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Risk, Time, and Psychological Distance: Does Construal Level Theory Capture the Impact of Delay on Risk Preference?

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Do people change their preferences when they are offered the same risky lotteries at different times (now vs. the future)? Construal level theory (CLT) suggests that people do because our mental representation of events is moderated by how near or distant such events are in time. According to CLT, in the domain of risk preferences, psychological distance causes payoffs and probabilities to be differentially weighted or attended between present and future timepoints: Temporal distance increases the influence of payoffs and decreases the influence of probabilities. Specifically, CLT predicts that high probability/low amount lotteries (i.e., %-lotteries) are preferred in the present, whereas low probability/high amount lotteries (i.e., $-lotteries) are preferred in the future, even when the expected value of these lotteries is identical. We present a functional characterization and systematic investigation of this putative pattern of risk preferences and develop a formal model that incorporates CLT's predictions. In five experiments, we examined several factors that could moderate the effect (e.g., outcome and probability magnitude, lottery presentation format, incentivization procedures). Both our behavioral observations and modeling results suggest the effect is labile, and if it does occur, it is not fully consistent with our formal model of CLT.

Public Significance Statement

Construal level theory (CLT) is an influential theory that is built on the concept of psychological distance and how the mental representation of events (also goals, items, and people) is regulated by how proximal or distal these events are. The theory has had a profound appeal and impact in many areas of psychological science, including individual and organizational decision making, categorization, social interactions, problem solving, and consumer psychology. In the present work, we examine CLT and temporal distance in the domain of risk preference and supplement the empirical investigation with a computational model that formalizes CLT's main predictions.

Keywords: risk, delay, construal level theory, prospect theory, computational modeling

We examine the effect of time on risk preference through the lens of construal level theory (CLT; see Trope & Liberman, 2003, 2010), a highly influential theory that is built upon the concept of *psychological distance*. CLT proposes that the psychological representation (i.e., construal) of items (or concepts, events, goals, and people) is regulated by whether an item is near or distant in certainty (hypothetical distance), space (geographical or spatial distance), time (temporal distance), or social space (see Trope & Liberman, 2010). The concept of psychological distance regulates the *mental concreteness* of an event or an item: Closer items are thought of as more concrete, detailed, and specific (low-level construals), whereas distant items tend to be represented as more broad, general, and abstract (high-level construals).

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To illustrate the concept of psychological distance and its impact on the mental representation of events, consider the following hypothetical scenario: You are planning to renovate your home in the near future. According to CLT, high-level construals (which consist of the *superordinate* features of the event or the *desirable* state) refer to the broad, abstract, and desirable aspects of the event (i.e., renovation), for example, the positive feelings that accompany a change in one's living environment, the potential uses of the new space, and so forth. However, when the time comes to begin the actual renovation (in this case temporal distance reduces to *zero*), the mental representation of the different aspects of the renovation event changes, and focus shifts toward the low-level construals (*subordinate* features or how *feasible* it is) of the event, such as finding appropriate contractors to complete the renovations and visiting the hardware store to buy the materials. CLT, as a theory of how people change their focus and the mental representation of events based on how proximal or distant the event is, has been applied to many domains such as judgment and decision making, categorization, consumer behavior, organizational research, and types of social relationships and interactions (e.g., Kanten, 2011; Liberman et al., 2007; Smith & Trope, 2006; Stephan et al., 2011; Wakslak et al., 2006; Wiesenfeld et al., 2017).

Our work builds on that of Sagristano et al. (2002), who examined CLT's main assumptions in the domain of risk preference. Sagristano et al. asked participants to evaluate hypothetical risky lotteries that were either played in the "near" future (i.e., present—after the end of the experiment) or in the "distant" future (after 2 months), using different formats to display and represent the payoff of the lottery and the risk associated with it (e.g., urn draws, card games, or entering raffles). For example, in one of their experiments, participants were presented with descriptions of urns containing green and red marbles, where the number of green marbles represented the probability of winning a predetermined amount of money (i.e., payoff of the lottery).

One central finding in all the experiments in Sagristano et al. (2002) was that lotteries that were played out in the distant future were evaluated differently from lotteries that were played out in the present. Such "asymmetric" risk preferences between different timepoints is a pattern that can be explained by CLT. Specifically, temporal distance alters the weight or importance given to the payoffs and probabilities of a lottery. The payoff is the *desirable* aspect of the lottery (the high-level or end-state feature), whereas the probability is the low-level aspect of the lottery and defines how *feasible* it is to acquire the end-state feature. According to CLT, attention should shift to the desirable feature (i.e., payoff) when temporal distance (or any other form of psychological distance) increases. On the other hand, lotteries that are offered presently should elicit more local and specific thinking, thus focusing attention on the feasibility aspect of the lottery (i.e., probability). Consistent with CLT, Sagristano et al. found that the influence of payoffs and probabilities on evaluating lotteries was dependent on temporal distance, with payoffs becoming more important in the future and probabilities becoming less important as temporal distance increased.

Previous Tests of CLT and Risk Preference

To expand on CLT's predictions in risky choice and to preempt our experimental approach, consider two lotteries with the same expected value: Lottery L_1 offers a relatively high amount, but with low probability of success, $2,000 with 10% probability or $0 otherwise; schematically, this is represented as L_1: $2,000, 0.10; 0 (henceforth, all lotteries of this type will be indicated as $-lotteries; see similar naming conventions in Butler & Loomes, 2007; Lichtenstein & Slovic, 1971), whereas lottery L_2 offers a relatively low amount, but with high probability of success, L_2: $250, 0.80; 0 (henceforth, %-lotteries). CLT predicts that even though the two lotteries have the same expected value, $\mathrm{EV}(L_1) = \mathrm{EV}(L_2) = \$200$, preference for either of them will depend on the point in time that each of these is evaluated. In the present, L_2 should attract higher ratings of preference because people would focus on the feasibility aspect of the lottery (and L_2 has higher probability than L_1), whereas in the future, L_1 should be preferred more as preferences are driven by the desirability aspect of the lottery (L_1 offers the potential for more money than L_2).

Trautmann and van de Kuilen (2012) tested CLT as a framework of risky decision making against cumulative prospect theory (CPT; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), as the two accounts make opposing predictions regarding risk preferences for many choice situations. While CPT's predictions are not influenced by when the lottery is played out, CLT's predictions are dependent on the psychological distance and level of construal (low or high). Specifically, the two theories predict different patterns of risk preference for lotteries resolved in the present (i.e., short psychological distance and low-level construal), while their predictions coincide for distant-future lotteries (long psychological distance and high-level construal).

CPT is probably the most influential descriptive model of risky decision making; the core mechanisms of the model assume that objective payoffs and probabilities of a lottery are transformed into *subjective values* and *decision weights*, respectively, via mathematical functions with adjustable free parameters. The subjectively transformed values are then multiplicatively integrated to define the subjective value of a lottery (similar to the expected value or expected utility models). Given the parameter values of the value and probability weighting functions in Tversky and Kahneman (1992), CPT makes particular predictions about risk preferences.[1] For payoffs, the value function is concave for gains leading to risk aversion (or evaluations smaller than the EV of the lottery). For probabilities, CPT predicts overweighting of small probabilities (leading to risk seeking, i.e., evaluations larger than the EV of the lottery) and underweighting of medium to high probabilities (leading to risk aversion). These patterns have been empirically observed in many behavioral studies (e.g., Glöckner & Pachur, 2012; Stott, 2006). Using lotteries L_1 ($-lottery) and L_2 (%-lottery) from the example above, for %-lotteries (e.g., L_2: $250, 0.80; 0), both value and probability weighting functions predict behavior consistent with risk aversion. On the other hand, the $-lotteries (e.g., L_1: $2,000, 0.10; 0) elicit either risk neutral (i.e., evaluations equal to the EV of the lottery) or risk-seeking behavior: The concavity of the value function suggests risk aversion (as with %-lotteries), but overweighting of small probabilities ($p = .10$) leads to risk seeking.

[1] The CPT model assumed here consists of a power value function of the form $v(x) = x^{\alpha}$ (where v is the subjective value of objective outcome x and α governs the curvature of the function) and a probability weighting function of the form $w(p) = p/[p^{\gamma} + (1 - p)^{\gamma}]^{1/\gamma}$, where w is the decision weight of probability p and γ is a parameter that governs the curvature of the function. The CPT predictions are generated using $\alpha = .88$ and $\gamma = 0.61$ (for lotteries in the gain domain).

Hence, the pattern predicted by CPT is that there would be more risk seeking for L_1 relative to L_2 (and thus L_1 attaining higher evaluations than L_2).[2,3]

CLT suggests that the degree of psychological distance at which lotteries are evaluated alters risk preferences (CPT predictions are not dependent on the time of play of a lottery). Under high-level construal, CLT's predictions match those of CPT, that is, \$-lotteries receive higher evaluations than %-lotteries (due to payoffs receiving more weight/attention and thus influencing preferences more than probabilities), but this pattern reverses under low-level construal with a higher preference for %-lotteries compared to \$-lotteries (probabilities receive more weight than payoffs)—this latter pattern is inconsistent with CPT, which assumes that \$-lotteries would be preferred (regardless of time of play). In a series of experiments testing the above predictions using different scenarios of low and high level construals, Trautmann and van de Kuilen (2012) found that CPT successfully predicted risk attitudes, but they did not find convincing evidence for CLT, highlighting that "construal level effects seem at best very *subtle*" (p. 259). Specifically, they tested the effect of different instantiations of psychological distance (including social, temporal, and geographical) in four studies where participants provided the certainty equivalence (CE—an amount of money that one is willing to accept for sure in order to forego playing the lottery) for (or made a choice between) sets of risky %- and \$-lotteries with matched expected values. For example, in one study, participants were asked to imagine making decisions (i.e., provide the CE) for a friend of theirs (thus, increasing personal/social distance) in the future (increasing temporal distance). In this and other studies, they found that psychological distance had no effect on lottery evaluations: In line with the predictions of CPT, participants were consistently evaluating \$-lotteries higher than %-lotteries, irrespective of low or high levels of construal or the risk preference elicitation method (choice between two lotteries vs. evaluating lotteries in isolation).

In the same work, Trautmann and van de Kuilen (2012) tested the possibility that the observed difference in evaluations in favor of the \$-lotteries would be larger under high-level than low-level construal. With attention shifting to superordinate features of the lottery (i.e., payoffs) when psychological distance increases, the influence of payoff would be stronger under high-level construal causing even larger differences between \$- and %-lotteries. In other words, construal levels do not define risk preference but moderate it. This pattern of results was termed the *weak* CLT hypothesis as opposed to the *strong* CLT hypothesis, which suggests a preference reversal in risk preference (%-lotteries are preferred in the present, while \$-lotteries are preferred in the future). Even under this *weaker* specification of CLT, they did not find any moderating effects of construal on risk preference across four empirical studies (we return to the distinction between weak and strong CLT at a later point).

Examining the effect of time on risk preferences, Abdellaoui et al. (2011) used a three-parameter Prospect Theory model consisting of a power value function, $v(x) = x^{\alpha}$, and a two-parameter probability weighting function accounting for the elevation and curvature of the function as proposed by Prelec (1998), $w(p) = \exp\{-\delta[-\ln(p)]^{\gamma}\}$. The behavioral data came from an experiment where participants' CE values for 10 lotteries offered at different timepoints (now, 6 months, 12 months, and an unspecified time between today and 12 months) were elicited via a bisection iterative method. Any differences in model parameters estimated at different timepoints would suggest a direct effect of time on elicited risk preferences. It was found that while time seemed to affect the subjective treatment of probabilities, it had no effect on subjective value. Specifically, the majority of the individual probability weighting functions showed higher probabilistic optimism (as indexed by a lower value of the elevation parameter δ) and higher sensitivity to (medium) probabilities (as indexed by a higher value of the curvature parameter γ) in the future (thus participants becoming more "rational" or linear when transforming probabilities), whereas there was no effect of time on estimates of the value function parameter (i.e., α) between present and future timepoints. This meant a decrease in the ratio of δ to α and an increase in γ when temporal delay increased. However, the formal model presented later in this article suggests that, according to CLT, *both* the ratio of δ to α and the value of the γ parameter should decrease as delay increases. Therefore, the finding of Abdellaoui et al. presents a challenge for CLT.

The authors suggested that this increased sensitivity to (medium) probabilities may be the result of a decreased affective reaction to the potential outcomes of the lottery caused by delaying its resolution in the future. This affect-based explanation is consistent with Rottenstreich and Hsee (2001), who showed that affect-rich stimuli (or risky choice options) can cause higher distortions to the probability weighting function compared to affect-poor stimuli (see also Suter et al., 2016). With temporal distance reducing the anticipatory feelings (either joy or disappointment) from playing a lottery (thus, making the lottery more affect-neutral), the probability weighting function assumes a more linear form (or higher sensitivity to changes in objective probabilities). Savadori and Mittone (2015) empirically tested the two competing accounts (CLT and affect-based explanation) by presenting participants with a choice between a %-lottery and \$-lottery at different timepoints and asking them to rate their affective reaction to the two lotteries before making a choice. While the main results showed an effect of temporal distance (with a higher percentage of participants preferring the %-lottery in the near future compared to the distant future where the \$-lottery was preferred more—consistent with CLT's behavioral prediction), this was driven by reduced positive reaction for the %-lottery but no change in the positive ratings for the \$-lottery. This pattern is more suggestive of the affect-based explanation.

Interpretations of CLT

One challenge in evaluating CLT's ability to account for and explain risk preferences is that its assumptions and predictions rely on verbal interpretations and descriptions of the theory's core principles. This poses limitations when attempting to test the validity of CLT as a framework of risky decision making and to compare it against other theoretical and formal accounts from decision sciences and behavioral economics (see Trautmann, 2019). For instance, direct comparisons between CLT and other theories/formal models that allow for moderating effects of time on risk

[2] It follows that these behavioral patterns are dependent on the parameter values of the value and probability weighing functions (e.g., if $\alpha > 1$, the model predicts risk seeking in the gains domain and not risk aversion).

[3] In the losses domain, the predictions of the model reverse: \$-lotteries elicit risk averse behavior, whereas %-lotteries elicit more risk seeking behavior.

preferences (see, e.g., Baucells & Heukamp, 2012) are constrained by the lack of a functional characterization of the interactions between time, probability, and payoff. In Sagristano et al. (2002), the theory is laid out using different verbal descriptions (and elsewhere, see Trope & Liberman, 2003, 2010), but this can present difficulties and misspecifications when attempting to provide explanations for risky choice, an area that has been traditionally examined with well-specified models (e.g., Prospect Theory, Kahneman & Tversky, 1979; Decision Field Theory, Busemeyer & Townsend, 1993). A core contribution of the current work is to provide an initial formalization of CLT in the context of risk preference, thereby aiding in the evaluation of its specific predictions.

CLT is a theory of adjustments to the influence (or weights) of means- (low level or *feasibility*; e.g., probabilities) versus ends-related (high level or *desirability*; e.g., payoffs) features as a function of psychological distance (see, e.g., Todorov et al., 2007; Trope et al., 2007; Trope & Liberman, 2003). A central and recurring assertion in the CLT literature is that "feasibility concerns [probabilities] are more important in near-future choices whereas desirability [payoffs] concerns are more important in distant-future choices" (Trope & Liberman, 2003, p. 414). While this statement has a rather intuitive meaning, it allows for a variety of (verbal) interpretations about the influence of payoffs and probabilities on risk preference at different points of psychological distance: For example, it may mean that "temporal distance increases the weight of information about payoffs and decreases the weight of information about the probability of winning those payoffs" (Savadori & Mittone, 2015, p. 27); or it may suggest that

> For decisions in the distant future, the desirability of an outcome plays a more important role than the feasibility of attaining that outcome. In contrast, the feasibility of attaining an outcome weighs more than the desirability of that outcome in decisions regarding the near future. (Onay et al., 2013, p. 364)

All previous statements may conceptually relate to the central CLT theme that psychological distance alters how we mentally represent payoffs and probabilities, with probabilities mattering more in the present and payoffs in the future. However, as we will show, differentiating between verbal statements of what CLT predicts has important implications for (a) the behavioral patterns explained by CLT, (b) the statistical analysis of empirical data, and (c) the development of the formal model. Past research on the effect of temporal distance on risk preferences (see, e.g., Onay et al., 2013; Öncüler & Onay, 2009; Savadori & Mittone, 2015) has largely disregarded the distinction and used the different interpretations rather interchangeably, which has amplified the confusion of what CLT suggests and how it can be reliably tested.

In what follows, we present what we see as three plausible explanations and interpretations of the effect of temporal distance on payoffs and probabilities within the theoretical framework of CLT. These interpretations assume *relative* and *absolute* influences of payoffs and probabilities on risk preferences: *relative* refers to the influence of a particular feature (payoff or probability) relative to that of the other feature, and *absolute* refers to the influence of a particular feature, independent of the influence of the other feature. In addition, these relative and absolute influences can be considered *between* points of psychological distance (between-distance interpretation, e.g., how the weight of probability changes between present and future timepoints) or *within* a point of psychological distance (i.e., *within-distance* interpretation, e.g., whether one attribute outweighs the other in terms of influencing risk preference for lotteries offered at a specific temporal distance). We define the weight (or influence) of probabilities at short (present) and long (future) temporal distance as $w_{\%}^{\text{Present}}$ and $w_{\%}^{\text{Future}}$, respectively. The weights for payoffs are $w_{\$}^{\text{Present}}$ and $w_{\$}^{\text{Future}}$.

Interpretation 1: Within-Distance Difference in Absolute Influence

This interpretation appears to have been suggested by Sagristano et al. (2002; see also Onay et al., 2013; Trautmann & van de Kuilen, 2012) and refers to when considering a lottery at any given point in time (e.g., present), one dimension/feature outweighs the other in terms of influencing risk preferences, that is, it is taken more into consideration or plays a bigger role than the other dimension. The main prediction of Interpretation 1 is that the absolute influence of probabilities is higher than that of payoffs for psychologically near gambles, whereas for psychologically distant gambles, the absolute influence of payoffs is higher than that of probabilities. This is consistent with the verbal description that

> Bids [CE evaluations] for near-future gambles were higher for high-probability, low-payoff gambles than for low-probability, high-payoff gambles, whereas bids for distant-future gambles showed the reverse pattern of preference. Thus, consistent with the preference-ratings results, in bidding for near-future gambles, probability was more important than payoffs, whereas in bidding for distant-future gambles, payoffs were more important than probability. (Sagristano et al., 2002, p. 369)[4]

Schematically, this is shown as $w_{\%}^{\text{Present}} > w_{\$}^{\text{Present}}$ and $w_{\%}^{\text{Future}} < w_{\$}^{\text{Future}}$. It is the strictest interpretation of CLT as it assumes a specific preference pattern resulting in reversal (or flip) of risk preferences when psychological distance increases, which resembles the strong CLT hypothesis in Trautmann and van de Kuilen (2012). Sagristano et al. tested this interpretation by comparing the CE evaluations of lotteries of the same EV, where probabilities and payoffs are varied systematically (when one increases, the other decreases, and vice versa). They found (in Experiment 1) that for lotteries of the same EV, %-lotteries were preferred (higher CEs and preference ratings) over \$-lotteries in the present because of the higher influence of probabilities over payoffs, whereas this preference pattern reverses in the future where payoffs are more important than probabilities, and \$-lotteries are evaluated more preferably than %-lotteries. However, this pattern of preference was not observed in other studies (e.g., Trautmann & van de Kuilen, 2012).

Interpretation 2: Between-Distance Change in Absolute Influence

The verbal description of this interpretation is common within the CLT literature (e.g., Savadori & Mittone, 2015; Trautmann & van de Kuilen, 2012), where primary or superordinate features of the event (or its mental representation) become more important as distance

[4] Similar verbal interpretations have appeared in the CLT literature: "Thus, in selecting a near future assignment, students were willing to sacrifice interest [desirability] for the sake of ease [feasibility]. In contrast, in selecting a distant-future assignment, students were willing to sacrifice ease for the sake of interest" (Liberman & Trope, 1998, p. 13).

increases while subordinate features become less important (Liviatan et al., 2008). In risky choice, it concerns how delaying a lottery into the future increases the absolute influence of payoff and decreases the absolute influence of probability, independently from each other. Schematically, $w_{\$}^{\text{Present}} < w_{\$}^{\text{Future}}$ and, independently, $w_{\%}^{\text{Present}} > w_{\%}^{\text{Future}}$. Sagristano et al. (2002) stated that "temporal distance increased the weight of payoffs and decreased the weight of probability in gambling decisions" (p. 375). To test this interpretation, Sagristano et al. used multiple regression models on CE evaluations with payoffs and probabilities as fixed effects (combined additively) and compared the regression coefficients between levels of temporal distance (in Experiments 1 and 3). They found that the payoff regression coefficients were higher for future lotteries than present lotteries, whereas the probability coefficients were higher for present lotteries than for future lotteries.

Interpretation 3: Between-Distance Change in Relative Influence

This is the most encompassing or generic interpretation of CLT and assumes that the relative influence of payoff (as opposed to that of probability) should increase as psychological distance increases. Any increase in the relative influence of payoff as the psychological distance of a lottery increases is consistent with this interpretation, regardless of whether the relative influence of payoff is positive or negative at any particular psychological distance. This can be schematically represented as: $w_{\$}^{\text{Present}} - w_{\%}^{\text{Present}} < w_{\$}^{Future} - w_{\%}^{\text{Future}}$. It suggests that if the relative influence of payoff is positive (negative) in the present, it will be more (less) positive (negative) in the future, showing a relative increase as distance increases. This interpretation also accounts for the preference reversal pattern presented before in Interpretation 1, with the relative influence of payoff being negative in the present but positive in the future, $w_{\$}^{\text{Present}} - w_{\%}^{\text{Present}} < 0$ and $w_{\$}^{\text{Future}} - w_{\%}^{\text{Future}} > 0$. This interpretation can account for three distinct empirical patterns: (a) \$-lotteries being preferred (or attaining higher evaluations) over %-lotteries in both present and future timepoints, but the difference in preference/evaluations increases in the future. This pattern is similar to the weak CLT hypothesis in Trautmann and van de Kuilen (2012); (b) %-lotteries being preferred (or attaining higher evaluations) over \$-lotteries in both the present and future, but the difference in evaluations is smaller in the future; and (c) %-lotteries preferred in the present but \$-lotteries preferred in the future (preference reversal or strong CLT hypothesis). As this is the most encompassing interpretation, it follows that if it is refuted, there would also be no support for Interpretations 1 and 2.

Overview

The preceding brief overview suggests mixed support for CLT's contribution to understanding the impact of time on risky choice. The overview also highlights ambiguities in the interpretation of CLT. Here, we present an empirical examination consisting of five experiments that aim to clarify the contribution of CLT to understanding risky choice across time. We then supplement this investigation with a formal account of CLT in the context of risky choice, where we seek to evaluate the three verbal interpretations of CLT.

In all of our experiments, we asked participants to provide the certainty equivalent (CE) of a set of two-outcome/no loss lotteries at different timepoints. The CE refers to the amount of money that one is willing to accept for sure in order to forego playing the lottery (i.e., a pricing task). For lotteries presented as occurring in the future, participants provided *future* CE values and *not discounted* values to the present (see also Abdellaoui et al., 2011; Onay et al., 2013). For example, consider a two-outcome delayed lottery of the following form L_t: x, p_t; y, where outcome x occurs with probability p and outcome y with probability $1 - p$ (identical to the ones used in the present study). t denotes the time at which the gamble is played out, uncertainty is resolved, and any earnings are received. In a discounting evaluation task, the *present* certainty equivalent (pCE) value of the lottery is elicited at $t = 0$ (i.e., *now*; see, e.g., Ballard et al., 2023; Berns et al., 2007). This evaluation incorporates risk preferences, delay preferences, and their associated discount functions. On the other hand, elicitation of a lottery's CE at time t necessarily ignores delay preferences and rather assesses how time impacts risk preferences. To better illustrate this difference, the elicitation of the pCE of a lottery may require two "discounting" steps[5]: first, the estimation of the certainty equivalent value at time t, $\text{CE}(L_i)^t$, and then the discounting of this sure amount into the present, $\text{CE}(L_i)^{t=0}$.[6] In the current work, there is only one step involved, that is, the elicitation of CE at time t, $\text{CE}(L_i)^t$, which does not involve delay discounting (see also Abdellaoui et al., 2011; Ahlbrecht & Weber, 1997; Öncüler & Onay, 2009).

Method

Materials, Design, and Procedure

All five experiments followed similar procedures, so we present a general Method section and highlight the relevant differences between experiments. Further details of the methods for each experiment are reported in Appendix A. In all the experiments, participants (N = 421) were instructed to provide a value (in Australian \$) that would make them indifferent or equally satisfied with receiving either a lottery ticket or an amount they indicated as an acceptable sure gain (certainty equivalent [CE]). They were told that the lotteries would be specified with a time of play (i.e., resolution of uncertainty/temporal distance), a winning amount (payoff), and the chance of winning that amount (probability). It was highlighted that the lottery and the amount of money participants had indicated (i.e., CE) would be available at the time of play, that is, today (i.e., after the end of the experiment) or in the future (the actual time point was defined by the experimental condition). Prior to the start of each experiment, participants were presented with an example screen that described the task in detail.

Across all five experiments and experimental conditions, there was a text box on the computer screen in which participants could type in their CE valuation. Figure 1 shows the three different presentation formats that we used (see also Table 1).

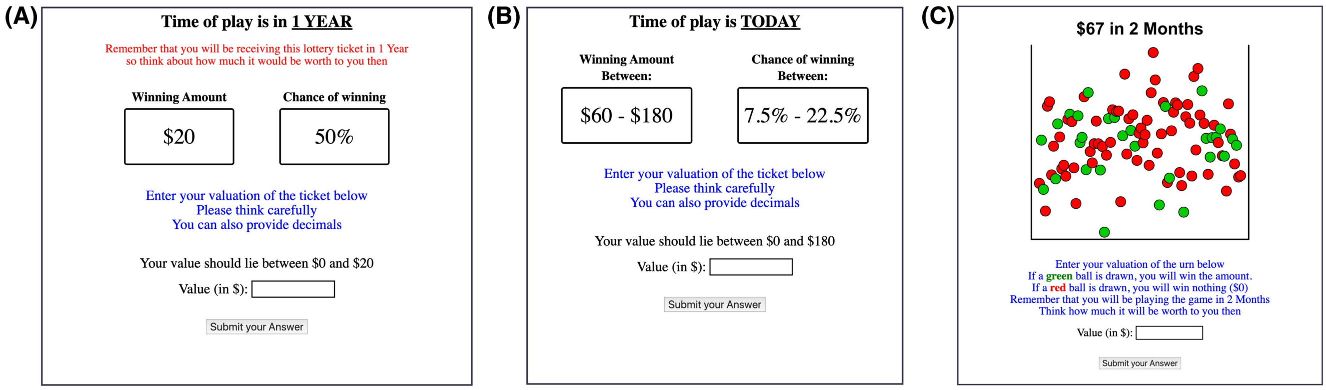
To rule out the possibility of high valuations, we did not allow CEs that were higher than the amount of money offered by the

[5] Here, discounting refers to both delay (decrease of a reward value with increases in delay) and probability (decrease of a reward value with decreases in probability).

[6] Naturally, elicitation of pCE may follow a different path, where time discounting occurs prior to probability discounting (see, e.g., Konstantinidis et al., 2017; Öncüler & Onay, 2009).

Figure 1

Example Displays of the Experimental Task and Presentation for Outcomes and Probabilities



Note. (A) Precise: Probabilities and outcomes are presented in their exact numeric form. (B) Imprecise: Probabilities and outcomes are presented as numerical quantities ranging between two uniformly distributed values. (C) Schematic: Probabilities are expressed as green and red marbles in an urn. The number of green marbles (out of 100) indicates the probability of winning the amount at the top of the urn. See the online article for the color version of this figure.

lottery in case of winning. For example, for the lottery *L*: $100, 0.50; 0, the highest possible CE value allowed was $100.

Experimental Factors

In each experiment, we manipulated a number of factors thought to have an effect on risk preferences across different temporal distances, such as the values of payoff and probability, the lottery presentation format, participants' incentivization procedure and type of rewards (hypothetical or real), and experimental manipulation of time (levels of temporal distance and whether time was treated as a between- or within-subjects variable). Participants in all experiments were UNSW Sydney undergraduates who completed all tasks in individual lab cubicles. Table 1 presents the experimental manipulations in the five experiments. See Appendix A for a detailed description of each experiment's task, materials, and procedure and Appendix D for more details on the influence of the different experimental factors.

To account for the possibility that lottery presentation may affect the way that lotteries are mentally represented and evaluated (see, e.g., Birnbaum, 2004; Birnbaum et al., 2008; Harless, 1992), we used three different formats for presenting payoffs and probabilities: *textual precise* (Figure 1A; Experiments 1, 2, and 3), *textual imprecise or ambiguous* (Figure 1B; Experiment 2), and *schematic* (Figure 1C; Experiments 4 and 5). The textual precise is arguably the most typical format to present a lottery, where the numerical values of payoffs and probabilities are fully and accurately provided to participants. However, this format may induce an automatic multiplicative integration of payoffs and probabilities (e.g., Mellers et al., 1992), and thus not allow for adequate "mental space or time" for the effect of temporal distance to moderate risk preferences. In other words, participants may automatically provide an evaluation of the lottery that combines (multiplicatively) payoffs and probabilities without much consideration of the time dimension. The two other presentation formats, *ambiguous* and

Table 1

Outline of the Experiments

Experimental factor	Experiment				
	1	2	3	4	5
Probability	1%, 10%, 30%, 50%, 70%, 90%, 99%	1%, 5%, 10%, 15%, 20%, 25%, 30%	10%, 30%, 50%, 70%, 90%	10%, 30%, 50%, 70%, 90%	10%, 30%, 50%, 70%, 90%
EV	$4, $6, $8, $10, $14, $16, $18, $20	10$, 14$, 16$, 18$, 20$, 25$, 30$, 35$	$4, $8, $16, $20	$4, $8, $16, $20	$4, $8, $16, $20
Time levels	Today, 2 months, 1 year	Today, 2 months, 1 year	Today, 2 months, 1 year	Today, 2 months, 1 year	Today, 2 months
Treatment of time	Between	Between	Within	Within	Between
Presentation	Precise	Precise and imprecise	Precise	Schematic	Schematic
Incentives	Hypothetical (course credit)	Hypothetical (course credit)	Hypothetical (standard participation fee, $7.50)	Hypothetical (standard participation fee, $7.50)	Real (BDM procedure)
Sample size	126	126	47	42	80

Note. EV = expected value; BDM = Becker–DeGroot–Marschak method.

schematic, were used to account for this potential automatic evaluation of lotteries.

Ambiguity in the current work took the form of imprecise numerical values for payoffs and probabilities: Participants were presented with a range from which potential values for payoffs and probabilities could be drawn (Figure 1B). Research has shown that in pricing tasks (similar to the one employed in the current work), people treat imprecise payoffs and imprecise probabilities differently (Du & Budescu, 2005). Specifically, imprecise payoffs have been shown to cause *vagueness seeking* (i.e., higher valuations for the imprecise lottery compared to the lottery with precise payoffs), whereas people are neutral or even averse to imprecise probabilities. In the current work, we used both imprecise payoffs and probabilities, as this presentation format seemed to have worked best in inducing moderating effects of time in previous research (see Onay et al., 2013). The rationale in the study by Onay et al. (2013) was motivated by CLT: Temporal distance would amplify the vagueness seeking with imprecise outcomes (as payoffs would become more prominent in the future) and, at the same time, would minimize the aversion toward imprecise probabilities, as probability would matter less in the future. We followed the same logic in the current work with the use of imprecise values. We also used another type of imprecision, that of schematic representation for probability information via winning (green) and losing (red) marbles that could be drawn from an urn (see Figure 1C).

To increase the saliency of temporal distance[7], in two experiments (see Table 1) we manipulated time as a within-subjects factor, that is, the same participants evaluated the same lotteries at each level of temporal distance. While this manipulation may control for between-subjects variability in risk preferences (see e.g., Birnbaum, 1999), it provides more information to realize what the task is about and the main research objectives (see Savadori & Mittone, 2015). In the same manner, to increase motivation and engagement, we manipulated incentives using hypothetical and real monetary rewards.

Transparency and Openness

This research was approved by the UNSW Sydney Human Research Ethics Advisory Panel C: Behavioral Sciences (HREAP-C: 153-212, File number: 2543 and HREAP-C: 173-053, File number: 2813). Informed consent was provided by all participants. This study was not preregistered. Materials, data sets, and analysis scripts are available online on the Open Science Framework at https://osf.io/yafsb/ (Konstantinidis et al., 2023).

Behavioral Results

As noted in the Method section, the experimental materials, procedures, and sample characteristics were similar across the five experiments; we therefore present the main statistical analyses on the data from all five experiments. Where appropriate, we highlight results that differ between experiments. Our core analysis focuses on the relationship between the three main variables of interest: time, payoff, and probability. In an attempt to find support for CLT's predictions based on the three different verbal interpretations, we used three methods to analyze the behavioral data: The first method focuses on the CE for each lottery elicited across points of temporal distance. In order to align with CLT's prediction of the differential impact of temporal distance, this analysis should reveal a reliable interaction between probability and time for each EV level (*within-distance difference in absolute influence*; see next section for details about the direction of the effects). The second method assesses CLT's differential impact of probabilities and payoffs via estimating parameters of a statistical model predicting each participant's reported CE from probability and payoff. The hypothesis is that the coefficients for probability will be higher in the present than in the future, whereas the regression coefficients for payoff will be higher in the future than in the present (*between-distance change in absolute influence*). The third method compares the predictions derived from CLT against CPT predictions and aligns with testing Interpretation 3 (*between-distance change in relative influence*).

Analysis on Interpretation 1: Within-Distance Difference in Absolute Influence

This interpretation suggests that the influence of probabilities on risk preferences is higher than the influence of payoffs for psychologically near lotteries, whereas this relationship reverses for psychologically distant lotteries, with payoffs becoming more influential than probabilities in determining risk preferences. In other words, for the same EV, %-lotteries will attain higher CE values in the present, whereas \$-lotteries will be evaluated higher in the future. To test these predictions, we used a linear mixed-effects model predicting CE values[8] with EV, probability, and time as fixed-effects and participant-specific random intercepts (separately for each experiment). We fit each model using Bayesian estimation techniques in R using Stan (Carpenter et al., 2017) and the package brms (Bürkner, 2017). For each model, we had 4 chains, each with a burn-in period of 1,000 samples. After burning in, each chain gave another 5,000 samples. The analysis was therefore based on 20,000 samples (i.e., 4 Chains × 5,000 Samples). For statistical inference, we used Bayesian–Frequentist p values, which combine the robustness of Bayesian estimation (e.g., Markov chain Monte Carlo [MCMC] sampling) with the simplicity and efficiency of Frequentist hypothesis testing (e.g., fixed effects with more than two levels or higher order interactions).[9]

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[7] We also used different ways to increase time saliency, such as presenting participants with a calendar indicating the date that the task would be played out and to think about how they would spend any earnings had this task/game been real and offered them real monetary rewards. See detailed methods for each experiment in Appendix A.

[8] CE values across all five experiments were cube-root transformed for the purposes of all statistical analyses in this article as their distribution was highly positively skewed.

[9] This approach uses the Wald test to calculate p values, which, in its simplest form, is the difference between an estimated parameter and a hypothesized test value (usually zero) divided by the parameter's standard error. In our case, the Wald statistic is calculated using the posterior mean of the vector of regression coefficients relevant for an effect (parameter estimates) and the variance–covariance matrix of these coefficients (the posterior mean of the variance–covariance matrix). The null hypothesis is that the estimated regression coefficients are jointly zero. The Wald test used here assumes infinite degrees of freedom for the denominator of the F-test, which is unlikely to cause any inference issues when sample size N is large (i.e., $N > 30$). All F-tests reported here contain Inf for the denominator degrees of freedom, that is, $F(df1, \text{Inf})$. The same procedure for statistical inference has been applied to all statistical analyses in this article. For more information, see Oh et al. (2023).

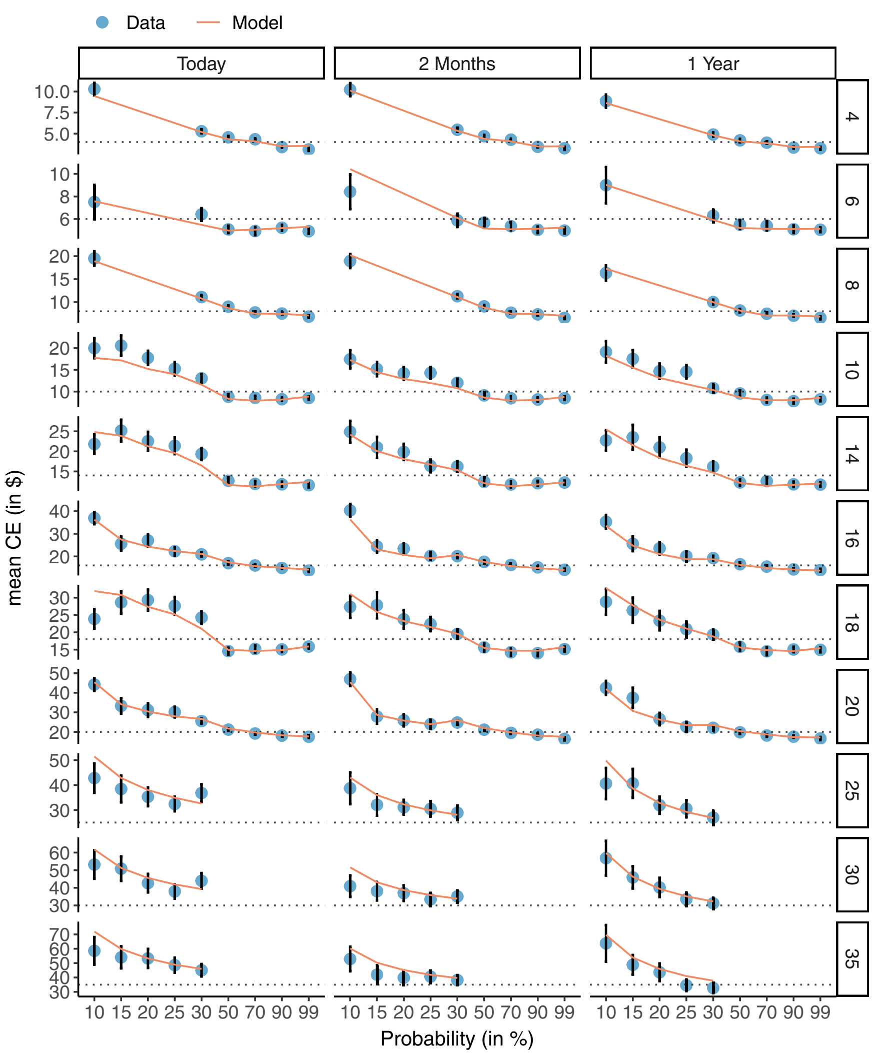
Based on this statistical model, CLT predicts that time interacts with probability (and EV). For example, consider two of the lotteries that result in an EV of \$20: L_1: 10% to win \$200 (\$-lottery) and L_2: 90% to win \$22 (%-lottery). Interpretation 1 of CLT predicts that despite having the same EV, the two lotteries should be differentially evaluated depending on the time of play (i.e., resolution of uncertainty): L_1 should receive higher values compared to L_2 when it is offered in the future, $\text{CE}(L_1) > \text{CE}(L_2)$, whereas the opposite pattern will be observed for present lotteries, $\text{CE}(L_1) < \text{CE}(L_2)$, as participants would pay more attention to the high probability in L_2. Interpretation 1 then predicts primarily that the Time × Probability interaction will be significant (also, the three-way Time × EV × Probability, i.e., whether the interaction between Time and Probability is dependent on the EV).

Figure 2 shows the mean CE for different levels of probability (*x*-axis), time delay (top side of the graph), and EV (left side), aggregated across all five experiments. Visually, the results are not consistent with Interpretation 1 of CLT; rather, \$-lotteries (datapoints in the lower end of the probability axis) attain higher valuations regardless of the time delay, which are much higher than the EV of the lottery (dotted horizontal lines).

The patterns in Figure 2 are confirmed in the statistical analyses conducted separately for each experiment. Table 2 presents the main effect of time and all interaction effects containing time (there are

Figure 2

Mean CE Values Across Probability, EV, and Time Levels for Experimental Data Across All Five Experiments ("Data": Circle Points) and Model Predictions ("Model": Red Lines)



Note. Model refers to the formal model for CLT based on prospect theory, which is presented in the "Formal Modeling" section (not to be confused with the statistical mixed-effects model in the "Behavioral Results" section). Error bars represent ±1 *SEM*. Horizontal dotted lines in each panel represent EV values, which are also shown in the boxes on the right-hand side of the figure. The 1% and 5% probability levels are omitted (see Appendix E for the graph including these probability levels). EV = expected value; CE = certainty equivalence; CLT = construal level theory; SEM = standard error of the mean. See the online article for the color version of this figure.

Table 2
Main and Interaction Effects Containing Time in the Five Experiments of the Present Study

Experiment	Time	Time × EV	Time × Probability	Time × EV × Probability
1	$F(2, \text{Inf}) = 0.34$	$F(14, \text{Inf}) = 0.35$	$F(12, \text{Inf}) = 5.14^{**}$	$F(84, \text{Inf}) = 0.36$
2				
Precise	$F(2, \text{Inf}) = 0.54$	$F(14, \text{Inf}) = 0.26$	$F(12, \text{Inf}) = 7.37^{**}$	$F(84, \text{Inf}) = 0.40$
Imprecise	$F(2, \text{Inf}) = 0.07$	$F(14, \text{Inf}) = 0.23$	$F(12, \text{Inf}) = 4.68^{**}$	$F(84, \text{Inf}) = 0.26$
3	$F(2, \text{Inf}) = 8.13^{**}$	$F(6, \text{Inf}) = 0.11$	$F(8, \text{Inf}) = 0.46$	$F(24, \text{Inf}) = 0.31$
4	$F(2, \text{Inf}) = 3.22^{*}$	$F(6, \text{Inf}) = 0.13$	$F(8, \text{Inf}) = 1.05$	$F(24, \text{Inf}) = 0.22$
5	$F(1, \text{Inf}) = 4.94^{*}$	$F(3, \text{Inf}) = 1.97$	$F(4, \text{Inf}) = 5.59^{**}$	$F(12, \text{Inf}) = 1.47$

Note. Bayesian–Frequentist p values. Inf denotes infinite denominator degrees of freedom for the F-test. EV = expected value.
$^{*} p < .05$. $^{**} p < .001$.

two rows for Experiment 2, *precise* and *imprecise*, for each presentation format). Starting with the main effect of time, there is mixed evidence across the five experiments that lotteries that are resolved in the future are evaluated differently than lotteries in the present. For example, in Experiment 5, future lotteries receive on average (across levels of EV and probability) higher evaluations, $F(1, \text{Inf}) = 4.94$, $p = .026$. In Experiments 3 and 4, on the contrary, the significant effect of time is driven by differences in favor of present lotteries: In both experiments, lotteries offered "today" attain higher values than lotteries offered in "2 months" or "1 year" (see Table 2). However, the mixed evidence for a significant main effect of time is not at odds with CLT.

The benchmark for Interpretation 1 of CLT is the Time × Probability interaction, which was significant in Experiments 1, 2, and 5. According to Interpretation 1, this interaction effect would suggest that in the near future, CE valuations for %-lotteries would be higher than $-lotteries, and in the distant future, $-lotteries would attain higher values than %-lotteries. To examine this prediction, we compared the most extreme $-lottery against the most extreme %-lottery in every experiment (across all EV levels). As seen in Figure 2, $-lotteries (plotted on the lower end of the x-axis in each panel) were evaluated higher than %-lotteries (plotted on the upper end) at every time level and across all experiments (suggesting a main effect of probability, which was significant in all experiments, all $ps < .001$, with low probability lotteries, i.e., $-lotteries, receiving higher evaluations regardless of EV and time). This pattern is inconsistent with Interpretation 1, which suggests that the Time × Probability interaction would be driven by the differential evaluation of $- and %-lotteries depending on the time delay. Rather, the significant interaction in Experiments 1, 2, and 5 was driven by an increase in the difference between $-lotteries and %-lotteries at future timepoints. While the pattern of the significant interaction does not support Interpretation 1 (or *strong* CLT hypothesis, i.e., we did not observe %-lotteries having higher CEs than $-lotteries in the present), it may be suggestive of a *weaker* effect of time (i.e., *weak* CLT hypothesis), to which we will return in the section "Analysis on Interpretation 3." It is also important to note that the difference in valuations of the lotteries with the lowest probability (1% or 10%, i.e., the most extreme $-lottery; note 1% not shown in Figure 2—see Appendix E) is significant when compared to all other probability levels and not just against lotteries with the highest probability (99% or 90%). The results also showed that different levels of EV do not moderate the Time × Probability interaction, as the three-way interaction was not reliable in any Experiment (see Table 2).

Analysis on Interpretation 2: Between-Distance Change in Absolute Influence

This analysis tests the CLT prediction that psychological distance increases the influence of payoff and decreases the influence of probability independently from one another. To test this interpretation, we used a linear mixed-effects model predicting CE values with payoff, probability, and time as fixed effects (and their interactions); for the random effects structure, we assumed random intercepts and slopes (probability and payoff and their interaction with time for the within-subjects experiments, Experiments 3 and 4) for each participant.[10] We followed the same statistical approach as in the previous section to estimate the model parameters and for statistical inference. Figure 3 shows the average standardized linear trends (coefficients) of payoffs and probabilities for each time level across the five experiments.

Overall, the statistical analyses provide little evidence for this CLT interpretation. The model coefficients for payoff were not higher in the future conditions than the present (all $ps > .40$), except for Experiment 5, $F(1, \text{Inf}) = 4.32$, $p = .038$, with the average payoff coefficient being higher in 2 months than today. Similarly, the probability regression coefficients did not differ across timepoints (all $ps > .074$). Even in cases where the numerical difference between time conditions might be suggestive of an effect of time (albeit, nonsignificant), the pattern of results is mixed. For example, in Experiment 2, the results show that the payoff coefficients are on average (numerically) higher for distant-future conditions (2 months and 1 year) and the probability coefficients higher for near-future conditions (today), but in Experiments 3 and 4, the pattern is opposite, with probability coefficients showing an increasing trend as temporal distance increases.

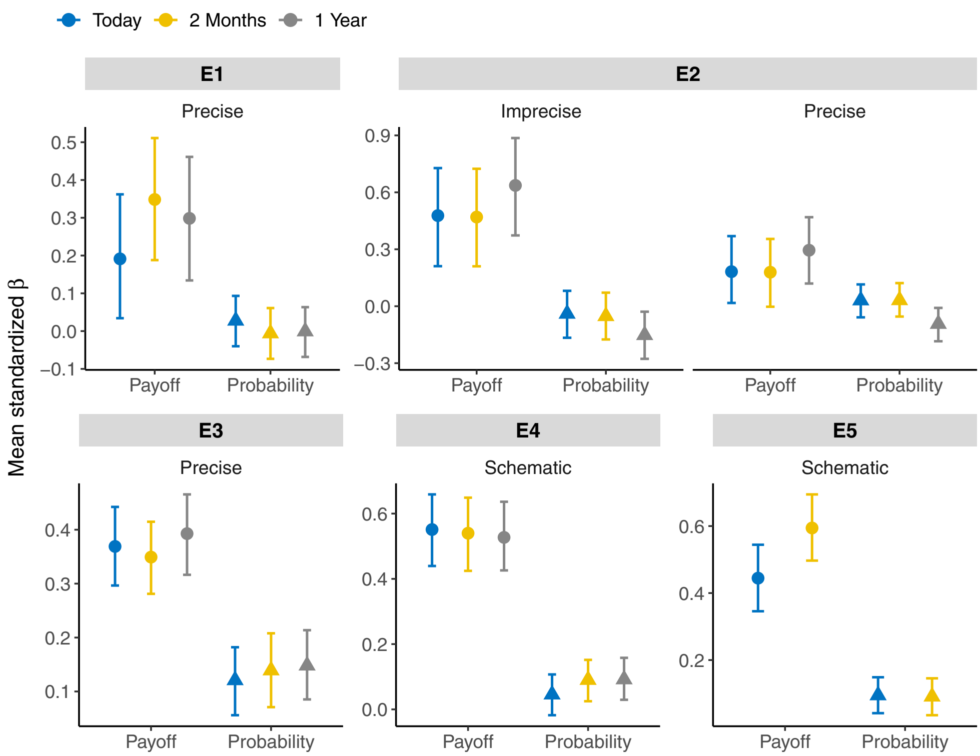
Analysis on Interpretation 3: Between-Distance Change in Relative Influence

This interpretation can accommodate the weak CLT hypothesis (see Trautmann & van de Kuilen, 2012), according to which construal levels may moderate risk preferences. Our findings so far have suggested that average CE values are more in line with CPT's predictions: Figure 2 and the analysis on Interpretation 1 showed that average CE values are considerably higher for the $-lotteries, and as probability increases, CE

[10] This type of analysis (and the previous one on Interpretation 1) assumes an additive combination of payoffs and probabilities, which may not be the most appropriate framework for risky lotteries as it contradicts established theories and models, which assume a multiplicative integration of payoffs and probabilities (e.g., prospect theory). We address this issue in the Formal Modeling section.

Figure 3

Model-Predicted Average Payoff and Probability Standardized Regression Coefficients β Across Different Timepoints



Note. The plot shows estimated coefficients for each of the five experiments (E1–E5) and lottery presentation formats (precise, imprecise, and schematic). Error bars indicate 95% highest probability density intervals. See the online article for the color version of this figure.

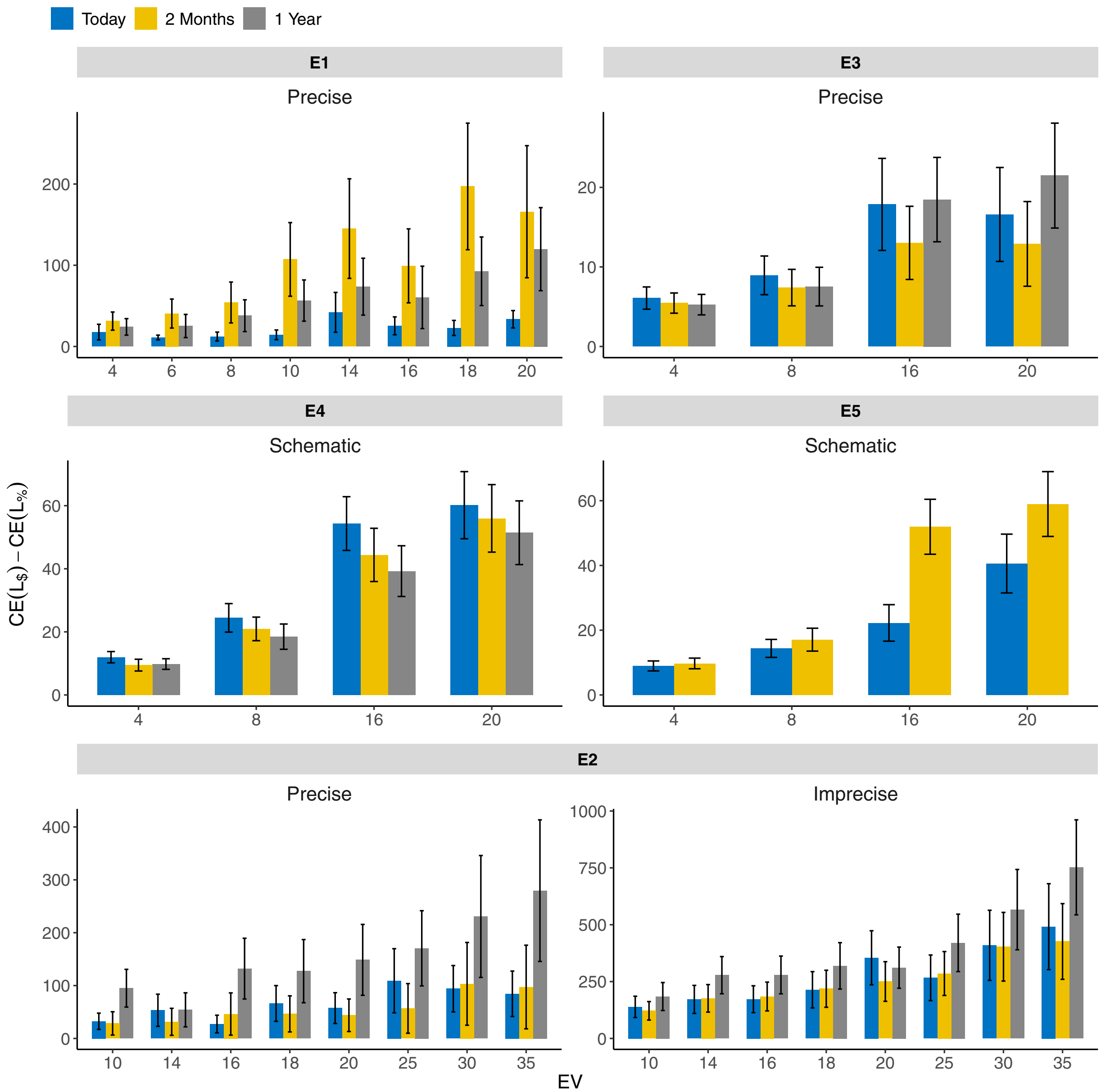
values reduce and almost match the EV of the lottery (dotted lines). CPT correctly explains and predicts CEs and risk preference in both levels of temporal distance, that is, CE($L_\$$) > CE($L_\%$) regardless of the context, but the magnitude of the difference may be affected by the level of construal. Specifically, one of the patterns that Interpretation 3 predicts is that the difference in CEs between $-lotteries and %-lotteries may be smaller in the present, where CLT assumes higher influence of probabilities, and larger in the future, where payoffs should matter more (see also Trautmann & van de Kuilen, 2012).

To test the *weak* CLT hypothesis, we used the difference in CE between the two most extreme $- and %-lotteries in each experiment for each EV level. For example, from all the lotteries with an EV of $8 in Experiment 1, we used $L_\$$: $800, 0.01; 0 and $L_\%$: $8, 0.99; 0; similarly, in Experiment 3, the lotteries for EV = $8 were $L_\$$: $800, 0.10; 0 and $L_\%$: $9, 0.90; 0, as the most extreme probabilities were 10% and 90% (see Table 1 for probability values in each experiment). Figure 4 shows the differences in CE between the most extreme $- and %-lotteries for each time point, EV, and experiment, with positive differences indicating higher valuations for the $-lottery. All bars have positive difference scores, indicating that mean CEs for the $-lotteries were higher than the %-lotteries, which is consistent with CPT's predictions, that is, risk seeking with small probabilities and higher CEs for the $-lotteries compared to %-lotteries. We analyzed the difference scores using a linear mixed effects model with EV and time as fixed effects and random intercepts for each participant, separately for each experiment (following the same statistical approach as in previous sections). The assumption of weak CLT was only (partially) supported for a single EV level in Experiment 5 (EV = 16), where the CE difference in favor of the $-lotteries was significantly larger in the future condition ($p = .021$; see Figure 4). All other contrasts in Experiments 1–4 were not significant (all $ps > .10$).[11]

[11] We conducted the same analysis but looked at the pairwise CE differences between *all* probability levels for all lotteries of the same EV (and not just the extreme $- and %-lotteries). For example, in Experiment 5 for lotteries with an EV = $8 and five probability levels (10, 30, 50, 70, 90), there are 10 such pairwise differences: CE(*L*: 80, .10) − CE(*L*: 27, .30), CE(*L*: 80, .10) − CE(*L*: 16, .50), CE(*L*: 80, .10) − CE(*L*: 9, .90), and so forth. In all these pairwise differences, there is always a lottery offering a higher amount (but with lower probability) than the other lottery (i.e., $- vs. %-lotteries). We then examined the main effect of time on the pairwise CE differences within each EV level, separately for each experiment. Across probability levels, the effect of time was significant only for EV = 16 in Experiment 5 (as in the analysis in the main text focusing on the extreme $- and %-lotteries). The effect of time was moderated by the difference in probability levels only in one EV level in Experiment 1 (out of eight), one EV level in Experiment 2 (out of 16, eight for each type of presentation), and two EV levels in Experiment 5 (out of four; no significant interaction effects in Experiments 3 and 4). For these EV levels, the effect of time is mostly observed in the low end of the probability scale (e.g., 1%, 10%), where the difference in favor of the $-lotteries is larger in the future conditions. However, this is only observed in four out of 36 EV levels across the five experiments. *p* values for multiple comparisons were adjusted using the Holm–Bonferroni method.

Figure 4

Mean CE Differences (on the Original CE Scale) Between the Most Extreme \$- and %-Lotteries Across EV Levels (x-Axis) and Experiments (Different Plots)



Note. The *strong* version of CLT predicts that the height of these bars should be positive in the future, $\mathrm{CE}(L_{\$}) - \mathrm{CE}(L_{\%}) > 0$, but negative in the present, $\mathrm{CE}(L_{\$}) - \mathrm{CE}(L_{\%}) < 0$. The *weak* version of CLT predicts that the differences should be positive (regardless of the context), but their magnitude should be affected by time with larger differences in the future conditions. Error bars indicate ±1 *SEM*. EV = expected value; CE = certainty equivalence; CLT = construal level theory; SEM = standard error of the mean. See the online article for the color version of this figure.

Formal Modeling

As already mentioned, CLT is a verbal theory without a formal representation. Therefore, it lacks a quantitatively precise description of the influence of payoff and probability on risk preference and how psychological distance can change such influence. As a result, it is impossible to strictly test its predictions regarding the changing influence, not to mention a quantitative comparison of different accounts of asymmetry in risk preference among different temporal distances (e.g., Abdellaoui et al., 2011). In this section, we present a formal model of CLT regarding risk preference within the framework of prospect theory (Kahneman & Tversky, 1979). The model will then be used to analyze our empirical data and to test the three CLT verbal interpretations and predictions.

Prospect theory requires two functions to describe and explain risk preferences, that is, a value function and a probability weighting function. In the formal model of CLT, we employ the power value function, $v(x) = x^{\alpha}$, and the compound invariance probability weighting function proposed by Prelec (1998), $w(p) = \exp\{-\delta[-\ln(p)]^{\gamma}\}$, to quantify the impacts of payoff and probability on risk preference, respectively.[12] The parameter α in the value function controls the shape of the function in that higher values of the parameter imply less concave functions and thus higher sensitivity to payoff differences. The value of α also influences the height of the function. Under the common condition of $x > 1$, the larger the parameter is, the higher the subjective value of a given payoff would be. The δ parameter in the probability weighting function primarily controls the elevation of the function, whereas the γ parameter primarily controls the curvature of the function. On the one hand, the larger the δ parameter is, the lower the decision weight for a given probability would be. Psychologically, this means that people will become more averse to risky rewards as opposed to certain ones. On the other hand, the larger the γ parameter is, the less inverse S-shaped the probability weighting function becomes. Psychologically, this means that people will become more sensitive to differences between moderate probabilities. In what follows, we will present a brief explanation of the properties of this formal model and how changes in its parameters can accommodate the three interpretations of CLT regarding the impact of psychological distance on risk preference. See Appendix B for the relevant mathematical derivations.

The evaluation tasks used in our experiments required some form of a CE measure of a lottery. Let CE(x, p) represent the certainty equivalent of a lottery with a payoff amount x and probability p. According to prospect theory,

$$v(\mathrm{CE}(x, p)) = v(x) \cdot w(p). \tag{1}$$

Given the power value function and compound invariance probability weighting function, we have

$$\begin{aligned}\mathrm{CE}(x, p) &= v^{-1}[v(x) \cdot w(p)] = x \cdot \exp\{-(\delta/\alpha)[-\ln(p)]^{\gamma}\} \\ &= \mathrm{EV} \cdot \frac{\exp\{-(\delta/\alpha)[-\ln(p)]^{\gamma}\}}{p}.\end{aligned} \tag{2}$$

Note that both the value and probability weighting functions (i.e., the relevant parameters) might depend on the length of psychological distance. Consequently, the CE of a lottery to be resolved at a particular psychological distance also depends on the length of the distance. We will focus on temporal distance (i.e., the time delay between now and the resolution time of the lottery) and thus use subscript t to indicate the resolution time (when necessary).

According to Interpretation 1 (*within-distance difference in absolute influence*), probability should have a higher impact than payoff on the CE for near-future lotteries, whereas payoff should have a higher impact than probability for distant-future lotteries. This means that for near-future lotteries with the same EV, CEs should be higher for %-lotteries than for \$-lotteries. The reverse should occur for distant-future lotteries. Such requirements might be fulfilled if both δ/α and γ assume large values for near-future lotteries and small values for distant-future lotteries. See Appendix B for the detailed mathematical derivation.

Interpretation 2 (*between-distance change in absolute influence*) suggests that, for payoffs $x > y > 0$ and probabilities $1 \geq p > q \geq 0$, $\mathrm{CE}_t(x, p) - \mathrm{CE}_t(y, p)$ is an increasing function of t (i.e., the absolute influence of payoff increases with temporal distance), and $\mathrm{CE}_t(x, p) - \mathrm{CE}_t(x, q)$ is a decreasing function of t (i.e., the absolute influence of probability decreases with temporal distance). Simultaneous decreases in δ_t/α_t and γ_t as t increases may fulfill the requirements of this interpretation of CLT for any amount of payoff and the majority of probabilities. See Appendix B for the detailed mathematical derivation.

Overall, with the power value function and Prelec's compound invariance probability weighting function, it is possible to satisfy both the within- and between-distance interpretations of CLT regarding absolute influences of payoffs and probabilities on risk preference across time for any amount of payoff and a large majority of probabilities. Specifically, values of δ_t/α_t and γ_t should both decrease from large to small ones as time delay increases.

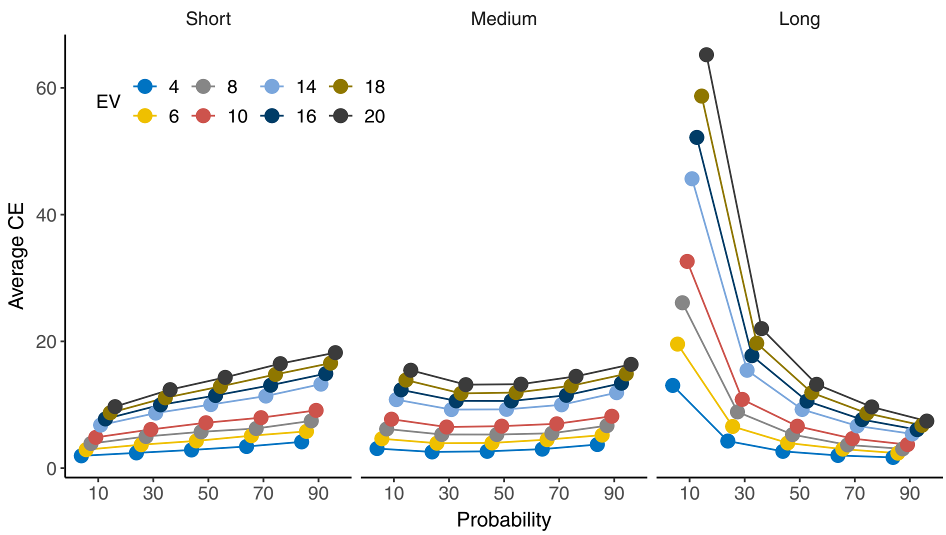
Finally, the third interpretation of CLT (*between-distance change in relative influence*) suggests that the relative influence of payoff should increase as temporal distance increases. Mathematically, this interpretation requires that the first derivative of the right-hand expression in Equation 2 with regard to probability (i.e., the variable p) should decrease as temporal distance increases. Such a requirement can be tested against the parameter values estimated from fitting the observed CEs. Since the two absolute-influence interpretations (i.e., Interpretations 1 and 2) posit stronger requirements than the third, relative influence interpretation, simultaneous decreases in the values of δ_t/α_t and γ_t are sufficient (but not necessary) for fulfilling the third interpretation. See Appendix B for the detailed mathematical derivation.

Figure 5 shows that the current model is able to account for the patterns predicted by CLT. The figure shows predicted CE values for different levels of probabilities and EVs across three levels of temporal distance (short, medium, and long). The presented payoff and probability values are identical to those used in the present empirical work and in Sagristano et al. (2002). For the predictions regarding the short temporal distance, the three model parameters (i.e., α, δ, and γ) were set to $\alpha = 0.7$, $\delta = 1$, and $\gamma = 0.9$. The corresponding values regarding the medium distance were set to $\alpha = 0.7$, $\delta = 1$, and $\gamma = 0.7$, and those for the long distance were set to $\alpha = 0.9$, $\delta = 1$, and $\gamma = 0.01$. It is clear that this particular parametric setting fulfills the requirements of the formal model of CLT, that is, δ/α and γ should change from large to small values as psychological distance increases. It can be seen that for the same EV, the model can capture the differential impact of payoffs and probabilities and how the CE evaluation is modified by psychological distance. For example, consider the lotteries with EV = 20: In short temporal distance, %-lotteries (e.g., \$22 with a probability of 90%; the rightmost data point on the EV = 20 line) attain higher CE values than \$-lotteries (e.g., \$200 with a probability of 10%; the leftmost data point on the EV = 20 line). This relationship reverses as psychological distance increases: in medium temporal distance, lotteries with the same EV lead to similar CE values irrespective of their payoffs (and probabilities), whereas in long temporal distance, it is the \$-lotteries that receive higher CE values than %-lotteries. It is worth noting that each aforementioned interpretation of CLT entails joint constraints regarding all three parameters involved in the formal model. Consequently, there is neither a direct mapping between the (absolute) weight of payoff and the value function parameter (i.e., α) nor such a mapping between the (absolute) weight

[12] We explored various combinations of value and probability weighting functions. The model presented here was the best among all competing models.

Figure 5

Formal Model Predictions (Mean CE) for Short, Medium, and Long Temporal Distance for Different Levels of Probabilities and EVs



Note. EV = expected value; CE = certainty equivalence. See the online article for the color version of this figure.

of probability and the two parameters (i.e., δ and γ) in the probability weighting function.

Model Fitting

To fit the formal model to the experimental data, we assumed that the reported CE followed a normal distribution with a mean determined by Equation 2 and a standard deviation proportional to its payoff. With parameter *c* for the constant of proportionality, the model has four (individual) parameters in total: α, γ, δ, and *c*. Since the CE of a lottery in the current model with the power value function and the compound invariance probability weighting function is determined by the ratio of δ to α together with the γ parameter and relevant attribute values (Equation 2), one can only estimate jointly δ and α (i.e., their ratio, δ/α) and the γ parameter when fitting the formal model to CE data. Consequently, there are three identifiable parameters: δ/α, γ, and *c*. The combined data set across all five experiments was fitted using a hierarchical Bayesian approach in which each individual parameter was assumed to follow a particular prior hyperdistribution. Specifically, for each identifiable individual parameter *par*, we assumed that

$$\begin{aligned}&\mu_\phi \sim N(0,1)\\&\sigma_\phi \sim U(0.1,1)\\&\phi_i \sim N(\mu_\phi,\sigma_\phi);\\&par_i = 0.01 + k\times\Phi(\phi_i),\end{aligned}\tag{3}$$

in which par_i represents the parameter value for participant *i*, Φ represents the cumulative distribution function of the standard normal distribution, and *k* equals 0.99 for *c*, 1.99 for γ, and 49.99 for δ/α. In this way, the individual values of parameter *c* were constrained between 0.01 and 1, the individual values of parameter γ were constrained between 0.01 and 2, and the individual values for parameter δ/α were constrained between 0.01 and 50. With this set of prior distributions and Equation 2, the whole data set (i.e., pooled data from the five different experiments) was used to estimate the individual and hyper-parameters. According to the formal model of CLT, we should obtain different μ_ϕ for δ/α and γ for lotteries resolved at different time delays. See Appendix C for detailed settings of the model fitting procedures for the analyses regarding each experiment and the overall analysis.

Results and Discussion

Here we report the results of the overall analysis using the pooled data across all five experiments for the estimation of the hyperparameters, $\mu_{\delta/\alpha}$, μ_γ, and μ_c. According to the within- and between-distance interpretations regarding absolute influences (Interpretations 1 and 2, respectively), we should observe simultaneous decreases in $\mu_{\delta/\alpha}$ and μ_γ as time delay increases. Table 3 shows the group means (i.e., μ_ϕ) at different time delays. There is a credible increase in $\mu_{\delta/\alpha}$ between today and 1 year (95% CI [0.022, 0.123]), and the increase between 2 months and 1 year is almost credible (95% CI [−0.006, 0.091]). There is also a credible decrease in μ_γ between today and 1 year (95% CI [−0.269, −0.024]) and the decrease between 2 months and 1 year is almost credible (95% CI [−0.226, 0.010]). Finally, there is no credible change in μ_c. Overall, longer delays appeared to increase the ratio δ/α but decrease γ. The change in the γ parameter was consistent with the two interpretations regarding absolute influences, but not the change in the ratio δ/α. Similar results were found when fitting individual data from each experiment separately.

Table 3
Group Mean Estimated Parameters From the Overall Hierarchical Bayesian Analysis

Parameter	Time		
	Today	2 months	1 year
δ/α	−2.16 [−2.20, −2.12]	−2.13 [−2.16, −2.09]	−2.09 [−2.13, −2.05]
γ	−0.22 [−0.30, −0.13]	−0.25 [−0.34, −0.17]	−0.36 [−0.46, −0.27]
c	−1.31 [−1.37, −1.25]	−1.34 [−1.40, −1.28]	−1.36 [−1.44, −1.28]

Note. Each cell shows the mean and 95% credible interval of the relevant hyperparameter at a specific time point.

To test Interpretation 3 of CLT, we compared the derivatives of the right-hand expression in Equation 2 at different temporal distances predicted by the formal model with parameter values estimated from fitting the observed CEs (see Figure 6). As it is readily seen, the derivatives did not get lower for increasingly longer temporal distances. Indeed, for most probabilities, the derivatives were lowest (i.e., most negative) when there was no delay (i.e., today) and highest (i.e., least negative) when the lotteries were delayed by 1 year. This pattern was starkly opposite to the requirement of the between-distance interpretation regarding relative influences, which suggests that the derivatives should be highest for today and lowest for 1 year. Also note that the empirical derivatives for today were all negative, suggesting that the within-distance interpretation regarding absolute influences (i.e., Interpretation 1) did not hold for immediate gambles.

In summary, as with the statistical analysis of the empirical data, the formal modeling analysis led to results that were at odds with CLT with regard to the impacts of payoff and probability on risk preference at different time delays. This was the case no matter whether we adopted the stronger interpretations regarding absolute influences or the weakest interpretation regarding relative influences. Figure 2 shows the posterior model predictions (orange lines) on the CEs averaged across participants from all five experiments for each combination of probability, EV, and time delay, together with the observed behavioral data. It is clear that the credible changes in model parameters produce the same pattern as in the behavioral data; it is also evident that the model provides a good account of the observed data. Therefore, the formal model could well replicate the observed data but not in the directions predicted by CLT. See Appendix C for the detailed procedure for calculating the posterior model predictions.

General Discussion

Does perceived psychological distance induce a shift in the attention assigned to the payoffs and probabilities of risky lotteries? In other words, are CLT's assumptions regarding the effect of temporal distance applicable to the domain of risky choice? In this work, we examined these questions by systematically analyzing the factors that could moderate the effect of temporal distance on risk preference. Overall, we observed results at odds with CLT's predictions: Analyzing the data from five experiments resulted in unreliable effects of time on the evaluation of risky lotteries. Temporal distance did not convincingly moderate the relative weight of payoff against probability, nor did these weights change across temporal distance in the way predicted by CLT.

We also provide a refinement of CLT's assumptions regarding risk preferences by examining three distinct interpretations of how psychological distance moderates the effect of probability and payoff. These interpretations of CLT were not differentiated in Sagristano et al. (2002; and elsewhere, e.g., see Onay et al., 2013; Savadori & Mittone, 2015), but their consideration is important for the development and test of a formal model of CLT.

CLT and Formal Modeling

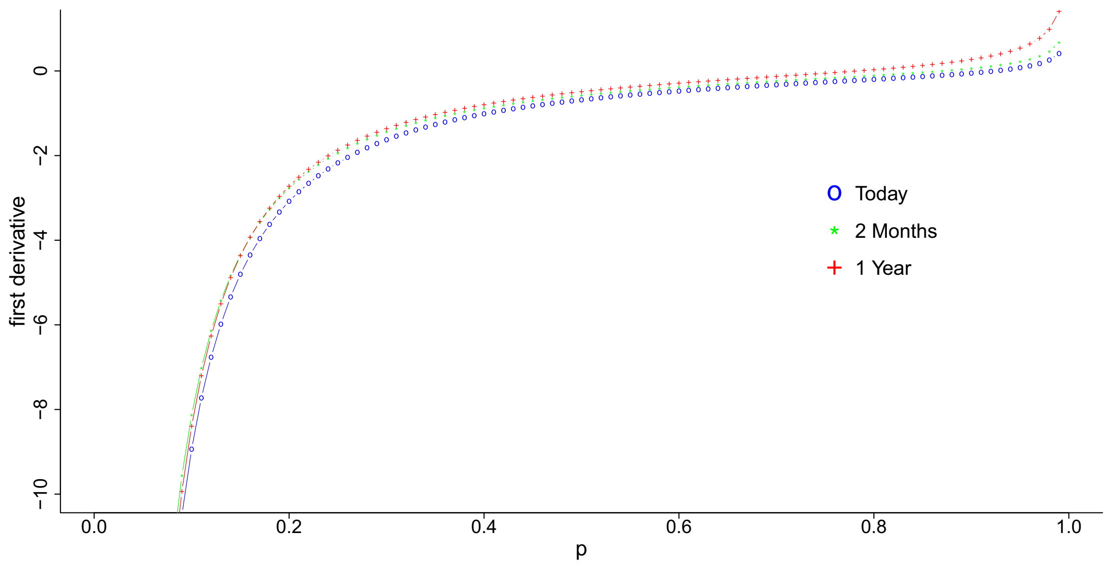
In this article, we developed a quantitative model under the framework of prospect theory to formalize different interpretations of CLT regarding the impact of psychological distance on risk preference. Such a model made it possible to derive precise constraints in terms of model parameters and their changes between psychological distances. With such constraints, one can test quantitatively the relevant verbal interpretations against observed data. Our results suggested that different temporal distances were associated with distinct values of model parameters. However, the revealed changes in parameter values were at odds with any of the three interpretations of CLT. Similar results were found in Abdellaoui et al. (2011), although the changes in parameter values revealed in the previous research differed from ours. This might be produced by differences between the current and previous research, such as the use of different gambles (i.e., gambles with only one nonzero outcome vs. gambles with potentially two nonzero outcomes) and distinct approaches to parameter estimation (i.e., hierarchical Bayesian estimation vs. individual estimation using the least squares method). In any case, both lines of research presented results against CLT about the impact of psychological distance on risk preference. This highlights the importance of developing and testing formal models of CLT for a more precise understanding of the potential impact of psychological distance on risk preference and other psychological constructs.

CLT and Risky Decision Making

CLT proposes that psychological distance alters the way risky lotteries are evaluated, but a strong test of that assumption is lacking. Importantly, CLT's assumptions about risky preferences/choices have rarely been contrasted to existing theories of risky decision making. An exception is Trautmann and van de Kuilen (2012), who tested CLT's predictions against CPT and found little support for the

Figure 6

The Derivative Function of the Right-Hand Expression in Equation 2 at Different Temporal Distances Given the Parameter Values Estimated From Fitting the Observed Data



Note. p = probability. See the online article for the color version of this figure.

moderating effect of psychological distance on risk preferences. Other studies have found partial support for CLT's assumptions and predictions with risky gambles (Onay et al., 2013; Savadori & Mittone, 2015). Potential explanations for these varying levels of support for CLT may relate to methodological manipulations (e.g., task instructions) and the nature of the risk-elicitation task (Fiedler, 2007). For example, in all our experiments (and also in Savadori & Mittone, 2015; Trautmann & van de Kuilen, 2012), participants were told explicitly that delayed lotteries would be resolved/played in the future (2 months or 1 year from now), whereas other research used additional experimental conditions where the time of play was also unspecified (e.g., Abdellaoui et al., 2011). While this might seem a trivial procedural difference, any effect of time (or psychological distance) on risk preference presumably operates on how people represent the choice/evaluation task, and this representation will be influenced by the information people attend to. Comparisons of formats that place different emphasis on time of play might be a fruitful avenue for future investigations.

The risk-elicitation task may also induce different degrees of perceived psychological distance. For example, the difference between a *pricing* (CE) task and a choice task is that the latter results in a nearer and more imminent behavior than evaluating gambles in isolation from each other. A choice naturally indicates some sort of commitment to the decision and the observation of the outcome of that decision; on the other hand, evaluating a lottery does not necessarily entail committing to choosing that specific lottery. This difference between the two tasks—choosing versus evaluating—may itself serve as a factor of psychological distance in the CLT theoretical framework.

The differences in risk preference between choosing and evaluating, a phenomenon termed *preference reversals* (see Lichtenstein & Slovic, 1971; Tversky et al., 1988), may be particularly interesting in the context of CLT and the differential influence of payoffs and probabilities. Reversals are observed when preferences are not invariant between different elicitation procedures: One of the most frequently studied preference reversal is when $-lotteries (similar to the ones used in the current work) attain higher valuations than %-lotteries of the same EV (pricing task), but they are preferred less in choice, where %-lotteries are chosen more frequently. Previous research has suggested that payoffs are weighted more in pricing than in choice tasks (and vice versa for probabilities), leading to this apparent inconsistency between tasks. Supporting this finding, process-tracing studies (e.g., Schkade & Johnson, 1989) have shown that participants spend more time looking at probability information in choice tasks, which results in higher risk aversion in choice than pricing tasks (see Kim et al., 2012). An interesting suggestion for future research is to explore different elicitation procedures or task modalities and the influence of payoffs and probabilities under different levels of psychological distance as suggested by CLT.

The idea that task modality can be conceived as a source of psychological distance poses the question of whether there are more types of psychological distance that operate in a given situation. For example, probability can also serve as distance (i.e., distance from certainty; see Todorov et al., 2007; Wakslak et al., 2006). Wakslak et al. (2006) observed that low likelihood events are represented at a higher level of construal than high likelihood events. In a similar vein, Maglio et al. (2013) suggested that experiencing any type of distance should reduce sensitivity to any other distance (but see Trautmann, 2019). In one of their studies, Maglio et al. found that people assigned to a distal spatial condition were more likely to select the high reward/low probability option compared to the small reward/high probability option (both options had the same EV). This indicates that the effect of spatial distance reduced sensitivity to the distance caused by probability, with participants ignoring the low probability and focusing on the high outcome of the lottery. In our experiments, time of play remained constant, while probability changed between lotteries. It is possible that overexposure to probability (the dimension or distance that was arguably most salient because it changed across trials) could have reduced participants' sensitivity to the dimension of time. In an attempt to combat this potential insensitivity to time, we encouraged participants to think about how they would spend any money received if the game produced real monetary incentives (Experiments 4 and 5), and we also included a calendar indicating the exact date of play for each lottery (Experiments 3–5). Neither of these manipulations appeared to increase sensitivity to the time dimension (see Appendix A).

An additional concern is whether the simplicity of risky lotteries (as compared to "richer" events or choice/judgment scenarios that have been used with CLT, e.g., see Maglio et al., 2013; Todorov et al., 2007; Wakslak et al., 2006) permits the exhibition of the moderating effect of time (or that of any other distance). Consider a richer scenario like renovating one's home (see introduction); here, the psychological representation of high- and low-level construals can include several features such as the desirable state of the completed renovation, imagining oneself in a new room, and the feasible states of obtaining quotes, materials, trips to the hardware store, and so forth. In comparison, the lotteries we used here have only two features, payoffs (desirable state) and probabilities (feasible state), which perhaps reduces the degrees of flexibility in how such events are psychologically represented. The lottery formats would appear to provide a very direct test of the specific predictions of CLT, but perhaps the impoverished nature of the representations leaves little room for psychological distance to play a role. Such a conclusion suggests a need for clearer explanations of how psychological distance operates under circumstances where there can be agreement over the nature of problem representation.

It may be the case, however, that even with simple stimuli like lotteries, there are individual differences with regard to the importance of different dimensions in people's choices. Research on risky intertemporal choice has shown that for some individuals, behavior can be captured by models that assume probability is translated in time units (e.g., Rachlin et al., 1991; Yi et al., 2006) or time can be treated as representing yet another source of uncertainty (e.g., Fehr, 2002; Keren & Roelofsma, 1995). Others have found that sequential presentation of probability and delay can have differential effects on choice and evaluation, with the primary dimension having an overt effect on such processes (Konstantinidis et al., 2017; Öncüler & Onay, 2009; Vanderveldt et al., 2015). This and related work (e.g., Konstantinidis et al., 2020; Luckman et al., 2020) all suggest that the interaction of the different types of distance may be more complex than originally prescribed by CLT, even when relatively simple stimuli are used.

Taken together, the current work provides convincing evidence (across five experimental settings) that CLT's assumptions about the moderating effect of time on risk preferences cannot be confirmed. Our results and conclusions are in close agreement with recent empirical (Özgümüs et al., 2024) and meta-analytic studies, which have shown that after accounting for publication bias, the evidence in favor of CLT is rather weak (Maier et al., 2022). They also align with the recent call for a multilab replication project aimed at replicating key experimental findings underlying CLT (https://climr.org/). At this point, CLT remains a highly influential theory that has been applied to a wide variety of behaviors and domains. Our results, along with those of others (e.g., Trautmann, 2019; Trautmann & van de Kuilen, 2012), suggest that its contribution to understanding risky choice may have been overstated in earlier work. One positive contribution of our work is that the formalization of CLT can be applied to other psychological distances, such as social and spatial distances, to further examine CLT and risk preference in a mathematically more rigorous way. Such application will, along with the important meta-analytic and replication projects, allow us to have a more concrete understanding of how construal level may or may not influence behavior.

Constraints on Generality

The present work examines incentivized judgments made by English-speaking psychology students. Given that a significant amount of work in psychological and behavioral sciences has used participant samples with the same characteristics as in our work, we expect the reported results and conclusions to produce high levels of generalizability. Nonetheless, we envisage that future work in the domain of psychological distance and risk preference will explore more realistic scenarios that may provide a more ecologically valid account and extension of the current work.

Context

The work in the current article was part of a research project (supported by the Australian Research Council and the National Natural Science Foundation of China) that aimed to understand choice behavior in situations where outcomes are risky *and* delayed. As a theory of psychological distance, CLT suggests that temporal distance influences risk preferences and how people mentally represent risky lotteries (i.e., its features, payoffs, and probabilities). Our work provides extensive empirical, computational, and theoretical tests of CLT and assesses its validity as a framework for risky choice and risk preference.

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Appendix A

Detailed Methods for Each Experiment

Experiment 1

Participants were asked to evaluate 56 hypothetical lotteries, each presented individually in randomized order. We used seven levels of probability (1%, 10%, 30%, 50%, 70%, 90%, and 99%) crossed with eight levels of expected value ($4, $6, $8, $10, $14, $16, $18, and $20). The probability-EV pairs matched those in Sagristano et al. (2002) with the addition of two levels of extreme probabilities (1% and 99%) and four levels of EV (14, 16, 18, and 20). The amount offered by each lottery was derived from the combination of each level of probability and EV; for example, the combination of 1% probability and EV of $4 produced the following gamble: 1% chance of winning $400, otherwise $0. The experiment ($N$ = 126, 97 female, 29 male[A1]; $M_{\text{age}} = 19.75$, $SD_{\text{age}} = 4.82$; UNSW undergraduate students who participated for course credit) consisted of three experimental conditions, each reflecting the time at which the lottery would be played. There were three levels of time delay: today (N = 42), 2 months (N = 42), and 1 year (N = 42), and participants were randomly allocated to one of them (between-subjects manipulation). The amount of money and the probability were presented in two different boxes on the right and left sides of the screen, respectively (see Figure 1A). Two participants were excluded from further analyses as their responses were random or showed reduced engagement with the task (e.g., providing the amount offered by the lottery as the CE).

Experiment 2

For this experiment (N = 126, 72 female, 54 male; $M_{\text{age}} = 19.75$, $SD_{\text{age}} = 4.39$; UNSW undergraduate students who participated for course credit), we manipulated the way information about lotteries was presented: Numerical values for probabilities and payoffs were either given in their precise or imprecise form (Onay et al., 2013), with each participant evaluating two sets of 56 lotteries.

The precise lotteries were of the following form L_{P}^{t}: $100, 0.50; 0 (P stands for "Precise"), and their presentation was identical to the lotteries in Experiment 1. For the imprecise lotteries, the exact numerical value of payoffs and probabilities served as the midpoint of a uniform distribution (from where the values of payoff and probability could be drawn), thus the lottery took the form of $L_{\text{I}}^{t}: U(\$50,\$150), U(0.25,0.75); 0$ and $EV(L_{P}^{t}) = EV(L_{I}^{t})$ (I stands for "Imprecise").

Because the purpose of this experiment was to explore the effect of time on lotteries with small probabilities and high magnitude amounts (relative to the value of amounts of the other experiments in the current work), we used seven levels of low probability (1%, 5%, 10%, 15%, 20%, 25%, and 30%), which were crossed with eight high-EV levels ($10, $14, $16, $18, $20, $25, $30, and $35).

The second set of lotteries consisted of the same probability and EV levels as in the *precise* set but were *imprecise*: Both winning amounts and probabilities were presented to participants as numerical quantities ranging between two values (uniformly distributed; see Figure 1B). Unbeknownst to participants, the midpoint of each range corresponded to the actual winning amounts and probabilities from the precise lottery set. For example, the precise prospect "10% of winning $300" (EV of $30) was presented as "5%–15% of winning $150–$450" (same EV = $30) in its imprecise format. There were three levels of delay: today (N = 42), 2 months (N = 42), and 1 year (N = 42), and participants were randomly allocated to one of them (between-subjects manipulation). As in Experiment 1, for both sets of lotteries, the amount of money

[A1] Across all experiments, participants were asked to indicate their gender between "female" and "male."

(*Appendices continue*)

and the probability were presented in two different boxes on the right and left sides of the screen, respectively. Fourteen participants were excluded from further analyses as their responses were random (e.g., a pattern of responding such as 1, 2, 3, 4) or showed reduced engagement with the task (e.g., providing the amount offered by the lottery as the CE). One datapoint was also removed as an invalid CE value was provided (the entry was ".").

Experiments 3–5

The same lotteries were presented in Experiments 3 and 4 (Experiment 3: 47 UNSW undergraduate students, 37 female, 10 male; $M_{\text{age}} = 19.21$, $SD_{\text{age}} = 3.05$; Experiment 4: 42 volunteers, 29 female, 13 male; $M_{\text{age}} = 21.38$, $SD_{\text{age}} = 2.19$; all participants received a constant participation fee of $7.50). We used five levels of probability (10%, 30%, 50%, 70%, and 90%) crossed with four levels of EV ($4, $8, $16, and $20) for each time delay (now, 2 months, 1 year; within-subjects). Since time was treated within-subjects, we blocked the presentation of lotteries for each delay level, and we counterbalanced the order with which these blocks were presented: There were two presentation orders, one that followed the natural time progression (i.e., now → 2 months → 1 year), and one that was the reverse (i.e., 1 year → 2 months → now).

The new feature of Experiments 3 and 4 was that time was manipulated within subjects in order to control for the possibility of between-subjects variability in risk preferences. The only difference between Experiments 3 and 4 concerned the visual presentation of probabilities: While in Experiment 3 we used the typical precise presentation format (Figure 1A), in Experiment 4, probabilities were expressed in terms of winning (green) and losing (red) balls in an urn, containing 100 balls in total. For example, the lottery "10% of winning $300" was represented as 10 green and 90 red balls in the urn (see Figure 1C). The amount that could be won (i.e., $300) was stated on the top of the urn. Three participants were excluded from Experiment 3 and 5 participants were excluded from Experiment 4 due to random responding and reduced engagement with the task.

Experiment 5 ($N = 80$ with 66 female, 14 male; $M_{\text{age}} = 19.15$, $SD_{\text{age}} = 2.49$) was identical to Experiment 4 with the following main changes: First, time had two levels (today and 2 months) and was manipulated between subjects, with participants being randomly allocated to either the "today" or "2 months" conditions. Second, participants were incentivized using the procedure outlined by Becker et al. (1964). Prior to the start of the task, they were given instructions and examples about the incentivization procedure. Specifically, they were told that one of the urns will be randomly selected at the end of the task. Their evaluation of this urn would be compared to a value, X, randomly drawn between the two possible outcomes of the urn: $0 (if a red marble was drawn) and the amount specified on top of the urn ($, if a green marble was drawn). If X was higher than participants' evaluation of that urn, they would receive that value X as reward. Otherwise, the lottery/urn would be played for real, and they would receive the outcome depending on whether the marble was green (success) or red (failure). Participants in the future condition were informed that the incentivization procedure would take place 2 months from the day of the experiment. They were given unique code identifiers (to match their responses in the task) and were told to bring these codes with them on the prespecified day. The Becker–DeGroot–Marschak method procedure was then followed; 17/40 participants in the future condition returned to play the game (total amount given in both conditions = $717, with participants earning on average $12.57). One participant was excluded from further analyses as they provided the amount of the lottery as the CE for every lottery they were presented with.

Across Experiments 3–5, in order to increase the salience of the dimension of time and ensure that participants had a complete understanding of the time at which the lottery will be played, we also presented a calendar with the exact date of uncertainty resolution on the right side of the experimental screen. For example, for the 2 months condition, the calendar depicted 3 months (as in any other typical calendar), with today's (i.e., the date of the experiment) and future (2 months from the date of the experiment) dates marked with red and yellow squares, respectively. In addition, in Experiments 4 and 5, prior to the start of each delay block of lotteries/urns, participants were encouraged to think how they would spend any money.[A2] After 1 min (i.e., the time that participants had to think about the use of any hypothetical earnings), a button appeared on the screen, and participants could proceed to the actual task upon clicking it. The same procedure was repeated for all time delay blocks.

[A2] Since winnings in Experiment 4 were hypothetical, we asked participants to think about any winnings had this been a real game and the outcome from playing the lottery was positive.

Appendix B

Detailed Mathematical Derivation of the Formal Model of CLT

For the formal model of CLT regarding risk preference within the framework of prospect theory, we adopt the power value function, $v(x) = x^{\alpha}$, and the compound invariance probability weighting function, $\omega(p) = \exp\{-\delta[-\ln(p)]^{\gamma}\}$, to capture the influence of payoff and probability on the certainty equivalent (CE) of a lottery. With the current combination of value and probability weighting functions,

$$\mathrm{CE}(x, p) = v^{-1}[v(x) \cdot w(p)] = x \cdot \exp\{-(\delta/\alpha)[-\ln(p)]^{\gamma}\}. \quad \text{(B1)}$$

Interpretation 1 (*within-distance difference in absolute influence*) suggests that, for near-future lotteries with the same EV, CEs should be higher for high-probability lotteries (%-lotteries) than for low-probability lotteries ($-lotteries). The reverse should occur for distant-future lotteries. Mathematically, this means that

(*Appendices continue*)

$$\mathrm{CE}(x,p) = \mathrm{CE}(\frac{\mathrm{EV}}{p},p) = \frac{\mathrm{EV}}{p} \cdot \exp\{-(\delta/\alpha)[-\ln(p)]^{\gamma}\}$$
$$= \mathrm{EV} \cdot \frac{\exp\{-(\delta/\alpha)[-\ln(p)]^{\gamma}\}}{p}, \quad \text{(B2)}$$

should be an increasing function of p for near-future lotteries and a decreasing function of p for distant-future lotteries. By taking the first derivative of the right-hand side of the above formula with regards to p and setting it to be above zero (for an increasing function) or below zero (for a decreasing function), we have that $\exp\{-[(\delta/\alpha)\cdot\gamma]^{\frac{1}{1-\gamma}}\}$ should be smaller than p for near-future lotteries and higher than p for distant-future lotteries. Since p lies between 0 and 1, the above conditions are equivalent to the requirements that $\exp\{-[(\delta/\alpha)\cdot\gamma]^{\frac{1}{1-\gamma}}\}$ approaches 0 for near-future lotteries and 1 for distant-future lotteries. It is easy to show that such requirements can be fulfilled for almost all probabilities if δ/α and γ assume large values (e.g., $\delta/\alpha = 1.3$ and $\gamma = 0.9$ so that $\exp\{-[(\delta/\alpha)\cdot\gamma]^{\frac{1}{1-\gamma}}\} = 0.008$) in the former case and small values (e.g., $\delta/\alpha = 0.1$ and $\gamma = 0.1$ so that $\exp\{-[(\delta/\alpha)\cdot\gamma]^{\frac{1}{1-\gamma}}\} = 0.994$) in the latter case.

According to Interpretation 2 (*between-distance change in absolute influence*),

$$\mathrm{CE}_t(x,p) - \mathrm{CE}_t(y,p) = (x-y)\cdot\exp\{-(\delta_t/\alpha_t)[-\ln(p)]^{\gamma_t}\}, \quad \text{(B3)}$$

indicates the absolute influence of payoff and thus should increase as t increases. This is equivalent to the condition that $f(\gamma_t, \alpha_t, \delta_t|p) = \exp\{-(\delta_t/\alpha_t)[-\ln(p)]^{\gamma_t}\}$ is an increasing function of t. This holds if δ_t/α_t decreases as t increases, regardless of the value of p. On the other hand, changing γ_t would not uniformly increase or decrease the output of $f(\gamma_t, \alpha_t, \delta_t|p)$ in that the direction of change in $f(\gamma_t, \alpha_t, \delta_t|p)$ depends on the value of p. Specifically, when $p < \exp(-1) = 0.368$, increasing γ_t would decrease $f(\gamma_t, \alpha_t, \delta_t|p)$, whereas the same change in γ_t would increase $f(\gamma_t, \alpha_t, \delta_t|p)$ when $p > \exp(-1)$. Overall, to guarantee that $f(\gamma_t, \alpha_t, \delta_t|p)$ is an increasing function of t for all probabilities, δ_t/α_t should decrease over time, and γ_t should not change too much relative to the change in δ_t/α_t. Note that the absolute influence of payoff depends on all three parameters of the formal model. The same applies to the following analysis regarding the absolute influence of probability.

Interpretation 2 also requires that

$$\mathrm{CE}_t(x,p) - \mathrm{CE}_t(x,q) = x\cdot\{\exp\{-(\delta_t/\alpha_t)[-\ln(p)]^{\gamma_t}\}$$
$$- \exp\{-(\delta_t/\alpha_t)[-\ln(q)]^{\gamma_t}\}\}, \quad \text{(B4)}$$

is a decreasing function of t, suggesting a decline in the absolute influence of probability as t increases. Since $g(p) = \exp\{-(\delta_t/\alpha_t)[-\ln(p)]^{\gamma_t}\}$ is a proper probability weighting function, it is possible to fulfill the above requirement for a wide range of probabilities but not for all. For example, when δ_t/α_t keeps constant and γ_t decreases as t increases, the above difference regarding two probabilities would decrease for a wide range of probabilities. The two conditions required by Interpretation 2 collectively suggest that both δ_t/α_t and γ_t should decrease as time delay increases, and they should vary in a way that the effect of decreasing γ_t does not counterbalance the effect of decreasing δ_t/α_t as time delay increases. Considering both the within- and between-distance interpretations regarding the absolute influences of payoff and probability (Interpretations 1 and 2), δ_t/α_t and γ_t should simultaneously decrease from large values to small ones as time delay increases.

Finally, Interpretation 3 suggests that the relative influence of probability should decrease as temporal distance increases (or, equivalently, the relative influence of payoff should increase with temporal distance). Mathematically, the relative influence of probability could be measured by the first derivative of the right-hand expression in Equation 2 with regard to the variable p as follows:

$$\frac{d}{dp}\left\{\mathrm{EV}\frac{\exp\{-(\delta/\alpha)[-\ln(p)]^{\gamma}\}}{p}\right\}$$
$$= \frac{\exp\{-(\delta/\alpha)[-\ln(p)]^{\gamma}\}}{p^2}\{(\delta/\alpha)\cdot\gamma\cdot[-\ln(p)]^{\gamma-1} - 1\}. \quad \text{(B5)}$$

Therefore, this interpretation requires that the right-hand side of Equation B5 should decrease as temporal distance increases. By testing this requirement against the parameter values estimated from fitting the observed certainty equivalents, we could infer whether the weakest interpretation of CLT is supported by the empirical data or not.

Appendix C

Detailed Setting of the Hierarchical Bayesian Analysis

In addition to the general settings of model parameters shown in the Model fitting section of the Formal Modeling section, the below settings were adopted when fitting data from each experiment separately as well as simultaneously.

Experiment 1

In this experiment, time delay was treated as a between-subjects variable. Therefore, hyperparameters (i.e., μ_ϕ and σ_ϕ) at different time delays were assumed to be independent.

Experiment 2

In this experiment, time delay was treated as a between-subjects variable, and each participant was presented with two types of lotteries with either precise or imprecise information on payoffs and probabilities. As in Experiment 1, μ_ϕ and σ_ϕ at different time delays were assumed to be independent. Untransformed individual parameters (i.e., ϕ_i) for the two types of lotteries (precise and imprecise) at each time delay were assumed to follow a potentially correlated bivariate normal distribution with the same μ_ϕ and σ_ϕ. In addition, the correlation coefficients for the untransformed individual

(*Appendices continue*)

parameters at each time delay were assumed a priori to be uniformly distributed between −0.5 and 0.5, and coefficients at different time delays were set to be independent just like μ_ϕ and σ_ϕ. Finally, for imprecise lotteries, the midpoints of the corresponding ranges of payoff and probability were used as the payoff and probability in fitting the empirical data.

Experiment 3

In this experiment, time delay was treated as a within-subjects variable, whereas the presentation order of time delay was treated as a between-subjects variable. Therefore, untransformed individual parameters for the two presentation orders were assumed to follow the same multidimensional normal distributions, with correlation coefficients among different time delays uniformly distributed between −0.5 and 0.5 a priori.

Experiment 4

This experiment was the same as Experiment 3, except for the way that probability information was presented (i.e., schematic presentation). Therefore, the same prior settings for model parameters were adopted in this experiment as in Experiment 3.

Experiment 5

This experiment was similar to Experiment 1, except that it involved only two time delays instead of three. As a result, the same general settings of prior distribution as those of Experiment 1 were adopted in fitting the empirical data from Experiment 5.

Simultaneous Analysis

When data from all five experiments were fitted simultaneously, we set μ_ϕ and σ_ϕ for each time delay to be the same across studies. The correlation coefficients among different time delays in Experiments 3 and 4 were also set to be the same in the two studies.

Detailed Procedure for Calculating the Posterior Model Predictions

Figure 2 shows the predicted CEs derived from the MCMC sample of the posterior parameter distributions of the formal model of CLT. To calculate the predicted CEs for each combination of probability, EV, and time delay, we first used each step of the corresponding MCMC joint sample of the individual parameters for each participant and the payoff and probability of the relevant lottery to obtain a (random) predicted CE of the lottery. We then averaged over steps of the MCMC sample for each participant to get a predicted value for the participant. Finally, we averaged across participants to obtain a single predicted CE for each combination of probability, EV, and time delay.

Appendix D

The Effect of the Experimental Manipulations in Experiments 1–5

In the Behavioral Results section, we analyzed the effect of temporal distance on risk preference without taking into consideration the different empirical manipulations in each experiment, as none of them caused a reliable effect of time on lottery evaluations.

One of the main manipulations related to different types of representing probabilities (presentation type): An observation that stood out was that moving from a precise textual presentation of payoffs and probabilities (Experiments 1, 2, and 3; Figure 1A) to a schematic representation with marbles/balls in an urn (Experiments 4 and 5; Figure 1C) made participants' evaluations considerably higher. Similarly, imprecise presentation of lotteries also induced higher evaluations (Experiment 2; see Figure 1B), with participants possibly focusing on the upper end of the probability and/or payoff ranges. Support for this finding can be seen in Figure 3 (Experiment 2), where payoff coefficients are larger in the imprecise than the precise presentation type, whereas the probability coefficients are almost invariant between the two presentation types. This is in line with previous research on imprecise lotteries showing higher evaluations with imprecise amounts but no change in evaluations when imprecise probabilities are used (see Du & Budescu, 2005).

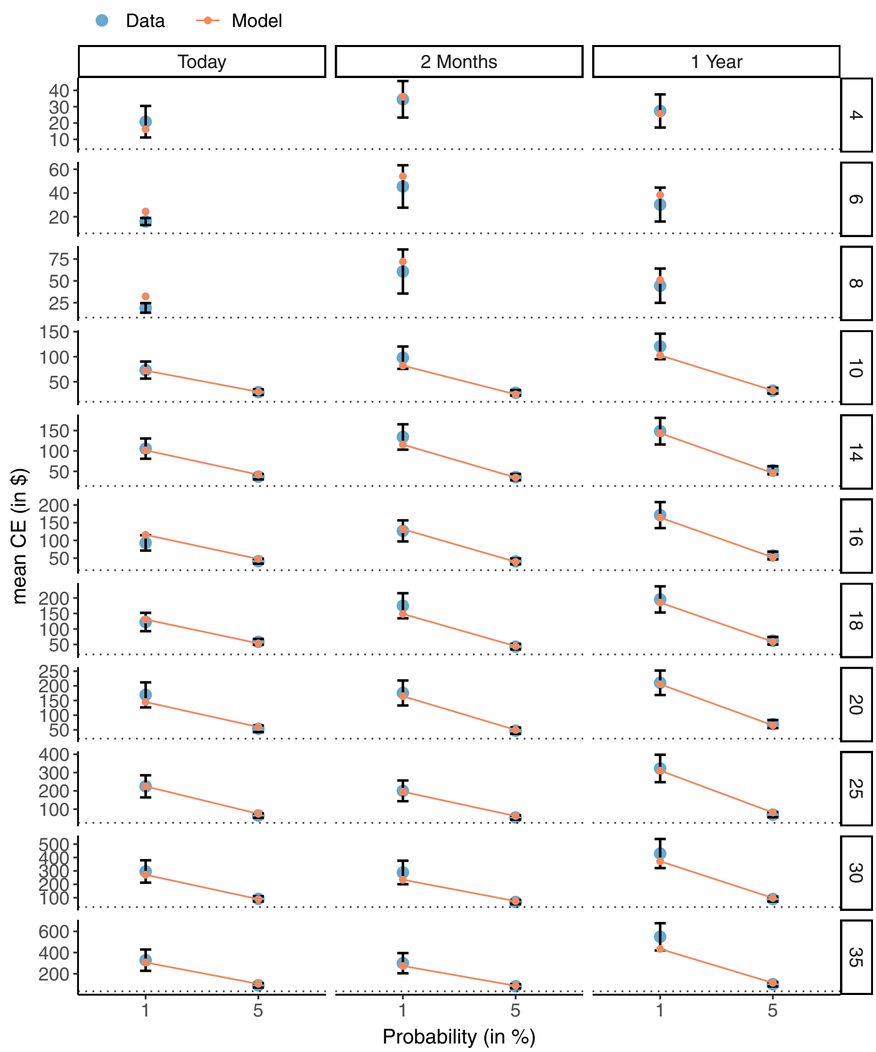
Also, the empirical manipulations that were used to induce an effect of time on lottery evaluations and risk preference (by making the dimension of time more salient) did not produce reliable effects. For example, treating time as a within-subjects variable (and thus, controlling for between-subjects variability in lottery evaluations) did not cause any moderating effects of time (see Experiments 3 and 4). In addition, auxiliary experimental alterations, such as calendars on the computer screen showing the exact time of play of the lottery or providing participants with time to think about how they would spend any lottery winnings, also had no effect on behavior.

We only found minimal evidence in favor of a *weak* effect of time for high EV lotteries (see Figure 4). This effect suggests that differences in favor of the $-lotteries can be amplified in the future. The question is whether the use of a different incentivization procedure—as in Experiment 5, where participants did receive earnings contingent on their choices and those in the future condition received them after 2 months—might have caused such a weak effect of time on risk preference. This is an interesting question for future research, but the general pattern of results and the lack of a time effect in Experiments 3 and 4 (where participants did receive a constant participation fee to increase motivation) suggest that this small effect may be unstable.

(*Appendices continue*)

Appendix E

Figure for Small Probability Lotteries: 1% and 5%



Note. Extension of Figure 2 in the main text with small probability lotteries (1% and 5%). These data are not presented in Figure 2, as the mean CEs are quite high. CE = certainty equivalence. See the online article for the color version of this figure.

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