Behavioural Brain Research 429 (2022) 113909

Contents lists available at ScienceDirect

Behavioural Brain Research

journal homepage: www.elsevier.com/locate/bbr

Asymmetric valuation and belief updating over gain and loss in risky decision making: A behavioral and electrophysiological investigation

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ARTICLE INFO

Keywords:
Valence
Belief updating
Outcome evaluation
Risk
FRN
P300

ABSTRACT

Decisions under risk, either for gain or loss, are ubiquitous in our daily life. However, the extent to which the valence (gain or loss) of risky financial choices shapes outcome valuation and belief updating is a relatively overlooked research area. In the current study, we image neural activity using electroencephalography (EEG) combined with a financial decision task to investigate outcome valuation and belief updating. In the experimental task, subjects can either choose to take the risky gamble (stock) or the safe option (bond) and then report their belief over the quality of stock option in a trial-by-trial manner. Although the actual probabilities of the risky option are symmetric over gain and loss, we found an asymmetric effect of belief updating and risk preference, viz. the subjects tend to both report a higher probability for the stock to win and be more risk taking for potential gains compared to symmetric losses. The EEG data following feedback of stock payoff represents a parallel pattern which is resonant with the behavioral results. Notably, there is generally a greater FRN difference for feedback (correct vs. incorrect) in the gain condition compared to the loss condition, and the deflection of P300 is more prominent in gain condition than loss condition irrespective of the correctness. Lastly, while the P300 could be predictive for the subsequent probability estimate in both conditions (gain and loss), the FRN is only predictive for belief updating in the gain rather than loss condition. Therefore, both the behavioral and electrophysiological findings indicate an unbalanced processing of valence in shaping decisions under risk within financial learning in an experiential framework.

1. Introduction

In our modern society, risk is ubiquitous in every aspect of our life and is especially evident now during the current protracted COVID-19 pandemic [1,2]. Indeed, in our daily lives, we perforce learn to make adaptive choices through trial and error. In the face of risk, the individual needs to recognize the correct choice out of several available options. If there is an opportunity with net reward, we need to seize the moment and gain the advantage, whereas if the option possibly entails loss, we must analyze and understand the state of affairs toward avoiding any unnecessary loss [3,4].

One aspect of research involving risky choices lies at the descriptive framework. For instance, with the options which involve different degree of uncertainty, subjects can choose to select one option out of them. As pioneered by Tversky and Kahneman (1979, 1992) in their seminal prospect theory, for decision under risk, individuals generally tend to loom larger for loss than that of equivalent gain which make subjects be risk averse in gain domain and be risk seeking in loss domain [5,6]. Nevertheless, on the other side of the same coin, under the framework of the experience, there might be a different story which is gaining academic attention recently from the fields of psychology, economics and neuroscience [7,8]. Notably, unlike the *descriptive* task which involves

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https://doi.org/10.1016/j.bbr.2022.113909
Received 31 August 2021; Received in revised form 2 April 2022; Accepted 27 April 2022
Available online 29 April 2022
0166-4328/

the static choice, while for the risky choice in *experiential* framework with learning ingredients, the subjects are exposed to the dynamic context where they need to figure out the regularities of the options with trial and error. In principle, in the instrumental learning scenario, people should treat the valence, whether gains or losses, of the outcome in a symmetric manner to objectively evaluate their strategies. However, recent studies from psychology and economics suggest that this apparent conclusion might not hold [9,10]. For instance, Lebreton et al. [10] and Ting et al. [11] implemented an instrumental learning task and found that confidence rating under gains is significantly higher compared to it under losses. In parallel, applying a financial learning task, Kuhnen suggested that there is an asymmetric effect of belief updating, the subjects tend to overestimate the probability of the risky option under gains compared to under losses [12]. Therefore, it's of great interest to examine to what extent that the subjects treat the gain and loss condition in a learning task within a experiential framework.

To fill the research gap of the prior literature, we intend to extend the previous studies to track the potential gain loss asymmetry when the subjects are involved in a dynamic learning task. Under the umbrella of experience framework, we have kept the following questions in mind. What's the exact asymmetric characteristics of belief updating? How does this asymmetry reflect by the risky preference over gain and loss, and more critically, what's the corresponding neural underpinnings that represent such a gain loss asymmetry revealed through experience, i.e., the revealed outcome [13,14] ?

In order to answer these unresolved questions, in our current study, we adapted a financial learning task initially developed by Kuhnen [12] and simultaneously recorded the EEG to examine how the brain tracks the outcome under gains compared to under losses. Specifically, both under gains and losses, subjects are instructed to make a binary choice between a safe option (a fixed payoff) and a risky option in which the subjects either obtain a larger or smaller payoff. The payoff outcome of the risky option is revealed to the subjects irrespective of whether they choose to take the gamble or not. In addition, subjects are instructed to estimate the probability that the risky option is good subsequent to the revelation of the outcome. Hence, the current design makes it possible to investigate how valence shapes the outcome evaluation at the consummatory stage and furthermore, whether choice itself modulates such a valence effect.

Our prediction of the EEG profile over feedback is based on the pioneering work of Gehring and Willoughby [15] who devised a 5/25 binary choice task and reported that the feedback related negativity (FRN) diverges under the gain versus loss outcomes. Subsequent studies, however, challenge Gehring and Willoughby [15] and suggest that FRN does not solely represent gain loss differentiation of outcome, but mainly responds to the correctness of the choice. Hajcak et al. [16] further suggested that FRN is sensitive to the binary evaluation of good versus bad outcomes and is not sensitive to the magnitude of the gain or loss. Moreover, Yeung and Sanfey [17] suggested the separate roles of the FRN and P300 following feedback about the outcome. With an orthogonal manipulation, Bellebaum et al. [18] suggested that the deflection of the FRN could nevertheless be modulated by the magnitude of the outcome. In terms of the P300, many of the previous studies suggest that it mainly responds toward the salience of the events [19,20]. However, some recent studies also indicate that it might also be sensitive to the reward; the reward rather than non-reward could have a relatively larger deflection of the P300 [21]. Altogether, ERP studies in the past two decades suggest that the FRN and P300 each plays an important role in representing reward processing under gains and losses.

More recent EEG studies have begun to examine how decisions under either gain or loss conditions shape the ERP deflection. For instance, employing a simple monetary task, Zheng et al. [22] found that whereas there is a FRN effect of outcome under gain condition, it is absent under the loss condition. Moreover, for the P300, there is no gain loss condition differentiation. However, one limitation of previous EEG studies is that they mainly focus on how the valence (gain/loss condition) modulates reward processing under static, simple-choice task without dynamic adaptation (e.g., [22,23]) or lacking the tradeoff between risk and safe options [24]. In the current study, subjects engage in a financial learning task in which they can choose a gamble involving a possible high or low payoff or take the fixed payoff and then are shown the outcome of the risky option, viz. taking the gamble. Based on their updated belief, they can subsequently decide to adjust their strategy to make more adaptive choices to maximize the reward or minimize the loss.

For the behavioral data, consistent with the recent literature of trial-and-error learning tasks under gain and loss conditions, we predict that subjects will differentially estimate the objective Bayes-derived probability of whether the current risk option is good. Specifically, subjects will be more optimistic toward estimating the goodness probability of the risky option and therefore take more risk under gain compared to under loss condition. With respect to the EEG results, at the consummatory (revealed outcome) stage, the FRN and P300 will be responsive to whether subjects make the correct choice or not and the incorrect choice will evoke a larger negative deflection of FRN and smaller P300 compared to the correct choice [16,21]. Given the potentially increased belief updating, we predict that there is an increased P300 response for the gain rather than loss condition and the risky instead of the safe choice mount to a heightened deflection of the P300 [23,25].

2. Methods

2.1. Subjects

Total forty-six students (22 males, average age is 21.13 ± 2.27 *SD*) from Zhejiang University of Technology completed the whole experiment and were paid for their participation. All of them were right-handed, healthy and had no history of current or past neurological disorders or mental diseases. This experiment was approved by the internal review board of Institute of Neuromanagement at Zhejiang University of Technology. All subjects provided written consent forms ahead of the start of the experiment. Data from seven subjects were removed because of excessive recording artifacts. Altogether, data from thirty-nine subjects were entered into the final data analysis.

2.2. Experimental design

This study adopted a modified version of the financial decision-making task from the original study by Kuhnen [12]. As illustrated in Fig. 1, a risky option (a stock) and a safe option (a bond) were presented to the subjects at each trial and then they were instructed to select one out of them at their own pace. The task consisted of gain loss conditions (valence) in which the two options provided either positive or negative payoffs. Specifically, the payoffs of the risky stock were either + 10 (−10) yuan or + 2 (−2) yuan as low variance condition and + 12 (−12) yuan or 0 (0) yuan as high variance condition in gain (loss) condition. The payoff of the safe bond was fixed + 6 (−6) yuan (Table 1).

Both for gain and loss conditions, the stock paid the payoffs either from a good (advantageous) distribution or a bad (disadvantageous) distribution, which was named as a good stock or bad stock for the assigned block. The good stock was that where the high payoff (12 and 10 in gain condition; 0 and −2 in loss condition) occurred with 70% probability, while the low payoff (0 and 2 in gain condition; −12 and −10 in loss condition) occurred with 30% probability in each trial. In contrast, the bad stock exhibited the opposite pattern where the high payoff occurred with 30% probability, while the low payoff occurred with 70% probability in each trial.

The whole task involved a total of 240 trials divided into 40 separate blocks. For each block, there were 6 trials and the quality of the stock (either good or bad stock) was unchanged across the trials, viz. the computer either paid the payoff from the good or bad stock distribution in each of these six trials. The computer randomly selected whether the

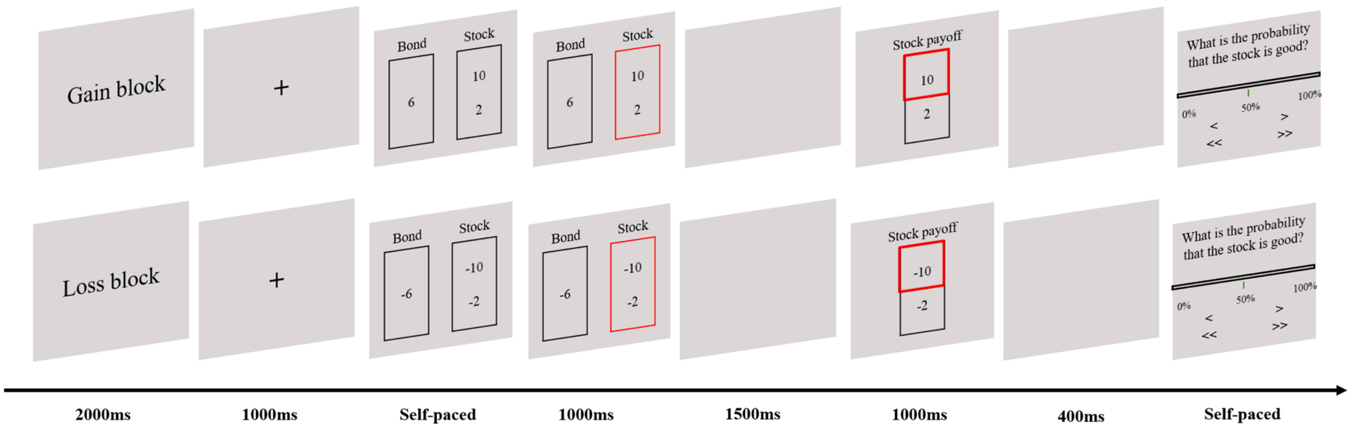

Fig. 1. Experimental procedure of an example trial in Gain block (top panel) and Loss block (bottom panel). At the beginning of each block, the cue indicated the condition (gain or loss, 2 s). The trial began with a fixation cross (+). Then, the choice screen appeared and the subjects made their choice between the stock and bond at their own pace. After the subjects made the choice, the selected option was highlighted (1 s), which was followed by a blank screen (1.5 s). Next, the stock payoff was revealed for the subjects (1 s) irrespective of their choice, which was then followed by a blank (0.4 s). At last stage of the trial, the subjects were asked to estimate the probability (ranging from 0% to 100%) that the current stock was a good one.

Table 1
Payoffs of Risky Stock and Safe Bond in different experiment conditions.

	Gain condition		Loss condition	
	Risky Stock	Safe Bond	Risky Stock	Safe Bond
High variance	+ 12 / 0	+ 6	-12 / 0	-6
Low variance	+ 10 / + 2	+ 6	-10 / − 2	-6

distribution was good or bad with half chance (50:50) probability at the beginning of each block and this information was announced to the subjects in advance. In total, all 40 blocks were split into either gain or loss and high or low variance conditions in a balanced manner, and the order of the blocks was pseudo-randomized.

In the current task, subjects firstly made the decision whether to invest either in the stock or the bond and were then instructed to provide an estimate of the probability from 0% to 100% that the stock was from the good distribution after they observed the stock payoff irrespective of their choice. We can calculate an objective Bayesian probability that the stock is a good one in each trial. Specifically, based on the number t of high stock payoffs out of the n trials so far in the current block, the Bayesian probability of the good stock at the current trial is given by the equation $\frac{1}{1+\frac{1-p}{p}\times\left(\frac{q}{1-q}\right)^{n-2t}}$ [12], where $p = 50\%$ is the prior that the stock is the good one before any payoffs are provided in that block and $q = 70\%$ is the probability that a good stock pays the high (rather than the low) payoff in each trial. This objective Bayesian posterior can be used to measure the accuracy of the subjects' subjective probability estimates.

The procedure of each trial is described in Fig. 1. Each block began with the cue "Gain" or "Loss" indicating whether the current condition was gain or loss for 2 s. A trial began with a fixation cross (+) for 1 s. Then the choice screen consisting of a stock and a bond was presented until the subjects made their choice by pressing either "4" or "6" on a numeric keyboard. Once selected, the chosen option was highlighted for 1 s. The position of the stock and bond was fixed within each block and was counterbalanced across blocks. Next, the payoff of the stock option at the current trial was revealed by indexing the actual payoff (1 s) no matter whether the subjects chose the stock or bond option, which was then followed by a blank of 0.4 s. At the final stage, subjects were asked to estimate the probability, ranging from 0% to 100%, that the current stock was the good one at their own pace. The subjects can adjust the step length of either ± 1 (key: 1, 3) or ± 5 (key: 4, 6) and confirm the estimate value with "Enter" key.

The subjects' payment was based on their accumulated payoffs earned from both the task as well as the accuracy of the probability estimate in each trial. Specifically, ten tokens were added if the probability estimate in each trial was within 5% of the correct answer (objective Bayesian probability). The tokens subjects received from the task were converted into real-money RMB at a ratio of 20:1, as compensation for participation in the experiment.

2.3. Electroencephalogram data recording

Electroencephalogram data was continuously recorded at the sampling rate of 512 Hz by the *BioSemi* active-two system with the 64-channel cap. The two electrodes mounted to the left and right mastoid served as the offline reference electrodes. The vertical electrooculogram was recorded from the infra-orbital and supra-orbital electrodes on the right eye, and the horizontal electrooculogram was recorded from electrodes on the outer canthi of both eyes. Electrode impedance was maintained below 5 kΩ across the whole experiment.

2.4. Data analyses

The EEG data was preprocessed offline by using *BrianVision Analyzer* 2.1 (Brain Products, Gilching, Germany) and *EEGLAB* [26]. First, the EEG data was re-referenced to the average of left and right mastoid channels, filtered with the bandpass between 0.1 and 30 Hz and the ocular artifacts were removed by *BrainVision Analyzer* [27]. Then the data were exported to *EEGLAB* for final data analysis. As this study mainly focused on subjects' learning from the stock payoff across conditions, we extracted the EEG data for the interval 200 ms before the onset of stock payoffs until 800 ms after the onset, with the first 200 ms as the baseline. Trials containing amplifier clipping, bursts of electromyography activity, or peak-to-peak deflection exceeding ± 80 μV were rejected. The mean accepted trial numbers in different conditions were listed in Table 2. The EEG were averaged separately for different conditions as described below (see also Table 2).

We focused on the ERP deflection at the stage of outcome (revealed payoff) evaluation and evaluated the ERP components including FRN in the frontal region and the P300 in the parietal region that typically reflect feedback processing. Specifically, we first conducted a 2 × 2 within-subjects repeated-measures analysis of variance (ANOVA) on the mean amplitude of FRN in the time windows of 250–330 ms with the pooled electrodes including F1, Fz, F2, FC1, FCz and FC2, taking *valence* (Gain vs. Loss) and *choice accuracy* (correct: choosing risky stock with high payoff or choosing safe bond with low payoff vs. incorrect: choosing risky stock with low payoff or choosing safe bond with high

Table 2
Experimental conditions for ERP analysis.

Valence	Choice	Choice accuracy	Accepted trial number
Gain / Loss	**risky choice** (*stock*)	**correct** (*high payoff* of the stock)	Gain: 35 Loss: 23
		incorrect (*low payoff* of the stock)	Gain: 28 Loss: 24
	safe choice (*bond*)	**correct** (*low payoff* of the stock)	Gain: 25 Loss: 33
		incorrect (*high payoff* of the stock)	Gain: 23 Loss: 31

payoff) as within-subject factors. Similarly, we conducted the 2 (*valence*: gain vs. loss) × 2 (*choice accuracy:* correct vs. incorrect) repeated-measures ANOVA over the average amplitude of P300 within the time duration of 370–470 ms with the pooled electrodes including C1, Cz, C2, CP1, CPz and CP2. Second, in order to detect the possible ERP asymmetry between gain and loss conditions more accurately, we further examined the choice effect (risky stock choice vs. safe bond choice). A 2 (*valence*: gain vs. loss) × 2 (*choice accuracy*: correct vs. incorrect) × 2 (*choice*: risky vs. safe) repeated-measures ANOVA on the FRN in the same time window and electrodes as mentioned above and a 2 (*valence*: gain vs. loss) × 2 (*choice accuracy*: correct vs. incorrect) × 2 (*choice*: risky vs. safe) repeated-measures ANOVA on the P300 in the same time window and electrodes as noted above were performed. Both the behavioral data and EEG data were analyzed with the open-source software R 4.0 (https://www.r-project.org/) and package *lme4* and *lmerTest* are used for the mixed-effect regression analysis.

3. Results

3.1. Behavioral results

The valence effect on subjects' beliefs regarding the likelihood that the stock is good can be seen in Fig. 2. The x-axis represents the values of the objective Bayesian probability and the y-axis represents the subjects' average probability estimate. As shown in Fig. 2, in either gain or loss

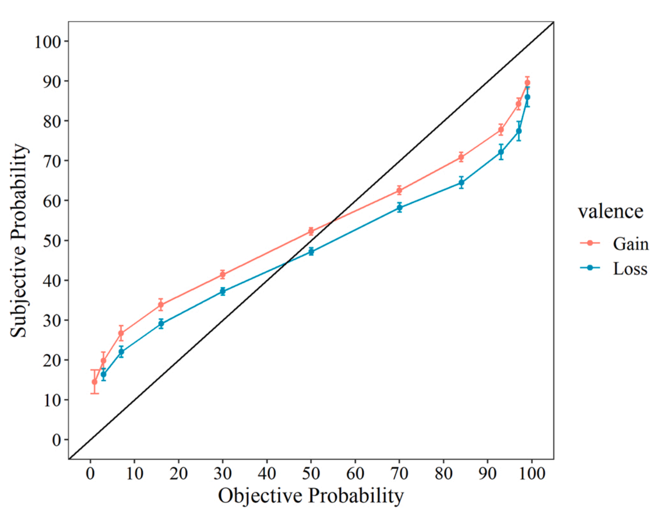

Fig. 2. Average subjective estimates for the probability that the stock is good as a function of the objective Bayesian probability. The subjective probability estimates (Y axis) given by the subjects for each level of the objective Bayesian probability (X axis) are presented for Gain (red line) and Loss (blue line) conditions. The black solid line represents the 45° degree line when the objective and subjective probability is perfectly matched.

condition, subjects' probability estimates deviate from the objective Bayesian probability values. Notably, these deviations are dissimilar for gains and losses. Specifically, subjects' probability estimates for losses are lower than those for gains, indicating that subjects are more pessimistic regarding whether the stock is good when considering losses.

To test the valence effect, we conducted a mixed-effect regression analysis as follows:

$$Probability \quad Estimate_{it} = \beta_0 + \beta_1 Valence_{it} + \beta_2 Objective \quad Probability_t + \varepsilon$$

Where the dependent variable is the ***Probability Estimate**$_{it}$*, which is subject *i*'s probability estimate of the good stock in the current trial *t*, whereas the independent variables include the ***Valence**$_{it}$* (equal to 1 if trial *t* is in a gain condition and 0 otherwise) and *Objective Probability$_t$* (the correct Bayesian probability that the stock is good up to trial *t* in the current block). Standard errors were robust to heteroskedasticity and were clustered at the individual level to account for the serial correlation within each subject and the random intercepts was considered for the mixed model.

As shown in Table 3, the results show that the valence indeed influences the subjects' posterior belief regarding whether the stock is good ($\beta = 4.98$, $p < 0.001$), viz. the probability estimated by the subjects in gain condition is higher than that in loss condition. The subjects have a higher frequency to choose the stock option in the gain ($Risk_{gain} = 56.86\%$, $SE = 3.09\%$) than that in the loss condition ($Risk_{loss} = 42.61\%$, $SE = 3.47\%$; $p < 0.001$). Considering the risk attitude, we define the 50% probability to choose the stock (or bond) as be risk neutral, the frequency to choose the risky option in the gain is higher than 50% ($t = 2.22$, $p = 0.03$) which indicates risk taking in the gain condition, whereas that in the loss is lower than 50% ($t = -2.13$, $p = 0.04$) which implies risk aversion in the loss condition.

3.2. ERP results

3.2.1. Valence × Choice Accuracy

In order to uncover the neural mechanism underlying how subjects processed the financial feedback information to form their belief about the stock, we mainly focused on the electrophysiological signals FRN (Fig. 3A) and P300 (Fig. 3B) at the stage reporting stock payoff. The ANOVA results of FRN shows that the main effect of Choice Accuracy is significant ($F_{(1,38)} = 23.04$, $p < 0.001$, $\eta^2 = 0.38$). The amplitude of FRN is more negative for incorrect feedback than correct feedback ($M_{incorrect} = 3.35$ μV, $SE_{incorrect} = 0.85$ μV; $M_{correct} = 4.89$ μV, $SE_{correct} = 0.75$ μV). However, the main effect of Valence is not significant ($F_{(1,38)} = 2.74$, $p = 0.11$, $\eta^2 = 0.07$). The interaction effect of Valence × Choice Accuracy is significant ($F_{(1,38)} = 4.62$, $p = 0.04$, $\eta^2 = 0.11$). Further simple effect analysis indicates that the effect of Choice Accuracy is both significant in gain ($p < 0.001$) and loss condition ($p = 0.01$). To clearly show differences of Choice Accuracy effect between Valence (gains, losses), we compared the d-FRN ($FRN_{incorrect}$ minus $FRN_{correct}$) and found that the d-FRN for gains is more negative than for losses (d-

Table 3
Regression analysis of Probability Estimate.

Dependent variable	Probability Estimate$_{it}$
Valence$_{it}$	4.98*** (1.21)
Objective Probability$_t$	0.59*** (0.03)
Constant	18.34*** (1.24)
AIC	68750.71
BIC	68822.16
Log Likelihood	-34365.36
Observations	9360

SE are reported in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ and the ICC is 0.34.

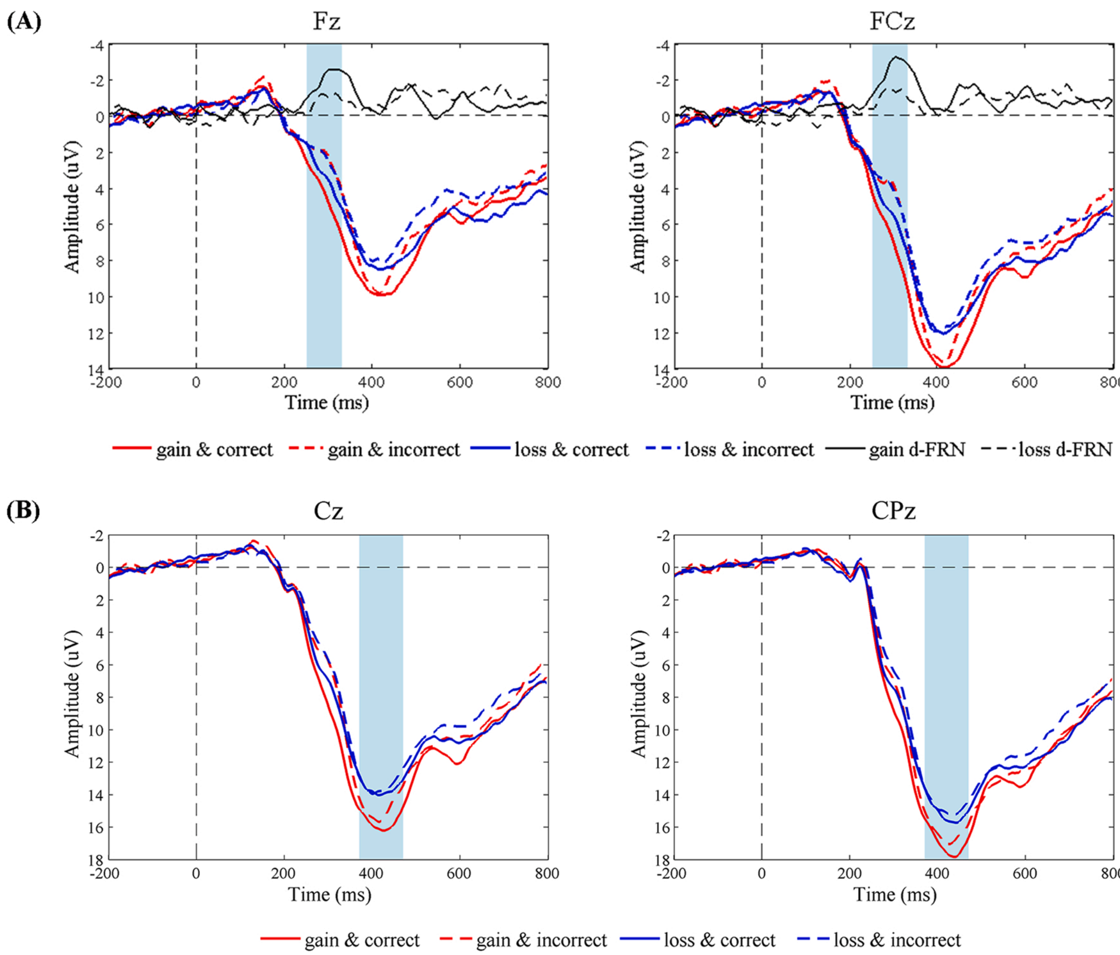

Fig. 3. The grand-average ERP waveforms at the stage of outcome evaluation for Valence (gain vs. loss) × Choice Accuracy (correct vs. incorrect) conditions. The ERP waveform is shown for correct (solid line) and incorrect feedback (dot-solid) in the gain condition with red color, and for correct (solid line) as well as incorrect feedback (dot-solid) in the loss condition with blue color. (A) Frontal FRN during 250–330 ms is represented by the shaded portion and d-FRN (incorrect minus correct) is shown for the gain condition (solid line) and loss (dot-solid line) condition in black at the two representative electrodes Fz and FCz. (B) Parietal P300 during 370–470 ms is represented by the blue shaded portion at the two representative electrodes Cz and CPz.

$FRN_{gain} = -2.07$ μV, $d\text{-}FRN_{loss} = -1.01$ μV, $p = 0.04$).

The ANOVA results for P300 show significant main effect of Valence ($F_{(1,38)} = 13.54$, $p = 0.001$, $\eta^2 = 0.26$). The amplitude of P300 is discernably more positive for gain than loss ($M_{gain} = 15.72$ μV, $SE_{gain} = 1.12$ μV; $M_{loss} = 14.00$ μV, $SE_{loss} = 1.07$ μV). However, the main effect of Choice Accuracy ($F_{(1,38)} = 2.10$, $p = 0.16$, $\eta^2 = 0.05$) and the interaction effect of Valence × Choice Accuracy ($F_{(1,38)} = 0.47$, $p = 0.50$, $\eta^2 = 0.01$) are not significant. In order to further confirm the findings that we observed from ANOVA, we also run the mixed-effect linear regression model with the single trial ERP components (FRN, P300). In general, the results arrive at similar results as what achieved from the ANOVA, see *Supplement* for detailed methods and results.

3.2.2. *Valence × Choice Accuracy × Choice*

In order to further explore the asymmetry effect of Valence on ERP responses when evaluating the feedback, we next considered the Choice factor (risky choice vs. safe choice). The ANOVA result of FRN shows that the main effect of Choice ($F_{(1,38)} = 5.98$, $p = 0.02$, $\eta^2 = 0.14$), the interaction effects of Choice Accuracy × Choice ($F_{(1,38)} = 6.22$, $p = 0.02$, $\eta^2 = 0.14$) and Valence × Choice Accuracy × Choice ($F_{(1,38)} = 15.63$, $p < 0.001$, $\eta^2 = 0.29$) are all significant. We next examined the interaction effects of Choice Accuracy × Choice in gain and loss conditions respectively.

3.2.2.1. FRN analysis in Gain condition. The ERP is presented in Fig. 4A. Results show that the interaction effect of Choice Accuracy × Choice is significant ($F_{(1,38)} = 22.24$, $p < 0.001$, $\eta^2 = 0.37$) for gains. Further simple effect analysis indicates that the effect of Choice Accuracy is only significant when subjects chose the risky option ($p < 0.001$), but not significant when they chose the safe option ($p = 0.61$). Additionally, the result of d-FRN analysis shows that d-FRN for the risky option is more negative than that for the safe option ($d\text{-}FRN_{risky} = -4.36$ μV, $d\text{-}FRN_{safe} = 0.33$ μV, $p < 0.001$).

3.2.2.2. FRN analysis in Loss condition. The ERP is presented in Fig. 4B. A marginally significant interaction effect of Choice Accuracy × Choice is observed ($F_{(1,38)} = 3.44$, $p = 0.07$, $\eta^2 = 0.08$) for losses. Further simple effect analysis indicates that the effect of Choice Accuracy is only significant when subjects chose the safe option ($p = 0.003$), but not significant when they chose the risky option ($p = 0.87$), in contrast to the finding for gains. The result of d-FRN analysis shows that d-FRN for the safe option is more negative than that for risky option ($d\text{-}FRN_{risky} = 0.12$ μV, $d\text{-}FRN_{safe} = -1.76$ μV, $p = 0.07$).

For P300, the ANOVA results also indicate a significant main effect of Choice ($F_{(1,38)} = 21.08$, $p < 0.001$, $\eta^2 = 0.36$), interaction effects of Choice Accuracy × Choice ($F_{(1,38)} = 3.95$, $p = 0.05$, $\eta^2 = 0.09$) and Valence × Choice Accuracy × Choice ($F_{(1,38)} = 3.98$, $p = 0.05$, $\eta^2 = 0.10$). Similarly, we further examined the interaction effects of Choice Accuracy × Choice for gains and losses respectively.

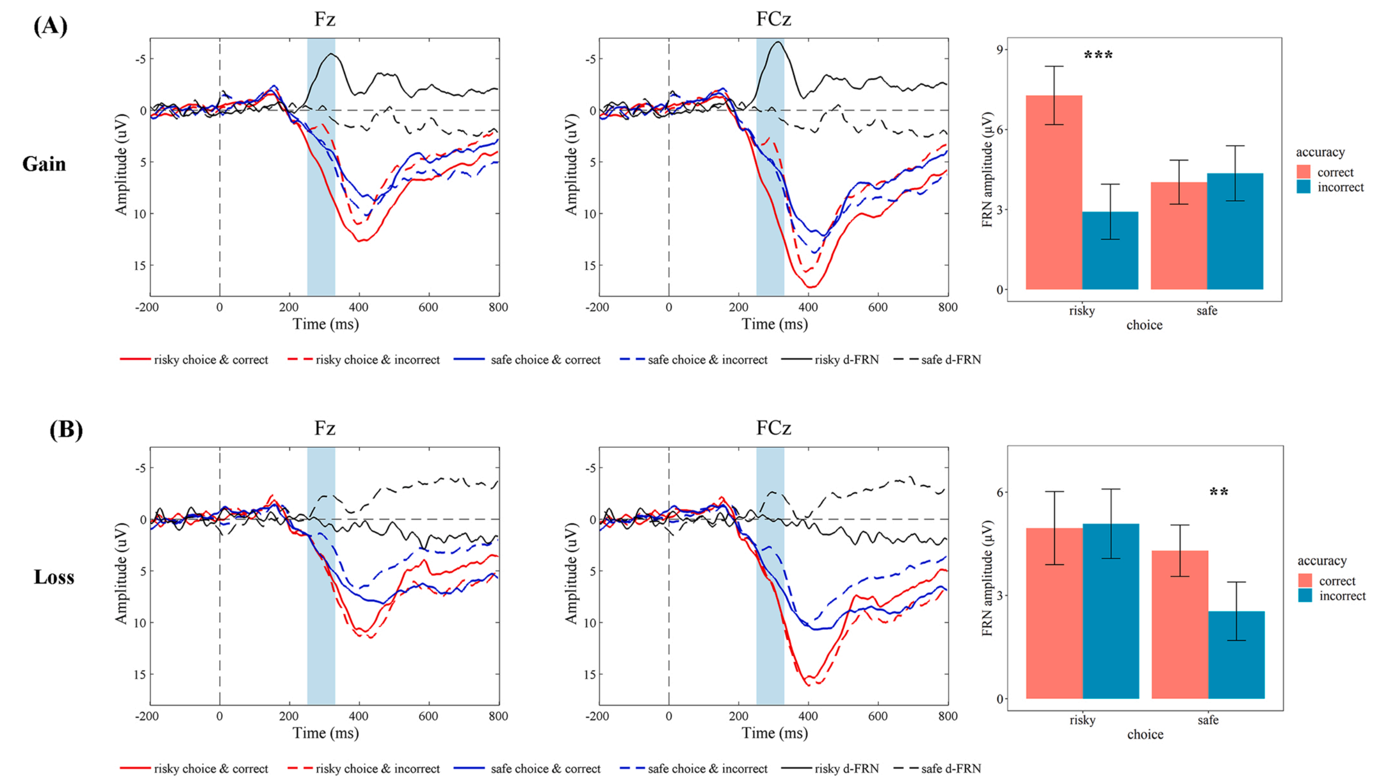

Fig. 4. The grand-average ERP waveforms at the stage of outcome evaluation for Valence (gain vs. loss) × Choice Accuracy (correct vs. incorrect) × Choice (risky vs. safe) conditions at two representative electrodes Fz and FCz. The ERP waveform is shown for correct (solid line) and incorrect (dot-solid) feedback with red color in risky choice condition, and for correct (solid line) and incorrect (dot-solid line) with blue color in the safe choice condition. The d-FRN (incorrect minus correct) is shown with the black solid line for the risky choice condition and black dot-solid line for the safe choice condition. Frontal FRN during 250–330 ms is represented by the shaded portion and the average FRN amplitude from six prefrontal electrodes (F1, Fz, F2, FC1, FCz and FC2) in different conditions is shown in the bar chart for gain condition (panel A) and loss condition (panel B).

3.2.2.3. P300 analysis in Gain condition. The ERP is presented in Fig. 5A. Results show that interaction effect of Choice Accuracy × Choice is significant ($F_{(1,38)} = 10.84$, $p = 0.002$, $\eta^2 = 0.22$) for gains. Further simple effect analysis indicates that the effect of Choice Accuracy is both significant when subjects chose the risky option ($p = 0.009$) as well as the safe option ($p = 0.03$). However, the P300 is more positive for correct feedback when choosing the risky option whereas the P300 is more positive for incorrect feedback when choosing safe option.

3.2.2.4. P300 analysis in Loss condition. The ERP is presented in Fig. 5B. We do not observe a significant interaction effect of Choice Accuracy × Choice ($F_{(1,38)} = 0.40$, $p = 0.53$, $\eta^2 = 0.01$) in loss condition. There is no difference of P300 between correct and incorrect feedbacks no matter whether subjects chose risky or safe option (both $p > 0.3$).

3.2.3. Link between ERP amplitude and Subjective probability estimate

To test the potential link between the deflection of ERP and the probability estimate, we conducted a mixed-effect regression analysis as follows:

$$\begin{aligned} Probability \quad Estimate_{it} = \beta_0 + \beta_1 ERP \quad component_{it} + \beta_2 Valence_{it} \\ + \beta_3 Choice \quad Accuracy_{it} + \beta_3 ERP \quad component_{it} \\ \times Valence_{it} + \varepsilon \end{aligned}$$

When considering the FRN, the independent variable *ERP component$_{it}$* represents the average FRN amplitude from six prefrontal electrodes (F1, Fz, F2, FC1, FCz and FC2) within the time window from 250 ms to 330 ms for subject *i* at trial *t*, whereas considering the P300, the *ERP component$_{it}$* represents the average P300 amplitude of the six centroparietal electrodes (C1, Cz, C2, CP1, CPz and CP2) within the time window from 370 ms to 470 ms for subject *i*'s in the trial *t*. The other independent variables include *Valence$_{it}$* (equal to 1 for gain condition and 0 otherwise); the *Choice Accuracy$_{it}$* (equals to 1 for correct condition: choosing risky stock with high payoff or choosing safe bond with low payoff; equals to 0 for incorrect condition: choosing risky stock with low payoff or choosing safe bond with high payoff), and the interaction between *ERP component$_{it}$* and *Valence$_{it}$*.

As shown in Table 4, for the link between FRN and probability estimate, we first observe that there is a main effect for FRN ($\beta = 0.07$, $p < 0.001$) and it is also significant for the interaction between Valence and FRN ($\beta = 0.15$, $p < 0.001$). Collapsed by the Valence (gain and loss), we find a prominently significant effect of FRN in the gain condition ($\beta = 0.13$, $p < 0.001$), indicating the lower the magnitude (positive coefficient for a negative ERP component), the higher the probability estimate value for the subjects. Nevertheless, the FRN effect is absent for the loss condition ($\beta = -0.005$, $p = 0.87$). With respect to the subsequent P300 component, we also observe a main effect ($\beta = 0.10$, $p < 0.001$), and there is an interaction between Valence and P300 ($\beta = 0.09$, $p = 0.005$). Collapsed by the Valence (gain and loss), we find a prominently significant effect of P300 both in the gain ($\beta = 0.14$, $p < 0.001$) and loss condition ($\beta = 0.06$, $p = 0.04$). Namely, the higher the deflection of P300, the larger the probability estimate for both conditions.

4. Discussion

The quality of financial decisions that people make is crucial to ensure their security, well-being, self-sufficiency and long-term happiness. The market is volatile and at its most extreme “boom or bust”, similar in many ways to how an individual experiences both financial and non-financial ones encountered across a life-span. Faced with

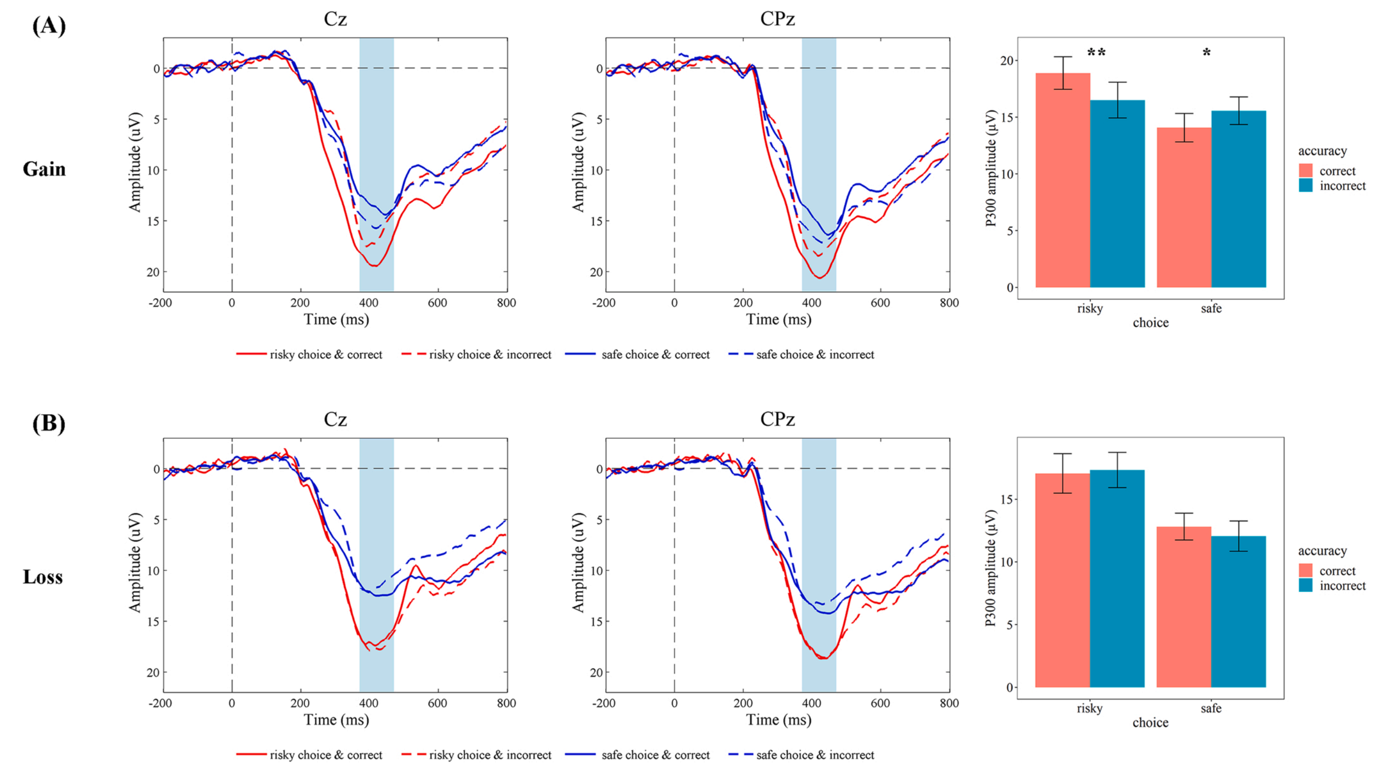

Fig. 5. The grand-average ERP waveforms at the stage of outcome evaluation over Valence (gain vs. loss) × Choice Accuracy (correct vs. incorrect) × Choice (risky vs. safe) conditions at the two representative electrodes Cz and CPz. The ERP waveform is shown for correct (solid line) and incorrect feedback (dot-solid line) in red for risky choice, and correct (solid line) and incorrect (dot-solid line) in blue for the safe choice. Parietal P300 during 370–470 ms is represented by the shaded portion and the average P300 amplitude from six centroparietal electrodes (C1, Cz, C2, CP1, CPz and CP2) in different conditions is shown in the bar chart for gain (panel A) and loss condition (panel B).

Table 4
Probability estimate prediction with ERP amplitude.

Dependent variable	Probability Estimate$_{it}$							
	FRN				P300			
	All trials	All trials	Gain trials	Loss trials	All trials	All trials	Gain trials	Loss trials
ERP component$_{it}$	0.07***	-0.004	0.13***	-0.005	0.10***	0.05*	0.14***	0.06*
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
Valence$_{it}$	8.35***	7.71***			8.23***	6.95***		
	(1.39)	(1.40)			(1.40)	(1.49)		
Choice Accuracy$_{it}$	2.55	2.51	5.50***	-0.47	2.61	2.60*	5.61***	-0.45
	(1.34)	(1.35)	(1.53)	(1.43)	(1.34)	(1.32)	(1.49)	(1.42)
ERP component$_{it}$×Valence$_{it}$		0.15***				0.09**		
		(0.03)				(0.03)		
Constant	42.38***	42.69***	48.69***	44.18***	41.18***	41.78***	46.98***	43.26***
	(1.11)	(1.13)	(0.95)	(1.17)	(1.10)	(1.12)	(0.99)	(1.31)
AIC	76115.57	76103.59	38136.56	37932.70	76074.76	76073.92	38116.47	37907.47
BIC	76221.49	76216.58	38200.22	37996.41	76180.69	76186.90	38180.13	37971.18
Log Likelihood	-38042.79	-38035.80	-19058.28	-18956.35	-38022.38	-38020.96	-19048.23	-18943.73
Observations	8618	8618	4297	4321	8618	8618	4297	4321

SE are reported in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, The ICCs for the regression models of FRN are 0.09, 0.09, 0.09 and 0.09. The ICCs for the models of P300 are 0.09, 0.09, 0.09 and 0.11.

prospective events, how does an economic agent understand and evaluate market feedback on their investments, interpret such information and update their belief? Importantly, whether they treat positive and negative outcomes differently? These considerations prompted us to carry out a financial learning task coupled with simultaneous electrophysiological recordings from subjects, enabling us to track both behavior and neural signals and hence providing insights into how individuals learn and shape their beliefs in a paradigm where they receive feedback regarding the outcome of their investment choice.

The behavioral data shows that individuals can learn the quality of risky options at the current stage in an efficacious manner and update their belief system through feedback accordingly (Fig. 2). Critically, consistent with our prediction, subjects reported a higher probability estimation of the stock for gains compared to losses. In addition to that, defining the even chance to choose the stock or bond option as risk neutrality, we also observed that the subjects are likely to be risk seeking in the gain condition while become risk averse in the loss condition. Therefore, at odds with the descriptive context where loss looms larger than gain, in an experiential task with instant feedback, the subjects tend to be optimistic toward the gain rather than loss, in accordance with recent findings [10,12,28].

With respect to the electrophysiological results, at the consummatory stage when the outcome of risky option is revealed, it shows a prominent effect of outcome and the incorrect outcome elicits a larger deflection of FRN than the correct outcome for both gain and loss conditions, consistent with the general findings that the FRN is sensitive to the reward (Fig. 3A, [15,16,29]). Interestingly, in accordance with and reflecting the behavioral finding, both the d-FRN and P300, show a prominent effect of valence. On the one hand, the FRN difference (incorrect vs. correct) of outcome for gains is larger than that for losses (Fig. 3A). In parallel, the gains rather than losses evoke a larger deflection of the P300 irrespective of the correctness of the choice (Fig. 3B). Although FRN is often considered to reflect the correctness of the choice, recent studies also suggest a potential role of the FRN that reflects the salience of the outcome. For example, Bellebaum et al. [18] carefully manipulated the magnitude of the potential reward (5, 20, 50) and found that the FRN is not only responsive toward the non-reward vs. reward difference, it also responds to magnitude. The larger the magnitude of the outcome, the larger the FRN difference between reward and non-reward outcomes. Similarly, applying a simple reinforcement task for gains and losses, KreuSSel et al. [24] also found that the feedback for gains induces a larger FRN difference compared to the losses. Altogether, the d-FRN difference between gains and losses validates differential processing of the outcome across gain and loss conditions.

To account for the pessimistic belief formation for losses compared with gains, Kuhnen [12] argues that the oversensitivity over the low outcome for losses could be a likely explanation. However, the electrophysiological findings here suggest an alternative explanation, viz. there is a general reduced processing for the outcome for losses and not due to an increased processing. For instance, if we closely examine the raw FRN deflection, the d-FRN difference between gain loss conditions is mainly driven by the reduced deflection of the high outcome in the gain condition and the negative deflection toward the low outcome fails to exhibit such a difference over gains and losses (Fig. 3 A). To further confirm that, as illustrated in Table 4, after controlling for the apparent effect of valence and accuracy, it still evidently exhibits that reduced deflection of FRN and increased P300 could link with the optimistic estimation of the probability in the gain condition; whereas only the greater deflection of the P300 could link with increased probability estimation in the loss condition. Given the notion that feedback outcome is ahead of belief estimate within each trial, these ERP deflections could be predictive for the subsequent belief updating in a trial-wise manner. It also indicates an asymmetric representation which is indexed by FRN amplitude at the stage of outcome evaluation.

Finally, as the subjects choose the risky or safe option, the outcome of the risky option could be either factual or counterfactual to the subjects. Therefore, we further stratify the outcomes with the trial-wise option selection (*risky* vs. *safe*). As over the P300, consistent with our prediction, the risky-choice contingent outcome elicits a larger deflection of the P300 compared to the safe option, notwithstanding for either gains or losses. Intuitively, we expect that self-contingent financial interest links with the salience of the stimuli [19,20]. Although at the aggregate level for the FRN, we observe a divergence between correct and incorrect outcome, the drive of such a pattern might differentiate over gain loss condition. Specifically, under gains, the incorrect outcome of risky choice (*low payoff*) elicits a larger deflection of the FRN compared to the correct outcome (*high payoff*) whereas this discrepancy is not observed for the safe choice selection (Fig. 4A). However, for losses, the correctness representation of the FRN is solely prominent for the safe choice (Fig. 4B), viz. the incorrect choice (*high payoff*) elicits a larger deflection of the FRN compared to the correct choice (*low payoff*). Altogether, the current findings demonstrate that although the factual outcome drives the high low payoff discrepancy for gains, it might be considered that the counterfactual outcome contributes to such a difference in the loss condition albeit at a reduced intensity. Recent studies have started to investigate the extent to which both the factual and counterfactual outcomes contribute toward learning behavior [25,30,31]. However, few studies have reported the extent of the interaction between valence (gain and loss) and counterfactual thinking and especially how the brain represents the chosen and unchosen outcome under gain and loss conditions. The current electrophysiological findings offer a clue to the dissociated representation of the reward or not, under gain and loss conditions. To our knowledge, the current study is one of the first which finds such a pattern and subsequent studies could fruitfully apply a combined behavioral, neural imaging and eye tracking strategy to further validate the current findings as well as further explore the underlying mechanism for the asymmetry between gains and losses.

Altogether, both the behavioral and electrophysiological findings evidently suggest a gain loss divergence in an instrumental learning task with experiential characteristics. Critically, such an asymmetry systematically deviates from those observed in a description context where individuals assign higher weight toward losses rather than gain [6,32], which is well resonant with the recent advances about the description vs. experience gap [8]. Specifically, the disproportionate reward processing for the outcome over gain and loss conditions represented by d-FRN and P300, is in parallel with the behavioral findings of belief updating in the current study. Moreover, the deflection of the ERP amplitude at the experience stage could be predictive for the subsequent belief updating especially the FRN, which is solely responsive in the gain rather than loss condition. Therefore, in the experiential context, the brain tends to respond in an unbalanced manner for the mirrored monetary outcome in gain and loss condition. This is represented both at the behavioral and neural level, enriching our understanding of the asymmetric processing of the reward in the gain and loss condition [9,12,33].

5. Conclusion

The current study applies a financial learning task together with EEG recording to investigate the extent to which valence (gain vs. loss) modulates belief updating and reveals its underlying neurophysiological mechanism and how the risky choice modulates such a process. The present findings suggest that the reduced (represented by d-FRN and P300) rather than the increased neural response coincidentally corresponds to the pessimistic belief formation under losses compared to the gains. The present study also suggests that, under gain and loss conditions, the FRN not only represents a differential processing of factual and counterfactual outcome, but also plays a dissociated role for the prediction of the subsequent belief updating. In summary, the current findings both from the behavioral and electrophysiological results deepen our understanding of decision over risk under gain and loss conditions.

CRediT authorship contribution statement

Qiang Shen: Conceptualization, Methodology, Validation, Data curation, Writing – original draft, Writing – review & editing, Supervision. **Shiguang Fu:** Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Yuxing Huang:** Software, Formal analysis, Investigation. **Yina An:** Software, Investigation, Writing – original draft, Writing – review & editing. **Jia Jin:** Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Yiquan Wang:** Resources, Writing – original draft, Writing – review & editing. **Linfeng Hu:** Conceptualization, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Richard P. Ebstein:** Conceptualization, Validation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that there is no conflict of interest.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (No. 71971199, 71942004 and 72002202) and the Humanities and Social Sciences Foundation of the Ministry of Education of China (No. 20YJC630040). We thanks Zhang Xing for his kind assistance of the statistical analysis.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.bbr.2022.113909.

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