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Do you have a choice?: Implications for belief updating and the disposition effect[☆]

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ABSTRACT

The present paper evaluates the importance of belief updating for the prevalence of the disposition effect – the reluctance to sell assets at losses as compared to gains. In particular, the present paper studies whether restricting choices in investment risk taking decisions motivates different learning from the decision outcomes and whether such differences in learning cause differences in the emergence of the disposition effect. The results show that investors learn from negative outcomes more like Bayesians if their risk-taking decisions are restricted. Causal mediation analysis reveals that such differences in learning increases the probability to sell after losses, which improves the overall investment performance. Compared to gains, the differences in learning after losses explain also why investors making active risk-taking choices are less likely to sell after losses as compared to gains, while the effect is reversed when choices are restricted. These findings suggest that restricting the discretion in decisions influences the way investors learn from decision outcomes and these differences in learning can explain puzzling differences in the risk-taking behavior of individual investors.

1. Introduction

One of the most robust observations describing individual trading behavior is the disposition effect: investors are less willing to sell assets at losses than at gains (Shefrin and Statman, 1984). The disposition effect has been documented in stocks (Odean, 1998), in online betting markets (Hartzmark and Solomon, 2012), in option markets (Chiang et al., 2020), and in numerous lab studies (Corneille et al., 2018; Deaves et al., 2018; Fischbacher et al., 2017; Hermann et al., 2019; Janssen et al., 2020; Jiao, 2017; Kadous et al., 2014; Ploner, 2017; Rau, 2015; Summers and Duxbury, 2012; Weber and Camerer, 1998). Across investors types, it has been found among individual investors in the US (Dhar and Zhu, 2006; Odean, 1998), in Finland (Grinblatt and Keloharju, 2001), in the UK (Richards et al., 2018), and in China (Chen et al., 2007; Feng and Seasholes, 2005), on social trading platforms (Danbolt et al., 2021), as well as among mutual fund managers (Andreu et al., 2020; Frazzini, 2006). The effect is not only wide-spread, it is also costly for investors (Odean, 1998). While the question of whether there is a disposition effect has been settled, the question of why there is such an effect is still under debate.

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The existing literature on the drivers of the disposition effect refers mainly to drivers related to the investor's preferences (Barberis and Xiong, 2009,2012; Ingersoll and Jin, 2013; Ploner, 2017; Shefrin and Statman, 1984). The investor's beliefs on the future development of their investments – incremental to every decision under uncertainty – have received much smaller attention. Previous research highlights the importance of such beliefs (Odean, 1998; Weber and Camerer, 1998), but the previous empirical (Ben-David and Hirshleifer, 2012; Kaustia, 2010) and experimental (Corneille et al., 2018; Jiao, 2017; Kadous et al., 2014) studies evaluating the importance of beliefs consider only the erroneous belief in mean-reversion as a potential driver of the disposition effect. However, the belief in mean-reversion cannot explain the emergence of the disposition effect across different assets as documented in various studies (Calvet et al., 2009; Chang et al., 2016; Kadous et al., 2014; Lehenkari, 2012), since they imply a general tendency on the part of investors to trade in opposition to price movements.

To address these shortcomings, the present paper studies the importance of different patterns in the way investors update their beliefs on the prospects of their investments for the prevalence of the disposition effect. A very long history of research in psychology and economics suggest that investors do not behave as Bayesians when they make conditional probability judgments while also highlighting the existence of systematic cognitive biases (Camerer, 1987; Edwards, 1982; Grether, 1980,1992; Holt and Smith, 2009; Kahneman and Tversky, 1973). While the cognitive biases concern all new information, another strand of the literature on belief updating suggests that there are also patterns in belief updating related to the valence of information (Sharot and Garrett, 2016). According to that literature, people are more willing to update their beliefs when receiving desirable than undesirable information such as feedback on their intellectual abilities and beauty (Eil and Rao, 2011; Möbius et al., 2022), personality (Korn et al., 2012), future earnings (Wiswall and Zafar, 2015), or future life events (Sharot et al., 2011). With respect to the question of what information is desirable, previous research on motivated reasoning suggest that information is desirable if it can be used in a way that allow decision-makers to reach a conclusion that is consistent with their previous beliefs, attitudes or decisions (Kunda, 1990). In a broader context, information is avoided if it makes previous judgment less defensible (Mata et al., 2022), or if it provides an opportunity to behave selfishly without having to take potential harm imposed on others into account (Momsen and Ohndorf, 2022). Regarding the importance of previous decisions, several studies provide evidence that decisions motivate optimistic expectations on the prospects of these decision (Arkes and Hutzel, 2000; Knox and Inkster, 1968; Lawler et al., 1975) and a bias recall of performance from memory (Goetzmann and Peles, 1997); decisions can also shape the future preferences of the decision-makers (Sharot et al., 2009). With respect to the question of whether decisions affect belief updating, Kuhnen and Knutson (2011) find that investors ignore new information that contradict their previous investment decisions. In support to the view that previous decisions have an affective impact on belief updating, previous research show that belief updating can be improved when investors make only predictions and no investment decisions (Kuhnen and Knutson, 2011), when the outcomes of previous decisions are not associated with a success or a failure (Charness and Levin, 2005), and when the information value of decision experience can be uncoupled from the reward (Achtziger and Alós-Ferrer, 2014).

The present paper extends this line of research by evaluating whether externally imposed restrictions in the decisions matters for the observed patterns in belief updating that can potentially explain the prevalence of the disposition effect. In standard theory of decision-making, people should be at least as well off, if not better, without restrictions in their decisions as more choices mean more possibilities for achieving attractive outcomes. However, previous research suggest that restrictions can lead to better decisions, because restrictions make the avoidance of psychologically painful decisions more costly, which reduces decision biases (Heimer and Imas, 2022). In belief updating tasks, when decision-makers are asked to make estimates by observing the choices of others or the choice of a computer, they evaluate outcomes less extremely (Botti and Lyengar, 2004), rely more on their analytical skills (Fernandez-Duque and Wifall, 2007), behave more like Bayesians (Kuhnen, 2015), and they do not use their memory self-servingly (Saucet and Villeval, 2019). Building on these findings, the present paper investigates whether restricting choices in the previous risk-taking decisions affects the way investors update their beliefs on the prospects of their investments. More importantly, the paper analyses whether such differences in belief updating can explain differences in the prevalence of the disposition effect.

The analysis is based on a simplified version of an investment game that has been previously used by Kuhnen and Knutson (2011) and Kuhnen (2015) to analyze belief updating after gains and losses. Over several periods, participants decided to hold cash or to invest in a risky asset with payoffs coming from either a good or a bad distribution. Both distributions have the same support, but the probability for a positive (negative) outcome was higher in the good (bad) distribution. In each period, participants estimated the probability that the risky asset was paying from the good distribution after seeing the payoff of the risky asset, and then they made an investment decision.

Two treatments have been implemented to investigate the importance of making choices in risk taking. In one treatment, investors who have decided to invest in the risky asset were allowed to choose the shares of the risky asset. In the other treatment, investors had to accept the random choice of shares made by a virtual manager (computer). As participants were randomly distributed to the different treatments, it was possible to identify the causal effect of eliminating choices in risk taking on how participants updated their beliefs on the prospects of their risky investments while distinguishing between decisions associated with gains and decisions associated with losses. Causal mediation analysis allowed identifying the importance of such learning effects for observing the emergence of the disposition effect while considering that the disposition effect can appear for reasons related directly to the previous payoffs. Such payoffs can influence the subsequent investment decisions as a response to some form of risk preferences as reflected in the investor's utility function. It is also possible that previous outcomes affect subjects decisions because of inertia motivating decision-makers to repeat previous decisions independent of feedback (Alós-Ferrer et al., 2016; Alós-Ferrer and Garagnani, 2023).

The empirical analysis showed that starting with the same beliefs and observing the same payoff, risk takers in each treatment learnt differently from losses. After losses, risk takers with a choice held more optimistic beliefs on the prospects of their investments than investors without a choice with the same risk exposure and after controlling for their prior probability estimates and other confounding factors. A comparison with the probability estimates of a Bayesian using the same prior probability estimate revealed that, after losses, the beliefs of the risk takers with a choice were indeed too optimistic.

The further causal mediation analysis revealed that these differences in learning from losses caused differences in the subsequent risk-taking behavior. Restricting choices in risk taking increased the willingness to sell after losses. More importantly, the analysis revealed that about one half of the effect of previous losses on the willingness to sell was caused by the difference in the way risk takers with and without a choice learnt from adverse information. Consequently, investors without a choice achieved significantly higher returns in rounds when it was more likely to see negative payoffs than positive payoffs.

The difference in belief updating of restricted and unrestricted risk takers explained also why investors making choices are less likely to sell after losses than after gains, while the effect was reversed in the group of investors following the choices of the computer. Causal mediation analysis showed that the disposition effect was observed when losses motivated beliefs revisions that are too weak as compared to other effects that losses may have on the willingness to sell. Hence, considering how risk takers learnt from losses as compared to gains allowed explaining why there was a disposition effect among investors making choices and why the effect was reversed among investors restricted to follow the random choice of the virtual manager.

The main contribution of the present paper is to provide evidence for the existence of a new channel based on different patterns of belief updating that can explain differences in the prevalence of the disposition effect. Empirical studies find that when investors delegate investment choices to managers, they are more likely to sell after losses than when they invest directly on the financial market (Calvet et al., 2009). Chang et al. (2016) confirm this observation in the lab and explain it with the salience of the manager who can reduce the utility loss by taking over the blame for the losses. The authors considered the possibility that learning effects can explain the stronger willingness to sell losing delegated investments, but the employed experimental design did not allow for estimating such learning effects. The present paper overcomes this shortcoming by explicitly evaluating how investors with a different involvement in the investment process update their beliefs on the prospects of their investments. The employed causal mediation analysis then made it possible to estimate the relative importance of those beliefs for the subsequent investment decisions. While investors may want to reduce risk in delegated investments after losses because of the uncertainty in the choices of the manager, this paper showed that a significant part of the willingness to sell after losses was caused by a stronger revision of beliefs when following the choice of the virtual manager than when choosing the risk exposure autonomously.

The results contribute also to the literature on belief updating where new information can have an affective meaning. When dealing with such information, decision makers are motivated to actively seek for reasons to disregard disconfirming evidence (Lord et al., 1979). In the context of investment decisions, Kuhnen and Knutson (2011) show that investors update their beliefs in a way that is consistent with the self-preservation motive of maintaining positive affect and avoid negative affect by not fully considering information that is in odds with the prior decisions. The results of the present paper show that the motivation to make use of information that supports or contradicts prior risk-taking decisions depends on whether the risk exposure was actively chosen by the investors or decided by the computer.

Finally, the provided evidence extends the previous literature on the question of how to eliminate the disposition effect (Fischbacher et al., 2017; Frydman et al., 2018; Gemayel and Preda, 2018). In particular, recent work argues that restriction in the choice of financial leverage can be beneficial for overcoming the disposition effect (Heimer and Imas, 2022). The results in the present paper confirm the observation that restrictions can be beneficial for eliminating the disposition effect but suggest a different mechanism that operates through the way restrictions affect how decisions-makers learn about the prospects of their investments.

2. Method

2.1. Experimental design

The experiment is based on a simplified version of an investment game used by Kuhnen (2015) and Kuhnen and Knutson (2011). In this game, there was one risky asset and cash. The payoff of the risky asset could be either 0.25 euro or −0.25 euro; cash paid nothing. The payoff of the risky asset could come either from a good distribution or from a bad distribution. In the good distribution, the positive outcome occurred with 70 % probability, while the negative outcome occurred with 30 % probability. In the bad distribution these probabilities were reversed: the positive outcome occurred with 30 % probability, and the negative outcome occurred with 70 % probability.

The investment game used only one risky asset. This allowed to control for potential rationalizations of the disposition effect including diversification (Lakonishok and Smidt, 1986), variations in mental accounting effects (given that the extent to which investors set up individual mental accounts for each asset is unknown), and the impact of members of a choice set on each other, which might arise in a portfolio situation.

At the beginning of the experiment, participants were randomly assigned to one of two treatments. In cases where participants decided to invest in the risky asset, the participants in the one treatment were additionally asked how many shares of the asset (1, 2, or 3) they would like to hold. The participants in the other treatment saw the same options of shares of risky asset, but they were not able to choose among them. For those participants, one of the options was highlighted as being chosen randomly by a virtual manager. The participants were only able to confirm the choice of the virtual manager. They were not allowed to revise their decision to invest in the risky asset after seeing the selected option. The participants remained in the assigned group for the duration of the experiment. They were not aware of the existence of another group. The instructions are provided in Section B of the Online Appendix. Screenshots of the tasks are included in Section C of the Online Appendix.

Fig. 1 summarizes the information available to the participants in both treatments and the order of decisions for the first two payoffs of the risky asset that participants saw in each round. At the beginning of each round, a fair coin was tossed to choose the distribution of the risky asset for the corresponding round. The beginning of each round was clearly showed. Before making any decisions, participants have been informed that, at the beginning of each round, it was equally likely that the good or the bad asset was selected. Participants without understanding of this feature have been excluded at the beginning of the experiment. Then, the participants have been asked to decide whether they would like to invest in the risky asset or to hold cash, followed by a choice of the risk exposure in the treatment with a choice or a confirmation about the risk exposure selected by the virtual manager in the treatment without a choice. Independent of the investment decision of the participants, the payoff of the risky asset has been revealed. Based on this payoff information, participants have been asked to assess the probability that the risky asset is good again and to make an investment decision again.

In each round, participants made decisions based on six payoffs of the risky asset. The investment game lasted ten rounds.

By convention (see, for example, Fischbacher et al., 2017), the order of the good and bad distribution in each round as well as the payoffs of the risky asset in each period were decided in advance by drawing them from the corresponding distributions. All participants completed their tasks facing the same payoffs of the risky asset in the same order. This facilitates a between subject analysis of how choice affects belief updating conditional on seeing the same payoff of the risky asset and having the same risk exposure.

Participants' compensation depended on their forecast accuracy and on their investment decisions. Participants were informed that in each period there was a clearly specified correct probability that the risky asset was good and that their estimation payoff would increase with the precision of their estimates. For every perfect estimate, they would receive 0.20 euros. The exact estimation payoff (in euros) was $\frac{1}{5+\text{forecast error}^2}$, which was given to participants together with some examples. This simple procedure for eliciting expectations with incentives is preferable to more complex mechanisms such as versions of the binarized scoring rule (e.g., quadratic scoring rule) since recent research show that simpler mechanisms – such as the one used in the present paper – result in more truthful reporting while imposing a lower cognitive burden on participants (Danz et al., 2020). The investment payoff was decided by the accumulated investment payoff at the end of a randomly selected round. To avoid feedback effects that may change participants' strategy during the experiment, the compensation related to feedback accuracy and the relevant investment payoff were provided at the end of the experiment.

Each participant started a new round with an endowment of 4.50 euros. Depending on the payoff of the risky asset and participants' investment decisions, it was possible to double the initial endowment or to lose it completely. A total loss was possible if a participant were to always hold three shares of the risky asset and the payoff of the risky asset were to be negative in all six periods. On average, participants received 6.50 euros in addition to a fixed participation fee of five euros. The average completion time was 17 min.

After completing all learning rounds, participants were asked to provide information about their professional education and income. The age and gender of participants was assessed at the beginning to define the sampling quotas for the treatments.

2.2. *Participants*

The subjects of this experiment were recruited from a participants' pool provided by Bilendi in Germany. The participants registered in this pool have experience with online surveys on several topics including financial decisions. Their participation is remunerated with money (euros), which they receive via bank transfer initiated by the market research agency. Using the same pool of participants, Bachmann et al. (2023) replicate the main results of five experimental studies on financial decision making, each one requiring decisions in simulated tasks over several periods.

The participants were invited by an e-mail showing how much time they would be expected to need as well as their reward. Quotas were applied on participants' age and gender to receive a sample to be considered as representative of the 20–60-year-old population in Germany. To take part in the experiment, participants had to read the instructions and answer test questions that assessed their understanding of the instructions. The sample of participants who correctly answered these questions and completed all rounds consisted of 567 individuals.[1] Descriptive statistics of participants' demographic and socio-economic characteristics are reported in Table 1.

The participants in the sample were on average 36 years old. Forty-four percent of them were female. Most participants (32 %) had a net monthly income of between 1,300 and 2,600 euros. Most participants (31 %) had completed a polytechnic high school; one-fifth of all participants had a university degree or a degree of a university of applied sciences.

2.3. *Measures*

The probability that the asset is good was used to measure how participants updated their beliefs. In each period, it was also possible to calculate the Bayesian probability that the asset is good.

The decision to sell shares of the risky asset is used to measure the disposition effect, following the considerations of De Winne (2021) and the econometric approach of previous empirical and experimental studies on the disposition effect (Aspara and Hoffmann,

[1] The sample size was decided based on the number of treatments and by comparison with other related experimental studies, while considering the heterogeneity in the sample with respect to individual characteristics such as age and education level. The study of Kuhnen and Knutson (2011) is the closest to the present one. The study has only one treatment and uses 28 undergraduates. Rudorf et al. (2014) employ a similar task with one treatment and use 48 subjects.

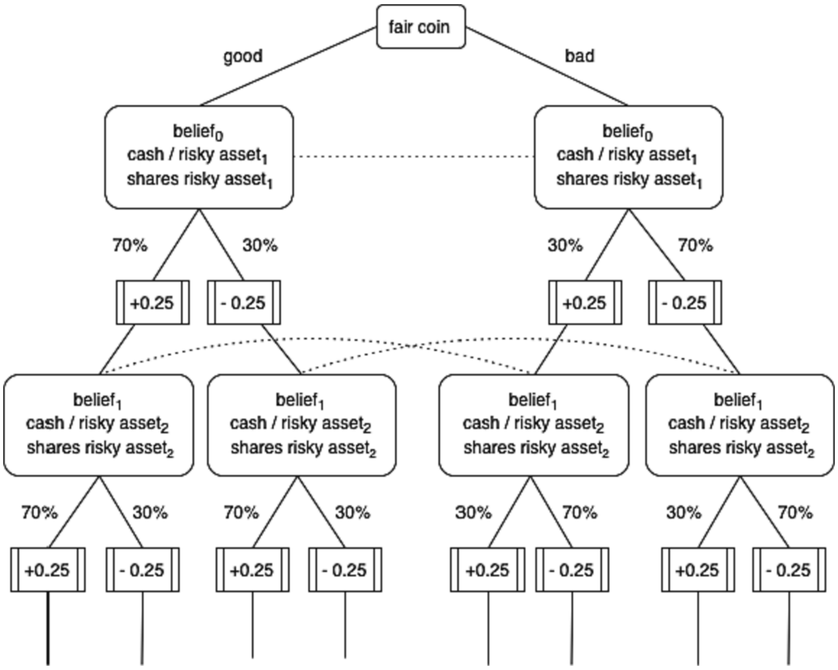

Fig. 1. Information and tasks in both treatments.

Table 1
Descriptive statistics of the sample.

	Choice	No Choice	all
Age (average)	37	36	36
Female	47 %	41 %	44 %
Net monthly income: less than 1 300 euros	16 %	10 %	13 %
Net monthly income: 1 300–2 600 euros	33 %	32 %	32 %
Net monthly income: 2 600–3 600 euros	22 %	26 %	24 %
Net monthly income: 3 600–5 000 euros	18 %	19 %	18 %
Net monthly income: more than 5 000	7 %	6 %	6 %
Net monthly income: unknown	5 %	8 %	6 %
Education: secondary school	5 %	8 %	7 %
Education: intermediate secondary school	6 %	6 %	6 %
Education: higher secondary school	10 %	12 %	11 %
Education: polytechnic high school	29 %	33 %	31 %
Education: high school	13 %	11 %	12 %
Education: university of applied sciences	9 %	9 %	9 %
Education: university	11 %	9 %	10 %
N	284	283	567

2015; Birru, 2015; Chang et al., 2016; Dierick et al., 2019; Grinblatt and Keloharju, 2001; Kaustia, 2010; Lehenkari, 2012; Linnainmaa, 2010). Using an econometric approach to estimate the disposition effect instead of measures based on the proportion or difference of the percentage of gains and losses allows estimating the relative importance of belief updating on the disposition effect.

Selling decisions are decisions that reduce the risk exposure. In the group without a choice such decisions are captured by a dichotomous variable for whenever risk takers switch to cash, since this is the only way to actively choose the risk exposure. Selling decisions in the group with a choice are captured by a dichotomous variable for whenever risk takers switch to cash or reduce the number of shares of the risky asset.

Defining selling as a switch to cash also in the group with a choice is used as an alternative definition of selling. The results of the corresponding analysis are included in Section A of the Online Appendix and commented in Section 3.2.2 and Section 3.2.3, respectively. The causal mediation analysis considers these group differences in the ability to sell where necessary.

3. Empirical findings

3.1. Group differences in belief updating

In the investment game used for the experiment, the information that every participant received at the end of each period was the payoff of the risky asset. The payoff of the risky asset was exogenously decided, i.e., it did not depend on earlier payoffs or earlier investment decisions. All investors saw the same payoffs of the risky asset in the same order.

If choice in decisions does not matter for how investors learn from payoffs, there should be no differences in the probability estimates of investors with and without a choice seeing the same payoff of the risky asset. To test this hypothesis, the empirical analysis considers that decision-makers may use different priors when updating their beliefs and they may learn differently in rounds with more positive or more negative payoffs. Individual differences that may affect the probability estimates are considered as well.

The empirical analysis is implemented using pooled ordinary least squares (OLS) regressions with the subjective probability estimates in each period as a dependent variable. The analysis uses different sub-samples depending on the shares of the risky asset that each participant held just before seeing the payoff of the risky asset. The independent variable of interest is the treatment variable, i.e., an indicator variable for investors without a choice, which is exogenously defined and constant over time. The control variables include the prior probability estimate, the objective probability, an indicator variable for whenever the good asset has been chosen and variables capturing the investors characteristics (age, gender, income, and education level).

Although the prior probability estimates were included as an independent variable, OLS estimations are expected to produce consistent and unbiased estimates for the independent variable of interest as the latter is exogenously determined and does not depend on any past realizations (Keele and Kelly, 2006; Nuamah, 1986). In all estimations, clustering the errors at the individual level makes it possible to control for a within-cluster error correlation over time. The results of this analysis are reported in Table 2.

The estimation results show that there are significant differences in the probability estimates of investors with and without a choice, but the differences depend on the payoff of the risky asset and on whether the investors held shares of the risky asset before estimating the quality of the risky asset or not. When the payoff of the risky asset is negative, the probability estimates of risk takers with no choice are on average lower than the probability estimates of risk takers with a choice. The group difference in the probability estimates is about 6 percentage points (see Columns 1). There are no significant group differences in the probability estimates of risky asset holders learning from positive payoffs (see Column 3). The probability estimates of cash holders seeing either a positive or a negative payoff of the risk asset do not differ significantly among the groups as well (see Columns 2 and 4). Overall, the probability estimates of risk takers without a choice are on average about 6 percentage points lower after losses than after gains as compared to the probability estimates of risk takers with a choice as the interaction term in Column 5 shows. There are no significant group differences among cash holders (see Column 6).

To visualize the group differences among risk takers with and without a choice, the probability estimates of investors holding shares of the risky asset are pooled and split based on the level of their prior probability estimates. To simplify the exposition, five equally large probability intervals are used to capture the level of the prior probability estimates. Four sub-samples are built depending on the payoff of the risky asset and whether investors were allowed to choose the shares of the risky asset. The average probability estimates of the investors within these four sub-samples together with their 95 % confidence intervals are presented in Fig. 2. In addition, Fig. 2 includes the probability estimate that Bayesians would give if they would observe the same payoff of the risky asset and would hold the

Table 2

Choices in decisions and probability estimates. Each column shows the results of one estimation. Each estimation uses a different sub-sample defined by the payoff of the risky asset (positive or negative) and the number of shares of the risky asset that participants held just before they saw the payoff of the risky asset and provided an estimate that the asset is good. *No choice* is an indicator variable that takes the value of 1 for participants with no choice. Standard errors clustered by participant are reported in parentheses. *** denotes statistical significance at $p < 0.001$, ** denotes statistical significance at $p < 0.01$, and * denotes statistical significance at $p < 0.05$.

	Probability estimate$_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Shares of risky asset$_{t-1}$	yes	no	no	yes	yes	no
Payoff of risky asset$_{t-1}$	negative	negative	positive	positive	all	all
No choice$_i$	−6.091***	−0.279	−0.192	−0.042	−0.204	0.073
	(1.189)	(1.052)	(1.756)	(1.106)	(1.126)	(1.715)
Negative$_{t-1}$					−30.358***	−19.778***
					(1.488)	(1.519)
Negative$_{t-1}$ | No choice$_i$					−5.825**	−0.485
					(2.059)	(2.070)
Constant	24.125***	13.125***	30.030***	46.566***	50.653***	31.350***
	(3.941)	(3.511)	(5.562)	(3.084)	(2.755)	(3.052)
Observations	10,819	4,891	3,762	8,516	19,335	8,653
Independent observations	567	507	499	567	567	519
R-squared	0.236	0.391	0.239	0.123	0.472	0.429
Controls	prior probability estimate, objective probability, type of risky asset (good or bad) randomly selected in each round, individual characteristics (age, gender, income level, professional education)					

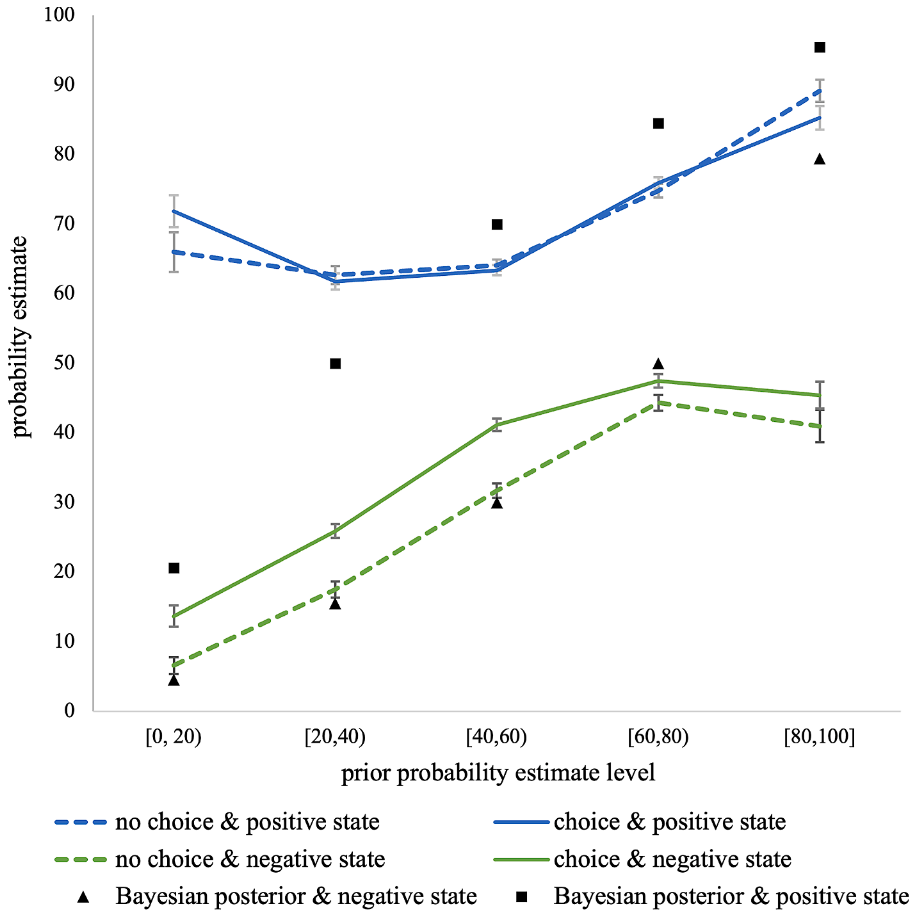

Fig. 2. Group differences in the probability estimates of risky asset holders after gains and losses The y-axis is the average probability estimate of risky asset holders for each category of prior probability estimates represented on the x-axes, along with 95% confidence intervals. The observations are grouped in four categories depending on whether the risk expose was chosen or not ("choice" and "no choice") and on the payoff of the risky asset at the end of the previous period ("positive state" or "negative state").

average of the minimum and maximum belief in each sub-sample. To behave as Bayesians, participants do not need to remember the whole payoff history of the risky asset. The Bayesian posterior can be calculated based on the prior probability estimate and the last observed payoff of the risky asset.[2]

Fig. 2 shows that when the payoff of the risky asset is positive, all risk takers with a similar prior beliefs report on average similar probability estimates (compare the solid and the dotted lines in the upper half of the figure). In contrast, when risk takers with similar prior probability estimates see negative payoffs, their average probability estimates differ. On average, risk takers without a choice revise their probability estimates stronger than risk takers with a choice holding similar prior beliefs (compare the solid and dotted lines in the lower half of the figure). This observation is in line with the estimation results reported in Table 2.

In addition to comparing the probability estimates of risk takers with and without a choice, Fig. 2 allows comparing the average estimate in each group with the estimate of a Bayesian investor with a similar prior probability estimate. The prior used to visualize the data is the average of the lowest and the highest estimate in each interval of prior probability estimations. A visual comparison with the Bayesian posterior reveals that risk takers without a choice behave more like Bayesians when learning from negative payoffs, in particular when their prior probability estimates are not too high.

To assess the statistical significance of this observation, the following analysis uses pooled OLS regressions and estimates whether there are significant group differences in the errors that investors make when they learn about the quality of the risky asset. This learning error is defined as the absolute value of the difference between the individual probability estimate and the Bayesian posterior calculated based on the individual prior estimate that the risky asset is good. The results of this analysis are reported in Table 3.

The results show that risk takers without a choice are less biased in the way they update their beliefs than risk takers making choices

[2] If the prior probability estimate that the risky asset is good is p, then following a positive payoff, the posterior following Bayes rule is 7p/(3+4p). The posterior after a negative payoff is 3p/(7-4p).

Table 3
Learning errors. The table reports the estimations of pooled OLS regressions with the absolute value of the difference between the probability estimates and the Bayesian posterior calculated based on the prior subjective probability estimates as a dependent variable. *No choice* is an indicator variable that takes the value of 1 for participants without a choice. Standard errors clustered by participant are reported in parentheses. *** denotes statistical significance at $p < 0.001$, ** denotes statistical significance at $p < 0.01$, and * denotes statistical significance at $p < 0.05$.

	$\mid$ Probability estimate$_{i,t}$ – Bayesian posterior with subjective prior$_{i,t}$ $\mid$			
Sub-sample: prior probability estimate	<=50 %	>50 %	<=50 %	>50 %
Sub-sample: risky asset payoff	negative	negative	positive	positive
	(1)	(2)	(3)	(4)
No choice$_i$	−2.341**	−0.163	−1.250	−1.048
	(0.830)	(1.246)	(1.309)	(0.662)
Controls: prior probability estimate, individual characteristics (age, gender, income level, professional education), type of risky asset (good or bad) randomly selected in each round				
Observations	4,775	6,044	3,996	4,520

when they learn from losses and their prior probability estimate is not greater than 50 %. In the rest of the cases, the learning error in the group without a choice is smaller than in the group with a choice, but the differences are not statistically significant.

3.2. *Subsequent risk-taking decisions*

As the previous analysis has shown, risk takers with and without a choice learn differently from losses. After losses, risk takers without a choice are more willing to revise their beliefs than risk takers with a choice. The following analysis explores the question whether those group differences in learning from losses affect the subsequent risk-taking behavior. Additionally, the analysis addresses the question whether the disposition effect differs between risk takers with and without a choice and how much of these differences can be explained by differences in the way investors with and without a choice learn from gains and losses.

3.2.1. *Estimating learning effects on selling decisions*

To be able to disentangle the causal effect of learning from other effects that outcomes may have on the decision to sell, the following analysis uses the mediation analysis framework. In general, the mediation analysis framework aims to elucidate the causal process by which an independent variable affects an outcome. The relationship is decomposed into two causal paths. One links the independent variable to the outcome directly (direct effect) and the other links the independent variable to the outcome though a mediator (indirect effect or mediation effect). The existence of a mediation effect implies that the independent variable causes the mediator, which, in turn causes the outcome (Sobel, 1990).

In the following analysis, the outcome of interest is the decision to sell in each period, which is a dichotomous variable. This requires using non-linear estimation techniques such as logit and probit models. Since linear structural equation modelling usually used to estimate mediation effects are not generalizable to such nonlinear models, the following analysis employs the method proposed by Imai et al. (2010). The method is a general approach of decomposing the total effect by placing the causal mediation analysis within the counterfactual framework of causal inference widely used in statistics. Averaging among all investors of the population, of which the sample can be considered as representative, gives the average causal mediation effect, the average direct effect, and the average total effect.

To gain an indication of the existence of a mediation effect, the further analysis applies the three steps suggested by Baron and Kenny (1986). First, it is evaluated whether there is an effect that can be mediated. As mediation is possible even if there is no significant total effect, it is then evaluated whether there are differences in the probability estimates caused by the independent variable. Finally, it is evaluated whether the estimated differences in selling change after considering the probability estimates as a confounder. Afterwards, the analysis uses the method of Imai et al. (2010) to estimate the size of the direct and the indirect effects in each mediation model.

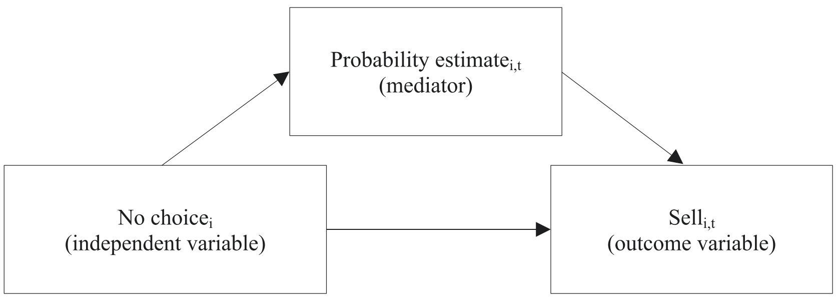

Fig. 3. Mediation model estimating the direct and indirect effect of choice elimination on selling.

3.2.2. Group differences in selling caused by group differences in learning

To estimate whether risk takers without a choice are more willing to reduce their risk exposure after losses than risk taker with a choice because they learn differently after losses, the following analysis estimates the mediation model illustrated in Fig. 3. The main goal of the analysis is to estimate how much of the observed group differences in selling are caused by group differences in learning. The learning effect is estimated for gains and losses separately.

The estimation results after applying the mediation procedure suggested by Baron and Kenny (1986) are reported in Table 4.

The results show that when the payoff of the risky asset is negative, risk takers without a choice are more likely to sell than risk takers with a choice (see Column 1). When the probability estimates are considered as a confounder, the estimated effect of having no choice on selling decreases (see Column 2). This suggests that one part of the effect of restricting choices in decisions is caused by differences in the probability estimates. Such differences are significant, i.e., after losses, risk takers without a choice hold significantly lower probability estimates than risk holders with a choice (see Column 3). After gains, there are no significant differences in the selling behavior of risk takers with and without a choice (see Columns 4 and 5). There are also no significant differences in the probability estimates that could potentially mediate the effect of having a choice on the decision to sell after gains (see Column 6).

This analysis provides evidence of the existence of a mediation effect after losses but not after gains. The method suggested by Imai et al. (2010) makes it possible to decompose the total effect of having no choice on the decision to sell into a direct effect capturing group differences in the decision environment and an indirect effect capturing differences in learning. The estimated decomposition of the total effect is reported in Table 5.

After losses, the estimated total effect of having no choice in investment decisions increases the probability to sell by about 10 %. About one half of the effect (49 %) is caused by lower probability estimates that risk takers with a choice report as compared to risk takers with a choice. The estimated indirect effect of having no choice is positive since risk takers without a choice report more pessimistic probability estimates after losses than risk takers with choice, and lower probability estimates motivate more selling, as evident in Table 4. After gains, there are no significant differences in the selling behavior of risk taker with and without a choice and no significant differences in the mediation effect of holding different beliefs on the quality of the risky asset.

Using an alternative definition of selling as a switch to cash in the group with a choice does not change these results qualitatively (see Table A in the Online Appendix). Neglecting some of the selling decisions in the group with a choice increases only the direct effect of having no choice. The indirect effect remains the same as the effect of the probability estimates on the decision to sell does not depend much on how selling decisions are defined (compare Column 3 and Column 6 of Table 4 with the Column 1 and Column 2 of Table B in the Online Appendix).

The analysis allows the conclusion that restricting choices in decisions motivates different learning from losses and this difference in learning increases the likelihood of selling after losses. At the same time, restricting choices in decision does not change the selling behavior after gains or it might increase it if selling is defined as a switch to cash in both groups. These observations raise the question of whether there are significant differences in the selling behavior after losses as compared to gains. More importantly, the observations raise the question how these differences in selling are related to the way risk takers in each group learn from losses as compared to gains.

3.2.3. Differences in the disposition effect caused by differences in learning

The mediation analysis framework is also used to disentangle the effect of learning from losses as compared to gains from other

Table 4

Estimated effect of having no choice in decisions on the probability estimates and the selling decisions. The table reports the estimated coefficients of pooled OLS regressions (Columns 3 and 6) with the probability estimates at the beginning of each period as dependent variable and pooled logistic regressions (Columns 1, 2, 4, and 5) with the decision to sell at the end of each period as a dependent variable. The decision to sell is captured by the dummy variable *Sell* for whenever investors intentionally reduce their risk exposure in one period as compared to the previous period. *No choice* is a dummy variable that equals one if the participant is in group without a choice and zero otherwise. The individual characteristics used as controls include participants' individual characteristics such as age, gender, income level, and professional education. Standard errors clustered by participant are reported in parentheses. *** denotes statistical significance at $p < 0.001$, ** denotes statistical significance at $p < 0.01$, and * denotes statistical significance at $p < 0.05$.

	$Sell_{i,t}$	$Sell_{i,t}$	Probability $estimate_{i,t}$	$Sell_{i,t}$	$Sell_{i,t}$	Probability $estimate_{i,t}$
Condition: $payoff_{i,t-1}$	negative	negative	negative	positive	positive	positive
	(1)	(2)	(3)	(4)	(5)	(6)
No $choice_i$	0.514***	0.386***	−6.034***	−0.142	−0.163	−1.080
	(0.089)	(0.104)	(1.141)	(0.098)	(0.102)	(1.142)
Probability $estimate_{i,t}$		−0.052***			−0.024***	
		(0.003)			(0.002)	
Constant	−0.705**	1.178***	20.549***	−0.224	1.227***	52.461***
	(0.232)	(0.265)	(3.279)	(0.247)	(0.296)	(3.275)
Probability $estimate_{i,t-1}$	no	no	yes	no	no	yes
Risky asset $type_r$	yes	yes	yes	yes	yes	yes
Controls (individual characteristics)	yes	yes	yes	yes	yes	yes
Observations	12,045	12,045	9,229	8,572	8,572	6,769

Table 5
Direct and indirect effect of having no choice on selling. The table reports the decomposition of the total effect of having no choice in decisions on the decision to sell in terms of marginal effects. The decision to sell is captured by the dichotomous variable *Sell* for whenever risk takers intentionally reduce their risk exposure. The total effect of having no choice is decomposed into a direct effect and an indirect effect through the way choice in decisions influence belief updating. Clustering by subject is applied in all estimations. Controls for participants' characteristics (age gender, income level, and professional education), for the type of the risky asset, and for the prior probability estimates are included in all estimations.

Dependent variable:	$Sell_{i,t}$	$Sell_{i,t}$
Condition: $payoff_{i,t-1}$	negative	positive
Total effect of having no choice	0.094	−0.016
95 % CI	[0.078; 0.110]	[-0.056; 0.024]
Average direct effect of having no choice	0.048	−0.017
95 % CI	[0.017; 0.081]	[-0.055; 0.023]
Average indirect effect of having no choice through learning from payoffs	0.046	0.000
95 % CI	[0.029; 0.063]	[-0.011; 0.011]
Total effect mediated	0.490	
95 % CI	[0.421; 0.598]	
Observations	9,091	6,587

effects that losses may have on the decision to sell. In this framework, the independent variable is the exogenously determined payoff of the risky asset. The mediation model is presented in Fig. 4.

The goal of the analysis is to estimate whether losses motivate different selling decisions in each group as compared to gains (total effect) and whether the effect is caused by differences in way risk takers in each group learn from losses as compared to gains (indirect effect). The mediation procedure suggested by Baron and Kenny (1986) is applied to receive an indication of the existence of a mediation effect. The results of applying this procedure are reported in Table 6.

The results show that when the payoff of the risky asset is negative, risk takers with a choice are less likely to sell than when the payoff of the risky asset is positive (see Column 1). When the probability estimates are considered as a confounder, the estimated effect of losses on the willingness to sell is greater (see Column 2). This observation shows that the negative effect of losses on the willingness to sell is reduced. Indeed, losses motivate lower probability estimates (as in Column 3), and lower probability estimates increase the probability to sell (see Column 2).

In the group without a choice, losses motivate more selling than gains, but the effect is not statistically significant (see Column 4). When the probability estimates are considered as confounders, the estimated effect of losses on the willingness to sell is negative (see Column 5). This observation shows that the negative effect of losses on the willingness to sell is reversed. Indeed, losses motivate lower probability estimates (as evident in Column 6), and lower probability estimates increase the probability to sell (see Column 5). The results of decomposing the total effect of losses as compared to gains on the decision to sell are reported in Table 7.

The results show that losses as compared to gains reduce the willingness to sell in the group with a choice by about 9 %. In the group without a choice, the willingness to sell is about 2 % larger after losses than after gains, but the effect is not significant at the 5 % level. These group differences in the total effect emerge because risk takers in the group with a choice do not reduce their probability estimates after losses as strong as risk takers in the group without a choice and their selling decisions are less sensitive to changes in the probability estimates as evident in Table 6. Consequently, the total indirect effect of losses on the decision to sell is smaller in the group with a choice than in the group without a choice. After considering how risk takers in each group learn from losses as compared to gains, the estimation reveals that losses reduce the willingness to sell in the group with a choice, while the effect is reversed in the group without a choice.

Using the decision to switch to cash as an alternative definition of selling in the group with a choice does not lead to qualitatively different results (see Table C in the Online Appendix). The direct and the indirect effect of losses decrease slightly, but since the indirect effect through belief updating remains smaller than the absolute direct effect of losses, the total effect of losses on switching to cash remains negative in the group with a choice.

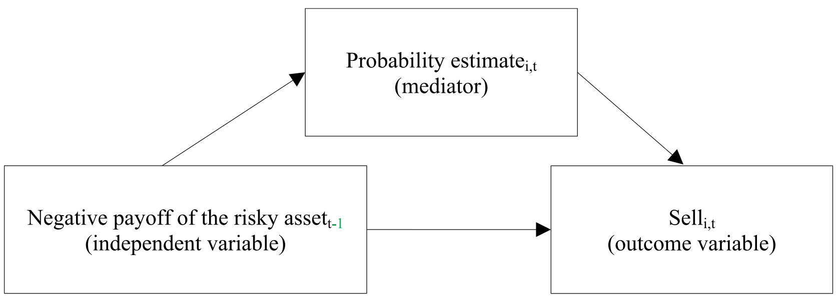

Fig. 4. Mediation model estimating the direct and indirect effect of losses on selling.

Table 6
Estimated effect of losses on the probability estimates and the selling decisions. The table reports the estimated coefficients of pooled OLS regressions (Columns 3 and 6) with the probability estimates at the beginning of each period as dependent variable and pooled logistic regressions (Columns 1, 2, 4, and 5) with the decision to sell at the end of each period as a dependent variable. The decision to sell is captured by the dummy variable *Sell* for whenever investors intentionally reduce their risk exposure in one period as compared to the previous period. *Negative payoff of risky asset* is an indicator variable that equals one if the payoff of the risky asset is negative and zero otherwise. The individual characteristics used as controls include participants' individual characteristics such as age, gender, income level, and professional education. Standard errors clustered by participant are reported in parentheses. *** denotes statistical significance at $p < 0.001$, ** denotes statistical significance at $p < 0.01$, and * denotes statistical significance at $p < 0.05$.

	$Sell_{i,t}$	$Sell_{i,t}$	Probability $estimate_{i,t}$	$Sell_{i,t}$	$Sell_{i,t}$	Probability $estimate_{i,t}$
Condition: $group_i$	Choice	Choice	Choice	No choice	No choice	No choice
	(1)	(2)	(3)	(4)	(5)	(6)
Negative payoff of risky $asset_{t-1}$	−0.421***	−1.630***	−32.878***	0.164	−1.525***	−39.331***
	(0.080)	(0.138)	(1.443)	(0.090)	(0.104)	(1.344)
Probability $estimate_{i,t}$		−0.036***			−0.045***	
		(0.003)			(0.003)	
Constant	0.067	2.412***	53.607***	−0.683***	2.373***	50.717***
	(0.200)	(0.263)	(3.112)	(0.317)	(0.379)	(2.770)
Probability $estimate_{i,t-1}$	no	no	yes	no	no	yes
Risky asset $type_r$	yes	yes	yes	yes	yes	yes
Controls (individual characteristics)	yes	yes	yes	yes	yes	yes
Observations	11,909	11,909	9,359	8,388	8,388	6,319

Table 7
Direct and indirect effect of losses on selling. The table reports the decomposition of the total effect of losses as compared to gains on the decision to sell in terms of marginal effects. The decision to sell is captured by the dichotomous variable *Sell* for whenever risk takers intentionally reduce their risk exposure. The total effect of losses is decomposed into a direct effect and an indirect effect through the way risk takers learn from losses as compared to gains. Clustering by subject is applied in all estimations. Controls for participants' characteristics (age gender, income level, and professional education), for the type of the risky asset, and for the prior probability estimates are included in all estimations.

Dependent variable:	$Sell_{i,t}$	$Sell_{i,t}$
Condition: $group_i$	With choice	Without choice
Total effect of losses	−0.085	0.017
95 % CI	[-0.116; −0.054]	[-0.023; 0.056]
Average direct effect of losses	−0.260	−0.250
95 % CI	[-0.292; −0.224]	[-0.280; −0.218]
Average indirect effect of losses through learning from losses	0.175	0.267
95 % CI	[0.149; 0.202]	[0.235; 0.298]
Observations	11,909	8,388

3.3. Group differences in the investment performance

If risk takers with a choice are more sluggish to revise their expectations after losses than risk takers without a choice, does this affect their investment performance? The investment performance is calculated as the ratio of the investment payoff at the end of each learning round and the endowment at the beginning of the round. In each learning round, either the good or the bad asset is selected. When the bad asset is selected, investors are more likely to see negative payoff than positive payoffs. The analysis uses pooled OLS regressions to estimate whether there are significant group differences in the investment performance of risk takers with and without a choice and whether these differences depend on whether the good or the bad asset is selected. The results of the analysis are reported in Table 8.

The results show that the payoff of investors in the group without a choice is 1 % smaller than the payoff of investors in the group with a choice in rounds when the good asset was selected (see Column 1). When the bad asset was selected, the payoff of the investors without a choice is on average 14 % greater than the payoff of investors with a choice (see Column 2). These group differences in the investment return when the good and the bad asset was selected accumulate to 15 % as the interaction term in Column 3 shows.

These results suggest that investors without a choice achieve better investment returns in rounds in which the bad asset has been selected. In other words, when the returns of the risky asset are more likely to be negative than positive, investors without a choice perform better. In the context of the previous results showing that risk takers with a choice are less likely to sell after losses than after gains, these observations suggest that keeping losses can be costly in tough times when the likelihood for negative payoffs is greater than the likelihood for positive payoffs.

Table 8
Group differences in the investment performance. The table reports estimations of pooled OLS regressions with the investment payoff of each investor at the end of each learning round as a dependent variable. *No choice* is an indicator variable for investors in the group without a choice. *Bad asset* is an indicator variable for whenever investors were making decisions when the bad asset was randomly selected for the corresponding round. All estimations include the personal characteristics (age, gender, income level and professional education) as controls. Standard errors clustered by participant are reported in parentheses. *** denotes statistical significance at $p < 0.001$, ** denotes statistical significance at $p < 0.01$, and * denotes statistical significance at $p < 0.05$.

Dependent variable:	Investment return$_{i,6}$		
Sub-sample	good asset	bad asset	all
	(1)	(2)	(3)
No choice$_i$	−0.012*	0.141***	−0.013*
	(0.005)	(0.007)	(0.005)
Bad asset$_t$			−0.350***
			(0.009)
No choice$_i$ | bad asset$_t$			0.154***
			(0.011)
Constant	1.077***	0.801***	1.114***
	(0.016)	(0.021)	(0.010)
Observations	2,835	2,835	5,670

4. Conclusion

The present paper investigates whether eliminating choices in the risk-taking decisions affects the way investors update their beliefs on the prospects of their investments. More importantly, the paper analyses whether such differences in belief updating can explain differences in the prevalence of the disposition effect. The results show that choices motive investors to hold more optimistic beliefs after losses, which represent a bias when compared to a Bayesian benchmark. This bias in learning induced by choices explain about one half of the effect that choices have on the willingness to sell after losses. Investors allowed to make choices also achieve a significant lower return in rounds when negative payoffs were more likely. Regarding the disposition effect, the analysis shows that eliminating choices in risk taking decisions eliminates the effect. Causal mediation analysis allows the conclusion that the effect is eliminated because investors without a choice are more willing to revise their beliefs after losses than the other investors.

In addition to extending our understanding of how investors learn from new information and why the disposition effect emerges, the results can be used to shape the collaboration process of individual investors and financial advisors. The results suggest that the performance of individual investors can be moderated by measures that influence the individual involvement in the investment process. Individual investors learn better from new information in the face of adverse information associated with losses, if they do not choose the risk exposure that determines the size of their losses. This improved learning from adverse information help them avoid holding losers, which improves their investment performance in times when losses are more likely than gains.

Future research is needed to further examine the hypothesis that the way previous decisions are made has implications for how people learn from feedback on these decisions. It will be interesting to examine whether the effect changes if decision-makers choose among different managers and whether it matters if the manager is virtual or human. Another promising direction would be to examine how to eliminate the bias in the beliefs without delegating responsibility. For example, could interventions be designed to reduce the salience of previous decisions? Or there are personal characteristics that can be cultivated to reduce the emotional bias in belief updating? Finally, the idea that beliefs depend on the cognitive dissonance with the associated decisions may be included in models of decision-making under uncertainty to yield novel predictions about individuals' risk-taking on financial markets.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.joep.2024.102718.

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