

## BRIEF REPORT

# How Outcome Dependencies Affect Decisions Under Risk

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Many economic theories of decision making assume that people evaluate options independently of other available options. However, recent cognitive theories such as decision field theory suggest that people's evaluations rely on a relative comparison of the options' potential consequences such that the subjective value of an option critically depends on the context in which it is presented. To test this prediction, we examined pairwise choices between monetary gambles and varied the degree to which the gambles' outcomes covaried with one another. When people evaluate options by comparing their outcomes, a high covariance between these outcomes should make a decision easier, as suggested by decision field theory. In line with this prediction, the observed choice proportions in 2 experiments ( $N = 39$  and  $24$ , respectively) depended on the magnitude of the covariance. We call this effect the *covariance effect*. Our findings are in line with the theoretic predictions and show that the discriminability ratio in decision field theory can reflect the choice difficulty. These results confirm that interdependent evaluations of options play an important role in human decision making under risk and show that covariance is an important aspect of the choice context.

*Keywords:* covariance, outcome associations, decision making under risk, decision field theory, cognitive modeling

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Decisions under risk and uncertainty play an important role in daily life. Explaining and predicting risky decisions is an important area of research in psychology, economics, and cognitive science. Many cognitive models of decision making predict that people compare the potential consequences of options with each other, yielding context-dependent evaluations. For ex-

ample, when choosing between health insurances, decision makers might compare the coverage for different illnesses against each other. In contrast to this, standard economic theories of choice such as expected utility (EU) theory (von Neumann & Morgenstern, 1954) assume that the subjective value of a single offer does not change depending on the availability of other available options and, therefore, its utility is independent of the context.

### Theories of Decision Making

Empirical research on decision making has repeatedly shown that people compare options' outcomes with each other, rather than evaluating each option independently of the other available options (for a review see Rieskamp, Busemeyer, & Mellers, 2006). For example, Tversky and Shafir (1992) found that people's preferences depend on the context of other choice options in which an option is presented.

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Likewise, according to Tversky's (1969) lexicographic semiorder heuristic, a person choosing between two health insurances might order the attributes (i.e., coverage in case of different illnesses) of the two insurance offers according to their perceived importance. If one of the offers is substantially better than the other for the most important attribute, the model predicts that this offer will be chosen. If both offers are comparable for the most important attribute, the decision should be based on the second best attribute, and so on.

Context-dependent decision theories, such as Tversky's (1969) lexicographic semiorder heuristic; Tversky's (1972) elimination-by-aspects theory; González-Vallejo's (2002) stochastic difference model; or Brandstätter, Gigerenzer, and Hertwig's (2006) priority heuristic, predict outcome-/attribute-wise comparison of options. A further example is regret theory (RT; Loomes & Sugden, 1982), which assumes that decision makers anticipate feelings of regret when obtaining lower outcomes relative to forgone outcomes of alternative options. Here, the association between choice options is represented by a specific regret utility function that expresses the summed regret of each attribute of an option compared to the regret of the forgone option. What these theories have in common is that they predict that the similarities and associations of the options' outcomes, which we will refer to as the "choice context" in this paper, will systematically affect people's choices.

Another distinguished theory is decision field theory (DFT; Busemeyer & Townsend, 1993), which assumes that preferences accumulate over time by comparing the outcomes of the options with each other one at a time and by accumulating the differences between the outcomes. The attention to the different outcomes shifts stochastically. A decision is reached when the accumulated differences exceed a predefined threshold, or when a predefined time limit has been reached. In the following, we will focus on RT and DFT as two prominent examples that provide two alternative explanations of the underlying decision process and that also allow quantitative predictions. Both RT and DFT stress the importance of the association between the outcomes of choice options. In contrast, fixed utility theories (cf. Rieskamp et al., 2006) assume that each option can be assigned a value representing a subjective value to

the decision maker that is independent of how the outcomes of one option relate to other available options. Therefore, according to this class of theories, the utility of a single option does not change relative to the choice context in which it is presented.

Standard EU theory represents the most eminent fixed utility theory. However, similar to EU theory, the assumption of independence can also be traced in more descriptively inspired decision theories such as rank-dependent utility theories (see, e.g., Green & Jullien, 1988; Luce, 1990). Another prominent representative, cumulative prospect theory (CPT; Tversky & Kahneman, 1992), distinguishes gains and losses and includes a weighting function to represent subjective probabilities, but in the end still assigns a value to each option independently of the other options' outcomes.

### Research Goal

Past research has provided substantial evidence that the context, in which choice options are presented, influences people's preferences (Johnson & Busemeyer, 2005). For example, Diederich and Busemeyer (1999) showed that people display more consistent preferences for options with positively correlated outcomes as compared to options with negatively correlated outcomes. This is because negatively correlated options lead to a conflict. Similar findings were presented by Fasolo, McClelland, and Lange (2005), who showed that negatively as compared to positively correlated attribute values of options changed people's preferences. Fasolo et al. (2005) argued that negatively correlated options lead to a decision conflict and the selection of different decision strategies. Likewise, Mellers and Biagini (1994) tested the contrast-weighting theory, which states that "when gambles have similar levels along one attribute, differences along the other attribute are enhanced" (p. 509). To test this theory in an experiment, they manipulated the probabilities of gambles' outcomes and showed that a higher correlation between the options' probabilities results in stronger choice preferences. They ascribed this effect to the similarity between options' probabilities, where options are more discriminable in high similarity situations, as compared to the dissimilar situations.

Another example of the influence of the context on people’s choices was presented by [Jes-sup, Bishara, and Busemeyer \(2008\)](#), whose results indicate that the higher the similarity between the expected values of one risky option and a “sure thing,” the less likely people are to choose the more profitable risky option. Likewise, [Dhar and Glazer \(1996\)](#) experimentally showed that similarity between choice options depends on the context of the presented attributes and that when options become less similar on the key attribute the preference for the “better” option increases. Related to this, [Carlson, Meloy, and Russo \(2006\)](#) showed that if consumers choose between two products, the alignment of the products’ attributes has a systematic influence on people’s preferences. When one product is presented as superior on the leading attribute, the product is preferred more strongly over the competitive product.

In this paper, we build on this previous work by examining how the associations between the outcomes of options systematically affect people’s choices. In extension to past research, we quantify the association between the outcomes

of choice options to test how different degrees of covariance influence decisions between monetary gambles. Thus, rather than comparing negatively against positively correlated outcomes, here, we focus only on positively correlated outcomes with different levels of association. Furthermore, based on simulation studies, we examine how the predictions of four established decision models are affected by the strengths of these associations and then compare these predictions to our empirical results. Toward a better understanding of the underlying cognitive processes, these results are then used to rigorously test and compare the decision models on qualitative and quantitative grounds.

### Characterizing the Association Between Choice Options

The idea of context-dependent evaluations can be illustrated with a choice between two monetary gambles A and B whose outcomes depend on the throw of a die, as shown in [Figure 1](#). In Case 1, Gamble A leads to substantially higher payoffs than Gamble B if the die

Case 1)



<i>Event</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>
Gamble A	20	10	25	30	15	30
A - B	5	5	5	-1	-1	-1
Gamble B	15	5	20	31	16	31

Case 2)



<i>Event</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>
Gamble A	20	10	25	30	15	30
A - B	-11	-6	-6	15	10	10
Gamble B*	31	16	31	15	5	20

*Figure 1.* Choice between two monetary gambles, A and B, whose outcomes depend on the throw of a die. In Case 1, the gambles appear similar, and in Case 2, they appear dissimilar. Gamble B is identical to Gamble B\*, with the only difference being that the outcomes have been swapped for Events 1–3 and 4–6. For both pairs of gambles, the expected value difference is 4, but the covariance of the outcomes is 78.67 for the first and 24.67 for the second case.

lands on 1, 2, or 3, whereas for the numbers 4–6, Gamble B has a small advantage over A. Presumably, most people would prefer Gamble A over B due to the large advantage of A for numbers 1–3 and disregard the small disadvantage for numbers 4–6. In contrast, in Case 2, Gamble A is worse than Gamble B\* when throwing 1, 2, or 3, whereas it is better when throwing 4, 5, or 6. In this case, we expect that the choice is much more complicated, even though Gambles B and B\* both result in the same outcomes with identical probabilities and thus yield the same expected utility. In this situation, EU and CPT cannot predict any difference for the two cases, whereas context-dependent theories can.

The difference between the two cases can also be illustrated by the cognitive decision process assumed by DFT. According to DFT, people compare the respective options' outcomes with each other and accumulate the outcome differences in a preference state over time. In Case 1, these differences are 5, 5, 5, -1, -1, and -1, which stochastically receive the attention of the decision maker according to the outcome probabilities. Due to the assumed stochastic nature of the information accumulation process, it could happen that only the negative differences are considered for some time. However, most likely this will not lead to the choice of the option with the smaller expected value, because these negative differences have low magnitudes and often may not be sufficient to let the preference state cross the decision threshold. In contrast, in Case 2 the differences are 15, 10, 10, -6, -6, -11, so that if only the negative differences are considered then the option with the smaller expected value could be chosen. Here, the negative differences have substantially larger magnitudes, so that the decision threshold could be passed.

In formal terms, the smaller variability of the differences in Case 1 can be expressed as a higher covariance between two options' outcomes. Likewise, the larger variability of the differences in Case 2 is reflected in a lower covariance for Case 2. This example illustrates why different magnitudes of covariance of the options' outcomes should affect people's choices.

As we will outline next, the covariance directly feeds into the decision process assumed by DFT. DFT assumes that the probability of choosing an option A over an option B can be

quantified as a function of the expected difference between the two options ( $d$ ) and the variance of that difference ( $\sigma_d$ ):

$$\Pr(A|A, B) = \frac{1}{1 + \exp\left[-2\left(\frac{d}{\sigma_d} \cdot \theta_{DFT}\right)\right]}, \quad (1)$$

where  $\theta_{DFT}$  is a decision threshold and where the variance of the difference  $\sigma_d$  is defined as

$$\sigma_d = \sqrt{\sigma_A^2 + \sigma_B^2 - 2\sigma_{AB}}, \quad (2)$$

where  $\sigma_{AB}$  quantifies the strength of relationship between the options' outcomes, such that when  $\sigma_{AB} = 0$  the options' outcomes are independent, and the higher the  $\sigma_{AB}$ , the stronger the statistical relationship between the options' outcomes.

Figure 1 can also illustrate the predictions of the other model of interest—the RT. The differences of the outcomes will affect the RT predictions. RT assumes that disadvantageous outcomes of a choice option in comparison to an alternative option lead to regret, where disadvantages outweigh advantages in a nonlinear fashion. Therefore, in Case 2 with large negative differences, the option with the larger expected value does not appear as attractive as in Case 1 where only small negative differences are observed. Again, the variability of the differences between the respective outcomes can be precisely quantified by the covariance. However, the underlying mechanism that predicts how covariance affects people's choices differs between RT and DFT.

Figure 1 illustrates how different degrees of covariance between the outcomes of two gambles may influence people's choices between gambles. In Case 1, the covariance is 78.7, which is much higher than in Case 2 with a covariance of 24.7. However, the main drawback of covariance as an association measure is that its scale depends on the range of the outcomes, which varies from minus infinity to plus infinity. The logarithm or square root of covariance changes its scale, but the scale is still unbounded, which makes the objective definition of different levels of association difficult to compare. A viable solution would be to use a standardized measure of the association be-

tween any two choice options. Using correlations would be one possibility but it does not provide a feasible solution for gambles with only two outcomes that are frequently used in decision-making research. That is because in case of two-outcome gambles, correlation equals either  $-1$  or  $1$  (see Rodgers & Nicewander, 1988, for a detailed explanation). As an alternative scaling, we propose the standardized covariance ( $\sigma_{AB}^*$ , Andraszewicz & Rieskamp, 2014):

$$\sigma_{AB}^* = \frac{2\sigma_{AB}}{\sigma_A^2 + \sigma_B^2}, \tag{3}$$

In Equation 3, we treat the gambles' outcomes as discrete random variables whose variances are measurement of risk (Weber, Siebenmorgen, & Weber, 2005) defined as  $\sigma_{AB}^2 = E[(A - E[A])^2]$  and the covariance between outcomes of two gambles equals  $\sigma_{AB} = E[(A - E[A])(B - E[B])]$ . The main advantage of  $\sigma_{AB}^*$  is that it is a continuous variable that ranges

from  $1$  (maximum positive association) to  $-1$  (maximum negative association), whereas  $\sigma_{AB}^* \rightarrow 0$  characterizes options with low association. When  $\sigma_{AB}^* = 0$ , the options are statistically independent of each other or one option is a sure option whose variance is  $0$ . Andraszewicz and Rieskamp (2014) provide an elaborated description of the standardized covariance's properties.

Figure 2 presents three examples of pairs of dependent gambles, where each pair is characterized by different level of association. In the leftmost example in Figure 2, the association between the gambles is low because one gamble is an almost sure option and has very low variance, while the second gamble has a substantially higher variance. Therefore, the outcomes of each gamble corresponding to the same probabilities are not similar. Consequently, the covariance between the gambles' outcomes is low. The middle example shows an intermediate stage between low and high covariance.

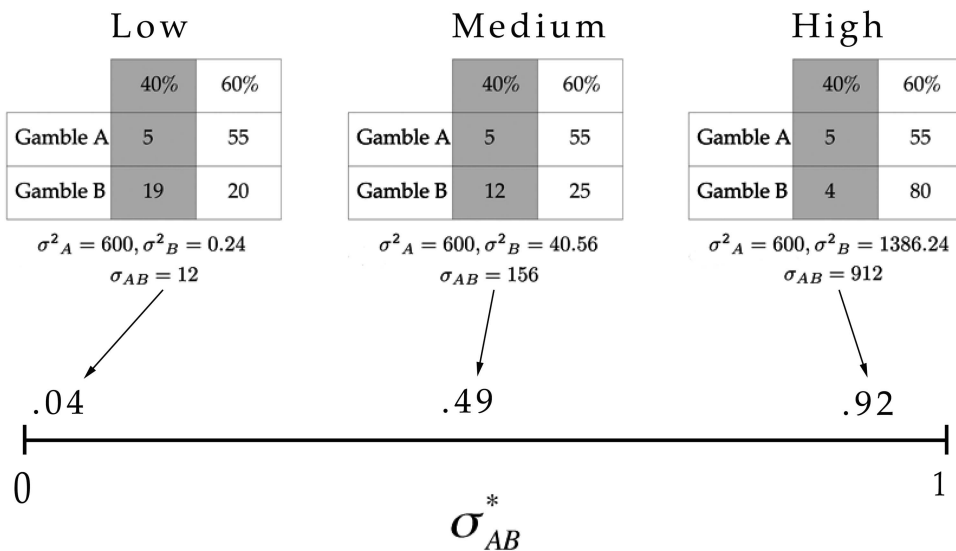


Figure 2. Three examples of pairs of gambles with low, medium, and high standardized covariance. The horizontal line shows the scale of  $\sigma_{AB}^*$ . In each example, percentages and their corresponding colors (gray or white) are probabilities of occurrence of the corresponding outcomes of gambles A and B. Gamble A is the same in all three examples. The higher the standardized covariance, the more similar the outcomes of Gamble B are to the outcomes of Gamble A (i.e., 5 and 4 in Example 3, vs. 5 and 19 in Example 1). Increase of variance of Gamble B ( $\sigma_B^2$ ) results in a nonlinear increase of covariance between Gambles A and B ( $\sigma_{AB}$ ). The difference in expected values ranges between 14.6 and 15.4 points. Gamble A is more advantageous in the first two examples.

In contrast, the rightmost example in Figure 2 shows a case where both gambles have high variances and their outcomes corresponding to the same probabilities are similar. Therefore, the covariance between the outcomes of Gamble A and B is high. As variances and covariance are nonlinearly related, it is impossible to manipulate one while keeping the other constant. Therefore, the covariance also carries some information about the variances.

### Associations Between Options' Outcomes Affect the Predictions of Decision Theories

To explore how choice probabilities are influenced by the association between the choice options as measured by the standardized covariance, we ran a simulation study. This simulation is helpful because it is difficult to analytically derive the exact impact of the standardized covariance on the predictions of the different models. We chose RT and DFT to represent two context-dependent decision theories. As a comparison benchmark, we included EU and CPT to capture the predictions of two fixed utility theories that should not be influenced by standardized covariance. The Appendix provides mathematical specifications of the respective models. All models predict the probability with which a decision maker chooses one gamble over another. For EU, CPT and RT, the probability of choosing option A over option B was estimated by means of an exponential choice function:

$$\Pr(A|A, B) = \frac{1}{1 + \exp[\theta(EU(B) - EU(A))]} \quad (4)$$

where  $\theta$  is a choice sensitivity parameter that defines how strongly decision maker responds to the differences of the options' expected utilities, such that the higher  $\theta$ , the more strongly the decision maker responds. For RT, we assume that expected utility is defined as expected regret (see Equation A9).

### Simulation

For the simulation, we generated pairs of stochastically nondominant two-outcome gambles whose outcomes varied between 0 and 100

integer points with outcome probabilities equal to .4, .5, or .6. The absolute difference in expected value ( $\Delta EV$ ) within each pair of gambles was kept constant at 15 points. Within these bounds, we created all possible gamble pairs and then assigned each pair of gambles to one of three standardized covariance categories: small ( $\sigma_{AB}^* \leq 0.2$ , 21.2% of all cases), medium ( $0.2 < \sigma_{AB}^* \leq 0.5$ , 34.7% of all cases), or large ( $0.5 < \sigma_{AB}^*$ , 44.1% of all cases). Finally, we converted all the outcomes from gains to losses to create a second set of gambles with only negative outcomes.

### Results and Discussion

Results of the simulation show that  $\sigma_{AB}^*$  has a strong effect on the mean predictions of DFT and RT, whereas, as expected, it has no effect for EU and CPT ( $M = .86$  for EU and CPT in all conditions). Although all four models predicted that the gamble with the larger expected value was more likely to be chosen, only RT and DFT predicted that the choice probabilities were affected by covariance. For DFT and RT, the predicted choice probabilities for the gambles with the larger expected value increased with standardized covariance (DFT:  $M_{SMALL} = .79$ ,  $M_{MEDIUM} = .81$ ,  $M_{LARGE} = .85$ ; RT:  $M_{SMALL} = .77$ ,  $M_{MEDIUM} = .78$ ,  $M_{LARGE} = .80$ ). We call this effect the *covariance effect*. Presumably, this effect occurs because when comparing options outcome-wise, higher  $\sigma_{AB}^*$  yields more distinct differences between the expected values and hence a clearer preference. This positive relation is systematic and nonlinear, such that there is a greater difference between the medium and large covariance conditions than between the small and medium conditions.

The standardized covariance also affected the variability of the models' predictions: The larger the  $\sigma_{AB}^*$ , the smaller the variability of the DFT and RT predictions (DFT:  $\sigma_{SMALL} = .06$ ,  $\sigma_{MEDIUM} = .05$ ,  $\sigma_{LARGE} = .04$ ; RT:  $\sigma_{SMALL} = .06$ ,  $\sigma_{MEDIUM} = .06$ ,  $\sigma_{LARGE} = .04$ ), whereas, once again, no such relationship was observed for EU and CPT (EU:  $\sigma = .03$ ; CPT:  $\sigma = .02$  across all conditions).

Thus, according to DFT and RT, choices with small  $\sigma_{AB}^*$  should be more difficult and the models predict less consistent choices as reflected in the larger variability of the predicted choice

probabilities. Both models, RT and DFT, predicted a higher variability of the choices when the standardized covariance was small; that is, the smaller the covariance, the greater the variability of the predictions.<sup>1</sup>

### Study 1

The simulation illustrates that the two context-dependent theories, DFT and RT, but not EU and CPT, predict that stronger associations between two choice options lead to stronger preferences for one option. In Study 1, we tested whether the systematic differences observed in the simulation can also be traced in human choice behavior in a laboratory.

### Procedure

Participants repeatedly chose from each pair of gambles on a computer screen presented in a random order, as shown in Figure 3. Gambles were framed as hypothetical stocks with outcomes representing the return on investment along the corresponding probabilities of its occurrence. The outcomes were matched by color with their corresponding probabilities and the same colors were used for both gambles to indicate that the outcomes of both were dependent on the same external event. By using this way of presenting the gambles, we also aimed at highlighting the gambles' outcomes. At the end of the experiment, one gamble was randomly chosen and played out. Two percent of the gamble's outcome was added to or subtracted from the initial endowment of 8 Swiss Francs ( $\approx$  \$8 USD). Participants were informed about the payment procedure before they started the experiment. The experiment was completely self-paced.

The choice task was preceded by six practice trials presented in a fixed order. During these practice trials, each gamble was played out and the participants saw the results. After the experiment, the participants completed a short demographic questionnaire.

### Materials

As a basis for the experiment, we randomly selected gambles from the set used in the simulation study. In Study 1, we narrowed down the values of  $\sigma_{AB}^*$  ranges to obtain a clear-cut

distinction among small, medium, and large  $\sigma_{AB}^*$  given the limited amount of stimuli we could present to the participants. Therefore, 60 pairs of gambles had a standardized covariance such that  $\sigma_{AB}^* \leq .1$ , another 60 pairs  $.4 \leq \sigma_{AB}^* \leq .5$ , and a third set  $.8 \leq \sigma_{AB}^* \leq .95$ . Half of the gambles had only positive outcomes and the other half only negative. Gambles were randomly assigned as the upper Gamble A or the lower Gamble B on the screen, so that in 53% of all pairs of gambles, Gamble A had a larger expected value. In the simulation, we used the whole population of gambles with the predefined described properties. For half of the gamble pairs, the outcomes of the gamble with the larger expected value varied less, whereas in the remaining half of pairs it was the other way round.

### Participants

A total of 39 people (16 male), aged 19–52 years ( $M_{age} = 25$  years), mainly students from the University of Basel, participated in the study. Four participants were excluded from further analyses because they made purely random choices.

### Results and Discussion

Figure 4 shows that the observed choice proportions were systematically influenced by the strength of the association between the gambles, thus resembling the simulation results: The share of choices of gambles with the larger expected value monotonically increased with  $\sigma_{AB}^*$ . For each participant, we calculated three average choice proportions of the gamble with the larger expected value, separately for each condition—(a) small, (b) medium, and (c) large—where, in each condition, the average was calculated from 60 trials. There were sig-

<sup>1</sup> The higher the parameter value of  $\beta$  for RT, the greater the differences between the conditions and the larger the variability within each condition. However, the value of the prediction for the small covariance condition depends on the sensitivity parameter  $\theta$ . In contrast, in DFT, the magnitude of the difference between conditions, variability within each condition and the prediction for the small condition depend on the sensitivity parameter  $\theta$ . Therefore, when RT and DFT predict similar differences between conditions, RT predicts higher variability. In contrast, when RT and DFT predict similar variability, RT predicts smaller differences between conditions.

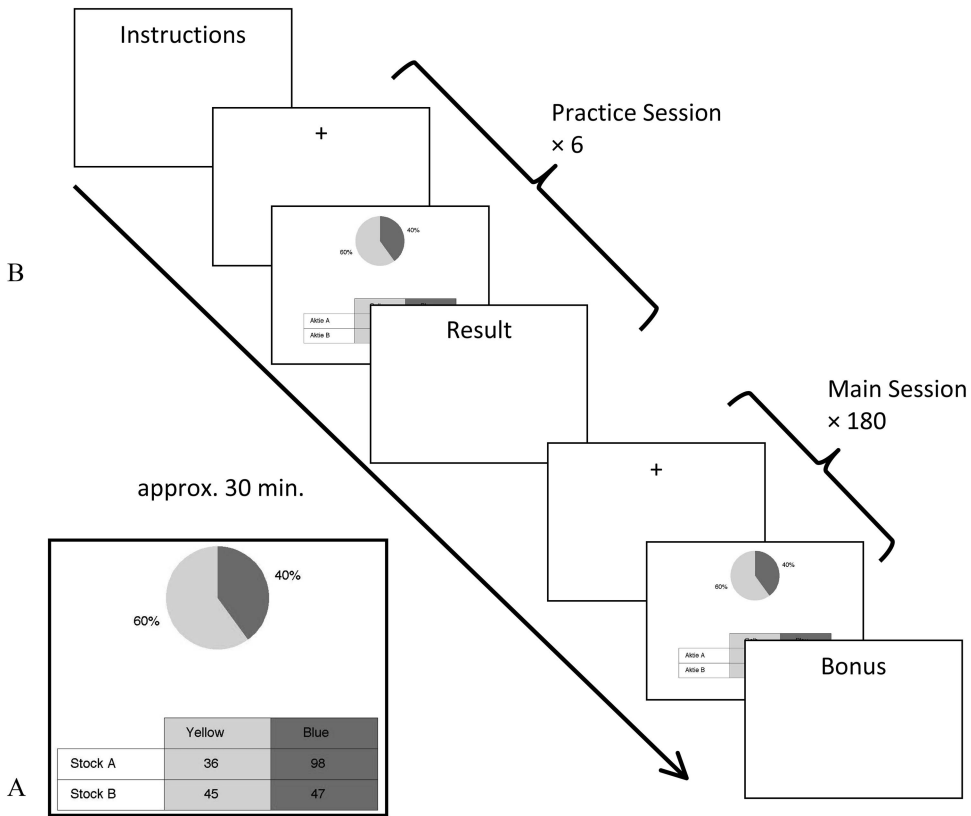


Figure 3. (A) Example of a stimulus used in Study 1. (B) Experimental paradigm.

nificant differences in the choice proportions according to a Friedman test for not-normally distributed within-subject data,  $p < .001$ ,  $\chi^2(2) = 15.48$ , 95% confidence interval (CI) = [0.05, 7.40]. To further explore the differences between the three conditions, we applied a series of post hoc paired-comparisons using one-sided Wilcoxon signed-ranks test with Bonferroni correction of  $\alpha$ . There was a significant difference between the small and large ( $p < .001$ ), and medium and large ( $p < .001$ ) covariance conditions, but no differences between the small and medium covariance conditions ( $p = .34$ ). There was a greater difference between the medium and large conditions than between the small and medium conditions.

In a next step, we fitted the free parameters of EU, CPT, RT, and DFT to the data using a maximum log-likelihood approach. Table S1 in the online supplementary material presents the individual parameter estimates. When compar-

ing the fit of the models based on the Bayesian information criterion (BIC; Kass & Raftery, 1995), all models clearly performed better than a baseline model that predicts random guessing. Furthermore, as shown in Table 1, DFT provides the best fit (i.e., the lowest BIC value), followed by RT, EU, and CPT<sup>2</sup>. In the case at hand, EU predicted the behavior relatively well as compared to CPT. This is probably due to the fact that EU has fewer free parameters and that the additional parameters of CPT were not critical in the present choice context. When comparing DFT with EU on an individual level by their BICs, 74% of the participants were better described by DFT. Figure 5 shows the corresponding Bayes factors (Kass & Raftery, 1995) of this comparison separated for the three cova-

<sup>2</sup> Table S1 in the online supplementary materials contains fits and estimated parameters at the individual level.



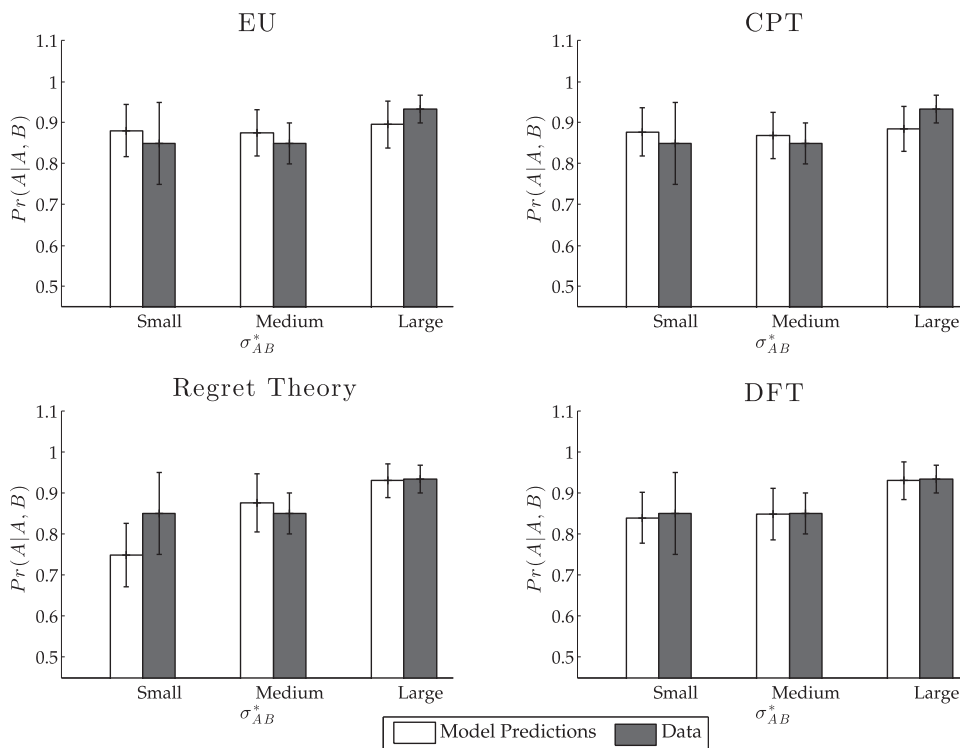


Figure 4. Median predictions of expected utility (EU) theory, cumulative prospect theory (CPT), regret theory (RT), and decision field theory (DFT) for each covariance condition in Study 1. Dark bars indicate the observed data and are the same in all four cells. Error bars indicate median absolute difference.

riance conditions. In each condition, the majority of participants were better described by DFT than EU and the evidence is either strong or very strong.

When comparing the models on qualitative grounds, a similar picture emerges. Based on the estimated parameter values, we averaged the predictions that each model generated for each participant across all 180 choices. The resulting patterns shown on Figure 4 indicate that DFT predicts a stronger increase between the medium and large covariance conditions and almost no differences between the small and medium covariance conditions, which is consistent with the observed choice patterns. In contrast to this, RT predicts a more proportional increase in choice proportions across all three covariance conditions.

Apart from evaluating choices, DFT further predicts decision times. The observed mean response times were 1.44 log(sec) in the small covariance condition, 1.46 log(sec) in the me-

dium covariance condition, and 1.45 log(sec) in the high covariance condition. These response times were not significantly different from each other. Apparently, the participants made their decisions at a constant pace, which is inconsistent with the DFT predictions. However, the experiment was not designed for a sensible response time analysis. Perhaps the results would have looked differently if we had incentivized participants to make a quick decision.

### Study 2

To test whether the results of Study 1 can be generalized to more complex gambles with more than two outcomes, we conducted a second experiment. This study also provides a basis for a generalization test of the considered decision models (Busemeyer & Wang, 2000).

Table 1  
*Estimated Parameter Values (Standard Deviations) and Results of Model Comparison (Cumulative BIC for All Participants and Percentage of Participants for Whom the Model Had a Better Fit Than the Baseline Model) for Each of the Four Models*

Model	Median parameters (SD)	BIC	Individual BIC < Baseline
Baseline	None	5,489.7	—
EU	$\alpha = .90 (.25)$ $\theta = .24 (.70)$	4,897.3	89%
CPT	$\alpha = .82 (.38)$ $\beta = .87 (.52)$ $\gamma = .89 (.37)$ $\delta = .42 (.41)$ $\phi = .27 (1.8)$	5,361.8	83%
RT	$\beta = .04 (.05)$ $\theta = 7.16 (10.60)$	4,881.4	89%
DFT	$\theta = 1.48 (.92)$	4,702.9	91%

Note. BIC = Bayesian information criterion; EU = expected utility theory; CPT = cumulative prospect theory; RT = regret theory; DFT = decision field theory.

## Materials and Procedure

Like in Study 1, participants in the experiment repeatedly chose between 180 pairs of gambles, presented on a computer screen. The gambles were randomly generated such that each gamble had four possible outcomes that varied between 1 and 100, or  $-100$  points and  $-1$  point, with outcome probabilities of .1, .2, .3, or .4. In each gamble pair, Gamble A had two outcomes that were higher and two outcomes that were lower than the respective outcomes of Gamble B. The order of the better outcomes was randomized. Ninety pairs had positive outcomes, while the other 90 pairs had only negative outcomes. Within each set, 30 gambles had small ( $\sigma_{AB}^* \leq .1$ ), 30 had medium ( $.4 \leq \sigma_{AB}^* \leq .5$ ), and 30 had large ( $.8 \leq \sigma_{AB}^* \leq .95$ ) standardized covariance. The base payment for participants was 15 Swiss Francs, with the bonus equal to 20% of the outcome of a randomly chosen and played out gamble.

As the gambles had more than two outcomes, we could also calculate Pearson's correlation coefficients for each gamble pair. The mean correlations within each of the three covariance conditions were  $M_{SMALL} = .06$ ,  $M_{MEDIUM} = .56$ ,  $M_{LARGE} = .88$ . The correlation coefficient itself was highly correlated with the standardized covariance,  $r = .98$ ,  $p < .001$  indicating

that for gambles with more than two outcomes, both measures converge (see also Andraszewicz & Rieskamp, 2014).

## Participants

Twenty-four persons (seven male), aged between 19 and 52 years ( $M_{age} = 28$  years), recruited through a database maintained at the University of Basel, participated in the study.

## Results and Discussion

Results confirm the findings of Study 1. As shown in Figure 6, an increase in  $\sigma_{AB}^*$  leads to higher choice proportions for the option with the larger expected value. People's choices differed between the three conditions, as indicated by a Friedman test,  $p < .001$ ,  $\chi^2(2) = 31.32$ . A series of comparisons calculated based on Wilcoxon signed-ranks test with Bonferroni correction of  $\alpha = .05$  indicated significant differences among all three covariance conditions ( $p = .005$  small vs. medium,  $p < .001$  small vs. large and medium vs. large). Also, participants' choices became more systematic (as indicated by a lower variance) for higher values of  $\sigma_{AB}^*$ .

In order to conduct the model generalization test, we first generated the predictions of the models for each pair of gambles in Study 2 on the basis of the medians of the estimated parameters in Study 1 (see Table S1 in online supplementary materials). Thus, we used one set of parameter values. This set was then used to predict the observed choice probabilities of participants in Study 2, leading to identical predictions for all participants. Based on these predictions we then calculated the log-likelihood (LL) of the observed choice proportions for each participant. The sum of the individual LLs provided the basis for comparing the models against each other. This comparison showed that DFT predicted the choice data best (LL = 3,322), followed by EU (LL = 3,340), CPT (LL = 4,610), and RT (LL = 4,670). Median predictions for each condition are presented in Figure 6.

Generalization tests provide a strong comparison of theories that implicitly take the models' complexities into account. However, a poor generalization performance of a given model might be due to the new test situation in the generalization experiment that may have triggered a different decision process. To rule out

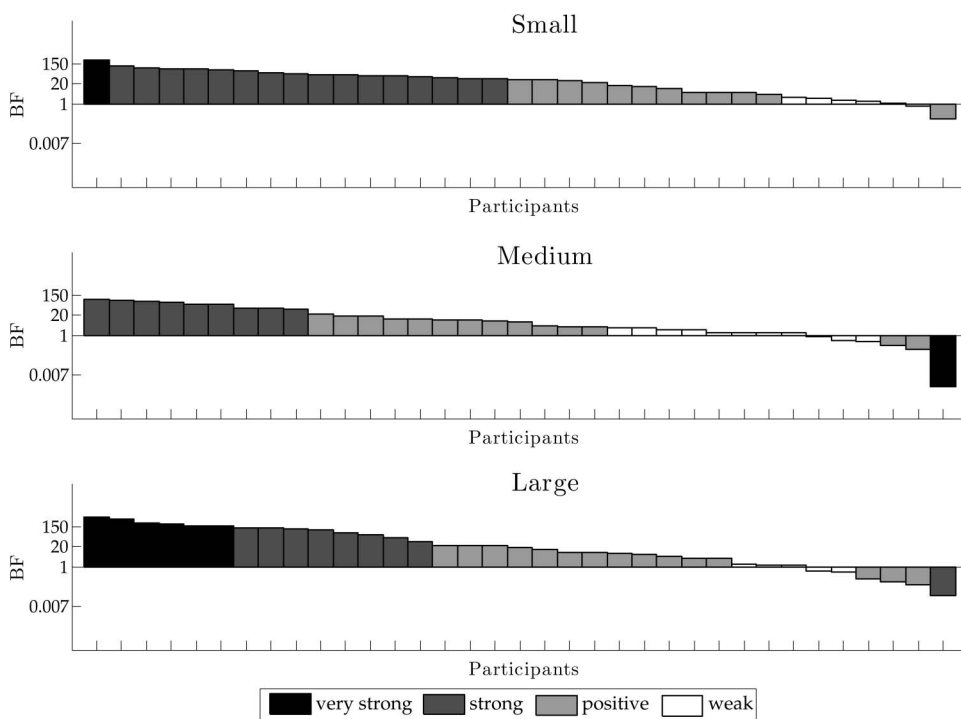


Figure 5. Evidence in favor of decision field theory as compared to expected utility theory, expressed by the Bayes factor (BF) on a logarithmic scale, in Study 1. The strength of the evidence is categorized following Kass and Raftery (1995).

this alternative explanation, we also estimated the models' parameters based on the data of Study 2, again using a maximum likelihood approach. According to BIC, all models predicted the data better than the baseline model, but only DFT did so for all participants (see Table 2).<sup>3</sup> Similar to Study 1, DFT was the best model for predicting the data, followed by EU. For 79% of the participants the BF was in favor of DFT compared to EU. Figure 7 shows this advantage separately for each condition.

We compared estimated models' parameters for Study 1 and Study 2. Wilcoxon signed-ranks test indicated no significant differences for all models except CPT.<sup>4</sup> This could explain why in the generalization study, CPT predicted differences among the covariance conditions. Namely, the CPT parameters in the first study did not fit the new choice situation in Study 2.

Like in Study 1, only RT and DFT correctly predicted the increased choice proportions for gambles with larger  $\sigma_{AB}^*$  in Study 2. However, as the predictions of the models with the esti-

mated parameters show (see Figure 6), RT overall predicted less extreme choice probabilities and greater variance of these probabilities than the observed data. In contrast, DFT predicted the observed differences between the conditions and observed choice proportions more accurately. In contrast to Study 1, in Study 2, the difference between the small and medium conditions was more similar to the difference between medium and large conditions. Importantly, the RT and DFT predictions matched this pattern. As before, there was no difference in peoples' response times, which were 1.81, 1.82,

<sup>3</sup> Table S2 in the online supplementary materials contains fits and estimated parameters at the individual level.

<sup>4</sup> When trusting the estimated parameters of CPT, participants in Study 1 were risk-averse, whereas participants in Study 2 were risk-seeking.  $\delta$  was significantly lower in Study 2 than in Study 1.

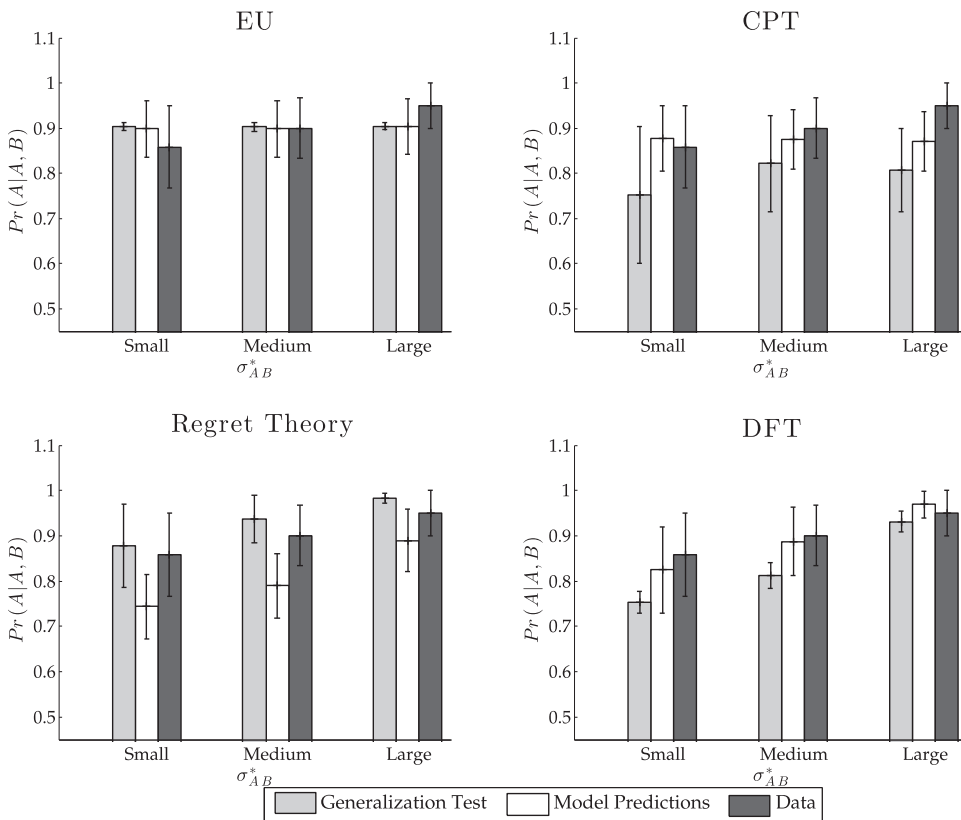


Figure 6. Light-gray bars: Median model predictions obtained by generalization criterion model comparison (Busemeyer & Wang, 2000) for each of the three conditions. We generated model predictions for gambles in Study 2, using parameters estimated in Study 1 (see Table S1). White bars: Median predictions of expected utility (EU) theory, cumulative prospect theory (CPT), regret theory (RT), and decision field theory (DFT) for each covariance condition in Study 2 obtained by model fitting using maximum log-likelihood approach. Dark-gray bars (identical for all panels): median observed data. The error bars indicate the median absolute difference.

and 1.82 log(sec) for the small, medium, and large conditions, respectively<sup>5</sup>.

### General Discussion

The present work investigates the influence of different levels of association between choice options on people's preferences. To quantify the association between the consequences of options, we used a standardized measure of covariance that is easy to interpret and that can be applied to pairs of options with only two outcomes. We further showed empirically that the association between outcomes systematically influenced decisions under risk. A rigorous

comparison of four choice models indicated that these influences are best accounted for by DFT. Together, these results provide clear evidence that the context in which an option is presented, in particular the strength of the association between the option's outcomes, affects people's decisions under risk. Our results build on the previous work on the influence of context on risky choice (i.e., Carlson et al., 2006; Dhar & Glazer, 1996; Mellers & Biagini, 1994) by quantifying the strength of the association and

<sup>5</sup> Data, stimuli and scripts used for the analysis in Studies 1 and 2 are included in the online supplementary materials.

Table 2  
*Estimated Parameter Values (Standard Deviations) and Results of Model Comparison (Cumulative BIC for All Participants and Percentage of Participants for Whom the Model Had a Better Fit Than the Baseline Model) for Each of the Four Models*

Model	Median parameters (SD)	BIC	BIC < Baseline
Baseline	None	5,988.8	—
EU	$\alpha = .78 (.37)$ $\theta = .42 (1.16)$	2,865.9	96%
CPT	$\alpha = 1.29 (.4)$ $\beta = 1.35 (.36)$ $\gamma = 1.0 (.26)$ $\delta = 1.0 (.25)$ $\phi = .04 (1.03)$	3,616.3	92%
RT	$\beta = .04 (.03)$ $\theta = 5.66 (2.75)$	3,502.4	92%
DFT	$\theta = 2.00 (1.14)$	2,856.7	100%

*Note.* BIC = Bayesian information criterion; EU = expected utility theory; CPT = cumulative prospect theory; RT = regret theory; DFT = decision field theory.

showing that the stronger this association, the higher the probability that the option with the larger expected value is chosen.

Presumably, the covariance effect occurs because decision makers compare corresponding outcomes with each other and then base their evaluation on the accumulated differences between these outcomes. In cases of a high association between the outcomes, these differences do not vary a lot, making it easier to determine the better option. In contrast, in cases of a low association, the differences vary substantially and thus do not favor any one option. To characterize this association, we used a standardized covariance (Andraszewicz & Rieskamp, 2014). From our results, we conclude that the standardized covariance and, if applicable, also Pearson’s correlation coefficient, can be used to quantify and predict the difficulty of a choice such that a large standardized covariance yields a less conflicted choice. In contrast, when facing options with a small standardized covariance people have to make more difficult trade-offs, making it harder to identify the better option.

### Theories That Take Covariance Into Account

How can the observed effects of associations between the consequences of choice options be

explained? As described above for the decision situations of Figure 1, DFT assumes that people accumulate information about the differences between the outcomes over time until a decision threshold is reached. The smaller the variance of the differences, the more likely it is that the threshold for the option with the larger expected value will be passed. This variance of the difference incorporates the variance of the outcomes within both choice options and also the covariance between them. Busemeyer and Townsend (1993, p. 439) noted that increasing the similarity, expressed by a higher covariance between outcomes, makes the better choice option easier to discriminate. They named the valence difference divided by the variance of this difference the “discriminability ratio.” The closed form representation of DFT reflects the process of accumulation of evidence by this discriminability ratio, such that the smaller the discriminability ratio, the less evidence is accumulated. This ratio is multiplied by the decision threshold, which reflects how much information has to be accumulated for the decision to be made.

Our results confirm these theoretic predictions by showing that the discriminability ratio in DFT can reflect the choice difficulty. Because in our studies, we kept the valence difference constant, the discriminability ratio depends only on the variance of the differences. When the variance of the difference is large, the choice is difficult and the decision maker accumulates evidence in favor of both options. In contrast, when this variance is low, the choice is easy and the accumulated evidence mainly favors one option.

The predictions of DFT for the small and medium covariance conditions did not differ very much in Study 1, whereas the predictions differed substantially in Study 2. Presumably, this is because the gambles in Study 2 had four outcomes, which makes the similarities between gambles’ outcomes easier to distinguish. For example, if a four-outcome Gamble A is characterized by variance  $\sigma_A^2$ , this variance will describe the difference between the smallest and the largest outcomes of Gamble A. However, there are intermediate outcomes, which provide additional information. In contrast, when a gamble has two outcomes, variance  $\sigma_A^2$  of the same size will describe the difference between all two outcomes. Therefore, options in the me-

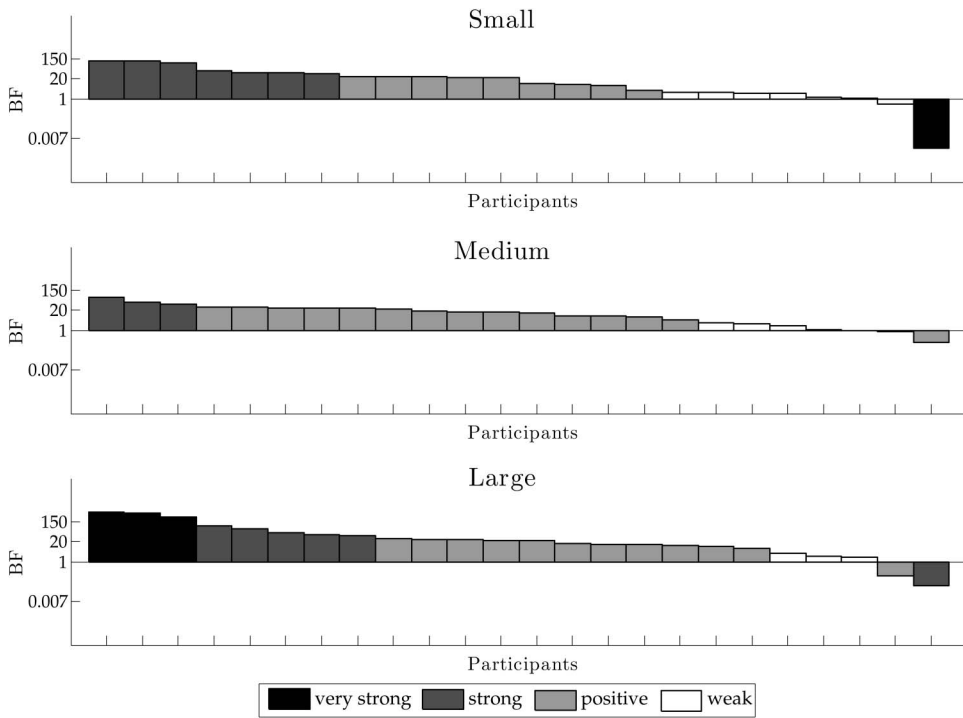


Figure 7. Evidence in favor of decision field theory over expected utility theory, expressed by the Bayes factor (BF) on a logarithmic scale, in Study 2. The strength of the evidence is categorized following Kass and Raftery (1995).

dium covariance condition in Study 1 may seem less similar to each other than options in Study 2 because there is less information (fewer attributes) that can be sampled.

RT (Loomes & Sugden, 1982) incorporates the variance of the valence difference in the regret function. When two choice options have similar outcomes, the regret of not having chosen the slightly better option is very low, whereas it is high for the events for which the options differ substantially. When two options are dissimilar for all events, the total regret will be particularly high, making the choice difficult.

DFT and RT are not the only theories that can explain how covariance can affect people's preferences. For example, the similarity model described by Rubinstein (1988) or Leland (1994, 1998) provides an alternative account. The similarity model assumes that attributes for which the two choice options have similar values are disregarded when comparing the options with each other. Therefore, the decision is then

based on the attributes for which one of the options has a clear advantage.

González-Vallejo's (2002) proportional difference model proposes that options are compared attribute-wise and for each attribute the proportional differences between options are accumulated to favor one or the other option (see also Scheibehenne, Rieskamp, & González-Vallejo, 2009). Analogously, Payne, Bettman, and Johnson (1988) describe a number of decision strategies, including lexicographic rules, that assume a comparison of the options' outcomes with each other (see also Rieskamp & Hoffrage, 1999, 2008).

In contrast, fixed utility theories, including EU and CPT that assume independent evaluations of options, cannot explain the systematic influence of covariance. However, attempts have been made to relax the independence assumption in these models to capture these effects, for example by adding a specific error model to the theory (Hausman & Wiese, 1978).

Accordingly, one could specify a choice rule that determines the choice probabilities by taking the covariance into account (see [Appendix](#)). Despite the fact that such an amendment might improve the prediction of the theory, it lacks the psychological explanation that RT and DFT provide.

Here, the only mathematical difference between EU with a covariance error model and DFT was that EU defined the difference between utilities rather than between the valences. EU with the covariance error model successfully described the pattern observed in the data but had higher log-likelihood values as compared to DFT. When comparing the models by their BIC values, DFT did better for 89% of the participants, indicating that a more complex EU model with the error model overall did not provide a better description of the decision process compared to DFT.

In sum, there is a large body of research showing that people make choices by comparing the options' outcomes against each other. The present work shows that the strength of the association has a systematic, nonlinear influence on people's preferences that can be quantified based on a standardized covariance measure. Along the same lines, [Mellers and Biagini \(1994, p. 506\)](#) pointed out that "similarity effects are predicted [ . . . ] when [the function describing the difference between two options' attributes] is nonlinear." Here, we showed that the covariance effect is quantifiable and that it can be explained by decision theories such as DFT and RT that assume an interdependent evaluation of choice options.

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Appendix

Specification of Selected Models of Decision Making

Expected Utility Theory

Expected utility (EU) theory (von Neumann & Morgenstern, 1954) defines the expected utility of an option A with I outcomes by

$$EU(A) = \sum_{i=1}^I p_i u(x_i), \tag{A1}$$

where p represents the probability that outcome i will occur, and x is the outcome's value. We defined the utility of an outcome x<sub>i</sub> (i.e., a monetary payoff) by a power function:

$$u(x_i) = \begin{cases} x_i^\alpha, & x_i \geq 0 \\ -(-x_i)^\alpha, & x_i < 0 \end{cases} \tag{A2}$$

where the parameter α determines a person's risk attitude. Equation 4 defines the choice probability of EU.

Cumulative Prospect Theory

As defined in Tversky and Kahneman (1992), the overall subjective value of option A is defined as

$$V(A) = \sum_{i=1}^I \pi(p_i) \cdot v(x_i), \tag{A3}$$

where the subjective value of an outcome is defined as

$$v(x_i) = \begin{cases} x_i^\alpha, & x_i \geq 0 \\ -\lambda(-x_i)^\beta, & x_i < 0 \end{cases} \tag{A4}$$

where α and β define the curvature of the utility function of gains and losses correspondingly and λ ≥ 1 specifies loss aversion.

The probability weighting function π(p<sub>i</sub>) accounts for the individual perception of the outcomes' probabilities and is defined as

$$\pi(p_i) = \begin{cases} \sum_{x_i \geq x} w(p_i, \gamma) - \sum_{x_i > x} w(p_i, \gamma), & x_i \geq 0 \\ \sum_{x_i \leq x} w(p_i, \delta) - \sum_{x_i < x} w(p_i, \delta), & x_i < 0 \end{cases} \tag{A5}$$

$$w(p_i) = \frac{p_i^c}{(p_i^c + (1 - p_i)^c)^{1/c}} \tag{A6}$$

with c = γ for positive and zero payoffs and c = δ for negative payoffs. The choice probability of cumulative prospect theory (CPT) can be defined by Equation 4.

Regret Theory

In the current work, following Pathan et al. (2011), we define the regret function R<sub>i</sub> of choosing option A with outcomes x<sub>i</sub>, i ∈ {1, . . . , I} and probabilities p<sub>i</sub>, over option B with outcomes y<sub>i</sub> and probabilities p<sub>i</sub> as

$$R_{iA} = \ln(1 + \exp(\beta \cdot (x_i - \max(x_i, y_i)))) \tag{A7}$$

where β is a parameter of the sensitivity to the losses and corresponds to the curvature steepness of the exponential function. The total

(Appendices continue)

regret of choosing an option with several possible outcomes (Loomes & Sugden, 1982) is

$$R_A = \sum_{i=1}^I R_{iA}. \tag{A8}$$

The probability of choosing option A over option B is estimated using an exponential choice rule:

$$\Pr(A|A, B) = \frac{1}{1 + \exp[\theta(R_B - R_A)]}, \tag{A9}$$

with  $\theta$  as a free sensitivity parameter of the model (in contrast, Pathan et al., 2011 used a constant sensitivity parameter of  $\theta = 1$ ).

### Decision Field Theory

Decision field theory (DFT) is similar to the probabilistic versions of the regret theory (RT) such that the regret effects results from dividing the mean valence difference by the standard deviation of the valence difference (Busemeyer & Townsend, 1993). The difference between the options can be determined by

$$d = v(A) - v(B), \tag{A10}$$

where  $v$  is an option's subjective value defined as

$$v = \sum_{i=1}^I W(p_i)u(x_i) \tag{A11}$$

and  $I$  is the number of possible outcomes,  $W$  is a continuous random variable representing attention weights assigned to each possible outcome of an option, and  $u(\cdot)$  represents the utility of outcome  $x$ . In the current study, for simplicity, we assume that  $W(p_i) = p_i$  and  $u(x_i) = x_i$ . The decision threshold chosen by the decision maker  $\theta_{DFT}^*$  is proportional to the standard deviation of the differences, and the threshold  $\theta$  (see Equation 1) is equal to  $\theta_{DFT}^*/\sigma_d$ .

### Expected Utility Theory With a Covariance-Depending Error Model

Equation 4 presents a standard way of specifying the choice probabilities. However, by combining Equation 4 with Equation 2, the choice probabilities could also take dependencies between options' outcomes into account. Thereby, the error model of EU accounts for the covariance. Accordingly the choice probabilities could be specified as

$$\Pr(A|A, B) = \frac{1}{1 + \exp\left[\frac{\theta(EU(B) - EU(A))}{\sigma_d}\right]}, \tag{A12}$$

where  $\sigma_d$  is defined by Equation 2 and  $\theta$  represents the choice sensitivity.

The estimated  $\alpha$  parameters in both experiments oscillated around 1 ( $M_\alpha = .98$ ,  $SD_\alpha = .08$ ) for most of the participants, indicating that the variance of the difference already accounts for both the association and riskiness of the options and in the case at hand,  $\alpha$  becomes redundant.

### Simulation and Parameter Estimation

Following Harrison and Rutström (2009) and Rieskamp (2008), the predictions in the simulation are based on parameter values that lead to predicted choice probabilities that are on average, on the similar level for the different theories. These were EU:  $\alpha = .867$ ,  $\theta = .23$ ; CPT:  $\alpha = .93$ ,  $\beta = .89$ ,  $\gamma = .77$ ,  $\delta = .76$ ,  $\lambda = 1$ ,  $\phi = .18$ ; RT:  $\beta = .05$ ,  $\theta = 4.6$ ; and DFT:  $\theta = 1.19$ .

In Study 1 and Study 2, we estimated parameters using a maximum log-likelihood approach. The parameter space was restricted to reasonable ranges: EU:  $\alpha \in [0, 3]$ ; CPT:  $\alpha \in [0, 3]$ ,  $\beta \in [0, 3]$ ,  $\delta \in [0, 1]$ ,  $\gamma \in [0, 1]$ ; and RT:  $\beta \in [0, 1]$ . The loss aversion parameter  $\lambda$  of CPT was irrelevant as no mixed gambles were included (i.e.,  $\lambda = 1$ ). The sensitivity parameters ( $\theta$  or  $\phi$  for CPT) were allowed to range between 0 and 40.

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