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Can prospect theory be used to predict an investor's willingness to pay?

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ABSTRACT

Cumulative prospect theory (CPT) is widely considered to be the most successful descriptive theory for decision making under risk and uncertainty. Sophisticated methods have been developed to reliably elicit CPT parameters on an individual basis. The aim of this paper is to analyze whether such methods are suited to be applied in real world situations, particularly in the context of investment counseling for retail investors. Specifically, we examine whether CPT parameters elicited via standardized computer tools are successful in predicting an individual's preference for different structured financial products. Surprisingly, we find only low predictive power of the elicited CPT parameters on the WTP. Using a second set of experiments, we examine possible explanations for the low prediction quality. Overall, we have to conclude that it is too much of a leap to draw conclusions about the attractiveness of complex financial products from CPT parameters elicited via simple lotteries.

1. Introduction

Consider an investment advisor who sells financial products to retail investors. It is in his interest to recommend products that fit the risk preferences of his clients well. First, doing so might establish a comparative advantage. Second, the interest might be driven by legal requirements such as those defined in the MiFID, the Markets in Financial Instruments Directive (The European Parliament and the European Council, 2004). While the MiFID asks the banks to collect "information on the length of time for which the client wishes to hold the investment, his preferences regarding risk taking, his risk profile, and the purposes of the investment" (Article 36(4), The European Parliament and the European Council, 2006), the directive is silent about how such an ambitious goal can be achieved. The common practice among financial advisors is to use simple questionnaires to gain insight into their customer's preferences, with risk aversion and investment experience self-reported on a five- or seven-point scale (Barclays Wealth, 2008).

From an academic perspective, such a procedure leaves much to be desired. Extensive research shows that risk behavior follows complex patterns that cannot be described by a simple five-point scale. Furthermore, empirical evidence suggests that non-expected utility theories, such as cumulative prospect theory (CPT) (Tversky and Kahneman, 1992), explain risk behavior better than the traditional expected utility approach (see Starmer (2000) for a general survey, and Camerer (2000) for a survey of field evidence on the descriptive relevance of prospect theory). Accordingly, over the last few years, elaborate elicitation mechanisms for CPT have been developed (see, e.g., Wakker and Deneffe, 1996; Bleichrodt and Pinto, 2000, and Abdellaoui et al., 2007). These methods allow for a non-parametric elicitation of the value function and the probability weighting function.

The aim of this paper is to analyze whether such methods are suited to be applied in real world situations, particularly in the context of investment counseling. Through experimental research we examine whether CPT parameters derived via such elicitation procedures are successful in predicting an individual's willingness to pay (WTP) for different investment products. Because of the difference in the domains used for eliciting the parameters and deriving the predictions, our experiment can be considered an out-of-task evaluation of CPT. Out-of-task tests are important because they shed light on the applicability of decision theories in practice.

The saying "time is money" is probably nowhere more relevant than in a banking environment. Therefore, one fundamental

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requirement for an implementation of such elicitation procedures in everyday bank business is the economic utilization of resources. As advisory time is a scarce resource, we analyze whether the whole procedure can be implemented using standardized computer tools, especially without time-consuming investor–advisor interactions. A transfer to real world banking on a large scale would only be conceivable from the viewpoint of a financial intermediary if such a computerized procedure would produce promising results.

To answer our research question, we bring the same participants to the lab twice. During the first visit, we elicit CPT preference parameters on an individual basis by applying a modified version of the elicitation procedure of Abdellaoui et al. (2007).[1] During the second visit, participants state their WTP for various investment products with different risk profiles. Our analysis compares theoretical predictions based on the CPT parameters from the first part with the actually stated WTPs from the second part. We use the method of ABP07, because it is not very susceptible to the influence of decision errors (Blavatskyy, 2006). As a second nice property, the method provides a completely parameter-free elicitation that allows for both parametric and non-parametric predictions.

To cover the full range of complex risk profiles, we use structured financial products as investment opportunities. Structured financial products allow issuers to form almost any type of tailor-made payoff profile to serve clients with specific preference structures. This is achieved by combining an underlying, typically a stock or a stock index, with one or more derivatives on that underlying. CPT, designed to capture complex patterns of risk behavior, should be especially suited to explain differences in the WTPs of these financial products.

Surprisingly, we find that CPT has virtually no predictive power if we run the procedures in a fully computerized environment. Based on these findings we explore alternative means of conducting the elicitation in bank practice (e.g. through personal interviews), which we test in a second set of experiments. Our main findings are: (1) more personal forms of interactions (i.e. personal interviews) enhance the internal consistency but do not improve the prediction quality, (2) competence effects seem to play a role but only a minor one, (3) an explanation based on the propagation of decision errors only can be ruled out, (4) the prediction quality increases substantially when we examine binary choices for simple prospects instead of WTPs for elaborate investment products. Overall we have to conclude that trying to predict an individual's WTP for complex financial instruments based on individually elicited CPT parameters seems too much of a leap.

The remainder of the paper is structured as follows. In Section 2, we introduce the procedure to elicit individual CPT parameters. In Section 3, we describe the structured products that we use to determine WTPs. Section 4 presents the design and the main results from our first experiment, Section 5 documents the results from the second set of experiments, and Section 6 contains the discussion of potential explanations for our findings. Section 7 concludes.

2. Eliciting risk preferences in cumulative prospect theory

2.1. Cumulative prospect theory

Cumulative prospect theory (Tversky and Kahneman, 1992) is widely considered to be the most successful descriptive theory for decision making under risk and uncertainty. One of its main features is reference dependence and the distinct treatment of gains and losses. Building on this distinction, risk attitude within the CPT framework is driven by three components, probability weighting, basic utility (curvature), and loss aversion (e.g., Köbberling and Wakker, 2005; Wu and Markle, 2008). CPT allows the evaluation of n-outcome lotteries and since we treat the payoff structures of our investment products as discrete distributions with a finite number of outcomes, they can be evaluated by a standard CPT function. Any analysis of CPT evaluations depends on assumptions about the choice of a reference point and the segmentation of the problem (i.e. whether overall payoff distributions are evaluated or its components). To minimize respective ambiguity, we have been particularly careful in designing our experiment and conveying unequivocal information. Even though the evaluated products are combinations of various more basic components, we never explicitly mention these components but only display the aggregated distribution for each product and use the labeling to induce subjects to code outcomes as gains and losses relative to the price paid.

To be more explicit, consider a prospect P with n outcomes x_i with probability p_i: $P = (x_1, p_1; \ldots; x_n, p_n)$. In our case, the outcome represents the gain or loss yielded from an investment in the product. More formally, the outcome is defined by the difference of the product's payoff at maturity ($P_{Product,T,i}$) and the product price at the time of the investment ($P_{Product,t}$): $x_{Product,T,i} = P_{Product,T,i} - P_{Product,t}$. The monotonicity of the product's payoff function ensures ascending order of the outcomes ($x_n \geqslant \cdots \geqslant x_{k+1} \geqslant 0 \geqslant x_k \geqslant \cdots \geqslant x_1$), with $n-(k+1)$ gains and k losses. The reference point is assumed to be at outcome zero, i.e. where the product payoff equals the product price. Defining $\upsilon(\cdot)$ as the value function and $w(\cdot)$ as the probability weighting function, the CPT utility of a prospect (and hence of an investment product) is given by:

$$CPT(Product) = \sum_{i=1}^{k}\left[w^-\left(\sum_{j=1}^{i}p_j\right) - w^-\left(\sum_{j=1}^{i-1}p_j\right)\right]\cdot \upsilon^-(x_i) + \sum_{i=k+1}^{n}\left[w^+\left(\sum_{j=i}^{n}p_j\right) - w^+\left(\sum_{j=i+1}^{n}p_j\right)\right]\cdot \upsilon^+(x_i).$$

2.2. Elicitation procedure

Several elicitation procedures have been put forward in previous literature (see, e.g., Blavatskyy (2006) or Fox and Poldrack (2008) for an overview). We use a modified version of the nonparametric procedure for value function elicitation by ABP07. Blavatskyy (2006) proposes a three-stage approach, which is efficient with regard to the propagation of decision errors in chained elicitation procedures. The method of ABP07 provides the first two stages. We extend the approach by adding stage three of Blavatskyy (2006) to elicit different probabilities with given decision weights (see Appendix A – Panel 0).

In step 1, we seek the probabilities $p^-_{0.5}$ and $p^+_{0.5}$ that give a decision weight of one-half: $w^-(p^-_{0.5}) = 0.5$ and $w^+(p^+_{0.5}) = 0.5$. These decision weights are elicited using the tradeoff method with $(L_Y, p'; L_M) \sim (L_X, p'; L_N)$ and $(L_Z, p'; L_M) \sim (L_Y, p'; L_N)$ followed by a probability-equivalent query $(L_Y) \sim (L_Z, p^-_{0.5}; L_X)$. L denotes a loss outcome with L_M; L_N; $L_X = -1; -6; -10$ and $p' = \frac{1}{3}$. The same is done for the gain domain. In step 2, the loss value function is elicited through chained certainty-equivalent queries using utility midpoints. L_1 as the maximum loss outcome is fixed to be $L_1 = -100$, with $U(L_1) = -1$. Amounts are chosen to be within the interval of $[0; -100]$ since the gains and losses from the products are similarly scaled. A sequence of outcomes is elicited through queries $L_r \sim (L_A, p^-_{0.5}; L_B)$ with $U(L_r) = -r = 0.5\cdot U(L_A) + 0.5\cdot U(L_B)$. We derive 14 points with $r \in \{\frac{1}{64}, \frac{1}{32}, \frac{1}{16}, \frac{3}{32}, \frac{1}{8}, \frac{3}{16}, \frac{7}{32}, \frac{15}{64}, \frac{1}{4}, \frac{3}{8}, \frac{1}{2}, \frac{5}{8}, \frac{3}{4}, \frac{7}{8}\}$ and $m = 6$ iterations (see Appendix A – Panel I). In step 3, losses and gains are linked using three indifference statements $L_{0.25} \sim (l, 0.5; 0)$,

[1] In the following we refer to Abdellaoui et al. (2007) as ABP07.