Separate Neural Mechanisms Underlie Choices and Strategic Preferences in Risky Decision Making

Supporting Online Material

Behavioral Experiment 1

One hundred twenty eight young adults participated in the first behavioral experiment conducted at the Fuqua School of Business. All subjects were compensated for their participation in this study with a fixed payout ($8) not related to their choices. All subjects provided informed consent as a part of a protocol approved by the Institutional Review Board of Duke University.

Subjects were presented with eight three-outcome and eight five-outcome mixed gambles on a computer using the Psychophysics Toolbox program in MATLAB (Brainard, 1997; Pelli, 1997). Cognitive load was also manipulated between-subjects by asking subjects to memorize 3 or 7-letter pseudo-words for each trial. For compatibility with the imaging data, only results from the eight five-outcome gambles, collapsed across both the load conditions, are presented here. First, each subject was presented with a risky gamble and asked to rate its attractiveness. Subsequently, they were given two choices for modifying the gamble, one of which always involved adding a fixed amount to the reference to maximize the overall probability of winning (P_{max} option) and another which involved adding the same amount to either the extreme loss to minimize the worst possible loss (L_{min}) or the extreme gain outcome to maximize the best possible gain (G_{max} option). Subjects were shown both versions of the modified gamble on the screen beside each other and were asked to choose one of the options. There was no time constraint for making the choice. In four gambles, the probabilities of the two outcomes were matched (equal expected value) while for the remaining four gambles, the probability associated with P_{max} choice was less than the probability of the alternative choice by 5 or 10% (unequal expected value).

As hypothesized, there were significant biases toward P_{max} choice (overall proportion = 0.69) when expected value was matched (**Supplementary Fig. 1**). Even when choosing the P_{max} option required sacrificing expected value (i.e., when the alternative option resulted in a bigger increase in value and/or probability), they preferred the P_{max} option in 59% of the trials. The results of this experiment are consistent with and extend prior findings in the behavioral literature (Payne, 2005). We also found substantial inter-individual variability: some subjects nearly always preferred the P_{max} option; others nearly always preferred the G_{max} or L_{min} options while still others switched based on trial variables, resulting in both intra- and inter-subject variability in strategy (**Supplementary Fig. 2A**). We further note that P_{max} choices were also associated with faster response times (**Supplementary Fig. 2C**), consistent with it representing a simplifying strategy.

Behavioral Experiment 2

The second behavioral experiment (E2) manipulated the basic paradigm in three ways – to maintain, eliminate, or exaggerate the probability-maximizing choice – to rule out potential confounding factors and establish that these effects were indeed driven by the need to maximize the overall probability of winning. Seventy one young adults participated in a second behavioral experiment conducted at the Fuqua School of Business. Compensation for subjects was similar to the previous experiment. All subjects provided informed consent as a part of a protocol approved by the Institutional Review Board of Duke University.

Subjects were presented with eight five-outcome mixed gambles similar to the first experiment on a computer. Four of these gambles were matched for expected value and the other four were not. Additionally, subjects were also presented with eight gambles where adding value to the middle option did not involve a change in overall probability. In these P_{max}-unavailable trials, we made one very subtle change to the experimental design: we added or subtracted a small amount from the central choice option (e.g., adding value to an option that was already \$5 and not \$0; or adding money to an option that changes it from -\$20 to -\$5). Thus, there were no options in the gamble whose selection would change the overall probability of success.

Finally, subjects were presented with four additional trials where adding values to the *extreme* loss or gain outcomes changed the overall probability of the gamble. In these P_{max}-exaggerated trials, we altered the basic gambles so that one of options, if selected, would translate a certain loss gamble to an uncertain loss gamble (by modifying an all loss-outcome gamble to a gamble with one gain outcome) or translate an uncertain gain gamble to a certain gain gamble (by modifying a gamble with one loss outcome to an all gain-outcome gamble). These gambles were created by selecting two basic gambles from the set of four equal expected value core problems above and transposing them by adding or subtracting a constant value from all outcomes. For e.g., the core gamble: {60, 0.2; 45, 0.2; -20, 0.2; -40, 0.2; -80, 0.2} was transposed it to the new gamble: {130, 0.2; 115, 0.2; 50, 0.2; 30, 0.2; -10, 0.2} and subjects were given a choice between adding \$30 to the -\$10 option (making it a certain win gamble) or to the \$50 reference option (which would correspond to the P_{max} option in the untranslated version).

In the control trials, which replicates the design of the first behavioral experiment, subjects still showed a systematic bias (65%) towards the P_{max} choices (**Supplementary Fig. 1**). Again, the preference for P_{max} response reduced slightly (58%, but was still the majority response) when it was associated with lower expected value. In the critical P_{max}-*unavailable* trials, we found a significant shift in the pattern of subjects' choices: subjects now chose the option nearest to \$0 only 39% of the time. This result provides confirmation that many subjects do preferentially select the choice that improves the overall probability of winning when it is available, but readily switch to magnitude-sensitive choices otherwise. Moreover, these results also indicate that the choices of subjects for these mixed gambles cannot be explained solely by parameters within standard descriptive economic models, because the addition of \$5 to one option of a complex, large-magnitude gamble should have negligible effects upon the predictions of those models. Finally, in the P_{max}-*exaggerated* trials, subjects overwhelmingly preferred the probability-maximizing option (83%). Thus, our behavioral data not only demonstrate the robustness of the preferences toward the P_{max} choices, but more importantly that this bias can be reversed or accentuated by experimental manipulations.

Consistent with our first behavioral experiment, we also found substantial inter-individual variability in this subject population (**Supplementary Fig. 2B**). Again, P_{max} choices were associated with faster response times (**Supplementary Fig. 2C**). Moreover, across subjects, the proportion of P_{max} choices was negatively correlated with an independent measure of behavioral maximizing (Schwartz et al., 2002) ($r = -0.26$; $p < 0.05$), which assesses an individual's tendency to seek the best possible option in all situations. Finally, the proportion of Pmax choices was also significantly negatively correlated with a trait measure of sadness (Fordyce, 1988) ($r = -0.29$; $p < 0.05$).

Does P_{max} Represent a Simplifying Strategy?

Across both experiments, we find four lines of evidence that support the view that P_{max} choices represent an effort-reduction simplifying strategy. First, P_{max} choices were significantly faster in terms or response times, as would be expected of a less effortful strategy. Second, individual differences in the preference for P_{max} were significantly and negatively correlated with a trait measure of maximizing in E2, consistent with effort-reduction. Third, individual variability in proportion of P_{max} choices also significantly and negatively correlated with a trait measure of sadness in E2, consistent with sadness being associated with reduced heuristic processing (Bodenhausen et al., 1994; Schwarz et al., 1991). Finally, the proportion of P_{max} choices decreased with increasing cost in terms of expected value. Together, these findings are consistent with P_{max} representing a simplifying strategy. Additionally, as discussed below in the comparison of choice models, these choices were also inconsistent with compensatory models like expected utility and cumulative prospect theory.

Supplementary Methods: fMRI Experiment

Stimuli: Trial Types.

There were a total of five different types of conditions: (i) the value (amount added to the option) and probability were higher for the central reference outcome (Ref_EV^+), (ii) the value and probability were the same for both reference and extreme outcomes ($Ref\_EV^=$), (iii) the value was the same but the probability of the reference outcome was lower (Ref_P^-), (iv) the probability was the same but value added to the reference outcome was lower (Ref_V^-) and (v) both the probability and the value were lower for the reference option (Ref_EV^-). The proportion of P_{max} choices was systematically modulated by the tradeoff in expected value of the two types of choices, indicating that subjects were not simply insensitive to expected value (**Supplementary Table 1**). As seen from the table, the greatest conflict existed when the expected values were equal or similar (when only one of value or probability was lower). Therefore, only these trials were included for analyzing the neural correlates of decisions.

Subject Payments.

Subjects were informed at the beginning of the fMRI session that a portion of their earnings would depend on their choices. Specifically, they would gain or lose money based on the outcomes of two randomly selected gambles (plus a fixed $40 participation payment). They were told that the outcome of each trial would be multiplied by an unknown, but fixed percentage, and that they could lose some or all of a monetary endowment that was given to them at the start of the experiment. To ensure that choices were incentive-compatible, we gave each subject (before they entered the scanner) a sealed envelope containing both a cash endowment and a message indicating the payment multiplier. The values of the endowment and multiplier were both unknown to the subjects. For all subjects, the endowment was set at $20 and the multiplier was set at 10%. The final total payoffs ranged from $46 to $76 (mean = $61, s.d. = $8.66).

***Behavioral Trait Measures*.**

At the end of the scanning session, subjects completed a series of questionnaires. These included:

(i) A Maximization Scale that consists of 13 questions aimed at distinguishing people based on those who try to get the best out of a situation from those who settle for something good enough (Schwartz et al., 2002),

(ii) Barratt's Impulsiveness Scale (BIS) that consists of 30 questions categorized into cognitive, planning and motor subscales (Patton et al., 1995),

(iii) A cognition-intuition questionnaire, where the two subscales are faith-in-intuition that leads to more heuristic experiential processing and need-for-cognition that leads to more analytic rational processing (Epstein et al., 1996),

(iv) A decision-making styles inventory (DMSI) with sub-scales as rational, intuitive, avoidant, dependent and spontaneous (Scott and Bruce, 1995) and

(v) A second decision styles inventory (WN_DMSI) with the sub-scales as analytical, intuitive and regret (Nygren and White, 2002).

***Factor Analysis*.**

Individual subject responses from all subscales of these five questionnaires, along with the behavioral measure of choice tendency from the fMRI experiment, were then subjected to a factor analysis using SPSS. We used principal components analysis to extract the factors and performed varimax rotation of the resulting loading matrices to facilitate interpretation. The extraction criterion was set to an eigenvalue of one or greater.

The behavioral data loaded onto four factors which together accounted for approximately 75% of the total variance; these can be broadly labeled as impulsiveness, magnitude-focus, intuitiveness, and regretfulness in decreasing order of explained variance. The rotated factor matrix for each of the four factors is summarized in **Supplementary Table 3**. Loading values with absolute value of 0.5 and greater are shown in the table. We then calculated scores for each factor for each subject, which were then used as covariates in the third-level fMRI analyses to evaluate the robustness and specificity of our findings to strategic variability.

We included subjects' scores on each of these factors as across-subjects regressors in out third-level analysis looking at differences between magnitude-sensitive compensatory and simplifying P_{max} choices. We found that the difference in activation between the two choices within the dmPFC was significantly negatively correlated with the magnitude-focus factor (the preference for simplifying strategy loaded negatively on this factor) but not with any other factor, replicating the interaction effect in **Fig. 3** in the main text of the manuscript (**Supplementary Fig. 7**).

Dorsomedial Prefrontal Cortex: Strategy or Response Conflict?

We conducted two additional analysis to rule out the possibility that dmPFC activation was related to response conflict, as has been found in several previous studies (Botvinick et al., 1999; Kerns et al., 2004). First, we evaluated whether there was any correlation, across subjects, between response time and dmPFC activation, as would be expected in the case of response conflict. No such correlations were found, whether considering each strategy independently or their interaction (**Supplementary Fig. 8A-C**). Second, subjects who were indifferent to compensatory and simplifying strategies (hence having maximal response conflict as they choose both options equally often) exhibited low dmPFC activation that was equal for both choices (**Supplementary Fig. 8D**), a finding that is inconsistent with a response-conflict explanation.

Comparison of Choice Models.

Given the significant preference for P_{max} choices across our subjects, we sought to characterize if these biases were consistent with traditional economic models. We focused mainly on Expected Utility (EU) and Cumulative Prospect Theory (CPT) models. Note that we do not discuss Original Prospect Theory (OPT) as it was primarily introduced for simple two-outcome gambles and it violates first-order stochastic dominance, which is particularly important consideration in multi-outcome gambles like the ones used in this study. We stress that the model testing to be reported should not be viewed as implying that an overall probability of winning is a new and “better” general model of risky choice behavior. Clearly this “simplifying strategy” does not even apply to risky choice problems that involve only “pure” gain or loss options. This purpose of model comparisons is simply to highlight the potential value added by incorporating an overall probability of winning metric in any descriptive theory of how people respond to complex risky choices.

The gambles used in this study were of the form $G = \{x_1,p_1; x_2,p_2; x_3,p_3; x_4,p_4; x_5,p_5\}$ with x_i representing the outcomes and p_i the associated probabilities The outcomes are ordered so that x_1 is the largest gain, x_5 is the largest loss, and k is the index of the smallest gain (k=2 or k=3 for the gambles in this paper). The values for the gambles presented during the imaging study were chosen such that expected value, expected utility and cumulative prospect theory make unique predictions.

The **expected utility** (**EU**) of a gamble G is given by:

$$EU = \sum_{i=1}^{5} u(x_i)p_i, \text{ where } u(x_i) = \begin{Bmatrix} x_i^{\beta}, x_i \geq 0 \\ -|x_i|^{1+(1-\beta)}, x_i < 0 \end{Bmatrix}.$$

The **cumulative prospect theory** (**CPT**) predictions were obtained using:

$$CPT = \sum_{i=1}^{5} v(x_i)c(i) \text{ where } v(x_i) = \begin{Bmatrix} x_i^{\beta}, x_i \geq 0 \\ -\lambda |x_i|^{\beta}, x_i < 0 \end{Bmatrix},$$

$$c(i)=\begin{cases} w^{+}(p_i), i=1 \\ w^{+}\left(\sum_{j=1}^{i} p_j\right)-w^{+}\left(\sum_{j=1}^{i-1} p_j\right),\ i=2,..,k\ (gains) \\ w^{-}\left(\sum_{j=i}^{5} p_j\right)-w^{-}\left(\sum_{j=1+1}^{5} p_j\right),\ i=k+1,..,4\ (losses) \\ w^{-}(p_i), i=5 \end{cases},$$

$$w^{+}(p)=\frac{p^{\gamma^{+}}}{[p^{\gamma^{+}}+(1-p)^{\gamma^{+}}]^{1/\gamma^{+}}} \text{ and } w^{-}(p)=\frac{p^{\gamma^{-}}}{[p^{\gamma^{-}}+(1-p)^{\gamma^{-}}]^{1/\gamma^{-}}}$$

For the first level of model comparisons, we made predictions for each of the 72 nearly equal expected-value gambles (the set of gambles that were used in choice analyses) using standard parameter values for each of the models. This included using a concave utility function for the expected utility model with $\beta = 0.88$. For the cumulative prospect theory model, we used the following values for each of the parameters: $\gamma^{+} = 0.61$, $\gamma^{-} = 0.69$ and $\lambda = 2.25$ based on previous experimental studies (Tversky and Kahneman, 1992). The findings were inconsistent with observed behavior. For example, for equal EV problems, expected utility predicts that subjects should choose P_{max} option only in trials involving comparison to G_{max} and not in trials where P_{max} is contrasted against L_{min}. However, subjects showed no such difference in their choices, choosing the P_{max} option in 70% of trials when compared to G_{max} and 68% of trials when compared to L_{min}. Similarly, in all trials where the P_{max} option is associated with equal or lesser expected value compared to the alternative option, CPT model with the parameters above predicts the choice of G_{max} or L_{min} option, inconsistent with the actual choices observed in this study. These findings suggest that existing models of risky choice fail to account for this bias towards the choice that maximizes overall probability of winning, which plays an important role in multi-outcome mixed gambles.

To account for the fact that there could be individual differences in parameter values for each subject, we performed a split-sample analysis. We selected one half of the choices of each participant and estimated a subset of parameters for the above models that best fit the subject's choices. We estimated one parameter, β, for the EU model and two parameters, $\{\beta,\gamma\}$, for the CPT model, keeping λ fixed at 2.25. Note that we also simplified the equation for CPT in our estimation by assuming $\gamma^{+} = \gamma^{-}$. We then assessed how well the fitted models predicted the other half of that subject's data, comparing the performance of the EU and CPT models. These findings are summarized in **Supplementary Fig. 3**. As seen from the figure, the parameters estimates from one half of the sample failed to significantly predicted choices in the complementary sample across subjects. However, the proportion of P_{max} choices was highly correlated across the two samples, indicating that subjects were highly consistent in their choices across the experiment.

Supplementary Tables

Supplementary Table 1: Summary of the proportion of P_{max} choices made by subjects (N=23) and response times across all condition types, within our fMRI experiment.

	Proportion of P_{max} Choices (%)		**Response Time (s)**	
	Mean	**S.E**	**Mean**	**S.E.**
Ref_EV^{+}	90.58	2.63	0.883	0.068
Ref_EV$^{=}$	69.38	5.18	0.994	0.083
Ref_V^{-}	45.65	5.45	1.091	0.118
Ref_P^{-}	33.70	5.47	1.031	0.117
Ref_EV^{-}	29.17	5.45	0.992	0.088

Supplementary Table 2: Regions whose activation was significantly modulated by the decision that was made (i.e., compensatory magnitude-sensitive or simplifying probability-maximizing) or whose choice-related activation was modulated by the proportion of P_{max} choices across subjects. The coordinates and z-values correspond to the peak activated voxel within the region.

	MNI Coordinates			**Brodmann Area**	**z-value**
	x	**Y**	**Z**		
Compensatory > Simplifying					
Right anterior Insula	38	28	0	13	3.42
Right ventromedial PFC	16	21	-23	11	2.74
Simplifying > Compensatory					
Right Posterior Parietal Cortex	20	-76	57	40	3.40
Precuneus	3	-72	57	7	2.79
Right dorsolateral Prefrontal Cortex	44	44	27	46	2.99
(Compensatory - Simplifying) * Strategy Preference					
Right Inferior Frontal Gyrus	47	42	8	46	3.64
Right dorsolateral Prefrontal Cortex	42	25	22	44	3.14
Dorsomedial Prefrontal Cortex	10	22	45	32	2.99
	10	42	29	32	2.77

Supplementary Table 3: Behavioral data from twenty subjects loaded onto four main factors that could be categorized as reflecting impulsiveness, maximizing, intuitiveness, and regretfulness; here ordered in increasing proportion of explained variance. Only responses with rotated component matrix loading of greater than 0.5 (or lesser than -0.5 for negative loadings) are shown.

	Factor 1	**Factor 2**	**Factor 3**	**Factor 4**
Inferred Factor Label	**Impulsiveness**	**Magnitude-focus**	**Intuitiveness**	**Regretfulness**
BIS				
Nonplanning	0.76	-	-	-
Cognitive	-	0.67	-	-
Motor	0.87	-	-	-
WN-DMSI				
Analytical	-0.78	-	-	-
Intuitive	-	-	0.90	-
Regret-based	-	-	-	0.56
DMSI				
Spontaneity	0.86	-	-	-
Avoidant	-	0.75	-	-
Dependent	-	0.51	-	0.55
Intuitive	-	-	0.91	-
Rational	-0.80	-	-	-
Cognitive-Intuitive				
Need for Cognition	-	-	-	-0.88
Faith in Intuition	-	-	0.76	-
Maximizing Scale	-	0.78	-	-
Preference for Simplifying Strategy	-	-0.71	-	-

Supplementary Figure Captions

Supplementary Figure 1. Subjects prefer choices that increase the overall probability of winning. In behavioral experiment E1 (N=128), subjects show a significant bias towards P_{max} choices. This effect is replicated in E2 (N=71). More importantly, the preference for the P_{max} choices can be reversed or accentuated by experimental manipulations. When values were modified slightly such that none of the options could change the overall probability, subjects now avoided the middle option in the gamble (i.e., they now preferred to add money to an extreme value). Similarly, when provided with an option to eliminate the chance of losing or to create a chance for winning where none existed, P_{max} choices increased dramatically. Finally, the bias towards P_{max} choices was replicated in the fMRI experiment. Note that the P_{max}-unavailable condition did not have any choice that changed the overall probability, and the value in the plot represents the proportion of choices of the central outcome in these gambles.

Supplementary Figure 2. Results from the behavioral experiments. (A,B) To provide validation of our experimental task in a large sample, subjects made decisions about a series of eight gambles in two experiments (E1: N=128 and E2: N=71), each constructed according to the rules described in the Supplementary Methods. In both experiments, subjects' choices were biased toward the P_{max} option, with substantial inter-individual variability. **(C)** Response times were significantly faster ($p < 0.05$) when subjects chose the P_{max} option in both behavioral experiments, consistent with a speeding of choices that involve a simplifying strategy.

Supplementary Figure 3. Evidence that a focus on overall probability of winning (and not economic models) best explain subjects' choices. We used a split-sample analysis to evaluate the relative consistency of possible choice parameters. **(A)** The proportion of P_{max} choices (mean-subtracted) in one sample significantly predicted the proportion of P_{max} choices in the complementary sample. However, choice models based on **(B)** expected utility (EU) and **(C)** cumulative prospect theory (CPT) were poor predictors of choices, even though those latter models included additional free parameters.

Supplementary Figure 4. Individual differences in strategy correlated with a trait measure of Maximization. The participants' strategic preferences during the fMRI experiment (x-axis) had a strong negative correlation with an independent trait measure of maximization (y-axis).

Supplementary Figure 5. Differences in dmPFC connectivity strength predict subjects' choices. Functional connectivity analysis showed differential connectivity of the dmPFC with posterior parietal cortex and anterior insula as a function of choice. Individual differences in the strength of these connections tracked strategic variability. These findings suggest that differences in the magnitude of functional connectivity between dmPFC and PPC predict P_{max} choices while differences in the magnitude of functional connectivity between dmPFC and aINS predict magnitude-sensitive compensatory choices.

Supplementary Figure 6. Activation of the ventral striatum was predicted by an independent behavioral measure of maximization. Within the ventral striatum region that exhibited a significant activation difference between observed monetary gains and losses (x = 14, y = 16, z = -10; indicated with arrow; see also **Fig. 4**), we found a significant correlation with an independent behavioral maximization scale. Subjects with lower values on the maximization scale exhibited a very large difference between gain- and loss-related activation in this region. Conversely, experienced gains and losses had little effect on subjects with larger values on the maximization scale.

Supplementary Figure 7. Areas of activation associated with specific decision factors. Subjects in our sample were differentiated into four main factors based on their responses to a battery of questionnaire-based decision-making responses. Each of these factors were then used as a covariate, across subjects, for the activation difference between compensatory magnitude-sensitive and simplifying choices. This generated a set of four maps, each reflecting a different decision * trait interaction. **(A)** The cognitive impulsiveness factor positively predicted activation in the posterior parietal cortex. **(B)** The magnitude focused factor negatively predicted activation in dorsomedial prefrontal cortex (i.e., exhibited greater difference in activation between the two choices for subjects loading heavily on this factor). This region overlaps with the dmPFC region that predicts strategy in **Fig. 3**. **(C)** Intuitiveness positively predicted activity in ventromedial prefrontal cortex. **(D)** Activation in ventral striatum negatively predicted the fourth factor, which we roughly characterize as reflecting regretfulness.

Supplementary Figure 8. Dorsomedial prefrontal cortex activation is not correlated with responses. To evaluate whether decision difficulty could explain the observed activation in dorsomedial prefrontal cortex (dmPFC), we evaluated the correlation between response time (x-axes) and **(A)** Magnitude-sensitive choice activation, **(B)** P_{max} choice activation, and **(C)** the difference in activation between choices. Response time was not significantly correlated with any activation measure. **(D)** We split our fMRI subject sample into three groups of subjects, the middle of which consisted of individuals (N = 6) who were equally likely to prefer the compensatory or simplifying strategy. These subjects can be assumed to have poorly developed strategies (i.e., minimal strategy conflict) such that no particular choice is preferred on each trial (i.e., maximal response conflict). Under a strategy-conflict explanation, these individuals would be expected to have low dmPFC activation, whereas under a response-conflict explanation they should have high dmPFC activation. We found that the neutral subjects had low-amplitude dmPFC activation that was equal between the two choices, supporting the strategy-conflict interpretation.

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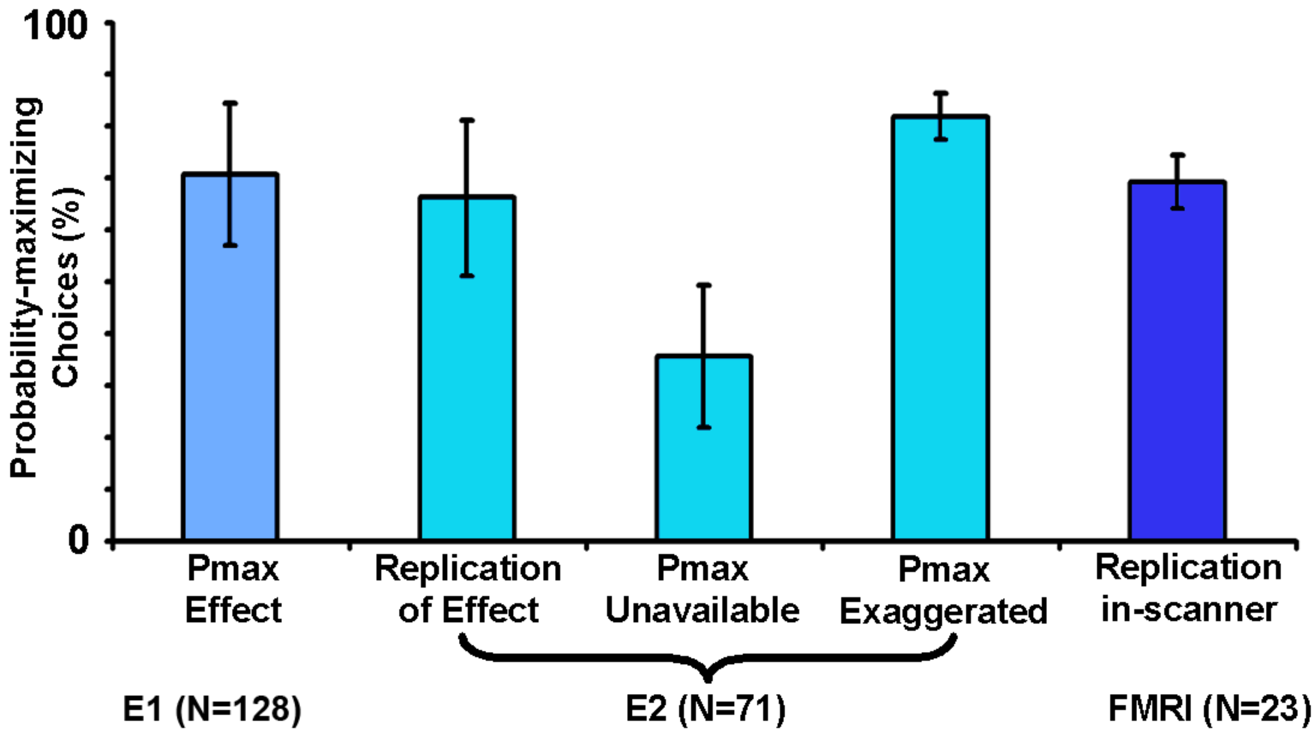
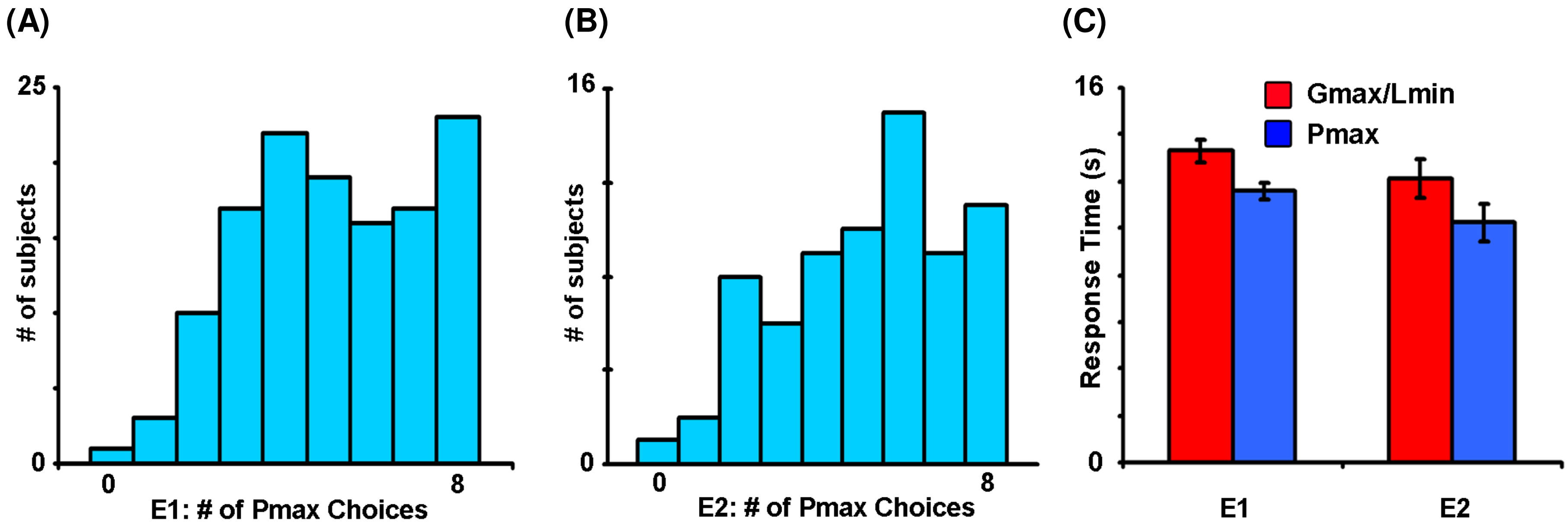


Supplementary Figure 1



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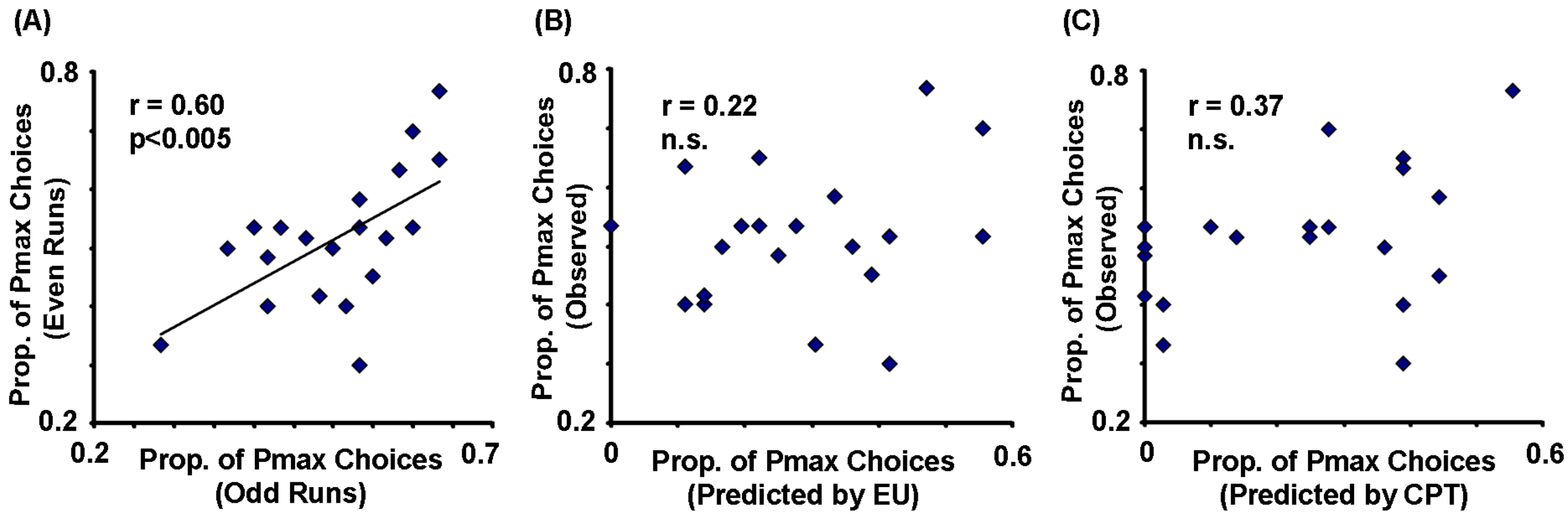
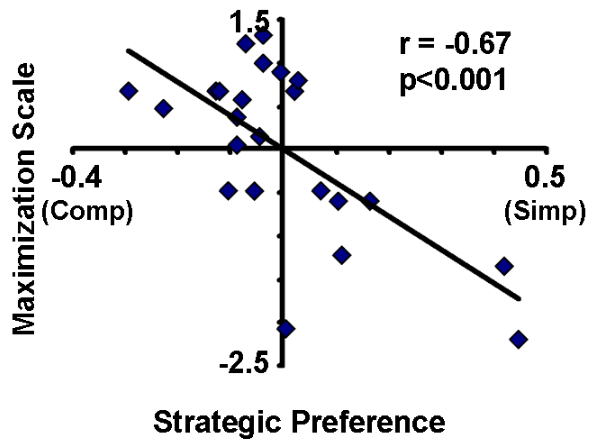


Supplementary Figure 3



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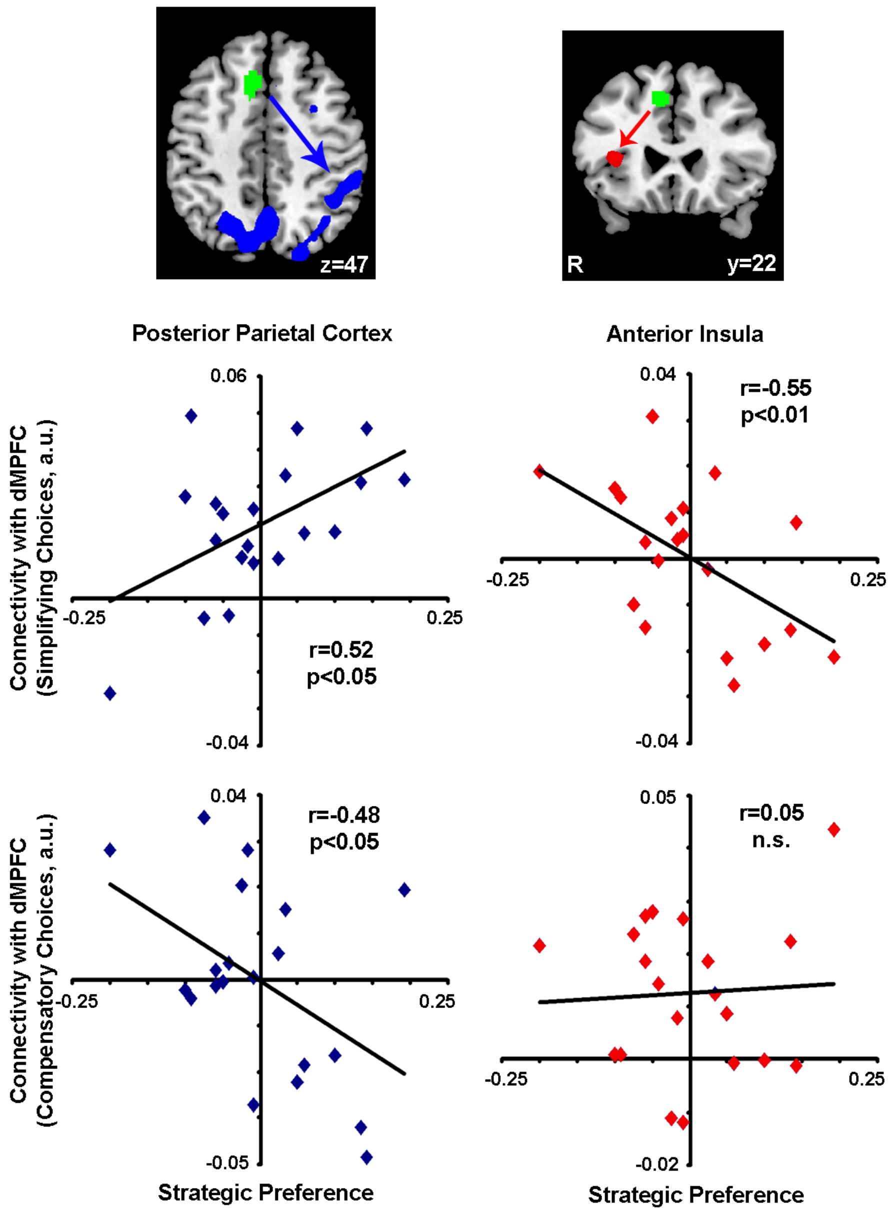

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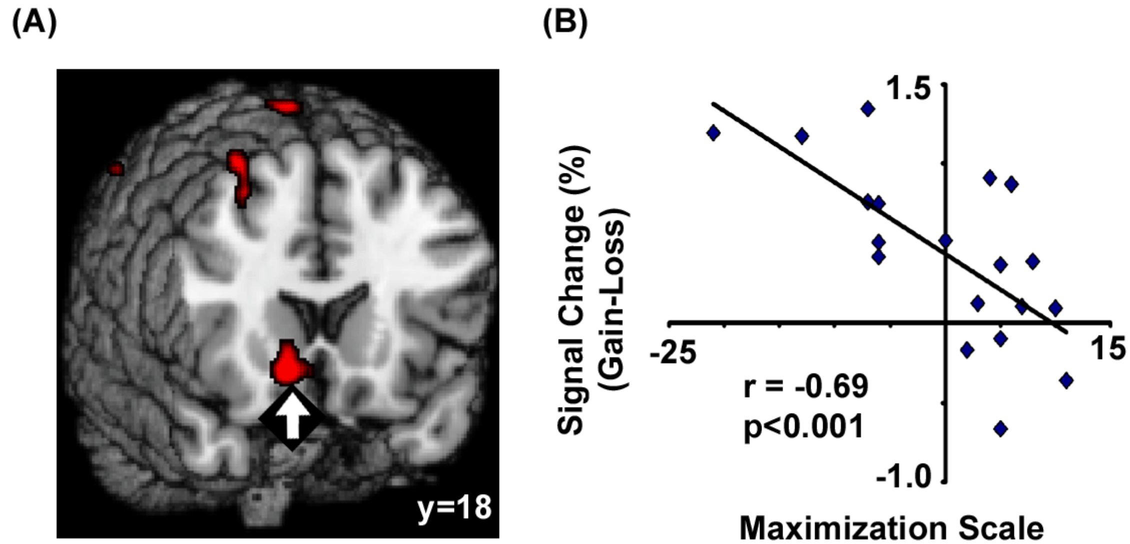

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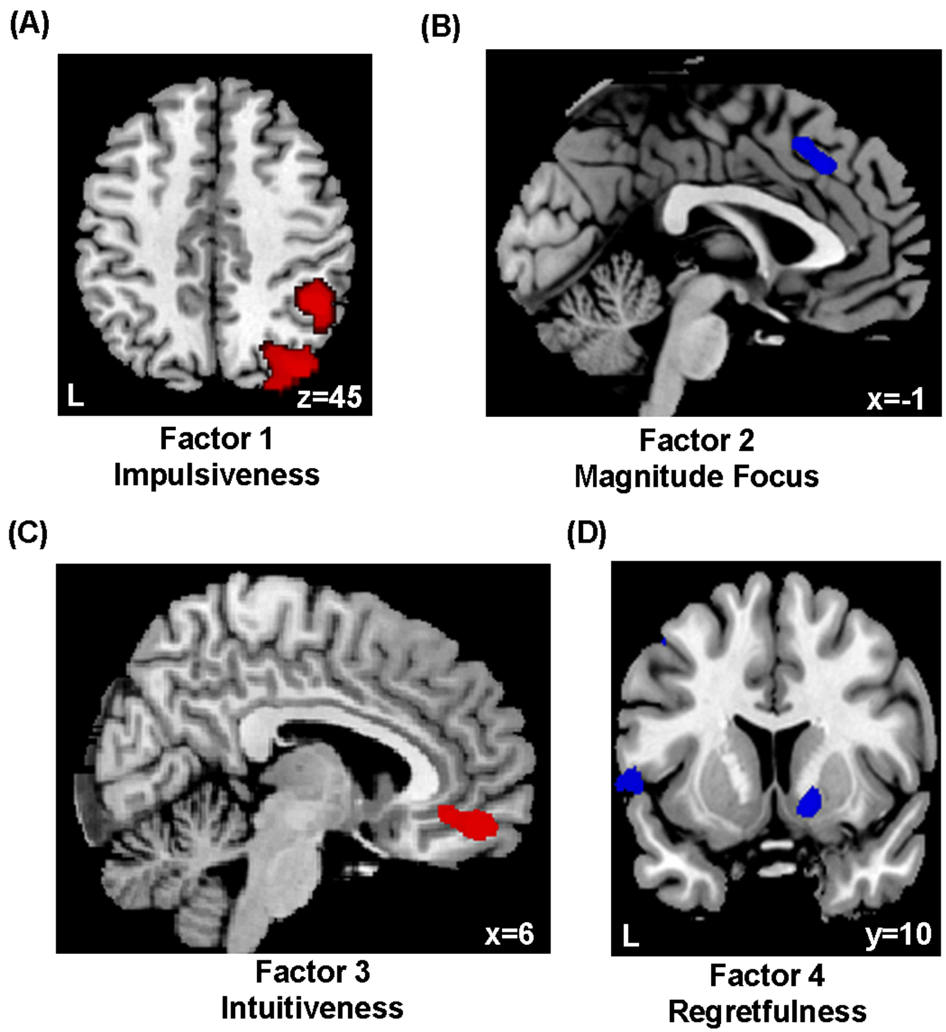
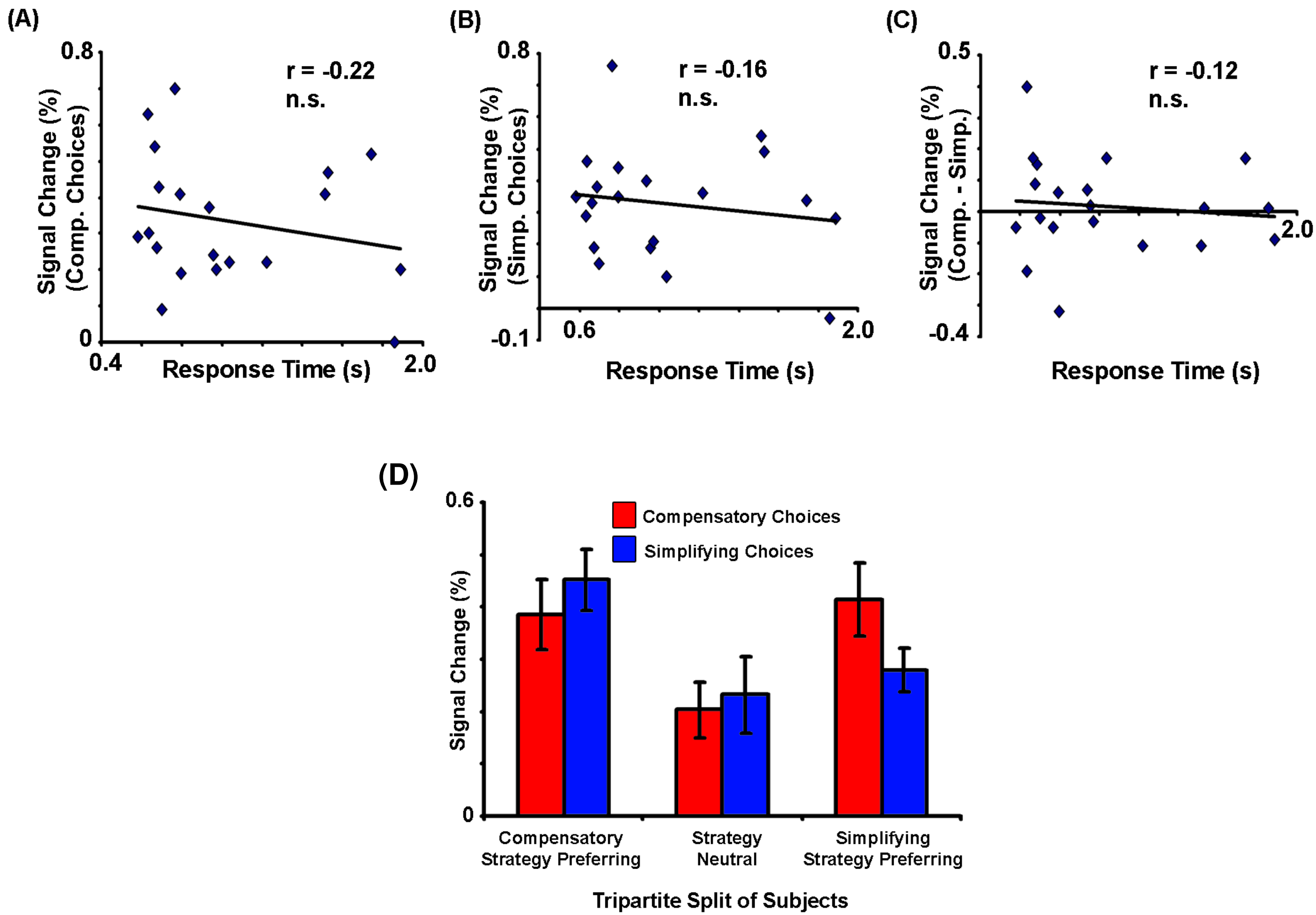


Supplementary Figure 7



Supplementary Figure 8