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The effects of payoff manipulations on temporal bisection performance

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ABSTRACT

There is growing evidence that alterations in reward rates modify timing behavior demonstrating the role of motivational factors in interval timing behavior. This study aimed to investigate the effects of manipulations of rewards and penalties on temporal bisection performance in humans. Participants were trained to classify experienced time intervals as short or long based on the reference durations. Two groups of participants were tested under three different bias conditions in which either the relative reward magnitude or penalty associated with correct or incorrect categorizations of short and long reference durations was manipulated. Participants adapted their choice behavior (i.e., psychometric functions shifted) based on these payoff manipulations in directions predicted by reward maximization. The signal detection theory-based analysis of the data revealed that payoff contingencies affected the response bias parameter (B'') without altering participants' sensitivity (A') to temporal distances. Finally, the response time (RT) analysis showed that short categorization RTs increased, whereas long categorization RTs decreased as a function of stimulus durations. However, overall RTs did not exhibit any modulation in response to payoff manipulations. Taken together, this study provides additional support for the effects of motivational variables on temporal decision-making.

1. Introduction

Organisms are equipped with a mechanism that enables the timing of intervals across timescales of seconds and minutes, which is denoted as interval timing (Buhusi & Meck, 2005). Research on interval timing suggests that the characteristics of timed response patterns are sensitive to experimental manipulations that presumably affect the motivational states of subjects (e.g., Balcı, 2014; Galtress, Marshall, & Kirkpatrick, 2012). For instance, changes in payoff structures can yield facilitatory effects on timing behavior (Avlar et al., 2015; Çavdaroğlu, Zeki, & Balcı, 2014), expected reward magnitude can modulate the time to initiate anticipatory responding as evidenced by shifts in the timed response curves (e.g., Galtress & Kirkpatrick, 2009; Ludvig, Balcı, & Spetch, 2011; Ludvig, Conover, & Shizgal, 2007), or pre-feeding might lead to the flattening of timed response curves (Ward & Odum, 2007). However, since previous research investigating motivational factors on timing performance was mostly carried out with nonhuman animals (also see Bizo & White, 1994, 1995; Grace & Nevin, 2000; Guilhardi, MacInnis, Church, & Machado, 2007), how the same factors (e.g., payoff) affect human timing performance remains relatively unclear (but see Balcı, Freestone, & Gallistel, 2009; Balcı, Wiener, Çavdaroğlu, & Coslett, 2013; Çavdaroğlu et al., 2014; Wearden & Grindrod, 2003). This study aims to fill this gap by investigating the changes in temporal discrimination performance of humans as a function of either the reward or penalty attributed differentially to correct and incorrect categorizations of durations.

A common procedure for studying interval timing performance is the *temporal bisection* task (e.g., Church & Deluty, 1977). This method requires the classification of a set of time intervals as *short* and *long* based on their subjective temporal similarity to previously acquired reference durations. Temporal categorizations in this task rely on both retrospective and prospective decision dynamics (Balcı & Simen, 2014), and yield a variety of measures including choice proportions, the imprecision characteristics of temporal judgments as well as the response times associated with different temporal judgments (a relatively more recently appreciated behavioral endpoint of temporal bisection). Given the advantages of this versatile method, the present study aimed to address the empirical gap that relates to the lack of studies investigating payoff effects on temporal bisection performance of humans. In addition, as recent research conducted with nonhuman animals produced evident but inconsistent biasing effects of reward magnitude on the shifts in choices and noise characteristics of timed responses in the temporal bisection task (e.g., Avlar et al., 2015; Galtress & Kirkpatrick, 2010), we were further motivated to delineate the adjustments in temporal choice behavior under asymmetrical payoff matrices.

Despite discrepancies in the reported outcomes of reward manipulations in the temporal bisection procedure, motivation-mediated

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changes in temporal choices implicate an important role for non-temporal factors in time-based responses. Probabilistic information regarding the occurrence of different standard durations is another such parameter that has been shown to shape temporal bisection performance by leading participants to prefer one temporal choice over another (Akdoğan & Balcı, 2016; Çoşkun, Sayalı, Gürbüz, & Balcı, 2015; Jozefowiez, Polack, Machado, & Miller, 2014). Although similar payoff and stimulus probability manipulations have been shown to produce biasing effects in perceptual decision-making (e.g., Hanks, Mazurek, Kiani, Hopp, & Shadlen, 2011; Leite & Ratcliff, 2011; Mulder, Wagenmakers, Ratcliff, Boekel, & Forstmann, 2012; Noorbaloochi, Sharon, & McClelland, 2015; Simen et al., 2009), several studies posited systematic differences in the integration of these two sources of information into choices which led to varying degrees of bias (e.g., Lynn & Barrett, 2014; Maddox & Bohil, 1998; Mulder et al., 2012). Therefore, the investigation of whether unbalanced payoffs yield similar adaptive changes in temporal decisions and associated response times as those manifested due to stimulus probabilities (Akdoğan & Balcı, 2016; Çoşkun et al., 2015; Jozefowiez et al., 2014) is useful in understanding how these exogenous factors impact temporal judgments.

Temporal decision-making is also susceptible to substantial internal temporal uncertainty (for review see Balcı et al., 2011). An integral component of interval timing ability is indeed the imprecision exhibited in timing behavior despite the, on average, high accuracy in timed responses. The scalar property of interval timing defines this feature and assumes that the standard deviation of time estimates grows proportionally to their mean as indicated by constant coefficients of variation (CVs) within individual subjects (Gibbon, 1977). Therefore, the investigation of the effects of rewards and penalties on timing behavior should also incorporate timing uncertainty (as indexed by CV values) to understand how payoff contingencies and internal timing imprecision produce concomitant changes in temporal choice behavior.

One such framework that is based on the statistical decision theory evaluates the optimality of timing performance and posits that it is essential to assess (1) the presentation probability of the reference durations (stimulus probabilities), (2) gains and losses attributed to different temporal choices (payoffs), and (3) the levels of internal timing uncertainty (trial-to-trial variability in temporal judgments) to achieve reward maximization (Balcı et al., 2009, 2011). In light of the previous work showing both humans and nonhuman animals are indeed able to adopt reward-maximizing temporal strategies by monitoring these exogenous task contingencies and endogenous timing uncertainty levels (e.g., Akdoğan & Balcı, 2016; Balcı et al., 2009; Çavdaroğlu et al., 2014; Çoşkun et al., 2015; Freestone & Church, 2016; Jazayeri & Shadlen, 2010; Kheifets & Gallistel, 2012), we also evaluated the optimality of temporal decisions under varying payoff structures in the temporal bisection task.

Specifically, we manipulated either the relative reward or penalty associated with correct and incorrect categorization of short and long reference durations. In one group of participants (*reward* group), we altered the gains for correct categorizations of the reference durations, and in another group (*penalty* group), we manipulated the penalty associated with incorrect categorizations of reference durations. We hypothesized that these shifts in payoff contingencies would affect participants' response strategies such that they would result in loss avoidance in the penalty group and gain maximization in reward group. For instance, we expected the reward group to be more likely to categorize stimulus durations as short when correctly categorizing the short reference duration as short yielded larger reward than correctly categorizing long reference duration as long [$\mathrm{Gain}(\mathrm{Resp}_{\mathrm{Short}}|\mathrm{T}_{\mathrm{Short}}) > \mathrm{Gain}(\mathrm{Resp}_{\mathrm{Long}}|\mathrm{T}_{\mathrm{Long}})$; Gain(Hit) > Gain(Correct Rejection) when signal is defined as the short duration]. For the penalty group, we expected the participants to more frequently emit a temporal response associated with the reference duration that resulted in higher penalty when categorized incorrectly. Under this prediction, participants were expected to favor short responses when incorrectly categorizing the short reference duration as long results in greater loss [$\mathrm{Loss}(\mathrm{Resp}_{\mathrm{Long}}|\mathrm{T}_{\mathrm{Short}}) > \mathrm{Loss}(\mathrm{Resp}_{\mathrm{Short}}|\mathrm{T}_{\mathrm{Long}})$; Loss(Miss) > Loss(False Alarm) when signal is defined as the short duration]. The effects of these critical manipulations, which were implemented across three different experimental sessions in each payoff group, were quantified in terms of changes in the choice proportions, the sensitivity and response bias parameters of the signal detection theory (SDT; Green & Swets, 1966), and in relation to optimality.

Finally, as response times (RTs) associated with temporal choices also provide information about time-based decisions, and have been shown to manifest a systematic relationship to the timing stimulus in temporal bisection (Akdoğan & Balcı, 2016; Çoşkun et al., 2015; Lindbergh & Kieffaber, 2013; Rodríguez-Gironés & Kacelnik, 1998; Tipples, 2015), we also analyzed the RTs associated with short and long categorizations. A recent decision-theoretic framework of the processing dynamics of temporal bisection (Balcı & Simen, 2014) posits that duration categorizations involve two evidence accumulation processes; one that evolves throughout the presentation of the timing stimulus and the other that evolves following the stimulus offset. Thus, this framework suggests that temporal choices rely on both prospective and post-decision decision dynamics. In the light of this framework of sequential decision processes, we expected the long categorization RTs to decrease and short categorization RTs to increase as stimulus durations grow longer.

This decision model further proposes an asymmetry between short and long decisions in terms of pre-commitment to these decisions before the end of stimulus duration presentation. Specifically, as temporal evidence would be integrated only in favor of long categorizations with elapsing time, participants can commit to a long decision before the cessation of the timing stimulus, which would lead to motor preparedness, thus lowering response latencies for long categorizations. On the other hand, committing to short decisions does not benefit participants. As further implicated by this pre-commitment assumption, since long decisions can be made prior to the end of the timing stimulus, whereas short decisions rely more on post-stimulus dynamics, we expected the short categorization RTs to be more readily affected by bias manipulations. Recent research on the effects of alterations in the frequency of temporal referents presented in the temporal bisection task indeed substantiated the presumed asymmetry between short and long decisions, and showed that short categorization RTs were more sensitive to probabilistic manipulations (Akdoğan & Balcı, 2016; Çoşkun et al., 2015). In a similar vein, we predicted these relations to hold true for the biasing effects of unequal rewards and penalties, and expected specifically the short categorization RTs to be modulated as a function of changes in the payoff structures.

2. Methods

2.1. Participants

A total of 40 adults (28 females, $M_{\mathrm{age}} = 21.6$, $SD_{\mathrm{age}} = 2.9$ yrs), studying or working at Koç University, were recruited for the experiment. Participation was compensated with a maximum of 45 TRY (~16 USD) depending on the task performance. Participants had no history of neurological or psychiatric disorder, and they provided informed consent prior to their participation in the study. All experimental procedures were approved by the Institutional Review Board at Koç University.

2.2. Stimuli and apparatus

Participants were seated at a distance of approximately 60 cm from the monitor. Stimulus durations were signaled with a blue square (100 × 100 pixels) centered on a dark gray background. Experimental stimuli were generated using Matlab (Mathworks, Natick, MA) supported by the Psychophysics toolbox extension (Brainard, 1997; Pelli, 1997). Responses were collected via standard iMac keyboard.

2.3. Procedure

2.3.1. Duration discrimination training

Prior to each experimental session, participants were presented with two reference durations (i.e., 1000 vs. 1500 ms) four times in an alternating order with a text display indicating whether they were short or long reference durations. After the familiarization trials, participants were asked to categorize these durations as *short* and *long* by pressing the "V" and "N" keys, respectively. Feedback was provided for each correct categorization by a text display of "Correct" lasting for one second, whereas incorrect categorizations immediately terminated the trial. The inter-trial interval (ITI) was 1.75 s. The duration discrimination training lasted for a minimum of 25 trials, and continued until participants achieved a 90% discrimination accuracy level in the last 20 trials.

2.3.2. Temporal bisection testing

In the test phase, participants were presented with intermediate durations along with the reference durations, and asked to classify all durations as short or long according to their subjective temporal proximity to the reference durations. Prior to testing, participants were instructed to respond as accurately and quickly as possible for indicating their temporal judgments. In total, they were tested with nine durations that were spaced at logarithmically equal distances (i.e., 1000, 1052, 1107, 1164, 1225, 1288, 1355, 1426, 1500 ms). The overall proportion of reference durations (defined over all trials) was set to 0.36 in all sessions. The gains and losses associated with duration categorizations were manipulated across two payoff groups (Table 1). In the *reward* group ($n = 20$, 15 females), correct categorizations of reference durations were differentially rewarded, whereas in the *penalty* group ($n = 20$, 13 females), incorrect categorizations of reference durations were differentially penalized. Both groups were tested separately under three bias conditions in separate sessions, and the order for bias conditions was randomized across participants. Prior to each testing phase, participants were informed about the payoff structure in the upcoming session, and were reminded of it prior to each test block within a session.

In the *long-bias* condition, participants were expected to favor long categorizations. The reward group received 8 points for categorizing the long reference duration as long, and 2 points for categorizing the short reference duration as short (correct categorizations). On the other hand, the penalty group had 8 points deducted after categorizing the long reference duration as short, and 2 point after categorizing the short reference duration as long (incorrect categorizations). Conversely in the *short-bias* condition, participants were expected to favor short categorizations. The reward group gained respectively 8 and 2 points after correct, whereas the penalty group lost 8 and 2 points after incorrect categorizations of short and long reference durations, respectively. In both bias conditions, the reward group was penalized by 5 points after incorrect categorizations, whereas the penalty group gained 5 points for correct categorizations of each reference duration. In the *unbiased* condition, the payoff structures were symmetrical and identical in both reward and penalty groups. Therefore, we did not expect the participants to be biased towards any temporal option in this condition. They gained 5 points and lost 5 points for correctly and incorrectly categorizing each reference duration, respectively. Participants were informed about the accuracy of their categorizations of reference durations after each trial. On the other hand, neither feedback nor reward was provided for the categorizations of intermediate durations in order to capture the perceptual aspects of temporal information-processing. The ITIs were sampled from a uniform distribution ranging between 1.5 and 2 s. Each experimental session contained 495 trials divided into five test blocks, and lasted approximately 50 min.

Table 1
Payoff matrices (in points) separately for bias conditions and payoff groups.

Response accuracy	Reward group: Short-bias	Reward group: Unbiased	Reward group: Long-bias	Penalty group: Short-bias	Penalty group: Unbiased	Penalty group: Long-bias
Short duration						
Correct ($Resp_{Short}$)	+8	+5	+2	+5	+5	+5
Incorrect ($Resp_{Long}$)	−5	−5	−5	−8	−5	−2
Long duration						
Correct ($Resp_{Long}$)	+2	+5	+8	+5	+5	+5
Incorrect ($Resp_{Short}$)	−5	−5	−5	−2	−5	−8

Note. The "+" and "−" symbols represent gain and loss, respectively. See text for further details.

2.4. Data analysis

Cumulative Gaussian distribution functions were fit to choice proportions which were produced by plotting the proportion of long responses as a function of stimulus durations. We used the best-fit mean parameter to compute the point of subjective equality (PSE), which represents the stimulus duration that yields 50% of long responses. Moreover, in order to obtain an estimate of trial-to-trial variability in temporal judgments, we computed the coefficient of variation (CV) by taking the ratio between the best-fit standard deviation and mean parameters. Additionally, we analyzed the response times associated with short and long categorizations. For the RT analyses, trials with RTs below 0.15 s and above 2.5 s were excluded (1.18% of trials in the reward group, and 0.99% of trials in the penalty group).

These measures were then submitted to separate mixed ANOVAs with bias condition as the within-subjects factor (long-bias, unbiased, and short-bias) and the type of payoff manipulation as the between-subjects factor (reward and penalty). When necessary, Greenhouse-Geisser correction was applied to account for the violation of sphericity assumption, and Holm-Bonferroni correction was used to adjust for multiple comparisons. For all statistical analyses, an alpha level of 0.05 (two-tailed) was used.

2.4.1. Signal detection theory-based analysis

In order to further investigate how payoff manipulations shaped temporal choices, we evaluated short and long responses within the SDT framework (Green & Swets, 1966) according to different possible response categories. The *signal* and *noise* were arbitrarily defined as short and long durations, respectively (see also the Bayet et al. (2015) study for a similar approach in a two-alternative forced choice paradigm). The first four stimulus durations (1000, 1052, 1107, 1164 ms) and the last four stimulus durations (1288, 1355, 1426, 1500 ms) composed the short (signal) and long (noise) durations, respectively. In addition to the reference durations, this set of durations is composed of all intermediate durations except the fifth stimulus duration, which can be rather readily categorized as short or long with respect to the temporal standards. As the PSE is assumed to be near the geometric mean of the reference durations when the spacing of test intervals is logarithmic (e.g., Wearden & Ferrara, 1995), we excluded the fifth stimulus duration (1225 ms) from the SDT-based analysis. With the remaining eight durations, we then quantified the hit rate (*HR*) and false alarm rate (*FAR*).

Since the scalar property of interval timing assumes that the standard deviation of temporal estimates will grow in proportion to their mean, thus resulting in constant CV values for different stimulus durations (Gibbon, 1977), we used the nonparametric indices of sensitivity, A', and response bias, B'' (Stanislaw & Todorov, 1999). When $HR \geq FAR$, $A' = .5 + [(HR - FAR)(1 + HR - FAR)/4\mathrm{HR}(1 - \mathrm{FAR})]$, and $B'' = [\mathrm{HR}(1 - \mathrm{HR}) - \mathrm{FAR}(1 - \mathrm{FAR})]/[HR(1 - HR) + FAR(1 - FAR)]$. When $HR < FAR$, $A' = .5 - [(FAR - HR)(1 + FAR - HR)/4\mathrm{FAR}(1 - \mathrm{HR})]$, and $B'' = [\mathrm{FAR}(1 - \mathrm{FAR}) - \mathrm{HR}(1 - \mathrm{HR})]/[FAR(1 - FAR) + HR(1 - HR)]$. A' ranges from 0 to 1, in which 0.5 corresponds to the discrimination performance at chance-level and 1 indicates perfect discrimination between short and long durations. B'' ranges from −1 to 1, and negative values provide an indication of participants' tendency to report the experienced duration as short (i.e., liberal criterion). A' and B'' were calculated for each individual separately for three bias conditions and both payoff groups, and were then submitted to mixed ANOVAs. Note that, we also computed the d' and c parameters, parametric measures of sensitivity and response bias, and obtained very similar results.

2.4.2. Optimality analysis

We evaluated the optimal temporal strategy in the temporal bisection task (Akdoğan & Balcı, 2016; Çoşkun et al., 2015). For each individual, we calculated the expected gain for different hypothetical PSEs ($\hat{t}$) given the CV estimate ($\hat{\omega}$; which indexes internal timing uncertainty), payoff matrix, and the presentation probability of short and long reference duration. As indicated earlier, the optimality framework also attributes importance to stimulus probabilities, however since the presentation probability of each reference duration was fixed at 0.5, we excluded the stimulus probabilities from the expected gain function and used the following equation (for the generalized form of the function, refer to Balcı et al., 2009).

$$EG(\hat{t}) = g(\sim T_S)\Phi(T_S, \hat{t}, \hat{\omega}\hat{t}) + g(T_S)(1-\Phi(T_S, \hat{t}, \hat{\omega}\hat{t})) \\ +g(T_L)\Phi(T_L, \hat{t}, \hat{\omega}\hat{t}) + g(\sim T_L)(1-\Phi(T_L, \hat{t}, \hat{\omega}\hat{t}))$$

where $\hat{\omega}$ is the ratio of the standard deviation ($\hat{\sigma}$) to the PSE ($\hat{t}$) which are obtained from the best-fit cumulative Gaussian distribution function. Short and long reference durations are denoted as T_S and T_L, respectively. The payoff matrix is represented with g, such that $g(T_S)$ and $g(T_L)$ are the gains associated with correct categorizations, and $g(\sim T_S)$ and $g(\sim T_L)$ are the losses associated with incorrect categorizations of the short and long reference durations, respectively. The normal cumulative distribution function, $\Phi = 0.5[1 + erf((x-\hat{t})/(\sqrt{2}\hat{\omega}\hat{t}))]$ with mean $\hat{t}$ and standard deviation $\hat{\omega}\hat{t}$, is evaluated for various hypothetical $\hat{t}$s at T_S and T_L. As a consequence, given the level of internal timing uncertainty and task parameters, the optimal PSE can be defined for each participant as the $\hat{t}$ that maximizes the expected gain function, thus yields the maximum possible expected gain (MPEG). It should be noted that due to endogenous timing uncertainty, participants may have different optimal PSEs even under identical task conditions (e.g., payoff contingencies). For instance, given the scalar relationship between the variability and central tendency of timed responses, participants can decrease the absolute level of uncertainty by aiming to respond at an earlier time point and increase it by aiming to respond at a later time point. The resultant variability in timed responses in turn determines the probability by which two reference durations would be categorized correctly and incorrectly, as well as the optimal PSEs which would maximize the gain given the payoff structures and the levels of internal timing uncertainty.

Based on this analysis, proportions of MPEG (obtained by comparing the expected gain of the participant to the MPEG) were subjected to a mixed ANOVA. Furthermore, we conducted paired-samples t-tests for the PSEs obtained from the best-fitting cumulative Gaussian distribution (denoted hereafter as empirical PSEs) and optimal PSEs in each bias condition separately for payoff groups. For these pairwise comparisons, we utilized the Bayesian inference framework to be able to provide evidence for the theoretically critical null hypothesis regarding the equivalence of the empirical and optimal strategies (Rouder, Speckman, Sun, Morey, & Iverson, 2009; Wetzels et al., 2011). Following Rouder et al. (2009), we used a Cauchy prior distribution with a scaling factor $r = 1$, and calculated the Jeffreys, Zellner and Siow (JZS) Bayes factor using the R package "BayesFactor" (Morey, Rouder, & Jamil, 2015). A Bayes factor (BF_{01}) represents the likelihood of data under null hypothesis (H_0) relative to the likelihood of data under alternative hypothesis (H_1). Therefore, $BF_{01} = 1$ is interpreted as favoring neither the H_1 nor H_0, whereas, for instance, BF_{01} between 3 and 10 provides substantial evidence in favor of the H_0, and BF_{01} between 1/10–1/3 provides substantial evidence in favor of the H_1 (Jeffreys, 1961; see also Wetzels et al., 2011).

3. Results

3.1. Choice proportions

Fig. 1A and B depict the average choice proportions separately for three bias conditions along with the best-fit cumulative Gaussian distribution functions for the reward and penalty groups, respectively. All R^2 values for the average fits were over 0.99 in both the reward and penalty groups. The mean R^2 values for the individual fits were over 0.96 in both payoff groups.

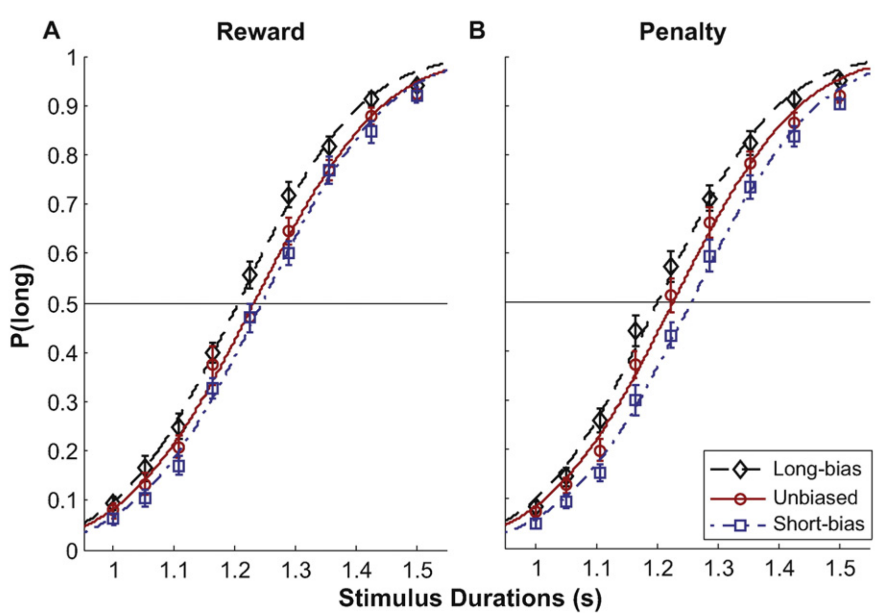

Fig. 1. Choice proportions as a function of stimulus durations separately for different bias conditions for the reward (A) and penalty groups (B). Curves represent the best-fit cumulative Gaussian distribution functions to average choice proportions. Error bars represent *SEM*.

Table 2
The mean empirical PSEs, CVs, A′s, and B″s depicted separately for bias conditions and payoff groups.

	Reward				Penalty			
Bias condition	PSE	CV	A'	B''	PSE	CV	A'	B''
Long-bias	1.20	0.13	0.70	0.16	1.20	0.12	0.69	0.18
	(0.04)	(0.04)	(0.06)	(0.27)	(0.04)	(0.02)	(0.04)	(0.26)
Unbiased	1.23	0.13	0.69	−0.03	1.23	0.13	0.69	0.01
	(0.04)	(0.04)	(0.06)	(0.28)	(0.05)	(0.03)	(0.05)	(0.29)
Short-bias	1.25	0.13	0.70	−0.09	1.26	0.13	0.70	−0.18
	(0.04)	(0.03)	(0.06)	(0.23)	(0.04)	(0.03)	(0.05)	(0.33)

Note. The values in parentheses are standard deviations. Note that "Bias condition" is defined based on the expected effect on responding.

Fig. 1 reveals that participants modulated their temporal categorizations with respect to the changes in payoff structures. Specifically, psychometric functions shifted leftward with the larger gain associated with correct categorization of the long reference duration in the reward group and larger loss associated with incorrect categorizations of the long reference duration in the penalty groups. Visual inspection of Fig. 1 further suggests that increasing the gain associated with correct categorizations of short reference duration in the reward group and increasing the loss associated with incorrect categorizations of the short reference duration in the penalty group led to an increase in the empirical PSEs (points of intersection between horizontal straight lines and psychophysical curves). The average empirical PSEs obtained from the cumulative Gaussian distribution fits to choice proportions are presented in Table 2.

The comparison of empirical PSEs revealed a main effect of the bias manipulation, $F(2, 76) = 14.97$, $p < 0.001$, $\eta_p^2 = 0.28$. There was not a main effect of the type of payoff manipulation (rewards or penalties), $F(1, 38) = 0.07$, $p = 0.80$, nor a significant interaction, $F(2, 76) = 0.39$, $p = 0.68$. Pairwise comparisons revealed that the empirical PSE estimates differed significantly between all pairs of bias conditions (all *ps* < 0.02), and that they were highest in the short-bias condition and lowest in the long-bias condition (short biased: $M = 1.25$, unbiased: $M = 1.23$, long-bias: $M = 1.20$). These results suggest that altering the gain associated with correct temporal categorizations or the loss associated with incorrect temporal judgments had biasing effects in participants' preference of one temporal choice over another.

We also investigated whether there was a change in the trial-to-trial variability of participants' temporal choices in different bias conditions based on the CV estimates obtained from the best-fit cumulative Gaussian distribution (Table 2). Our findings showed no significant (a) main effect of bias, $F(2, 76) = 0.24$, $p = 0.79$, (b) main effect of the type of payoff manipulation, $F(1, 38) = 0.37$, $p = 0.55$, or (c) interaction between bias and payoff, $F(2, 76) = 0.15$, $p = 0.86$. Taken together, these findings indicate that reward/penalty contingencies had biasing effects on choice proportions but no effect on the trial-to-trial variability exhibited in temporal choices.

3.2. Sensitivity and response bias

A mixed ANOVA was conducted to investigate whether payoff manipulation altered sensitivity (Table 2). We found that A's did not differ across bias conditions, $F(2, 76) = 0.26$, $p = 0.78$, or between payoff groups, $F(1, 38) = 0.02$, $p = 0.89$. We also did not find a significant interaction between bias condition and type of payoff manipulation, $F(2, 76) = 0.04$, $p = 0.96$. As can be visualized in Fig. 2A, these results indicate that participants were able to discriminate stimulus durations with high accuracy in all test conditions, and that their sensitivity levels did not differ as a function of the alterations in the reward or penalty structures.

In order to further evaluate how bias was manifested in participants' subjective temporal estimates, we also computed the response bias parameter (B''; Table 2). The visual inspection of Fig. 2B suggests that the change in the B''s had a decreasing trend as a function of the increase in the gain or loss associated with the correct or incorrect categorizations of the short reference duration, respectively (indicating the adoption of a liberal criterion). The mixed ANOVA results indicated a main effect of bias on B''s, $F(2, 76) = 15.70$, $p < 0.001$, $\eta_p^2 = 0.29$. Pairwise comparisons revealed that B''s in the long-bias condition ($M = 0.17$) were higher than those in both unbiased ($M = -0.01$) and short-bias ($M = -0.13$) conditions, and these differences between all three bias condition pairs were significant (all *ps* < 0.04). There was no main effect of the type of payoff manipulation, $F(1, 38) = 0.02$, $p = 0.89$, or significant bias-payoff interaction, $F(2, 76) = 0.74$, $p = 0.48$.

When B''s in each bias condition were compared to 0 (no response bias) with one-sample *t*-tests, B''s in the long-bias condition indeed differed from 0, $t(19) = 2.62$, $p = 0.02$, $d = 0.59$, in the reward group, and $t(19) = 3.05$, $p = 0.01$, $d = 0.68$ in the penalty group. In the short-bias condition, B''s in the reward group did not differ significantly from 0, $t(19) = -1.74$, $p = 0.10$, whereas the short response bias in the penalty group reached significance, $t(19) = -2.38$, $p = 0.03$, $d = 0.53$. As expected, no response bias was exhibited in the unbiased conditions, $t(19) = -0.43$, $p = 0.67$ in the reward group, and $t(19) = 0.13$, $p = 0.90$ in the penalty group. The SDT-based analysis results collectively suggest that testing under unequal rewards or penalties caused participants to be inclined to manifest response biases without affecting their sensitivity in discriminating between different stimulus durations.

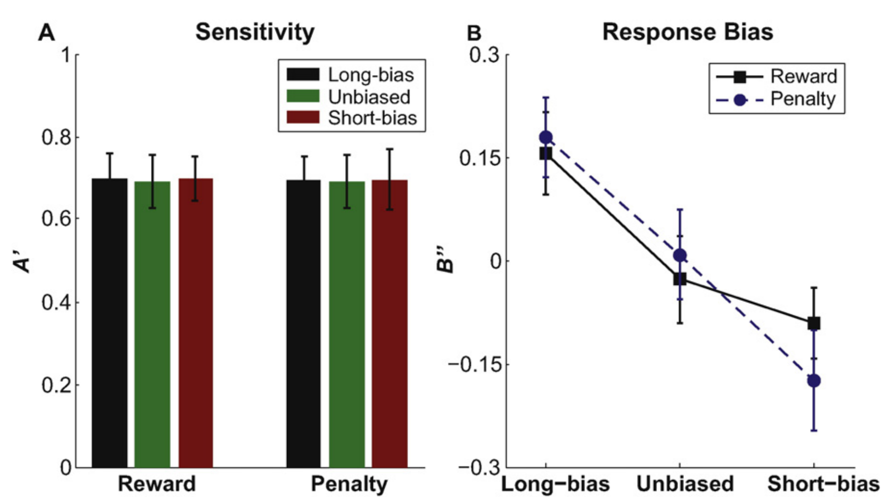

Fig. 2. SDT-based analysis of temporal choices. A's (A) and B''s (B) are depicted as a function of bias conditions separately for two payoff groups. Error bars represent *SEM*.

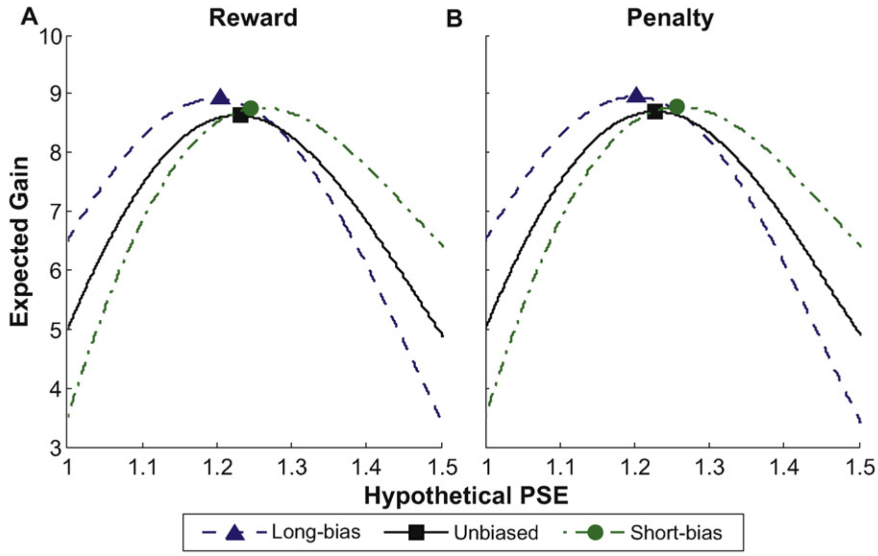

Fig. 3. Expected gain as a function of hypothetical PSEs in different bias conditions depicted separately for the reward (A) and penalty (B) groups. Expected gains were calculated with average empirical CV estimates obtained from the corresponding bias conditions in each payoff group. Filled symbols represent the average empirical PSEs obtained in the corresponding bias conditions and payoff groups.

3.3. Expected gains

The expected gain calculated for hypothetical PSEs and the localization of the average empirical PSE on the expected gain curve in each bias condition can be visualized in Fig. 3 both for the reward (A) and penalty (B) groups. When we compared the expected gain values with the MPEGs, we found that both payoff groups were able to maximize their reward to a great extent. Specifically, the reward group gained 98.7 ($SD = 0.02$), 98.5 ($SD = 0.02$), and 98.7% ($SD = 0.01$) of the MPEG for increasing reward associated with correct categorizations of the short reference duration. Similarly, the penalty group gained 98.3 ($SD = 0.02$), 98.2 ($SD = 0.02$), and 98.8% ($SD = 0.02$) of the MPEG for increasing loss associated with incorrect categorizations of the short reference duration. The proportions of MPEG did not vary as a function of bias condition, $F(2, 76) = 0.62$, $p = 0.54$, or the type of payoff manipulation, $F(1, 38) = 0.36$, $p = 0.55$. The interaction between bias and payoff types also was not significant, $F(2, 76) = 0.22$, $p = 0.80$. In another set of analyses, we adopted a more conservative approach by integrating the minimum gain associated with random responding into the computation of proportion of MPEG (i.e., expected gain − minimum gain)/(MPEG − minimum gain), and found that the average proportions of MPEG were over 98.2% and 97.9% in the reward and penalty groups, respectively.

These results suggest a high correspondence between the empirical and optimal (peaks of the expected gain curves) PSEs. To elucidate this relationship, we first investigated the change in the optimal PSEs as a function of bias conditions. Optimal PSEs increased with gain associated with correct short categorizations in the reward group. The mean optimal PSEs were 1.20 ($SD = 0.03$) in the long-bias, 1.23 ($SD = 0.01$) in the unbiased, and 1.26 ($SD = 0.01$) in the short-bias condition. These changes were supported with a one-way repeated-measures ANOVA, $F(1.19, 22.70) = 58.31$, $p < 0.001$, $\eta_p^2 = 0.75$, and with the follow-up pairwise tests showing that optimal PSEs differed significantly between all three pairs of bias conditions (all $ps < 0.001$). A similar relation in the optimal PSEs was observed in the penalty group in which the mean optimal PSEs were 1.20 ($SD = 0.02$) in the long-bias, 1.23 ($SD = 0.01$) in the unbiased, and 1.26 ($SD = 0.01$) in the short-bias condition. We found a significant change in the optimal PSEs as a function of bias conditions, $F(1.34, 25.47) = 150.76$, $p < 0.001$, $\eta_p^2 = 0.89$, and follow-up pairwise tests revealed that the differences in optimal PSEs across all three pairs of bias conditions were significant (all $ps < 0.001$).

In order to further delineate the correspondence between empirical and optimal PSEs, we also compared the slope values obtained from the orthogonal regression of each individual's empirical PSE on the optimal PSE in the corresponding bias condition. In the reward group, the mean slope value ($M = 0.60$, $SD = 2.09$) did not differ, either from 0, $t(19) = 1.30$, $p = 0.21$, or from 1, $t(19) = -0.85$, $p = 0.41$. In the penalty group, the mean slope value ($M = 1.41$, $SD = 1.73$) differed significantly from 0, $t(19) = 3.64$, $p = 0.002$, $d = 0.81$, but not from 1, $t(19) = 1.05$, $p = 0.31$. The correspondence between the empirical and optimal PSEs was substantiated by paired-samples t-tests of empirical and optimal PSEs in each bias condition which did not reveal any significant differences, either in the reward group (all $ps > 0.10$) or in the penalty group (all $ps > 0.70$). Additionally, in order to assess the evidence for the null hypothesis which predicts no difference between empirical and optimal PSEs, we conducted Bayesian t-tests (Rouder et al., 2009). The JZS Bayes factor BF_{01} ranged from 1.65 to 5.46 in the reward group and from 5.46 to 5.86 in the penalty group. Except for the BF_{01} of 1.65 (anectodal evidence in favor of the null hypothesis) obtained in the reward group, these values provide strong evidence for the null hypothesis. Taken together, our optimality analysis of the adjustments in temporal choices as a function of payoff contingencies revealed that both payoff groups were able to maximize their gain to a great extent in all of the bias conditions.

3.4. Response times

To further investigate the modulation of timing performance as a function of unequal rewards and penalties, we also analyzed the response times associated with short and long judgments. We first examined the RTs for short and long categorizations made for each stimulus duration in different bias conditions (see Table 3 for descriptive statistics). Visual inspection of Fig. 4 reveals that short categorization RTs slowed down, whereas long categorization RTs speeded up with elapsing time. In order to quantify this change in the RTs as a function of stimulus durations, we conducted linear regressions of short and long categorization RTs on stimulus durations in different bias conditions. The statistical results of the linear regression analyses corroborated our observations in all cases for both payoff groups (all $ps < 0.01$; Table 3).

Table 3
Mean RTs (in s) and the statistical results of linear regression of short and long categorization RTs on stimulus durations.

	Reward				Penalty			
	M (*SD*)	*t*(7)	β	R^2	*M* (*SD*)	*t*(7)	β	R^2
Long-bias								
Short RT	0.59 (0.17)	10.23**	0.97	0.94	0.68 (0.17)	3.69*	0.81	0.66
Long RT	0.52 (0.18)	−23.77**	−0.99	0.99	0.59 (0.15)	−12.94**	−0.98	0.96
Unbiased								
Short RT	0.58 (0.19)	19.57**	0.99	0.98	0.69 (0.15)	10.84**	0.97	0.94
Long RT	0.51 (0.16)	−9.84**	−0.97	0.93	0.58 (0.11)	−13.62**	−0.98	0.96
Short-bias								
Short RT	0.59 (0.21)	17.74**	0.99	0.98	0.69 (0.17)	9.97**	0.97	0.93
Long RT	0.51 (0.18)	−21.49**	−0.99	0.99	0.60 (0.16)	−10.67**	−0.97	0.94

Note. βs are the standardized coefficient estimates.
* $p < 0.01$.
** $p < 0.001$.

Differences in the RTs were investigated with a three-factor mixed ANOVA. The within-subjects factors were the bias condition (long-bias, unbiased, and short-bias) and categorization type (short and long), the between-subjects factor was the type of payoff manipulation (reward or penalty). We found a main effect of categorization type on response times, $F(1, 38) = 47.99$, $p < 0.001$, $\eta_p^2 = 0.56$. Pairwise comparisons revealed that long categorization RTs were significantly faster than short categorization RTs, $p < 0.001$. There were not any significant changes in the RTs as a function of the bias conditions, $F(2, 76) = 0.10$, $p = 0.90$, or they did not differ between payoff groups, $F(1, 38) = 3.44$, $p = 0.07$. Collectively, these RT patterns indicate that, although RTs associated with short and long responses showed a systematic relation to the test durations, altering the reward or penalty associated with temporal categorizations had no effect on average response times.

4. Discussion

This experiment aimed to investigate the payoff effects on temporal bisection performance by manipulating the differential reward and penalty associated with correct and incorrect categorizations of reference durations, respectively. Our results indicated that participants were biased towards emitting the response associated with the temporal option yielding higher reward magnitude for its correct categorization, and that they were biased towards emitting the response associated with the temporal option resulting in higher penalty when it was categorized incorrectly. Specifically, participants made more frequent short choices with the increasing gain or loss associated with correct or incorrect categorizations of the short reference duration, respectively. Conversely, participants were inclined to report more frequent long choices when correct categorizations of the long reference duration yielded more gain, or incorrect categorizations of the long reference duration resulted in greater loss.

The changes in choice behavior were illustrated with two sets of findings. The first one was based on the psychometric functions and revealed that payoff manipulations led to shifts in the PSEs. Moreover, these adaptive changes in choices were not accompanied by alterations in timing precision, as indicated by no modulation of CVs as a function of payoff structures, which is in line with SET Gibbon, 1977. In addition to the quantification of the shifts observed in psychometric functions, in a second set of analyses, we utilized the signal detection theory framework (Green & Swets, 1966) to understand how the sensitivity and response bias parameters changed as a function of reward or penalty configurations. Consistent with our analysis of the PSE and CV estimates, we found that the sensitivity levels of participants to discriminate between time intervals were high and did not differ across test conditions. On the other hand, biases in choice behavior were accompanied by parallel adjustments in the decision criterion placement. Specifically, participants had the tendency to judge a stimulus duration as short more frequently in the short-bias conditions of both payoff groups, which indicates the adoption of a liberal criterion as signal and noise were arbitrarily defined as short and long durations, respectively. On the other hand, they adopted a more conservative criterion, in other words, reported long categorizations more frequently in the long-bias conditions of both payoff groups (given the same signal and noise assignments to reference durations). Taken together, the use of both the conventional measures of temporal bisection performance and the signal detection

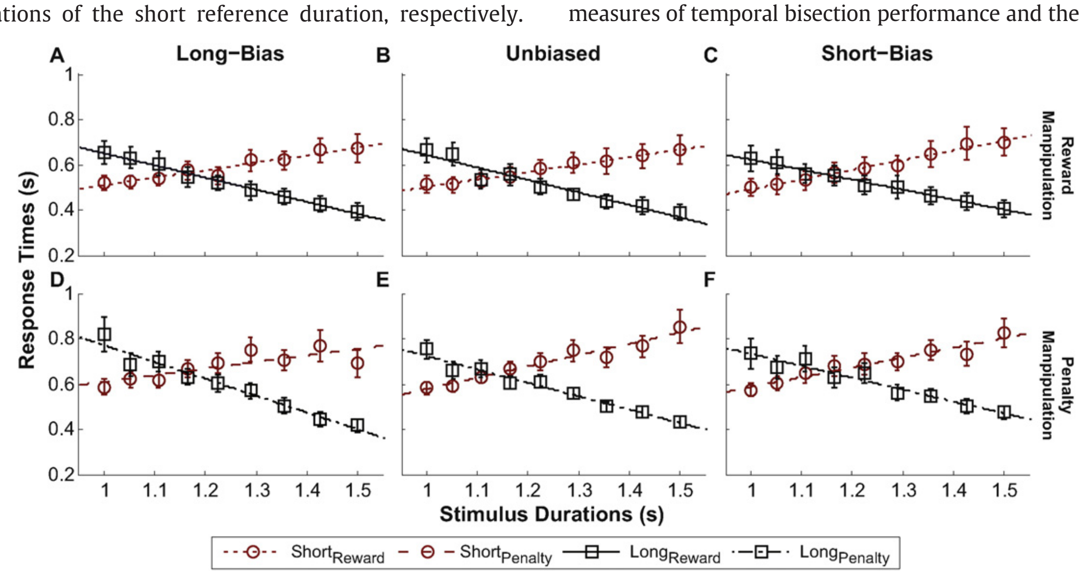

Fig. 4. Average short and long categorization response times as a function of stimulus durations separately for three bias conditions for the reward (A–C) and penalty (D–F) groups. Lines are best-fit linear regression lines. Error bars represent *SEM*.

theory-based analysis rendered a more thorough assessment of the temporal choice behavior under unequal rewards or penalties.

A wealth of research shows that most decision-making tasks require individuals to represent and combine external noise and internal sources of uncertainty to make choices (e.g., Battaglia & Schrater, 2007; Gureckis & Love, 2009; Trommershäuser, Maloney, & Landy, 2003). Similarly, time-based decision-making necessitates the integration of both exogenous factors (e.g., reward magnitudes) and the inherent uncertainty characteristics of interval timing (which can be observed through the trial-to-trial variability in temporal choices) in shaping decision outputs. Therefore, in order to elucidate how payoff structures and internal timing uncertainty collectively govern temporal decisions, we also assessed the adaptive changes in choice behavior within the optimality framework based on the statistical decision theory. Our participants were able to maximize their gain to a great extent in all bias conditions by taking normative account of their timing uncertainty as well as monitoring changes in payoff contingencies. These findings not only corroborated previous studies illustrating the optimal temporal performance of humans and nonhuman animals in a variety of interval timing tasks (e.g., Akdoğan & Balcı, 2016; Balcı et al., 2009; Çavdaroğlu et al., 2014; Freestone & Church, 2016; Jazayeri & Shadlen, 2010; Kheifets & Gallistel, 2012), but also substantiated the optimality of temporal decisions in experimental scenarios where differential gain or loss was attributed to correct or incorrect temporal categorizations.

In addition to the assessment of temporal choices, the speed with which those judgments are made or reported also provides valuable information about temporal decision-making in various temporal discrimination settings (e.g., Balcı & Simen, 2014; Klapproth & Wearden, 2011). To better characterize the nature of temporal decisions, we analyzed the RTs associated with choices. As expected, short categorization RTs slowed down, whereas long categorization RTs speeded up as stimulus durations grew longer in all bias conditions. Moreover, overall RT patterns revealed that RTs associated with short judgments were slower than the RTs associated with long judgments. These results lend further evidence for a temporal decision-making process that evolves over the course of a trial, and consolidate the presumed asymmetry in short and long temporal judgments (see Balcı & Simen, 2014 for a detailed discussion).

However, even though we expected the modulation of RT patterns as a function of reward and penalty manipulations to resemble the biasing effects of stimulus probabilities (modulation of short categorization RTs; Akdoğan & Balcı, 2016; Çoşkun et al., 2015), we failed to find such an effect. In one of the previous studies that manipulated probabilistic information in the temporal bisection task in two experimental phases with varying overall reinforcement rates (Akdoğan & Balcı, 2016; the presentation probability of reference durations was 0.5 and 0.8 in Phase 1 and 2, respectively), the lack of RT modulation and less pronounced alterations in choice proportions observed in Phase 2 were argued to be indicators of diminished response biases caused by testing under high overall reinforcement rate, which was presumably linked to more frequent updates of memory representations regarding temporal standards (Lustig & Meck, 2005). Although there was no change in the overall reinforcement rate in the current study, the absence of changes in the overall RTs under unequal reward or penalty conditions might simply indicate that our experimental protocol has not been influential enough also to bias the response times associated with choices. One approach to enhance the biasing effects of payoffs in the temporal bisection task might include increasing the absolute point difference and/or the ratio between the amount of gain (or loss) attributed to the correct (or incorrect) categorization of one reference duration relative to the other. Future studies, particularly those with more distinct gain and loss parameterizations, are thus needed to delineate whether and how payoffs affect response times and processing dynamics underlying temporal choices.

Additionally, the differences in the biasing effects of probabilistic manipulations and unequal payoffs might indicate that two sources of response bias might operate differently in shaping decision outputs. Previous studies utilizing a variety of decision-making scenarios suggest that reward and penalty structures, when compared to the effects of probabilistic information, create less pronounced biases in accuracy (determined with respect to the proportion of short and long responses in temporal bisection) and the RTs associated with choices (e.g., Leite & Ratcliff, 2011; Mulder et al., 2012). One possible explanation is that, when probabilistic information varies in neutral payoff conditions, adjustments in choice behavior occur more readily as alterations in the accuracy performance result in highly correlated changes in the amount of gain earned (Lynn & Barrett, 2014). For instance, when the short reference duration is presented more frequently than the long reference duration, participants will be biased towards emitting short responses, and the amount of adjustments in choices that maximizes accuracy will also maximize reward. On the other hand, under payoff manipulations, accuracy and reward attained are not as tightly coupled as in the case of probabilistic manipulations due to differential effects of outcomes. Specifically, unequal payoff structures result in a tradeoff between reward and accuracy maximization (Bohil & Maddox, 2001; Maddox & Bohil, 1998) and require an estimation of the payoff parameters to gauge the bias in behavior (Lynn & Barrett, 2014). As some individuals might prioritize accuracy at the expense of reward maximization (or vice versa), these biasing factors, in turn, might also interact with decision-makers' sensitivity to reward or accuracy (Mulder et al., 2012), thus resulting in distinct alterations in behavioral tendencies.

Payoff manipulations alone might also exert different amounts of influence on choice behavior. Even though the expected gain was identical in both payoff groups, a number of our findings suggest that the biasing effects of unbalanced payoffs on choices were more pronounced in the penalty group than in the reward group. For instance, the SDT-based analyses revealed that, compared to the penalty group, alterations in decision criterion (indexed by B''s) were less evident in the short-bias condition of the reward group. Moreover, the close inspection of the relation between the empirical and optimal PSEs revealed by the orthogonal regression fits and pairwise comparisons suggests that the correspondence was less obvious in the reward group. The differences in the amount of shifts in the psychometric curves across bias conditions in both payoff groups (Fig. 1) also corroborate these indications, suggesting that manipulating the relative loss associated with incorrect categorizations resulted in more marked adjustments in choices than the relative gain associated with correct categorization of reference durations. These findings are in line with previous research demonstrating the importance of how the consequences of temporal responses are framed in terms of gain and losses, and implicate that individuals' inclination to avoid loss (even when the gain is identical for the accurate discriminations of both referents) might have led the penalty manipulations to engender greater impact on the adaptations in their decisions than reward manipulations (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981).

These presumed differences in payoff effects indicate that motivation itself is a multifaceted concept. Therefore, it is not surprising that previous manipulations of payoff structures (without changing the stimulus probabilities) in different temporal discrimination tasks yielded inconsistent results (e.g., Avlar et al., 2015; Daniels, Fox, Kyonka, & Sanabria, 2015; Galtress & Kirkpatrick, 2010; Wearden & Grindrod, 2003). For instance, in the Wearden and Grindrod (2003) study, human participants received differential incentive to emit a specific type of temporal response in the temporal generalization procedure. Adjustments in decision processes were evidenced by the shifts in the frequency of reporting different types of responses but not in the trial-to-trial variability of temporal judgments. On the other hand, Galtress and Kirkpatrick (2010) reported that changes in the reward magnitude led to an increase in timing imprecision of rats as evidenced by the flattening of psychophysical curves without revealing consistent effects on the location of PSEs. Additional research has recently depicted that in wild-type mice both the PSEs and precision in timing were modulated by the reward magnitude manipulation (Avlar et al., 2015). Although they do not provide a coherent picture of the alterations in the timing performance under different payoff conditions, these studies collectively point to the link between motivation and timing performance.

However, these contradictory findings, which could be simply due to species differences, illustrate the complexity of the theoretical interpretations regarding the link between timing processes and payoff effects. It is particularly important to understand how temporal choices become tuned to varying payoff structures as well as other environmental contingencies, as these behavioral dynamics have been largely overlooked in the interval timing literature. One relevant associative account of timing, the behavioral economic model (BEM; Jozefowiez, Staddon, & Cerutti, 2009), however, proposes that the probability of reinforcement and stimulus probabilities play a fundamental role in temporal information-processing, and therefore should be integrated into the formalization of the decision dynamics underlying the interval timing ability. Specifically, it provides a mathematical framework for understanding how differential reinforcement and/or varying stimulus probabilities interact with temporal representations, and illustrates how these factors, parameterized as two separate constituents of a bias term, can lead participants to favor one temporal choice over another in different timing tasks including the temporal bisection procedure (Jozefowiez & Machado, 2013; Jozefowiez et al., 2014).

Behavioral economic model can account for the response tendencies observed in choice behavior more successfully than the majority of theoretical approaches to interval timing, including the highly influential scalar expectancy theory (Gibbon, Church, & Meck, 1984) which originally neglects the link between temporal processing and biasing factors (but see, for instance, Gibbon, 1981; Wearden & Grindrod, 2003). However, BEM still has some drawbacks that deter its widespread implementation. For example, it does not take into account the possible differences in the magnitude of biases manifested in choices due to reward versus penalty manipulations. Similarly, although it treats stimulus probabilities and reinforcement effects as separate sources of bias, it is largely deficient in predicting whether they can lead to differential biases in behavior. Therefore, both the limited scope of timing models regarding the effects of payoffs as well as other extraneous variables and the lack of consensus regarding the resultant alterations in choices necessitate further investigation of how manipulations of payoffs as well as other non-temporal factors affect the interval timing behavior and temporal decision-making. Such studies in turn would also lead to a better formulation of the role of motivational factors in temporal information-processing, and augment our understanding of the interaction between payoffs and other sources of bias in shaping timing behavior.

5. Conclusions

This study contributes to the growing body of evidence indicating that motivational factors as investigated by manipulating the differential gain or loss associated with temporal judgments alter temporal choice behavior. As revealed by the shifts in psychometric functions and the response bias parameter of the signal detection theory (Green & Swets, 1966), participants exhibited a clear tendency to more frequently report the temporal judgment that produced more gain and to be biased towards the response associated with the temporal option that incurred higher loss when categorized incorrectly. In addition, these adaptations in the choice data were nearly optimal, indicating that participants not only monitored the payoff contingencies, but were also able to assess their levels of internal timing uncertainty, which enabled them to maximize their gain to a great extent. Although response times associated with short and long categorizations exhibited a systematic change throughout the presentation of the timing stimulus, the lack of modulation in the response times as a function of payoff structures might necessitate more distinct biasing conditions where the differentiation between rewards and penalties is more apparent. Furthermore, future studies investigating motivational effects by providing neurophysiological evidence would be particularly useful in enhancing our understanding of the brain circuitry of both interval timing and motivation given the assumed overlap in the neural underpinnings of these cognitive phenomena (e.g., Avlar et al., 2015; Balcı, 2014; Kirkpatrick, 2014).

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