Watch out for Bears: Information Processing in Perceptual vs. Financial Decisions

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Abstract

Financial decisions such as those involved in stock trading should, at least partly, be based on similar features as detecting trends in time-series data. When presented as a purely perceptual task, people's accuracy in detecting trends is generally considered good, but real-world individual investors underperform the market globally. In a series of controlled experiments, we contrast financial decisions to perceptual ones, presenting participants with real-time evolving time series whilst manipulating the reward structure and the context. Our results show that participants' decisions were not affected by trend direction in a classic perceptual decision-making scenario, whilst in a classic trading scenario they performed worse in both speed and accuracy during downward (i.e., bear markets) compared to upward trends (i.e., bull markets). In a final experiment where we carefully controlled the reward structure of both scenarios and the only relevant differentiating factor was the labels of the decisions, we did not find evidence for this difference between scenarios, but participants were slower in the trading scenario. Employing the Drift-Diffusion Model, we found evidence of lower efficiency in the classic trading, compared to the classic perceptual decision-making scenario. Our results provide much-needed insight into the cognitive basis of trading decisions and the general underperformance of real-world individual investors.

Keywords: financial decision making; information processing; evidence accumulation model; investor behaviour

Introduction

Financial decisions, such as stock trading, play an increasingly crucial role in modern economics and finance. However, are individual investors adept at making these decisions? A substantial body of research, encompassing both real-world equity market analyses (Odean, 1998; Barber & Odean, 2000; Barber et al., 2008; Hoffmann, Post, & Pennings, 2013) and laboratory experiments (Weber & Camerer, 1998; Frydman et al., 2014; Frydman & Camerer, 2016; Bazley, Cronqvist, & Mormann, 2021), suggests otherwise. On average, investors have been shown to make significant losses and/or underperform the market, frequently exhibiting a range of behavioural biases. One such bias is the disposition effect (Shefrin & Statman, 1985), whereby investors tend to sell winning stocks prematurely and hold onto losing stocks for too long.

Economic and psychological research highlights the importance of human judgemental forecasting in stock investment (Slovic, 1972; Camerer, 1987; Hilton, 2001; Frydman & Camerer, 2016). Although mainstream economic theories on stock pricing suggest that in an efficient capital market, prices follow a random walk (Fama, 1970), real-life traders base their trading strategy on technical analysis, which aims to mine information underlying the stock prices (Marshall et al., 2006). Consequently, one's ability to discern whether a stock's price is rising or falling can be crucial for technical traders. Whilst other factors undoubtedly influence trading decisions, at their core these decisions represent a trend-detection problem. Previous work has indicated the cognitions underlying perceptual and financial decisions may be similar (Frydman and Nave, 2017). However, there were large differences between the perceptual and trading tasks in that study, which makes direct comparisons difficult.

Stock trading generally features a different reward structure from perceptual decisions. Traditional perceptual decision-making experiments typically incentivise participants based on the simple correctness of their responses (e.g., Balci et al., 2011; Reinagel, 2018). Stock trading, however, introduces a more complex relationship between decision and outcome. The reward of a trading decision depends not only on its correctness (buying when the price will rise, selling when it will fall) but also on the direction of the price movement. For instance, correctly buying a stock that rises yields a gain, while correctly selling a falling stock may result in a loss, albeit a smaller one than when selling later when the price has fallen even further. Thus, the reward is tied to both the *direction* and the *correctness* of the decision. Previous studies documented that people handle rewards and punishment differently (Kahneman & Tversky, 1979; Leknes & Tracey; Ballard et al., 2019), making it possible that trading decisions differ from perceptual ones due to a difference in reward structure.

This study investigates whether trading decisions differ from perceptual decisions, even when both are ostensibly based on the same information and rewards. To investigate this, we present the results of two experiments using traditional reward structures in perceptual and trading tasks,

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and then of a third one where the potential rewards are made exactly equal between trading and perceptual decisions. Our results reveal that participants make slower and less accurate decisions in standard trading tasks compared to perceptual decision-making tasks. Crucially, after equating the reward structure, the difference in accuracy disappears, while the difference in decision time persists.

Experiment 1: perceptual trend detection task

In the first experiment, we investigated human behaviour in a perceptual decision-making task without a financial context. Participants performed a trend detection task where they were asked to indicate if a real-time evolving time series is more likely to increase or decrease in value. To instigate a speed-accuracy tradeoff, rewards for a correct decision decreased with time. In the Penalty condition, they would lose points for an incorrect decision, but the penalty would decrease over time. In the No-Penalty condition, they would not lose points for an incorrect decision.

Participants 45 participants (15 females, M = 30.84, SD = 7.91) from Prolific (http://www.prolific.ac/) participated in Experiment 1 and were paid £4.5 for their participation plus a performance-based bonus of up to £2. [1]Informed consent was obtained from all participants. The study was approved by the UCL Research Ethics Committee (EP/2023/012).

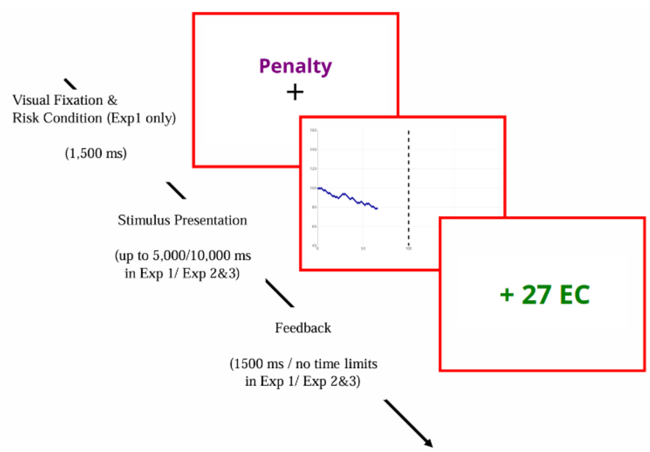

Figure 1. Sequence of an experimental trial. The stimuli are similar in all three experiments, apart from a dashboard presenting numerical stock price (Exp2 & 3) and the balance of points and shares (Exp2).

Procedure and stimuli Following instructions and a comprehension check, participants performed a perceptual decision-making task where they were presented with a line graph evolving in real-time. Figure 1 presents the sequence of a trial. During the main task, the dot marking the current value continuously moves forward and from one moment to the next, moves either upward or downward by 1 unit. Participants were instructed to report whether, on average, the dot is more likely to move upward or downward. In each trial, participants were first presented with a fixation cross for 1,500 ms with text that indicated the risk level (see below). The main stimulus (evolving graph) was then presented, with the dot moving 10 times per second for a maximum of 5,000 ms (each trial ended as soon as a participant made a response). The participants registered their responses through key pressing (Q = up; P = down). In a feedback screen lasting for 1,500 ms, they were informed whether their decision was correct, and the number of tokens they earned or lost. If they did not give a response in the 5,000 ms maximum trial window, they saw a message of “Too Late” and ended the trial with no rewards nor penalties. Participants completed a total of 320 trials.

The experiment used a 2 (trend direction) x 2 (trend strength) x 2 (reward structure) within-subjects design. The manipulations were counterbalanced, which led to 40 trials in each combination of levels, and the order of trials was randomised. Four sets of probabilities of the dot moving upward were randomly assigned to each trial: 65% (++), 55% (+), 45% (-), and 35% (--), as in previous experimental finance literature (e.g., Weber and Camerer, 1998; Frydman et al., 2014). Thus, there are two trends (up vs down), each with two levels of strength/difficulty. Moreover, to investigate whether reward structure shifts participants' decision-making, there were two payoff structures (see Figure 2): a. (Penalty) participants could gain 100 points or lose 100 points if they made a correct/incorrect decision immediately at the beginning of a trial, with these rewards/punishments decaying over time at a fixed rate of 16 points per second; b. (No-penalty) participants could gain 100 points if they made a correct decision immediately at the start of a trial with the reward decaying over time at the same rate as in Penalty condition. If they made an incorrect decision, they would not lose points. The No-penalty condition accounts for a traditional speed-accuracy trade-off, whilst the Penalty condition serves as a closer approximation to investment decisions: investors can trade time for certainty; specifically, investors can gather more information by waiting longer, and the longer they wait, the less uncertain the outcome is and the smaller the size of the reward/penalty is.

Participants were instructed to respond as accurately and as quickly as they could to maximise their rewards. In all experiments, participants were required to answer comprehension questions to ensure they understood the task after reading the instructions, and those who failed to pass this within two attempts were excluded. Demographics were

[1] In Experiment 1 & 2, the bonus is based on the overall performance throughout the experiment: i.e., we summed up the trialwise rewards and penalties and converted the value into bonus. In Experiment 3, we randomly selected a trial and added or subtracted the rewards/penalties to/from a baseline bonus equals £1. The bonus was capped and non-negative across all the three experiments and the computation was explicitly informed to the participants.

collected after the main tasks, and at the end of the experiment, participants were debriefed.

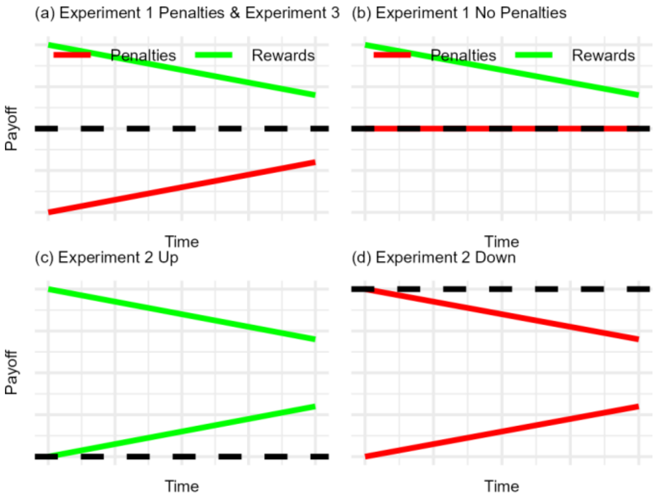

Figure 2. (Expected) Payoff Structures in Experiments. The broken lines indicate a zero outcome.

Behavioural results We first examine whether the speed and accuracy of participants' decisions vary across the scenarios and payoff structures. For all analyses, we used (generalised) linear mixed-effect models (G/LMM), and the maximal feasible random effects structure as suggested by Barr et al. (2013). We removed trials with RTs faster than 200 ms and those without a response from all analyses (375 observations which is 2.64% of the data). Reaction time was log-transformed before analysis. To account for practice effects, we included a "block" factor in all analyses, dividing the trials in four equal-size blocks. We used effect coding for all factors apart from block, for which we used a polynomial contrast code. Figure 3 displays the distribution of the reaction time and the participant-level accuracy rate across treatments in different experiments.

The model for log RT includes fixed effects for trend (2 levels: up vs. down), difficulty (2 levels: easy vs. hard), risk (2 levels: Penalty vs. No-Penalty), and block, as well as all interactions. The maximal feasible model includes a random intercept and slope of Penalty condition at the participant level. Participants responded significantly faster in easy trials ($\beta = -.04, SE = .01, t(13604.98) = -11.65, p < .001$). Responses in No-penalty trials were significantly faster than in Penalty trials ($\beta = -.07, SE = .03, t(42.59) = -2.37, p = .022$), and decision time decreased significantly by block [2] (linear effect: $\beta = -.03, SE = .007, t(13605.65) = -3.52, p < .001$; quadratic effect: $\beta = .02, SE = .01, t(13620.40) = 2.55, p = .011$). The log-RT did not significantly vary across trend ($\beta = .01, SE = .01, t(13605.15) = .24, p = .808$), and no significant interactions of trends, risk, or difficulty were observed.

We next employed a mixed-effects logistic regression to analyse the accuracy of decisions. The model includes the same fixed effects as the model of log-RT. The maximal feasible model includes a random intercept and random slope of trend at participant level. Responses in easy trials were significantly more accurate than difficult ones ($\beta = .54, SE = .02, z = 25.48, p < .001$), and this effect is stronger in trials with upward trends ($\beta = .05, SE = .02, z = 2.20, p = .028$). No other fixed effects were significant.

Experiment 2: stock trading task

Next, we investigate participants' decision-making in a stock-trading scenario. Experiment 2 was similar to Experiment 1, but participants were instructed to make trading decisions (i.e., buy vs. sell) here.

Participants 101 participants (30 females, M = 31.78, SD = 9.96) from Prolific were recruited and paid £5.25 plus a performance-based bonus of up to £1.5.

Procedures and stimuli Methods were similar to Experiment 1, apart from the following changes: (1) participants were instructed to make trading decisions (i.e., buying vs. selling one share in the stock), (2) an additional flat trend (50%, O) condition was also introduced, where the price of the stock is equally likely to go up or down from time to time, (3) after a decision was made, participants were shown the evolution of the stock price until the end of the trial at a faster rate, participants performed the task for 200 trials, the payoff structure was changed to better approximate stock trading: at the start of each trial, participants were endowed with 1 share and 150 tokens, and all the shares in their account were sold automatically for the price at the end of the trial. The reward of a trial is the difference between the value of their account at the beginning and the end of the trial. Participants were instructed that to maximise their rewards, they should, as quickly as possible, buy the stock when they think the stock price will go up and sell the stock when they think the stock price will go down.

Due to the trading scenario, the (expected) rewards differ from Exp 1 (see Figure 2). Here, the rewards/penalties depend on both the decision and the trend. In upward trials, participants almost always get a reward, although making an incorrect decision (i.e., selling the endowed share) results in a smaller reward than making a correct one (i.e., buying one more share); in downward trials, on the contrary, participants almost always lose tokens, although making a correct decision (i.e., selling the endowed share) results in a smaller loss than making an incorrect one (i.e., buying one share).

[2] The practice effect was generally stable and consistent across all experiments: participants performed the tasks significantly faster and more accurately in later trials compared to the average, with positive quadratic correlations on log-RT only. We omit description of these results from now on, unless otherwise mentioned.

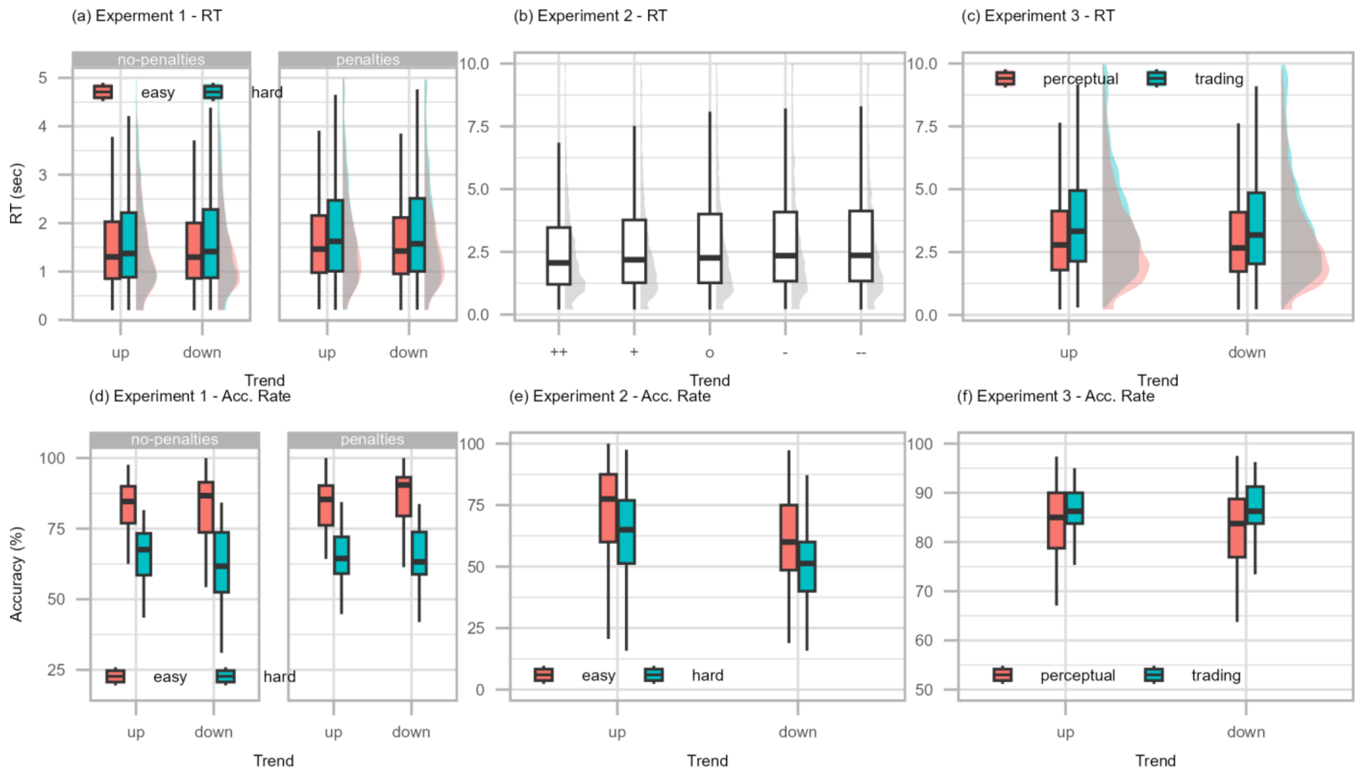

Figure 3. RT and Accuracy rate distributions. All RTs are in seconds, and all accuracy rates are in %. RTs are plotted at trial-level, accuracy rates are plotted at participant-level.

Behavioural results 885 observations were removed according to the excluding criteria. We also excluded from analysis the flat trend trials due to the absence of objective correctness. 15,457 responses were entered into the analyses. We employed an LMM that included fixed effects of trend, difficulty, and block, as well as all interactions. We found that participants were significantly slower in downward trends than upwards trends ($\beta = .05, SE = .01, t(15341.21) = 9.29, p < .001$), and this effect is stronger in easy trials than difficult ones ($\beta = .02, SE = .01, t(15341.04) = 3.00, p = .003$). An additional analysis showed participants spent longer time to sell during downward trends than during upward trends ($\beta = .08, SE = .02, t(15340) = 5.39, p < .001$).

We then analysed the accuracy using a mixed-effect logistic regression. The model included the same fixed effects as the model for log-RT. Participants were significantly less accurate in downward trends compared to upward ones ($\beta = -.19, SE = .09, z = -2.01, p = .044$), and they were more accurate in easy trials compared to difficult ones ($\beta = .19, SE = .02, z = 10.18, p < .001$). Accuracy increased as the experiment progressed (linear effect: $\beta = .15, SE = .04, z = 4.15, p < .001$). No significant interaction between difficulty and direction was found.

Comparison between Experiment 1 and 2

To directly compare the results between Experiment 1 and 2, we performed an additional analysis. Due to the different experimental settings in trial duration and number of trials, we excluded all responses with RT slower than 5 seconds in Experiment 2 and all the trials later than the 200th trial in Experiment 1, so that we had a dataset where observations from both experiments share a maximum reaction time of 5 seconds and from the first 200 trials. 21,677 trials were entered to the analysis.

We used an LMM for log-RT with fixed effects for experiment (2 levels: Exp1 vs. Exp2), trend, difficulty, and block, as well as all interactions. The maximal feasible model includes random intercepts and a slope for trend at participant-level. Participants were significantly faster whilst performing the perceptual task compared to the trading task ($\beta = -.19, SE = .09, z = -2.01, p = .044$). This difference in log-RT was stronger in easy trials ($\beta = -.01, SE = .004, t(98.86) = -3.39, p < .001$) and downward trends ($\beta = -.01, SE = .01, t(21434.15) = -3.56, p < .001$).

A mixed-effect logistic regression was used to analyse the accuracy of decisions. The model includes similar fixed effects as in the model for log-reaction time and the random intercept at participant-level. Participants were significantly more accurate in Experiment 1 than 2 ($\beta = .30, SE = .05, z = 6.69, p < .001$). This difference was increased in easy trials ($\beta = .17, SE = .02, z = 10.82, p < .001$) and trials with downward trends ($\beta = .11, SE = .01, z = 7.04, p < .001$).

These results reveal different decision-making patterns in perceptual choices and investment choices: when trading, participants were less accurate and slower for downward vs upward trends, and generally less accurate and slower compared to participants detecting trends. The latter participants did not show asymmetrical performance in detecting upward and downward trends. However, it is noticeable that besides the scenarios (perceptual vs financial decisions), the reward structures are also different in our first two experiments. For a direct comparison between perceptual and financial decisions, a more strictly controlled experiment is needed, where only the context of both decisions differs.

Experiment 3: perceptual vs. financial decisions with identical payoffs

Participants 120 participants (51 females, M = 30.60, SD = 9.74) from Prolific were recruited and paid £5.55 plus a performance-based bonus of up to £2. Participants were randomly assigned to either the perceptual or trading condition, and there were 60 participants in each condition.

Procedures and stimuli Experiment 3 uses similar methods as the previous ones. In both conditions participants were told that the time-series concerned stock prices. Participants in the perceptual condition were instructed to judge whether the stock price is more likely to increase or decrease, while those in the trading condition were instructed to decide whether to buy or short-sell the stock. The stimuli and the user interaction were the same in both conditions, except for the labels. We eliminated the difficulty for simplicity and the probability of a stock price increase was either 60% (upward) or 40% (downward), and the participants were informed explicitly the possible probabilities of upward movements. We also tried to keep the instructions for both conditions as similar as possible. The maximum duration of a trial was 10,000 ms and participants performed a total 160 trials.

To ensure that the payoff structures are identical for both conditions, the two options for participants in the trading condition were to buy one share in the stock or to short-sell one share in the stock[3]. At the end of each trial, all the remaining shares were automatically sold, and all the borrowed shares are automatically repurchased. Thus, the trial-wise gain/loss is the difference between the price at decision and the price at the end of a trial. The expected payoff in Experiment 3 is the same for both conditions and the same as that in the Penalties trials in Experiment 1.

Behavioural results 202 trials were removed according to the excluding criteria, which accounts for 1.05% of the dataset. The final sample has 18,998 responses. We used an LMM with a fixed effect of condition (2 levels: perception vs. trading), trends, and blocks, as well as their interactions to test whether log-RT varies across manipulations. The model includes a random intercept and slope of trends at participant-level. Participants were significantly faster in the perceptual compared to the trading condition ($\beta = -.09, SE = .04, t(117.99) = -2.31, p = .023$), and in later blocks compared to earlier ones ($\beta = -.03, SE = .01, t(18753.82) = -4.65, p < .001$), and the latter effect was larger in the perceptual condition ($\beta = -.03, SE = .01, t(18753.82) = -4.18, p < .001$). Contrary to Experiment 2, participants were faster in downward trends than upwards ones ($\beta = -.01, SE = .01, t(116.63) = -2.77, p = .007$). No other significant effects were found.

We also employed a mixed-effect logistic regression to analyse the accuracy of decisions. No significant main effects or interaction of condition and trend were found. The accuracy increased by block ($\beta = .22, SE = .04, z = 5.53, p < .001$), but this practice effect was inhibited in the perceptual tasks ($\beta = -.15, SE = .04, z = -3.86, p < .001$).

Computational modelling

To investigate the cognitive mechanisms that may lead to the difference across scenarios and reward structures, we used a well-developed computational model: the Drift Diffusion Model (DDM, Ratcliff, 1978; Ratcliff & McKoon, 2008). The DDM assumes that relative evidence, which follows a Brownian motion, is accumulated towards two decision boundaries, and a decision is made once sufficient evidence has been collected and the relative evidence exceeds one of the bounds. There are four key parameters in the DDM: the drift rate (v), which reflects the strength of information or the efficiency of the information processing; the boundary separation (a), which reflects the quantity of evidence required to make a decision; the initial bias (z), which reflects the decision-makers' preference to the options; and non-decision time (t0), which accounts for the time consumed in non-decision processes like sensory encoding and motor execution. We fitted the DDM to individual participant data by maximum likelihood.

Information processing efficiency We allowed information processing efficiency (drift rate) to vary across risk, trends, and difficulty in Experiment 1. The linear model includes risk, trends, and difficulty, as well as their interactions as independent variables. Figure 4 presents the distribution of individual-level model parameters across all three experiments. Participants showed significantly higher drift rate in easy trials ($\beta = .25, SE = .02, t(352) = 15.25, p < .001$). No other significant effects were observed.

We fit a similar DDM for Experiment 2, where information processing efficiency was allowed to vary across trends and difficulties. The model reveals a similar effect of difficulty as in Experiment 1 ($\beta = .07, SE = .02, t(400) = 4.07, p < .001$). However, in Experiment 2, participants had significantly lower information processing efficiency in downward trends compared to upwards ones ($\beta = -.08, SE = .02, t(400) = -4.95, p < .001$).

[3] Short selling is a way for an investor to profit if the target stock price falls. By deciding to short-sell, participants will borrow one share from a hypothetical lender and sell the borrowed share in the stock immediately for the current price. The option to short sell is described as "borrow and sell" in the instruction rather than being put as "short sell" to avoid confusing participants with the jargon.

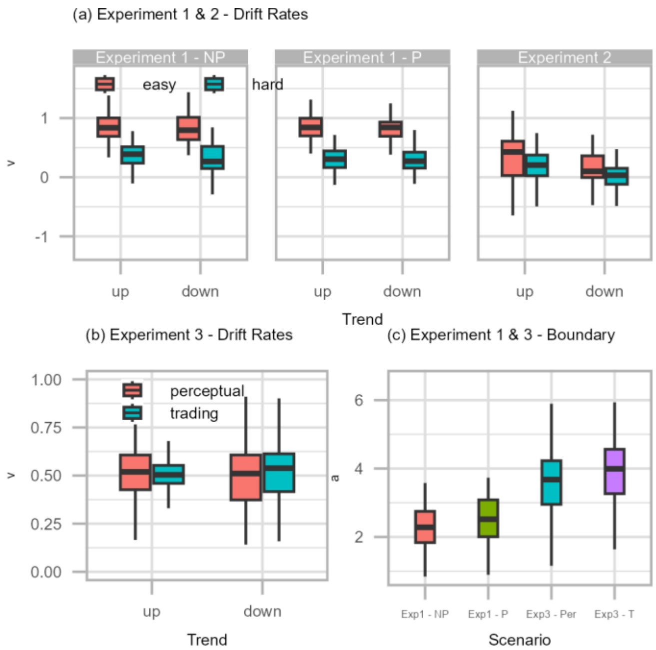

Figure 4: Distribution of DDM parameters. Exp 1 P/NP = Penalties/No-penalties; Exp 3 Per = perceptual condition; Exp 3 T = trading condition; v = information processing efficiency; a = quantity of required information. All model parameters are plotted at participant-level

Directly comparing the parameters between the first two experiments, participants in Experiment 2 showed significantly reduced information processing efficiency compared to Experiment 1 ($\beta = -.29, SE = .016, t(756) = -18.25, p < .001$), and the difference is further enhanced in downward trends ($\beta = -.03, SE = .02, t(756) = -2.19, p = .029$) and in easy trials ($\beta = -.12, SE = .02, t(756) = -7.93, p < .001$).

Finally, we also fitted the DDM to responses in Experiment 3 and allowed the drift rate to vary across trends and conditions. The effect of the trend on information processing efficiency of Experiment 2 was not found in Experiment 3. Moreover, we did not find significant effects of the condition on information processing efficiency.

Amount of required information We next considered the amount of evidence required for a decision, which we assumed to be determined by pre-trial factors only. Therefore, boundary separation was allowed to vary across conditions in Experiment 1 & 3, but to only vary across participants in Experiment 2. We found no effect of risk in Experiment 1. In the experiment-wise comparison, participants in Experiment 2 required more information than in Experiment 1 ($\beta = .60, SE = .074, t(189) = 8.06, p < .001$). In Experiment 3, participants in perceptual conditions required less evidence on average, but the difference was not significant ($\beta = -.18, SE = .10, t(118) = -1.84, p = .068$).

Discussion

Comparing a classic perceptual decision-making and trading scenario, we found that participants were generally slower to make trading decisions. This effect of scenario was maintained in the final more controlled experiment, where the expected rewards were the same and the only real difference being the labels of the decisions (up/down vs buy/sell). One straightforward explanation for the increase in RT in trading decisions is the perceptual decision whether the share price is increasing or decreasing is required in both, but that to trade this decision needs to be further translated into a buy or sell decision. Alternatively, the results may be due to different cognitive processes underlying perceptual and financial decisions. Note that although previous work (Frydman and Nove, 2017) revealed common cognitive mechanisms, their work did not strictly control the task structure. Other explanations are of course possible, and further research is needed to arbitrate between these.

Considering Experiment 2, we found that participants' trading decisions were poorer in downwards compared to upwards trends. This is consistent with the disposition effect (Shefrin & Statman, 1985; Weber & Camerer, 1998; Barberis & Xiong, 2009). We did not find this effect in Experiment 3. One important difference between Experiment 2 and 3 is that in the former, in a downward trend, participants would always be expected to lose, whether making a correct (selling) or incorrect (buying) decision. In the downward trends of Experiment 3, participants could gain points in expectation after a correct (short-selling). The difference in results between Experiment 2 and 3 could therefore be due to a general difficulty with making decisions in a loss domain (e.g. Ballard., 2019). Although further examination is necessary, our results therefore reveal a potential alternative explanation for the disposition effect: investors fail to sell out losing stocks earlier than optimal due to the loss-only payoff in selling stocks during a downturn. A general bias towards suboptimal decision making during downward trends could be reduced by introducing short-selling as an alternative action. Short selling is constrained or prohibited in many countries and territories, and not commonly practiced even in markets that have relatively limited restrictions on short-selling (Jain et al., 2013), but our results reveal the potential bright side of short-selling in protecting investors, especially during "bear" (downwards) markets.

By contrasting perceptual and trading decisions in experimentally controlled conditions, we believe the three experiments presented here provide an important initial step in uncovering the cognitive principles underlying financial trading decisions. By uncovering these principles, we may not only learn to better predict financial markets but may also devise techniques to help traders overcome biases and help them make better decisions.

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