Belief in Mean Reversion and the Disposition Effect:

An Experimental Test

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Current Version: October 28, 2013

Abstract

The disposition effect refers to the investors' tendency to disproportionately sell more gaining assets than losing ones. This paper experimentally evaluates two of its important competing behavioral mechanisms: belief in mean reversion and prospect theory. In the experiment, fully 61% of the participants significantly exhibited the disposition effect. I use the participants' elicited risk preferences, and beliefs about price movements to explain their selling decisions, and find that belief in mean reversion alone explains 17% of the between-subject variation in the disposition effect. The prospect theory parameters and demographic variables turn out to be insignificant after controlling for beliefs. Additionally, the results from a goodness-of-fit test on the predicting performance of the two models also favor the belief mechanism.

JEL classification: C91, D03, G02

Keywords: the disposition effect, belief in mean reversion, prospect theory, experimental test

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I. Introduction

Despite the common adage to "let your profits run and cut your losses," which has been embedded in various forms of investor education, individual investors in the financial markets often do the opposite. Studies constantly show that they follow the impulse to sell winning stocks but are reluctant to sell losing ones. In doing so, they commit one of the most robust mistakes discovered in empirical finance, the disposition effect.

This effect, first documented by Shefrin and Statman (1985), refers to the tendency to disproportionately realize more gains than losses in the investment portfolio, affecting various types of investors in the markets of a wide range of asset classes.[1] However, for almost three decades, the profusion of studies on the disposition effect have not uncovered its cause. My paper contributes to this literature by presenting evidence on the behavioral mechanism underlying the disposition effect, comparing the largely neglected belief in mean reversion explanation to the long-standing prospect theory explanation using a lab experiment. A thorough understanding of this mechanism can potentially refine predictions on investors' behavior and more effectively improve their performances.

In the beginning, researchers attempted to rationalize the disposition effect under the neoclassical assumptions, making allowance for portfolio rebalancing, transaction costs, and private information in investors' portfolio optimization, but without success (e.g. Odean, 1998).[2] Studies repeatedly find the fully rational explanations fail to account for all aspects of the disposition effect observed in the field and the lab.[3]

The sub-optimality of the disposition effect directs our attention to explanations that

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[1] For example, among individual investors in the common stock market (Odean, 1998; Grinblatt and Keloharju, 2001), professional futures traders (Heisler, 1994), individual commodity and currency traders (Locke and Mann, 2005), mutual fund managers (Wermer, 2003; Scherbina and Jin, 2005), home sellers (Genesove and Mayer, 2001), and so forth. Experiments, such as that in Weber and Camerer (1998), also successfully replicate behavior consistent with the disposition effect in the lab. O'Connell and Teo (2009) find that institutional currency traders have no disposition effect.

[2] Using individual brokerage account data, Odean (1998) shows that the selling of entire winning positions is too aggressive for portfolio rebalancing and that the repurchasing of more losers than winners conflicts with the incentive to avoid high transaction costs.

[3] See, e.g., Brown et al., 2006 and Vlcek and Wang, 2008.

acknowledge investors' psychological biases and heuristics. Prospect theory, suggested by Shefrin and Statman (1985),[4] has been the most commonly referenced mechanism in the literature. Prospect theory can generate the disposition effect with its assumption of loss aversion (Meng, 2011), asymmetric risk attitudes (Gomes, 2005), or the two combined (Barberis and Xiong, 2009). However, some recent studies question the validity of this approach, by demonstrating that prospect theory does not generate the disposition effect with its usual parameterizations (Barberis and Xiong, 2009), by showing in an intertemporal choice model that investors would not buy the assets on which they may later exhibit the disposition effect (Hens and Vlcek, 2005), and by finding a lack of correlation between the prospect theory parameters and the disposition effect observed in the lab (Vlcek and Wang, 2008).

While allowing for the role of the preference-based approach, this paper compares its explanatory power for the disposition effect to that of the belief-based approach. Odean (1998) first suggests the possibility that belief in mean reversion, i.e. the belief that winning stocks will decline while losers will regain value, may lead to the disposition effect. But he shows that stock prices do not mean-revert in his data and points out investors may still hold biased beliefs of mean reversion. His data and methodology do not allow for the direct test of beliefs. Since then, papers following this line of reasoning provide at most scant and inconclusive evidence. Empirical studies (e.g. Lehenkari, 2012) could not directly observe beliefs, meeting the same difficulty as Odean (1998), while experiments so far (e.g. Chui, 2001 and Kadous et al., 2011) are not designed to directly measure beliefs. Some indirect evidence (e.g. Odean, 1999 and Barber and Odean, 2004) reveals that investors' buying and repurchasing decisions are inconsistent with belief in mean reversion. Yet no evidence suggests the same pattern of beliefs applies when investors are buying as when they are selling.[5] To the knowledge of this author, there has not been any direct evidence relating belief in mean reversion to the disposition effect.

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4 Shefrin and Statman (1985) explain the disposition effect by combining prospect theory with three other behavioral biases: mental accounting, regret aversion and self-control.

5 Standard economics assume that people use the Bayes' Rule, regardless of whether they are buying or selling. However, behavioral theories, such as wishful thinking or desirability bias (Mayraz, 2011), suggest that holding the asset to sell may bias beliefs.

My experiment is adapted from the Weber and Camerer (1998)[6] design, with simplified decision tasks and the elicitation of risk attitude parameters and beliefs. The participants were randomly assigned to one of three conditions, Predict, Sell and Both. The first stage was the same across conditions, asking the participants to choose between a lottery and a certainty amount in each question, in order to structurally estimate their risk preference parameters in the domains of gains and losses. In the second stage, the participants in condition Predict saw 10-period price sequences of 50 hypothetical assets and guessed the probability that the price would go up after the 10th period; the participants in condition Sell were endowed with 10 shares of each asset at the initial price,[7] observed the prices and decided how many to sell after the 10th period, knowing that unsold shares were to be automatically sold at the predetermined 11th-period price; the participants in condition Both completed both tasks. Each price sequence was generated by one of two equally likely stochastic processes known to the participants. The advantage of using a lab experiment is the direct elicitation of the participants' beliefs when they make the selling decisions, which enables a direct test of the beliefs approach.

This experimental design rules out another potential mechanism, self-justification, which holds that investors are reluctant to sell losers because selling a position at loss is equivalent to admitting previous mistakes (Kaustia, 2010), inconsistent with a positive self-image.[8] However, this explanation still lacks formal tests or convincing evidence.

Participants in this experiment sell on average 50% of the shares on sequences ending in gains, but only 36% on sequences ending in losses, where gains and losses are measured in the 10th period relative to the initial prices. I measure the disposition effect using the difference between the percentages of gains and losses realized following Odean (1998). Although the magnitude of this measure varies across participants, 61% of them exhibited significant disposition effect.

I define belief in *mean reversion* as the belief that the price is more likely to go up (or down), when there are more downs (or ups) in the sequence, and the belief of *continuation* as the

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[6] Henceforth, WC.

[7] Participants don't make buying decisions. This is to eliminate the psychological motive of self-justification in making selling decisions.

[8] In this sense, investors are reluctant to sell losers because doing so may cause cognitive dissonance (e.g. Falk and Zimmermann, 2011).

opposite. I use a measure of belief in mean reversion modified from Asparouhova et al. (2009) and find a considerable amount of beliefs in both continuation and mean reversion.

To determine the relationship between the observed disposition effect and the two competing mechanisms, I conduct analyses at the decision level and at the individual level. Firstly, I use regressions at the decision level to correlate selling decisions with the reported beliefs and the parameters of risk preference. The optimal strategy of an agent with Bayesian beliefs in this experiment is to hold most, if not all, winners and sell all losers. Actual selling decisions are attributable to participants' beliefs, but inconsistent with choices of a Bayesian decision maker. Stronger belief in mean reversion correlates with selling more winners and fewer losers. Controlling for beliefs, the participants' risk preference parameters are significant in explaining selling decisions only in the domain of losses, but the sign goes against the predicted direction. Between the two competing explanations, beliefs provide a better goodness of fit.

Consistent with Dhar and Zhu (2006), I find considerable between-subject variation in the strength of the disposition effect. Additional regression analysis reveals that participants with greater tendency to believe in mean reversion sell more winners and fewer losers, contributing to stronger disposition effect. This is compatible with the predictions of Hung and Yu's (2006) model with agents of heterogeneous beliefs. Beliefs alone explain 17% of the variation in the disposition effect across participants. The prospect theory parameters are insignificant in explaining participants' propensity to sell winners and marginally significant in the domain of losses; neither is significant in explaining the individual level disposition effect. No demographic variable measured demonstrates an influence on the disposition effect, except that participants with college level statistics backgrounds tend to realize more winners, but hold fewer losers.

Additionally, I conduct a simulation to compare the goodness of fit of the two competing mechanisms. I use the elicited risk attitude parameters and the reported beliefs to simulate selling decisions, and then predict magnitudes of the disposition effect for all participants. Four models are compared: (1) the benchmark model with risk-neutral expected utility and Bayesian beliefs, (2) risk-neutral expected utility with the reported beliefs, (3) prospect theory utility with

Bayesian beliefs and (4) prospect theory utility with the reported beliefs. Prediction performances are measured by root mean squared errors (RMSE).[9] Model (3) fits best, lowering the RMSE by 76.5% from the benchmark; introducing actual beliefs to the benchmark lowers the RMSE by 70.4%; incorporating prospect theory makes a smaller improvement, only lowering the RMSE by 61.7%. This suggests that beliefs are more important in generating the disposition effect than prospect theory in this experiment.

I also evaluate the alternative explanation of realization utility (Barberis and Xiong, 2012), which posits that people derive utility from realizing gains or losses and that they prefer realizing gains, which boosts utility. Realization utility, combined with an appropriate discount factor, does not rely on other biases to generate the disposition effect. Putting it in the context of this experiment, realization utility predicts that participants realize more winners than losers even after controlling for risk attitudes and beliefs. However, I find the opposite: participants behave as if they prefer realizing losers after controlling for beliefs and prospect theory risk preferences.

The organization of the paper is as follows: Section II introduces the related literature; Section III develops the hypotheses; Section IV explains the experimental design and procedures; Section V presents the results; Section VI offers concluding remarks, with a discussion of the implications and future research directions.

II. Related Studies

There are quite divergent views regarding the link between belief in mean reversion and the disposition effect. In studies such as Chui (2001) in the lab and Hartzmark and Solomon (2012) and Borghesi (2012) in sports-race betting, the authors doubt this link based on evidence for the disposition effect in an environment without belief in mean reversion, as the authors claim, due to clear experimental instructions, the structure of the market, etc. The problem with this conclusion is that mean-reverting beliefs can possibly emerge even when the price sequences do not mean revert. WC and Vlcek and Wang (2008) both find experiment participants believing in

[9] RMSE is calculated as the square root of the mean of squared deviations from the predicted values to the actual values.

mean reversion despite that the instructions preclude this as a possibility. Another view rejects the beliefs approach by arguing that belief in mean reversion would logically lead to behavior that contradicts the disposition effect. For instance, Kaustia (2010) posits that investors, believing in mean reversion, would exhibit the reverse disposition effect for stocks with paper gains (or losses) and bad (or good) recent performance. However, the validity of this argument depends on whether belief in mean reversion and the evaluation of gains and losses are relative to the entire holding period, or just recent outcomes, or even some other criteria.

Some empirical (Ranguelova, 2001) and experimental (Vlcek and Wang, 2008) studies favor the beliefs approach. The former reports that analysts' advice reduces the disposition effect, because analysts are good at predicting trends; the latter finds that participants use belief in mean reversion as the justification for sales. Hung and Yu (2006) construct a portfolio-choice model with agents holding heterogeneous beliefs and show that those who predict more reversals in returns exhibit more severe disposition effect. This proposition is tested in my experiment.

My design retains some key components of WC and Weber and Welfens (2007), but has substantial modifications. WC test the last-period price and the purchase price as the reference points under prospect theory. In their seminal experiment, participants buy and sell six artificial assets, each following one of six stochastic processes with drifts. To determine the price each period, the direction of price movement is first decided according to the underlying process, and the price change magnitude is randomly selected from three possible values. They have two conditions: one asks the participants to make selling decisions, while the other lets the computer automatically sell all shares after each period.[10] The authors find both reference points valid, but a substantial reduction of the disposition effect in the automatic selling condition, inconsistent with belief in mean reversion, which predicts the repurchase of automatically sold losers and an un-attenuated disposition effect. However, WC also find the purchase of additional losing shares towards the end, as if the participants mistakenly believed those shares would bounce back.

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[10] Experimental procedures similar to this were replicated and the disposition effect found by Chui (2001) in Macau and by Da Costa, Jr. et al. (2008) in Brazil. Oehler et al. (2002) and Kirchler et al. (2004) provide more experimental evidence of the disposition effect.

Like WC, I use predetermined price sequences with known price-generating processes, instead of using sequences adapted from real-world assets. The advantage of this is an objective Bayesian posterior belief that can be used as a benchmark. Furthermore, it is common knowledge that the underlying price movement is i.i.d., making mean-reverting beliefs fallacious, so that the experiment is a strong test of belief in mean reversion. All participants view the same sequences in randomized orders.

This experiment does not include the buying decisions of WC. I endow the participants with each hypothetical assets at the initial price; they observe the sequence and decide how many to sell after 10 periods.[11] This paper is not the first to exclude buying decisions—Weber and Welfens (2007) find the disposition effect in a design with only selling decisions in a hypothetical real estate market. There are several reasons for this design choice. Firstly, multiple buying decisions complicate the reference point.[12] In this study for subjects endowed with the assets in the 1st period, the initial price is the plausible reference point, the validity of which has been shown in several studies (e.g. Weber and Camerer, 1998 and Genesove and Mayer, 2001). Secondly, eliminating buying decisions reduces the task to a binary choice between selling and holding the asset in the last period. The model in the next section has very clear predictions on behavior in such a circumstance, allowing for a sharp test of theory. Thirdly, this also eliminates the impact of self-justification, or cognitive dissonance: the initial positions are not self-selected, avoiding the participants' attribution of winning or losing to own talent and/or skill.

Instead of using three possible price change magnitudes as in WC, I use a fixed price change magnitude to eliminate the possibility that the price crosses the reference point (the initial price) in the final period. So when a participant makes the selling decision, the prospect is either fully in the domain of gains or fully in the domain of losses. This further simplifies the task, making asymmetric risk attitudes the only component in prospect theory that may cause the disposition

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[11] I do not let the participants make selling decisions in every period, because theoretical predictions on behavior become complicated with multiple selling decisions.

[12] Hens and Vlcek (2011) include buying decisions in their model for the disposition effect, and argue that the disposition effect, in conventional analyses, are *ex post* disposition effect, without justification for the initial purchase decision.

effect in this context, rendering loss aversion irrelevant.

Additionally, several studies point out that the disposition effect may diminish with experience (e.g. Feng and Seasholes, 2005 and Dhar and Zhu, 2006); more generally, trading frequency may reduce behavioral biases in experiments (List, 2003). With high-frequency decisions, the potential learning effect is a confounding factor in this experiment. To mitigate learning, I allow the participants to make only one selling decision after the last period, so that they do not get feedback after each decision. And, I refrain from immediately showing them the actual predetermined 11th-period prices. To reduce their worries about deception, the participants were told they could view those prices after the experiment.

Although the current design avoids the issue of multiple reference points, participants may still use historical prices as the reference point (Gneezy's, 2005). To alleviate this, I make historical extreme prices less salient by letting the participants see all prices of each sequence concurrently on a chart, instead of seeing them evolve over time.

III. Theoretical Framework and Hypotheses

Both belief in mean reversion and prospect theory may give rise to behavior consistent with the disposition effect. This section builds the theoretical framework of beliefs and preferences and generates hypotheses regarding the disposition effect, under the null hypothesis that belief in mean reversion does not correlate with the disposition effect.

A. The Biased Belief in Mean Reversion

Conventional economic agents use new information to update beliefs in a Bayesian manner, but people in the real world are, in fact, clumsy in applying the correct statistical rules to everyday decisions (e.g. Kahneman and Tversky, 1972). Suppose an agent faces the following problem: she observes a sequence of N independent binary outcomes (Up or Down) generated by one of M stochastic processes, each having a probability of Up equal to θ_j, j=1, 2 … M, so the probability of Down is $1-\theta_j$. Suppose the prior probability of the sequence being generated by process j is π_j. In order to figure out which stochastic process is the one that generates the observed sequence, the agent forms a Bayesian posterior, denoted by $\hat{\pi}_j$, after observing a sequence with the number of Ups equal to I, according to the following formula:

(1) $$\hat{\pi}_j = \Pr(\theta_j \mid I) = \frac{\Pr(I \mid \theta_j)\pi_j}{\Pr(I)},$$

where $\Pr(I) = \sum_{j=1}^{M} \Pr(I \mid \theta_j)\pi_j$ and $\Pr(I \mid \theta_j) = \begin{pmatrix} N \\ I \end{pmatrix} \theta_j^I (1-\theta_j)^{N-I}$. Therefore, if asked to assess the probability of the next outcome being Up after the last one, a Bayesian agent would predict $\Pr(\mathrm{up} \mid I) = \sum_{j=1}^{M} \theta_j \hat{\pi}_j$. In forming a Bayesian posterior, the only factor that matters is the number of Ups and Downs in the sequence. So a simple way to apply the Bayes' rule in this hypothetical setting is to infer that the sequence with more Ups than Downs is more likely generated by the upward-drifted process, and vice versa. Furthermore, in this experiment I use only two equally likely underlying processes with $\theta_1 = 65\%$, $\theta_2 = 35\%$, then observing more Ups than Downs makes the agent believe the underlying process is more likely the upward-drifted one, thereby predicting a larger probability for the next outcome to be Up, and vice versa.

Suppose, the agent is endowed with one share of the asset at P_1, holds the asset for 10 periods and then must choose between selling at P_{10} and holding the asset until period 11, at which time she would be forced to sell all shares at P_{11}. The price could only increase or decrease by ΔP each period. The simplest preference under uncertainty, the risk neutral expected utility, predicts that the agent would compare the certain utility from selling with a profit of $P_{10} - \Delta\ P_1$ with the expected utility from holding, either getting $P_{10}+\Delta P-P_1$ or $P_{10}-\Delta P-P_1$. A Bayesian agent assigns a higher probability to $P_{10}+\Delta P-P_1$, when there are more Ups than Downs, and vice versa. Therefore, she would hold when there are more Ups,[13] and sell otherwise.

Alternatively, facing the same problem, a risk-averse agent would hold the winning share if

[13] Equivalent to $P_{10}>P_1$. Winning share here necessarily have more Ups, because there is only one possible price change magnitude.

she believes the probability of the price going up is sufficiently large, but could possibly sell it if this probability is not large enough; she would more certainly sell the losing share than a risk-neutral agent, leading to a weaker tendency to hold winners, but a stronger tendency to sell losers, still suffering from no disposition effect[14]. Therefore, the optimal strategy of a Bayesian expected utility maximizer is to hold most, if not all, endowed shares on sequences with more Ups than Downs and to sell all when there are more Downs, exhibiting no disposition effect.

However, if the participants believe instead that price sequences mean revert, they can exhibit the disposition effect even with standard expected utility.[15] Belief in mean reversion (more conservative than a Bayesian, who always believes in continuation) leads to the willingness to sell winners and to hold losers. Thus, if participants in this experiment believe in mean reversion and that causes the disposition effect, the correlation in Hypothesis 1 should emerge.

Hypothesis 1: Stronger belief in mean reversion correlates with stronger propensity to sell winners and to hold losers, and with a stronger individual-level disposition effect.

B. Prospect Theory

The prospect theory value function extensively used in the literature takes the following form:

(3)
$$U(x)=\begin{cases} x^{\alpha} & \text{if } x\geq 0 \\ -\lambda(-x)^{\beta} & \text{if } x<0 \end{cases},$$

where x is the gain or loss relative to a chosen reference point; $\lambda>1$, measuring loss aversion; $0<\alpha,\beta<1$, reflecting the risk preferences in the domains of gains and losses. According to the estimation of Tversky and Kahneman (1992), λ takes the value of 2.25; α and β are 0.88. The estimated values of these parameters can differ considerably under different circumstances. Even with Bayesian beliefs, prospect theory readily generates the disposition effect, with its component of either loss aversion, or diminishing sensitivity (or the dual risk attitudes), or both. With loss aversion, investors exhibit first-order risk aversion (Rabin, 2000), when facing the

14 Because the disposition effect is about a larger tendency to sell winners than losers.

15 For instance, Hung and Yu's (2006) model, disposition investors have standard CRRA utility, but believe in mean reversion.

possibility of crossing the reference point.[16] However, in making selling decisions, arguably, it does not always involve comparing a gain and a loss from the reference point; in such cases, the dual risk attitudes of prospect theory can give rise to the disposition effect. This paper focuses on the latter, allowing for the participants' risk aversion in the domain of gains and risk seeking in the domain of losses as the only component of prospect theory to cause the disposition effect.

To see how the dual risk attitudes lead to the disposition effect, suppose the agent places each asset in a separate mental account: capital gains push her into the concave risk-averse segment of the value function, so that even with $\Pr(up \mid s) > 0.5$ if this probability is not large enough, she would still sell the asset to secure the gain; meanwhile, when the agent faces a loss and steps into the convex risk-seeking segment, she would hold even when $\Pr(up \mid s)$ is below 0.5, as long as it is not too small.[17] This gives rise to the possibility of selling more winners than losers. Therefore, with the asymmetric risk attitudes, the agent can exhibit the disposition effect, even if she weakly believes in continuation, because the chance of doing worse looms larger than that of doing better. Hypothesis 2 deals with the correlation between risk attitudes and the disposition effect.[18]

Hypothesis 2: Controlling for beliefs, stronger risk aversion in the domain of gains and stronger risk seeking in the domain of losses correlate with a stronger disposition effect.[19]

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16 See, for example, Meng (2011) for a model that generates the disposition effect with the loss aversion component of prospect theory using expected return as the reference point.

17 Note that *s* represents the observed sequence; $\Pr(up|s)$ is the belief that the next outcome is Up given the sequence. This is different from the previously defined $\Pr(up|I)$ where *I* represents the number of Ups in the sequence, which is the only factor that matters for the Bayesian. For a non-Bayesian updater, other characteristics of the price sequence may affect belief.

18 As discussed in Section II, the coefficient of loss aversion is not relevant because when making decisions, participants do not have the chance to cross the reference point, which is the initial price.

19 The correlation of the disposition effect with the belief in mean reversion and the risk preference parameters can be easily proved in the context above. See Appendix A for the proof.

IV. The Experiment

A. Experimental Design

The experiment has two stages. Stage 1 is the same for all conditions. I ask participants to make paired choices, each between a lottery and a certainty amount, in the domains of gains (Part 1), and losses (Part 2), in order to structurally estimate their risk preference parameters.[20] This stage of the experiment is based on Abdellaoui et al. (2008).[21] The probability of high reward, p_g, is fixed for all lotteries in Part 1 and the probability of low reward, p_l=1-p_g, is fixed in Part 2. By fixing these probabilities, the elicitation procedure allows for a nonlinear probability weighting, although it is not directly measured.

I use 5 questions to elicit each certainty equivalent, generated by the bisection method. For example, using Experimental Cash (EC) as the unit to measure rewards, the first question in Part 1 is "Which do you prefer: A. Getting 2000 EC with probability 2/3 or 0 EC with probability 1/3; or B. Getting 1330 EC for sure."[22] The next question will compare the same lottery with a smaller certainty amount (the average of 1330 and 0), if the participant selects the riskless option in the previous question, while selecting the lottery will lead to a larger certainty amount (the average of 1330 and 2000).[23] Since prospect theory predicts risk neutrality for small stakes in each domain, I maintain large experimental cash values. After obtaining the certainty equivalents, I use the nonlinear least squares method on equation (3) to estimate α and β for each participant.

In Stage 2, participants see 50 price sequences one at a time, with each displayed on a separate chart containing 10 periods of independently determined prices. All sequences start at the same initial price of 10,000 EC.[24] Each sequence is generated by one of two equally likely underlying processes: one has a 65% probability that the price goes up each period, and the other has this

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20 The lotteries used are in Appendix B.

21 The advantage of their procedure, as they put it, is the minimum requirement of numbers of elicitation and cognitive burden for participants. The measure of the coefficient of loss aversion is not essential to this experiment as discussed earlier.

22 The exchange rate between EC and dollars is 1,000 EC = 1 USD.

23 The first certainty to compare with a lottery is the expected value of the lottery; and all numbers are rounded to the nearest tens digit.

24 The prices take large values so as to be consistent with the order of magnitude in Stage 1 where risk attitudes are estimated.

probability equal to 35%.[25] The probability that the price goes down is just 1 minus the probability it goes up. The price can only change by one magnitude, 1,000 EC, which, combined with the fact that there are 9 price changes following the initial price, implies that no price sequence ends up breaking even. Therefore, the price sequences bear the aforementioned properties: (1) a Bayesian decision-maker should never believe in mean reversion; (2) there is no chance of crossing the reference point when the selling decisions are made. All price sequences are predetermined, including the 11th-period prices which participants do not see unless they request after the experiment. All participants observe the same price sequences in randomized orders. Each of the two processes generates half of the 50 sequences; 20 of the resulting sequences end in gains and 30 end in losses in period 10.

The participants are randomly assigned to one of three conditions. First, in condition Predict, the participants only observe the price sequences and guess the probability that the price will go up in the 11th period. They are rewarded by the prediction accuracy relative to the actual predetermined 11th-period prices, according to the quadratic scoring rule (Offerman and Sonnemans, 2001). Suppose a participant's stated probability is b. The prediction reward is:

$$(5) \quad Q(b) = \begin{cases} m + 2n \times b - n \times \left[b^2 + (1-b)^2 \right], & \text{if price increases in the 11th period} \\ m + 2n \times (1-b) - n \times \left[b^2 + (1-b)^2 \right], & \text{if price decreases in the 11th period} \end{cases} .$$

The parameters m and n allow for the manipulation of the maximum and minimum rewards. Both parameters are 2000 here, so that the maximum reward is 4000 EC and the minimum is 0 EC. After a participant answers all the questions, one of her/his predicted probabilities is randomly selected to determine the reward. After observing each sequence one just pick a number between 0 and 100 to represent the probability for Up price movement. Although the quadratic scoring rule may be hard to understand for the participants, the instruction makes it clear that the payoff-maximizing strategy is to always reveal what one truly believes. The

[25] Instead of calling them "upward-drifted" and "downward-drifted" processes, the experiment instructions use neutral words and refer to them as the Red and Green processes.

participants are also provided with numerous examples and a table of payoffs to explore.[26]

Participants in the second condition, Sell, are endowed with 10 shares of each hypothetical asset at the initial price and only decide how many to sell after seeing each sequence. They choose an integer number of shares, from 0 to 10, to sell at the 10th-period price. They are told that any unsold shares will be automatically sold at the predetermined 11th-period price. Thus, shares sold at period 10 earn a reward according to the difference between the P_{10} and P_1; any unsold shares earn a reward according to the difference between the P_{11} and P_1.

As in WC, the practical optimal strategy for a Bayesian participant in these tasks is to count the number of Ups and Downs, believe a sequence with more Ups (or Downs) to be generated by the upward-drifted (or downward-drifted) process, and hold (or sell) all shares for such a sequence.

Finally, the participants in condition Both complete both the prediction and selling tasks. Doing both may give rise to cross effects between the two decisions, which may obscure the test of belief in mean reversion and the disposition effect. Namely, having to report beliefs of future prices may cost the participants more cognitive efforts on the price sequence, reducing the disposition effect; and having a stake in the asset may weaken biased beliefs. One of the possible connections between the two tasks take the form of desirability bias (Mayraz, 2011), because the participants may tend to bias their beliefs in the more desirable direction when they hold the asset. To avoid these potential problems, in condition Both, the order of the two tasks for each price sequence is random. Additionally, a comparison between conditions Predict and Both can reveal whether having a stake generates less biased beliefs, while a comparison between conditions Sell and Both sheds light on whether having to explicitly report beliefs makes the participants less prone to the disposition effect.

B. Participants

A total of 154 participants volunteered for this experiment. After removing the results

[26] The quadratic scoring rule may not be reliable in belief elicitations on complicated tasks (Palfrey and Wang, 2009). This is another reason why in this experiment I use the simple prediction task that boils down to forecasting the probability of binary outcomes.

generated by those who reported being very confused in the exit survey, the participant pool consisted of 133 undergraduate and graduate students (42.1% female) from the Claremont Colleges, with an average age of 23.7;[27] 61.7% of them took college level economics, and 82.0% took college level statistics; 19.5% have experience trading in the financial markets. Among the participants who trade financial assets, 69.2% have less than 2 years of experience.

C. Procedure

The Institutional Review Board of the Claremont Graduate University (CGU) approved the experimental procedures. We conducted 20 sessions at the Center for Neuroeconomics Studies of CGU. Because the main goal of this experiment is to determine whether the disposition effect can be explained by belief in mean reversion, more participants were assigned to condition Both. Out of the 133 participants, 25 were in condition Predict, 45 in condition Sell and 63 in condition Both. Each session of the first two conditions lasted for around 60 minutes; and each session of condition Both lasted for around 90 minutes.

In the beginning of each session, participants were greeted in the lobby, consented, and then provided with an ID number, used throughout the experiment, for the purpose of anonymity. An experimenter orally introduced the experiment procedures to the participants. After that, each participant was seated at a partitioned computer station in the lab. They read instructions, did practice questions, and then completed the experimental tasks through computer interface.[28]

Upon finishing all the tasks, the participants see the monetary rewards on their respective screens, calculated by randomly selecting one question from each stage. Specifically, in Stage 1, on the selected question, if the participant had chosen certainty, the corresponding monetary reward was paid; if the lottery was chosen, she/he would have to go to the experimenter at the end and roll a die to determine which reward was paid, so that they knew they were not

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[27] The Claremont Colleges is a consortium of five undergraduate liberal arts colleges and two graduate institutions, situated in Southern California.

[28] The instructions and practice questions for the participants can be found in Appendix D.

cheated.[29] For the second stage, one of the price sequences was randomly selected to calculate the prediction reward and/or the asset-selling reward according the actual choices made.

Each participant received \$6 participation fee irrespective of choices in the experiment and was additionally endowed with \$10 in the prediction task and \$4 for the asset-selling task to avoid negative payments, because both stages might involve losses and we could not take money from the participants. The monetary reward of the first stage can potentially range from \$-10 to \$10; in the second stage, the prediction reward ranges from \$0 to \$4, and the asset-selling reward from \$-4 to \$4. The average reward was \$16.88 for condition Predict, \$15.10 for condition Sell, and \$20.57 for condition Both.

After the second stage, the participants took an exit survey about (1) demographic information, such as gender, age, college-level training in economics and statistics, trading experience, etc., and (2) experience in the experiment, such as confusion, self-evaluated performance, strategies used if any, etc. Upon finishing the survey, they are paid in private by the experimenter.

V. Results and Discussion

A. Belief in Mean Reversion

Elicited beliefs.—This experiment tests the explanatory power of belief in mean reversion by directly eliciting beliefs about the probability that the price will go up after period 10. Table 1 reports the median, the mean, and the standard deviation of these reported beliefs for sequences ending in gains and losses, respectively. SRM is a measure of belief in mean reversion, slightly modified from Asparouhova et al. (2009). The formula for SRM is in equation (6):

$$SRM = \begin{cases} (belief - 0.5) & \text{if there are more Ups} \\ (belief - 0.5) \times (-1) & \text{if there are more Downs} \end{cases}, \tag{6}$$

where *belief* refers to the participants' reported belief. In the original definition, -1 is multiplied when the last outcome is Down, but not when it is Up, which, however, implicitly defines belief

[29] This works in the following way: the participant rolls a die, and if it comes up with 1 or 2, the participant is paid the payoff associated with probability 1/3 in the lottery; if it comes up with 3 to 6, the participant is paid the payoff associated with probability 2/3.

in mean reversion as believing an Up to be more likely when the last observed outcome is Down. Here, I define belief in mean reversion as the belief that the price is more likely to go up (or down), when there are more Downs (or Ups) in the sequence, relative to the whole sequence as opposed to just the last outcome. SRM is negative when a belief is mean reverting.

[Insert Table 1 Here]

According to Table 1, using regressions with standard errors clustered by subject, I find participants in the two conditions do not report significantly different beliefs ($p=0.24$ for gains; $p=0.13$ for losses).[30]

The average SRM at the individual level is significantly positive for 22, and significantly negative for 20 out of the 88 participants in conditions Predict and Both at the 5% level. However, beliefs in mean reversion and continuation may cancel out in calculating the average SRM. The standard deviation of SRM is 0.23, which implies considerable variation in beliefs.

[Insert Figure 1 Here]

Figure 1 shows the distribution of SRM for the two conditions on winning and losing sequences. Komogorov-Smirnov tests reveal that the distributions of SRM are significantly different between the two conditions (Gain: $p=0.02$; Loss: $p<0.01$). According to the histograms, only a few beliefs exhibit neither continuation nor mean reversion (having SRM close to 0).

Another measure of belief, SRMB, provides quantification as to how much participants' reported probabilistic beliefs deviate from the Bayesian benchmarks.

$$SRMB = \begin{cases} (belief - Bayesian) & \text{if there are more Ups} \\ (belief - Bayesian) \times (-1) & \text{if there are more Downs} \end{cases} . \tag{7}$$

Table 1 also reports the descriptive statistics of SRMB. When a belief is more conservative than the Bayesian, SRMB is negative; otherwise, it is positive. Figure 2 shows the distributions of SRMB in the two conditions. Out of the 88 participants, on average 10 of them are more mean-reversal, while 11 are more trend-following than the Bayesian at the 5% significance level.

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[30] The SRM of condition Predict is slightly positive for sequences ending in gains, but slightly negative for sequences ending in losses; and the opposite is true for condition Both. This may suggest that the participants in condition Predict were slightly more optimistic than those in condition Both. But the difference between the two conditions is not significant ($p>0.10$). More studies are needed to further test this.

Based on these observations, there are beliefs in both continuation and mean reversion in this experiment. The considerable between-subject heterogeneity and within-subject variation of beliefs can be exploited to study the influence of beliefs on selling decisions. Another result from the analyses above is that having a stake or not does not significantly affect beliefs.

B. The Disposition Effect

Many would suspect the existence of the disposition effect in my incredibly simple design. However, I do successfully find it. The participants in conditions Sell and Both make selling decisions after observing each price sequence. Table 2 shows the summary statistics.

[Insert Table 2 Here]

It is evident that, at the group level, the participants on average sell more shares at gains than at losses ($p<0.01$ for condition Sell; $p=0.53$ for condition Both). The distribution of shares sold is more positively skewed for losses, meaning that participants tend to sell fewer shares at a loss. As discussed earlier, a Bayesian agent should sell few winning shares and all losing shares due to belief in continuation. Thus, the observed behavior shows a clear departure from this prediction.

To measure the individual level disposition effect, Odean (1998) divides the number of shares sold at gain (or loss) by the total opportunities to sell at gain (or loss), producing two measures for each participant: percentage of gains realized (PGR) and percentage of losses realized (PLR). A risk-neutral Bayesian decision-maker would have PGR of 0 and PLR of 1.

(8) $$PGR = \frac{\text{number of gains realized}}{\text{number of gains realized+number of gains unrealized}};$$

(9) $$PLR = \frac{\text{number of losses realized}}{\text{number of losses realized+number of losses unrealized}}.$$

In the denominators the total number of opportunities to realize gains or losses is counted using the total number of shares ending at gain (or loss) in period 10. According to Table 2, there are 2,160 opportunities to realize gains and 3,240 to realize losses. On average the participants in condition Sell have PGR of 52% and PLR of 36% (different from each other with $p<0.01$); the participants in condition Both have PGR of 49% and PLR of 35% (different from each other with p<0.01). The participants exhibit a significant disposition effect, realizing more winners than losers. The two conditions do not generate significantly different results (p=0.15 for PGR and p=0.47 for PLR). This suggests that having to forecast future price movements does not necessarily induce participants to make better selling decisions in a way that reduces their disposition effect, i.e. the act of forecasting does not change behavior.

To evaluate the magnitude of the disposition effect at the individual level, the difference between PGR and PLR is computed for all participants, which ranges from -1 to 1, with positive numbers indicating the disposition effect. According to the foregoing discussion, a decision maker with Bayesian beliefs should not exhibit any disposition effect, being either risk neutral or risk averse. Specifically, a risk-neutral Bayesian agent should have a PGR−PLR of -1. The average PGR−PLR for condition Sell is 0.17 (significantly positive, p<0.01) and the average for condition Both is 0.13 (significantly positive, p<0.01). The two conditions are not significantly different (p=0.49), again confirming that they do not have different strengths of the disposition effect. Combining the two conditions, the average PGR−PLR is 0.15. Figure 3 shows the individual measures of PGR−PLR in the two conditions. The standard error bars are added according to the method in Odean (1998).[31] I compute the t statistics based on these standard errors and find that the majority of participants (33 out of 45 in condition Sell and 33 out of 63 in condition Both) have significantly positive PGR−PLR at the 5% significance level.

[Insert Figure 3 Here]

Consistent with Dhar and Zhu (2006), I find considerable between-subject variation in the magnitudes of the disposition effect. The standard deviation of PGR−PLR is 0.30 in condition Sell, and 0.21 in condition Both. Though 11 participants exhibit significantly negative

31 Specifically, the standard deviation is given by: $S.E. = \sqrt{\frac{PGR(1-PGR)}{n_{rg}+n_{pg}} + \frac{PLR(1-PLR)}{n_{rl}+n_{pl}}}$, where n_{rg}, n_{pg}, n_{rl} and n_{pl} are the number of realized gains, paper gains, realized losses and paper losses (Odean, 1998, p.1784).

PGR−PLR, no one is even close to the Bayesian risk-neutral prediction of -1 at the 5% level.[32]

C. Analysis at the Decision Level

The disposition effect fundamentally involves the tendency to sell winners and to hold losers. This section explores the factors that contribute to this tendency, and to the disposition effect in this experiment. In the following analyses at the decision level, each price sequence is an observation. I first use regression analysis to test the hypotheses and later conduct simulation to compare the predictive power of different theories on selling decisions, as well as the disposition effect. The decision level regressions use standard errors clustered by participant IDs, to allow for within-subject correlations.

I start with testing the first half of Hypothesis 1 regarding the link between belief in mean reversion and selling behavior at the decision level. In the following regressions, the number of shares sold is the dependent variable, which is a count variable with integer values from 0 to 10. I use negative binomial regressions to deal with the limited dependent variable issue.

[Insert Table 3 Here]

If the participants were Bayesian, their decisions would be correlated with the number of Ups, and thus, with the size of gain or loss. However, according to regressions (1), (2), (4) and (5) in Table 3, this is not the case. Consistent with Hypothesis 1, beliefs significantly affect selling decisions: stronger belief in mean reversion (smaller SRM) correlates with more shares sold in the domain of gains and fewer shares sold in the domain of losses. This result indicates that the participants make selling decisions consistent with the theoretical predictions given their beliefs.

Hypothesis 2 centers upon the role of prospect theory in selling decisions: given their beliefs, the more risk averse participants in the domain of gains should sell more winners and more risk seeking participants in the domain of losses should hold more losers. Still using the number of shares sold on each sequence as the dependent variable, regressions (3) and (6) in Table 3

[32] Interestingly, I also find among subjects who suffer from the disposition effect the correlation coefficient between PGR and PLR is 0.49 in condition Sell ($p<0.01$) and 0.41 in condition Both ($p=0.01$), suggesting that the disposition investors tend to be biased in just one domain.

incorporate the participants' risk attitude parameters. These parameters are structurally estimated in the first stage from the elicited certainty equivalents. Across all participants, the average of α is 0.65 in the domain of gains with a standard deviation of 0.31, while the average of β is 0.75 in the domain of losses, with a standard deviation of 0.28. These two parameters are significantly different ($p<0.01$).[33]

Controlling for risk attitudes, the coefficients on SRM are still significant with the correct signs and similar magnitudes as in regressions (2) and (5). Conditional on beliefs, in the domain of gains, α has a negative sign, consistent with the theoretical prediction, i.e. when α decreases, the agent becomes more risk averse, and sells more winners; however, this coefficient is insignificant. The coefficient on β is significant, but has the incorrect sign. The negative sign on β suggests that the participants hold more shares when β increases, i.e. when they are less risk seeking. Therefore, these results confirm the robustness of the effect of beliefs, but do not appear to be completely consistent with prospect theory.

D. Analysis at the Individual Level

The previous section has demonstrated that the participants' belief in mean reversion leads to the tendency to sell winners and to hold losers. But this is insufficient to conclude on the mechanism for the disposition effect, which fundamentally entails the examination of multiple decisions made by an individual on both winners and losers. Therefore in this section, I analyze the determinants of the magnitudes of the disposition effect at the individual level, specifically the risk preferences, belief in mean reversion, and the demographic variables, in order to see their power in explaining the between-subject variation of the disposition effect. A test of the link between belief in mean reversion and the individual level disposition effect is a test of the second half of Hypothesis 1.

At the individual level, the prospect theory risk attitudes for each participant is measured by α

[33] The participants in condition Sell have an average α of 0.66 (standard deviation 0.27) and an average β of 0.72 (standard deviation 0.25); the participants in condition Both have an average α of 0.68 (standard deviation 0.32) and an average β of 0.77 (standard deviation 0.31).

and β; yet the measure of belief in mean reversion in the previous sections, SRM, is at the decision level. In order to measure the individual level belief in mean reversion, I create two measures for frequency and magnitude, respectively. The former is the percentage of price sequences on which a participant exhibits belief in mean reversion; and the latter is the average SRM per participant across all price sequences. The demographic variables are collected from the participants' responses in the exit survey, including gender, age, college level economics and statistics/probability training, and real-world investment experience. Each of them is coded as a binary variable except for age. The exit survey also asks participants, if they have trading experience, their years of trading experience and size of managed portfolio, but both turn out to practically add little to the results below.

I first examine how these factors correlate with the participants' propensity to sell winners and losers, using PGR and PLR as the dependent variables. Both PGR and PLR are percentages between 0 and 1, therefore I use generalized linear regression with a logistic link function, binomial family and robust standard errors. The results, reported in Appendix C, show that again, risk attitudes are insignificant with the correct sign in the domain of gains and significant with incorrect sign in the domain of losses. The effect of beliefs remains robust, and consistent with theoretical predictions. No demographic variable turns out to be significant except for the mathematics background of the participants.

In the following regression, I test whether the independent variables above perform well in explaining the individual levels of the disposition effect, using PGR-PLR as the dependent variable. The results are reported in Table 4.

[Insert Table 4 Here]

According Table 4, α and β are both insignificant, failing to explain the individual differences of the disposition effect. The frequency and magnitude measures of belief in mean reversion at the individual level remain significant, but mostly in the domain of losses, and the signs of the coefficients on these variables are consistent with theoretical predictions. Unfortunately, no demographic variable has an effect here. The additional insight from Table 4, when compared with Table 8 and 9, is that although risk attitude in the domain of losses explains the individual level propensity to sell losers, it does not contribute to the individual differences in the magnitude of the disposition effect. Participants have varying degrees of the disposition effect in this experiment primarily because they believe in mean reversion on losing sequences to varying extents. Their belief in mean reversion and risk preferences in the domain of gains play a less important role. Removing the risk preference parameters from regression (1) of Table 4, the remaining regression with belief in mean reversion alone explains 17% of the variation across participants in the magnitude of the disposition effect.

While the empirical study of Dhar and Zhu (2006) find that investor literacy and trading frequency influence the investors' likelihood to fall prey of the disposition effect in real-world settings, this experiment document the role of belief in mean reversion. In this controlled setup, other than investors' personal background, I am able to identify factors related to their preferences and beliefs. My results indicate that the dual risk preferences are not the main reason why participants exhibit varying magnitudes of the disposition effect, but their differences in how much they believe price sequences, especially losers, mean revert plays an important role.

E. The Simulation Analysis

The foregoing regression analyses establish the significance and size of the correlation between belief in mean reversion and the disposition effect. To further compare the goodness of fit of belief in mean reversion and prospect theory, I conduct the simulation analysis. With data of participants' risk preference parameters and reported beliefs, I generate predictions on selling decisions using four candidate models: (1) risk neutrality with Bayesian beliefs as the benchmark model, (2) risk neutrality with the actual beliefs, (3) prospect theory with Bayesian beliefs, and (4) prospect theory with the actual beliefs. Then using the predicted selling decisions, I compute PGR−PLR to measure the disposition effect of each participant under all four models, and compare them with the actual PGR−PLR data from the experiment. The goodness of fit is measured by the Root Mean Squared Error (RMSE), the square root of the mean of squared deviations from the predicted values to the actual values, so that smaller RMSE is preferable.

In Section III, I explained the theoretical framework of each model using the simple setup. In order to generate predictions on selling decisions, I add a few more parameters specific to this experimental setting. I denote the gain on a sequence by G, the loss by L, and the participants' reported belief about the price going up in period 11 by b. The problem of a participant becomes to maximize utility by choosing the number of shares to sell, denoted by X, after period 10.

A noteworthy observation from the participants' selling behavior is an overall tendency for to hold shares, as is evident in in Table 2 and the statistics of PGR and PLR. The participants hold more than 50% of the shares on average in most cases. Although the reason why they prefer to hold is unclear,[34] none of the four theories predict such behavior and the failure to capture this may compromise the predicting performance of the simulation test. I deal with it by adding a parameter ρ ($0<\rho<1$) in the utility function, representing the weight on the utility from selling, so ($1-\rho$) is the weight on the utility from holding. The participants prefer to hold when $0<\rho<0.5$.

When the sequence ends in gain, the participants' problem is:

$$\max_X U(X) = b\left[\rho GX + (1-\rho)(G+\Delta P)(10-X)\right]^\alpha + (1-b)\left[\rho GX + (1-\rho)(G-\Delta P)(10-X)\right]^\alpha$$

s.t. $0 \le X \le 10$ and X is an integer

When the sequence ends in loss, the participants' problem is:

$$\max U(X) = -b\lambda\left|\rho LX + (1-\rho)(L+\Delta P)(10-X)\right|^\beta - (1-b)\lambda\left|\rho LX + (1-\rho)(L-\Delta P)(10-X)\right|^\beta$$

s.t. $0 \le X \le 10$ and X is an integer

When the participant is a risk-neutral expected utility maximizer, the two optimization problems coincide with $\alpha=\beta=1$, and $\lambda=1$. Under that circumstance, it is easy to show that utility is strictly increasing in X when $b<0.5$ and is strictly decreasing in X otherwise. Therefore, the optimal choice is to sell all 10 shares when she believes the price is more likely to go down and to hold all when she believes otherwise. Specifically for this experimental setup, a participant with Bayesian beliefs should always believe $b<0.5$ for sequences ending in loss and $b>0.5$ for

[34] This is possibly due to the fact that the choice of the number of shares to sell is made by selecting from a drop down menu that starts with 0 on the top, so that participants are more likely to choose small numbers.

those ending at gain, exhibiting no disposition effect, thus, the prediction on PGR−PLR of -1 for all sequences. By contrast, after adding belief in mean reversion to the risk neutral model, selling decisions are still in the corner solutions, yet the participants can exhibit the disposition effect, because beliefs can be excessively conservative compared to Bayesian on a sequence. To add the prospect theory utility, I use the elicited α and β from the first stage of the experiment to calculate the X that maximizes utility on each sequence, combined with Bayesian beliefs and the actual beliefs, respectively. λ can still be normalized to 1, because loss aversion is not relevant here.

To compare the performances of the four models in predicting the number of shares sold on each sequence, I follow the progression of analyses in the regressions of the previous section, starting with the decision level and then moving into the individual level disposition effect. I generate the predicted selling decisions using the four models, and report the RMSE for each participant's decisions with the summary statistics in Table 5. Model (1), the benchmark model, produces a mean RMSE of 5.89, while in model (2) adding the actual beliefs improves it to 5.09, a significant improvement (one-tailed $p<0.01$). The prospect theory models perform better: the model with Bayesian belief generates a mean RMSE of 4.81, an insignificant improvement from model (2) (one-tailed $p=0.10$); the best model is prospect theory with actual beliefs, generating a mean RMSE as low as 4.48, a significant improvement from model (2) ($p=0.01$) and from model (3) ($p=0.05$).

[Insert Table 5 Here]

At the decision level, adding prospect theory to the benchmark model leads to a better prediction performance than adding actual beliefs. This better performance of prospect theory could reflect the significance of the parameter β in explaining selling decisions in the domain of losses with the wrong sign, from the regression analysis.

Further analyses at the individual level reveals that prospect theory does contribute much to the prediction of the individual level disposition effect. Table 6 reports the summary statistics of the actual and predicted PGR−PLR for all four models, as well as the RMSE of each model.

[Insert Table 6 Here]

According to Table 6, the benchmark model has RMSE of 1.15. Instead of using Bayesian beliefs, the introduction of the participants' reported beliefs to the benchmark model lowers the RMSE to 0.34, a significant improvement (one-tailed $p<0.01$). Although adding prospect theory generates better predictions on selling decisions than just adding actual beliefs, it fails to improve in predicting the disposition effect, producing RMSE of 0.44. The best model is still the prospect theory model with the actual beliefs, with RMSE of 0.27, so adding prospect theory to model (2) provides just an insignificant improvement (one-tailed $p=0.13$). Therefore, the best goodness of fit comes from adding the actual beliefs, which in this environment is equivalent to introducing belief in mean reversion, because a Bayesian agent always believes in continuation. Belief in mean reversion plays an important role in determining the participants' selling decisions and their disposition effect, whereas adding prospect theory provides marginal improvement.

F. An Alternative Explanation

This experiment tests the belief in mean reversion explanation against the prospect theory dual risk attitude explanation for the disposition effect, while controlling for other potential mechanisms, but one confounding factor may be the presence of realization utility (Barberis and Xiong, 2012). The key proposition of realization utility is that investors derive utility from realizing gains or losses, instead of the conventional carriers of utility, such as consumption and/or wealth, and that the utility term depends on the size of the gains or losses relative to the initial purchasing price.[35] As Barberis and Xiong (2012) put it, this proposition is a "related but distinct" theory to the prospect theory mechanism. While both involve an increase of utility associated with realizing gains and decrease of utility associated with realizing losses, to generate the disposition effect, prospect theory additionally requires the concavity of the value function in the domain of gains and convexity in the domain of losses or an appropriate coefficient of loss aversion, whereas realization utility can use a linear value function but needs

[35] In Barberis and Xiong (2012), the motivation for selling losers comes from a random liquidity shock.

an appropriate discount factor. Realization utility does not rely on belief in mean reversion either, because with belief in continuation the agent with realization utility may still sell a winner (or hold a loser) as the larger expected gain (or loss) in the future is discounted. The main proposition of the realization utility mechanism is that the disposition effect can result from the combination of (1) utility derived from realizing a capital gain/loss and (2) the timing of realizing a capital gain/loss with a sufficiently large discount factor.

The experimental environment here precludes discounting as all payments are made at the end irrespective of whether a participant decides to hold or sell after the 10th period. However, decisions to sell do involve closing a mental account promptly at a gain or loss. Thus, if this is the carrier of utility, controlling for risk attitudes and beliefs, participants should have an additional tendency towards realizing winners. To test this, I run a regression in Table 7 with the number of shares sold as the dependent variable, in order to identify whether participants realize more winners conditional on their beliefs and risk preferences. Dummy variable Gain is equal to 1 for sequences ending at gain and 0 otherwise. The interaction between risk attitude parameters and Gain is trying to distinguish the effect of risk attitudes on sequences ending in gains and losses: for sequences ending in gains, α is insignificant; the effect of β is still significantly inconsistent with the predictions of prospect theory. The participants' probabilistic beliefs still play an important role: when a participant believes in mean reversion for winners and continuation for losers, she/he sells more. However, controlling for risk attitudes and beliefs, the coefficient on Gain is negative, meaning that participants are less likely to sell winners than losers, which stands in opposition to the prediction of the realization utility. But this coefficient is insignificant. This reduces the worries about realization utility being a confounding factor in the present experiment.

[Insert Table 7 Here]

However, although the realization utility plays no role in this experiment, it does not imply the same in other environments. The result here is probably due to at least two features of this experimental design. One is that there is little room for discounting future utilities in this experiment, because all cash rewards are only paid at the end of the experiment. That is, realizing gain/loss in period 10 or 11 creates no difference in the timing of cash payments, unless the participants also derive utility from selling without getting any feedback. The other factor is that participants in this experiment face no liquidity shock.

VI. Conclusion

In a parsimonious experimental design that combines asset-selling with the elicitation of risk preferences and beliefs, participants exhibit both belief in mean reversion and varying degrees of the disposition effect. The disposition effect significantly correlates with belief in mean reversion, but not with the risk attitude parameters of prospect theory. The participants with stronger disposition effect are those who predict more mean reversion especially when losing. Additionally, I find evidence against the realization utility (Barberis and Xiong, 2012) approach given risk attitudes and beliefs, ruling it out in this experiment. Although realization utility is not a necessary condition for the disposition effect here, it may still play a role in real-world settings.

Belief in mean reversion can help to explain various empirical facts on the disposition effect. For instance, investors are more likely to suffer from the disposition effect on small winners and losers than on large ones (Odean, 1998; Grinblatt and Keloharju, 2001). This is probably because they are more prone to belief in mean reversion on small winners and losers.[36] Furthermore, analyst coverage diminishes the disposition effect possibly because analysts forecast trends better, reducing investors' belief in mean reversion on a sector or a stock (Ranguelova, 2001).

If belief in mean reversion is the underlying mechanism, I conjecture that the disposition effect may be subject to the influence of factors related to the intensity of biased beliefs. For example, once investors believe the asset price will revert to the mean, they may interpret ambiguous news as supporting their hypothesis, committing the confirmation bias (e.g. Rabin and Schrag, 1999). Experimental evidence (e.g. Mayraz, 2011) suggests that more biased participants are more

[36] Rabin and Vayanos (2010) and Barberis, Shleifer and Vishny (1998) both model belief in mean reversion and draw the implication that investors tend to expect short streaks (small winners or losers) to reverse and long streaks (large winners or losers) to continue.

confident, and investors' confidence in their beliefs can be reflected in trading volumes. These possibilities will intensify the biased belief in mean reversion and the disposition effect, while they do not emerge with other alternative mechanisms for the disposition effect.

A deeper understanding of the mechanism for the disposition effect can potentially improve individual investors' performance through investor education via channels such as the Individual Investor Association (IIA). Dhar and Zhu (2006) also point out its value to brokerage firms in improving the performance of clients, especially the low-income nonprofessional investors. With the knowledge of the role of beliefs, the instructions for investors can be more specific, teaching them the incorrectness of the over-prediction of mean reversion, and reminding them not to overweigh unfavorable information for stocks with good previous performance, nor to overweigh favorable information for recent bad performers. A diminished level of the disposition effect can potentially mitigate under-reaction in equity prices and increase the market efficiency. Admittedly, only providing the guidance may be insufficient to fully eliminate biases.

While finding supporting evidence for belief in mean reversion, this paper casts doubt on the popular prospect theory approach. This calls for more research efforts testing the competing explanations in controlled environments and addressing the limitations of the current experiment. For instance, it would be interesting to introduce buying decisions and endogenously determined prices in a disposition effect experiment with participants' belief elicitations.

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APPENDIX A

This appendix is to demonstrate how beliefs and risk attitudes are correlated with the tendency to sell winners and losers, and are thus correlated with the strength of the disposition effect.

Suppose that a decision maker is endowed with 10 shares of an asset at the 1st-period price, observe 10 periods of prices of this asset, and then decide how many shares to sell (denoted by X) at the 10th period. Unsold shares are automatically sold at the 11th-period price. Price sequences are generated by one of two underlying processes, upward and downward drifted, which only differ in terms of the probability that price goes up each period. The price of the asset goes either up or down each period by ΔP. Suppose that the gains or losses in period 10 are measured relative to period 1 price, $P_{10} - P_1$ (gains are denoted by G, and losses by L). The decision maker's subjective belief of the probability that price will increase in period 11 is denoted by b. She solves the following problem in the domain of gains, given her prospect theory utility:

$$\max_X U(X) = b\left[GX + (G+\Delta P)(10-X)\right]^{\alpha} + (1-b)\left[GX + (G-\Delta P)(10-X)\right]^{\alpha}$$
$$s.t.\ X \in \mathrm{Z},\ \text{and } 0 \le X \le 10$$

The optimal choice of X is defined by the first order condition.

Denote $GX + (G+\Delta P)(10-X)$ by M and $GX + (G-\Delta P)(10-X)$ by N.

$$R(X(\alpha,b),\alpha,b) = (1-b)\left[N\right]^{\alpha-1} - b\left[M\right]^{\alpha-1} = 0$$

The comparative statics can be derived using the Implicit Function Theorem.

$$\frac{\partial X}{\partial \alpha} = -\frac{\frac{\partial R}{\partial \alpha}}{\frac{\partial R}{\partial X}} = -\frac{(1-b)\left[N\right]^{\alpha-1}\ln\left[N\right] - b\left[M\right]^{\alpha-1}\ln\left[M\right]}{(1-b)(\alpha-1)\Delta P\left[N\right]^{\alpha-2} + b(\alpha-1)\Delta P\left[M\right]^{\alpha-2}}$$

$$\frac{\partial X}{\partial b} = -\frac{\frac{\partial R}{\partial b}}{\frac{\partial R}{\partial X}} = -\frac{-\left[N\right]^{\alpha-1} - \left[M\right]^{\alpha-1}}{(1-b)(\alpha-1)\Delta P\left[N\right]^{\alpha-2} + b(\alpha-1)\Delta P\left[M\right]^{\alpha-2}}$$

Because $\alpha - 1 < 0$, $\frac{\partial R}{\partial X} < 0$.

According to the first order condition, $(1-b)\left[N\right]^{\alpha-1} = b\left[M\right]^{\alpha-1}$.

Because $M > N$, $\ln M > \ln N$. Thus, $\frac{\partial R}{\partial \alpha} < 0$.

Therefore, $\frac{\partial X}{\partial \alpha}$<0. If α is smaller, which means the decision maker is more risk averse in the domain of gains, then X is larger, i.e. she sells more shares in period 10. *Ceteris Paribus*, stronger risk aversion in the domain of gains is correlated with selling more winners.

Additionally, since $-\left[N\right]^{\alpha-1}-\left[M\right]^{\alpha-1}<0$, $\frac{\partial X}{\partial b}$<0. If b is smaller, which means the decision maker believes that a price decrease is more likely, then X is larger, i.e. she sells more shares in period 10. *Ceteris paribus*, stronger belief in mean reversion on a winner is correlated with selling more winners. The correlation between belief in mean reversion and selling losers can be demonstrated in a similar way.

Appendix B

This appendix shows the lotteries used in the elicitation of participants' risk attitude parameters in the domain of gains and losses respectively. The first six lotteries only involve gains, and the last six only involve losses. The lotteries are formulated in the following way: Get x with probability p, or get y with probability 1-p.

	x	y	p
Gains	2000	0	2/3
	4000	0	2/3
	6000	0	2/3
	10000	0	2/3
	10000	6000	2/3
	10000	8000	2/3
Losses	-2000	0	1/3
	-4000	0	1/3
	-6000	0	1/3
	-10000	0	1/3
	-10000	-6000	1/3
	-10000	-8000	1/3

Appendix C

This appendix shows the results of the regressions at the individual level, with PGR and PLR as the dependent variable, in order to determine how risk attitudes, beliefs and demographic variables affect the propensity to sell winners and losers.

[Insert Table 8 Here]

According to Table 8, the risk aversion in the domain of gains is insignificant in explaining the individual disposition effect, controlling for beliefs. Both the frequency and magnitude measures of belief in mean reversion are significant in a way consistent with the theoretical predictions: if a participant has a smaller average SRM, or predicts mean reversion more frequently, she/he sells more winners. The only demographic variable that appears to have an effect is the mathematical background, but in a counterintuitive way: those who took college level statistics, who are expected to understand of the price-generating processes better, realize more winners.

[Insert Table 9 Here]

With regard to the domain of losses, Table 9 shows again that β is significant, but has a sign that is the opposite to what prospect theory predicts: less risk-seeking participants hold more losers. Again, both the frequency and magnitude measures of belief in mean reversion are significant: if a participant predicts mean reversion more frequently or has a smaller average SRM, she/he would hold more losers. Math background is significant in regression (4) of Table 9: participants who took statistics/probability at college sell more losers.

Appendix D

This appendix shows the instructions to participants in the experiment.

Instructions for Stage I

Welcome to this experiment of individual decision making and thank you for your participation! This experiment comprises two parts. In each part, you will be given some tasks that ask you to make decisions. Please try your best in all the questions because this is an experiment that involves real cash payments to you depending on both the decisions you make and luck. The risks to participants in this experiment are minimal, but should you feel uncomfortable at any point, you have the right to leave and we will pay you $5 for showing up.

If you have any questions during the instruction period or during the experiment, please raise your hand and an experimenter will come and answer your questions *privately*. We ask you not to communicate with each other during the experiment.

The currency used within this experiment is called experimental cash or EC. Your ECs will be converted to USD at the end of the experiment at the rate of 1000 EC= 1 USD. The exact amount of money you earn will depend on your decisions and luck, because after you finish, we will randomly pick one question in each part of the experiment and pay you according to your answer to that question. So it is in your interest to do your best in all questions.

Part I

This section is about tradeoffs. Please take your time answering questions as they may be difficult and affect how much money you can earn. Please read the following explanations attentively. In this part of the experiment, there are no right or wrong answers.

Probabilities play an important role in this experiment. Probabilities indicate the likelihood of certain events. For example, if you hear the weatherman say that the probability that it will rain tomorrow is equal to 20%, he means that rain will fall on 20 out of 100 days with the same weather condition.

Besides probabilities, lotteries are important in this experiment. Lotteries are prizes with certain probabilities. The possible outcomes of the lotteries in this experiment can be gains or losses. If a lottery yields a gain (or a loss), you gain (or lose) a specific amount in your total reward. Here are some examples of lotteries:

Example 1: A gain of 1000 EC with probability 1/3 and 0 EC with probability 2/3.

This lottery means that you have a 1 in 3 chance of winning 1000 EC and a 2 in 3 chance of getting nothing (no gain and no loss).

Example 2: A loss of 1000 EC with probability 1/2 and a loss of 200 EC with probability 1/2.

This lottery means that you have a 1 in 2 chance of losing 1000 EC and a 1 in 2 chance of losing 200 EC.

Example 3: A gain of 1000 EC with probability 1/3 and a loss of 1000 EC with probability 2/3.

This lottery means that you have a 1 in 3 chance of winning 1000 EC and a 2 in 3 chance of losing 1000 EC.

You will only face these three types of lotteries that involve only gains in Section I(a), only losses in Section I(b). **Be aware that these are not just hypothetical choices but are all backed by real stakes.**

Instructions to Section I(a) and I(b):

In each question, you will choose whether you wish to play the lottery, OR win or lose a certain amount of money with certainty. For any given lottery, we will ask you to choose between the lottery and five different certain amounts of money. For example:

Which one do you prefer:

A. A gain of 300 EC with probability 1/3 and 0 EC with probability 2/3, or
B. A gain of 100 EC for sure?

Once you make a decision, we will give you another question with the same lottery, but to compare with a different certain amount of money. For example, if you prefer the lottery in the above question, your next question might be:

Which one do you prefer:

A. A gain of 300 EC with probability 1/3 and 0 EC with probability 2/3, or

B. A gain of 200 EC for sure?

We ask you five questions for this lottery like this, and then the next lottery will be presented. We will present a total of 6 lotteries of gains in Section I(a) and 6 lotteries of losses in Section I(b).

In this part, your reward is determined by both your responses and luck. Once you finish the experiment, one of your answers will be randomly chosen and the experimenter will pay you according to your choice in that question. If you choose the certain amount of money, then we will pay you that amount exchanged to USD. If you choose the lottery, you will be asked to roll a die and determine the payments: if the die comes up with 1 or 2, you are paid the outcome associated to the probability of 1/3; if the die comes up with a number larger than 2, you are paid the outcome associated to the probability of 2/3. **Given how the payment is determined, please carefully evaluate which option you prefer.**

Here are some practice questions. Please feel free to ask the experimenter if you have questions.

Example:

Q1.

Which one do you prefer:

A. A gain of 1200 EC with probability 1/3 and 0 EC with probability 2/3, or

B. A gain of 400 EC for sure?

For the same lottery above (A gain of 1200 EC with probability 1/3 and 0 EC with probability 2/3), you will be asked a total of 5 questions.

Now to determine your reward, if this question is randomly chosen and you answered B, then you will directly get a reward of 400 EC; if you answered A, then you will roll a die. If the die comes up with 1 or 2, then you will receive 1200 EC of reward, otherwise you will receive 0 EC.

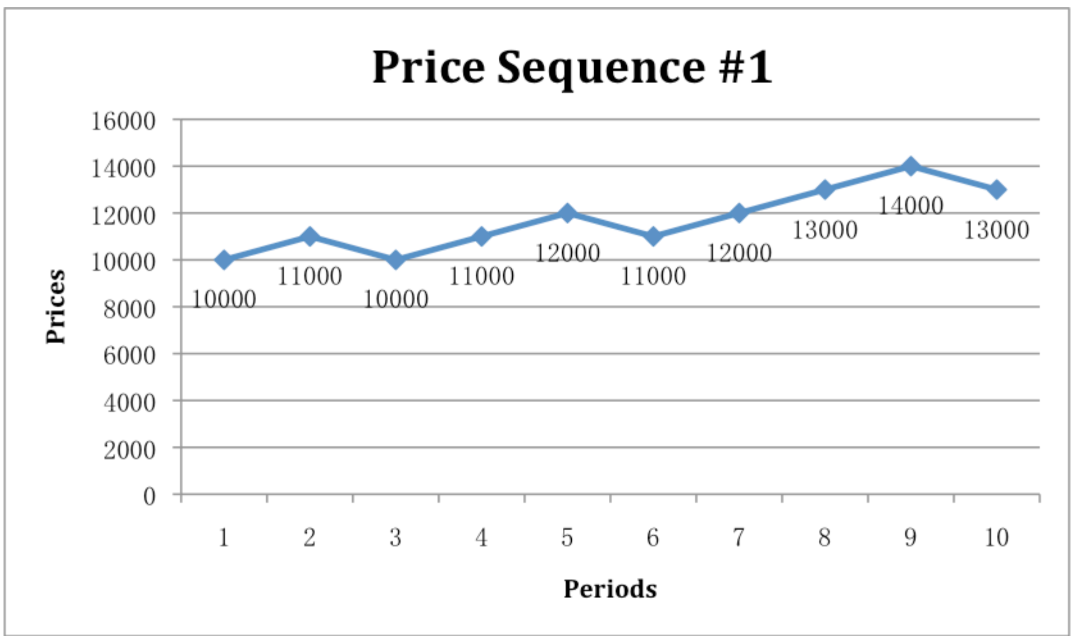
You don't know which of your answers will be randomly picked, so please do your best in all questions.

Instructions for Stage II

Condition Predict

You will observe sequences of prices of a share of stock. Your goal is to guess the price movements and you will earn money according to your accuracy.

There are a total of 50 price sequences that you will see, each containing 10 consecutive periods of prices (from period 1 to period 10). All starting (period 1) prices are normalized to 10000 EC. You can observe the prices of each sequence from period 1 to period 10 on a chart like the one below. If you wish, you can move the cursor to the dots on the chart to see the exact price of that period.



Each period the price will either go up or down by 1000 EC (so the price never stays the same). All of the 50 sequences that you will observe are generated by one of two underlying states, GREEN and RED, but they WON'T be generated all by the same state. You can imagine that the price of a stock goes up or down, reflecting good or bad performance of the stock-issuing company. These two states differ only in terms of the probability that price goes up each period. The GREEN state has a constant probability of 65% that price goes up each period; while the RED state has a constant probability of 35% that price goes up each period. Since prices cannot stay the same, the probability of price going down is equal to 1 minus the probability of price going up. Note that the price change each period is independent from the price changes in other periods.

After you see each chart showing prices from period 1 to period 10, we will ask you to indicate how likely you think in the 11th period price will go up using probability judgments expressed in percentages. Your earnings in ECs associated with each possible probability you enter are shown in the table provided to you. When you finish making the choices, we will randomly pick up one sequence, and pay you according to your answer and the table provided to you in the beginning of the experiment. **With this table to calculate payoffs, someone who wants to maximize expected earnings should state their true belief about the likelihood.**

Example: Suppose you enter a probability 30% that the price will go up in the 11th period (equivalent to a probability assessment of price going down of 70%). After you provide your assessment, the 11th outcome will not be revealed to you, but it is predetermined before the experiment according to the true underlying state, GREEN or RED. If in the 11th period price goes up, according to the schedule, your reward is 2040 EC; if in the 11th period price goes down, your reward is 3640 EC. If you give a different probability assessment, you get different rewards as shown in the table. If you wish, you are welcome to review the 11th period outcomes after the experiment so you can see that they were set in advance of your choices.

To ensure you understand the relationship between probability assessment you provide and the reward you receive depending on the outcome, answer the following questions.

Question 1

You enter a probability of 45%. What is your reward if price goes up in period 11? ____EC What is your reward if price goes down in period 11? ____EC

Question 2

You enter a probability of 60%. What is your reward if price goes up in period 11? ____EC What is your reward if price goes down in period 11? ____EC

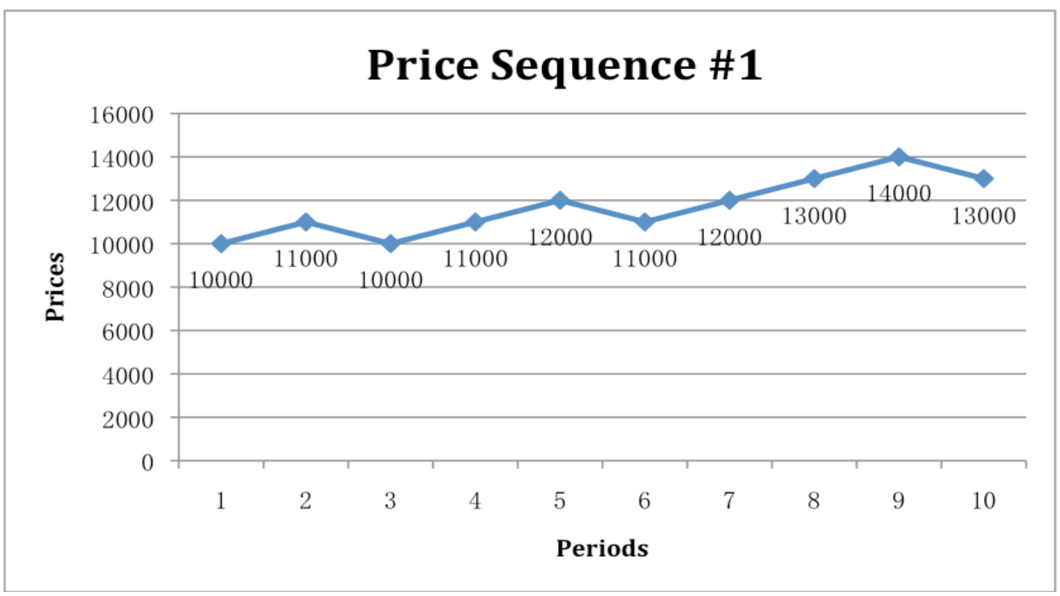
Answers: Question 1: 2790; 3190. Question 2: 3360, 2560.

<u>It is important to note that the rewards in the table are constructed in such a way that you will get the highest reward if you enter what you truly believe to be the probability.</u> Suppose you truly believe that 30% is the probability and you enter 30%, then you will expect a reward of 0.3*2040+0.7*3640= 3160 EC. Now suppose you believe the probability is 30% but enter 20%. Based on the table, you will receive 1440 EC if the price goes up, and 3840 EC if the price goes down. Your expected reward is 0.3*1440+0.7*3840= 3120 EC, which is lower than 3160 EC. So your reward is maximized only if you tell the truth about what you believe is the probability that price will go up in period 11.

Condition Sell

You will observe sequences of prices of a share of stock. Your goal is to guess the price movements, make selling decisions, and your earnings depend on the accuracy of your choices.

There are a total of 50 sequences that you will see, each containing 10 consecutive periods of prices (from period 1 to period 10). All starting (period 1) prices are normalized to 10000 EC. You are automatically endowed with 10 shares of each asset at its period 1 price. From period 1 through 10, you do not need to do anything but observe the prices on a chart like the one below. If you wish, you can move the cursor to the dots on the chart to see the exact price of that period.



Each period the price will either go up or down by 1000 EC (so the price never stays the same). All of the 50 sequences that you will observe are generated by one of two underlying states, GREEN and RED, but they WON'T be generated all by the same state. You can imagine that the price of a stock goes up or down, reflecting good or bad performance of the stock-issuing company. These two states differ only in terms of the probability that price goes up each period. The GREEN state has a constant probability of 65% that price goes up each period; while the RED state has a constant probability of 35% that price goes up each period. Since prices cannot stay the same, the probability of price going down is equal to 1 minus the probability of price going up. Note that the price change each period is independent from the price changes in other periods.

After you see each chart showing prices from period 1 to period 10, we will ask you out of the 10 shares you are endowed, how many you want to sell (you can only enter integers from 0 to 10). And you will receive a reward based on your two answers to a randomly chosen sequence. **Note that unsold shares in period 10 will be carried on to period 11 and automatically sold at period 11 price.**

Reward:

Your reward to this part is calculated according to your decision of whether and how many shares to sell, and the actual period 11 price. Your 10 shares of stock are initially valued at the period 1 price, 10000 EC, so are worth 10*10000=100000 EC. For example, if you enter 8 in response to the question of how many shares to sell (which implies you want to keep 2 shares until period 11), and if the period 10 price is 11000 EC and the true 11th period price is 12000 EC, then your reward for this sequence will be 8*(11000-10000)+2*(12000-10000)=12000 EC, where 10000 is the period 0 price.

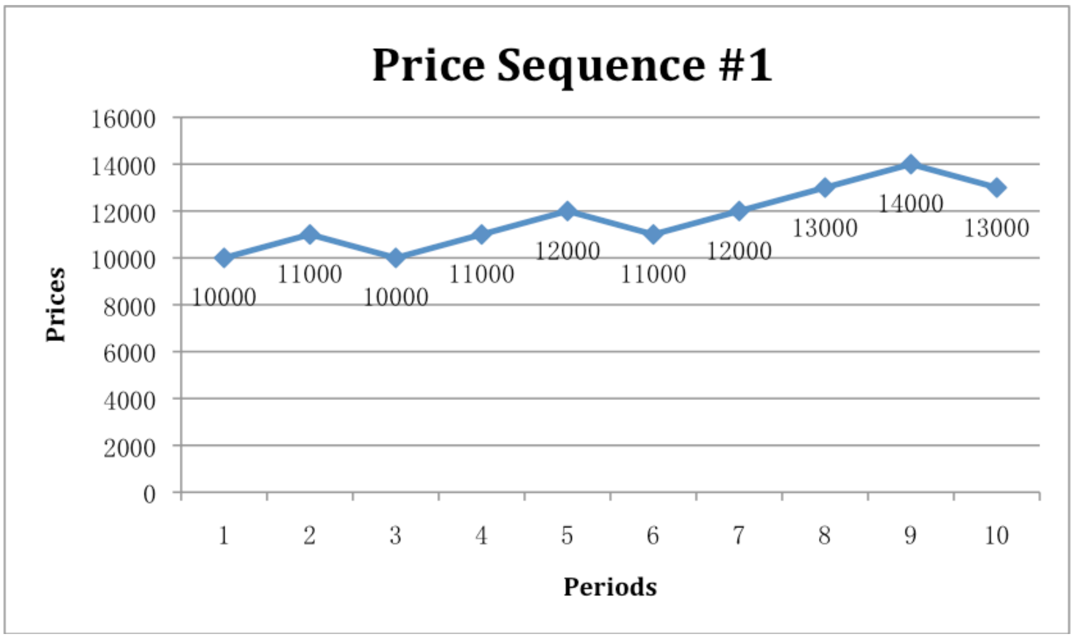
As another example, if you enter 3 (which implies you want to keep 7 shares until period 11), and if the period 10 price is 9000 EC and the true 11th period price is 8000 EC, then your reward for this price sequence will be 3*(9000-10000)+7*(8000-10000)=-17000 EC. **Note that losses of EC will be deducted from your total payments in the end.**

After you finish all the 50 price sequences, we will randomly choose one price sequence to determine your reward.

Condition Both

You will observe sequences of prices of a share of stock. Your goal is to guess the price movements, make selling decisions, and your earnings depend on the accuracy of your choices.

There are a total of 50 sequences that you will see, each containing 10 consecutive periods of prices (from period 1 to period 10). All starting (period 1) prices are normalized to 10000 EC. You are automatically endowed with 10 shares of each asset at its period 1 price. From period 1 through 10, you do not need to do anything but observe the prices on a chart like the one below. If you wish, you can move the cursor to the dots on the chart to see the exact price of that period.



Each period the price will either go up or down by 1000 EC (so the price never stays the same). All of the 50 sequences that you will observe are generated by one of two underlying states, GREEN and RED, but they WON'T be generated all by the same state. You can imagine that the price of a stock goes up or down, reflecting good or bad performance of the stock-issuing company. These two states differ only in terms of the probability that price goes up each period. The GREEN state has a constant probability of 65% that price goes up each period; while the RED state has a constant probability of 35% that price goes up each period. Since prices cannot stay the same, the probability of price going down is equal to 1 minus the probability of price going up. Note that the price change each period is independent from the price changes in other periods.

After you see each chart showing prices from period 1 to period 10, we will ask you (1) out of the 10 shares you are endowed, how many you want to sell (you can only enter integers from 0 to 10) and (2) to indicate how likely you think in the 11th period price will go up using probability judgments expressed in percentages. And you will receive two-part rewards based on your two answers to a randomly chosen sequence. **Note that unsold shares in period 10 will be carried on to period 11 and automatically sold at period 11 price.**

Asset reward:

The asset reward is calculated according to your decision of whether and how many shares to sell, and the actual period 11 price. Your 10 shares of stock are initially valued at the period 1 price, 10000 EC, so are worth 10*10000=100000 EC. For example, if you enter 8 in response to the question of how many shares to sell (which implies you want to keep 2 shares until period 11), and if the period 10 price is 11000 EC and the true 11th period price is 12000 EC, then your asset reward for this sequence will be 8*(11000-10000)+2*(12000-10000)=12000 EC, where 10000 is the period 0 price.

As another example, if you enter 3 (which implies you want to keep 7 shares until period 11), and if the period 10 price is 9000 EC and the true 11th period price is 8000 EC, then your asset reward for this price sequence will be 3*(9000-10000)+7*(8000-10000)=-17000 EC. **Note that losses of EC will be deducted from your total payments in the end.**

After you finish all the 50 price sequences, we will randomly choose one price sequence to determine your asset reward.

Prediction reward:

Your earnings in ECs associated with each possible probability you enter are shown in the table below. When you finish making the choices, we will randomly pick up one sequence (which may or may not be the same sequence chosen to determine your prediction reward, due to the randomness of choice), and pay you according to the table.

Example: Suppose that you enter a probability 30% that the price will go up in the 11th period (equivalent to a probability assessment of the price going down of 70%). After you provide your assessment, the 11th outcome will not be revealed to you, but it is predetermined before the experiment according to the true underlying state, GREEN or RED. If in the 11th period price goes up, according to the schedule, your reward is 2040 EC; if in the 11th period price goes down, your reward is 3640 EC. If you give a different probability assessment, you get different rewards as shown in the table. If you wish, you are welcome to review the 11th period outcomes after the experiment so you can see that they were set in advance of your choices.

To ensure you understand the relationship between probability assessment you provide and the reward you receive depending on the outcome, answer the following questions.

Question 1

You enter a probability of 45%. What is your reward if price goes up in period 11? ____EC What is your reward if price goes down in period 11? ____EC

Question 2

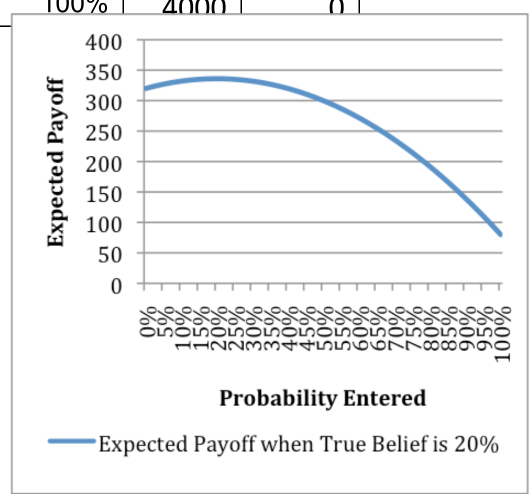
You enter a probability of 60%. What is your reward if price goes up in period 11? ____EC What is your reward if price goes down in period 11? ____EC

Answers: Question 1: 2790; 3190. Question 2: 3360, 2560.

It is important to note that the rewards in the schedule are constructed in such a way that you will get the highest reward if you enter what you truly believe to be the probability. Suppose you truly believe that 30% is the probability and you enter 30%, then you will expect a reward of 0.3*2040+0.7*3640= 3160 EC. Now suppose you believe the probability is 30% but enter 20% (i.e. the chance that price goes down is 80%). Based on the schedule, you will receive 1440 EC if the price goes up, and 3840 EC if the price goes down. Your expected reward is 0.3*1440+0.7*3840= 3120 EC, which is lower than 3160 EC. So your reward is maximized only if you tell the truth about what you believe is the probability that price will go up in period 11.

Prediction Reward Determination Example

Probability Entered	Reward if Up	Reward If Down	Probability Entered	Reward if Up	Reward If Down	Probability Entered	Reward if Up	Reward If Down
0%	0	4000	42%	2654.4	3294.4	84%	3897.6	1177.6
1%	79.6	3999.6	43%	2700.4	3260.4	85%	3910	1110
2%	158.4	3998.4	44%	2745.6	3225.6	86%	3921.6	1041.6
3%	236.4	3996.4	45%	2790	3190	87%	3932.4	972.4
4%	313.6	3993.6	46%	2833.6	3153.6	88%	3942.4	902.4
5%	390	3990	47%	2876.4	3116.4	89%	3951.6	831.6
6%	465.6	3985.6	48%	2918.4	3078.4	90%	3960	760
7%	540.4	3980.4	49%	2959.6	3039.6	91%	3967.6	687.6
8%	614.4	3974.4	50%	3000	3000	92%	3974.4	614.4
9%	687.6	3967.6	51%	3039.6	2959.6	93%	3980.4	540.4
10%	760	3960	52%	3078.4	2918.4	94%	3985.6	465.6
11%	831.6	3951.6	53%	3116.4	2876.4	95%	3990	390
12%	902.4	3942.4	54%	3153.6	2833.6	96%	3993.6	313.6
13%	972.4	3932.4	55%	3190	2790	97%	3996.4	236.4
14%	1041.6	3921.6	56%	3225.6	2745.6	98%	3998.4	158.4
15%	1110	3910	57%	3260.4	2700.4	99%	3999.6	79.6
16%	1177.6	3897.6	58%	3294.4	2654.4	100%	4000	0
17%	1244.4	3884.4	59%	3327.6	2607.6			
18%	1310.4	3870.4	60%	3360	2560			
19%	1375.6	3855.6	61%	3391.6	2511.6			
20%	1440	3840	62%	3422.4	2462.4			
21%	1503.6	3823.6	63%	3452.4	2412.4			
22%	1566.4	3806.4	64%	3481.6	2361.6			
23%	1628.4	3788.4	65%	3510	2310			
24%	1689.6	3769.6	66%	3537.6	2257.6			
25%	1750	3750	67%	3564.4	2204.4			
26%	1809.6	3729.6	68%	3590.4	2150.4			
27%	1868.4	3708.4	69%	3615.6	2095.6			
28%	1926.4	3686.4	70%	3640	2040			
29%	1983.6	3663.6	71%	3663.6	1983.6			
30%	2040	3640	72%	3686.4	1926.4			
31%	2095.6	3615.6	73%	3708.4	1868.4			
32%	2150.4	3590.4	74%	3729.6	1809.6			
33%	2204.4	3564.4	75%	3750	1750			
34%	2257.6	3537.6	76%	3769.6	1689.6			
35%	2310	3510	77%	3788.4	1628.4			
36%	2361.6	3481.6	78%	3806.4	1566.4			
37%	2412.4	3452.4	79%	3823.6	1503.6			
38%	2462.4	3422.4	80%	3840	1440			
39%	2511.6	3391.6	81%	3855.6	1375.6			
40%	2560	3360	82%	3870.4	1310.4			



Example: The curve of expected payoffs above is drawn by assuming your true belief is that the price will go up next period with 20% probability. As you can see your expected payoff is maximized only when you enter the probability 20%. So to maximize your payoff, please enter your true belief.

TABLE 1 SUMMARY STATISTICS OF REPORTED BELIEFS

This table reports the median, the mean and the standard deviation of participants' reported probabilities, as well as the calculated measures SRM and SRMB, for conditions Predict and Both, separating sequences ending in gains and losses. This table also reports the p-values of the coefficient on the dummy variable for the condition Both in a regression that tests the difference between the two conditions with standard errors clustered according to participant IDs.

		Gain		Loss	
		Predict	Both	Predict	Both
	n	500	1260	750	1890
Belief	Median	0.55	0.50	0.50	0.50
	Mean	0.52	0.50	0.53	0.50
	Std Dev	0.22	0.23	0.23	0.23
	Mean Difference	0.02		0.03	
	Significance	p=0.24		p=0.13	
SRM	Median	0.050	0.00	0.00	0.00
	Mean	0.019	-0.0041	-0.026	0.0081
	Std Dev	0.22	0.23	0.23	0.23
	Mean Difference	0.0231		0.0341	
	Significance	p=0.24		p=0.13	
SRMB	Median	0.0095	0.045	-0.045	-0.045
	Mean	0.041	0.068	-0.084	-0.050
	Std Dev	0.23	0.23	0.23	0.23
	Mean Difference	0.027		0.034	
	Significance	p=0.24		p=0.13	

TABLE 2 SUMMARY STATISTICS OF SELLING DECISIONS

This table reports the summary statistics of participants' selling decisions in conditions Sell and Both, including number of observations (n), the mean, standard deviation, skewness and kurtosis of the number of shares (out of 10) that they chose to sell at the end of period 10, in the domain of gains and losses respectively.

		n	Mean	Std Dev	Skewness	Kurtosis
Gain	Sell	900	5.22	3.34	-0.09	1.79
	Both	1260	4.50	2.87	0.13	2.17
	Sell & Both	2160	4.80	3.09	0.07	1.98
Loss	Sell	1350	3.57	3.25	0.52	2.16
	Both	1890	4.33	2.90	0.08	2.05
	Sell & Both	3240	4.01	3.08	0.25	2.03

TABLE 3 THE EFFECT OF BELIEF IN MEAN REVERSION ON SELLING DECISIONS

This table reports the regression results regarding the effects of belief in mean reversion on the selling decisions. The dependent variable is Selling, the number of shares sold on each sequence. GainSize (or LossSize) is equal to the number of Ups (or Downs) in a sequence ending at gain (or loss). SRM is the measure of belief in mean reversion. α and β are the parameters of risk attitudes. Negative binomial regression is used because this is a count-dependent variable. Regressions (1)-(3) are in the domain of gains, (4)-(6) in the domain of losses. The dispersion coefficient, the log likelihood of constant only model and the fully fitted model are reported. Clustered standard errors are in parentheses. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)

VARIABLES	(1) Gain Selling	(2) Gain Selling	(3) Gain Selling	(4) Loss Selling	(5) Loss Selling	(6) Loss Selling
Constant	1.281***	1.454***	1.624***	1.195***	1.176***	1.749***
	(0.171)	(0.232)	(0.0730)	(0.213)	(0.254)	(0.152)
GainSize	0.0543*	0.00805				
	(0.0325)	(0.0436)				
LossSize				0.0313	0.0450	
				(0.0346)	(0.0413)	
SRM		-0.345***	-0.341***		0.275***	0.290***
		(0.0914)	(0.0910)		(0.0789)	(0.0780)
α			-0.190			
			(0.123)			
β						-0.389**
						(0.198)
Dispersion Coefficient	0.316	0.258	0.254	0.580	0.344	0.328
Log Likelihood Constant Only	-5518.849	-3118.372	-3118.372	-8027.548	-4696.045	-4696.045
Log Likelihood Fitted Model	-5517.563	-3109.863	-3105.280	-8027.238	-4688.865	-4668.177

TABLE 4 DETERMINANTS OF BETWEEN-SUBJECT DIFFERENCES OF THE DISPOSITION EFFECT

This table reports regressions that try to identify determinants of between-subject differences of the disposition effect measured by PGR-PLR which is used as the dependent variable. Independent variables: α and β measure risk attitudes; Pct(SRM<0)_Gain and Mean(SRM)_Gain are the percentage of negative SRM, and the average SRM for sequences ending at gains for each participant; Pct(SRM<0)_Loss and Mean(SRM)_Loss are the percentage of negative SRM, and the average SRM for sequences ending at losses for each participant; Male, Age, Econ, Math and Trade are all demographic variables. Except for Age, all demographic variables are binary. Robust standard errors are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1)

	(1)	(2)	(3)	(4)
VARIABLES	*PGR-PLR*	*PGR-PLR*	*PGR-PLR*	*PGR-PLR*
Constant	-0.239*	0.195**	-0.0869	0.281**
	(0.137)	(0.0806)	(0.174)	(0.119)
α	-0.0191	-0.0180	-0.0256	-0.0212
	(0.0778)	(0.0811)	(0.0812)	(0.0852)
β	-0.0483	-0.0310	-0.0129	-0.00232
	(0.0816)	(0.0850)	(0.0859)	(0.0889)
Pct(SRM<0)_Gain	0.364**		0.254	
	(0.183)		(0.200)	
Pct(SRM<0)_Loss	0.677***		0.657***	
	(0.219)		(0.226)	
Mean(SRM)_Gain		-0.362		-0.215
		(0.356)		(0.392)
Mean(SRM)_Loss		-1.138**		-1.055**
		(0.450)		(0.483)
Male			-0.0519	-0.0439
			(0.0525)	(0.0548)
Age			-0.00419	-0.00336
			(0.00342)	(0.00376)
Econ			-0.00950	-0.00967
			(0.0542)	(0.0566)
Math			0.0159	-0.0208
			(0.0536)	(0.0567)
Trade			0.0580	0.0787
			(0.0734)	(0.0744)
Adjusted R-squared	0.145	0.0787	0.117	0.0439

TABLE 5 PREDICTING SELLING DECISIONS

This table reports four models' performance in predicting each participants' selling decisions on all price sequences. This performance is measured by RMSE, which is calculated by comparing the predicted number of shares sold using the four models with their actual values in the experiment. The table reports the summary statistics of RMSE across participants.

	(1) Risk Neutral EU & Bayesian Belief	(2) Risk Neutral EU & Actual Belief	(3) Prospect Theory & Bayesian Belief	(4) Prospect Theory & Actual Belief
Mean	5.89	5.09	4.81	4.48
Median	5.85	4.87	4.67	4.47
1st Quartile	5.14	4.15	4.27	3.73
3rd Quartile	6.50	5.94	5.13	5.27

TABLE 6 PREDICTING THE INDIVIDUAL-LEVEL DISPOSITION EFFECT

This table reports summary statistics (including the mean, the median, the 1st and 3rd quartile) of the actual and predicted PGR-PLR from the four models. The RMSE is calculated for each model to measure the predicting performance.

	Actual	(1) Risk Neutral EU & Bayesian Belief	(2) Risk Neutral EU & Actual Belief	(3) Prospect Theory & Bayesian Belief	(4) Prospect Theory & Actual Belief
Mean	0.13	-1	0.06	0.05	0.19
Median	0.08	-1	0.04	0.34	0.17
1st Quartile	-0.01	-1	-0.12	-0.20	0.04
3rd Quartile	0.26	-1	0.16	0.37	0.38
RMSE	NA	1.15	0.34	0.44	0.27

TABLE 7 A TEST OF REALIZATION UTILITY

This table reports the results of a regression that tests realization utility in this experiment. The dependent variable is Selling, the number of shares sold. Independent variables: α and β are the risk attitude parameters in the domain of gains and losses respectively; Belief is participants' reported probabilistic beliefs; Gain is a dummy variable that is equal to 1 for sequences ending at gains, and 0 otherwise. Clustered standard errors are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1)

VARIABLES	Selling
Constant	1.748***
	(0.151)
α *Gain	-0.191
	(0.123)
β *(1-Gain)	-0.387**
	(0.198)
SRM*Gain	-0.341***
	(0.0907)
SRM*(1-Gain)	0.290***
	(0.0779)
Gain	-0.123
	(0.132)
Dispersion Coefficient	0.296
Log Likelihood-Constant Only	-7818.793
Log Likelihood-Fitted Model	-7776.224

TABLE 8 DETERMINANTS OF PGR DIFFERENCES ACROSS PARTICIPANTS

This table reports the regression results that help identify factors related to individual levels of PGR, percentage of gains realized. Independent variables: α measures risk attitude in the domain of gains; Pct(SRM<0)_Gain and Mean(SRM)_Gain are the percentage of negative SRM, and the average SRM for sequences ending at gains for each participant; Male, Age, Econ, Math and Trade are all demographic variables. Except for Age, all demographic variables are binary. Robust standard errors are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1)

VARIABLES	(1) PGR	(2) PGR	(3) PGR	(4) PGR
Constant	-0.541**	0.105	-0.0771	0.501
	(0.244)	(0.165)	(0.423)	(0.410)
α	-0.338	-0.280	-0.392	-0.348
	(0.230)	(0.255)	(0.221)	(0.247)
Pct(SRM<0)_Gain	1.623***		1.403***	
	(0.510)		(0.453)	
Mean(SRM)_Gain		-2.399**		-1.430
		(0.935)		(0.895)
Male			-0.0993	-0.115
			(0.122)	(0.130)
Age			-0.0144	-0.0149
			(0.0124)	(0.0127)
Econ			-0.143	-0.126
			(0.146)	(0.149)
Math			0.353**	0.323**
			(0.145)	(0.152)
Trade			0.0848	0.178
			(0.137)	(0.149)
Deviance/Degrees of Freedom	0.091	0.095	0.088	0.094
Log Pseudolikelihood	-29.381	-29.506	-29.073	-29.237

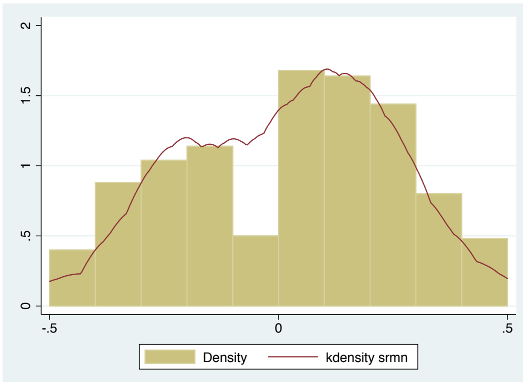
TABLE 9 DETERMINANTS OF PLR DIFFERENCES ACROSS PARTICIPANTS

This table reports the regression results that help identify factors related to individual levels of PLR, percentage of losses realized. Independent variables: β measures risk attitude in the domain of losses; Pct(SRM<0)_Loss and Mean(SRM)_Loss are the percentage of negative SRM, and the average SRM for sequences ending at losses for each participant; Male, Age, Econ, Math and Trade are all demographic variables. Except for Age, all demographic variables are binary. Robust standard errors are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1)

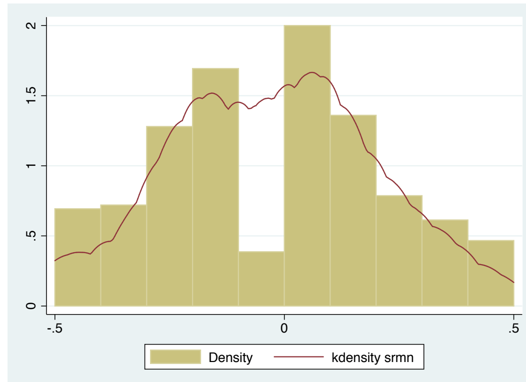
	(1)	(2)	(3)	(4)
VARIABLES	PLR	PLR	PLR	PLR
Constant	1.373***	-0.305	1.129**	-0.370
	(0.368)	(0.288)	(0.533)	(0.453)
β	-0.621*	-0.594*	-0.736**	-0.703**
	(0.333)	(0.346)	(0.319)	(0.324)
Pct(SRM<0)_Loss	-3.958***		-3.726***	
	(0.638)		(0.665)	
Mean(SRM)_Loss		5.328***		5.615***
		(1.093)		(1.131)
Male			0.152	0.0836
			(0.184)	(0.196)
Age			0.00655	0.000370
			(0.0105)	(0.0121)
Econ			-0.143	-0.129
			(0.198)	(0.212)
Math			0.296	0.473**
			(0.191)	(0.199)
Trade			-0.182	-0.188
			(0.190)	(0.191)
Deviance/Degrees of Freedom	0.133	0.155	0.137	0.154
Log Pseudolikelihood	-27.649	-28.299	-27.415	-27.890

Panel A – Condition Predict

Gain

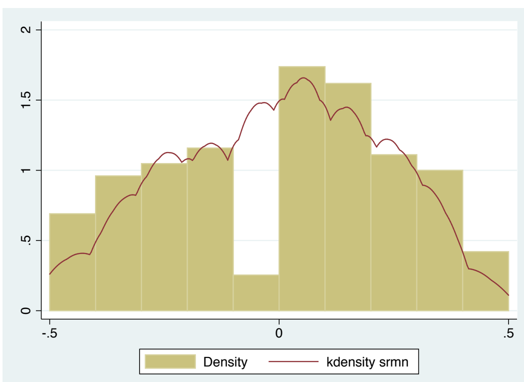


Loss



Panel B – Condition Both

Gain



Loss

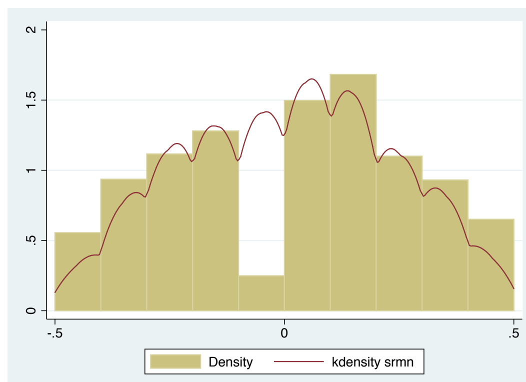
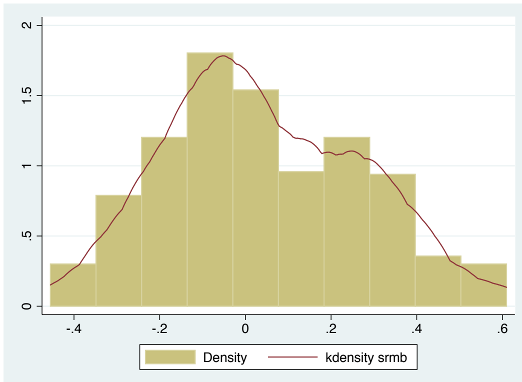


FIGURE 1. THE DISTRIBUTION OF SRM

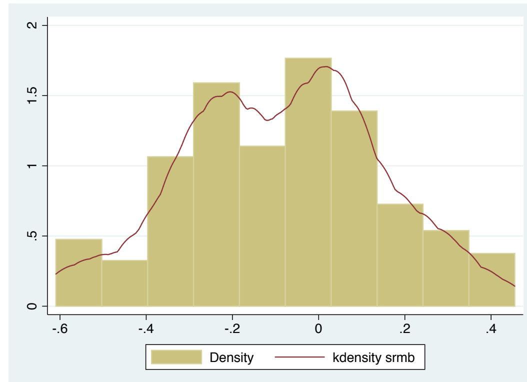
Notes: This figure shows the histograms of SRM. Panel A for condition Predict and Panel B for condition Both. The histograms place SRM values into bins of 0.1 widths. The curves are the fitted line of the kernel density estimation.

Panel A – Condition Predict

Gain

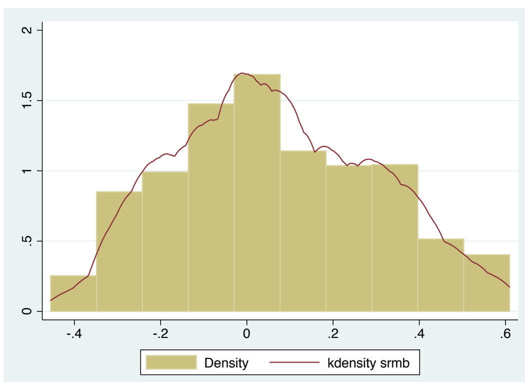


Loss



Panel B – Condition Both

Gain



Loss

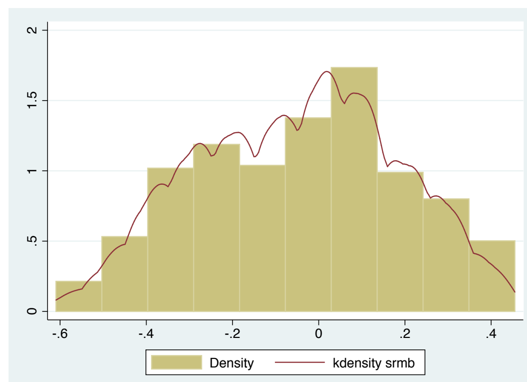
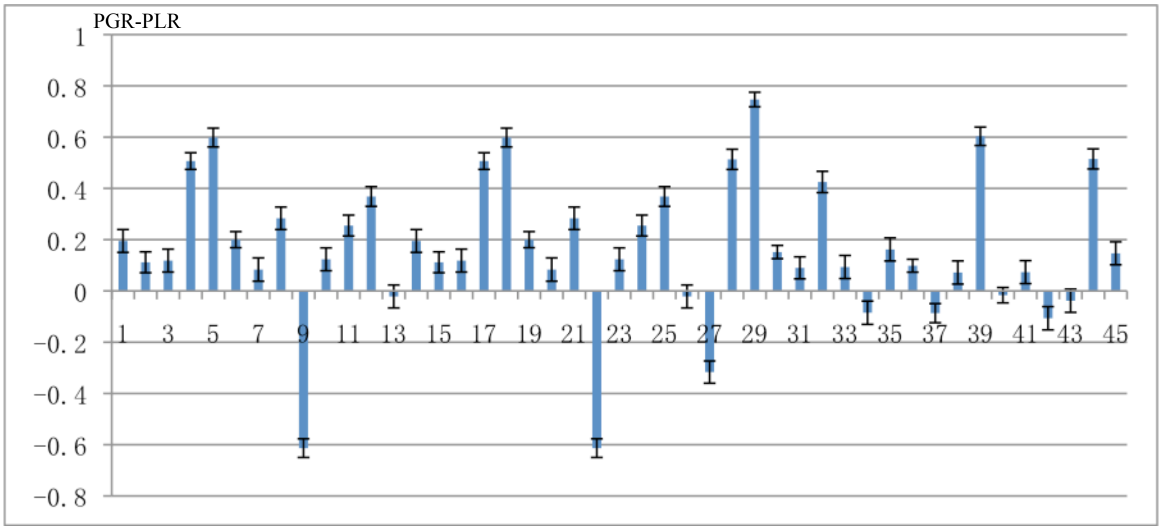


FIGURE 2 THE DISTRIBUTION OF SRMB

Notes: This figure shows the histograms of SRMB. Panel A for condition Predict and Panel B for condition Both. The histograms place SRMB values into bins of 0.1 widths. The curves are the fitted line of the kernel density estimation.

Panel A – Condition Sell



Panel B – Condition Both

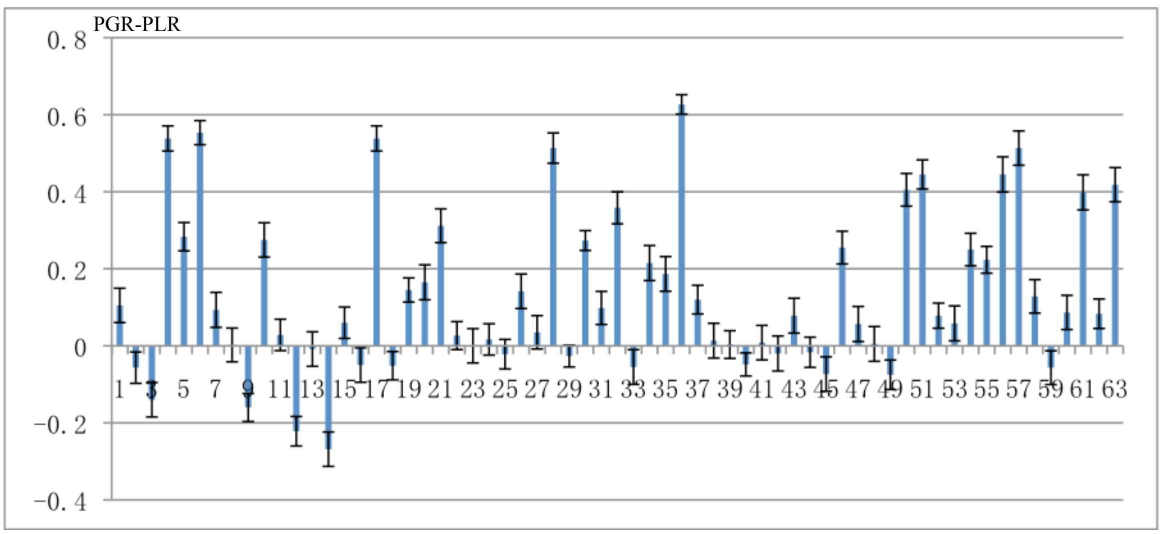


FIGURE 3 *PGR-PLR* AT INDIVIDUAL LEVEL

Notes: This figure shows the individual-level measure of the disposition effect. Panel A is for condition Sell, and Panel B for condition Both. The height of the bars shows the magnitude of *PGR-PLR*, and the standard error bars are added according to the standard errors calculated following Odean (1998). 35 out of 45 participants in condition Sell and 41 out of 63 in condition Both have significantly positive PGR-PLR at 5% level.