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Acute stress does not affect risky monetary decision-making

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ABSTRACT

The ubiquitous and intense nature of stress responses necessitate that we understand how they affect decision-making. Despite a number of studies examining risky decision-making under stress, it is as yet unclear whether and in what way stress alters the underlying processes that shape our choices. This is in part because previous studies have not separated and quantified dissociable valuation and decision-making processes that can affect choices of risky options, including risk attitudes, loss aversion, and choice consistency, among others. Here, in a large, fully-crossed two-day within-subjects design, we examined how acute stress alters risky decision-making. On each day, 120 participants completed either the cold pressor test or a control manipulation with equal probability, followed by a risky decision-making task. Stress responses were assessed with salivary cortisol. We fit an econometric model to choices that dissociated risk attitudes, loss aversion, and choice consistency using hierarchical Bayesian techniques to both pool data and allow heterogeneity in decision-making. Acute stress was found to have no effect on risk attitudes, loss aversion, or choice consistency, though participants did become more loss averse and more consistent on the second day relative to the first. In the context of an inconsistent previous literature on risk and acute stress, our findings provide strong and specific evidence that acute stress does not affect risk attitudes, loss aversion, or consistency in risky monetary decision-making.

1. Introduction

Because risky decisions are both ubiquitous and must often be made under stress, it is imperative to understand the interactions between stress and choices under risk. However, despite a number of studies examining acute stress and risky monetary decision-making (see Table S1), it is as yet unclear whether and how they interact. In the gain domain, several studies find evidence for more gambling[1] under acute stress (i.e. riskier choices; less risk aversion; more utility function convexity) (Preston et al., 2007; Starcke et al., 2008; Putman et al., 2010; Pabst et al., 2013b, 2013c), while others find *less* gambling under stress (i.e. safer choices; more risk aversion; more utility function concavity) (Porcelli and Delgado, 2009; Cingl and Cahlikova, 2013), no changes in gambling (von Dawans et al., 2012; Delaney et al., 2014; Kandasamy et al., 2014), or both more and less gambling depending on factors like gender (Lighthall et al., 2009; van den Bos et al., 2009), time (Pabst et al., 2013a), trait anxiety and depressive symptoms (Robinson et al., 2015), or outcome magnitude (von Helversen and Rieskamp, 2013). Even with respect to gender, the findings are equivocal: roughly equal numbers of studies found interactions with gender (Preston et al., 2007; Lighthall et al., 2009; van den Bos et al., 2009) as did not (Starcke et al., 2008; Pabst et al., 2013b; von Helversen and Rieskamp, 2013; Kandasamy et al., 2014).

One reason for this apparent inconsistency may be that, with one exception (Kandasamy et al., 2014; see Table S1), all the studies mentioned above used the same problematic measure of risky

Abbreviations: HPA, Hypothalamic-Pituitary-Adrenal; CPT, Cold Pressor Test; CI, Confidence Interval.

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[1] Risk attitudes are commonly represented by the curvature of the utility function (concave for gains, and convex for losses, a difference known as the reflection effect). This curvature leads to risk aversion for gains, and risk seeking for losses. More pronounced curvature entails more risk aversion for gains *and* more risk seeking for losses, while less curvature (more linearity) entails the opposite: less risk aversion for gains, and less risk seeking for losses. For legibility and for consistency with the extant literature, when we state "more gambling" and the like in this paper, we are referring to the gain domain unless specifically indicated otherwise, and we mean to imply the opposite for the loss domain.

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decision-making: a simple probability of gambling. This coarse measure is inadequate because choices between more and less risky options reflect the combined contributions of multiple different processes. For example, someone under stress might gamble less (that is, their probability of gambling might go down) because they dislike the element of chance or risk in the gamble (termed risk attitudes), because they overweight the risky loss relative to the risky gain (termed loss aversion), or simply because they are choosing more (or less) consistently than before despite having the same risk attitudes and loss aversion. Depending on the kinds of choices, other factors can also influence the probability of gambling, including probability weighting (the subjective, as opposed to objective, probability of an event occurring), ambiguity aversion (the distaste for unknown probabilities in decision options), or even dynamic updating when learning in complex, changing, or experiential settings.

Concluding that changes in the probability of gambling are due to changes in attitudes toward risk without dissociating other relevant processes would be analogous to concluding that stress affects memory recall after a study in which participants memorized items and performed a recognition test all while under stress. Such a conclusion would be obviously flawed as differences in recognition could reflect changes in perception, encoding, consolidation, familiarity, or recall — and without careful design and analysis, would all be thoroughly confounded. By the same token, the fundamentally different processes underlying risky choices must be simultaneously and separately quantified, or otherwise accounted for, in order to understand the ways in which acute stress does and does not affect decisions under risk.

In this study, we sought to dissociate and quantify three separable decision-making processes under acute stress in a fully-crossed within-subjects design. Briefly, participants came in on each of two days, identical except for experiencing an acute stress or control manipulation with equal probability on each day. Individual differences in HPA axis activity were objectively quantified with four measurements of salivary cortisol per day (Velasco et al., 1997; McRae et al., 2006). Participants' decision-making was also quantified with a risky decision-making task (Sokol-Hessner et al. 2009, 2013, 2015a, 2015b) that, in combination with an econometric model of valuation and decision-making, allowed the separation of risk attitudes, loss aversion, and consistency in decision-making for each participant on each day. Finally, statistically powerful hierarchical Bayesian analysis methods were used to pool the data from 120 participants, both leveraging individual differences and group-level analysis to identify how acute stress affects or spares the three measured processes contributing to risky decision-making.

2. Methods

2.1. Participants

A total of 122 participants completed the task. Two participants were subsequently dropped when it became apparent that they did not understand the mechanics of the task, leaving a total of 120 participants (64 female; mean age = 22.4, standard deviation = 4.5). Our fully crossed design (Stress or Control condition on each of Day 1 and Day 2) resulted in four groups (Stress-Stress, Stress-Control, Control-Stress, or Control-Control). Participants were evenly distributed (N = 30) across these four groups. One participant was excluded from cortisol analyses as their mean salivary cortisol level was more than thirty standard deviations above the group mean.

All participants provided informed consent in accordance with procedures approved by NYU's University Committee on Activities Involving Human Subjects.

2.2. Study design

2.2.1. Overall study design

All participants came in for two nearly identical sessions, separated by a mean of 5.3 days (standard deviation = 2.7; see Fig. 1; delay between sessions did not differ as a function of Group: $F(3,119) = 1.48$, $p = 0.22$). All sessions began between 11:30a.m. and 5:20p.m. (Day 1 mean = 2:17p.m., standard deviation = 1.6 h; Day 2 mean = 2:12p.m., standard deviation = 1.5 h). Following consent, participants were immediately endowed with $30 and told they would be paid the outcome of a subset of the trials in the decision-making task. The experimenter then read the task instructions out loud as the participant silently read along, after which participants completed a brief comprehension quiz on task details, and completed practice trials under experimenter supervision.

The first of four saliva samples was then taken (see below), after which participants underwent either the cold pressor test (CPT; a common acute stress induction procedure; Velasco et al., 1997; McRae et al., 2006) or a lukewarm water control. In the CPT, participants submerge their non-dominant arm up to and including their elbow in 0–4 °C water for three minutes. The participant is asked to not speak during the CPT, and the time elapsed is not shared with the participant. The lukewarm water control used 30–32 °C water. Participants had an equal chance of undergoing the CPT or control condition on each of the two days. Immediately following the conclusion of the CPT (or control), a second saliva sample was collected, and then participants were given an 8-min break during which they were asked to sit quietly without using any digital devices. They then gave a third saliva sample, after which they completed the risky decision-making task which took roughly 23 min (see below; Sokol-Hessner et al. 2009, 2013, 2015a, 2015b). Finally, participants gave a fourth saliva sample and completed a post-study questionnaire.

Participants were paid $15 per hour, plus their adjusted $30 endowment at the end of each day. Fifteen trials were selected at random from the task and their outcomes summed with the endowment to produce the adjusted endowment. The mean adjusted endowment at the end of Day 1 was $53.08 (standard deviation = $22.08), and Day 2 was $51.80 (standard deviation = $18.19). The difference in payment between days was not significant (paired samples *t*-test, $p = 0.62$).

2.2.2. Risky decision-making task

The main task of interest was a risky monetary decision-making task. As the task we used has been described in detail elsewhere (Sokol-Hessner et al., 2009, 2013), we will briefly summarize it here. Participants made 150 decisions between risky binary gambles and guaranteed alternatives. For 120 of the trials, termed “gain-loss trials”, the risky gamble consisted of equal chances of winning some amount or losing a different amount (amounts varied trial-to-trial), versus a guaranteed alternative of zero dollars. In the remaining thirty “gain-only trials”, the risky gamble yielded a positive amount or zero dollars with equal probability, and the guaranteed alternative was a smaller positive amount. The values used on each trial were unique (i.e. no trials were repeated). Trial order was random. The 50/50 probabilities used throughout the task effectively eliminated possible roles for ambiguity and probability weighting in the task, as all probabilities were explicitly known, and probabilities did not vary.

On each trial, the choice options were initially presented for 2s. After two seconds had passed, a response prompt (“?”) appeared prompting participants to enter their choice within two seconds. This was followed by an inter-stimulus interval (1s), the display of

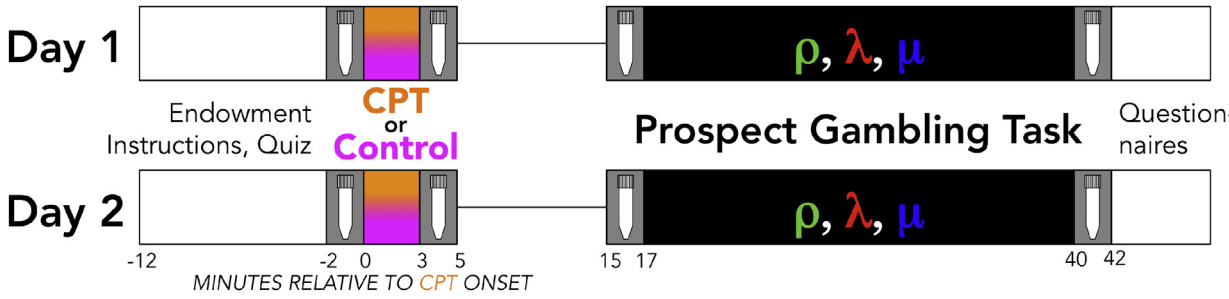

Fig. 1. Study procedure. Participants came into the lab for two sessions, a minimum of 2 days apart at roughly the same time of day (see Methods). The first day began with monetary endowment, task instructions, and a basic comprehension quiz before the first (baseline) cortisol sample was taken (represented in the figure by a schematic salivary collection tube). After either undergoing the cold pressor test (CPT) or the lukewarm water control, participants gave a second salivary sample, waited 10 min for salivary cortisol levels to rise, and gave a third (pre-task) salivary sample. Participants then completed the risky decision-making task allowing estimation of risk attitudes (ρ, in green), loss aversion (λ, in red), and choice consistency (μ, in blue), after which they gave the fourth and final salivary sample, and completed a few basic debriefing questionnaires assessing their experience. The second day was identical to the first, except participants had an equal and independent chance of performing the CPT or lukewarm water control on each day. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the outcome (either the outcome of the gamble or the guaranteed alternative depending on the participant's choice; 1s), and an inter-trial interval (1, 2, or 3s, uniformly distributed) before the next trial began.

The task had no temporal component to eliminate temporal discounting, included only two simple probabilities (0.5 and 1) to minimize the effect of any probability weighting, and was thoroughly instructed in detail and practiced to minimize learning and eliminate ambiguity.

2.2.3. Cortisol measurement

Salivary samples were collected four times each day for each participant (see Fig. 1). For each sample, participants held a sterile synthetic polymer-based oral salivette under their tongue for two minutes, after which the swab was placed in a sterile collection tube and frozen at −20 °C. Frozen salivary samples were analyzed by Salimetrics Testing Services (a Clinical Laboratory Improvement Amendments-certified lab; Carlsbad, CA) using high-sensitivity enzyme immunoassay kits to assay cortisol levels.

2.3. Analysis

2.3.1. Cortisol analysis

An initial visual inspection of raw cortisol values identified one participant (mentioned in Section 2.1, Participants) with a mean salivary cortisol level more than thirty standard deviations above the group mean. This participant was removed from any subsequent cortisol analyses.

To confirm the efficacy of the CPT, we first analyzed the change in cortisol measurement from the baseline cortisol sample taken immediately before the CPT to the three later time points (immediately after the CPT, prior to the decision-making task, and immediately after the task). The Stress condition resulted in significantly larger increases in cortisol relative to the Control condition across both the pre- and post-task time points (see Supplemental Materials for tests within each group, across days and timepoints). To quantify individual differences in cortisol reactivity for use as a covariate in behavioral analyses, we focused on the change in cortisol between the baseline (1) and pre-task (3) time points. Because raw cortisol change values were positively skewed, but spanned zero, we used a modified log procedure similar to that used elsewhere (e.g. Otto et al., 2013) to reduce skewness while maintaining the meaningfulness of zero values ($\Delta\text{Cortisol} = \log([\text{Cortisol}_3\text{-Cortisol}_1]+0.5)\text{-}\log(0.5)$).

2.3.2. Behavioral analysis

Behavioral analysis proceeded in two main portions, the first of which consisted of examining changes in the simple probability of choosing the risky gamble across days as a function of condition (Stress vs. Control), replicating the analysis approach used in many other studies of risky decision-making under stress (see Table S1).

For the second main analysis, we fit prospect theory-inspired models of the non-linear processes underlying valuation and choice using a hierarchical Bayesian approach. The basic model was identical to that used previously (see Equations (1)–(3); Sokol-Hessner et al. 2009, 2013, 2015a, 2015b).

$$u\left(x^{+}\right) = p(x) \times x^{\rho} \tag{1}$$

$$u\left(x^{-}\right) = p(x) \times -\lambda \times (-x)^{\rho} \tag{2}$$

$$p(\textit{choose gamble}) = \left(1 + e^{-\mu \times (u(\textit{gamble}) - u(\textit{guaranteed}))}\right)^{-1} \tag{3}$$

Equations (1) and (2) determine the utility ($u(x)$) of the objective monetary amounts in the risky gamble and the guaranteed alternative. The difference in utility between the gamble and the guaranteed alternative is then used to calculate the probability of choosing the gamble as given by the standard softmax function in Equation (3). The model fits three parameters describing three distinct aspects of participants' decision-making. The parameter ρ (rho), captures risk attitudes or the diminishing marginal utility of money (represented by the curvature of the utility function), and is constrained to be the same across the gain and loss domains. When $\rho = 1$, participants are risk neutral; less than 1 indicates risk aversion for gains and risk seeking for losses, and greater than 1 indicates risk seeking for gains and risk aversion for losses. The parameter λ (lambda) quantifies loss aversion defined as the relative multiplicative weighting of losses to gains in choices. A λ of 1 indicates gain-loss neutrality (i.e. similar weight), while values greater than 1 indicate loss aversion, and less than 1 indicate gain-seeking. Finally, μ (mu) quantifies participants' internal consistency in choices. Higher values of μ represent greater consistency across decisions, versus lower values which indicate noisiness in decision-making. Critically, the inclusion of a number of both gain-loss and gain-only trial types in the task (see Section 2.2.2 Risky Decision-Making Task) allowed the separation of these three free parameters.

The hierarchical Bayesian approach to fitting this model gave us a statistical advantage by explicitly modeling and fitting

parameters at the level of the participant (e.g. participant 1's risk attitude) as well as at the level of the group (e.g. the mean population risk attitude). Using such a model, and therefore fitting all participants' data simultaneously, has the effect of reducing the influence of outliers or noise, and thus maximizing 'signal'. It also has the benefit of allowing us to directly model the effect of interest – that is, the effect of acute stress on each of the three valuation and decision processes at both the population and individual participant levels.

Formally, we fit two main models: Model 1 took a "condition" approach (i.e. Stress/Control as a binary variable), while Model 2 took a "covariate" approach (i.e. the continuous effect of ΔCortisol).

$$\theta_{i,j} = e^{\theta_i + Stress_j \times \Delta\theta_{Si} + Day_j \times \Delta\theta_{Di}} \quad (4)$$

$$\theta_i \sim Normal(\theta_M, \theta_V) \quad (5)$$

$$\Delta\theta_{Si} \sim Normal(\Delta\theta_{SM}, \Delta\theta_{SV}) \quad (6)$$

$$\Delta\theta_{Di} \sim Normal(\Delta\theta_{DM}, \Delta\theta_{DV}) \quad (7)$$

Equation (4) describes how each parameter (ρ, λ, and μ; any one of which is represented here by θ) was modeled for participant *i* on day *j*. θ_i is participant i's baseline parameter value, $Stress_j$ is a binary indicator for whether day j occurred in the Stress (1) or Control (0) condition, $\Delta\theta_{Si}$ is the parameter capturing the change in parameter θ due to Stress ("S") for participant i, Day_j is a binary indicator for whether day j is Day 1 (0) or Day 2 (1), and $\Delta\theta_{Di}$ captures the change in parameter θ due to Day ("D"; e.g. repeated performance) for participant i. The three components (individual baseline parameter value; effect of Stress; effect of Day) were summed within an exponential to prevent final parameter values ($\theta_{i,j}$) from being non-positive (zero is the lower bound for each of ρ, λ, and μ). Equations (5)–(7) illustrate how individual level parameters (e.g. θ_i) were Gaussian-distributed around population means (e.g. θ_M) and standard deviations (e.g. θ_V).

Although Equation (4) is written for the "condition" approach (Model 1), the "covariate" approach (Model 2) is identical, with the exception of the $Stress_j$ binary indicator being replaced by $\Delta Cortisol_{i,j}$, representing the change in cortisol for participant i on day j (see Section 2.3.1 Cortisol Analysis).

These models were fit to the data using standard Markov-Chain Monte Carlo sampling methods in rStan (v2.2.0; Stan Development Team, 2015) as implemented in R (v3.0.2; R Core Team, 2015). For each of Model 1 and Model 2, 3000 samples were collected after a burn-in of 3000 samples (to allow chains to reach steady sampling states) on each of four chains, for a final total of 12,000 samples collected for each parameter (representing the posterior distribution over that parameter's possible values). For parameters of interest, 95% confidence intervals (CIs) were calculated using the samples, and examined to see if they contained zero (if they did not, we could be 95% confident that the true value of the relevant parameter was not zero). To calculate the magnitude of the effects of Stress (or ΔCortisol) and Day on the value function, parameter values were reconstructed with Equation (4), using mean sample values for the relevant parameters.

3. Results

3.1. Cortisol

Generally speaking, cortisol levels gradually decreased in the Control condition across the 2nd, 3rd, and 4th timepoints relative to the 1st (consistent with our afternoon testing time), and significantly increased in the Stress condition at the 3rd and 4th timepoints (pre- and post-risky decision-making task). For detailed comparisons as a function of timepoint, group, day, and condition, see Supplementary Materials and Fig. S1.

Focusing on the change in cortisol at the 3rd timepoint (Fig. 2), we found large and significant differences between Day 1 and Day 2 using paired t-tests for the Control-Stress group (Day 1 = –0.01 μg/ml; Day 2 = 0.16 μg/ml; $t(29) = 5.3$, $p = 0.00001$), and the Stress-Control group (Day 1 = 0.10 μg/ml; Day 2 = 0.01 μg/ml; $t(29) = 3.2$, $p = 0.003$), and a small but significant difference in the Control-Control group (Day 1 = –0.05 μg/ml; Day 2 = –0.01 μg/ml; $t(29) = 2.5$ $p = 0.02$). The Stress-Stress group was not significantly different across days (Day 1 = 0.17 μg/ml; Day 2 = 0.11 μg/ml; $t(28) = 1.7$, $p = 0.1$). The modified log transformation used on these values to create the ΔCortisol variable used in covariate analyses (see below, Section 3.2.2) did not change the pattern of findings, as expected (paired t-tests on Day 1 vs. Day 2: Control-Control, $p = 0.04$; Control-Stress, $p = 0.000008$; Stress-Control, $p = 0.002$; Stress-Stress, $p = 0.06$).

We also performed a mixed-effects linear regression in R across all participants using the lmer package (Bates et al., 2015), predicting individuals' change in cortisol at the 3rd timepoint with a random intercept and fixed effects for Day, Stress, and a Day × Stress interaction. We found significant effects for the intercept ($\beta = 0.06$, $p = 1.8 \times 10^{-8}$) and Stress ($\beta = 0.07$, $p = 8.9 \times 10^{-16}$), but not Day ($\beta = 0.01$, $p = 0.35$), nor the Day x Stress interactive term ($\beta = -0.01$, $p = 0.14$), indicating that the CPT

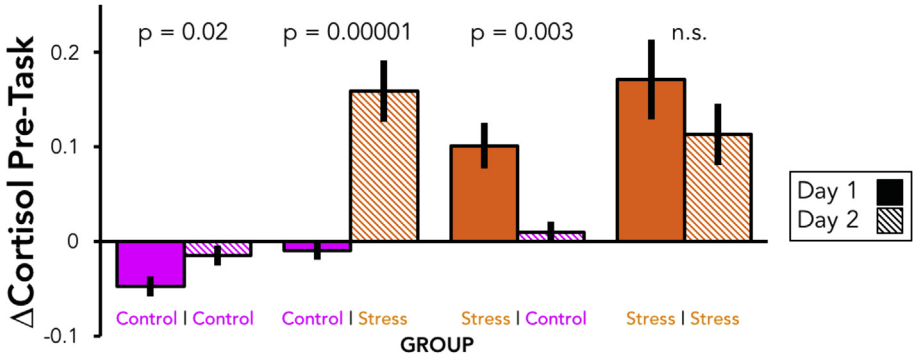

Fig. 2. Change in cortisol at the third (pre-task) time point. Bars reflect the mean change in salivary cortisol (ug/ml) from the baseline sample to the pre-task sample. Orange bars indicate the stress condition, and purple bars the control condition, while solid bars indicate day 1, and striped bars indicate day 2. Bars are paired by participant group (each N = 30), and P values reflect paired t-tests between the change in cortisol values across days, within group. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

was effective in inducing increases in cortisol and that Day had neither simple nor interaction effects on cortisol.

3.2. Behavior

3.2.1. Simple probability of gambling

Replicating previous analysis approaches (see Table S1), we examined the simple probability of choosing the gamble in our task. In paired t-tests within condition groups (e.g. Control-Control) comparing the probability of gambling across days, no group showed a significant change in gambling behavior (each N = 30; all p's > 0.18; see Fig. S2). Collapsing across the Stress-Control and Control-Stress groups (N = 60), paired t-tests revealed no significant difference in gambling under Stress versus Control (p = 0.80).

3.2.2. Hierarchical behavioral models

3.2.2.1. Model 1: stress/control condition. Estimates of the convergence of the chains on similar distributions of parameter samples (Rhat; when Rhat = 1, the model has converged and chains are very similar to each other; values above 1 suggest lack of convergence, i.e. chains that are very different from one another) indicated that the model fit well (mean Rhat for group-level parameters = 1.01).

First, we checked the baseline parameter estimates for risk attitudes, loss aversion, and consistency to ensure they replicated previous work (Tom et al., 2007; Sokol-Hessner et al., 2009; De Martino et al., 2010; Sokol-Hessner et al. 2013, Chumbley et al. 2014, Sokol-Hessner et al. 2015a, 2015b). Computing the mean sample values for each of the group-level baseline parameters and then using Equation (4) to transform those values to value function parameter space produced appropriate values (mean recovered $\rho = 0.92$, 95%CI = [0.85 0.97]; mean recovered $\lambda = 2.22$, 95% CI = [1.88 2.61]; and mean recovered $\mu = 25.9$, 95% CI = [21.3 31.1]). These indicated participants were mildly risk averse for gains (risk seeking for losses), moderately loss averse, and somewhat consistent in their choices.

Examining the 95% CIs for the parameters capturing the change in each of ρ, λ, and μ due to Day (that is, the changes in each parameter on Day 2 relative to Day 1) illustrated that though there was no consistent change in risk attitudes (95% CI for $\Delta\rho_{DM}$ = [-0.05 0.03]), on Day 2 people became more loss averse (95% CI for $\Delta\lambda_{DM}$ = [0.06 0.23]; mean recovered Day 2 $\lambda = 2.57$) and more consistent in their choices (95% CI for $\Delta\mu_{DM}$ = [0.15 0.39]; mean recovered Day 2 $\mu = 34.3$).

In contrast to the effects of Day, when examining the 95% CIs for the effects of the Stress condition, no consistent changes were found for any of the decision processes modeled (95% CI for $\Delta\rho_{SM}$ = [-0.05 0.06], mean recovered Stress $\rho = 0.92$; 95% CI for $\Delta\lambda_{SM}$ = [-0.13 0.12], mean recovered Stress $\lambda = 2.19$; 95% CI for $\Delta\mu_{SM}$ = [-0.16 0.16], mean recovered stress $\mu = 25.8$). As can be seen by a visual inspection of the 95% CIs, each is roughly centered on zero (see Fig. 3). These confidence intervals are small, as compared to the mean sampled standard deviations (e.g. θ_V from Equation (5)) for the group-level Gaussian distributions around which individual participants' overall mean parameter values are distributed (mean $\rho_V = 0.24$; mean $\lambda_V = 0.84$; mean $\mu_V = 0.87$).

As the effects of stress inductions may be inconsistent in women (Kirschbaum et al., 1999; McCormick and Teillon, 2001; Andreano et al., 2008), we additionally ran Model 1 with only male participants (N = 56), generally replicating the findings of Model 1 when estimated for all participants. The mean recovered baseline parameters were comparable (mean recovered $\rho = 0.90$, 95% CI = [0.83 0.97]; mean recovered $\lambda = 2.47$, 95% CI = [1.79 3.25]; and mean recovered $\mu = 23.4$, 95% CI = [16.9 32.2]). Examining the change due to Day replicated the null effect on risk attitudes (95% CI for $\Delta\rho_{DM}$ = [-0.03 0.06]) and the positive effect on consistency (95% CI for $\Delta\mu_{DM}$ = [0.30 0.70]), but the 95% confidence interval for the effect of Day on loss aversion no longer excluded zero (95% CI for $\Delta\lambda_{DM}$ = [-0.07 0.28]; the CI had to be relaxed to 75.7% to exclude zero). The null effects of the Stress condition were replicated for all three value function parameters (95% CI for $\Delta\rho_{SM}$ = [-0.08 0.05]; 95% CI for $\Delta\lambda_{SM}$ = [-0.22 0.24]; 95% CI for $\Delta\mu_{SM}$ = [-0.27 0.26]).

To test whether payment at the end of Day 1 altered decision-making on Day 2, we correlated the change in endowment at the end of Day 1 with the mean sample values of the change in ρ, λ, and μ for each participant. There was no significant correlation between the change in endowment and changes in risk attitudes ($\Delta\rho_{Di}$; $r(118) = 0.06$, $p = 0.54$) or consistency ($\Delta\mu_{Di}$; $r(118) = 0.06$, $p = 0.49$), but there was a correlation with the change in loss aversion ($\Delta\lambda_{Di}$; $r(118) = -0.32$, $p = 0.0004$), such that small (or negative) changes to the endowment on Day 1 were correlated with more loss aversion on Day 2. The pattern and relative significance of the correlations held when using outlier-resistant non-parametric tests (e.g. Spearman's rho).

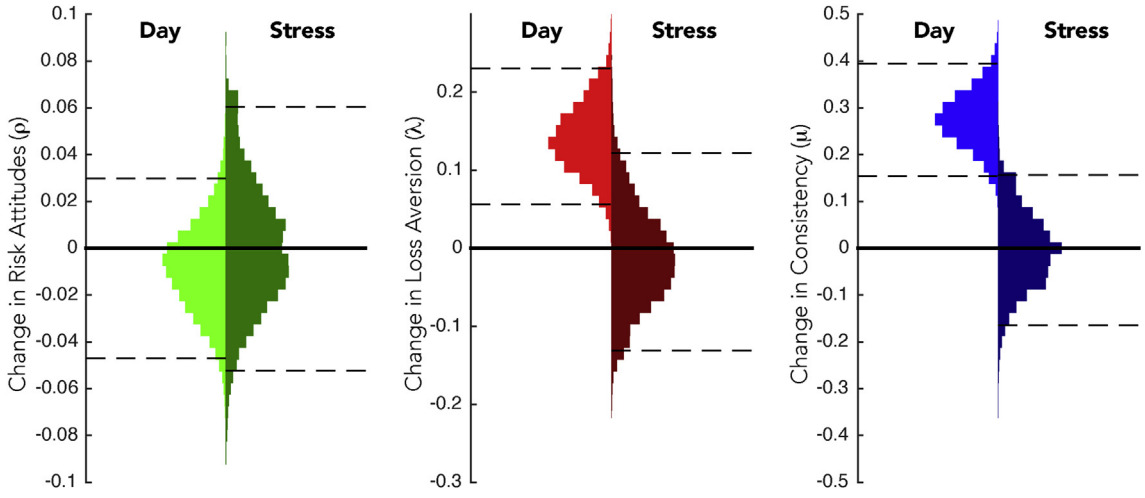

Fig. 3. Changes in decision-making due to Day and Stress. Group mean changes in each of risk attitudes (ρ, green), loss aversion (λ, red), and consistency (μ, blue) due to repeated participation ("Day") or the cold pressor test ("Stress"). Each histogram represents 12,000 samples from Model 1 (see Methods). 95% Confidence intervals are indicated for each histogram with dashed lines. Intervals excluded zero only for changes in loss aversion and consistency due to Day. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2.2.2. Model 2: ΔCortisol. While Model 1 (binary Stress/Control coding) maximally leverages random experimental assignment, doing so ignores individual differences in responses to the stress manipulations. To address this issue, we fit Model 2, in which we included a ΔCortisol covariate (see Section 2.3.1) instead of the binary Stress/Control variable, to examine whether there was some more continuous relationship between cortisol levels and changes in risk attitudes, loss aversion, and/or consistency.

As with Model 1, Model 2 appeared to fit behavior well (mean Rhat for group-level parameters = 1.02), and replicated the mean baseline parameter estimates from Model 1 (mean recovered $\rho = 0.92$, 95%CI = [0.88 0.97]; mean recovered $\lambda = 2.19$, 95% CI = [1.87 2.57]; and mean recovered $\mu = 26.0$, 95% CI = [21.7 30.4]).

Model 2 also replicated the finding that there was no consistent change in risk attitudes as a function of Day (95% CI for $\Delta\rho_{DM}$ = [-0.05 0.03]), but that participants were more loss averse and consistent on Day 2 relative to Day 1 (95% CI for $\Delta\lambda_{DM}$ = [0.05 0.23], mean recovered Day 2 $\lambda = 2.51$; 95% CI for $\Delta\mu_{DM}$ = [0.18 0.40], mean recovered Day 2 $\mu = 34.6$).

Finally, we found that there was no evidence for a continuous relationship between ΔCortisol and any of the value parameters (95% CI for $\Delta\rho_{CM}$ = [-0.17 0.09]; 95% CI for $\Delta\lambda_{CM}$ = [-0.21 0.35]; 95% CI for $\Delta\mu_{CM}$ = [-0.27 0.43]; see Fig. S3 for histograms of sample distributions). It should be noted that because of the scaling of the ΔCortisol variable, these distributions additionally reflect very small effects if any. To illustrate this, we can use the mean ΔCortisol value from the Control condition (−0.04) and the Stress condition (0.20) to reconstruct the effect of cortisol on behavior (ΔCortisol = −0.04 vs. ΔCortisol = 0.20: $\rho = 0.92$ vs. 0.91; $\lambda = 2.18$ vs. 2.22; $\mu = 25.9$ vs. 26.3).

As with Model 1, we additionally ran Model 2 on men only to check for gender specificity, generally replicating the findings from Model 2 estimated on all participants. Baseline parameter estimates were similar (mean recovered $\rho = 0.89$, 95%CI = [0.82 0.96]; mean recovered $\lambda = 2.47$, 95% CI = [1.82 3.28]; and mean recovered $\mu = 23.0$, 95% CI = [16.6 30.6]). Like with Model 1's estimates from men only, we replicated the null effect of Day on risk attitudes (95% CI for $\Delta\rho_{DM}$ = [-0.02 0.07]) and the positive effect on consistency (95% CI for $\Delta\mu_{DM}$ = [0.31 0.70]), but did not replicate the effect of Day on loss aversion (95% CI for $\Delta\lambda_{DM}$ = [-0.08 0.29]; the CI had to be relaxed to 71.5% to exclude zero), while ΔCortisol was found to have no consistent effect on any of the value parameters (95% CI for $\Delta\rho_{CM}$ = [-0.15 0.14]; 95% CI for $\Delta\lambda_{CM}$ = [-0.60 0.56]; 95% CI for $\Delta\mu_{CM}$ = [-0.25 1.12]). See Fig. S3 for histograms of Model 2's parameter samples.

We ran additional models to test the sensitivity of these findings to the use of fixed instead of random effects, the use of more constrained models, and non-hierarchical maximum likelihood models. Findings of these ancillary models were identical to those above (see Supplementary Materials).

As with Model 1, the change in endowment at the end of Day 1 was significantly correlated with Model 2's $\Delta\lambda_{Di}$ ($r(117) = -0.31$, $p = 0.0007$) but not with $\Delta\rho_{Di}$ ($r(117) = 0.06$, $p = 0.53$) or $\Delta\mu_{Di}$ ($r(117) = 0.07$, $p = 0.47$), findings that replicated with non-parametric Spearman's correlations.

3.2.3. Basal cortisol and behavior

As some studies have found that baseline cortisol values may be related to risky decision-making (Chumbley et al., 2014), we tested whether basal cortisol values (i.e. the very first cortisol samples, taken prior to any CPT intervention) correlated with any of the individual parameter estimates from the hierarchical Bayesian analysis (see Section 3.2.2) for ρ, λ, and/or μ. Because estimates of behavior were calculated after the CPT, this analysis was limited to the 60 participants who were in the Control condition on Day 1 and whose behavior is most clearly at "baseline". We used the parameter estimates calculated from Model 2, but findings were virtually identical using those from Model 1. Correlating the basal cortisol values on Day 1 with mean individual-level parameter samples on that day found no relationships with risk attitudes (Pearson's $r(58) = 0.06$, $p = 0.65$) nor loss aversion (Pearson's $r(58) = -0.05$, $p = 0.68$), and although there was a correlation with consistency (Pearson's $r(58) = 0.35$, $p = 0.006$), visual inspection suggested it was driven by outliers (Spearman's rho = 0.16, $p = 0.23$).

4. Discussion

Fully 78% of adults in the United States report experiencing stress at some point in the past month (APA, 2016), making it critical to understand whether and how intense and pervasive affective states like stress interact with decision-making. Here, we pursued this question using a large within-subjects design, an econometric model of valuation and decision-making that dissociates three underlying decision processes in risky decision-making, hierarchical Bayesian analysis that maximally combines data while allowing for heterogeneity in behavior, and objectively quantified endogenous acute stress responses. In doing so, we find no evidence for an effect of acute stress on risk attitudes, loss aversion, or consistency over choices.

We do find effects of repeated participation in the study, in that participants are more loss averse and more consistent on the second day relative to the first. A previous study from our lab also used a two-day design with the same task and although we observed increases in loss aversion on the second day, the increases were unrelated to Day 1 payment, and there were no changes in consistency (Sokol-Hessner et al., 2015b). Thus, while we encourage caution, especially in interpreting the effect of repetition on consistency, it does appear that participants weigh losses more heavily on their second day. One explanation could be that participants treated the money as "house money" (e.g. not their own) on the first day, despite our detailed instructions. When participants were paid real money at the end of the first day, they might have then returned on the second day, somehow more invested in the task, leading to greater loss aversion and consistency. However, while payment on Day 1 was correlated with the change in loss aversion, it did not correlate with changes in consistency. Additionally, this mechanism might also predict greater risk aversion for gains (risk seeking for losses), which we did not observe. As our study was not designed to test this hypothesis, we must rely upon future work for more definitive tests.

Though we find no effect of acute stress on risk attitudes (or loss aversion or consistency), what might explain previous findings to the contrary? First, it's possible that acute stress alters a decision-making process that we did not measure or manipulate in our study (e.g. probability weighting, temporal discounting, learning rates, ambiguity attitudes), but which was confounded with risky choices in other studies. As the vast majority of previous studies used the simple probability of gambling to assess risk attitudes (see Table S1), such conflation is very possible. For example, the Iowa Gambling Task and the Game of Dice Task are particularly popular paradigms, accounting for no fewer than seven of the previous studies on risky decision-making and stress, but their variable-probability, mixed gain & loss designs conflate many possible decision-making processes. Our task also had real monetary consequences and showed participants their outcomes on a trial-by-trial basis – hypothetical choices (or choices without feedback) may be differentially affected. Finally, it is of course possible that an overarching explanation for previously inconsistent findings may be relatively weak statistical power, either within the task (e.g. few trials) or at the study level (e.g. few participants; a brief review of

the literature identifies a preponderance of low-power between-subjects designs, and an average of ~60 participants/study; see Table S1).

More generally, this study examined decisions made over relatively simple explicitly described risky monetary options. To the extent to which decisions in other situations may involve other kinds of options, it is possible that stress may affect decision-making – but our findings suggest that such an effect would not be due to changes in risk attitudes, loss aversion, or choice consistency.

Additionally, while this study focused on acute stress, there is evidence that chronic, longer-term stress may alter decisions under risk. One study found that cortisol administration for eight consecutive days increased risk aversion (decreased gambling; Kandasamy et al., 2014), while another used hair samples to estimate approximate cortisol exposure over the previous two months, finding that chronic levels of cortisol were unrelated to risk attitudes but instead were negatively correlated with loss aversion (Chumbley et al., 2014).

The differences between endogenous and exogenous cortisol, acute and chronic stress levels, physiological and social stressors, cortisol and other biomarkers of stress, and other factors governing when, how, and in what context stress responses occur may ultimately prove critical to our understanding of the interactions between stress and decision-making. Nevertheless, the findings from our robust design and analysis combining for the first time quantitative estimation of risky decision-making and objective manipulations of acute stress, in the context of inconsistent previous findings, suggest that acute stress does not affect risk attitudes, loss aversion, or consistency in risky monetary decision-making.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.ynstr.2016.10.003.

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Appendix: Supplementary Analyses & Discussions

Sokol-Hessner, Raio, Gottesman, Lackovic, & Phelps, *Acute stress does not affect risky monetary decision-making.*

1. Cortisol

Participants could be divided into groups on the basis of which conditions they experienced (Stress and Control) on which days: Group 1 was Control/Control, Group 2 was Control/Stress, Group 3 was Stress/Control, and Group 4 was Stress/Stress.

The CPT consistently raised cortisol levels. In Group 2 and Group 3 (groups experiencing both the Stress and Control conditions), the change in cortisol relative to baseline at the third (pre-task) and fourth (post-task) time-points was significantly greater in the Stress condition than in the control condition. For Group 4 (Stress/Stress), there were weak differences in stress responses at the third (pre-task) time-point (paired t-test, $p = 0.097$), and significant differences at the fourth (post-task) time-point ($p = 0.04$).

Testing the third and fourth time-points against each other, there were no significant differences across all participants on Day 1 ($p = 0.43$), though there was a significant difference on Day 2 ($p = 0.00002$) with the fourth timepoint being less than the third.

A mixed effects regression on ΔCortisol values on both days (defined as $\log([\text{Cortisol}_3\text{-Cortisol}_1]+0.5)-\log(0.5)$, as in the Methods) with random effects for

the subject-level intercept, and fixed effects regressors representing day, stress condition, gender, and the two- and three-way interactions between day, condition, and gender found a significant intercept ($p = 0.0003$) and a significant effect of condition ($p = 0.04$), but no other significant effects (all p's > 0.2).

See Figure S1 for plots of mean cortisol levels separated by group, timepoint, and day.

Baseline cortisol was weakly correlated with the session start time across participants on both Day 1 (Spearman's Rho = -0.28, $p = 0.002$) and Day 2 (Spearman's Rho = -0.17, $p = 0.065$), but the change in cortisol showed no such correlation on either Day 1 (Spearman's Rho = 0.003, $p = 0.97$) or Day 2 (Spearman's Rho = 0.01, $p = 0.91$).

There were no significant differences in baseline cortisol when collapsing across groups and testing Day 1 versus Day 2 ($t(118) = 1.17$, $p = 0.25$), nor when testing Day 1 versus Day 2 independently for each of the four groups (all p's > 0.28).

CPT effects on the change in cortisol did not significantly differ between males and females. A mixed-effects linear regression in R (with lmer) predicting individuals' change in cortisol at the 3rd timepoint with a random intercept and fixed effects for Day, Stress, Gender, and all interactions found significant effects for the intercept ($\beta = 0.06$, $p = 1.3 \times 10^{-8}$) and Stress ($\beta = 0.07$, $p = 8.9 \times 10^{-16}$), but no main effects for Day, Gender, or any of the interaction terms (all p's > 0.17).

2. Additional hierarchical Bayesian models of decision-making

In addition to the hierarchical Bayesian models of behavior mentioned in the main text, we ran two additional models to ensure that the lack of a finding for stress was not simply due to model complexity.

Model 3 was identical to Model 1 (modeling the effect of day and the stress condition), with the exception that hierarchical group- and individual-level terms were included to model the effect of the stress condition on risk attitudes (ρ) only (i.e. not for loss aversion [λ] or consistency [μ]). If the effect of stress on risk attitudes was weak, the extra degrees of freedom given to the effects of stress on loss aversion and consistency might have soaked up that variance, hiding the weak effect. However, the samples from Model 3 indicate that this was not the case, as the 95% CIs for the group mean effect of stress on risk attitudes still squarely spanned zero ([-0.05 0.05]).

Model 4 was identical to Model 2 (modeling the effect of day and the effects of parametric variation with ΔCortisol), save that the effect of ΔCortisol was modeled as single, fixed-effects terms (e.g. only one term was estimated for the change due to ΔCortisol in risk attitudes for all participants; one term was estimated for the change due to ΔCortisol in loss aversion for all participants, etc). Nevertheless, this model produced identical results as Model 2, with all 95% CIs spanning zero for the effect of ΔCortisol on risk attitudes ([-0.17 0.06]), loss aversion ([-0.22 0.32]), and consistency ([-0.29 0.39]).

3. Nonhierarchical Maximum Likelihood Models

In addition to using hierarchical Bayesian fitting procedures, we also used classic maximum likelihood estimation (MLE), exactly as implemented in previous studies with this task (Sokol-Hessner et al. 2009; Sokol-Hessner et al. 2013; Sokol-Hessner et al. 2014; Sokol-Hessner et al. 2015). Though we believe the Bayesian approach superior to MLE, for consistency's sake with prior literature, we additionally applied MLE procedures to our data and model.

Briefly, equations 1, 2, and 3 (from the main text) were used to compute a probability of selecting the risky option (given values for parameters ρ, λ, and μ) that was then matched with participants' observed choices to compute the likelihood of the data given those parameters. This likelihood was then maximized (technically, the negative log likelihood was minimized) using interior-point algorithms as implemented in MATLAB's "fmincon" function. This was done independently for each individual on each day (so each participant had two ρ values, two λ values, etc).

For all participants, MLE-fit parameters predicted participants' behavior significantly better than chance (likelihood ratio tests of the full model against a null [chance] model; all p's < 0.05).

Collapsing across the Stress/Control and Control/Stress groups (N = 60), paired t-tests of stress versus control revealed no systematic differences in ρ, λ, or μ (all p's > 0.4).

Performing linear regressions on the parameter estimates with regressors for, Day, Condition, and Day x Condition revealed only trending effects of Day to increase λ ($p = 0.1$) and a significant effect of Day in increasing μ ($p < 0.001$) (the regression also included constants for each parameter, akin to a baseline value). An identical regression substituting ΔCortisol for Condition identified a significant effect of Day in increasing μ ($p = 0.006$) and a trending effect of ΔCortisol to increase μ ($p = 0.1$).

To look at our data from a between-subjects perspective, we eliminate half our data and only use that from Day 1 to compare the 60 Stress participants with the 60 Control participants. We note that this approach obviously greatly reduces our statistical power, and fails to take into account individual differences in decision-making as well as the two-day design with the Bayesian hierarchical modeling that we used in the main manuscript. Nevertheless, if we use the maximum likelihood estimates for behavior on Day 1 and two-sample t-tests, we find that there is no difference between Stress and Control for ρ ($p = 0.92$), λ ($p = 0.35$), or μ ($p = 0.59$).

As mentioned above and in the main text, we believe the Bayesian approach to be substantially superior to the MLE approach, as the Bayesian approach includes the (reasonable) assumption that our participants are similar to one another, and thus directly estimates the group-level parameters that here we must noisily and imperfectly infer.

4. Curvature in the gain and loss domains

One possible weakness of our design and analysis is that our task and model were not designed to allow the estimation of separate curvature coefficients (i.e. risk attitudes) for the gain domain and the loss domain. While it is well understood that the utility function is generally concave for gains and convex for losses (as modeled here and in many other places), the literature is generally equivocal as to whether the *degree* of curvature differs as a function of domain (see page 661, Booij and van de Kuilen 2009). Additionally, while some studies have found that the effect of stress on risk taking differs in the gain and loss domains, their effects have been in opposite directions (Porcelli and Delgado 2009; Pabst et al. 2013) (see Table S1).

Were stress to affect curvature in one domain but not the other, it's still possible we would have picked up this change in our study as a small, subtle shift in risk attitudes (due to averaging over a change in curvature and a lack of a change in curvature), but we did not see any such effect in our model fits. Even if the effect was isolated to the loss domain, then a change in estimates of loss aversion might have been observed instead (which we also did not see). Thus, perhaps the only possibility we cannot reasonably reject is that stress affects risk attitudes in the gain and loss domains in opposite directions (e.g. reducing risk seeking over losses while increasing risk aversion over gains), thus canceling out any global, average effect on curvature. We think this unlikely, but again, cannot rule it out.

5. Participant exclusion criteria

We excluded any potential participants who reported possibly being pregnant, taking antidepressants or anti-anxiety medication, or having a history of heart problems or blood pressure problems. All participants also reported not eating or drinking anything except water for 1 hour prior to the beginning of the experiment.

Captions

Table S1. Brief summaries of 15 extant papers examining the effect of acute stress on risky decision-making. This set of papers is meant to be representative, not necessarily exhaustive. Under "Stressor", TSST = Trier Social Stress Test; CPT = Cold Pressor Test. Under "Task", IGT = Iowa Gambling Task; GDT = Game of Dice Task; Rogers gambles = a gamble set from Rogers et al 2004; BART = Balloon Analogue Risk Task. To facilitate the comparison of studies, the column identified as "Pwr" illustrates the power of that study to detect a theoretical effect size of 0.3 (a small-to-medium size effect) as calculated by MATLAB's `sampsizepwr` function. For each study, the simplified power calculation assumed either a two-sample t-test (between-subjects) or a paired-sample t-test (within-subjects), with two-tailed $\alpha = 0.05$. For between-subjects designs, the number of participants in each group was assumed to be half the total N, rounded up (actual group sizes were used for Buckert et al as their groups were different in size by a factor of 2.75). The power value for the current study is a simplified estimate – this study contained both between- and within-subjects elements that informed each other, as well as a more powerful and robust estimation procedure. The column identified as "M/F?" identifies studies that tested for gender effects, and if they did, whether they found them. Studies that tested for gender received either a "YES" or "NO" (to see the exact effect, see "Rough Finding" and "Notes"), whereas those that did not are left blank. The column identified as "G/L?" identifies studies that looked for effects separately in

the gain and loss domains; if they did so, they received an “X”, otherwise were left blank. The column identified as “Implied Effect on ρ” summarizes the finding in terms of the effects of acute stress on utility curvature as represented by the parameter ρ. It is commonly found that individuals are risk averse in the gain domain and risk seeking in the loss domain. If studies found more risk aversion for gains and/or more risk seeking for losses, that is consistent with a smaller ρ; less risk aversion for gains and less risk seeking for losses is consistent with a larger ρ. Papers are sorted by main finding and then year (within main finding). Chumbley et al (2014) is listed separately, as they examined chronic levels of cortisol, not acute stress. The current paper is included at the very bottom of the table, for comparison’s sake.

Figure S1. Changes in cortisol as a function of day and condition. Each graph depicts the average change in cortisol (ug/ml) for one group of participants (N = 30) on Day 1 and on Day 2 (solid and dashed lines respectively). The Control condition is indicated in blue, Stress in red. Error bars are standard errors of the mean.

Figure S2. Probability of gambling as a function of day and group. Each graph depicts the raw probability of gambling across all trials on Day 1 (x-axis) and Day 2 (y-axis) for a given group. Groups are indicated by the “C” and “S” squares in the upper left hand corner of each graph; the first square indicates the condition

on Day 1, and the 2nd square the condition on Day 2. Blue squares with “C” indicate the control condition, while red squares with “S” indicate the stress condition. Each circle is one participant, and the large circle in each graph is the group mean.

Figure S3. Changes in decision-making due to Cortisol and Day (Model 2). Group mean changes in each of risk attitudes (ρ, green), loss aversion (λ, red), and consistency (μ, blue) due to repeated participation (“Day”) or due to parametric changes in cortisol (“Cortisol”). Each histogram represents 12,000 samples from Model 2 (see Methods). 95% Confidence intervals are indicated for each histogram with dashed lines. Intervals excluded zero only for changes in loss aversion and consistency due to Day.

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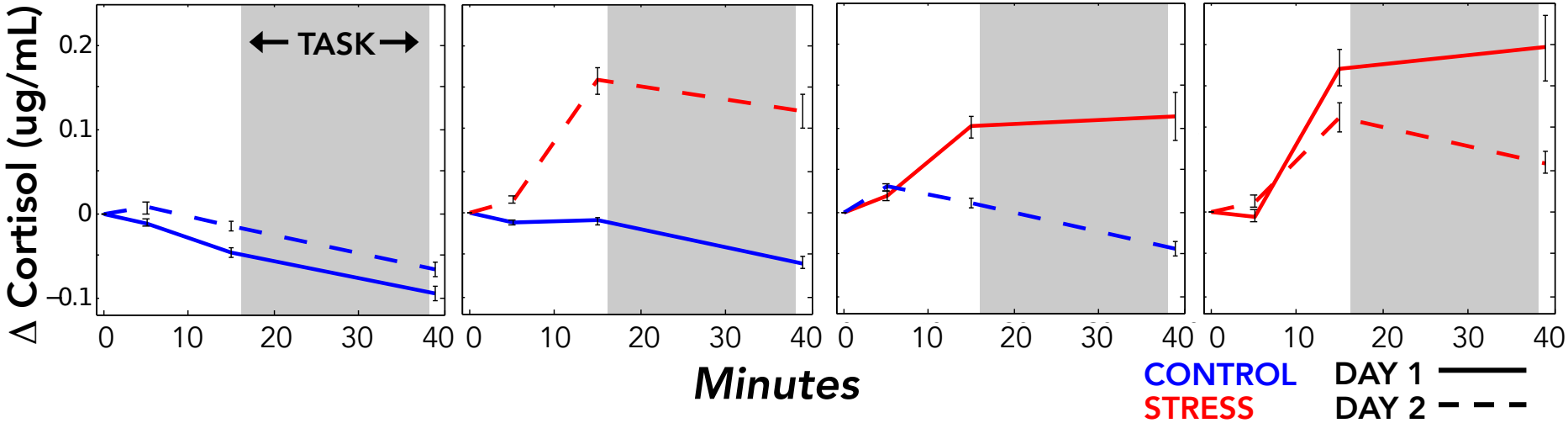
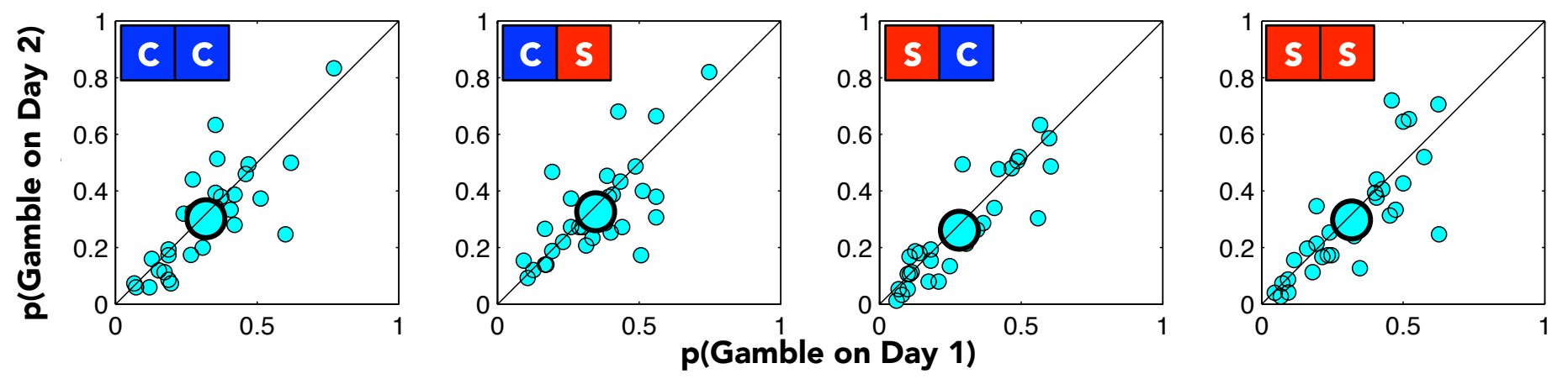
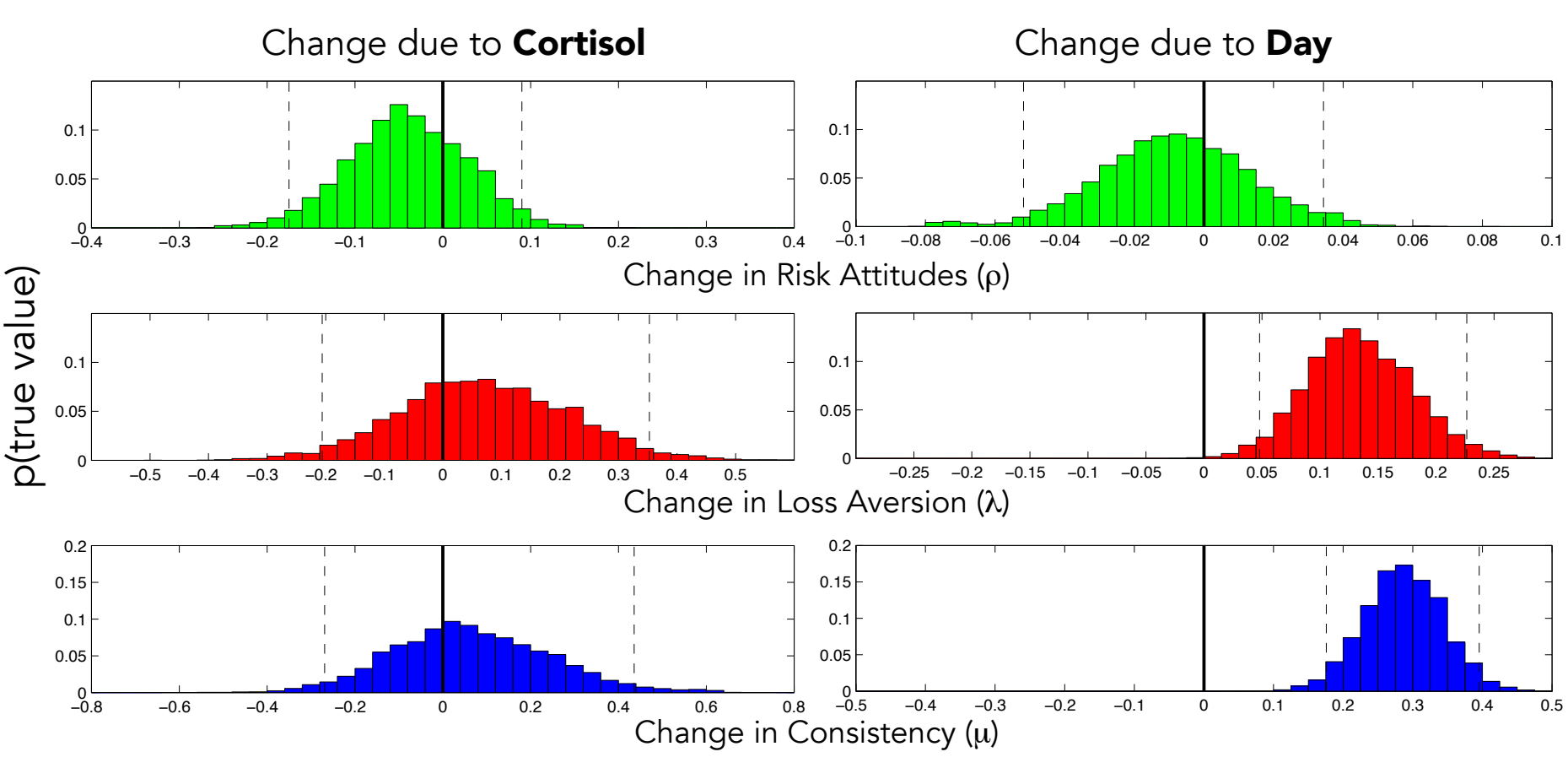

Δ Cortisol (ug/mL)
0.2
0.1
0
−0.1
TASK
0
10
20
30
40
Minutes
CONTROL
STRESS
DAY 1
DAY 2


p(Gamble on Day 2)
p(Gamble on Day 1)
C C
C S
S C
S S
0
0.2
0.4
0.6
0.8
1
0.5


Change due to **Cortisol**
Change due to **Day**
p(true value)
Change in Risk Attitudes (ρ)
Change in Loss Aversion (λ)
Change in Consistency (μ)

1st Author	Year	Journal	Stressor	Task	Risk Measure	Other decision measures	Btwn/ Within?	N	Pwr	Rough finding	M/F?	G/L?	Notes	Implied Effect on ρ
Preston et al	2007	Behavioral Neuroscience	TSST	IGT	IGT performance	N.A.	B	40	0.15	Stress slows down learning, men ultimately do poorly, women do fine.	YES		N.A.	Larger
Starcke et al	2008	Behavioral neuroscience	~TSST	GDT	GDT net score	N.A.	B	40	0.15	Lower GDT score.	NO		No gender effect	Larger
Pabst et al	2013	Behavioral neuroscience	TSST	GDT	GDT net score	N.A.	B	126	0.39	Lower GDT score.			Large subject pool	Larger
Putman et al	2010	Psychopharmacology	Cortisol admin	Rogers gambles	P(gamble)	N.A.	W	29	0.34	Gambled more when p(lose) was high.			N.A.	Larger (sort of)
Pabst et al	2013	Frontiers in behavioral neuroscience	TSST	GDT (gain only/loss only)	GDT net score	N.A.	B	80	0.26	Fewer risky choices in the loss domain; no effect in the gain domain.	NO	X	GDT EVs better matched.	Larger for losses
Buckert et al	2014	Frontiers in Neuroscience	~TSST	Gamble/guaranteed lotteries	P(gamble)	Ambiguity, working memory	B	75	0.21	More risk seeking for gains, only in cortisol responders (N = 26).	NO	X	55 stress, 20 control; variable probabilities	Larger for gains
Van Den Bos et al	2009	Psychoneuroendocrinology	TSST	IGT	IGT performance	N.A.	B	33	0.14	Males worse, females better if mild, worse if strong cort.	YES		N.A.	Larger & Smaller
Lighthall et al	2009	PLoS One	CPT	BART	# balloon pumps	N.A.	B	45	0.17	Men pump more, women pump less.	YES		N.A.	Larger & Smaller
Pabst et al	2013	Behavioral brain research	TSST	GDT	GDT net score	N.A.	B	40	0.15	More risk averse 5&18min after, less risk averse 28min after.			All males; 10 subj/4 groups	Larger & Smaller
Von Helversen & Rieskamp	2013	Conf. Proceedings	CPT	Two gamble task	P(gamble)	N.A.	B	69	0.24	More risk with low outcome, less risk with high outcome gambles.	NO		No gender fx w stress	Larger & Smaller
Robinson et al	2014	PeerJ	Threat of shock	IGT	IGT performance	N.A.	W	47	0.52	Low anx/dep, more risk averse; high anx/dep, more risk seeking.			Interaction w/ trait anx & BDI scores	Larger & Smaller
Porcelli & Delgado	2009	Psychological Science	CPT	Two gamble task	P(gamble)	N.A.	W	27	0.32	More risky in losses, less risky in gains.		X	Single valence trial types	Smaller
Cingl & Cahlikova	2013	Discussion paper	TSST	Gain-only simple lottery questionnaire	Change point	N.A.	B	78	0.26	Lower certainty equiv.			Dropped inconsistent subj; men are p = 0.1, women are p = 0.14; correlation w/ cort is sig	Smaller
von Dawans et al	2012	Psychological science	TSST	Two gamble task	P(gamble)	N.A.	B	67	0.23	No change in risk aversion.			Also had sharing game, punishment game, trust game	No change
Lempert et al	2012	Frontiers in Psychology	~TSST	Gain-only lotteries	AUC of prob. discounting rate	Temporal discounting	B	113	0.36	No effect of stress on gambling; interaction btwn chronic & acute stress on temporal discounting.			All males; variable probabilities; staircasing procedure	No change
Delaney et al	2014	Discussion paper	CPT	Holt and Laury scale	Change point	Temporal discounting and probability weighting	W	90	0.80	No change in risk aversion			N.A.	No change
Kandasamy et al	2014	PNAS	Cortisol admin	Two gamble task	Curvature	Probability weighting	W	36	0.42	More risk averse with chronic cort (and no fx with acute cort).	NO		No gender fx; lotteries are complex	No change
Chumbley et al	2014	Psychological science	N.A. (Tonic cortisol)	DOSE (based on Sokol-Hessner et al, 2009 task)	Curvature	Loss aversion	W	53	0.57	No relationship of cort to rho; neg corr w/ Lambda.			Only fx w/ chronic!	No change
Sokol-Hessner et al			CPT	Sokol-Hessner et al, 2009 task	Curvature	Loss aversion, consistency	W	120	0.90	No effect of acute stress on risk att, loss aversion, or consistency.	NO		N.A.	No change