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Distinguishing three effects of time pressure on risk taking: Choice consistency, risk preference, and strategy selection

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Abstract

Quick decision making under risk is ubiquitous in modern times, yet its consequences are not fully understood. Time pressure might change people's risk preferences, lead to less consistent choices, or change people's decision strategy. With the present work, we make the novel contribution of testing all hypotheses against each other in a unifying hierarchical Bayesian model. In two studies, participants decided repeatedly between two risky gambles either with or without high time pressure. We found a significant increase in risky choices under time pressure. With modeling, we show that time pressure decreased choice consistency but did not systematically affect people's risk preferences. In addition, the number of participants using simple, noncompensatory strategies increased slightly under time pressure. Finally, participants did not systematically choose easier gambles more often under time pressure. Thus, a reliable analysis of the effect of time pressure on preferential choice requires a model framework that allows for the distinction between the various effects time pressure can have.

KEYWORDS

finite-mixture model, gamble complexity, random utility, risky choice, time pressure

1 | INTRODUCTION

In business and in private, decisions are often made quickly. This happens when an investor needs to react quickly to incoming information in trading, when investment offers are made with a time limit, or when opportunity costs of evaluating an investment choice must be considered. Risk is ubiquitous in investment choices, and risk preferences are at the core of economic utility models. To understand how time pressure affects choices under risk is thus an important topic from both a practical and a theoretical standpoint.

Past research suggests that time pressure can make people more or less risk averse (e.g., Madan et al., 2015; Zur & Breznitz, 1981). Such an effect would have important consequences, as it implies that investment choices are systematically distorted when under time pressure and not in accordance with investors' risk preferences without time pressure.

Yet there is an often overlooked but very plausible alternative explanation of this effect, namely, that decisions could become more inconsistent because they involve more noise. This means choice consistency is reduced, but choices are on average still unbiased with respect to the underlying risk preferences under no time pressure. In addition, a change in observed choices could also be the result of people selecting simpler and thus quicker decision strategies under time pressure. Our goal in the present work was to test these competing hypotheses rigorously against one another to provide a better understanding of the effect of time pressure on decision making under risk.

1.1 | Preference shifts

Most previous studies suggested that people in the gain domain become less risk averse under time pressure compared with under low or no time pressure. This conclusion was based on choice proportions directly (Madan et al., 2015; Saqib & Chan, 2015), on modeling of certainty equivalents with cumulative prospect theory (Young et al., 2012), or on modeling behavior in a card game with a mean–variance model and cumulative prospect theory (Nursimulu & Bossaerts, 2014). Yet some studies did not find evidence for a preference shift in the gain domain: in one study, this inference was based on a preference rating of risky scenarios (Maule et al., 2000). In another, either individually time-constrained risky decisions or time-constrained multiple price lists were examined (Kocher et al., 2013). Finally, people were also found to become more risk averse when under time pressure by, again, comparing risky choice proportions under conditions of low and high time pressure (Zur & Breznitz, 1981). An explanation of a direct shift in risk preferences through time pressure could be an increased influence of intuition or affect (e.g., Young et al., 2012).

As a limitation, inferences about the effect of time pressure can be ambiguous when based on comparisons of choice proportions only. For instance, suppose participants in an experiment choose the riskier of two gambles with a similar expected value (EV) in around 40% of all cases, which could be interpreted as risk aversion. If the proportion of riskier choices increases to around 45% under high time pressure, this could be interpreted as a decrease in risk aversion due to time pressure. However, if participants make more unsystematic mistakes under high time pressure and choices become less consistent, the choice proportions would also change toward 50%. Thus, in this case, both a preference shift and a decrease in consistency could explain the observed choice data (see Olschewski et al., 2018).

1.2 | Decrease in choice consistency

A theoretical framework useful for understanding the effect of time pressure is the speed–accuracy trade-off, where higher decision speed is associated with more errors or less consistency (Heitz, 2014, for a review). This trade-off is predicted by the drift diffusion model, a prominent sequential sampling model of decision making (for a review, see Ratcliff & McKoon, 2008). Experimental evidence for this trade-off in human decision making was found, for instance, in the dot-motion task, where participants have to decide in which direction a cloud of dots is predominantly moving. Applying time pressure in such a task increases error rates (Forstmann et al., 2008).

This trade-off might have been given less attention in the preferential decision-making literature because in the domain of preferences, no (or only a few) outside criteria exist for classifying a single decision as an error. One way to address this problem is to make people rate options individually and define an error in a subsequent binary choice task as the choice of a lower rated option. Under these conditions, participants made more errors under time pressure than in a control condition in food choices (Milosavljevic et al., 2010). However, this method assumes that individual ratings translate to format-independent utility orders.

Here, we propose another method to measure decision errors. Assuming a person's risk preference can be represented by an expected utility framework, options can be ordered according to their utility. In this case, choice consistency is a measure of how many empirically observed choices are in accordance with the underlying utility order. The higher the consistency, the fewer deviations from a given utility order have been made. The random utility model we introduce below can estimate the best fitting utility order and the associated choice consistency simultaneously for a given choice pattern.

In risky choices, time pressure has rarely been associated with a decrease in choice consistency. As an exception, Dror et al. (1999) estimated a sequential sampling model and concluded that time pressure decreased the decision threshold parameter of the sequential sampling model, leading to a decrease in choice consistency. A limitation of this study is that it did not test a change in risk preferences as an alternative response to time pressure within the sequential sampling model.

1.3 | Strategy shifts

When people make decisions, they can in principle incorporate all information (i.e., all outcomes and probabilities of a gamble) and integrate the information for an overall assessment. But under time pressure, participants might realize that they cannot process all information or have insufficient time to integrate all information sensibly, so they may select a simpler strategy for making their choices. A strategy shift is an alternative explanation for a change in risk-taking behavior (e.g., Kocher et al., 2013) and the meta-decision to change strategies is at the core of the adaptive-decision-maker framework (Payne et al., 1993).

Decision strategies differ in various aspects, such as the number of steps they require. One fundamental distinction is that between compensatory and noncompensatory (NC) strategies: compensatory strategies usually make use of all available information and allow for compensation—that is, an option's disadvantages can be compensated for by its advantages. In contrast, NC strategies often focus on a single dimension of an option, and if an option is doing badly on this dimension, it cannot be compensated for by other dimensions. A prominent example of a compensatory strategy is the mean–variance model (e.g., Spiliopoulos & Hertwig, 2019), which summarizes all possible outcomes in the EV and captures the variability of these outcomes as the standard deviation (SD). Prominent NC strategies are the lexicographic rule (e.g., Fishburn, 1974) and the priority heuristic (Brandstätter et al., 2006), which both compare options by focusing on single pieces of information.

When making decisions under time pressure, people are more likely to select simple NC strategies over compensatory ones (e.g., Payne et al., 1988, 1996; Rieskamp & Hoffrage, 1999, 2008;

Svenson & Maule, 1993; Wright, 1974). However, most research about strategy shifts has not explicitly examined whether time pressure also leads to changes in people's risk preferences.

Another strategic reaction to an increase in time pressure could be to stick to options that are easier to comprehend and stay away from more complex options. There are formal ways to define complexity of choice problems (Bossaerts & Murawski, 2017), but for risky gambles, complexity is often operationalized as a gamble's number of outcomes (e.g., Moffatt et al., 2015): the higher the number of outcomes, the more numbers participants have to process. In addition, the more numbers there are, the more difficult it is to determine a gamble's characteristics, such as the EV or SD. Prior studies found that people chose easier gambles more often than complex ones regardless of time pressure (Huck & Weizsäcker, 1999; Mador et al., 2000; Wilcox, 1993). However, a recent study showed that only 50% of the participants systematically chose easier options more often (Moffatt et al., 2015). To our knowledge, the potential effect that time pressure leads to a higher frequency of choosing simpler gambles has not been tested yet.

1.4 | The current approach

In summary, there are three ways time pressure might change risk-taking behavior: by causing (a) a direct change in risk preferences, (b) a decrease in choice consistency within a compensatory strategy, or (c) a switch from a compensatory to an NC strategy. Most previous research has examined one of these hypotheses in isolation. As we showed above, this can be problematic, because all three explanations can lead to similar behavioral patterns. Mathematical models are necessary to distinguish among them.

Consequently, we chose to examine all three hypotheses simultaneously using a unifying hierarchical Bayesian modeling framework. We examined data collected in two experiments where participants decided repeatedly between risky gambles either under high time pressure or in a control condition with low time pressure using a within-subject design.

2 | MATHEMATICAL MODELS

2.1 | Random utility framework

To model risk preferences, we implemented the mean–variance approach as a compensatory model stating that both the EV and the SD of a gamble contribute to its utility:

$$U(a) = EV(a) + \beta * SD(a), \tag{1}$$

where a is a gamble with two or four outcomes. For gambles with one certain outcome, the SD is set to 0. The risk preference parameter β specifies whether and to what extent people are risk averse (i.e., $\beta < 0$), risk neutral (i.e., $\beta = 0$), or risk seeking (i.e., $\beta > 0$). Stochasticity in the choice process is modeled with a probit link function:

$$p(y) = \phi\left(\frac{U(y) - U(x)}{\theta}\right), \tag{2}$$

with $U(y)$ and $U(x)$ as the utility of two gambles x and y defined as in Equation 1. The probit link function $\phi()$ maps the utility difference into choice probabilities between 0 and 1. The consistency parameter θ determines how sensitively the model responds to utility differences, with smaller θ implying more consistent behavior.

There are other error models used in the literature (e.g., Stott, 2006) that we implemented for robustness analyses. Among the most prominent alternative link functions is the logit function:

$$p(y) = \frac{1}{1 + \exp(-\varphi * (U(y) - U(x)))}. \tag{3}$$

Here, larger φ implies more consistency, that is, less error. A simpler link function between utility order and choices that does not take the utility difference between gambles into account is the constant or trembling-hand error model (Harless & Camerer, 1994):

$$p(y) = I[U(y) > U(x)] * (1 - \rho) + I[U(y) < U(x)] * \rho + I[U(y) = U(x)] * 0.5, \tag{4}$$

with ρ a free parameter estimating the percentage of trials where an inferior gamble according to the assumed utility model is chosen. The higher ρ is, the larger the error and thus the lower the choice consistency. $I(a)$ is an indicator function that takes the value of 1 if statement a is true and the value of 0 if a is false.

We estimated all models with a hierarchical Bayesian approach. This means we estimated posterior distributions of the β and θ parameters for each participant. The individual posteriors then fed into a group posterior distribution. We experimentally manipulated time pressure and gamble complexity in the two experiments using a within-subject design. To incorporate the effects of both manipulations, we decomposed β and θ according to our within-subject design. For each trial i and each participant j, we got

$$\beta_{i,j} = \beta_{0,j} + \delta_{\beta,j} * cond_{i,j} + \beta_{safe,j} * easy_{safe,i,j} + \beta_{risky,j} * easy_{risky,i,j}, \tag{5}$$

$$\theta_{i,j} = \theta_{0,j} + \delta_{\theta,j} * cond_{i,j} + \theta_{safe,j} * easy_{safe,i,j} + \theta_{risky,j} * easy_{risky,i,j}. \tag{6}$$

Here, $\beta_{0,j}$ and $\theta_{0,j}$ are the individual means, and the δs estimate half of the difference between conditions operationalized as a dummy variable *cond* that is +1 in the control and −1 in the time pressure condition. Similarly, to assess the effect of gamble complexity on both risk preference and choice consistency, we used two effect-coded dummies ($easy_{safe}$ and $easy_{risky}$) for trials where the safer or the riskier gamble was easier, respectively, with the complex trials as the baseline. In the data model, $\theta_{i,j}$ is probit transformed to be between 0 and 1.

2.2 | Compensatory and NC strategies

To examine the hypothesis of a strategy shift under time pressure, we used a Bayesian finite-mixture model (Bartlema et al., 2014; Gelman et al., 2014) with two mixture variables: on the first layer, data were described by either a compensatory or an NC strategy. On the second layer, a mixture variable determined which of three NC strategies was implemented. Both mixture variables were implemented on the group level. This means we assume heterogeneity across participants with respect to the used strategies, but a given participant uses the same strategy in all trials in a given condition.

The compensatory strategy was represented by the stochastic utility model outlined in Equations 1 and 2. It is compensatory because a potential bad outcome of a gamble can be compensated for by a potential good outcome. Compensatory strategies are usually assumed to be attention and time consuming (e.g., Payne et al., 1993; but see Glöckner & Betsch, 2012).

We incorporated three NC strategies, which each use single outcome comparisons sequentially in different orders. In these strategies, a good second outcome cannot make up for a bad outcome used for comparison. The outcome comparison stops as soon as a comparison of two outcomes results in a noticeable difference and the gamble with the higher outcome is chosen. The NC strategies have two free parameters: one is the threshold μ that determines how large the difference between two outcomes has to be to lead to a decision. Theoretically, this threshold is motivated by research in psychophysics that shows two stimuli need a minimum difference for participants to reliably detect it (just noticeable difference: Thaler, 1980; Thurstone, 1927; see also Fishburn, 1974). The second free parameter ϵ is a trembling-hand error (see Equation 4) as the percentage of times the inferior gamble (i.e., the gamble with the lower outcome) is chosen by mistake. Although such a choice function usually does not fit data as well as the above-applied probit function, it is more plausible for NC strategies where we assume that comparisons are made on an ordinal scale. If no outcome comparison leads to a decision, then one of the two gambles is chosen randomly.

The choice probabilities are calculated as follows:

$$p(y) = \begin{cases} \text{if } x_1 > (y_1 + \mu) \Rightarrow \varepsilon \\ \text{if } y_1 > (x_1 + \mu) \Rightarrow 1 - \varepsilon \\ \text{else}: \\ \text{if } x_2 > (y_2 + \mu) \Rightarrow \varepsilon \\ \text{if } y_2 > (x_2 + \mu) \Rightarrow 1 - \varepsilon \\ \text{else}: \\ \ldots \\ \text{else} \Rightarrow 0.5 \end{cases} \tag{7}$$

where one outcome from gamble x will be compared with one outcome from gamble y and the subscripts signify a certain order of outcome comparisons: Order 1 sorts all outcomes according to their probability of occurrence, starting with the outcome with the highest probability. Order 2 sorts by outcomes and starts comparing the highest outcomes of each gamble. Finally, Order 3 again sorts by outcomes but starts comparing the lowest outcomes of each gamble. Although these NC strategies do not take risk preferences explicitly into account, the comparison order can produce risk-averse choices; for example, when starting by comparing the lowest outcomes of each gamble as in Order 3, the safer gamble usually has a higher minimum outcome then the more risky gamble implying risk-averse choices (see Pachur et al., 2017).

To examine whether time pressure increased the use of NC strategies, we again used the dummy variable *cond* and modified the mixture variable on the group level accordingly:

$$z_{\text{cond}} = z_0 + \delta_z * cond. \tag{8}$$

Here, z_{cond} is the probability of a Bernoulli distribution of implementing either the compensatory or one of the NC strategies on the group level. The higher z_{cond} is, the more participants are described by one of the NC strategies. In the data model, z_{cond} is probit transformed to be between 0 and 1. The mixture variables on the second layer (g_1, g_2, and g_3) determining which NC strategy was implemented as well as the threshold and the trembling-hand error for the NC strategies were fixed across both conditions on the group level.

We used uninformative group priors and estimated all parameters with the MCMC sampler from JAGS in R (Plummer, 2003). Convergence of estimation chains was checked with the Gelman and Rubin (1992) statistic, which was below 1.03 for all reported group posteriors.

3 | EXPERIMENT 1

3.1 | Method

3.1.1 | Experimental design

Participants made 240 choices between two gambles in two blocks. In each block, there was a countdown at the upper right corner of the screen that indicated the time until a decision was required. Participants saw the same 120 gambles in each block in randomized order.

Gambles were created by randomly drawing outcomes and probabilities, controlling for informative choice situations in terms of EV and SD differences. The complexity of the gambles was varied in three within-subject conditions. In the complex condition, both gambles consisted of two outcomes, where the outcomes and their respective probabilities were never multiples of 10. In the safe-easy condition, the safer gambles were always a sure outcome, and the riskier gambles were constructed as in the complex condition. In the risky-easy condition, the riskier gambles (i.e., those with the larger variance) both had outcomes that were multiples of 10 and occurred with equal probability of 50%, which made this option simpler to evaluate,

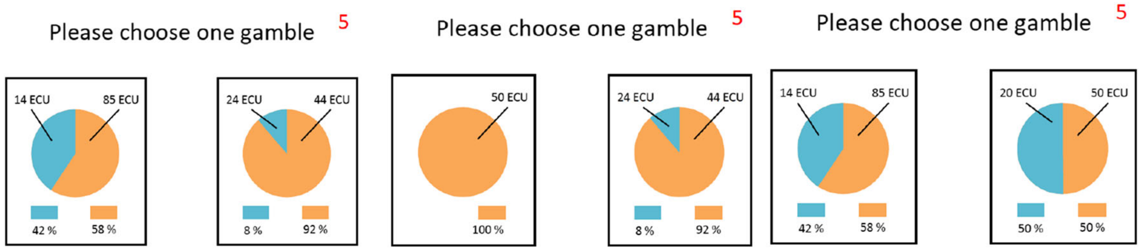

FIGURE 1 Schematic screenshots of the decision screen. Left: complex gambles; middle: safe-easy condition; right: risky-easy condition. ECU refers to the artificial currency used throughout the experiment, and the red number at the top-right corner indicates the time left

whereas the safer option was constructed as in the complex condition. That way, although the number of outcomes and probabilities were the same for both gambles, the riskier gamble was easier to process.

3.1.2 | Time pressure manipulation

In the control condition, we introduced very low time pressure by giving participants 30 s to make a choice, whereas under high time pressure, participants had only 2 s. We derived this manipulation through pretesting. We first gave people two certain outcomes with pie charts in the same format as in the main study and asked them to decide which outcome was larger. The median reaction time for that task was 1.80 s with high accuracy. This seemed to be a good estimate of the information-processing time needed by participants.

3.1.3 | Participants and incentive

We aimed for 40 participants, because previous experience with the hierarchical Bayesian model indicated that a comparable sample size with risky choices led to robust estimation results. The study was approved by the Institutional Review Board of the Department of Psychology at the University of Basel. Participants were 43 current or former students of the University of Basel (nine male, 34 female; M_{age} = 23.53 years; range 19 to 43 years).

Participants were given the choice between receiving course credit or a flat payment of CHF 20 per hour. In addition, one trial was randomly drawn and the outcome paid out. Participants earned an average bonus of CHF 6 (range: CHF 1 to 9.90). The experiment lasted around 1 h.

3.1.4 | Procedure

The experiment was conducted at individual computers. Participants read the instructions on paper and answered two questions to check if they understood the task. Only when they answered both questions correctly were they allowed to continue with the experiment. The order of the control and time pressure blocks was alternated. One block consisted of 120 trials with constructed gamble pairs presented in random order.

Prior to each trial a fixation cross appeared in the middle of the screen for 300 ms. Gambles were presented as pie charts (see Figure 1). Participants could choose one of the two gambles by pressing "D" for the left or "L" for the right option. After a choice, the respective gamble was marked with a blue rectangle for 300 ms, and then, a new trial was presented. Once the decision time was up, participants were not able to make a choice. Instead, a screen appeared for 1 s stating that they were too slow. Participants did not earn any bonus when a trial was chosen in which they did not make a choice in time.

3.2 | Results

3.2.1 | Choice data

Participants chose the riskier (i.e., higher SD) gamble in 36% of the trials in the control and in 40% in the time pressure condition, a significant difference, $W(n = 43) = 276.5$, $p = .029$.[1] Figure 2 plots the percentage of risky choices against the EV difference of the two gambles. Choices for riskier gambles increased with EV in both conditions ($b_{EV} = 0.05$, $SE = 0.002$, $p < .001$). The less steep slope in the figure shows that the EV difference had a stronger impact on choice proportions in the control than in the time pressure condition, indicating that choice consistency was lower in the high time pressure condition.

The complexity of gambles had an influence on choice proportions. The proportion of risky choices was lower in the safe-easy trials (34%; $b_{safe} = -0.24$, $SE = 0.06$, $p < .001$) and higher in risky-easy trials (43%; $b_{risky} = 0.30$, $SE = 0.06$, $p < .001$), each compared with the complex trials (37%). Figure 3 shows the choice proportions separately for the control and time pressure conditions and the three different gamble complexities.

3.2.2 | Reaction time data

Reaction times were significantly different in the control ($Mdn = 3.63$ s, $SD = 2.75$) and time pressure ($Mdn = 1.78$ s, $SD = 0.53$) conditions, $W(n = 43) = 946$, $p < .001$. Figure 4 shows the median

[1]*W* stands for a Wilcoxon test, which was used for the percentage of risky choices to make the test robust against a nonnormal distribution of the data.

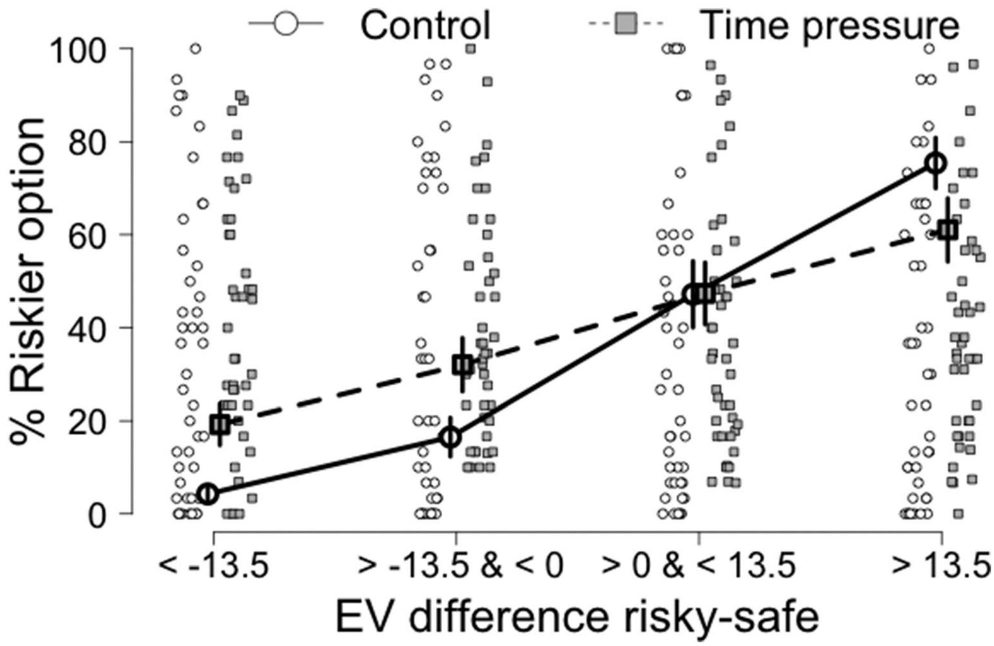

FIGURE 2 Choice percentages for the riskier gamble by expected value (EV) differences between riskier and safer gambles on the group (line and larger dots) and individual (smaller dots) level. Error bars are 95% confidence intervals

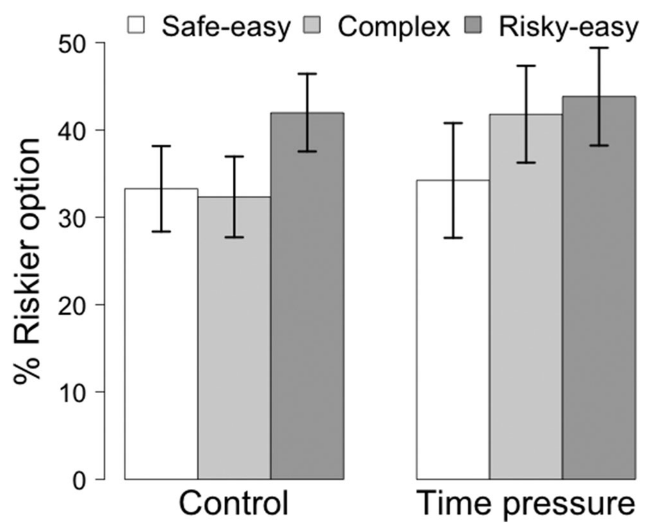

FIGURE 3 Percentage of riskier choices in control and time pressure conditions for each of the three levels of gamble complexity. Error bars are 95% confidence intervals

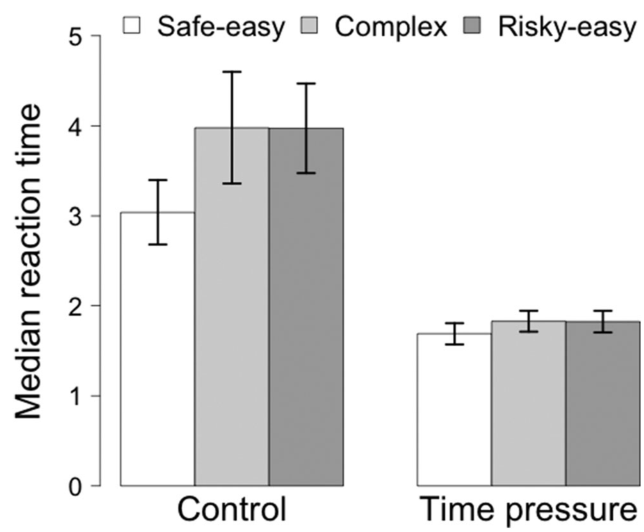

FIGURE 4 Median reaction times (in seconds) in control and time pressure conditions for each of the three levels of gamble complexity. Error bars are 95% confidence intervals

reaction times for the different conditions. Choices in the safe-easy condition were faster than in the complex condition (b_{safe} = −0.17, *SE* = 0.01, $p < .001$), but choices in the risky-easy condition were made at the same pace as in the complex condition. This could indicate that the risky-easy gambles were not perceived as easier than the complex gambles.

3.2.3 | Modeling choice data

We used the mean–variance model outlined in Equations 1 and 2 to estimate people's risk preferences and choice consistency simultaneously. In the baseline model, ignoring complexity, the group-level estimate for the risk preference parameter was β_0 = −0.39, 95% highest density interval (HDI) [−0.53, −0.25], meaning that people were risk averse on average. The group-level choice consistency parameter was θ_0 = −0.76, 95% HDI [−0.80, −0.72]. The group-level effect of time pressure on risk preference was δ_β = 0.01, 95% HDI [−0.06, 0.09]. The 95% posterior HDI included 0; thus, there was no credible effect of time pressure on participants' risk preferences. In contrast, the group-level effect of time pressure on choice consistency was δ_θ = −0.29, 95% HDI [−0.36, −0.23]. The posterior 95% HDI did not include 0; thus, time pressure credibly decreased participants' choice consistency. Retransformed to the scale of the data model, the consistency parameter was estimated to be 0.15 in the control condition and 0.32 under time pressure. Figure 5 shows that the individual effects of time pressure on risk preference were rather unsystematic, whereas the individual estimates of choice consistency decreased for almost all participants under time pressure.

Note that this result modified the model-free analysis of choice data reported above: whereas the regression revealed an effect of time pressure on choice proportions, the stochastic utility model decomposed this effect into a possible shift in risk preferences or in choice consistency. The model identified a decrease in choice consistency rather than a shift in risk preferences as the more likely explanation for the observed change in choice proportions under time pressure.

To test the robustness of this result, we implemented other stochastic link functions as discussed above, namely, the logit function (Equation 3) and the trembling-hand error (Equation 4). With a logit link function, we again found that risk preferences did not change, δ_β = 0.03, 95% HDI [−0.05, 0.10], whereas the logit consistency parameter did change under time pressure, δ_φ = 0.32, 95% HDI [0.25, 0.39]. This again implies less choice consistency under time pressure. Similarly, for the trembling-hand error, risk preference did not change, δ_β = 0.02, 95% HDI [−0.06, 0.11], but the trembling-hand error credibly differed between the two conditions with δ_ρ = −0.31, 95% HDI [−0.40, −0.21]. This means that under time pressure, participants more often chose the option with the lower latent utility. In sum, a credible decrease in choice consistency due to time pressure is robust to the use of these alternative error models.

3.2.4 | Gamble complexity

To incorporate the effect of gamble complexity, we included two dummies with the complex condition as a baseline as outlined in Equations 5 and 6. We added these dummies as well as the interaction of complexity with time pressure sequentially for both the risk preference and the consistency parameters. The full model with complexity as a main effect and the interaction effects for both risk preference and choice consistency parameters fitted the data best according to WAIC (Vehtari et al., 2017). In all specifications, the main effect of time pressure was credibly different from 0 for the choice consistency parameter but not for the risk preference parameter. Group posteriors were also comparable in magnitude to the more parsimonious specification discussed above. Gamble complexity had a credible effect on risk preference in that risk aversion was stronger in the safe-easy condition (β_{safe} = −0.14, 95% HDI [−0.23, −0.05]) and weaker in the risky-easy condition (β_{risky} = 0.16, 95% HDI [0.09, 0.23]), each compared with the complex condition. Furthermore, gamble complexity credibly increased choice consistency in the safe-easy condition (θ_{safe} = −0.07, 95% HDI [−0.13, −0.004]) but not in the risky-easy condition (θ_{risky} = −0.05, 95% HDI [−0.11, 0.01]). All model results, including estimates for interactions between complexity and time pressure, can be found in Table S1.

3.2.5 | Strategy shift

To examine whether participants applied different strategies under high and low time pressure, we added three NC strategies as described in Equations 7 and 8 to the model. The group-level mixture variable was z_0 = −1.33, 95% HDI [−1.83, −0.88], meaning that across both conditions, behavior of around 10% of the participants were best explained by one of the three NC strategies and 90% of participants were best explained by the compensatory mean–variance model. The group-level effect of time pressure was δ_z = −0.58, 95% HDI [−1.13, −0.08] and credibly different from 0. This means that the probability of classifying a participant as using the NC strategy increased from 4% in control to 23% under time pressure. Based on the individual level posteriors, only one participant in the control condition and eight in the time pressure condition had a higher than 50% posterior probability of their choices being better explained by the NC strategies rather than by the compensatory strategy.

Additionally, the group-level threshold for the three NC strategies was μ = 0.15, 95% HDI [0.05, 0.27] for a standardized outcome range between 0 and 1. The group-level trembling-hand error rate for the NC strategies was ε = 0.16, 95% HDI [0.07, 0.26]. Finally, the three

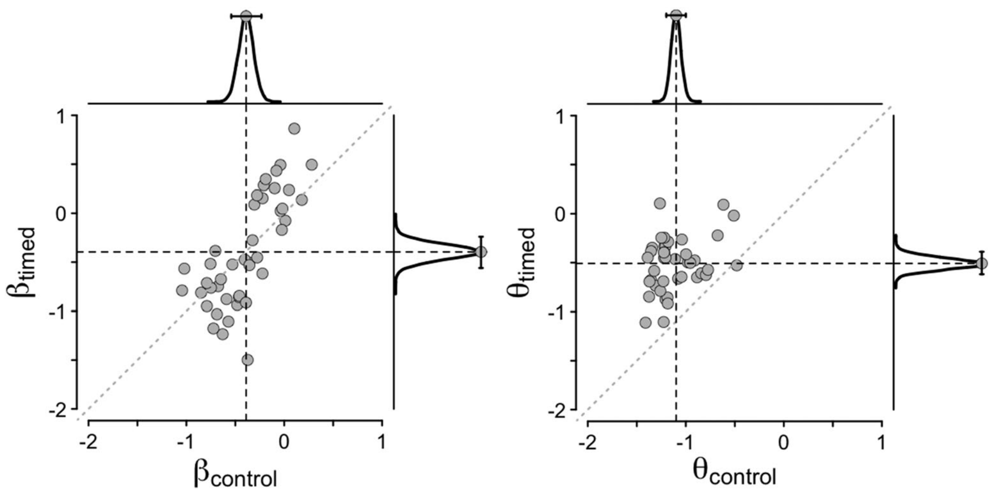

FIGURE 5 Risk preference β (left) and choice consistency θ (right) group posterior parameter estimates at the margins and individual mean posterior estimates in the main graphs. Estimates were retrieved from the full model with complexity main and interaction effects (Model 7 in Table S1)

group-level mixture probabilities were g_1 = 0.08, 95% HDI [0.0001, 0.24], for the probability order; g_2 = 0.18, 95% HDI [0.004, 0.39], for the decreasing outcome order; and g_3 = 0.74, 95% HDI [0.48, 0.96], for the increasing outcome order. This means that the outcome order starting with comparing the lowest outcomes was best suited to explain a participant's behavior if this participant was selected to use an NC strategy.

Finally, even when allowing for the use of NC strategies, the conclusion from the first model held: group-level choice consistency of the compensatory strategy was still credibly lower under time pressure, δ_θ = −0.25, 95% HDI [−0.31, −0.19], whereas risk preference did not differ between conditions, δ_β = −0.03, 95% HDI [−0.10, 0.04].

4 | EXPERIMENT 2

To examine the robustness of the results of Experiment 1, we conducted Experiment 2 in which we used a different complexity manipulation and determined time pressure individually.

4.1 | Method

4.1.1 | Experimental design

Again, we examined the effect of time pressure on risk taking in a within-subject design by asking participants to choose between two risky gambles repeatedly. Complexity was manipulated by the number of outcomes of a gamble. There were three conditions: complex (both gambles consisted of four outcomes each); safe-easy (the safer gamble with lower variance had only two outcomes); and risky-easy (the riskier gamble with higher variance had only two outcomes).

4.1.2 | Gamble stimuli

We randomly created gamble pairs for the experiment similarly to the procedure in Experiment 1. In addition, 10 pairs of gambles were created in each complexity condition where one gamble stochastically dominated the other (in equal numbers, either the safer or the riskier gamble dominated). In the complex condition, we created gambles with four outcomes each; in the safe-easy condition the gamble with the lower SD had only two outcomes; and in the risky-easy condition, the gamble with the higher SD had only two outcomes. Presentation of the gambles was similar to that in Experiment 1 (see Figure 6).

4.1.3 | Time pressure manipulation

Time pressure was individually determined by giving people 75 choices from all complexity conditions in a practice block at the beginning of the experiment. These gamble pairs were created according to the same principles as in the complex condition but were different from those in the main task and were not payoff relevant. As time pressure manipulation, we used the 25% quantile from the reaction times of all choices from the respective participant in the training block. This resulted in an average time limit of 4.12 s in the time pressure condition. In the control condition, there was again a very low time pressure of 30 s.

4.1.4 | Participants and incentives

We recruited 60 participants to increase power compared with Experiment 1. All participants were psychology students and were recruited via the online recruiting platform of the Department of Psychology at the University of Basel. Participants received course credit and a monetary bonus ranging from CHF 1.20 to 19.60 (mean CHF 10.86) for an average study duration of about 1 h. Participants had a median age of 22 years (range 19–51 years); 44 were female and 16 male.

4.1.5 | Procedure

The experiment was conducted on a computer at individual workstations, similarly to Experiment 1. Again, a quiz had to be passed to start

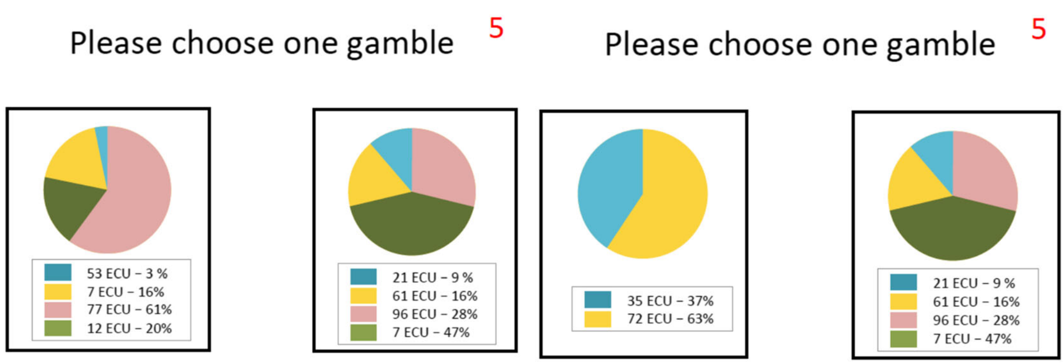

FIGURE 6 Schematic screenshot for the task in Experiment 2 with ECU the currency used during the experiment and the time left indicated at the top-right. Left: decision screen in the complex condition. Right: decision screen when one gamble had two outcomes

the experiment, which consisted of five blocks with 75 choices each. The first block was always the practice block. The second and third blocks were the control or the time pressure conditions with order alternated between participants. As incentive, one trial (excluding the practice block) was drawn to be paid out. If a participant failed to obey the time limit in a choice situation, a red warning message was presented for 1 s, and no choice could be made. If such a trial was drawn for payout, there was no bonus payment.

4.2 | Results

4.2.1 | Choice data

Similar to in Experiment 1, there were fewer risky choices in the control condition (34%) than under time pressure (38%), $W(n = 60) = 344$, $p < .001$. An effect of time pressure on choice consistency is suggested by looking at the percentage of risky choices against different bins of EV differences (Figure 7). As in Experiment 1, there was a crossing point between the control and time pressure lines. This means that under time pressure, choice proportions of the risky gamble were closer to 50% both when the risky gamble was very unattractive and when it was very attractive as compared with the control condition.

To examine the impact of time pressure on choice error, we added a set of gamble pairs with stochastically dominant gambles. Here, one can argue that participants should always choose the dominant option irrespective of their individual risk preferences. Consistently, in only a small proportion (3.33%) of trials did participants choose the dominated riskier gamble in the control condition. However, this error rate increased substantially to 9.70% under time pressure, $W(n = 60) = 69$, $p < .001$. Likewise, participants chose the dominated safe gamble in only 16.79% of trials in control, but this error rate increased to 22.49% under time pressure, $W(n = 60) = 793$, $p = .006$.

Across both conditions, complexity had an effect on the percentage of risky choices (Figure 8): in the complex condition, the risky option was chosen in 34% of all trials, compared with 35% in the safe-easy condition ($b_{safe} = 0.22$, $p < .001$) and 33% in the risky-easy condition ($b_{risky} = -0.22$, $p < .001$). This result differs from Experiment 1 and is not in line with the idea that people are always more likely to choose the easier of two gambles. As seen in Figure 8, the effect of time pressure increased the percentage of risky choices for all complexity conditions.

4.2.2 | Reaction time data

Reaction times were significantly different in control ($Mdn = 4.27$ s, $SD = 3.55$) and time pressure ($Mdn = 2.45$ s, $SD = 1.73$) conditions,

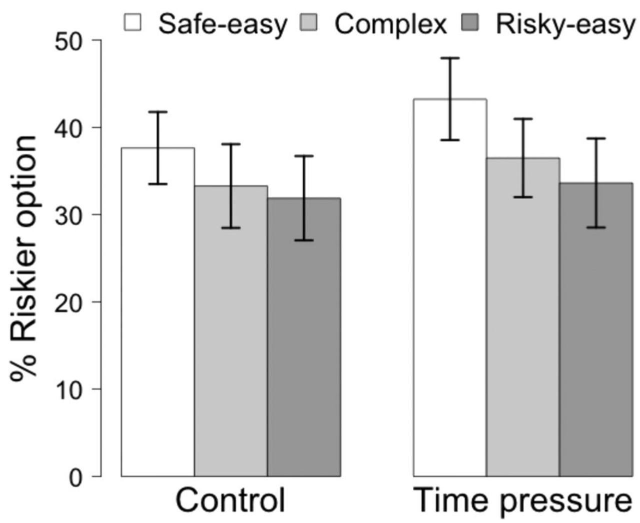

FIGURE 8 Percentage of riskier option choices in control and time pressure conditions for each of the three levels of gamble complexity. Error bars are 95% confidence intervals

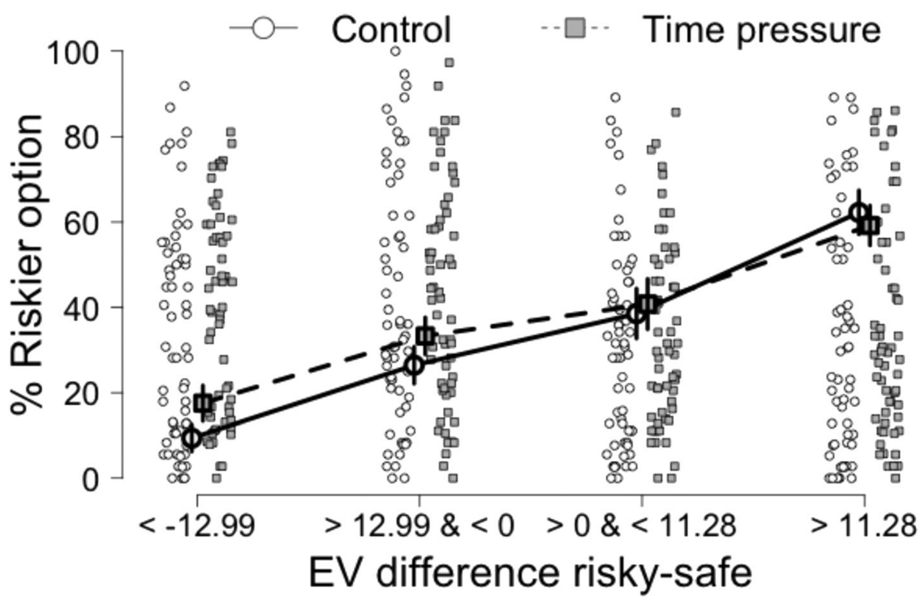

FIGURE 7 Percentage of riskier option choices by mean differences in expected value (EV) between riskier and safer gambles on the group (line and large dots) and individual (small dots) level

$W(n = 60) = 1{,}817$, $p < .001$. There was an effect of block on reaction times in the control trials in that participants were slower in the first blocks ($Mdn = 5.08$ s, $SD = 3.98$) than in the last blocks ($Mdn = 3.65$ s, $SD = 2.83$), $W(n = 60) = 1.686$, $p < .001$. That is, participants became faster during the experiment so that the induced time pressure might have been experienced as less severe at the end of the experiment than at the beginning. Figure 9 shows that participants took longer when both gambles were complex as compared with trials where one gamble had only two instead of four outcomes ($b_{\text{safe}} = -0.10$, $p < .001$; $b_{\text{risky}} = -0.16$, $p < .001$).

4.2.3 | Modeling choice data

Similar to in Experiment 1, we found that time pressure credibly affected the choice consistency parameter θ but not the risk preference parameter β. This result was robust to all model specification, as can be seen in Table S2. The model with the lowest WAIC included main effects of complexity for both the risk preference and the choice consistency parameters. In this model, the group-level risk preference parameter was $\beta_0 = -0.57$, 95% HDI [−0.76, −0.37], showing that people were in general risk averse. The group-level choice consistency parameter was $\theta_0 = -0.49$, 95% HDI [−0.59, −0.39]. The group-level effect of time pressure on risk preference was $\delta_\beta = -0.02$, 95% HDI [−0.06, 0.02]. Because the 95% posterior HDI included 0, there was no credible effect of time pressure on people's risk preferences. In contrast, time pressure credibly reduced people's choice consistency on the group level with $\delta_\theta = -0.14$, 95% HDI [−0.18, −0.09]. Retransformed to the scale of the data model, the consistency parameter was estimated to be 0.26 in the control condition and 0.36 under time pressure. Thus, again, it was choice consistency rather than risk preferences that explained the changes in risky choices under time pressure. Figure 10 shows the group posteriors and individual mean posteriors for both parameters.

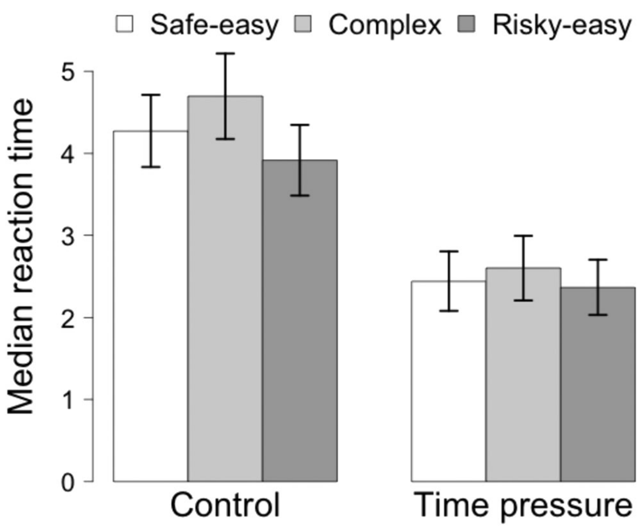

FIGURE 9 Median reaction times (in seconds) in control and time pressure conditions for each of the three levels of gamble complexity. Error bars are 95% confidence intervals

Again, we checked the robustness of this result with respect to other link functions. With a logit link function, we found that group-level risk preferences did not change because of time pressure, $\delta_\beta = -0.02$, 95% HDI [−0.06, 0.01], whereas the logit consistency parameter indicated credibly lower group-level consistency under time pressure, $\delta_\varphi = 0.10$, 95% HDI [0.07, 0.14]. For the trembling-hand error, group-level risk preference did not change, $\delta_\beta = -0.02$, 95% HDI [−0.08, 0.02], but the trembling-hand error parameter indicated credibly lower group-level consistency under time pressure, $\delta_\rho = -0.14$, 95% HDI [−0.19, −0.08].

4.2.4 | Gamble complexity

We report the group-level effects of gamble complexity on the preference and consistency parameter in the best fitting model (all main effects, no interactions): participants were less risk averse in choices when the safer gamble had only two outcomes compared with when both gambles had four outcomes ($\beta_{\text{safe}} = 0.20$, 95% HDI [0.09, 0.30]). However, the effect of the risky-easy condition on the risk parameter

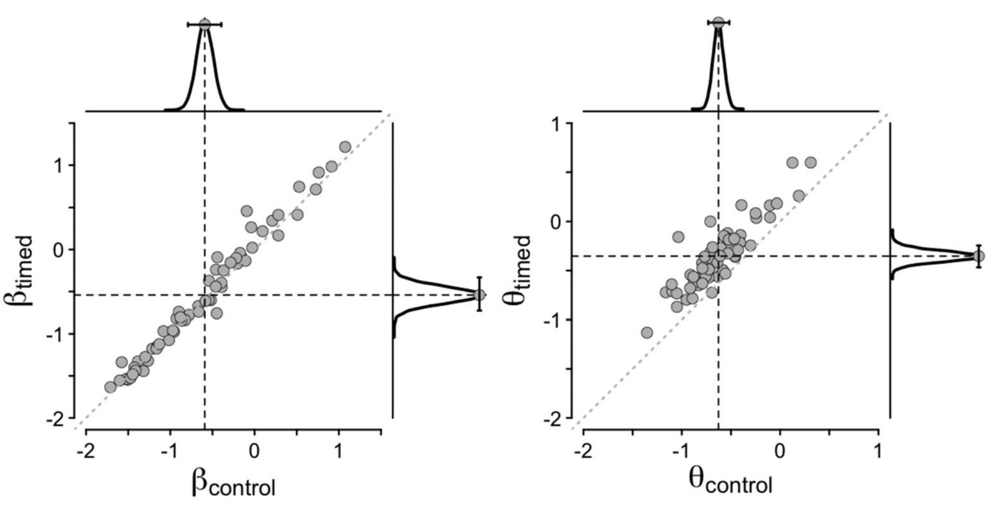

FIGURE 10 Group posterior distributions at the margins and individual mean posterior parameter estimates in the main graphs for risk preference β (left) and choice consistency θ (right) for the best model (Model 4 in Table S2) including main effects of condition and complexity

was not credibly different from 0 (β_{risky} = −0.09, 95% HDI [−0.19, 0.01]). The effect of gamble complexity on choice consistency was not credibly different from zero for the safe-easy condition (θ_{safe} = −0.04, 95% HDI [−0.09, 0.01]) but was for the risky-easy condition (θ_{risky} = −0.13, 95% HDI [−0.18, −0.08]). The trend in both conditions means that there was higher choice consistency when one gamble had only two outcomes.

4.2.5 | Strategy shift

We examined to what extent the change in choice proportions due to time pressure could be accounted for by a strategy shift. The group-level mixture variable was z_0 = −0.56, 95% HDI [−0.83, −0.30], meaning that across both conditions, the probability that a participants was classified as using one of the three NC strategies was 29%. The effect of time pressure was not statistically credible, δ_z = −0.25, 95% HDI [−0.50, 0.01]. However, descriptively, the probability of classifying someone as using an NC strategy was higher under time pressure (38%) than in the control condition (21%). Looking at the individual posterior distributions, 22 participants under time pressure and 10 in the control condition had a higher than 50% posterior probability of their choices being better explained by an NC than the compensatory strategy. Possibly, the higher gamble complexity in Experiment 2 increased the overall use of NC strategies compared with Experiment 1.

The group-level threshold for the three NC strategies was μ = 0.01, 95% HDI [0.0002, 0.02], and the group-level trembling-hand error rate was ε = 0.18, 95% HDI [0.13, 0.24]. The three mixture probabilities on the group level were g_1 = 0.16, 95% HDI [0.03; 0.32], for the probability order; g_2 = 0.26, 95% HDI [0.09, 0.42], for the decreasing outcome order; and g_3 = 0.58, 95% HDI [0.38, 0.77], for the increasing outcome order.

Similar to in Experiment 1, the conclusion concerning choice consistency held when allowing for the use of NC strategies: on the group level, choice consistency was still credibly decreased under time pressure, δ_θ = −0.10, 95% HDI [−0.15, −0.05], whereas risk preference was not, δ_β = −0.01, 95% HDI [−0.05, 0.03].

5 | DISCUSSION

In two experiments, we examined the effect of time pressure on repeated binary choices between risky gambles. We found that choice proportions differed between conditions with high versus low time pressure. To understand this behavioral change, we contrasted three explanations: (a) time pressure systematically affects people's risk preferences, (b) time pressure decreases choice consistency, and (c) time pressure leads to a strategy shift from a compensatory to an NC strategy. Across both studies using a random utility model implemented within a hierarchical Bayesian framework, we found converging evidence for a decrease in choice consistency as the main driver behind the time pressure effect of a change in risky choices: in both studies, the error variance of the random utility model increased under time pressure, meaning that choice behavior moved toward 50% each for the safer and riskier gamble. At the same time, there was no evidence for an influence of time pressure on people's risk preferences.

We found some evidence of a strategy shift: when we compared a compensatory (mean–variance) with several NC (comparing two single outcomes) strategies in a Bayesian finite-mixture model, participants were descriptively more likely to adhere to an NC strategy under time pressure in both experiments (see also Payne et al., 1988; Rieskamp & Hoffrage, 1999, 2008). On a group level, this shift in the mixture variable reached statistical credibility in Experiment 1 but not in Experiment 2. However, a strategy shift cannot fully account for the behavioral effect of time pressure because choice consistency in the compensatory strategy still decreased under time pressure, even when allowing for the strategy shift option in the mixture model in both experiments. This is consistent with the interpretation that most participants stuck to a compensatory strategy also under time pressure but performed this strategy less consistently under high time pressure.

5.1 | Strategy shifts under time pressure

In the strategy shift analysis, we used a Bayesian group-level finite-mixture model. We thus assumed that a given participant used the same strategy in every trial. That way, we limited the flexibility of the finite-mixture model, but it might be interesting to examine trial-by-trial shifts in strategies in future research (Scheibehenne et al., 2013). We restricted the set of NC strategies to sequential outcome comparisons in three different orders as a straightforward principle to reduce decision time. Yet other lexicographic strategies have been proposed in the literature (e.g., Payne et al., 1988), most prominently the priority heuristic (Brandstätter et al., 2006; Rieskamp, 2008). We cannot rule out that the inclusion of other NC strategies could increase the explanatory power of the strategy shift hypothesis. However, within the finite-mixture model, adding too many strategies could make the NC strategies overly flexible. A good design approach to examine which strategies were used exactly is to use specific choice problems and process measures to distinguish strategies from one another. We see this approach and ours as complementary: whereas our study has the advantage that results hold for the whole spectrum of possible risk–reward combinations in a standardized procedure, more targeted choice problem sets might be better suited to identifying the use of particular strategies.

There was little evidence that time pressure increased the propensity to choose easier gambles. In Experiment 1, participants chose the easier option more often when it was the safer one under time pressure than in the control condition (see estimated interactions in Table S1). However, this was not the case when the easier option was the riskier one, and this result was not replicated in Experiment 2. It might be that the safer option in Experiment 1 was a sure outcome and that the elimination of all risk had an effect on choice behavior beyond the complexity manipulation. An effect of time pressure on the propensity to choose the easier option could be expected when people did not have the chance to fully comprehend the more complex option under time pressure. However, when people shifted toward NC strategies, for example, by comparing just one value from each gamble to each other, complex gambles as defined in our experiments did not take longer to evaluate than easy gambles.

Interestingly, the main effect of complexity on choice was heterogeneous across both studies even in the control condition: whereas participants chose easier gambles more often than complex ones in Experiment 1, they chose complex gambles more often than easier ones in Experiment 2. Consequently, the difference in the complexity manipulations (two-outcome gambles in Experiment 1 vs. four-outcome gambles in Experiment 2) led to different effects on choice proportions. In manipulating complexity, we controlled for the EV and the variance but not for higher moments of the gamble, such as skewness and kurtosis. Yet, higher moments might in particular play a role in four-outcome gambles, contributing to the divergent findings across the two studies (Ebert & Wiesen, 2011; Trautmann & van de Kuilen, 2018). Consequently, gamble complexity seems to affect risk taking in more sophisticated ways than just decreasing choice proportions (see Moffatt et al., 2015; Zilker, Hertwig, & Pachur, 2020). Nonetheless, given the respective complexity manipulations in our two studies, we can robustly infer that time pressure did not systematically affect choices between gambles with different levels of complexity.

5.2 | The importance of choice-data modeling

Although past research has suggested that time pressure can affect people's risk preferences directly (e.g., Young et al., 2012), we did not find support for this claim. However, previous studies usually did not check for the choice consistency hypothesis. As described in our Section 1, without controlling for choice consistency, a change in choice proportions toward 50% is ambiguous with respect to its cause. Thus, merely on the basis of choice proportions, we could also interpret our participants' behavior as becoming less risk averse. Only with the help of a random utility model with risk preference and choice consistency as latent variables could we demonstrate that time pressure mainly affected choice consistency rather than risk preferences (for a similar approach compare Kirchler et al., 2017). Therefore, prior claims about changes in risk preferences due to time pressure should be reconsidered.

When under time pressure, people seemed to choose the option that had, on average, higher utility for them less often. This shows that a probit error variance parameter should not be treated as a nuisance parameter, as it carries psychological meaning (see Bhatia & Loomes, 2017; Hey, 2005; Woodford, 2014). In its effect of moderating the number of "correct" choices, the probit error variance has a similar function to the threshold in an evidence accumulation model (see Webb, 2019). However, evidence accumulation models also take reaction times into account and the threshold parameter might be more established as a measure of a psychological process than the probit error variance.

We can conceptualize the time pressure manipulation as a way of reducing the decider's cognitive resources. In the real world, cognitive resources are often limited in other ways as well, for example, in decision making under stress, acute alcohol intoxication, or sleep deprivation (e.g., Cahlíková & Cingl, 2017; Davis-Stober et al., 2019; Harrison & Horne, 2000; Porcelli & Delgado, 2009). Although under all these circumstance different cognitive and neuronal mechanisms might be at work, the basic problem of distinguishing between changes in preferences and in choice consistency is the same. We speculate that in real-world settings, such as high-stakes investments, job-related or competitive-sport decision making, where time pressure might be accompanied by social pressure, stress, and emotions, choice consistency could deteriorate even more than in our experiments. This should be a warning when people want to react quickly to new information. Reacting quickly can be an advantage, but comes with the cost of less accuracy (as in the speed–accuracy trade-off; Heitz, 2014).

Besides these situational factors, there might also be cognitive abilities, such as general intelligence, working memory capacity, or numeracy, that affect choices under risk (see Kocher et al., 2019). Although there have been attempts to link economic preferences to cognitive abilities (Burks et al., 2009; Dohmen et al., 2010; Lilleholt, 2019; Shamosh et al., 2008), future studies should also control for choice consistency when examining the impact of cognitive abilities on decision-making behavior (see Andersson et al., 2016).

Finally, the same logic of distinguishing between preference and consistency shifts can be applied to other domains of economic decision making besides risk taking: Olschewski et al. (2018) showed that the effect of cognitive load manipulations led to similar effects to those reported here in the domains of temporal discounting and social decision making. To better understand the causes of changes in behavior is also important in the debate about the social heuristic hypothesis and the question of whether time pressure leads to fairer choices or not (see Bouwmeester et al., 2017; Rand et al., 2012). In sum, the current work illustrates that the interpretation of the behavioral effect of cognitive resource manipulations such as time pressure in preferential decision making should rely on a theoretical approach that allows the testing of various hypotheses rigorously against each other.

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DATA AVAILABILITY STATEMENT

Data, modeling code, and supplemental online material including Tables S1 and S2 can be found at osf.io/2p4yj.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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