect a decision maker who prefers $E$ to $L$ to prefer $Y$ to $X$.

These heuristics are derived from introspection and are not implications of the KP model. Of course, any model that assumes con-
tinuous preferences, as does the KP model, will imply that choices that are sufficiently close to one another necessarily coincide. It is not obvious, however, how close is sufficiently close. Therefore, the above hypotheses are strictly speaking, not testable: even if for $p = 0.99$ preference between $X$ and $Y$ did not correspond to preference between $E$ and $L$ in the sense described above, maybe for $p = 0.9999$ it would.

We will proceed despite this remark. We will let $z_{\text{max}} = \text{DM} 1,000$, and $z_{\text{min}} = \text{DM} 0$. We will take $z = \text{DM} 900$ to represent a value close to $z_{\text{max}}$ and $z = \text{DM} 100$ to represent a value close to $z_{\text{min}}$. Also, $p = 0.99$ will be taken to represent a value close to $p = 1$ and $p = 0.01$ will be taken to represent a value close to $p = 0$.

Table I summarizes the KP implications and the similarity heuristics. It states the implied preferences between $X$ and $Y$ when $E \succ L$. Of course, when $E \prec L$, the converse preferences between $X$ and $Y$ are implied. For simplicity, these converse implications are omitted from Table I.

3. AN EMPIRICAL STUDY

3.1. Subjects, questionnaire, and design

3.1.1. Subjects
Graduate students from management courses at the Universities of Mannheim and Cologne participated ($n = 267$). Subjects were not paid for participation since implementing an incentive compatible payment scheme for delayed uncertainty resolution seemed impossible.

3.1.2. Questionnaire
Subjects were instructed to thoroughly work through a questionnaire that asked them to state preference between choice pairs $(E, L)$ and $(X, Y)$ of temporal lotteries. Consequences were losses or gains expressed in Deutsch Marks (DM). At the time of the experiment, $\$/ was roughly equivalent to DM 1.70. For each choice pair, subjects could state preference for one of the two alternatives or indifference between the two. The introductory sheet explained that there were no right or wrong answers, but that we were investigating people’s preferences. Each temporal lottery was both verbally described and depicted as an event tree (as in Figures 1 and 2). The resolution
TABLE I
KP implications and similarity heuristics.

<table>
<thead>
<tr>
<th>KP implications</th>
<th>Similarity heuristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p = 0.5 = q$</td>
<td></td>
</tr>
<tr>
<td>$z = DM 100$</td>
<td>$X \succ Y$</td>
</tr>
<tr>
<td>$z = DM 500$</td>
<td>$X \approx Y$</td>
</tr>
<tr>
<td>$z = DM 900$</td>
<td>$X \succ Y$</td>
</tr>
</tbody>
</table>

$p = 0.01$

| n.a.            | $X \prec Y$           |

$p = 0.5$

| see $p = 0.5 = q$, $z = DM 500$ |   |

$p = 0.99$

| n.a.            | $X \prec Y$           |

The process was described as a fair coin, or, where probabilities were not 50%, as the drawing of a ball from an urn. Stage 1 resolution was to take place on the same day while stage 2 resolution was to take place two months into the future.

3.1.3. Design

We had four types of questionnaires (A, B, C, and D), see Table II. Each questionnaire was answered by one fourth of the subjects. A and B dealt with gains, C and D are the equivalents of A and B, but dealt with losses. The order of the questions was changed within each type of questionnaire according to a random process.

The questions concerning one-time resolution were necessary because our hypotheses were formulated relative to one-time resolution preference. Three questions presented the choice $E$ vs. $L$ (see Figure 1) with $z_{\text{max}} = DM 1000$, $z_{\text{min}} = DM 0$, and three different probabilities $p$. In questionnaires A and C, we had $p = 0.01$, $p = 0.5$, and $p = 0.99$; in B and D, we had $p = 0.05$, $p = 0.5$, and $p = 0.95$. In addition, each subject was presented the choice $E$ vs. $L$ with $z_{\text{max}} = 1000$ DM, $z_{\text{min}} = 500$ DM and $p = 0.5$ (A and C) or with $z_{\text{max}} = 500$ DM, $z_{\text{min}} = 0$ DM (B and D).

Two questions concerning gradual resolution presented the choice $X$ vs. $Y$ (see Figure 2) with $z_{\text{max}} = 1000$, $z_{\text{min}} = 0$, $p = q = 0.5$ and two different values of $z$. In questionnaires A and C we had $z = 900$ and $z = 500$; in B and D, we had $z = 100$ and...
<table>
<thead>
<tr>
<th>Questionnaire</th>
<th>A: gains</th>
<th>B: gains</th>
<th>C: losses</th>
<th>D: losses</th>
</tr>
</thead>
<tbody>
<tr>
<td>one-time resolution</td>
<td>$z_{\text{max}}$</td>
<td>$z_{\text{min}}$</td>
<td>$p$</td>
<td>$z_{\text{max}}$</td>
</tr>
<tr>
<td>1000</td>
<td>0</td>
<td>0</td>
<td>0.01</td>
<td>1000</td>
</tr>
<tr>
<td>1000</td>
<td>0</td>
<td>0.5</td>
<td>1000</td>
<td>0.5</td>
</tr>
<tr>
<td>1000</td>
<td>0</td>
<td>0.99</td>
<td>1000</td>
<td>0.95</td>
</tr>
<tr>
<td>1000</td>
<td>500</td>
<td>0.5</td>
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<td>0.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$z_{\text{max}} = 1000, z_{\text{min}} = 0, q = 0.5$</td>
</tr>
<tr>
<td>gradual resolution</td>
<td>$z$</td>
<td>$p$</td>
<td>$z$</td>
<td>$p$</td>
</tr>
<tr>
<td>900</td>
<td>0.5</td>
<td>100</td>
<td>0.5</td>
<td>900</td>
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<tr>
<td>500</td>
<td>0.99</td>
<td>500</td>
<td>0.01</td>
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</tr>
</tbody>
</table>
TABLE III
Preference for one-time resolving lotteries (E vs. L).

<table>
<thead>
<tr>
<th></th>
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<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>constant early</td>
<td>40</td>
<td>38</td>
<td>49</td>
<td>43</td>
<td>43</td>
</tr>
<tr>
<td>constant indifferent</td>
<td>33</td>
<td>24</td>
<td>22</td>
<td>19</td>
<td>25</td>
</tr>
<tr>
<td>constant late</td>
<td>3</td>
<td>11</td>
<td>5</td>
<td>9</td>
<td>7</td>
</tr>
<tr>
<td>other</td>
<td>24</td>
<td>27</td>
<td>24</td>
<td>29</td>
<td>25</td>
</tr>
<tr>
<td>sum</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

z = DM 500. In addition, each subject was presented the choice X vs. Y either with \(z_{\text{max}}=1000 \text{ DM}, z_{\text{min}}=500 \text{ DM}, \) and \(p=0.99\) (A and C) or with \(z_{\text{max}}=500 \text{ DM}, z_{\text{min}}=0 \text{ DM}, \) and \(p=0.01\) (B and D).

3.2. Results
Two subjects were excluded from analysis since they did not answer all questions. Before turning to our hypotheses, we present preference for one-time early or late resolution.

The largest group for all four questionnaires is constant preference for early resolution, which accounts for 43% of the subjects, constant indifference is the second largest group, which accounts for 25%. Constant preference for late resolution is smallest among the constant preference groups with 7%. Combining these three groups, 75% of the subjects stated constant preferences.

When testing our hypotheses, we will only consider those subjects that stated constant resolution preference for one stage lotteries. Only for those subjects can we infer that their resolution preference is described by a convex (concave, linear) transformation function \(h\). Therefore, the following results are based on 99 subjects who have handled gains (questionnaire A: 51, B: 48) and 98 subjects who have handled losses (questionnaire C: 50, D: 48).

3.2.1. Implications of the Kreps-Porteus model
We tested
(i) if preferences between \(X\) and \(Y\) are at all related with preferences between \(E\) and \(L\), and, provided a relation exists,
(ii) if this relation is in accordance with the KP implications or contrary to it.

Figure 3 displays the results graphically. For gains, two \( z \)-values used showed a significant relation between gradual and one-time...
resolution preference \((z=\text{DM 500}: \chi^2=14.2, p<0.01 \text{ and } z=\text{DM 900}: \chi^2=8.01, p<0.03)\). The main significant result is obvious. Indifference judgments for gradual and one-time resolution questions are related and many subjects prefer early resolution in one-time resolution. For losses, we had a significant relation for one \(z\)-value \((z=\text{DM 900}, \chi^2=9.59, p<0.01)\). For the other \(z\)-values, no \(\chi^2\)-statistics were significant \((p>0.1)\).

The question is to identify the nature of this relation. We looked at those subjects that were not indifferent towards one-time uncertainty resolution, for these are the subjects the KP model was developed for. We repeated our tests among the nonindifferent subjects. We found that if one excludes the indifferent subjects, only one \(z\)-value still had a significant relation between one and two stage resolution preference (gains at \(z=\text{DM 500}, \chi^2=3.93, p<0.05\), however, the sense of the interdependency contradicts the KP prediction. The case \(z=\text{DM 500}\) case is important as it is special. The lower branch of \(Y\) degenerates into certainty branch, since both \(z\) and \(z_{\min} + z_{\max} - z\) equal DM 500. It therefore offers the possibility to learn about the exact outcome already after period 1 resolution (at the cost of the possibility of facing the ‘all-or-nothing’ lottery after period 1 resolution). This may be attractive for decision makers. Or, it may be that people find three branch trees easier to understand and that the chose the three branch tree over the four branch tree, our data is not able to discriminate between these two interpretations. However, the objective to verify or falsify the empirical validity of the KP model does not depend on what drove the subjects responses. Whatever it was, it is not captured by the KP specification of subject’s preferences.

In all, as for task (i), we find that where a relation between preference for gradual and one-time resolution exists, it mostly stems from subjects who are indifferent towards any form of uncertainty resolution. As for task (ii), we need to state that the only case where we found a significant relation among nonindifferent subjects contradicted the direction of the KP implication.

3.2.2. **Extreme values of \(z\)**

For \(z=\text{DM 900}\), similarity heuristics suggest the same preferences between \(X\) and \(Y\) as do the KP implications. Since the KP implications are not supported, neither are similarity heuristics.
The interesting case is \( z = \text{DM} 100 \), where similarity heuristics predicted indifference between \( X \) and \( Y \), regardless of what the preference between \( E \) and \( L \) was, while KP implied the same strict preferences between \( X \) and \( Y \) as for the cases \( z = \text{DM} 500 \) and \( z = \text{DM} 900 \). Summing the corresponding percentages in Figure 3, we find that 73% of the subjects (for gains), respectively, 69% of the subjects
(for losses), were indifferent between $X$ and $Y$ when $z =$ DM 100. This is significantly (at 1% level) more than both for $z =$ DM 500 (gains: 39%; losses: 43%) and $z =$ DM 900 (gains: 45%; losses: 54%).

3.2.3. **Extreme values of $p$**

Here, similarity heuristics predict strict preference for $E$ over $L$ to imply strict preference for $Y$ over $X$. We proceed analogously to our test of the KP implications. First, it needs to be established whether for $p = 0.01$ or $p = 0.99$ there is a relation between preferences between $E$ and $L$ as compared to preferences between $X$ and $Y$. Then, if there is a relation, we need to ask whether it is in accordance with the predictions of similarity heuristics.

Figure 4 displays the results graphically. We find no support for the hypothesis that there is a relation between preferences between $E$ and $L$ and $X$ and $Y$. The $\chi^2$ values both for $p = 0.01$ and $p = 0.99$ and both for losses and gains are not significant. Thus there is no point in asking whether this relation is in accordance with similarity heuristics’ predictions.

It is interesting to compare our different conclusions with regard to similarity heuristics. Where similarity stems from nearly equal outcome values $z$, it can explain subjects’ choices. Where similarity stems from nearly sure probabilities, it cannot. This may be due to the well known fact that the change from certainty to almost certain probabilities has great impact on decision makers.

4. SUMMARY AND CONCLUSION

This paper has explored individual choice behaviour for gradual and one-time resolution lotteries. In particular, we have tested the model of temporal choice proposed by Kreps and Porteus (1978). In doing so, we have analysed choice between temporal lotteries that do not differ except for their process of uncertainty resolution.

In summary, our data show that subjects have preferences for gradual resolution of uncertainty. The data do not support the implications of the KP model. In some cases, rather, subjects use similarity heuristics to construct a preference. The KP model implies a relation between one and two stage resolution preference. Where we were able to establish such a relation, we have found that it refers mainly
to subjects who are indifferent towards the timing of uncertainty resolution. The only case in which we found a significant relation among the nonindifferent, the special case $z = \text{DM} 500$, the relation is contrary to the prediction of the KP model. The model has been proposed explicitly to allow for nonindifference towards uncertainty resolution. Our results indicate that precisely those subjects whose behaviour the model is supposed to describe do not behave according to its predictions.

5. ACKNOWLEDGEMENT

We would like to thank Angelica Eymann, Rüdiger von Nitzsch and Rakesh Sarin for their helpful suggestions.

6. APPENDIX: PROOF OF THE THEOREM

Part (ii) follows from Kreps and Porteus (1978), Theorem 1, p. 192. Here, we prove (i) for the case $h$ strictly convex. The other cases follow similarly.

For $z \in [z_{\min}, z_{\max}]$ define $r = u(z) \in [0, 1]$ and $r' = u(z_{\min} + z_{\max} - z)$.

Consider the function $\Delta K P(r) = K P(X) - K P(Y)$. Clearly $K P(X) - K P(Y)$ depends on $u(z_{\max}), u(z_{\min}), r' = u(z_{\min} + z_{\max} - z)$ and $r = u(z)$. Therefore, in order to show that the above function is well defined, we first need to show that $K P(X) - K P(Y)$ is uniquely determined by $r'$ only. Note first that since $z_{\min}$ and $z_{\max}$ are assumed fixed, $K P(X) - K P(Y)$ can only depend on $r$ and $r'$. Therefore, if we show that $r$ uniquely determines $r'$, then it also uniquely determines $K P(X) - K P(Y)$, hence the above defined function $K P(r)$ will be well defined. Since $u$ has been assumed to be strictly increasing or decreasing, $u$ is one-to-one. So the value of $r$ uniquely determines $z$. Since $z_{\max}$ and $z_{\min}$ are fixed, this, in turn, uniquely determines $z_{\min} + z_{\max} - z$, and thus, $r'$.

The Theorem will follow once we show that $\Delta K P(r)$ is positive for all $r \in [0, 1]$.

Define

\[ e_1 = 0.5 \cdot (1 + r), \quad e_2 = 0.5 \cdot r', \]
\[ l_1 = 0.5, \quad l_2 = 0.5 \cdot (r + r'). \]
Then
\[ KP(X) = 0.5 \cdot (h(e_1) + h(e_2)) \quad \text{and} \quad KP(Y) = 0.5 \cdot (h(l_1) + h(l_2)). \]
Clearly, \( l_1, l_2 \in [e_1, e_2] \). Then there exist \( \beta, \gamma \in [0, 1] \) such that
\[
\begin{align*}
  l_1 &= (1 - \beta) \cdot e_2 + \beta \cdot e_1 \\
  l_2 &= (1 - \gamma) \cdot e_2 + \gamma \cdot e_1.
\end{align*}
\]
As will be shown,
\[ \beta = 1 - \gamma. \]
Then,
\[
KP(Y) = 0.5 \cdot (h(l_1) + h(l_2)) \\
= 0.5 \cdot (h((1 - \beta) \cdot e_2 + \beta \cdot e_1) \\
+ h((1 - \gamma) \cdot e_2 + \gamma \cdot e_1)) \\
\leq 0.5 \cdot ((1 - \beta) \cdot h(e_2) + \beta \cdot h(e_1)) \\
+ (1 - \gamma) \cdot h(e_2) + \gamma \cdot h(e_1)) \\
= 0.5 \cdot (h(e_1) + h(e_2)) \\
= KP(X).
\]
Since \( h \) is strictly convex, the above inequality is strict unless either \( \beta \) or \( \gamma \) equal 0 or 1, which would imply that \( z \) equals either \( z_{\text{max}} \) or \( z_{\text{min}} \). But this is excluded by the assumption of the Theorem. Thus, \( \Delta KP(r) \) is positive for all \( r \).

It remains to show \( \beta = 1 - \gamma \). Clearly, \( e_1 - l_1 = l_2 - e_2 \). Thus,
\[
\begin{align*}
  \gamma \cdot e_1 + (1 - \gamma) \cdot e_2 &= l_2 \\
  &= e_2 + e_1 - l_1 \\
  &= e_2 + e_1 - \beta \cdot e_1 - (1 - \beta) \cdot e_2 \\
  &= (1 - \beta) \cdot e_1 + \beta \cdot e_2.
\end{align*}
\]
Compare coefficients to verify \( \beta = 1 - \gamma \).

7. NOTES

1 KP consider a larger outcome space allowing consequences in every period. Their outcome space contains \( D(D(\mathbb{R})) \) as a subset.
What is to be understood by ‘close’ will depend on the metric or the topology underlying the specification of the choice space.

Not applicable.

We have to make a cautious remark about these results depending on χ²-tests. The χ²-statistics should only be used if the expected frequency for each field of the contingency table is at least 5, which is not true in all cases since too few subjects stated constant preference for late resolution.

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Lehrstuhl für Allg. Betriebswirtschaftslehre
Finanzwirtschaft, insb. Bankbetriebslehre
Universität Mannheim
68131 Mannheim, Germany