Computational modeling interpretation underlying elevated risk-taking propensity in non-labor income

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Abstract

Abstract: Individuals have been observed to show higher propensity to make risk investments using non-labor income compared to labor income, although the underlying mechanisms behind this phenomenon remain unclear. In this study, we proposed that non-labor income leads to a higher prior expectation of risky investment and a reduced sensitivity towards losses. To quantitatively test this hypothesis, we employed computational modeling. A total 103 participants were recruited and completed the Balloon Analogue Risk Task (BART) with an equal monetary endowment, either as a token for completion of survey questionnaires (labor income) or as a prize from a lucky draw game (non-labor income). We found that individuals endowed with non-labor income made more risky investments in the BART compared to those with labor income. To formally compare the differences in the dynamic risk investment process between individuals with different source of income, we built four candidate computational models (Bayesian Sequential Risk-taking Model, Target Model, Scaled Target Learning Model and Scaled Target Learning with Decay Model (STL-D)). Through computational modeling, we found that within STL-D, the optimal model, the non-labor income group preset a higher targeted number of pumps at the beginning, showed a lower learning rate towards loss trials where the balloon exploded, and had lower behavioral consistency. Our study suggests that the increased tendency for risky investments with non-labor income can be attributed to an increase in prior expectations on risk-taking and a diminished sensitivity towards loss. These findings provide potential intervention targets to mitigate irrational investments associated with non-labor income.

Full Text

Preamble

ORIGINAL RESEARCH

Computational modeling interpretation underlying elevated risk-taking propensity in the dynamic risky investment process of non-labor income

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Abstract: Money source influences risk-taking behaviors. Although studies consistently indicate that individuals demonstrate a higher propensity to make risk investments when utilizing non-labor income as opposed to labor income, explanations as to why non-labor income leads to continuously blowing money from non-labor sources into risky investments are scarce. The current study leverages a computational modeling approach to compare differences in the dynamic risk investment process among individuals endowed with income from different sources (i.e., non-labor income vs. labor income) to understand the shaping force of higher risk-taking propensity in individuals with non-labor income. A total of 103 participants were recruited and completed the Balloon Analogue Risk Task (BART) with an equal monetary endowment, either as a token for completion of survey questionnaires (representing labor income) or as a prize from a lucky draw game (representing non-labor income). We found that individuals endowed with non-labor income made more risky investments in the BART compared to those with labor income. With computational modeling, we further identified two key differences in the dynamic risk investment processes between individuals endowed with labor and those with non-labor income. Specifically, individuals endowed with non-labor income had a higher preset expectation for risk-taking and displayed desensitization towards losses during risk investments, in contrast to individuals with labor income. This study sheds light on the fundamental factors contributing to the increased tendency for risky investments with non-labor income, providing new insights into the psychological mechanisms underlying risk-taking behaviors.

Keywords: Non-labor income; Balloon Analogue Risk Task; Computational modeling; Hierarchical Bayesian analysis; Reinforcement learning

Introduction

The field of economics has widely recognized that investment decisions are not solely based on the evaluation of costs and benefits. Money sources influence how people spend money [**?**, **?**]. Individuals receive a wide variety of non-labor income (e.g., lottery gains, stock market booms, inheritance, gift coupons, etc.) apart from labor income, which constitutes more than one-third of personal income in family households [**?**]. From anecdotes of lottery winners ending up blowing all their money through irrational splurges to unplanned and excessive hedonic purchases [**?**, **?**] and even addictive gambling [**?**, **?**] observed in lottery winners, we know that a blessing of fortune is sometimes a curse in disguise, propelling individuals to make successive risky investments until it is all blown away. Although previous studies have discovered a robustly higher propensity to make a one-time splash from non-labor sources compared to money from labor sources \cite{8-10}, we still know little about why individuals continuously blow money from non-labor sources into risky investments, despite having the perfect opportunity to stop risking money whenever they are willing. The fact that seeing money blown away cannot prevent people from continuously making irrational splurges essentially implies that the inhibitive effect of negative feedback on subsequent risky investment decisions goes wrong. The current study seeks to depict and empirically test the malfunctioning negative feedback mechanism that prevents people from stopping risk-taking upon receiving losses in the dynamic risky investment process of non-labor income.

Control theory naturally fits well with the dynamics of continuous risk-taking investments upon receipt of non-labor income until splashing it all away. The dynamic process of money splashing closely resembles a self-reinforcing feedback loop in control theory, which constitutes two elements: namely the presence of an initial perturbation, and a malfunctioning feedback system that exacerbates the magnitude of the initial perturbation [**?**]. In the case of higher risk-taking propensity towards non-labor income, the initial perturbation is individuals' initial preset higher expectations on risk-taking investments. The malfunctioning feedback system is flawed in the sense of an attenuated negative feedback mechanism that prevents individuals from resisting risk-taking upon observation of negative consequences. In the next sections, we will review evidence in support of the existence of these two elements, respectively.

On the one hand, multiple theories and empirical evidence support the existence of an initial elevated perturbation to risk-taking tendency upon endowment of non-labor income. Mental account theory and the house money effect both posit that money sources influence risk-taking propensity via money organizational structures (i.e., labor income into regular earnings or the in-house part, and non-labor income into windfall gains or the extra part in addition to house money) [?, ?, ?]. Empirical studies along this line have discovered enriched psychological implications associated with 'windfall gains,' including less perceived easiness of money acquisition, less anticipation about the money, less planning on money usage, and discounted subjective value [?, ?]. These together imply that individuals may possess a schematized cognition towards non-labor income, which is strong and highly structured around multiple aspects spanning from money acquisition, money storage, and money valuation, to usage planning. The automatic activation of a strong schema might in turn push us towards a psychological preparedness to easily spend away non-labor income, which constitutes the initial elevated perturbation to risk-taking tendency upon receiving non-labor income.

On the other hand, the Quasi-Hedonic Editing Hypothesis [?] points to a lack of negative feedback mechanisms in dynamic risky investments with non-labor income, which increases individuals' risk tolerance upon observation of a loss consequence in the midst of investment \cite{14–16}. The Quasi-Hedonic Editing Hypothesis posits that the reference point at which investors psychologically distinguish gains from losses would be elevated into the gain domain upon receipt of non-labor income, such that losses are no longer net losses but a reduction of net gains [?, ?]. As individuals tend to integrate smaller losses with larger gains to maximize overall happiness [?], they cancel small losses in each trial, leading to a desensitization to losses in the dynamic investment process. This subsequently precludes individuals from reducing their investment levels after experiencing losses. Therefore, we expect a malfunctioning negative feedback mechanism associated with investing non-labor income, which constitutes the shaping force of a persistent inclination towards higher risk-taking. To summarize, incorporating control theories to account for malfunctioning dynamic control in risk investments with non-labor income, we propose that non-labor income would elicit: (1) an immediate higher preset expectation on risk-taking propensity upon receipt of non-labor income, and (2) engagement in a dynamic cycle of risk-taking behavior with desensitization towards loss outcomes (indexed by decreased learning rate towards loss outcomes) during the investment process.

To provide a direct empirical test of our hypothesized dynamic regulatory process, we leverage the Balloon Analogue Risk Task (BART) to capture individuals' risk-taking propensities in dynamic risk decision-making [?] and incorporate the computational modeling approach to depict their dynamic risk decisions beyond analyzing traditional indices of risk-taking indicators. BART is a prevalent measure of risk-taking propensities in dynamic investments [?, ?, ?]. BART coupled with computational modeling could capture how individuals differ in risk-taking at the beginning and how they learn from past gain or loss outcomes to decide future risk investments [?, ?], and thus enables a direct test of our hypothesized dynamic mechanisms of how non-labor income leads to higher risk investments. BART also has high ecological validity with a moderate correlation with real-life risk behaviors [?, ?, ?], especially gambling behavior, which is one major harmful avenue through which individuals splash non-labor income. In this study, we incorporated well-established computational models from previous studies as candidate models, including the Bayesian sequential risk-taking (BSR) [?], the Target model [?], the Scaled Target Learning (STL) model and its extension, the Scaled Target Learning with Decay (STL-D) [?]. Within the optimal model, by intergroup comparisons on key parameters depicting risk-taking propensities at the beginning and sensitivity (i.e., learning rates) towards losses, we can have a direct test of how labor versus non-labor income elicit different preset risk-taking expectations at the beginning and elicit different learning processes towards negative investment outcomes in the midst of dynamic investment.

In brief, in the current study, we investigate how income sources (i.e., non-labor versus labor income) influence individuals' dynamic risky decision-making process within the BART paradigm. We hypothesize that individuals with non-labor income show persistent higher risk preference across time in the dynamic risk investment process than those with labor income. Within a computational modeling approach, we further hypothesize that individuals with non-labor income would preset a higher target number of pumps and have a decreased learning rate towards loss in BART, which might be the underlying reason why they show persistent higher risk preference.

2.1 Participants

We selected a target sample size of 51 per group to ensure adequate power to detect a medium-sized effect (effect size Cohen' s d = .5, Type I error $\alpha = .05$, power $1 - \beta = .8$) (Faul et al., 2007) based on a G*power calculation. However, in consideration of the exclusion of participants with potential emotional issues (e.g., depression or anxiety) and the success rate in the manipulation of mental accounts, we finally recruited 172 participants from a local university through campus postings to ensure enough valid manipulations among participants free of emotional issues. Their age ranged from 17 to 26 (Mage = 20.92, SDage = 1.86). All participants reported no history of mental disorders or substance use.

Participants completed the Beck Depression Rating Scale (BDI) [?], Patient Health Questionnaire-9 (PHQ-9) [?], dimension of Neuroticism in NEO Personality Inventory (NEO-PI-N) [?], Trait Anxiety Inventory (TAI) [?], and the Barratt Impulsiveness Scale (BIS) [?] before the experiment to exclude outliers in personality and mood (anxiety or depression) measures. We also used the Positive and Negative Affect Schedule (PANAS) [?] to compare the arousal of positive and negative emotion after the manipulation of mental account.

For our final sample who had completed all questionnaires, we excluded individuals with potential mental disorders, extreme outliers, and those misclassifying endowment sources. Eventually, 103 participants were included in the analyses. Information on sample exclusion is available in Supplementary Material S1.

2.2 Manipulation of Sources of Income

We manipulated the sources of income by randomly assigning participants to one of two experimental conditions: the labor income condition and the non-labor income condition. Participants in both groups received different cover stories about the sources of the same amount of endowment. For the labor income group, ¥15 of the endowment was given to them immediately as a token for completing the questionnaire. For the non-labor income group, a gift was given as a token for completing the questionnaire as well. This step aimed to prevent their potential mental accounting of subsequent lucky prizes as labor income. Then, participants in the non-labor income group were invited to play a lucky draw game. They were told that in this game, they had a small chance (10%) to win a large prize (¥15) and a large chance (90%) to gain nothing. To facilitate the manipulation of a windfall gain, a confederate would draw together with the participant. Participants would see themselves win a large prize and the confederate win nothing. Upon hearing an announcement "Congratulations! You win ¥15!" , participants would immediately receive the money via WeChat or AliPay.

Immediately after receiving the money, participants were asked to complete the PANAS scale and were told that they could use the ¥15 as principal to complete the BART task. Participants were informed that they could win more money if they played well, but could lose money if they played badly. They could also avoid the BART task by giving up pumping any balloons. Participants first pumped two balloons for practice before the formal experiment to familiarize themselves with the task procedure. For the manipulation check, participants were asked to report their perceived reason for receiving the ¥15, which they could choose from "Labor income," "Non-labor income," or "Other Reason but Not Listed in the Choices." After the manipulation check, 10% of the amount of money obtained in BART was given as an additional bonus (Fig. 1 [Figure 1: see original paper]).

Fig. 1. Procedure. We manipulated participants' mental accounts by stating the source of the same amount of ¥15 monetary endowment as (1) a token for completion of questionnaires ("labor income" condition) or (2) a prize from a lucky draw game ("non-labor income" condition).

2.3 Balloon Analogue Risk Task

We administered a 30-trial BART task adapted from Lejuez' s study [?]. The task was programmed in E-prime 2.0. Participants were told that their goal was to earn as much money as possible. In each pump, participants had to choose between 'pumping' or 'stop pumping' by pressing one of two buttons (Fig. 1). If participants chose to pump, the balloon had a certain probability of explosion. If the balloon did not explode, ¥0.05 would be added to the temporary reserve. If the balloon exploded, participants would lose all the money from the temporary reserve. If participants stopped pumping before the balloon explodes (they could even give up pumping at the beginning of any balloon to avoid potential loss), the next trial would start either after the balloon explodes or after participants stop pumping. A new balloon would appear on the screen and the temporary reserve would be reset to zero at the beginning of each trial. The maximum number of pumps allowed for each balloon was 128. The conditional probability of explosion after each pump, if the prior pumps did not explode, was equally set to 1/128. Thus, the probability of explosion would increase as the balloon got bigger, and the balloon would explode for certain after 128 pumps. At the end of 30 trials, participants would collect all the money from their permanent reserve as part of their compensation.

2.4 Analytic Strategies

Beyond the manipulation check, we also used the PANAS scale to verify the effectiveness of the manipulation of mental accounts. We hypothesized that participants in the non-labor income group who won the lucky draw would show higher positive emotions than those in the labor income group. To test this hypothesis, we used independent sample t-tests to compare between-group differences in positive emotion.

Further, to test the hypothesis that participants in the non-labor income group showed higher risk preference than those in the labor income group, we used independent sample t-tests to compare between-group differences in risk preference. Four behavioral indicators related to risk decision-making in BART were analyzed: (1) adjusted pumps, or the average number of pumps of win balloons (AP); (2) the number of pop-balloons (NP); (3) the average number of pumps of win-balloons immediately following a win (AP+); (4) the average number of pumps of win-balloons immediately following a pop (AP-). To explore how the explosion outcomes on the last balloon influenced risk preference in the next balloon, we used a linear mixed model to investigate the main effects and interaction effects between the source of money, the number of trials, and feedback from the last trial on the number of pumps in each balloon. Learning was indicated by the main effect of feedback from the last trial on the number of pumps.

To formally compare differences in the dynamic risk investment process between individuals with different mental accounts, we built four candidate computational models (Bayesian Sequential Risk-taking Model, Target Model, Scaled Target Learning Model, and Scaled Target Learning with Decay Model) in Rstan (R version 4.1.3). Models were fit separately for participants with different mental accounts. Settings of prior distributions and ranges of estimated parameters are shown in Supplementary Material Table S2. Model comparisons were indicated by leave-one-out cross-validation (LOO) information criteria, a common method to estimate out-of-sample predictive accuracy from Bayesian models [?]. After selecting the optimal model, we used a hierarchical Bayesian approach to simultaneously acquire group and individual-level parameter estimation with hierarchical Bayesian estimators in Rstan. We then performed between-group parameter comparison for different mental accounts using the posterior distribution of different parameters within 89% of the highest density intervals (HDIs) [?].

We also performed model recovery and parameter recovery to validate the robustness of parameter estimation in the optimal model (Supplementary Material S3-S4). For model recovery, we first used the original parameter estimates for each individual to simulate their pumping process in each opportunity. We then calculated the Pearson correlation between the number of pumps in each opportunity in the original data and the simulated data to check if the simulated pump of each trial in BART could capture the key characteristics of participants' original responses. For parameter recovery, we first used individual-level parameter estimates to simulate the pumping process of each individual and derived parameter estimates for each individual from the simulated data. Then we calculated the Pearson correlation between original and recovered parameter estimates across different participants. We repeated the above procedure 20 times to derive the mean (SD) Pearson correlation indices for each parameter to evaluate the stability of parameter estimation.

In the following part of this section, we will outline the formalism of the computational models. If these specifics are not of interest to the reader, they can proceed to Section 3.

2.5.1 Bayesian sequential risk-taking model (BSR)

The BSR model assumes that individuals calculate an optimal number of pumps for each trial based on their perceived probability of explosion. The perceived probability of explosion is updated in a Bayesian Observer manner, determined by the number of successful (versus the total pumps ( ) occurred before trial k (f1) (Wallsten et al., 2005). Using this probability as evidence, participants then determine a target number of pumps (ωk) for the upcoming trial (f2). The BSR model further assumes that the probability that participants will pump on opportunity l on trial k is determined by ωk and behavioral consistency, denoted as β (f3) (Ji et al., 2021). Free parameters in this model include: (1) initial beliefs about the probability of balloon explosion $(1 -)$, with $0 < \alpha <$; (2) risk-taking propensity (γ); (3) behavioral consistency (β).

In the kth trial, the update process is:

$( ) = 1 - \alpha + +$

The target number of pumps to make on trial k is:

$= - \log(1-)$

And the actual probability that the participants will pump on trial k for a given pump opportunity l (=1, 2, ⋯) is calculated as:

$=$

2.5.2 Target model

The Target model assumes that participants select a target number of pumps (1) before the first trial at the very beginning (Wallsten et al., 2005). Then participants adjust the target number of pumps of the current trial ( ) down if the balloon prior to trial k explodes, and up if it does not (f4). Parameters that characterize the size of the adjustment (i.e., learning rate) are after a win, and after a loss. α controls how rapidly the adjustment decreases with experience [**?**]. The target number of pump is adjusted on each trial according to the following formula:

$+1 = \{ \quad + \quad * \exp(-\alpha \ ) \qquad - 1$
$\times [1 - \quad * \exp(-\alpha \ )] \qquad - 1$

Free parameters include: (1) the initial target number of pumps (1); (2) sensitivity for wins ( ): (3) sensitivity for losses ( ); (4) decay parameter (α); (5) behavioral consistency (β).

The probability of stop pumping in each pump is the same as (f3).

2.5.3 Scaled Target Learning (STL) model

The Scaled Target Learning (STL) model is similar to the Target Model except that it provides an alternative rule about how the target number of pumps ( ) is updated based on the outcome in the previous trial (f5). The separate learning rates for wins and losses (i.e., &) reflect an individual' s different sensitivity to win and loss outcomes. nmax is the total number of pumps allowed in each trial (i.e., 128). Because ωk is scaled by nmax when fitting STL-D, so that the value of ωk is between 0 and 1. Free parameters include: (1) the initial target number of pumps (1); (2) sensitivity for wins ( ): (3) sensitivity for losses ( ); (4) behavioral consistency (β).

$= \{ \ -1 * (1 + \quad * \quad -1 \ ) \qquad - 1$
$-1 \times [1 - \quad * (1 -)] \qquad - 1$
-1

The probability of stop pumping in each pump is the same as (f3).

2.5.4 Scaled Target Learning with Decay (STL-D) model

Both the STL model and STL-D model describe learning as adjustments of the target number of pumps in reaction to outcomes in the task. A critical advancement to the STL-D model compared to the STL model is that it assumes participants make adjustments to the target number of pumps denoted by α, with the size of adjustment smaller as k increases (f6) (Zhou et al., 2021):

$$= \{ \quad -1 * (1 + \quad * \quad -1\ 1{+}\alpha{*}(\ -1)\ ) \qquad\qquad -1$$
$$-1 \times [1 - \quad *(1- \quad -1\ 1{+}\alpha{*}(\ -1)\ ] \qquad\qquad -1$$

Free parameters include: (1) the initial target number of pumps (1); (2) sensitivity for wins ( ): (3) sensitivity for losses ( ); (4) discount parameter (α); (5) behavioral consistency (β). The probability of stop pumping in each pump is the same as (f3).

3. Results

Data from 103 participants (Mage = 21.02, SDage = 1.91) were included in the analysis. There were no significant between-group differences in demographics, personality, anxiety, or depression measurements between the labor income group and the non-labor income group (Table 1). Independent sample t-tests suggested that participants in the non-labor income group showed higher positive emotion than those in the labor income group (t(101)= 2.36, 95% CI = [1.05, 12.11], p < .05) while there was no significant difference in negative emotion between the two groups (t(101)= 0.57, 95% CI = [-3.86, 6.97], p = .57) based on the PANAS scale, suggesting the effectiveness of the manipulation of mental accounts.

Table 1 Group Differences in the Demographic Variables (M±SD).

Measure	labor income (N=57)	non-labor income (N=46)	Group difference statistics
Gender (%female)	59.65%	67.39%	Pearson chi-square(1) = 0.66, p = .418

Measure	labor income (N=57)	non-labor income (N=46)	Group difference statistics
Age (years)	20.88±1.92	21.20±1.92	$t(101) = 0.84, p = .404$
Year of College	3.26±1.48	3.33±1.54	Pearson chi-square(4) = 1.50, $p = .827$
BDI	3.51±3.34	3.04±2.96	$t(101) = -0.74, p = .461$
PHQ-9	4.65±2.97	4.74±3.14	$t(101) = 0.15, p = .882$
TAI	38.84±8.64	40.41±8.93	$t(101) = 0.90, p = .368$
NEO-PI-N	30.79±8.84	31.41±9.52	$t(101) = 0.34, p = .732$
BIS	62.11±7.47	64.83±8.85	t(101)= 1.69, p = .094

Note: BDI = Beck Depression Rating Scale; PHQ-9 = Patient Health Questionnaire-9; TAI = Trait Anxiety Inventory; NEO-PI-N = dimension of Neuroticism in NEO Personality Inventory; BIS = Barratt Impulsiveness Scale.

Independent sample t-tests suggested that individuals in the non-labor income group showed higher risk preference convergently across four behavioral indicators (Table 2): (1) adjusted pumps (AP): t(101)= 3.43, 95% CI = [2.76, 10.33], p < .001, Cohen' s d = 0.68; (2) number of pop-balloons (NP): t(101)= 2.04, 95% CI = [0.03, 2.20], p = .044, Cohen' s d = 0.41; (3) mean number of pumps of win-balloons immediately following a win (AP+): t(101)= 3.47, 95% CI = [2.99, 10.95], p < .001, Cohen' s d = 0.69; (4) mean number of pumps of win-balloons immediately following a pop (AP-): t(99)= 3.60, 95% CI = [3.20, 11.04], p < .001, Cohen' s d = 0.72.

Table 2 Group comparisons of BART indicators between labor income group and non-labor income group (M±SD).

indicators	labor income (N=57)	non-labor income (N=46)	Between-group comparison
AP	19.65 ± 8.25	26.20 ± 11.10	t(101)= 3.43, p < .001***
NP	4.30 ± 2.40	5.41 ± 3.14	t(101)= 2.04, p = .044*
AP+	20.28 ± 8.64	27.25 ± 11.73	t(101)= 3.47, p < .001***

indicators	labor income (N=57)	non-labor income (N=46)	Between-group comparison
AP-	17.16 ± 8.51	24.29 ± 11.35	t(99)= 3.60, p < .001***

Abbreviations: AP = adjusted pumps; NP = number of pop-balloons; AP+ = mean number of pumps of win-balloons immediately following a win; AP- = mean number of pumps of win-balloons immediately following a pop.

Note: *p < .05;* **p < .001

To explore trial-by-trial how the manipulation of income source and feedback from the last trial in BART would influence the current trial, we used a linear mixed model to examine the main and interaction effects between the source of income, the number of trials, and feedback (i.e., the explosion outcomes of the last trial) on the number of pumps in the current trial. We found significant main effects of the source of income ($F(1,110) = 12.04$, 95% CI = [-9.18, -2.55], $p < .001$), the number of trials ($F(29,2873) = 2.31$, $p < .001$), and feedback ($F(1,2884) = 23.85$, 95% CI = [1.45, 3.38], $p < .001$). The three-way interaction among the source of income, the number of trials, and feedback ($F(29,2876) = 1.18$, 95% CI = [-1.62, 2.25], $p = .234$), as well as the second-order interactions (between the source of income and the number of trials: $F(29,2873) = 1.36$, $p = .096$; between the source of income and feedback: $F(1,2884) = 0.10$, 95% CI = [-1.62, 2.25], $p = .749$; between the number of trials and feedback: $F(29,2876) = 1.07$, $p = .363$), were found to be non-significant in the linear mixed model analysis.

The post hoc test showed that the number of pumps in the current trial in the non-labor income group was significantly higher than the number of pumps in the current trial in the labor income group. The number of pumps in the current trial following a win was also significantly higher than the number of pumps in the current trial following a loss (Fig. 2a [Figure 2: see original paper]). In addition to re-verifying the previous conclusion that participants in the non-labor income group showed higher risk preference than participants in the labor income group, these results also implied that participants learn from past outcomes to adjust the number of pumps in the current trial based on outcomes from the last trial for both groups. Meanwhile, we did not find a significant interaction between the source of income and the number of trials. The result showed that in the non-labor income group, the number of pumps was higher than in the labor income group, and this higher risk-taking propensity persists with the evolution of time (Fig. 2b [Figure 2: see original paper]).

Fig. 2. The main effects of feedback from the last trial on the number of pumps in the current trial (a). Comparison of the number of pumps between the non-labor income group and labor income group across trials (b).

Model comparisons of four candidate models (i.e., BSR, Target, STL, and STL-D) between experimental conditions (i.e., labor income and non-labor income) are shown in Table 3 . For the labor income group, STL-D had the numerically smallest LOOIC. For the non-labor income group, BSR had the numerically smallest LOOIC and had no significant difference with STL-D for goodness of fit by model comparisons (Mean Difference < SE). As STL-D captured the learning rate for winning and losing trials, which could reflect our interested psychological processes of how individuals learn from gains and losses underlying risk-taking behavior, we selected the STL-D model as the optimal model for parameter comparison across conditions.

Model recovery showed that the simulated data from the optimal model STL-D could capture key characteristics of the original data (Supplementary Material S3). Parameter recovery showed stable parameter estimation of STL-D, indicated by the high correlation between original and recovered parameters (Supplementary Material S4).

Table 3. Mean (SE) of LOOICs for different candidate models and model comparison results

Group	Mean (SE) of LOOICs	Model comparison			
	BSR	Target	STL	STL-D	BSR-STLD
labor income	(213.0)	(276.7)	(209.0)	(213.7)	(21.2)
non-labor income	(162.3)	(201.1)	(161.8)	(158.9)	(22.9)

Descriptive statistics and 89% CI for the group-level estimation of each parameter are shown in Table 4 . We found credible between-group differences in learning rate in loss trials ( ) (89% HDI: (0.03, 0.19)), target number of pumps before the first trial (1) (89% HDI: (-0.11, -0.01)), and the inverse temperature (β) (89% HDI: (0.03, 0.24)) between the labor income and non-labor income groups. These results indicated that participants in the non-labor income group (1) preset a larger target number of pumps (1) at the beginning of the game; (2) were less sensitive to feedback of losses ( ); (3) acted more randomly, in which pump probability was less dependent on the target number of pumps (β).

Table 4. Parameter estimation and between-group comparison results (M±SD).

Parameters	Labor income	Non-labor income	Between-group 89% HDI (highest density intervals)

0.57$±0.04|0.48±0.05|[−0.02, 0.19)||N*loss*|0.44±0.04|0.34±0.03|[0.03, 0.19)|||0.20±0.02|0.26±0.03|[-

Note: For BART used in our experiment, we set the maximal total number of pumps allowed in each trial to 128 [?]. is the scaled target number of pumps ( ) with a 1/128 scaler. The numerical value of is between 0 and 1.

4. Discussion

The current study uncovers that the source of money affects the dynamic risk investment process. Individuals made persistently higher levels of risk investments with money from non-labor sources than from labor sources. Computational model analyses further revealed that individuals (1) preset a higher targeted number of pumps at the very beginning of the game upon money endowment (indicated by a higher 1), (2) had a decreased learning rate towards losses (indicated by a smaller), and (3) displayed more random decision-making (indicated by a smaller β) compared to individuals in the labor income group. These results suggest that individuals tended to splash non-labor income via continuous risky investments across time. Our study offered a direct empirical test of our proposed mechanism underlying this persistent higher risky propensity over non-labor income, i.e., higher preset risk-taking propensity at the beginning and the malfunctioning of the negative feedback loop in the dynamic control process.

Our finding that individuals with non-labor income showed higher risk preference in dynamic risk decision-making and had higher target number of pumps (1) aligns with our hypotheses and with existing studies in static decision-making [?, ?]. The higher values of 1 indicate that participants with non-labor income have more willingness to take risks than those with labor income even at the beginning of the BART. Previous consumption decision-making studies have also found that money in the windfall gains account has an irresponsibly higher marginal propensity to consume [?, ?] than other accounts even before consumption. Findings from multi-period gambling also show that individuals have the strongest willingness to take risks immediately after a large win [?].

Moreover, computational modeling showed that the of participants in the non-labor income group was significantly lower than that in the labor income group. That is, individuals with non-labor income were less sensitive to negative feedback in BART. This finding could be backed up by the editing rule elicited by the Quasi-Hedonic Editing Hypothesis [?]. The reference point for participants in our labor income group is likely to be 0, whereas the reference point could increase to 15 (i.e., the amount of gains from the lucky draw) for the non-labor income group, representing a large gain at the beginning. To maximize happiness, the non-labor income group is less likely to exhibit loss aversion because losses fewer than 15 are no longer 'losses' in their mind in the process of integration with larger gains, and thus this results in a desensitization to losses. Until the winnings are completely depleted, losses are canceled out [?, ?]. The increased target number of pumps ( ) and desensitization towards losses (loss) found in our experimental study provide clear support for the Quasi-Hedonic Editing Hypothesis. Further, the desensitization towards losses retains subsequent risk-taking at a continuously high level.

Moreover, outside of our proposed malfunctioning control mechanisms, we additionally found that participants in the non-labor income group based their actions less on the target number of pumps and more at random, and consequently had less rationality in decisions, indicated by their lower behavioral consistency parameter β. Further, because the target number of pumps is primarily based on learning from the previous trial, the β can also be interpreted as a segregation of outcomes between trials [**?**, **?**]. In other words, participants with lower β values will base their actions less on the target number of pumps they had in mind but on the outcome of a particular trial.

Our study has both theoretical and practical implications. In the theoretical setting, we provided direct empirical support for our proposed malfunctioning of control in the dynamic investment of non-labor income. That is, non-labor income leads to an initial perturbance (i.e., a higher prior expectation of risky investment) and a malfunctioned negative feedback loop to cool down this initial perturbance (i.e., desensitization towards loss outcomes in the investment process, indexed by a lower learning rate towards losses). These two elements together constitute the fundamental propeller of individuals' continuous risk-taking behaviors. With dynamics of how non-labor income elicits continuous risk investment understood, our study can shed important light on how to prevent individuals from immediately splashing non-labor income away, guiding them toward more rational investment and consumer behaviors. Effective intervention could target cooling down consumption or risky investment immediately upon individuals receiving the non-labor income, ameliorating loss desensitization, and enhancing investment rationality in the long term. This intervention, in some circumstances, could also prevent individuals from gambling addiction with non-labor income, as individuals with gambling disorders exhibit similar malfunctioning of control, indicated by desensitization to losses in the gambling process (Beck et al., 2009; FitzGerald et al., 2009; Romanczuk-Seiferth et al., 2015).

The present study has the following limitations. A key limitation is that our experiment only involves undergraduate students. A considerable proportion of participants were excluded due to failure in the manipulation of mental accounts. This insusceptibility to manipulation may be due to certain sample characteristics, i.e., higher educational background [**?**]. Future studies could replicate our results using non-student samples to eliminate the influence of higher educational background on mental account manipulations and test the generalizability of our results. Second, the success rate of manipulation of income sources to strictly labor versus non-labor sources is limited, as revealed by a direct manipulation check. This could also possibly result from individual differences in money source attribution or a lack of effort expenditure in the questionnaire completion task. Future studies could pay participants for completion of tasks involving a larger amount of labor.

5. Conclusion

The current study advanced our understanding of why non-labor income leads to continuous higher risk investments. We provided direct empirical support for our proposed psychological mechanism. Specifically, the non-stopping risk-taking behavior associated with investing non-labor income over time can be attributed to an initial heightened level of targeted risk investments, a desensitization towards investment losses, and a reduced level of rationality in the investment process. From getting a coupon to winning the lottery, receiving an extra fortune happens all the time and constitutes a large proportion of our income. Our study teaches the public that to keep windfall gains in the pocket for a longer time, we probably must consciously counter our automatic tendency of casual expenditure upon receiving the money and constantly alert ourselves of the stunning investment losses.

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Conflicts of Interest
The authors declare no conflict of interest.

Ethics approval
All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. This study was reviewed and given ethical clearance by the Institutional Review Board of Southwest University (IRB NO.H23171).

Consent to participate
Before participation, all participants provided written informed consent.

Consent to publish
Participants signed informed consent regarding publishing their data and photographs.

Data and/or Code availability
Data for this research project will be available upon reasonable request to the corresponding author.

Preregistration of Studies
We did not preregister the research in an independent, institutional registry.

Preregistration of Analysis Plans
We did not preregister the research with or without an analysis plan in an independent, institutional registry.

Preprint of This Study
The manuscript has been posted as a preprint on PsyChinaXiv to ensure timely access for the academic community to our research findings (DOI:10.12074/202309.00151V1).

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Note: Figure translations are in progress. See original paper for figures.