Early Caregiving Adversity Differentially Shapes Behavioral Sensitivity to Reward and Risk
during Decision-Making

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Abstract

Cognitive systems that track, update, and utilize information about reward (consequences) and risk (uncertainty) are critical for adaptive decision-making as well as everyday functioning and wellbeing. However, it remains unclear how individual differences in reward and risk sensitivity are independently shaped by environmental influences and give rise to decision-making. Here, we investigate the impact of early life experience—a potent sculptor of development—on behavioral sensitivity to reward and risk. We administered a widely used decision-making paradigm to 55 adolescents and young adults who were exposed to early deprivation in the form of early institutional (orphanage) care (a potent type of early life adversity) and 81 comparison individuals who were reared by their biological parents and did not experience institutional care. Leveraging random coefficient regression and computational models, we observed that previously institutionalized individuals displayed general reward hyposensitivity, contributing to a decreased propensity to make decisions that stood to earn large rewards relative to comparison individuals. By contrast, group differences in risk sensitivity were selectively observed on loss, but not gain, trials. These results are the first to independently and explicitly link early experiences to reward and risk sensitivity during decision-making. As such, they lay the groundwork for therapeutic efforts to identify and treat adversity-exposed individuals at risk for psychiatric disorders characterized by aberrant decision-making processes.

Key words: decision-making; early adversity; reward sensitivity; development; risk-taking

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Human decision-making is characterized by maximizing expected reward relative to cost (Rangel & Hare, 2010), while simultaneously tracking and appraising the degree of risk, or uncertainty, associated with potential choices (FeldmanHall et al., 2016; FeldmanHall & Shenhav, 2018; Kane et al., 2017; White & Monosov, 2016). Individual differences in reward and risk computations have sweeping implications for financial, social and emotional wellbeing (FeldmanHall & Shenhav, 2018; Genevsky & Knutson, 2015; Knutson & Heinz, 2015; Lamba et al., 2020; Smidts et al., 2014; Wu et al., 2012). However, research has only recently begun to examine how these individual differences arise in development. A rich body of work from developmental science submits that early life experiences have profound effects on cognitive and affective development, including systems that process reward and risk (Callaghan & Tottenham, 2015, 2016; Dannlowski et al., 2012; Gunnar & Quevedo, 2007). However, prior work has rarely examined the *independent* effects of early experiences on reward and risk sensitivities and how such effects may differentially drive inter-individual differences in decision-making behavior (Callaghan & Tottenham, 2015; Gunnar & Quevedo, 2007). Parsing the respective effects of early experiences on reward and risk sensitivities may illuminate the ontology of decision-making systems while informing efforts to avoid deleterious outcomes frequently associated with exposure to adverse experiences in childhood (e.g., depression) (Andersen & Teicher, 2008; Berardi et al., 2000; Bornstein, 1989, 2017; Desai et al., 2002; Knudsen, 2004; Scott, 1962). Here, we examine risk and reward sensitivities underlying decision-making in individuals who experienced social deprivation via institutional orphanage care, a profound form of early life adversity (ELA). In doing so, we aim to learn how early environmental factors influence the most fundamental of psychological systems implicated in goal-directed behavior.

Decision-Making Relies on Systems that are Sensitive to Reward and Risk. Stemming from centuries-old philosophies on the nature of the mind and motivation (Glimcher, 2004), contemporary theories of decision-making broadly posit that the brain dynamically tracks both the sign (positive or negative) and magnitude (amount) of outcomes associated with different decision outcomes (Daw et al., 2006; Platt & Glimcher, 1999), as well as the likelihood of each outcome. Neuroscientific evidence from animal models as well as human lesion studies suggests that related, though dissociable, systems process reward (sign, magnitude of outcome) and risk (uncertainty of options) (Baxter & Murray, 2002; FeldmanHall et al., 2016, 2019; Haber & Knutson, 2009; Heller et al., 2015; Zhou et al., 2019). The brain performs computations using information about reward and risk from the two systems to decide which option to select based on an internal rule, or policy (e.g., the option that maximizes the greatest subjective value, or produces the most novel information) (Constantinople et al., 2019; Daw et al., 2005; Niv & Schoenbaum, 2008; Rangel & Hare, 2010). While different theoretical perspectives prescribe different variations in the precise mathematical form of these computations, and changing contexts may alter said computations (Niv & Chan, 2011; Niv & Schoenbaum, 2008), that reward (sign, magnitude) and risk (uncertainty of options) computations drive decision-making is unequivocal.

Parsing the Effects of Early Experiences on Risk and Reward Sensitivities During Decision-Making. Both theoretical and empirical data strongly suggest that early experiences, particularly ELA, alter neurocognitive computations about reward and risk. Before reviewing how ELA affects said computations, we must note that modern theories draw meaningful

distinctions between different types of ELA either in their content or how they are perceived (McLaughlin et al., 2014; Smith & Pollak, 2021), and postulate that different forms of ELA are theoretically related to different developmental outcomes. To our knowledge, there is no definitive study that compares how various forms of ELA may uniquely influence reward or risk processing. Our ensuing summary therefore reflects the ‘piecemeal’ literature on this topic, and we note that we use of ‘ELA’ as an umbrella term out of necessity rather than to imply that results are likely to generalize to all individuals exposed to ELA.

In terms of reward, compelling evidence from rodent models suggest that early exposure to stress or deprivation alters core features of mesolimbic dopaminergic circuitry involved in reward processing (Gatzke-Kopp, 2011; McLaughlin, Weissman, et al., 2019; Peña et al., 2017). Work in humans has shown associations between early childhood adversities (e.g., abuse, neglect, poverty) and attenuated neural and behavioral responses to both reward anticipation and receipt (Dillon et al., 2009; Fareri & Tottenham, 2016; Goff & Tottenham, 2015; Hanson et al., 2017; Lloyd et al., 2022; Mehta et al., 2010; Novick et al., 2018; Pechtel & Pizzagalli, 2011). Several other studies have linked these apparent ELA-induced differences in reward processing to motivated behavior, most notably learning (Gee et al., 2018; Hanson et al., 2017; Lloyd et al., 2022; McLaughlin et al., 2019). By contrast to what is known about the effects of ELA on “pure” reward processing and links to *learning*, far less work has examined how ELA-related variations in reward processing give rise to differences in risky decision-making tendencies. Because ELA has been linked to disruptions in learning and related cognitive processes (e.g., cognitive flexibility) (Hanson et al., 2017; Harms et al., 2018), it is likely that ELA-related disruptions in reward sensitivity have cascading effects on behaviors that rely on reward motivation, including

risky decision-making. For example, one recently published study strongly suggests ELA induces blunted reward processing, which in turn predicts individual differences in decision-making (Birn et al., 2017). While informative, the paradigm employed by Birn and colleagues did not dissociate information about reward from risk, limiting the extent to which we can isolate the unique influences of ELA on behavioral sensitivity to reward and risk during decision-making. Further, while a pair of studies found that deprivation in particular is associated with a reduced rate of risky decision-making (Humphreys et al., 2015; Loman et al., 2014), these studies also did not dissociate risk from reward, nor did they explicitly model behavioral sensitivity to reward (i.e., it is unknown how rewards contributed to risky decision-making).

The relationship between early experiences and risk processing is less clear than that with reward sensitivity, but it appears that adverse early experiences are associated with increased difficulty in parsing risk and using it to infer outcome contingencies (Amir et al., 2018; Wright et al., 2015). To complicate the matter, existing associations between ELA and dampened reward sensitivity may actually reflect dampened sensitivity to *risk*. This is because reward and risk are often conflated in experimental paradigms, as many prior studies directly define ‘risk’ in terms of reward. For instance, one common approach prior studies have taken is to categorize riskiness on the basis of differences in expected value (return) between a certain and uncertain option, thereby framing uncertain choice options with larger expected values relative to the safe option to be less risky (such as in tasks that feature choices between a ‘safe’ option a ‘risky’ choice). While this approach is intuitive, it makes it difficult to parse reward and risk processes during decision making because risk is perfectly correlated with reward (Hartley & Somerville, 2015; Mohr et al., 2010; Tobler et al., 2009; van Duijvenvoorde et al., 2015). Thus, although prior research suggests ELA exposure may lead individuals to be less motivated by increasing rewards

and less sensitive to increasing risks when making decisions, a rigorous decomposition of reward and risk is needed to verify these notions.

Current Study. To address the aforementioned gaps in knowledge regarding the effects of early experience on reward and risk sensitivities during decision-making, we tested a sample of children, adolescents, and adults who experienced psychosocial deprivation (a type of ELA) in the form of institutionalized orphanage care (majority adopted before age 3; all adopted by age 10) and individuals who were reared with their biological parents since birth and did not experience such deprivation. Drawing inferences from a previously institutionalized (PI) sample may be particularly informative because (1) institutional orphanage care constitutes a significant form of adversity, (2) individuals in this sample likely only experienced deprivation which means we are able to map the effects of one specific type of adversity to behavioral outcomes (McLaughlin et al., 2014), and (3) deprivation in this sample is constrained to childhood, thus enhancing our ability to draw inferences regarding early versus more protracted childhood experiences on reward and risk sensitivity (Gunnar et al., 2000; McLaughlin et al., 2014; Rutter et al., 2010). To be clear, ELA is multifaceted and the present study tested individuals exposed to one form of ELA.

Participants completed a laboratory decision-making task where they could choose between a certain option (100% guarantee of gaining/losing a particular amount) and an uncertain, risky option (potential to win/lose a more extreme amount or win/lose nothing). Given the paucity of research on this topic, our work was guided by exploratory questions rather than formal hypotheses. In particular, we sought to test whether ELA, in the form of previous institutionalization, affected behavioral sensitivity to rewards and risks during decision-making. We investigated this using two complementary statistical frameworks. First, we partitioned

elements of the task into orthogonal reward and risk components and estimated their statistical association with the likelihood of selecting the risky, uncertain option. Because decisions were nested within participants, we were able to model said trial-level associations as a function of between-subject variables such as early experience (i.e., history of institutional care). Second, we used computational modeling (prospect theory, target model) to uncover whether PI and comparison individuals use common or distinct cognitive operations when evaluating task features during decision-making. Finally, to gather converging evidence for any behaviors observed with laboratory measures of risk-taking, we conducted supplemental analyses with a self-report measure of ‘real-world’ risky behavior.

Methods

Participants. Data from the current report are part of a larger, ongoing, longitudinal study examining the effects of early life experiences on socioemotional development. To be included in the current set of analyses, participants were required to have data from the experimental paradigm (see below). This resulted in a set of $N = 136$ adolescent and young adult participants: 55 PI participants (67% female, mean age = 16.68 years, age range = 12 - 22.90) and 81 comparison participants (51% female, mean age = 15.07 years, age range = 9.11 - 24.60). To ensure that differences in age ranges between PI and comparison participants did not drive our results, we ran all our main analyses a second time while excluding any comparison youths younger than 12 years of age (comparison group $N = 60$ for such analyses). The results of these age matched analyses are reported in the supplement. Since the total available sample size is larger than those of most previous relevant studies (Novick et al., 2018), we opted to report results from the full sample here. This increased sample size is a strength of current study, and is particularly important in the context of early experience research, where the need for larger

samples has been recently highlighted (McLaughlin, Weissman, et al., 2019). Demographic information for the two groups is displayed in Table 1. All participants resided in the United States at the time of testing. Participants were compensated in USD for participating and were informed their earnings would be related to their performance on the decision-making task (see below). Data collection took place at the University of California, Los Angeles. All participants under 18 years provided informed assent and their parents provided informed consent; all participants 18+ years provided informed consent. All research practices were approved by the University of California, Los Angeles Institutional Review Board. Our data, study materials, and analysis code are publicly available on the Open Science Framework (OSF; osf.io/3k9m6).

Measures.

Cups Task. To measure risky decision-making in the laboratory, we employed a computerized version of the cups task (Levin & Hart, 2003). The cups task involves making sequential decisions between certain and uncertain financial outcomes. This task has been frequently used in adult and developmental samples, as well in special populations, to evaluate risky decision-making behavior (Galván & McGlennen, 2012; Uy & Galván, 2017b, 2017a; Weller et al., 2009; Xue et al., 2010). The results reported here are focused on one run wherein participants completed the task to earn rewards for themselves; a forthcoming report will examine behavior on another run where participants played to earn rewards for a parent. The task was programmed in PsychoPy (Peirce, 2007).

On each trial, participants were shown a set of overturned cups on a computer screen (Figure 1). A vertical line divided the row of cups into a left side (1 cup) and a right side (2, 3, or 5 cups, representing unique payout probabilities for the uncertain option). Half of trials were gain trials (i.e., dollar values on both sides of the screen were positive) and the other half were

loss trials (i.e., dollar values were negative). The single cup on the left side of the screen always contained a fixed amount of money (+/- \$2). One of the cups on the right side contained a monetary reward greater in magnitude (+/- \$4, \$6, or \$10) and all other cups on the right side contained \$0. Reward magnitudes were crossed with all payout probabilities ($P = \{1/2, 1/3, 1/5\}$) and trial types (gain, loss) to yield eighteen unique decision scenarios. The eighteen decision scenarios were each repeated three times, totaling 54 decisions per run. These features of the task allow each trial of the task to be decomposed into orthogonal elements of risk (uncertainty) and reward (i.e., return; expected consequences associated with making a risky choice).

Participants were prompted to choose between the certain (safe) and uncertain (risky) decision alternatives on each trial. Participants had 3.5 seconds to make their decision on each trial, else there would be no outcome for said trial and that trial would be excluded when calculating the final bonus. After making a decision, participants received feedback about their choice (displayed for 2 seconds). If the certain option was selected, the feedback screen indicated participants had received the certain amount ('YOU WIN/LOSE +/- \$2'). If the uncertain option was selected, the task software randomly determined whether the participant would receive the non-zero outcome or the zero outcome according to appropriate payout probability (e.g., 'YOU WIN/LOSE +/- \$0' or 'YOU WIN/LOSE +/- \$[4, 6, 10]'). The order of decision scenarios varied randomly between participants, and the likelihood of payout for risky decisions was fair (e.g., actual payout likelihood = nominal payout likelihood). Participants were notified that outcomes in the task were not cumulative. Instead, they were told the computer would randomly select the outcome of one of their decisions at the end of the task and that amount would be added to or subtracted from their compensation, consistent with other similar studies (Galván & McGlennen,

2012; Uy & Galván, 2017a, 2017b). Task instructions emphasized that participants were making decisions that involved actual monetary outcomes to increase participant motivation. Participants were led to believe they could win or lose up to an additional \$10 based on performance, but in fact each participant received \$4 for their performance on the task.

Wechsler Abbreviated Scale of Intelligence. Two subsets of the Wechsler Abbreviated Scale of Intelligence (WASI-II) were administered in order to obtain a measure of general intellectual ability (Psychological Corporation, 2011). Participants were administered the Vocabulary and Matrix Reasoning subtests by a trained experimenter. IQ was approximated using the age-normed t-score conversions. We use percentile scores of IQ as a covariate in all analyses to control for potential confounds due to any group differences in IQ. We deliberately used percentiles because they may be more intuitive and accessible to those unfamiliar with this literature. PI participants had lower IQ (percentile) scores on the WASI ($t(111.7) = 4.106, p < 0.001$, Cohen's $d = 0.697$; PI Mean (SD) = 59.165(25.680), Comparison Mean (SD) = 76.736 (24.714)). Given observed group differences, IQ was included as a covariate in Models 2-4 below. We note that IQ differences between PI and comparison groups should not be taken as evidence of inherent deficiencies among PI individuals.

Analysis

Our analysis consisted of two overarching approaches. First, we modeled task responses at the trial level (i.e., likelihood of making a risky decision) to understand the effects that task-related and between-person variables had on the likelihood of risk-taking (Brooks & Sokol-Hessner, 2020). Next, we used formal computational models to better understand the mechanistic underpinnings (loss and risk aversion, choice consistency, target threshold) of task responses (Navarro et al., 2018). Put differently, the first approach of our analysis plan quantified *what*

influences trial-level and between-person factors have on decision-making behavior, whereas the second sought to answer *why*. Finally, we attempted to determine whether results obtained with these laboratory tasks generalized to self-reported ‘real-world’ risk-taking (see supplement). A detailed description of our two approaches follows.

Modeling Trial-Level Task Responses. In order to probe how institutional caregiving influences distinct facets of risky decision-making (sensitivity to reward versus risk), we performed a risk-reward (also known as ‘risk-return’) decomposition to parse the cups task into orthogonal components (Hartley & Somerville, 2015). Originating from the behavioral economics literature (Chen, 2009; Frazier & Liu, 2016), the idea behind a risk-reward decomposition is that risky scenarios have an element of ‘pure reward’ (sometimes termed ‘pure return’), summarizing the expected consequence of a risky decision, and ‘pure risk,’ summarizing the variability of outcomes associated with a risky decision (i.e., width of the distribution of possible outcomes associated with a risky choice). Here we note for clarity that risky *decisions* or are choices that involve any uncertainty (e.g., choices whose outcome probabilities are not equal to 1), whereas we use *risk* to describe the quantitative degree of uncertainty that accompanies a risky decision or option (i.e., ‘*how much risk is associated with a given risky choice?*’). By calculating orthogonal elements of reward and risk, one is able to then parameterize the trial-by-trial influences of these elements on the likelihood of making a risky decision. We defined reward (i.e., return) as the expected value (EV) associated with a risky decision, and risk as the standard deviation (SD) of the outcome distribution for risky choices (see ref. 67 for more details on calculating reward and risk in the context of the cups task). Reward (EV) values ranged from -\$5 to \$5, and risk (SD) values ranged from \$1.41 to \$3.85. A larger EV corresponds to a greater expected reward, and a greater SD represents a wider

distribution, and therefore uncertainty, around the EV. Notably, these particular mathematic operationalizations of reward and risk (i.e., using EV and SD) are (i) compatible with conceptual definitions of the constructs, (ii) consistent with the logic behind risk-return decompositions (e.g., breaking down risky scenarios into ‘pure reward’ and ‘pure risk’ components), (iii) designed to ensure that risk and reward values are orthogonal (i.e., $r(\text{reward values, risk values}) = 0$), and are (iv) consistent with prior work (Mohr et al., 2010; van Duijvenvoorde et al., 2015).

We used these metrics to specify a trial-level (i.e., within-person) logistic random coefficient regression model that accounted for the nested structure of the data, estimated the effect of risk and reward on decision probabilities, and accommodated between-person predictors by virtue of allowing coefficients to vary between participants. Random coefficient regression models were implemented with the ‘lme4’ package in R (Bates et al., 2014), and significance tests were obtained with the ‘lmerTest’ package (Kuznetsova, Brockhoff, Christensen, 2017). The form and specification of the final model follow.

Trial-level:

$$\text{Logit}(\text{Decision}_{ij}) = \pi_{0j} + \pi_{1j}(\text{Reward}_{ij}) + \pi_{2j}(\text{Risk}_{ij}) + \pi_{3j}(\text{Trial-Type}_{ij}) + e_{ij}$$

Decisions (1 = risky, 0 = certain) at the i -th trial for the j -th individual were modeled as a function of the expected value (EV) associated with taking a risk (Reward_{ij}), the variability in outcomes (SD) associated with taking a risk (Risk_{ij}), and whether the current decision was made on a gain or loss trial (Trial-Type_{ij}). Trial type was included due to prior work showing unequal weighting of gains and losses (Tversky & Kahneman, 1992). Reward and Risk values were each centered at the grand mean. Trial type was entered as a dummy coded variable (0 = loss trial, 1 = gain trial) in order to mirror the interpretation of direction for reward (i.e., greater values indicate relatively more positive rewards). The effect of trial type was only allowed to vary randomly in

one of four models (model 1, see below), in order to ensure model convergence. The notation above for the effect of trial type (π_3) is consistent with what is reflected in our final model.

The terms of the within-person (trial-level) model above were allowed to vary randomly across participants (i.e., decision-level associations could be different across participants). Thus, we were able to use between-person variables to further model within-person variability in trial-level associations. This approach was useful for examining how group affiliation (PI vs. comparison) impacts decision-level associations within individuals. We tested four possible model specifications for the between-person part of the model: a purely within-person specification (i.e., all trial-level coefficients were allowed to vary randomly across participants but no between-person variables were entered) (model 1); a specification that included the main effects of age, group (PI vs. comparison), gender, and IQ (model 2); a specification that tested the aforementioned effects in addition to moderating effects of group on all level 1 associations (π_{1j} , π_{2j} , π_3) (model 3); and a specification that tested the aforementioned main effects in addition to moderation effects of both group and age on all level 1 associations (π_{1j} , π_{2j} , π_3) (model 4). All model specifications are outlined in Table 2. Model 1 included a full random effects structure (i.e., all level 1 parameters varied randomly across subjects); models 2 and 3 allowed the intercept and effects of Reward and Risk to vary randomly across subjects; model 4 allowed the intercept and effect of Reward to vary randomly across subjects. The form of the final between-subjects model (model 3) follows (selection rationale is detailed below).

Subject-level:

$$\pi_{0j} = \gamma_{00} + \gamma_{01}(\text{Group}_j) + \gamma_{02}(\text{Age}_j) + \gamma_{03}(\text{Gender}_j) + \gamma_{04}(\text{IQ}_j) + u_{0j}$$

$$\pi_{1j} = \gamma_{10} + \gamma_{11}(\text{Group}_j) + u_{1j}$$

$$\pi_{2j} = \gamma_{20} + \gamma_{21}(\text{Group}_j) + u_{2j}$$

$$\pi_{3j} = \gamma_{30} + \gamma_{31}(\text{Group}_j)$$

In this model, the intercept was modeled as a function of dummy coded group status (0 = comparison, 1 = PI), age (mean centered), dummy coded gender (0 = male, 1 = female), and IQ (referring to the percentile scores from the WASI-II, mean centered). The coefficients associated with these terms (γ_{01} - γ_{04}) represented the main effects of subject-level predictors (group, age, gender, and IQ, respectively) on trial-by-trial risky decision likelihoods¹; γ_{00} represented the model-implied log odds of making a risky decision when all other variables are set to zero (i.e., for a mean-aged, mean-level intelligence male from the comparison group, when reward and risk values are at their average on a loss trial). The level 1 associations between log odds of making a risky decision and reward, risk, and trial type were further modeled as a function of group (comparison or PI). The γ_{10} , γ_{20} , and γ_{30} coefficients therefore represent the respective effects of reward, risk, and trial type on the log odds of making a risky decision for comparison participants. The γ_{11} , and γ_{21} coefficients were interpreted as the effect of group (comparison or PI) on within-person associations between reward and risk, and the log odds of making a risky decision. Alternatively, these coefficients could also be conceptualized as cross-level interactions and subsequently interpreted as the model-predicted differences in reward or risk effects between comparison and PI participants (the coefficients apply to PI participants, given that the PI group is dummy coded with a 1). The γ_{31} coefficient was the interaction between group and trial type.

The results of our logistic random coefficient regression analyses are summarized in Table 2. We report on the findings of model 3 in greater detail below. We selected model 3

¹ The coefficient associated with group (γ_{01}) is technically conditional on the effects of reward, risk, and trial type (γ_{10} , γ_{20} , γ_{30}) being set to zero, since group is implicated in three cross-level interactions.

(between person main effects of age, gender, IQ, in addition to cross-level interactions between trial-level associations and group) from the four previously discussed prospective models, for a number of reasons: First, the presence of significant cross-level interactions in models 3 and 4 meant that models 1 and 2 would have been inappropriate and misleading because they assumed each main effect is constant across levels of all other variables. Thus, model 3 was chosen over model 1, despite model 1 having the lowest AIC+BIC value. Second, model 3 was deemed preferable to model 4 because the cross-level interactions with age in the latter were not significant and therefore model 3 is more parsimonious. Third, the AIC+BIC value for model 3 was lower than the value for model 4, indicating better fit.

Computationally Modeling Cognition Underlying Reward-Risk Sensitivities. The first stage of our analysis involved estimating statistical relationships between features of our task and the likelihood of making a risky decision. The second stage of our analysis built upon the first stage by fitting established computational models of decision-making to further unpack group differences. Computational models are formal mathematical accounts of the implicit calculations that underlie a given behavioral or cognitive phenomena. Such computational models assume that when faced with a problem, broadly construed (e.g., vision, decision-making, memory retrieval, etc.), an individual takes inputs from the environment, uses an internal mathematical function to perform computations over said inputs, and uses the output to guide behavioral or other cognitive processes accordingly (Green, 2000; Megill, 2014). In the context of decision-making, the inputs to these models typically are typically comprised of a combination of ‘objective’ features of each decision, such as the probability and magnitude associated with each potential outcome.

Our goal in using computational modeling was to unpack group differences in the mechanisms behind reward and risk sensitivities. Notably, statistical relationships between decision tendencies (i.e., likelihood of being risky) and task features (e.g., reward, risk) are not necessarily descriptive of the cognitions that drive decision behavior. Evaluating formalized models of cognition may help determine whether reward (or risk) sensitivities are multi-component processes (e.g., is more than one cognitive operation reflected in reward sensitivity?), uncover evidence for non-linear cognitive processes, and further home in on potential mechanisms. In the context of the current group difference study, well-established computational models of decision-making can help provide additional mechanistic specificity about potential differences and similarities in reward and risk sensitivity between PI and comparison individuals.

Here we used two distinct computational models of decision-making: a *prospect theory model* (Sokol-Hessner et al., 2009; Tversky & Kahneman, 1992) and a *target model* (Wallsten et al., 2005).² We review the logic underlying each model below, outline what they can each uniquely tell us about decision-making, and describe how we implemented each. While we will pay attention and discuss the fit of each model to the data, we want to underscore the idea that using two models with unique parameterizations is meant to help gather as much unique information as possible about group differences in the cognitive processes that may underlie reward and risk sensitivity. In other words, without rejecting the idea that model fit is important, we believe elements of each model might prove to be useful and provide unique information about decision processes.

² We acknowledge here that our risk-reward framework is sometimes described as an alternative model to utility models such as prospect theory (Mohr et al., 2010; Tobler et al., 2009). However, we argue that risk-return models are better suited for measuring statistical relationships between task features and decision likelihoods, whereas utility models are better at capturing the inherent cognitive processes that underlie decision-making.

The Prospect Theory Model. Prospect theory, an influential computational model of decision-making behavior, argues that decision-making is motivated by a desire to maximize latent subjective value as a function of one's attitudes towards risk and loss (Tversky & Kahneman, 1992). In this study, we adopt a simplified version of prospect theory that is widely used within psychology (Brooks & Sokol-Hessner, 2020; Sokol-Hessner et al., 2009). This framework posits that individuals submit the objective value of a decision alternative and its associated probability to a power function in order to calculate the latent subjective value associated with each decision alternative. These subjective values in turn influence the likelihood of choosing a specific decision alternative. Formally, the subjective value,³ notated as $(u(x))$, of objective monetary outcomes during the cups task were calculated using the following piecewise functions:

$$u(x^+) = p(x^+) * (x^+)^{\rho}$$

$$u(x^-) = -\lambda * p(x^-) * (x^-)^{\rho}$$

The two equations above model the respective subjective values of gain and losses. The objective values (in our case, monetary outcomes in the cups task) are represented by x (the + superscript denotes gain values, the - superscript denotes loss values), and $p(x)$ denotes the probability of the objective value. In our case, the probability of certain values was always $p = 1$, and the probabilities of the uncertain values were $P = \{1/2, 1/3, 1/5\}$. The ρ parameter is termed *risk aversion* and λ is termed *loss aversion*. Risk aversion captures the extent to which diminishing sensitivity to marginal rewards reduces one's subjective valuation and subsequently engenders safe, risk-averse behavior. A risk aversion parameter equal to one indicates risk neutrality, a parameter less than one indicates risk aversion in the gain domain and risk seeking

³ This is sometimes also termed subjective utility.

in the loss domain, a parameter greater than one indicates risk seeking for gains and risk aversion for losses. Loss aversion describes an individual's propensity to overweight losses relative to gains. A loss aversion parameter equal to one indicates gain-loss neutrality, a parameter less than one indicates gain seeking, and a parameter greater than one indicates loss aversion. Subjective values were translated to choice probabilities using the SoftMax function:

$$p(\text{risky decision}) = (1 + e^{-\mu[u(\text{risky option}) - u(\text{safe option})]})^{-1}$$

Where e is Euler's number and μ is known as a choice consistency parameter. Greater μ values indicate more consistency across decisions, such that decision alternatives with higher subjective value are increasingly more likely to be selected over those with lesser subjective values.

We used Markov Chain Monte Carlo (MCMC) methods to hierarchically fit the prospect theory model to each subjects' data while simultaneously estimating group level parameters. Simulation studies demonstrate that this approach (that is, modeling individual subject and group-level parameters simultaneously) is better at recovering parameters relative to the common approach of performing maximum likelihood estimation on each subject separately and analyzing the resulting parameter estimates in a separate analytic step (Nilsson et al., 2011). Because hierarchical modeling with MCMC requires the specification of prior distributions, this method also offers an avenue to perform principled regularization and thus gracefully 'nudge' estimated parameters towards more plausible values to avoid overfitting (Gelman et al., 2013). A similar effect also occurs by virtue of hierarchical estimation, which uses pooled group level information to shrink outlying individual means (i.e., subject-level parameters) towards the overall group mean by virtue of the model structure (Kruschke, 2013).

Risky choices on the i -th trial from the j -th participant were modeled as being distributed Bernoulli, $\text{Risky Decision}_{ij} \sim \text{Ber}(P(\text{risky decision})_{ij})$. The structure for the hierarchical portion

of the model is the same for each parameter, so we use λ (loss aversion) as the exemplar. The j -th participant's natural log transformed loss aversion was modeled as being drawn from a normal distribution, centered around a group (grp) mean ($\ln(\lambda_j) \sim N(m_{\lambda\text{-grp}}, \sigma^2_{\lambda\text{-grp}})$). The natural log ($\ln$) was used to sample parameters in unrestricted space; parameters were transformed into restricted space to compute choice probabilities. Group means ($m_{\lambda\text{-grp}}$) and variances ($\sigma^2_{\lambda\text{-grp}}$), representing population parameters for each group, were in turn drawn from uniform distributions. We examined sensitivity to prior specifications for group means and variances by running the model with four different sets of priors (see supplement). This means differences between PI and comparison youths were modeled by differencing population means for each parameter (PI – comparison) on each MCMC iteration.

Because MCMC estimation results in a posterior distribution that indicates density at values along the parameter space, we are able to perform inference in a graded, rather than categorical, fashion. MCMC estimation was implemented in JAGS (Plummer, 2013) via the 'rjags' wrapper in the R statistical software package (Plummer et al., 2019). Similar with recent similar studies (Brooks & Sokol-Hessner, 2020), we ran 10 chains with 60,000 MCMC samples each. In order to achieve convergence and adequate sampling of the posterior distribution, we thinned at an interval of $k = 3$ and discarded the first 30,000 samples of each chain. This resulted in 100,000 total posterior samples across all 10 chains. We performed inference on the posterior samples of group differences (PI - comp) in computational parameters (λ, ρ, μ) by specifying a region of practical equivalence (ROPE) (Kruschke, 2011, 2013), calculating 89% credible intervals using the highest density interval method (Makowski et al., 2019; McElreath, 2018), and comparing their overlap (Spiegelhalter et al., 1994). Importantly, the comparison of such overlap is what drives inference with this approach. Depending on the degree of overlap between

ROPE and the credible interval, we can conclude robust evidence for a group difference, conclude equivalence to a null value(s), or rule out an effect in one particular direction (e.g., an effect is *not* negative, but still possibly null or positive). We defined our ROPE as spanning a $[-0.1, 0.1]$ effect size interval (i.e., we converted our posterior samples into an effect size metric as specified by (Kruschke, 2013)). We chose this interval because we deemed any difference between the two groups that was less than $1/10^{\text{th}}$ of a standard deviation would arguably result in no discernably meaningful difference in decision behavior. Diagnostic plots (trace plots, posterior distributions split separately by chain, autocorrelation plots, etc.) were inspected to ensure all chains converged (diagnostic plots can be found at osf.io/3k9m6).

The Target Model. Whereas the prospect theory model makes several assumptions about implicit tolerances for risk and reward and their effect on subjective value calculations, the target model (Wallsten et al., 2005) is more parsimonious. The target model simply assumes that individuals, either implicitly or explicitly, set a particular target threshold with respect to the features of a given risky decision. The likelihood of making a risky decision is relatively high if the features are below the target threshold, whereas the likelihood of making a risky decision is relatively low if the features are above target threshold. The likelihood of making a risky decision is 50/50 when relevant decision features are exactly at target threshold.

The decision features used here are the pure reward (EV; expected value) and pure risk (SD; standard deviation) values of a risky option from our aforementioned risk-return decomposition. It was assumed that individuals set a reward-to-risk ratio target threshold (EV/SD) for all decisions across the entire task, denoted by τ . Here, τ represents a point of subjective indifference (Tamir et al., 2015): the likelihoods of making a risky and safe decision are equivalent (i.e., $P(\text{risk}) = P(\text{uncertain}) = 1/2$) when the EV/SD ratio for a given trial is

equivalent to the threshold. Substantively, we interpret the threshold parameter τ as the amount of reward (in terms of expected value) needed to justify the degree of risk (in terms of uncertainty) associated with a risky option. For instance, if one's τ were equal to two, that would mean that the likelihoods of making a risky versus safe decision were even when every one unit of risk was matched by two units of reward. Lower values for this parameter effectively mean that lower expected rewards are needed to 'offset' a unit of risk, whereas higher values indicate that increasingly larger values of reward are needed to offset a unit of risk.

Formally, the τ parameter is related to choice probabilities via the following algebraic form.

$$p(\text{risky decision}) = 1 / (1 + e^{-\mu^*\delta})$$

Where e is Euler's number and μ is a choice consistency parameter similar to the one from the prospect theory model. The key term in this model is δ , which is the difference between a given participant's threshold (τ) and the reward/risk ratio for a given trial:

$$\delta = i - \tau^*$$

Where i represents the EV/SD ratio for a given trial and τ^* represents different thresholds for gain (τ^+) and loss (τ^-) trials.

The MCMC sampling procedure used for hierarchical estimation of the prospect theory model was implemented for the target model (e.g. binary decisions at the trial level were modeled with a Bernoulli distribution using model implied probabilities derived from individual level parameters; individual level parameters that were drawn from normal distributions centered on group means; group means were drawn from uniform distributions, etc.). The same number of chains, samples, burn-in period, and thinning intervals were used. The same inferential procedure involving a [-0.1, 0.1] ROPE and 89% HDI credible intervals was employed. Two sets of priors

were used to gauge sensitivity of target model results (see Supplement); two, instead of four, sets of priors were used for this model because the range potential inputs (e.g., EV/SD ratio) limited the range of candidate threshold parameters. Diagnostic plots (trace plots, posterior distributions split separately by chain, autocorrelation plots, etc.) were inspected to ensure all chains converged (osf.io/3k9m6).

Results

Descriptive Statistics and Group Differences

Collapsing across trial-level (e.g., expected reward) and between-person (e.g., age) features, PI and comparison participants made comparable numbers of risky decisions on the cups task overall ($t(120.55) = -0.388, p > 0.250$, Cohen's $d = 0.085$; PI Mean (SD) = 29.333 (8.144), Comparison Mean (SD) = 28.605 (8.970); Supplementary Figure 1). PI individuals tended to self-report less 'real-world' risk-taking than comparison individuals, as indexed by lower scores on the DOSPERT ($t(115.31)^4 = 1.92, p = 0.132$, Cohen's $d = 0.263$; PI Mean (SD) = 2.969 (0.693), comparison Mean (SD) = 3.151 (0.691)); however this difference only approached significance after controlling for other covariates (see Supplement). These particular results may lend clarity to the open question of whether stressful early life experiences predispose individuals to taking more (Birn et al., 2017) or fewer (Amir et al., 2018) real world risks.

Random Coefficient Regression Results of Trial-Level Task Responses

As described in the Methods, our final model (model 3) of risk-taking behavior was comprised of between-person main effects of gender, age (grand mean-centered), and IQ (grand mean-centered), in addition to cross-level interactions between trial-level associations and group

⁴ Per recent recommendations (Delacre, Lakens, & Leys, 2017), we did not assume equal variances for t-tests and used Welch's t-test by default.

(PI v comparison). Parameter estimates, standard errors, and results of significance tests discussed below are reported in Table 2. Virtually identical results with age matched groups (e.g., age ranges were constricted to be equal) is available in the Supplement.

Effects of risk and reward on within-subject behavior. An examination of trial-level analyses revealed significant effects of both risk and reward on within-subject risk-taking behavior. On average, a one-unit increase in risk at the trial level was associated with a 14.75% increase in the expected odds of making a risky decision while statistically adjusting for all other effects in the model. While it may seem counterintuitive that the likelihood of making a risky decision *increases* as the uncertainty associated with the risky option also increases, this effect appeared to be driven by decisions on loss trials. A follow-up, post-hoc analysis corroborated this by showing a near-zero association between risk (i.e., SD of the outcome distribution associated with the risky choice) and the likelihood of making a risky choice for gain trials, and a stronger, positive association between the two for loss trials (Gain: $\gamma_{20} = 0.019$, Loss: $\gamma_{20} = 0.118$). Because only one cup in risky sets contained a non-zero reward, participants likely believed that greater risk (i.e., variable outcome) in loss trials indicated greater opportunities to avoid a loss (i.e., greater risk meant that a loss was less certain), consistent with similar work (Guassi Moreira & Telzer, 2018).

Cross-level interactions involving risk and reward. The cross-level interaction between risk and group was not significant, indicating the effect of risk does not depend on group. However, in the process of probing the association between risk and the likelihood of making a risky decision, we observed a risk-by-group interaction when running a separate model for loss trials, such that comparison participants exhibited a direct relationship between risk and risky decision-making (i.e., likelihood of making a risky choice increased as risk increased), whereas

PI participants exhibited a near-zero association between risk and risky decision-making (i.e., PI participants did not change risky behavior across different levels of risk). In light of this, we ran a model to formally test the three-way interaction between deprivation, trial type, and risk, and observed a significant effect (interaction $\gamma = 0.364$, $p = .022$). Although these findings should be interpreted with caution given their post hoc nature, they present some evidence to suggest that ELA affects behavioral sensitivity to risk during decision-making, but only under certain contexts (i.e., when there is a chance of loss).

Interrogating group $\times$ reward interaction. We observed a significant interaction between group and reward magnitude on the expected log odds of making a risky decision. Probing this interaction revealed that, for comparison participants, a one unit increase in reward was associated with a 94.43% increase in the expected odds of making a risky decision while statistically adjusting for other effects. In contrast, the cross-level interaction between reward and group suggested the effect of reward on risk-taking was blunted for PI participants, such that every one unit increase in reward was associated with an expected 45.63% increase in the odds of making a risky decision (statistically adjusting for all other variables). This is less than half the size of the effect for comparison participants.

Because group status (PI vs comparison) was implicated in several cross-level interactions, the coefficient denoting group affiliation cannot be interpreted unambiguously for some terms in the model. As reported in Table 2, the group parameter indicates that PI participants were on average 33.02% less likely than comparison participants to make a risky decision when $EV=0$ and trial type = loss (statistically adjusting for other terms in the model). Re-centering the EV variable revealed that relative to comparison participants, PI participants were (i) 184.06% more likely to make risky decisions when $EV = -5$ ($\gamma_{01} = 1.044$, $SE = 0.379$, p

<.01), (ii) only 19.36% more likely to make risky decisions when $EV = -2$ ($\gamma_{01} = 0.177$, $SE = 0.224$, $p > .250$), (iii) 62.43% less likely to make risky decisions when $EV = +2$ ($\gamma_{01} = -0.979$, $SE = 0.291$, $p < .001$), and (iv) 84.21% less likely to make risky decisions when $EV = +5$ ($\gamma_{01} = -1.846$, $SE = 0.480$, $p < .001$).

Although the results above suggest that PI participants have blunted reward sensitivity and were more equivocal with respect to trial type (gain versus loss) during risky decision-making, interactions in logistic regressions can behave in non-intuitive ways (Ai & Norton, 2003).⁵ To help probe the observed interaction between group and reward, we used the fixed effects from Table 2 to plot model-implied probabilities of making a risky decision on gain and loss trials broken down by group status and level of reward (i.e., level of expected value). Figure 2 visualizes model-implied blunted reward sensitivity in PI participants; Figure 3 confirms this is not an artifact of the model by plotting group differences in rates of risky decision-making across unique EV values. Specifically, the largest differences between the PI and comparison groups occurred at the lowest and highest levels of reward (EV), such that individuals in the PI group were more likely to take risks when the expected value of doing so is highly negative and the comparison group was more likely to take risks when the expected value of doing so was highly positive. Importantly, both groups became more likely to take risks with increasing reward (EV) values, but this effect was less pronounced in the PI group than the comparison group. Figure 4 shows this, highlighting the flatter relationship between reward (EV) and the probability of a risky decision for PI individuals. Group differences were most exaggerated at the extremes: PI individuals were more likely to take risks at extremely negative values of rewards, whereas

⁵ More precisely, the cross-product terms used to estimate interaction effects may actually be insufficient estimators of the true interaction effect (which is best captured by a cross-derivative; see McCabe, Halvorson, King, Cao & Kim, 2020). In absence of solutions to accommodate this reality in a random coefficient regression framework, we acknowledge this issue here and plot model-implied probabilities to fully unpack predictions made by the model.

comparison individuals were more likely to take risks at extremely positive values of rewards (Supplementary Figure 2 shows the same relationship with log odds instead of probabilities). In the context of the current experiment, PI youths may have been trying to make more deliberate reward or risk calculations under a time constraint, which led to suboptimal decision patterns at extreme expected values. Notably, probing the interaction indicates that PI individuals were simply not responding at random – they still titrated their behavior according to the level of reward (albeit less strongly than comparison individuals) and even responded more strongly than comparison individuals when rewards were in the loss domain.

In addition to our primary analyses involving prior institutional care and task features, we examined age, gender and IQ. Age was inversely associated with risk-taking propensity (i.e., a one year difference in age between participants was associated with a 4.29% decrease in the expected odds of making a risky decision). Gender was not a significant predictor of risk-taking behavior. Additionally, IQ was not significantly associated with risky decision-making (a one unit difference in IQ percentile between two hypothetical participants was associated with only a .41% decrease in the expected odds of making a risky decision for the participant with the higher IQ score). The aforementioned effects statistically adjust for all other terms in the model. Given group differences between comparison individuals and PI individuals on IQ, we ran an additional model to ensure IQ was not confounding between-group results by testing for a subject-level interaction between IQ and deprivation. We did not find evidence of such an interaction, ruling out an additional avenue by which group difference in IQ could contribute to observed group differences in decision making.

Computational Modeling Results

Prospect Theory. Using inferential guidelines described in the methods section and visualized in Figure 5 (Spiegelhalter et al., 1994), we can conclude that PI youths are not more loss averse than comparison youth, but cannot conclude whether they are less or similarly loss averse than comparison youth. Concretely this means that PI youths do not overweight losses (compared to gains) more than comparison youths. The same pattern was observed for risk aversion (PI youths are not less risk averse than comparison youths), but not for choice consistency, where the groups were practically equivalent (i.e., the two groups selected the choice option with higher value equally consistently). To arrive at these conclusions, we standardized each posterior distribution of differences between parameters of interest (e.g., $\lambda_{PI} - \lambda_{Comp}$) to linearly transform the posterior samples into an effect size metric, and compared the 89% HDIs of these distributions to our pre-defined ROPE. Median values for each standardized posterior distribution and 89% HDI values are reported in Table 3; posterior distributions and the overlap between 89% HDIs and ROPE are depicted in Figure 6. Across the four different sets of priors for loss aversion, we see that the 89% HDI for loss aversion (λ) usually crosses the lower, but not upper, bound of our ROPE, and a considerable amount of mass falls below ROPE's lower bound (as a reminder, $\lambda > 1$ indicates loss aversion). The same trend was observed for risk aversion (ρ), but not choice consistency (μ) which saw its HDIs virtually overlap with ROPE. Virtually identical results with age matched groups (e.g., age ranges were constricted to be equal) is available in the Supplement.

Target Model. Results revealed that PI youths do not set lower values for target model parameters than comparison youth. It is unknown whether the sign of the effect is positive (i.e., we cannot distinguish between $PI = comparison$ and $PI > comparison$), but it is not negative (i.e., it is not $PI < comparison$). This suggests that either PI and comparison youths have similar target

thresholds with respect to the features of a given risky decision, or that PI youths set a higher threshold. Put differently, the reward needed to offset the degree of risk for a given decision is either comparable between the groups or greater for PI youths. Posterior samples of differences between PI and comparison youths on target model parameters were also standardized. Median values for each standardized posterior distribution and 89% HDI values are reported in Table 3; posterior distributions and the overlap between 89% HDIs and ROPE are depicted in Figure 7. Across the two different sets of priors, all three parameters see their 89% HDIs overlap with the upper, but not lower bound of ROPE, and a considerable amount of mass falls above ROPE's upper bound. Virtually identical results with age matched groups (e.g., age ranges were constricted to be equal) is available in the Supplement.

Discussion

Decision-making scenarios frequently demand that individuals parse, process, and act upon unique but related information about reward and risk. To date, little is known about how early childhood experiences differentially impact behavioral sensitivity to reward and risk during decision-making. The present experiment sought to address this in sample of PI and comparison individuals by using risk-reward decomposition techniques from behavioral economics alongside computational modeling. Overall, we found strong evidence to indicate that ELA in the form of previous institutionalization is associated with dampened behavioral sensitivity to rewards, in turn appears to drive a propensity to engage in less risk-taking. This is corroborated by our findings with self-reported out-of-lab risk-taking likelihood. Some evidence of ELA-related disturbances in behavioral risk sensitivity was present, but these effects were less striking than those observed with reward. These results help clarify the nature of both ELA and reward and risk processing while providing promising leads for future studies and applications of this work.

Early Life Adversity is Associated with Blunted Reward Sensitivity During Decision-Making. Our most prominent finding is that ELA in the form of previous institutionalization is associated with reduced behavioral reward sensitivity. These results replicate and extend prior work showing that ELA dampens reward sensitivity (Novick et al., 2018; Pechtel & Pizzagalli, 2011), and are the first to show that ELA affects sensitivity to ‘pure reward’ (independent of risk) in the context of decision-making (Birn et al., 2017). Specifically, differences in reward magnitude had smaller effects on risky decision-making preferences for PI individuals compared to comparison individuals. While individuals in the PI group were not indifferent to rewards overall, their behavioral sensitivity was relatively blunted. Notably, group differences were most exaggerated at the extremes: PI individuals were more likely to take risks at extremely negative values of rewards, whereas comparison individuals were more likely to take risks at extremely positive values of rewards. This aspect of our findings in particular serve to underscore the idea that the effect size of group differences varies depending on the context, such that decision tendencies of PI youth may closely resemble comparison youths or may not resemble them at all depending on the features of the current choice options (e.g., risk, reward). The notion that decision tendencies can vary drastically as a function of context is even more critical when considering we observed no statistically significant group differences between comparison and PI youths in the average number of risky decisions. Indeed, decision-making always occurs in context and future studies must consider this when examining group differences of aggregate decision behavior.

The present findings stand to inform our understanding of depressive symptomatology that is frequently associated with both ELA and reductions in reward-motivated behaviors (Gee, 2016; Heller et al., 2013; Kessler et al., 2001, 2010). Our results are particularly promising

because they explicitly link reward sensitivity and decision-making behavior. Our random effects modeling suggested a large degree of within-group variability in behavioral reward sensitivities, indicating that identifying behavioral sensitivity to risk could be one avenue to help target ELA-exposed individuals who are at risk for psychiatric disorders commonly associated with dampened reward sensitivity and reduced reward-motivated behaviors (e.g., major depressive disorder; Heller et al., 2009, 2013). These findings could also be useful for establishing personalized treatments as part of increasingly popular ‘deep phenotyping’ approaches (Delude, 2015; Robinson et al., 2015; Yehia & Eng, 2019). Importantly, these findings do not necessarily indicate that PI individuals are deficient in some aspect of reward or risk processing. Instead, our results could possibly reflect motivational or goal-based differences that may represent adaptations to early experiences. We highlight the need to investigate this in future studies that are specifically designed to test this possibility.

The Effect of Early Life Adversity on Risk Sensitivity. Our findings involving risk sensitivity were not as straightforward as those involving reward sensitivity. On the one hand, our final model indicated there was no interaction between group status (PI vs. comparison) and risk values on the cups task, rejecting the notion that the two groups differ in their risk sensitivity. On the other hand, follow-up analyses decomposing the main effect of risk indicated group differences in risk sensitivity between PI and comparison on loss trials. This suggests that PI individuals do not differ in risk sensitivity between gain trials and loss trials, while comparison individuals titrate decision-making across levels of risk for loss trials only, consistent with prior work showing differences on the basis of risk in the loss domain (Amir et al., 2018; Wright et al., 2015). Furthermore, our computational target model revealed that PI individuals may have a greater target threshold, such that lower levels of risk were needed to

offset the effect of reward on the likelihood of making a risky decision (Mohr et al., 2010). This would suggest PI individuals are *more* sensitive to risk. Thus, the results here suggest there *may* be ELA-related alterations in risk processing, but it is unclear to what extent and in what direction. Thus, future research might benefit from administering a battery of risk-taking tasks, each assessing risk-taking in distinct ways (e.g, in the presence of ambiguity, using delayed rewards, varying reward contingencies over time, etc.), and fitting a bevy of models that include an explicit parameterization of risk.

Another useful avenue of future work might involve using brain imaging methods to better disentangle signatures of risk from reward in hopes of determining whether the inconsistent risk sensitivity observed here is actually just ‘leaking’, or ‘spillover’ reward sensitivity. Although we mathematically partitioned reward and risk into orthogonal components in this study, human neuroimaging research suggests that value-based processes in certain brain regions (e.g., prefrontal cortex) are modulated to reflect information about risk (compared to regions such as the striatum that seem to more purely represent reward) (Tobler et al., 2009). Neuroimaging data could potentially allow us to determine whether value-based signals in regions that also support risk calculations relate more strongly to the behavioral reward or risk sensitivities observed here. Another benefit of an imaging approach would be to clarify how ELA affects risk perception in relation to perceived threat or aversiveness (independent of reward calculations). An array of studies have shown that ELA has profound effects on salience, aversiveness, and threat processing (McLaughlin, Weissman, et al., 2019), yet we did not observe any such parallel findings with risk. Thus, our results would imply that risk (i.e., uncertainty), at least in the monetary domain, is not perceived to be aversive to ELA-exposed individuals relative to those who have never experienced ELA. Using imaging modalities to

examine similarities and differences in the processing of threat and uncertainty may help identify decision-making processes affected by ELA. Regardless of the exact method of future investigation, it is clear that more studies geared towards understanding ELA and risk, not just reward sensitivity, is increasingly needed.

Computational Parameters Appear Relatively Unaffected by ELA. Results from our prospect theory and target models provide modest evidence that ELA may affect basic, value-based computations. As they relate to prospect theory, our results help inform our understanding of how early experiences affect risk and loss aversion. That PI youths may exhibit less loss aversion (relative to comparison youths) supports the growing literature that ELA blunts affective processes that serve as inputs to decision-making and other motivated behaviors (Birn et al., 2017; Gee et al., 2018; Hanson et al., 2017; McLaughlin, DeCross, Jovanovic, & Tottenham, 2019). While this has been primarily observed in the context of rewards and positive affect, here we observe evidence to suggest that ELA is linked with a greater propensity to take disadvantageous risks (e.g., on loss trials with negative expected values), perhaps as a function of reduced loss aversion. A similar trend was observed with the risk aversion parameter, which controls exponential weighting of subjective value. This could indicate that ELA exposure is associated with less reliance on common decision heuristics and biases, a potential byproduct of ELA environments that are often marked by low predictability (McLaughlin et al., 2019). In the context of the current experiment, PI youths may have been trying to make more deliberate reward or risk calculations under a time constraint, which led to suboptimal decision patterns at extreme expected values.

Whereas prospect theory gave information on non-linear decision processes, the target model tells us how ELA might affect joint evaluations of reward and risk (by considering them

together as a ratio) (Wallsten et al., 2005). With the target model, we again found modest evidence that ELA may be associated with different processing of risk and reward. A more stringent target threshold could explain why PI youths were seemingly less motivated across a range of expected values (e.g., the threshold is set high enough that it pushes decisions likelihoods across expected values to uniformity), consistent with the idea that ELA may prompt less adherence to common decision heuristics and instead promote a more calculating or involved decision strategy. In this sense, risks may not be evaluated independently of reward but rather as the cost of pursuing rewards. Given that the evidence in the present sample is modest, future work may focus on enhancing the precision of evidence by increasing the sample size, including both the number of participants and number of repeated measures (i.e., decisions). Another related focus for future research is to interrogate qualitative differences between ELA-exposed and non-exposed individuals in the algebraic form of the models used to formalize reward and risk computations (Cohen et al., 2020). This may be particularly helpful for studies like the present one, wherein we observed the prospect theory and target models as having comparable fit.

Limitations. There are a number of limitations readers should keep in mind when interpreting and reviewing our results. First, we note the need for additional computational modeling work. Despite modest evidence, we could only conclude that PI youth showed lower or comparable (not greater) loss and risk aversion (as well as target thresholds). We view these results as signaling a relatively novel line of research that is ripe for future, more targeted work. Second, potential group differences in risk sensitivity should also be interpreted with caution considering that differences as a function of trial type (i.e., a risk x group x trial type interaction) could not be formally tested here (the model would not converge). Third, future work ought to

follow-up on our group and age effects to examine whether exposure to ELA elicits different or consistent effects on reward and risk sensitivity at different points in development. A fourth issue regards the group differences in IQ. While the PI and comparison groups differed in terms of IQ, it is unlikely that this difference contributed to differences in decision making given that our results still held when controlling for IQ, and past studies have not found convincing and consistent evidence that IQ affects decision-making behavior (Barbey, 2019). Sixth, we did not find an association between behavior on the Cups Task and the DOSPERT. We interpret this lack of an association as a reflection of the fact that risk-taking is a multifaceted process (Highhouse et al., 2017) and that the two measures tapped distinct features of risky decision making, rather than an indication that our experimental task lacks validity (Enkavi et al., 2019). Whereas our experimental task was designed to identify mechanisms that drive decision making behavior in a constrained context, the DOSPERT ignores granularity and instead surveys decision-making behavior across a variety of contexts. A final limitation concerns the generalizability of these results to other forms of ELA that vary on dimensions of threat and deprivation. Previous institutionalization is one form of ELA and it is likely that decision-making processes differ depending on whether an individual has experienced a threat-based form of ELA (e.g., physical abuse; McLaughlin et al., 2014), a deprivation-based form of ELA like PI, or a both (complex ELA exposure; McLaughlin et al., 2019).

Conclusion. This study is the first to explicitly link independent components of behavioral indices of reward and risk sensitivity to differences in decision-making as a function of ELA. We found strong evidence to suggest ELA affects reward sensitivity during decision-making, while also finding additional, albeit mixed, evidence to suggest ELA also affects risk

sensitivity. These results provide mechanistic specificity in how ELA affects decision-making behaviors and can be used to inform future basic, as well as applied, research.

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Table 1. Demographic information about the previously institutionalized (PI) and comparison groups.

	PI	Comparison
<i>Ethnicity</i>		
Hispanic/Latinx	5.5%	13%
Not Hispanic/Latinx	89.5%	87%
Declined	4%	0%
<i>Race</i>		
American Indian/Native American	0%	0%
Asian/Asian American	42%	11%
Native Hawaiian/Other Pacific Islander	0%	2.5%
African American/Black	0%	16%
Caucasian/White	38%	47%
Other	14%	6%
Mixed	4%	10%
Declined	2%	7.5%
<i>Gender</i>		
Male	33%	49%
Female	67%	51%
<i>IQ</i>		
Mean	59.165	76.736
SD	25.680	24.714

Note. Exact rates were rounded to the nearest half number. “Declined” refers to participants who did not wish to indicate their ethnicity or race. “PI” refers to individuals who spent part of early childhood being reared in orphanage care outside the United States (US) and were then adopted to US families. “Comparison” refers to individuals who were reared with their biological families. IQ refers to age-adjust percentile scores on the WASI-II; these means were significantly different.

Table 2. Random coefficient regression models of the cups task

Term	Model 1	Model 2	Model 3	Model 4
Intercept	0.703 (0.160)***	0.549 (0.139)***	0.730 (0.151)***	0.721 (0.151)***
Reward (EV)	0.564 (0.054)***	0.543 (0.038)***	0.665 (0.050)***	0.652 (0.050)***
Risk (SD)	0.103 (0.036)**	0.096 (0.034)**	0.138 (0.045)**	0.116 (0.042)**
Trial Type	-0.935 (0.267)**	-0.908 (0.121)***	-1.256 (0.160)***	-1.236 (0.161)***
Group	-	0.021 (0.164)	-0.401 (0.211)'	-0.402 (0.202)'
Age	-	-0.044 (0.021)*	-0.044 (0.021)*	-0.034 (0.028)
Gender	-	0.208 (0.150)	0.207 (0.150)	0.177 (0.153)
IQ	-	-0.004 (0.003)	-0.004 (0.003)	-0.004 (0.003)
Reward x Group	-	-	-0.289 (0.076)***	-0.292 (0.077)***
Risk x Group	-	-	-0.104 (0.067)	-0.092 (0.065)
Trial Type x Group	-	-	0.819 (0.242)***	0.857 (0.249)***
Reward x Age	-	-	-	0.005 (0.010)
Risk x Age	-	-	-	-0.007 (0.009)
Trial Type x Age	-	-	-	-0.029 (0.034)
AIC	8150.9	8370.9	8359.4	8366.5
BIC	8247.5	8467.4	8476.7	8483.8

Note. ' refers to $p < .10$, * refers to $p < .05$, ** refers to $p < .01$, *** refers to $p < .001$. Group was coded such that comparison = 0, PI = 1. Gender was coded such that 0 = male, 1 = female. Trial type was coded such that 0 = loss, gain = 1. Reward refers to the expected value of the risky option for a given trial. Risk refers to the outcome variability of the risky option for a given trial. IQ refers to age-adjust percentile scores on the WASI-II. Reward, Risk, Age, and IQ were grand mean centered. Parameter estimates are in log odds (logit) units. Model 3 was selected as the final model. Trial-level associations between decision behavior and reward and risk were allowed to vary randomly across all models. The parameter involving trial type was allowed to vary randomly in Model 1, but none of the others in order to facilitate model convergence. AIC and BIC respectively refer to Akaike and Bayesian Information Criteria; these values were used to help select our final model (lower scores indicate better fit). Coefficients represent unstandardized associations between regressors and the log odds of making a risky decision.

Table 3. Standardized group differences in posterior probabilities of computational parameters between PI and Comparison participants.

<i>Prospect Theory</i>	Prior Set 1	Prior Set 2	Prior Set 3	Prior Set 4
$\lambda_{PI} - \lambda_{Comp}$	-0.02 [-0.15, 0.12]	-0.08 [-0.24, 0.08]	-0.02 [-0.18, 0.15]	-0.03 [-0.13, 0.07]
$\rho_{PI} - \rho_{Comp}$	-0.19 [-0.36, 0.02]	0.20 [-0.08, 0.43]	-0.17 [-0.35, 0.01]	-0.20 [-0.39, 0.00]
$\mu_{PI} - \mu_{Comp}$	0.00 [-0.03, 0.04]	-0.06 [-0.11, -0.02]	0.00 [-0.03, 0.04]	0.00 [-0.03, 0.04]
DIC	9058.4	9455.1	9188.7	8888.9
<i>Target Model</i>	Prior Set 1	Prior Set 2		
$\tau^+_{PI} - \tau^+_{Comp}$	0.00 [-0.17, 1.61]	0.02 [-0.15, 0.86]		
$\tau^-_{PI} - \tau^-_{Comp}$	0.15 [-0.02, 2.17]	0.16 [-0.02, 1.22]		
$\mu_{PI} - \mu_{Comp}$	0.72 [-0.02, 1.89]	0.44 [-0.22, 1.94]		
DIC	9156.3	9525.2		

Note. All estimates in this table come from standardized posterior distributions. The first number in each cell represents the posterior median; the numbers in brackets represent an 89% highest density interval. λ represents loss aversion; ρ represents risk aversion; τ^+ represents the target threshold for gain trials; τ^- represents the target threshold for loss trials; μ represents choice consistency (separate estimates for each model). DIC refers to Deviance Information Criterion, a model fit statistic appropriate for hierarchical Bayesian models.

Figure 1. Schematic of the cups task

Note. The white line divides the certain outcome (left) and the uncertain outcome (right). Rewards associated with each option are listed below (in USD). Probabilities for each choice are represented by the number of cups (i.e., $P(\text{listed outcome}) = 1/\text{number of cups}$). The option on the left represented the safe choice and the option on the right represented the risky choice. Here, the potential outcomes of risky decisions, one in the loss domain (above) and another in the gain domain (below), are shown. The outcome of a safe decision in either domain was not depicted.

Figure 2. Model implied probabilities of making a risky decision for gain and loss trials across +/- five different reward (EV) levels, broken down by group.

Note. EV refers to the expected value of the risky choice for a given trial. Group consists of comparison ('Comp') and PI participants; PI refers to individuals who experienced ELA in the form of previous institutionalization. The probabilities depicted above are computed for an individual whose age and WASI-II score were both equal to the sample mean, and collapse across gender (i.e., the effect of gender was averaged). Model implied probabilities for negative expected values are shown in the top plot, whereas such probabilities for positive expected values are shown in the bottom. Probabilities increase going left to right along the X-axis; EV increases going top to bottom along the Y-axis.

Figure 3. Verifying group differences in risky decision-making as a function of reward (EV).

Note. ‘Expected Value’ (EV) refers to the expected value of the risky choice for a given trial. Group consists of comparison (‘Comp’) and PI participants; ‘PI’ refers to individuals who experienced ELA in the form of previous institutionalization. ‘Rate of Risky Choices’ refers to the percentage of risky decisions made on the Cups task (number of risky decisions divided by number of all decisions).

Figure 4. Unpacking the interaction between ELA and reward sensitivity

Note. Reward refers to the expected value (EV) of the risky option for a given trial. ‘Comp’ refers to comparison participants and ‘PI’ refers to those who experienced ELA in the form of previous institutionalization. The left plot shows the fixed effect for each group; the right plot shows the random effects per group. Only the isolated effect of reward is plotted (i.e., predicted probabilities are computed assuming all other terms, including the intercept, are set to zero). Importantly, the presence of the outlier in the PI group (apparent in both plots in the right column) did not appreciably impact our results (indicated by comparing analyses with and without the subject). This same plot is reproduced with logits on the Y-axis (instead of probabilities) in the supplement.

Figure 5. Five potential inferential scenarios for our Bayesian computational models.

Note. Consistent with recommendations by Spiegelhalter et al., 1994.

Figure 6. Standardized group differences in posterior probabilities of prospect theory computational parameters between PI and Comparison participants

Note. The dashed lines represent the region of practical equivalence (ROPE), set to be [-0.1, 0.1]. The first number in each cell represents the posterior median; the solid black line at the bottom of each plot represents the 89% HDI (exact estimates listed in Table 3). λ represents loss aversion; ρ represents risk aversion; μ represents choice consistency (separate estimates for each model).

Figure 7. Standardized group differences in posterior probabilities of target model computational parameters between PI and Comparison participants

Note. The dashed lines represent the region of practical equivalence (ROPE), set to be $[-0.1, 0.1]$. The first number in each cell represents the posterior median; The solid black line at the bottom of each plot represents the 89% HDI (exact estimates listed in Table 3). τ^+ represents the target threshold for gain trials; τ^- represents the target threshold for loss trials; μ represents choice consistency (separate estimates for each model).

Supplement

Early Caregiving Adversity Differentially Shapes Behavioral Sensitivity to Reward and Risk during Decision-Making

Guassi Moreira et al.

Methods

Domain Specific Risk-Taking Scale.

We used developmentally appropriate versions of the Domain Specific Risk-Taking Scale (DOSPERT) (Figner & Weber, 2011) to measure the self-reported likelihood of participants engaging in ‘real-world’ risky behaviors across five domains (social, recreational, financial, health, ethical). Participants rated the likelihood of engaging in a series of risk-taking behaviors using a seven point Likert scale (1 = “Extremely Unlikely”, 2 = “Moderately Unlikely”, 3 = “Somewhat Unlikely”, 4 = “Not Sure”, 5 = “Somewhat Likely”, 6 = “Moderately Likely”, 7 = “Extremely Likely”). Participants below the age of fourteen were administered the child version of the measure (40 items; sample items: social - ‘Admitting your tastes are different from those of a friend’; recreational - ‘Going camping in the wilderness’; financial - ‘Betting all of your money on who would win rock-paper-scissors’; health - ‘Sharing food with a friend using the same spoon’; ethical - ‘Cheating on an exam’). Participants aged fourteen or older were administered the adolescent version of the measure (39 items; sample items: social - ‘Telling your friend a lie’; recreational - ‘Taking a skydiving class’; financial - ‘Betting all of your pocket money on an online gambling game’; health - ‘Engaging in unprotected sex’; ethical - ‘Downloading pirated music on the internet’). We opted to administer the adolescent version of the questionnaire to our young adult participants (e.g., 20+ years) because the situations described in adolescent version are more consistent with what young adults encounter than what is described in the adult version of the DOSPERT (Shulman et al., 2016). Using age-appropriate versions of questionnaires is a recommended methodological practice by developmental researchers (Telzer et al., 2018). Both versions of the measure evinced good multi-dimensional reliability⁶ (Child: $\omega = 0.931$, ω -hierarchical = 0.455; Adolescent: $\omega = 0.887$, ω -hierarchical = 0.398).

Self-Report Measures of Real-Life Risky Decision-Making. Although laboratory experiments of risky decision-making offer great precision in defining and quantifying risk, they sometimes lack external validity (Tebes, 2000). In order to gather converging evidence on the impact of ELA on risky behavior, we used multiple regression models to examine whether any group differences in risky behavior (adjusting for age, gender, and IQ) on the cups task also extended to self-reported, ‘real-world’ risky behavior as assessed by the Domain Specific Risk Taking Scale (DOSPERT). Prior work has linked DOSPERT responses with other ‘real-world’ metrics of risk-taking behavior (Highhouse, Nye, Zhang, & Rada, 2017).

Results

Self-Reported Risk-Taking

Results and statistics from the DOSPERT are shown in Supplementary Table 3. Even after statistically adjusting for age, gender, and IQ, PI participants tended to be less likely than comparison participants to report taking ‘real-world’ risks. The effect of group (PI vs.

⁶ We are aware of evidence suggesting the DOSPERT does not possess a unidimensional structure (Highhouse et al., 2017), thus rendering Cronbach’s alpha inappropriate to report. In light of this, we report ω and ω -hierarchical.

comparison) explained 2.4% of the variance. Here, there was a positive effect of age on risk-taking such that greater age was associated with greater self-reported endorsement of real-world risky behaviors. Self-reported risk-taking was not related to behavior on the Cups task when including DOSPERT scores in Model 3.

Supplementary Table 1. Four different sets of priors for the hierarchical prospect theory model

Parameter	Prior Set 1	Prior Set 2	Prior Set 3	Prior Set 4
ρ (group mean)	$U(-5, 5)$	$U(-4, 4)$	$U(-2.5, 2)$	$U(-30, 30)$
λ (group mean)	$U(-5, 5)$	$U(-4, 4)$	$U(-2.5, 2)$	$U(-30, 30)$
μ (group mean)	$U(0, 7.5)$	$U(-3, 10)$	$U(0, 30)$	$U(0, 30)$
ρ (variance)	$U(0, 1)$	$U(0, 0.75)$	$U(0, 1.13)$	$U(0, 2.5)$
λ (variance)	$U(0, 1.5)$	$U(0, 1)$	$U(0, 1.13)$	$U(0, 2.5)$
μ (variance)	$U(0, 2)$	$U(0, 1.5)$	$U(0, 2.5)$	$U(0, 2.5)$

Note. ρ refers to risk aversion; λ refers to loss aversion; μ refers to choice consistency. U refers to the uniform distribution. ‘Group mean’ refers to group-level mean of a given parameter; this value is used as the mean of the normal distribution from which subject-level parameters were drawn from. ‘Variance’ refers to the variance of subject-level parameters; this value is used as the variance of the normal distribution from which subject-level parameters were drawn from.

Supplementary Table 2. Two different sets of priors for the hierarchical target model

Parameter	Prior Set 1	Prior Set 2
τ^+ (group mean)	$U(-5, 1.75)$	$U(-4, 1)$
τ^- (group mean)	$U(-5, 1.75)$	$U(-4, 1)$
μ (group mean)	$U(0, 1.61)$	$U(-1, 1.61)$
τ^+ (group variance)	$U(0, 1)$	$U(0, 1)$
τ^- (group variance)	$U(0, 1)$	$U(0, 1)$
μ (group variance)	$U(0, 2)$	$U(0, 2)$

Note. τ^+ refers to the target threshold for gain trials; τ^- refers to the target threshold for loss trials; μ refers to choice consistency. U refers to the uniform distribution. ‘Group mean’ refers to group-level mean of a given parameter; this value is used as the mean of the normal distribution from which subject-level parameters were drawn from. ‘Variance’ refers to the variance of subject-level parameters; this value is used as the variance of the normal distribution from which subject-level parameters were drawn from.

Supplementary Table 3. Group differences in self-reported real world risky behavior.

Term	DOSPERT
Intercept	1.808 (0.320)***
Group	-0.240 (0.124)'
Age	0.069 (0.016)***
Gender	0.034 (0.114)
IQ	0.004 (0.002)
Group ΔR^2	0.024

Note. ' refers to $p < .10$, * refers to $p < .05$, ** refers to $p < .01$, *** refers to $p < .001$. DOSPERT refers to the Domain Specific Risk Taking scale, a self-report measure of one's likelihood to engage in real world risky behaviors. IQ refers to age-adjust percentile scores on the WASI-II. Group ΔR^2 refers to the unique variance explained in the DOSPERT by the Group variable after partialing out the effects of the other variables.

Supplementary Table 4. Random coefficient regression models of the cups task using age matched PI and comparison participants

Term	Model 1	Model 2	Model 3	Model 4
Intercept	0.676 (0.178)***	0.510 (0.153)***	0.791 (0.171)***	0.785 (0.170)***
Reward (EV)	0.571 (0.061)***	0.550 (0.042)***	0.726 (0.060)***	0.709 (0.059)***
Risk (SD)	0.087 (0.038)*	0.082 (0.038)*	0.131 (0.053)*	0.126 (0.049)**
Trial Type	-0.978 (0.304)**	-0.949 (0.132)***	-1.468 (0.190)***	-1.430 (0.190)***
Group	-	0.060 (0.166)	-0.494 (0.220)*	-0.484 (0.217)*
Age	-	-0.035 (0.024)	-0.035 (0.024)	-0.047 (0.032)
Gender	-	0.196 (0.160)	0.194 (0.160)	0.164 (0.166)
IQ	-	-0.005 (0.003)	-0.005 (0.003)'	-0.005 (0.003)'
Reward x Group	-	-	-0.347 (0.082)***	-0.341 (0.081)***
Risk x Group	-	-	-0.103 (0.073)	-0.106 (0.068)
Trial Type x Group	-	-	1.022 (0.262)***	1.017 (0.263)***
Reward x Age	-	-	-	-0.009 (0.013)
Risk x Age	-	-	-	-0.013 (0.011)
Trial Type x Age	-	-	-	0.005 (0.041)
AIC	6800.6	7005.6	6989.9	6995.2
BIC	6894.6	7099.5	7104.0	7109.4

Note. ' refers to $p < .10$, * refers to $p < .05$, ** refers to $p < .01$, *** refers to $p < .001$. Group was coded such that comparison = 0, PI = 1. Gender was coded such that 0 = male, 1 = female. Trial type was coded such that 0 = loss, gain = 1. Reward refers to the expected value of the risky option for a given trial. Risk refers to the outcome variability of the risky option for a given trial. IQ refers to age-adjust percentile scores on the WASI-II. Reward, Risk, Age, and IQ were grand mean centered. Parameter estimates are in log odds (logit) units. Model 3 was selected as the final model. Trial-level associations between decision behavior and reward and risk were allowed to vary randomly across all models. The parameter involving trial type was allowed to vary randomly in Model 1, but none of the others in order to facilitate model convergence. AIC and BIC respectively refer to Akaike and Bayesian Information Criteria; these values were used to help select our final model (lower scores indicate better fit). Coefficients represent

unstandardized associations between regressors and the log odds of making a risky decision. Number of comparison youths reduced to $N = 60$.

Supplementary Table 5. Standardized group differences in posterior probabilities of computational parameters between age matched PI and Comparison participants.

<i>Prospect Theory</i>	Prior Set 1	Prior Set 2	Prior Set 3	Prior Set 4
$\lambda_{PI} - \lambda_{Comp}$	-0.06 [-0.21, 0.10]	-0.14 [-0.33, 0.04]	-0.06 [-0.24, 0.13]	-0.06 [-0.19, 0.06]
$\rho_{PI} - \rho_{Comp}$	-0.17 [-0.35, 0.01]	0.26 [-0.04, 0.50]	-0.14 [-0.33, 0.04]	-0.18 [-0.38, 0.02]
$\mu_{PI} - \mu_{Comp}$	0.00 [-0.04, 0.04]	-0.09 [-0.15, -0.03]	0.00 [-0.04, 0.04]	0.00 [-0.04, 0.04]
DIC	7521.2	7942.8	7617.8	7382.2
<i>Target Model</i>	Prior Set 1	Prior Set 2		
$\tau^+_{PI} - \tau^+_{Comp}$	-0.01 [-0.19, 1.58]	0.01 [-0.17, 0.86]		
$\tau^-_{PI} - \tau^-_{Comp}$	0.14 [-0.02, 2.14]	0.15 [-0.03, 1.22]		
$\mu_{PI} - \mu_{Comp}$	0.72 [-0.02, 1.92]	0.44 [-0.24, 1.94]		
DIC	7559.5	7587.8		

Note. All estimates in this table come from standardized posterior distributions. The first number in each cell represents the posterior median; the numbers in brackets represent an 89% highest density interval. λ represents loss aversion; ρ represents risk aversion; τ^+ represents the target threshold for gain trials; τ^- represents the target threshold for loss trials; μ represents choice consistency (separate estimates for each model). DIC refers to Deviance Information Criterion, a model fit statistic appropriate for hierarchical Bayesian models.

Supplementary Figure 1. Visualizing group differences in distributions of risky decision-making.

Note. ‘Comp’ refers to comparison participants and ‘PI’ refers to those who experienced ELA in the form of previous institutionalization. ‘Rate of Risky Choices’ refers to the percentage of risky decisions made on the Cups task (number of risky decisions divided by number of all decisions).

Supplementary Figure 2. Unpacking the interaction between ELA and reward sensitivity (log odds)

Note. Reward refers to the expected value (EV) of the risky option for a given trial. ‘Comp’ refers to comparison participants and ‘PI’ refers to those who experienced ELA in the form of previous institutionalization. The left figure shows the fixed effect for each group; the right figure shows the random effects per group. Only the isolated effect of reward is plotted (i.e., predicted logits and probabilities are computed assuming all other terms, including the intercept, are set to zero). Importantly, the presence of the outlier in the PI group (apparent in the righthand plot) did not appreciably impact our results (indicated by comparing analyses with and without the subject).