

Dynamic Regret Avoidance

Fioretti, Vostroknutov, Coricelli

Online Appendix

A Experimental Design

In the experiment participants made choices in 48 “stock markets,” presented to each of them in individually generated random order. In each market a participant was shown the price dynamics unfolding in real time either until the asset was sold or until market closure after 50 periods. The price updated each 0.8 seconds. First, participants observed the market price evolve for 15 periods. Then they “entered” the market. In the instructions this was presented as if they bought an asset in period 15. After this, participants kept observing the evolution of the market price and had to decide when to “sell the asset.” The payoff, or profit, that each participant received in each market was equal to the selling price minus the entry price. Participants were paid for only one randomly chosen market. No one could lose money if the profit of the chosen market was negative, since participants were given an initial endowment of €10 that covered the highest possible loss.

Each participant was making choices in two types of markets, which differed only in the amount of information that participants received *after* they have sold the asset. In the No Info condition, after selling the asset, no information about the future evolution of the price was provided. In the Info condition, after selling the asset, participants observed how the price changed until the end of that market. In both cases the participants could not change their decision after they have sold the asset. The market condition (No Info or Info) was shown from period 1 on in the upper-left corner of the market graph (see figures below).

Overall, 154 participants took part in the experiment. All sessions were run in March 2017 at the CEEL laboratory, Department of Economics, University of Trento. Another set of 135 participants took part in the experiment in June 2016 in the same laboratory. These data are not reported in this paper. In the June 2016 experiment participants were not informed about the process that generated the price and were not given initial training (see below). Otherwise the two experiments were identical. One session in the June 2016 experiment was aborted due to the network overload and the data was discarded. The data for one participant in the June 2016 experiment was discarded, as she had to leave the experiment in the middle of the market task. No other sessions or pilots were conducted. The experiments were programmed in z-Tree (Fischbacher, 2007).

A.1 Market Details

The price dynamics for each market was generated randomly using the process $y_{t+1} = \alpha y_t + (1 - \alpha)\varepsilon$, where y_{t+1} is the price in period $t + 1$, $\alpha = 0.6$ is a fixed constant for all markets and $\varepsilon \sim U[0, 10]$ is an iid random variable (uniform on $[0, 10]$). In period 1 each market started from price €2.5, €5, or €7.5. Thus, the price changed in the range from €0 to €10. All participants saw the same price dynamics for a given market. Each market lasted for 50 periods, which was known to the participants. In period 15 of each market the participants were forced to enter the market. This was explained to them in the instructions in terms of their buying an object on the market in period 15 for the current market price (see instructions in Appendix J). Then the participants were instructed that they can sell the asset at any time before period 50 and that their earnings in that market would be equal to the difference between the selling price and the entry price (if they did not sell their earnings were equal to the price in period 50 minus the price in period 15). The prices on the market were presented in actual Euros, so no tokens were used and there was no need for having an exchange rate. All the information about the current market condition, the entry price, the selling price and the current price was presented on the screen at appropriate times. Descriptions under Figures A1 and A2 explain.

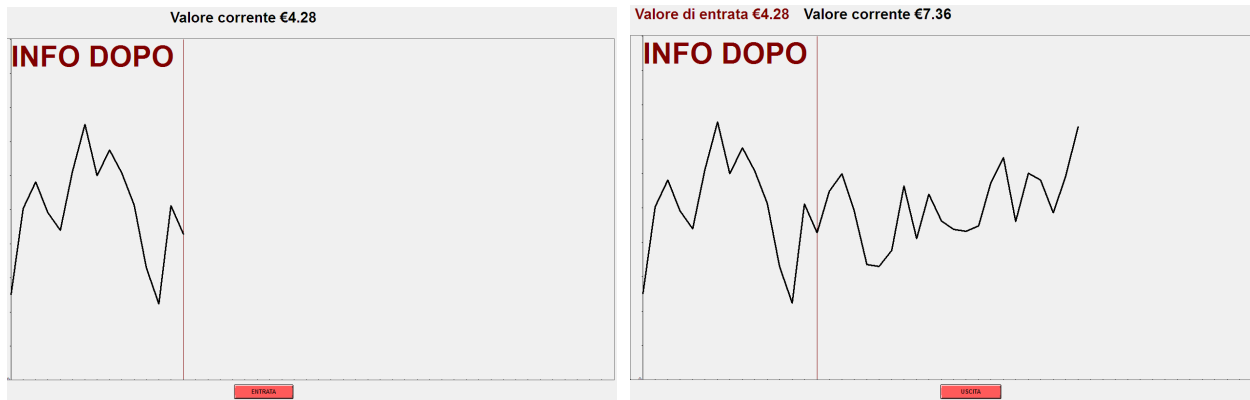


Figure A1: The left picture shows the market price evolution before period 15, which is marked by a vertical red line. At period 15 the market “stopped,” so that participants could inspect the entry price. An ENTER (ENTRATA) button should have been pressed to start the market again. After period 15 the participants could check the entry price by looking at the top left of the screen where it was indicated in red (right picture). To sell the asset participants needed to press EXIT (USCITA) button.



Figure A2: The right picture shows the market in Info condition *after* a participant sold the asset (the period of selling is indicated by a blue vertical line). After selling the asset, the participant could see the selling price in blue and the profit in green or red, depending on whether the profit was positive or negative (on top of the screen). In addition, the participant observed the future evolution of the price until period 50 (the price changed each 0.8 seconds). In the No Info condition (left picture) everything was the same except that the participant did not observe the future price, but still had to wait until the market closure. The sentence at the bottom of the left picture says: “Please wait until the market is closed.”

The timing of each market was as following. The new price was shown each 0.8 seconds.¹ This was long enough for participants to be able to react and sell the asset at the current price if they chose to do so. In the Info condition participants had to observe the evolution of the price until period 50: they could not skip to the next market. In the No Info treatment, after selling the asset, they had to wait until the market reached period 50 (without observing the price). This was done in order to 1) remove the incentive to go quicker through the task and 2) make No Info and Info conditions as similar as possible.

¹The experiment was implemented in z-Tree (Fischbacher, 2007), which does not allow for precise time control. Thus, the actual time between periods could have been slightly larger.

A.2 Price Dynamics and Training

Participants were explicitly informed about the process that generates the price (see instructions in Appendix J). The formula $y_{t+1} = \alpha y_t + (1 - \alpha)\varepsilon$ was explained to them and four examples of the price range in the next period depending on the current price were given.

Participants went through a series of six training markets which could not be chosen for the payment. The training markets were in all respects identical to the real markets except the phrase ROUND DI PROVA (“training round”) written across the background in a very large font. Out of six training markets two started at €2.5, two at €5, and two at €7.5. One market in each pair was presented in the No Info and one in the Info condition. The sequence of markets and conditions were independently randomized individually for each participant.

A.3 Overall Design Details

Participants chose in 48 markets. The price dynamics for each market was pre-generated using the rule described above (see Figure A3 below). Thus, each participant chose in exactly the same markets. For the three subsets of 16 markets the starting price was equal to €2.5, €5, or €7.5. The order of the markets was randomized in real time for each participant. Thus, there is only an infinitesimal probability that any two participants saw the same sequence of markets. The market condition, No Info or Info, was determined in the following way. Half of the 16 markets of each kind (starting at €2.5, €5, €7.5) were randomly assigned to the condition No Info and another half to the condition Info. Thus, equal number of markets of each of the three kinds were shown in the two conditions. The participants assigned to the computers with odd numbers saw markets in these predetermined conditions. The participants assigned to the computers with even numbers saw the same markets in the opposite conditions. Thus, for each given market, there is an (approximately) equal number of participants who saw that market in the No Info and Info conditions.

When participants sold the asset they could see their profit (see Figure A2). However, the participants were informed that they will be paid for only one randomly chosen market. In order to avoid losses, the participants were given €10 at the beginning of the experiment, so their earnings after the market task were €10 plus the profit in one randomly chosen market (which could have been negative).

A.4 Additional Tasks

After choosing in the sequence of 48 markets the participants were presented with the Holt and Laury task (Holt and Laury, 2002). We did not use the original payoffs from Holt and Laury (2002) as our participants could have seen those before. Instead we took the equivalent payoffs from Eijkelenboom *et al.* (2016). The instructions and the screenshots are presented in Appendix K.2. The participants, in addition to their earnings in the market task, received the payoff from one of the lotteries that they chose in the Holt and Laury task.

In the end of the experiment the participants were given a sequence of standard demographic questions.

A.5 Market Prices

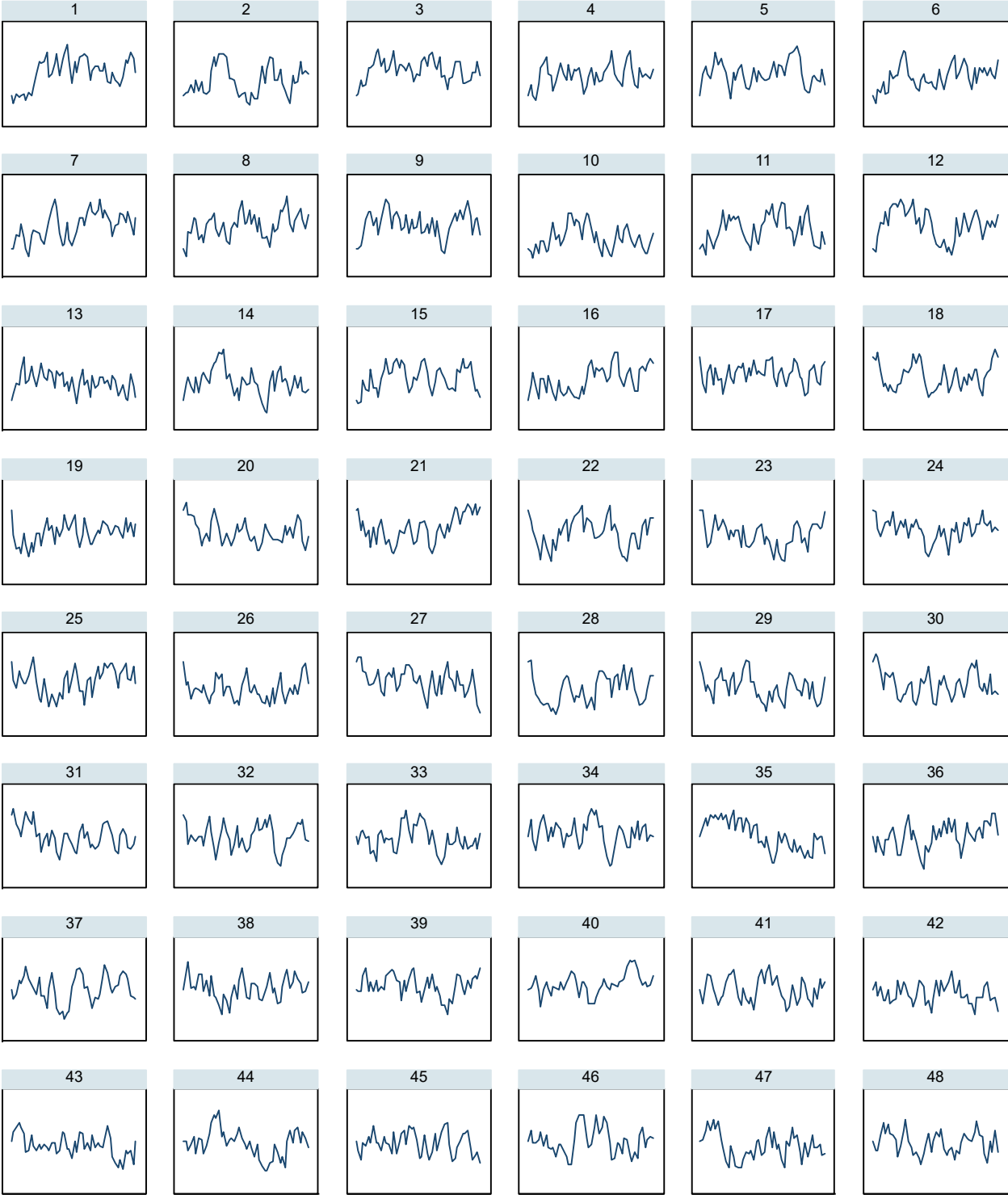


Figure A3: Prices in 48 markets.

B Behavior of Regret-Free Agent

The regret-free rational agent obtains utility $u(y_t)$ when she sells the asset at time t at the price y_t . In each period she estimates the expected future utility that takes into account her optimal choices and sells the asset if

$$u(y_t) \geq \max\{\mathbb{E}_{y_{t+1}}[u(y_{t+1})|y_t], \mathbb{E}_{y_{t+1}}[v_{t+2}|y_t]\}$$

where $v_{t+2} = \max\{\mathbb{E}_{y_{t+2}}[u(y_{t+2})|y_{t+1}], \mathbb{E}_{y_{t+2}}[v_{t+3}|y_{t+1}]\}$ and the value function in the last period T is $v_T = \mathbb{E}_{y_T}[u(y_T)|y_{T-1}]$.² In the experiment the price evolution is described by a Markov chain, thus, all expectations are conditional on the past price.

We show analytically that a risk-averse agent should optimally sell the asset at a lower price than a risk-neutral agent and risk-loving agent should sell at a higher price. Intuitively, an extremely risk-averse agent sells immediately at any price level as a sure outcome today outweighs an uncertain outcome tomorrow, whereas the certainty equivalent required by a risk-loving agent to sell at the same price is higher. Thus, we formulate a prediction concerning risk attitudes:

Proposition. *The optimal policy for an agent with CRRA preferences is to sell the asset above some threshold different for each period. Other things equal, the probability of selling the asset increases in the degree of risk aversion.*

Proof. An agent without regret sells if

$$u(y_t) \geq \max\{\mathbb{E}_{y_{t+1}}[u(y_{t+1})|y_t], \mathbb{E}_{y_{t+1}}[v_{t+2}|y_t]\} \quad (\text{B.1})$$

where $v_{t+2} = \max\{\mathbb{E}_{y_{t+2}}[u(y_{t+2})|y_{t+1}], \mathbb{E}_{y_{t+2}}[v_{t+3}|y_{t+1}]\}$ and $v_T = \mathbb{E}_{y_T}[u(y_T)|y_{T-1}]$. Assuming that agent has CRRA utility function, this implies that the selling rule is

$$y_t^{1-\rho} \geq \max\{\mathbb{E}_{y_{t+1}}[y_{t+1}^{1-\rho}|y_t], \mathbb{E}_{y_{t+1}}[\dot{v}_{t+2}|y_t]\}$$

where $\dot{v}_{t+2} = \max\{\mathbb{E}_{y_{t+2}}[y_{t+2}^{1-\rho}|y_{t+1}], \mathbb{E}_{y_{t+2}}[\dot{v}_{t+3}|y_{t+1}]\}$ and $\dot{v}_T = \mathbb{E}_{y_T}[y_T^{1-\rho}|y_{T-1}]$.

Let \tilde{v}_t denote the value function in inequality (B.1) with $u(y_t) = y_t$ and let \tilde{y}_t be the price at which a risk-neutral agent is indifferent whether to sell the asset or not:

$$\tilde{y}_t = \max\{\mathbb{E}_{y_{t+1}}[y_{t+1}|\tilde{y}_t], \mathbb{E}_{y_{t+1}}[\tilde{v}_{t+2}|\tilde{y}_t]\} \quad (\text{B.2})$$

Would a risk-seeking (averse) agent sell at the same value or continue? The answer depends on ρ . Agent sells at \tilde{y}_t if and only if

$$\tilde{y}_t^{1-\rho} \geq \max\{\mathbb{E}_{y_{t+1}}[y_{t+1}^{1-\rho}|\tilde{y}_t], \mathbb{E}_{y_{t+1}}[\dot{v}_{t+2}|\tilde{y}_t]\}. \quad (\text{B.3})$$

Plugging (B.2) into (B.3) we get

$$\max\{\mathbb{E}_{y_{t+1}}[y_{t+1}|\tilde{y}_t]^{1-\rho}, \mathbb{E}_{y_{t+1}}[\tilde{v}_{t+2}|\tilde{y}_t]^{1-\rho}\} \geq \max\{\mathbb{E}_{y_{t+1}}[y_{t+1}^{1-\rho}|\tilde{y}_t], \mathbb{E}_{y_{t+1}}[\dot{v}_{t+2}|\tilde{y}_t]\}.$$

This inequality holds (strictly) only for a risk-averse agent with $\rho \in (0, 1)$. To show this we start from period $T - 1$. Notice that

$$\begin{aligned} \mathbb{E}_{y_{T-1}}[\tilde{v}_T|y_{T-2}]^{1-\rho} &= \left(\sum_i \Pr\{y_{T-1,\mu}|y_{T-2}\} \mathbb{E}_{y_T}[y_T|y_{T-1,\mu}] \right)^{1-\rho} \\ &\quad \text{and} \\ \mathbb{E}_{y_{T-1}}[\dot{v}_T|y_{T-2}] &= \sum_i \Pr\{y_{T-1,\mu}|y_{T-2}\} \mathbb{E}_{y_T}[y_T^{1-\rho}|y_{T-1,\mu}] \end{aligned} \quad (\text{B.4})$$

²By design the participants in the last period are forced to sell at the current price.

where, given y_{T-2} , ι enumerates all possible values of y_{T-1} denoted by $y_{T-1,\iota}$. Next notice that the RHS's of (B.4) can be rewritten as

$$\left(\sum_{\iota} \Pr\{y_{T-1,\iota}|y_{T-2}\} \sum_{\xi_i} \Pr\{y_{T,\xi_i}|y_{T-1,\iota}\} y_{T,\xi_i} \right)^{1-\rho} = \left(\sum_{\zeta} p_{\zeta} y_{T,\zeta} \right)^{1-\rho} \quad (\text{B.5})$$

and

$$\sum_{\iota} \Pr\{y_{T-1,\iota}|y_{T-2}\} \sum_{\xi_i} \Pr\{y_{T,\xi_i}|y_{T-1,\iota}\} y_{T,\xi_i}^{1-\rho} = \sum_{\zeta} p_{\zeta} y_{T,\zeta}^{1-\rho}$$

respectively. Here ξ_i enumerates y_T for each ι and ζ enumerates all combinations of ι and ξ_i . Now, the RHS of the first equation in (B.5) is bigger than the RHS of the second by strict concavity of $(\cdot)^{1-\rho}$. Thus we can conclude that $\mathbb{E}_{y_{T-1}}[\tilde{v}_T|y_{T-2}]^{1-\rho} > \mathbb{E}_{y_{T-1}}[\dot{v}_T|y_{T-2}]$ for all $\rho \in (0, 1)$.

Now we consider period $T - 2$. For some fixed y_{T-2} we want to show that

$$\max\{\mathbb{E}_{y_{T-1}}[y_{T-1}|y_{T-2}]^{1-\rho}, \mathbb{E}_{y_{T-1}}[\tilde{v}_T|y_{T-2}]^{1-\rho}\} > \max\{\mathbb{E}_{y_{T-1}}[y_{T-1}^{1-\rho}|y_{T-2}], \mathbb{E}_{y_{T-1}}[\dot{v}_T|y_{T-2}]\}. \quad (\text{B.6})$$

This is straightforward since we have just shown that $\mathbb{E}_{y_{T-1}}[\tilde{v}_T|y_{T-2}]^{1-\rho} > \mathbb{E}_{y_{T-1}}[\dot{v}_T|y_{T-2}]$, which are the second terms of the max operators. According to the same strict concavity argument as above, $\mathbb{E}_{y_{T-1}}[y_{T-1}|y_{T-2}]^{1-\rho} > \mathbb{E}_{y_{T-1}}[y_{T-1}^{1-\rho}|y_{T-2}]$, the first terms of the max operators. Thus, LHS max operator has all terms bigger than corresponding terms of the RHS max operator, which proves that the inequality (B.6) holds.

Since (B.6) holds for all y_{T-2} , it is true that

$$\mathbb{E}_{y_{T-2}}[\tilde{v}_{T-1}|y_{T-3}]^{1-\rho} = \mathbb{E}_{y_{T-2}}[\max\{\mathbb{E}_{y_{T-1}}[y_{T-1}|y_{T-2}]^{1-\rho}, \mathbb{E}_{y_{T-1}}[\tilde{v}_T|y_{T-2}]^{1-\rho}\}|y_{T-3}] > \mathbb{E}_{y_{T-2}}[\max\{\mathbb{E}_{y_{T-1}}[y_{T-1}^{1-\rho}|y_{T-2}], \mathbb{E}_{y_{T-1}}[\dot{v}_T|y_{T-2}]\}|y_{T-3}] = \mathbb{E}_{y_{T-2}}[\dot{v}_{T-1}|y_{T-3}].$$

This is a precursor to the one more step of the same derivation for period $T - 3$ as $\mathbb{E}_{y_{T-1}}[\tilde{v}_T|y_{T-2}]^{1-\rho} > \mathbb{E}_{y_{T-1}}[\dot{v}_T|y_{T-2}]$ was for the period $T - 2$ step. Therefore, iterating this process, we show that (B.3) holds with strict inequality for all t as long as $\rho \in (0, 1)$. When the agent is risk-seeking, or $\rho < 0$, (B.3) holds strictly with the opposite sign. The proof is the same only with all $>$ replaced by $<$.

Next we show that for any admissible ρ and each period there is a unique threshold such that an agent with CRRA utility, who follows optimal policy, always sells above this threshold and always keep the asset below it. Notice that $\mathbb{E}_{y_{t+1}}[y_{t+1}^{1-\rho}|y_t] = \mathbb{E}_{\varepsilon}[(\alpha y_t + (1 - \alpha)\varepsilon)^{1-\rho}]$ is a strictly increasing continuous function of y_t .³ Consider $m(y_t) = \max\{\mathbb{E}_{y_{t+1}}[y_{t+1}^{1-\rho}|y_t], \mathbb{E}_{y_{t+1}}[\dot{v}_{t+2}|y_t]\}$. This is a function of y_t that for some y_t is equal to $\mathbb{E}_{\varepsilon}[(\alpha y_t + (1 - \alpha)\varepsilon)^{1-\rho}]$ and for some y_t to $\mathbb{E}_{y_{t+1}}[\dot{v}_{t+2}|y_t]$. Now, we can use the expressions $\dot{v}_{\tau} = \max\{\mathbb{E}_{y_{\tau}}[y_{\tau}^{1-\rho}|y_{\tau-1}], \mathbb{E}_{y_{\tau}}[\dot{v}_{\tau+1}|y_{\tau-1}]\}$ for all $\tau \geq t + 2$ to expand $\mathbb{E}_{y_{t+1}}[\dot{v}_{t+2}|y_t]$ into a sequence of expectations and max operators. Thus, eventually, $m(y_t)$ is a piecewise function that is equal to $\mathbb{E}_{\varepsilon}[(\alpha y_t + (1 - \alpha)\varepsilon)^{1-\rho}]$ or pieces of weighted averages of functions of the form

$$\mathbb{E}_{y_{t+1}}[\dots \mathbb{E}_{y_{\tau}}[y_{\tau}^{1-\rho}|y_{\tau-1}] \dots |y_t] = \mathbb{E}_{\varepsilon_{t+1}} \dots \mathbb{E}_{\varepsilon_{\tau}}[(\alpha^{\tau-t} y_t + (1 - \alpha^{\tau-t}) E_{\tau})^{1-\rho}] \quad (\text{B.7})$$

where E_{τ} is a weighted average of random variables $\varepsilon_{t+1}, \varepsilon_{t+2}, \dots, \varepsilon_{\tau}$. All functions in (B.7) are continuous and strictly increasing in y_t . Therefore, $m(y_t)$ is a continuous and strictly increasing since it is a series of max operators applied to weighted averages of continuous increasing functions. It is also true that m is strictly concave (convex) for $\rho \in (0, 1)$ ($\rho < 0$), which also follows from the fact that it is a series of max operators of weighted averages of strictly concave (convex) functions.

Now, we would like to know the relationship between $m(y_t)$ and $y_t^{1-\rho}$. This will tell us what the

³Here and below ε , possibly with sub-indexes, is a uniformly distributed random variable on $[0, 10]$.

optimal policy is. Notice that $m(0) > 0^{1-\rho}$ and $m(10) < 10^{1-\rho}$ since $m(y_t)$ consists of mean reverting expectations. So for low y_t the optimal policy is to keep the asset and for high y_t to sell. It is left to show that $m(y_t)$ crosses $y_t^{1-\rho}$ at a single point. Consider any point y where $y^{1-\rho} = m(y)$. We want to show that at this point the derivatives of $y^{1-\rho}$ and $m(y)$ are different. As was mentioned above, $m(y)$ is a weighted average of functions in (B.7). Thus,

$$y^{1-\rho} = \sum_t p_t \mathbb{E}_{\varepsilon_{t+1} \dots \varepsilon_{\tau_t}} [(\alpha^{\tau_t-t} y + (1 - \alpha^{\tau_t-t}) E_{\tau_t})^{1-\rho}] = \sum_t p_t \mathbb{E}_{\tau_t} [(\alpha^{\tau_t-t} y + (1 - \alpha^{\tau_t-t}) E_{\tau_t})^{1-\rho}] \quad (\text{B.8})$$

for some enumeration $\{p_t, \tau_t\}_t$ and with \mathbb{E}_{τ_t} being short for $\mathbb{E}_{\varepsilon_{t+1} \dots \varepsilon_{\tau_t}}$. Notice that the derivatives of functions (B.7) with respect to y_t are of the form $\alpha^{\tau-t}(1-\rho)\mathbb{E}_{\tau}(\alpha^{\tau-t}y_t + (1-\alpha^{\tau-t})E_{\tau})^{-\rho}$, since \mathbb{E}_{τ} transforms into a summation of the terms $(\alpha^{\tau-t}y + (1-\alpha^{\tau-t})E_{\tau})^{1-\rho}$ weighted with some probabilities and the derivative transcends the summation. Keeping this in mind let us rewrite (B.8) as

$$(1-\rho)y^{-\rho} = \sum_t p_t \alpha^{\tau_t-t} (1-\rho) \mathbb{E}_{\tau_t} [(\cdot)^{-\rho}] + \frac{1-\rho}{y} \sum_t p_t \mathbb{E}_{\tau_t} [(1-\alpha^{\tau_t-t}) E_{\tau_t} (\cdot)^{-\rho}]$$

where $(\cdot)^{-\rho}$ stands for $(\alpha^{\tau_t-t}y + (1-\alpha^{\tau_t-t})E_{\tau_t})^{1-\rho}$. This, in turn, can be seen in terms of derivatives

$$(1-\rho)y^{-\rho} = \frac{dm(y)}{dy} + \frac{1-\rho}{y} \sum_t p_t \mathbb{E}_{\tau_t} [(1-\alpha^{\tau_t-t}) E_{\tau_t} (\cdot)^{-\rho}].$$

Here LHS is the derivative of LHS of (B.8) at y and RHS is the derivative of m at y plus a positive number. Thus, at y the derivative of $y^{1-\rho}$ is higher than the derivative of $m(y_t)$. This implies that these two functions cross at a unique point: they cannot coincide on an interval, since then their derivatives would have been equal and they cannot cross on a disjoint set since this would have contradicted the strict concavity or convexity of m .

Thus, we have established that the optimal policy for any CRRA utility function is to sell above some unique threshold y_t and to keep the asset below it. Combining this observation with the result that risk the averse agent sells at a price where risk-neutral agent is indifferent and that the risk-seeking agent keeps the asset at that price, we can conclude that risk-averse agent must have the selling threshold at a price below the risk-neutral agent and the risk-seeking agent must have the threshold above it. Therefore, a risk-averse agent, given the same prices, sells before a risk-neutral agent and a risk-seeking agent sells after. ■

C Supplementary Graphs

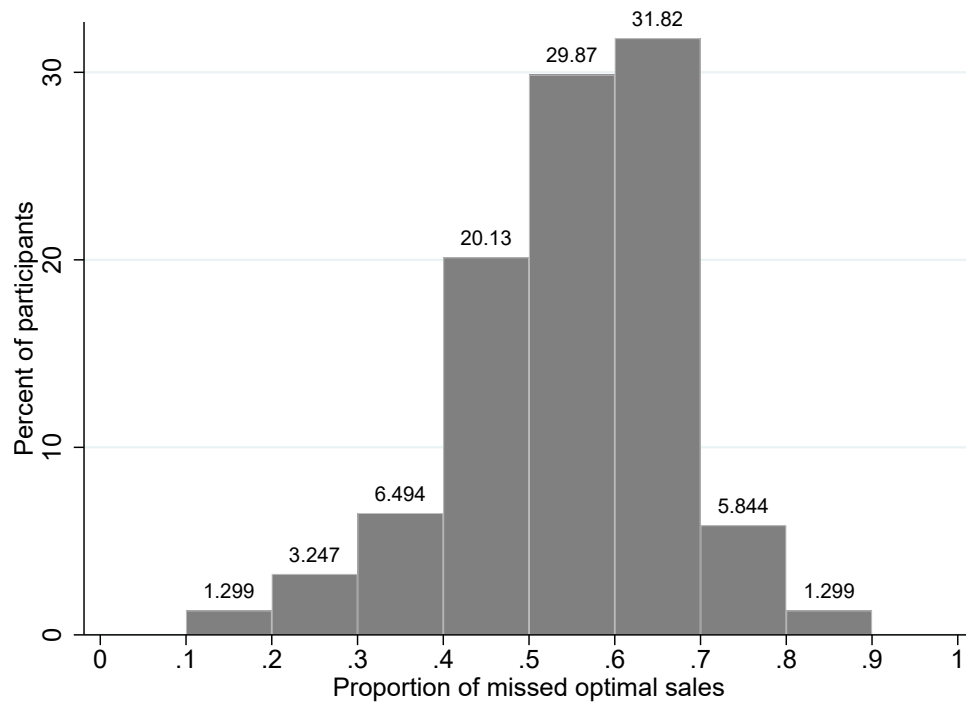


Figure C4: The distribution of participants by the proportion of missed optimal sales. The proportion is calculated separately for each participant.

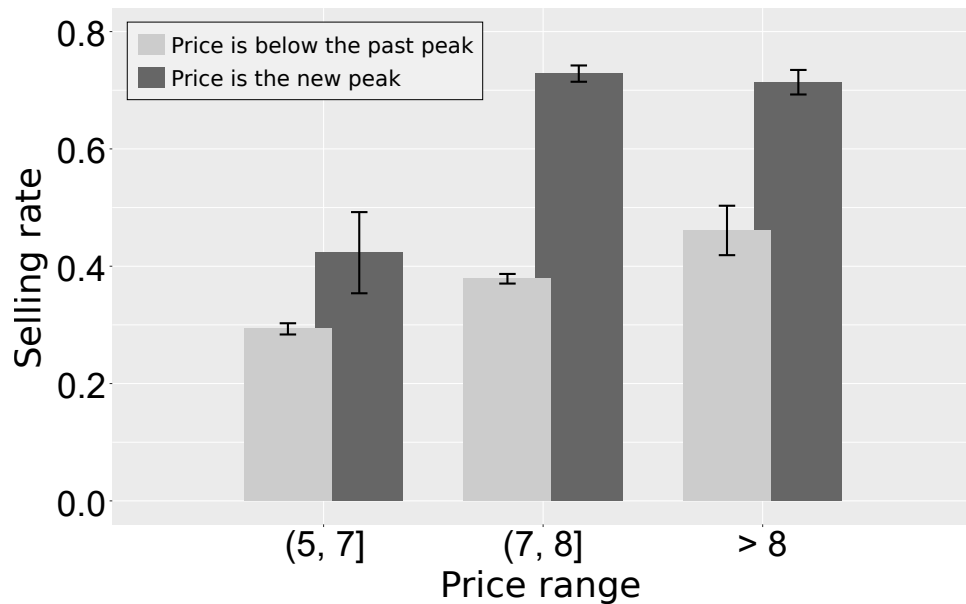


Figure C5: The percentage of sales when the price reaches a new peak (dark grey) and when the price is below the current past peak (light grey). Only observations above the optimal selling price threshold of the risk-neutral no regret agent are considered. The error bars are $\pm 1SE$.

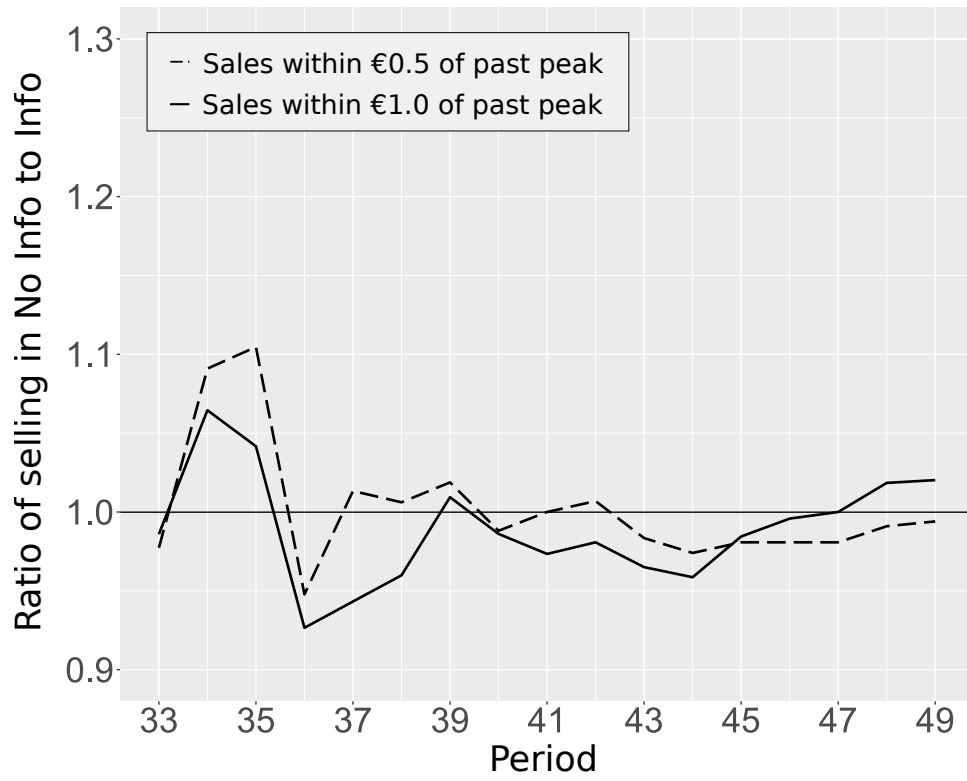


Figure C6: The ratio of the number of sales up to period t in the No Info to Info condition starting from period 33.

D Description of the Variables

Variable	Mean	Median	St. Dev.	Range	Definition
choice	0.94	1.00	0.24	{0, 1}	1 if the participant keeps the asset and 0 if she sells it
info				{0, 1}	1 if the market condition is Info and 0 if it is No Info
time	26.61	25.00	8.44	[16, 49]	Time period
price	4.79	4.86	1.43	[1.20, 8.36]	Current price
price ²	24.96	23.59	13.83	[1.43, 69.95]	Current price squared
future expected price	5.00	5.00	0.08	[3.48, 7.02]	Expected future price in period 50 conditional on the current price, the number of periods left, and the Markov process that generates the prices
past peak	7.58	7.52	0.59	[5.53, 8.56]	Highest price in the past
future expected peak	7.64	7.78	0.45	[3.48, 8.24]	Highest expected future peak conditional on the current price and time (see Appendix F for details)
hl	0.60	0.60	0.17	[0, 0.9]	Risk aversion parameter from Holt and Laury task (normalized from [0, 10] to [0, 1]). 1 is very risk-averse, 0 is very risk-seeking
early				{0, 1}	1 for first 25, 28, 30, or 32 markets depending on specification, 0 otherwise

Table D1: Variables used in the regressions in Tables 1, E2, and E3 (Appendix E). The statistics refer to all periods when a choice is made (periods 16 to 49).

E Additional Regressions

Pr[choice = keep]	I	II	III	IV	V	VI
price	-0.497*** (0.146)	-0.416*** (0.161)	-0.237 (0.145)	-0.243* (0.145)	-0.243* (0.145)	-0.243* (0.145)
price ²	-0.102*** (0.013)	-0.113*** (0.014)	-0.136*** (0.013)	-0.136*** (0.013)	-0.136*** (0.013)	-0.136*** (0.013)
time	-0.088*** (0.004)	-0.090*** (0.004)	-0.082*** (0.005)	-0.083*** (0.005)	-0.083*** (0.005)	-0.083*** (0.005)
future expected price	1.423*** (0.230)	1.223*** (0.251)	1.226*** (0.205)	1.218*** (0.203)	1.218*** (0.203)	1.217*** (0.203)
past peak			0.522*** (0.041)	0.617*** (0.053)	0.617*** (0.053)	0.643*** (0.140)
future expected peak			0.343*** (0.080)	0.272*** (0.093)	0.271*** (0.093)	0.247 (0.244)
past peak × info				-0.208*** (0.072)	-0.208*** (0.072)	-0.209*** (0.072)
future expected peak × info				0.132* (0.074)	0.133* (0.074)	0.133* (0.074)
info				0.511 (0.754)	0.552 (0.757)	0.553 (0.756)
hl		-0.649** (0.301)	-0.646** (0.304)	-0.651** (0.305)	-0.620** (0.307)	-0.622 (2.902)
info × hl					-0.062 (0.205)	-0.060 (0.206)
hl × past peak						-0.038 (0.201)
hl × future expected peak						0.038 (0.353)
constant	4.525*** (1.161)	5.939*** (1.274)	-1.044 (1.090)	-1.116 (1.214)	-1.135 (1.222)	-1.139 (2.259)
<i>N</i>	112,137	89,951	89,951	89,951	89,951	89,951

Table E2: Random effects logit regression of the choice to keep the asset with risk preferences. choice is zero at the time the participant sells the asset and one otherwise. Observations are all periods in all markets for all participants in which they made a choice (periods 16 to 49). Participants whose choices in Holt-Laury task were inconsistent with expected utility maximization were dropped. Errors are clustered by participant and robust.

***, **, * denote statistical significance at the 1, 5 and 10 percent level.

	I	II	III	IV
Pr[choice = keep]	early: 25	early: 28	early: 30	early: 32
price	-0.331** (0.134)	-0.323** (0.135)	-0.280** (0.133)	-0.292** (0.134)
price ²	-0.124*** (0.012)	-0.124*** (0.012)	-0.128*** (0.012)	-0.128*** (0.012)
time	-0.092*** (0.005)	-0.120*** (0.006)	-0.130*** (0.006)	-0.112*** (0.006)
future expected price	1.470*** (0.191)	1.646*** (0.191)	1.621*** (0.190)	1.484*** (0.186)
past peak	0.602*** (0.045)	0.588*** (0.045)	0.604*** (0.045)	0.586*** (0.045)
future expected peak	0.190** (0.084)	0.057 (0.088)	0.022 (0.096)	0.179** (0.088)
past peak × info	-0.204*** (0.065)	-0.196*** (0.065)	-0.212*** (0.065)	-0.205*** (0.065)
future expected peak × info	0.089 (0.078)	0.095 (0.079)	0.227** (0.088)	0.168** (0.085)
info	0.728 (0.726)	0.624 (0.714)	-0.136 (0.765)	0.199 (0.755)
info × early	0.176** (0.072)	0.159** (0.081)	-0.065 (0.087)	0.022 (0.089)
early	-0.239*** (0.070)	-0.718*** (0.072)	-0.854*** (0.078)	-0.657*** (0.074)
constant	-1.670 (1.086)	-0.385 (1.095)	0.185 (1.121)	-0.704 (1.090)
<i>N</i>	112,137	112,137	112,137	112,137

Table E3: The logit regressions support the intuition in Figure 4B. The dummy variable early is 1 if the current period is smaller or equal than the value specified in each column title and 0 otherwise. Participants in the Info condition sell less often early on because of the possibility of future regret: the coefficient on the interaction of info and early is significant and positive until Column III. Observations are all periods in all markets for all participants in which they made a choice (periods 16 to 49). Errors are clustered by participant and robust. The descriptions of all the variables can be found in Appendix D.

***, **, * denote statistical significance at the 1, 5 and 10 percent level.

F The Computation of Future Regret

At period t future regret is defined as the expectation of the highest order statistic of the future $T - t$ prices. At every period $t \in \{2, \dots, T\}$, $y_{t+1} = \alpha y_t + (1 - \alpha)u_t$ is observed, where u_t is an i.i.d. random draw from the uniform distribution on $[a, b]$. We use the notation y_t^k to indicate the price expected in period t given the current price in period k . T , α and y^k (price at time k) are known. Assume a given period $k \in \{1, \dots, T - 2\}$, noting that the expected future peak in the period before the last is just the expectation of the price in the next period. Then we can recover the expected price for any future period beyond the current period ($\forall t > k$) with the following formula:

$$y_t^k = \alpha^{t-k} y_k + (1 - \alpha) \sum_{j=1}^{t-k} u_{t-j} \alpha^{j-1} \quad (\text{F.1})$$

The distribution of y_t^k is

$$\begin{aligned} P\{y_t^k \leq v\} &= P\{\alpha^{t-k} y_k + (1 - \alpha) \sum_{j=k}^{t-1} u_{t-j} \alpha^{j-1} \leq v\} \\ &= F_{(t-k)}(v) = \int_0^v f_{(t-k)}(s) ds \end{aligned}$$

where $f_{(t-k)}(s)$ is the pdf of the sum of $(t - k)$ uniform distributions with different supports. The support of this distribution is $(\alpha^{t-k} y_k, \alpha^{t-k} y_k + 10(1 - \alpha) \sum_{j=1}^{t-k} \alpha^{j-1})$. This is again when all u 's are 0 or all u 's are 10. Note that when $t - k = 1$ $f_{(1)}(s) = \frac{1}{\alpha y_k + (1 - \alpha)10 - \alpha y_k} = \frac{1}{(1 - \alpha)10}$ and $F_{(1)}(s) = \frac{s - \alpha y_k}{(1 - \alpha)10}$.

The expected future peak is computed as:

$$\begin{aligned} \text{Future peak}_{\text{period } k} &= \int_0^{10} v d \prod_{j=1}^{T-k} F_{(j)}(v) \\ &= \int_0^{10} v \sum_{j=1}^{T-k} f_{(j)}(v) \prod_{h \neq j}^{T-k} F_{(h)}(v) dv \\ &= \int_0^{10} v \sum_{j=1}^{T-k} f_{(j)}(v) \prod_{h \neq j}^{T-k} \int_0^v f_{(h)}(s) ds dv \end{aligned}$$

To derive $f_{(t-k)}(v)$ analytically we use recent results in the statistical literature ([Potuschak and Muller, 2009](#)). For simplicity assume that $k = 1$. In fact, the random variable in (F.1) is the sum of independent uniformly distributed $[0, 10]$ random variables times $(1 - \alpha) \times \alpha^{j-1}$, plus $\alpha^{t-1} \frac{y_1}{t-1}$, which is equal to the summation of $t - 1$ uniformly distributed random variables in $[\alpha^{t-1} \frac{y_1}{t-1}, \alpha^{t-1} \frac{y_1}{t-1} + 10(1 - \alpha) \alpha^{j-1}]$, $\forall j \in \{1, \dots, t - 1\}$. According to Potuschak and Muller (2009, section 2.2.2, page 180), the density is

$$f_{(n)}(s) = \frac{1}{2^n (n - 1)! \prod_k a_k} \sum_{j=1}^{2^n} \sigma_j \max\{\underline{a} \cdot \underline{\varepsilon}_j - |s - \sum_k c_k|, 0\}^{n-1} \quad (\text{F.2})$$

where \cdot indicates the dot product, lower bar means vector, $a = \{5(1 - \alpha), 5\alpha(1 - \alpha), 5\alpha^2(1 - \alpha), \dots, 5\alpha^{t-1}(1 - \alpha)\}$, $c = \{\alpha^{t-1} \frac{y_1}{t-1} + 5(1 - \alpha), \alpha^{t-1} \frac{y_1}{t-1} + 5\alpha(1 - \alpha), \alpha^{t-1} \frac{y_1}{t-1} + 5\alpha^2(1 - \alpha), \dots, \alpha^{t-1} \frac{y_1}{t-1} + 5\alpha^{t-1}(1 - \alpha)\}$, $\forall 1 \leq j \leq t - 1$. σ_j and $\underline{\varepsilon}_j$ are matrices which deal with positive and negative signs (see [Potuschak and Muller \(2009\)](#)). We can rewrite the distribution as follows:

$$P\{y_t^1 \leq v\} = F_{(t)}(v) = \int_0^v f_{(t-1)}(s) ds$$

The support of this distribution is $[\alpha^{t-1}y_1, \alpha^{t-1}y_1 + 10(1-\alpha)\sum_{j=1}^{t-1}\alpha^{j-1}]$. Note that $f_{(1)}(s) = \frac{1}{\alpha y_1 + (1-\alpha)10 - \alpha y_1} = \frac{1}{(1-\alpha)10}$ and $F_{(1)}(s) = \frac{s - \alpha y_1}{(1-\alpha)10}$.

F.1 Normal Approximation

(F.2) is problematic, because, as the number of uniform RVs to be summed increases, the denominator goes to zero since $a_k \rightarrow 0$. This makes estimation intractable. Another unappealing feature of this equation is that computation is extremely slow. Therefore, we follow [Potuschak and Muller \(2009\)](#) who proposed to approximate $f_{(n)}(v) = f_{(t-k)}(v)$ with the following normal distribution:

$$y_t^k \sim \mathcal{N}\left(\sum_k c_k, \sum_k \frac{(2 \cdot a_k)^2}{12}\right)$$

The approximation is based on the fact that the sum of uniform distributions is centered around $\sum_k c_k$ with variance $\frac{1}{12}(b-a)^2$, where b and a are the upper and lower bounds of the support of the sum of uniform distributions.

It can be shown that the sum of such i.n.d. uniformly distributed random variables converges to a normal distribution by the Liapounov Central Limit Theorem. The condition for convergence is:

$$\lim_{N \rightarrow \infty} \frac{\sum_{i=1}^N E[|y_i - \mu_i|^{2+\beta}]}{(\sum_{i=1}^N \sigma_i^2)^{\frac{2+\beta}{2}}} = 0,$$

for some choice of $\beta > 0$, where $E[y_i] = \mu_i$ and $V[X_i] = \sigma_i^2$. To see this assume $\beta = 1$ for simplicity and denote $X_i = y_i - \mu_i$. Because $\mu_i = c_i$ and the support of y_i is $[c_i - a_i, c_i + a_i]$, X_i is uniformly distributed in the interval $[-a_i, a_i] = [-5(1-\alpha)\alpha^{i-1}, 5(1-\alpha)\alpha^{i-1}]$. The numerator of the CLT condition involves $E[|X_i|^3] = \int_{-a_i}^{a_i} |s|^3 f_i(s) ds = \int_{-a_i}^{a_i} |s|^3 \frac{1}{2a_i} ds$. Solving the integral we get:

$$\begin{aligned} E[|X_i|^3] &= \frac{1}{2a_i} \frac{1}{4a_i} s^4 \text{sgn}(s) \Big|_{-a_i}^{a_i} \\ &= \frac{125}{4} (1-\alpha)^3 \alpha^{3(i-1)} \end{aligned}$$

Therefore, the numerator is $\frac{125}{4} \sum_i^N (1-\alpha)^3 \alpha^{3(i-1)}$. Similarly, the denominator can be rewritten using the formula for the variance of the normal distribution as $(\frac{25}{3})^{\frac{3}{2}} (\sum_i^N (1-\alpha)^2 \alpha^{2(i-1)})^{\frac{3}{2}}$ (use the fact that $\sigma_i^2 = \frac{1}{12}(c_i + a_i - (c_i - a_i))^2 = \frac{1}{12}(2 \times a_i)^2$). Taking the ratio of these two quantities, the result is $W \times \frac{\sum_i^N (1-\alpha)^3 \alpha^{3(i-1)}}{(\sum_i^N (1-\alpha)^2 \alpha^{2(i-1)})^{\frac{3}{2}}}$, where $0 < W < 1$ is a constant. Finally, we can establish that:

$$\begin{aligned} \lim_{N \rightarrow \infty} &= \frac{\sum_{i=1}^N E[|X_i|^3]}{(\sum_{i=1}^N \sigma_i^2)^{\frac{3}{2}}} \\ &= W \times \frac{\sum_{i=1}^N (1-\alpha)^3 \alpha^{3(i-1)}}{(\sum_{i=1}^N (1-\alpha)^2 \alpha^{2(i-1)})^{\frac{3}{2}}} \\ &= 0 \end{aligned}$$

because the denominator contains positive interaction terms. Therefore, $\sum y_i \sim \mathcal{N}(\sum_k c_k, \sum_k \frac{(2 \times a_k)^2}{12})$.

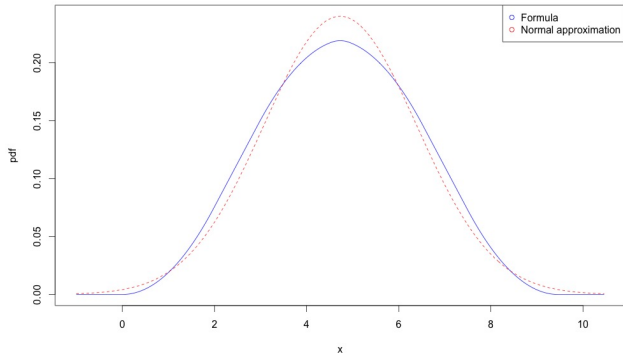


Figure F7: pdf, sum of 3 uniform RVs

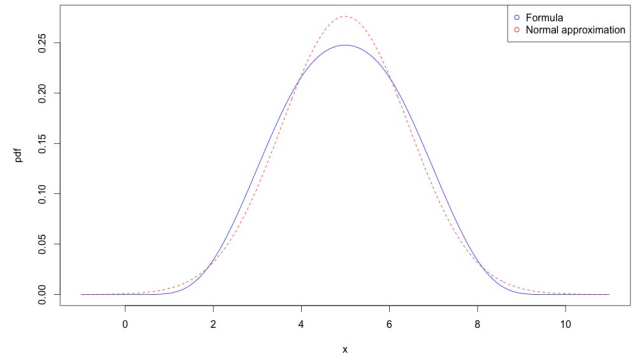


Figure F8: pdf, sum of 13 uniform RVs

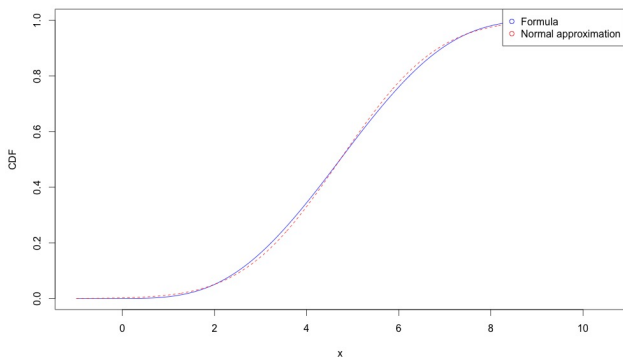


Figure F9: CDF, sum of 3 uniform RVs

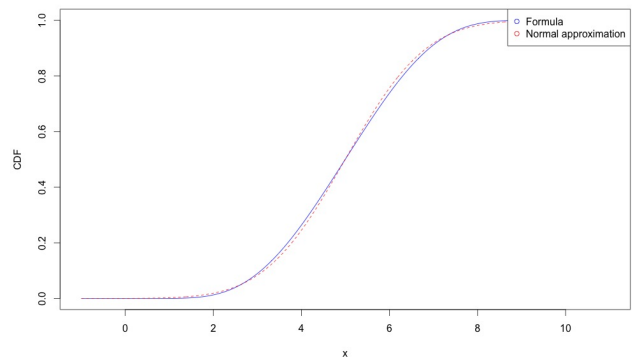


Figure F10: CDF, sum of 13 uniform RVs

G Discretization of the State Space and Transition Matrix

After discretization of the state space, the process describing the evolution of the price at each period of time can be represented by a discrete Markov chain. In fact, the only determinant of price in the next period is the price in the previous period. The discretization is done following [Tauchen \(1986\)](#). See also [Aguirregabiria and Magesan \(2016, page 23\)](#).

The stochastic shock follows the following AR(1) process:

$$y_{i,t+1} = \mu + \rho y_{i,t} + \varepsilon \quad (\text{G.1})$$

where $y_{i,t+1}, y_{i,t}$ are the prices for participant $i = \{1, \dots, N\}$ at time $t + 1$ and t respectively, and $\varepsilon \sim N(0, \sigma^2)$. This panel structure is composed of 48 sequences (the individual dimension) and 50 periods (the time dimension). $\hat{\mu}$ and $\hat{\rho}$ are found using the covariance estimator. The estimates are $\hat{\mu} = 1.97$, $\hat{\rho} = 0.60$ and $\hat{\sigma} = 1.16$. The estimate of ρ is very close to the parameter α which updates the price from period y_t to y_{t+1} ($\alpha = 0.6$).

Let $\{y^1, \dots, y^K\}$ denote the support of the discretized variable $\tilde{Y}_{i,t}$, where $y^1 > y^2 > \dots > y^{K-1} > y^K$ with $K = 400$ are the points in the support. [Tauchen \(1986\)](#) suggests using

$$y^K = \frac{\mu}{1-\rho} + m \times \left(\frac{\sigma^2}{1-\rho^2} \right)^{\frac{1}{2}}$$

$$y^1 = \frac{\mu}{1-\rho} - m \times \left(\frac{\sigma^2}{1-\rho^2} \right)^{\frac{1}{2}}$$

and y^k are $K - 2$ equidistant points within y^K and y^1 , such that the distance between any two points is ω . m is the density of the K points (m is set to 3). This choice of the parameters results in a support with lower bound (y^1) equal to €0.59 ca., upper bound (y^{200}) equal to €9.32 ca., and interval between adjacent points (ω) equal to €0.02 ca.

The probability of transitioning from state y to y' is defined as $p_{i,j} = Pr(y' = y^j | y = y^i)$, which describes the element in the transition matrix in row i and column j . Because of the normality assumption,⁴ the transition probability to a state k , $1 < k < K$, from i is:

$$p_{i,k} = \Phi\left(\frac{y^k + \frac{\omega}{2} - \hat{\mu} - \hat{\rho}y^i}{\hat{\sigma}}\right) - \Phi\left(\frac{y^k - \frac{\omega}{2} - \hat{\mu} - \hat{\rho}y^i}{\hat{\sigma}}\right)$$

which can be thought as the probability that $\rho y^i + \varepsilon \in [\rho y^j - \frac{\omega}{2}, \rho y^j + \frac{\omega}{2}]$. Analogously, the transition probability to the first and last state are:

$$p_{i,1} = \Phi\left(\frac{y^1 + \frac{\omega}{2} - \hat{\mu} - \hat{\rho}y^i}{\hat{\sigma}}\right)$$

$$p_{i,K} = 1 - \Phi\left(\frac{y^K - \frac{\omega}{2} - \hat{\mu} - \hat{\rho}y^i}{\hat{\sigma}}\right)$$

[Tauchen \(1986\)](#) shows that this conditional distribution converges in probability to the true conditional distribution for the stochastic process in (G.1). In fact, it can be shown that such a discretization implies a stationary distribution with AR(1) parameters of $\rho = 0.60$ (equal to the α used in the experiment).

⁴The standardization implies that the distribution is a standard normal.

H Full Derivation of the Dynamic Discrete Choice Model

In this section we present the dynamic discrete choice model that will be used for the structural estimation of the risk and regret parameters of the utility function. The following derivations are also sketched in Section 5. Analogously to the logit panel regressions in Table 1, participants' choice between selling the asset or continuing still follows a threshold rule. However, they now take into account the Markovian nature of the problem. In particular, a participant's intertemporal utility is

$$\mathbb{E} \left\{ \sum_{t=1} \beta^{t-1} u_t^d(x_t) + \varepsilon_t^{d_t} \right\}$$

where $\beta \in (0,1)$ is a discount factor and $\varepsilon_t^{d_t}$ is an error term. As is customary in the dynamic discrete choice literature (Abbring, 2010; Aguirregabiria and Mira, 2010) it is assumed to be known and equal for all participants.⁵ d is the participant's binary choice at time $t \leq T$:

$$d_t = \begin{cases} 1, & \text{keep the asset} \\ 0, & \text{sell the asset.} \end{cases}$$

$u^{d_t}(x_t)$ is the payoff after choosing alternative d_t ; the observables are described by the realization of x_t , which is a tuple consisting of the current price y_t , the past maximum $s_{p,t}$, and the expected future maximum price $s_{f,t}$. We use a utility function which incorporates past and future regret as well as risk preferences. That is, we are interested in a utility function of the type $u(x_t) = U(x_t) - R(x_t)$, where $U(x_t)$ is a consumption utility function and $R(x_t)$ measures regret.

The flow (per period) payoff from choice d_t at period t is $u^{d_t} + \varepsilon_t^{d_t}$ where the error term $\varepsilon_t^{d_t}$ is independent of x_t . As is customary, the error term is assumed to be $\varepsilon_t^{d_t} = \tilde{\varepsilon}^{d_t} - \sigma_\varepsilon \gamma$ where $\tilde{\varepsilon}^{d_t}$ is distributed Type I extreme value with location parameter equal to zero and scale parameter $\sigma_\varepsilon = 1$.⁶ By the properties of the Type I extreme value distribution, the mean of $\tilde{\varepsilon}^{d_t}$ is γ (the Euler's constant). $\varepsilon_t^{d_t}$ is therefore mean zero. Given these preliminaries, denote by $V_t(x_t, \varepsilon_t) = \max_{d_t \in \{0,1\}} \{v_t^{d_t}(x_t) + \varepsilon_t^{d_t}\}$ the value function at the beginning of period t with $\varepsilon_t^{d_t} = \{\varepsilon_t^0, \varepsilon_t^1\}$ and define the *alternative specific value function* (ASVF) for option $d_t \in \{0,1\}$ at time t as:

$$v_t^{d_t}(x_t) = \begin{cases} 0 + \beta \mathbb{E}\{v_{t+1}(x_{t+1}) | x_t, d_t = 1\} & \text{if } d_t = 1 \text{ (keep)} \\ u^0(x_t) & \text{if } d_t = 0 \text{ (sell)} \end{cases} \quad (\text{H.1})$$

where the payoff of continuing is normalized to 0. Note that choosing to sell the asset implies null future payoffs (*terminating action*). The ex-ante value function in (H.1), can be rewritten as the expectation over the error term, ε_t , of the value function at time t

$$v_t(x_t) \equiv \int V_t(x_t, \varepsilon_t) d\Lambda(\varepsilon_t)$$

where $\Lambda(\cdot)$ is the logit distribution and $V_t(x_t, \varepsilon_t) = \max_{d_t \in \{0,1\}} \{v_t^{d_t}(x_t) + \varepsilon_t^{d_t}\}$. Define the *alternative specific value function* (ASVF) as:

$$v_t^{d_t}(x_t) = u^{d_t}(x_t) + \beta \mathbb{E}\{v_{t+1}(x_{t+1}) | x_t, \}, \quad d_t \in \{0,1\}. \quad (\text{H.2})$$

⁵Identification of the discount factor is possible only under an exclusion restriction (Magnac and Thesmar, 2002), and its estimation is generally hard. In order to circumvent this issue, we show that the estimations are robust to different values of β .

⁶The standard deviation of the error term is not identifiable in general, and therefore assumed to be equal to 1.

Because of the property of the Bellman equation, the optimal decision rule can be summarized as follows:

$$d_t = \begin{cases} 1 & \text{if } v_t^1(x_t) - v_t^0(x_t) \geq \varepsilon_t^0 - \varepsilon_t^1 \text{ at } t \\ 0 & \text{otherwise} \end{cases}$$

where $v^{d_t}(\cdot)$ is defined as in (H.2). Denote the *Conditional Choice Probability (CCP)* of selling (action 0) in period t as $\Pr\{d_t = 0|x_t\} \equiv p_t^0(x_t)$:

$$p_t^0(x_t) = \frac{\exp(v_t^0(x_t))}{\exp(v_t^0(x_t)) + \exp(v_t^1(x_t))} = \frac{1}{1 + \exp(v_t^1(x_t) - v_t^0(x_t))}. \quad (\text{H.3})$$

Therefore $p_t^0(x_t) = \Lambda\{v_t^1(x_t) - v_t^0(x_t)\}$. Due to the properties of the logit distribution $\Lambda\{\cdot\}$:

$$\phi(p_t^0(x_t)) \equiv \ln(1 - p_t^0(x_t)) - \ln(p_t^0(x_t)) \equiv v_t^1(x_t) - v_t^0(x_t). \quad (\text{H.4})$$

$\phi(\cdot)$ is estimable from choice data using (H.3) and (H.4) for each period t . Hence the difference in the alternative specific value functions, $v_t^1(x_t) - v_t^0(x_t)$, is known for every t . We can write the two ASVFs as follows:

$$\begin{aligned} v_t^0(x_t) &= u^0(x_t) \\ v_t^1(x_t) &= 0 + \beta \int_{\mathcal{X}} \int_{\varepsilon} \max\{v_{t+1}^0(x_{t+1}) + \varepsilon_{t+1}^0, v_{t+1}^1(x_{t+1}) + \varepsilon_{t+1}^1\} d\Lambda(\varepsilon) dF(x_{t+1}|x_t), \end{aligned} \quad (\text{H.5})$$

where the expectation in the second equation is only over the continuation alternative (1), because the transition matrix in case the absorbing choice (0) is chosen is zero for all x_t (i.e. $F(x_{t+1}|x_t, d_t = 0) = 0$). The estimation is based on the difference of the two ASVFs in (H.5):

$$v_t^1(x_t) - v_t^0(x_t) = -u(x_t) + \beta \int_{\mathcal{X}} \int_{\varepsilon} \max\{v_{t+1}^0(x_{t+1}) + \varepsilon_{t+1}^0, v_{t+1}^1(x_{t+1}) + \varepsilon_{t+1}^1\} d\Lambda(\varepsilon) dF(x_{t+1}|x_t) \quad (\text{H.6})$$

Notice that the LHS of (H.6) can be computed directly from the data using (H.4). The properties of the logit distribution are helpful to rewrite equation H.6 in a form that allows for estimation by non-linear least squares. In fact, the ASVF for continuing (second equation in H.5) can be rewritten as follows

$$\begin{aligned} v_t^1(x_t) &= \beta \int_{\mathcal{X}} \int_{\varepsilon} \max\{v_{t+1}^0(x_{t+1}) + \varepsilon_{t+1}^0, v_{t+1}^1(x_{t+1}) + \varepsilon_{t+1}^1\} d\Lambda(\varepsilon) dF(x_{t+1}|x_t) \\ &= \beta \int_{\mathcal{X}} \gamma + \log(\exp(v_{t+1}^0(x_{t+1}) - \gamma) + \exp(v_{t+1}^1(x_{t+1}) - \gamma)) dF(x_{t+1}|x_t) \\ &= \beta \int_{\mathcal{X}} \gamma + \log\left((1 + \exp(v_{t+1}^1(x_{t+1}) - v_{t+1}^0(x_{t+1}))) \exp(v_{t+1}^0(x_{t+1}) - \gamma)\right) dF(x_{t+1}|x_t) \\ &= \beta \int_{\mathcal{X}} \left(u^0(x_{t+1}) - \log(p_{t+1}^0(x_{t+1}))\right) dF(x_{t+1}|x_t) \end{aligned}$$

where d_{t+1} is the decision in the next period and γ is the Euler's constant. The last row uses (H.3). Therefore the difference of the two ASVFs in (H.6) becomes

$$v_t^1(x_t) - v_t^0(x_t) = -u^0(x_t) + \beta \int_{\mathcal{X}} \left(v_{t+1}^0(x_{t+1}) - \log(p_{t+1}^0(x_{t+1}))\right) dF(x_{t+1}|x_t).$$

By replacing the dependent variable in the last equation with $\phi(p_t^0(x_t))$ and by discretizing the state space

\mathcal{X} the objective function becomes

$$\phi(p_t^0(x_t)) = -u^0(x_t) + \beta \sum_{x_{t+1} \in \mathcal{X}} \left(v_{t+1}^0(x_{t+1}) - \log(p_{t+1}^0(x_{t+1})) \right) f(x_{t+1}|x_t)$$

which concludes the derivation.

Note that the regret components are functions of price (y_t is the only random variable) and time. In fact, $s_{p,t} = \max_{\tau \leq t} y_\tau$ and $s_{f,t} = g(y_t, t)$, where g is a known function that is increasing in the first argument and decreasing in the second.⁷ Therefore,

$$Pr\{y_{t+1}, s_{p,t+1}, s_{f,t+1} | x_t, d_t = 1\} = f(y_{t+1}, s_{p,t+1}, s_{f,t+1} | y_t, s_{p,t}, s_{f,t}) = f(y_{t+1}, s_{p,t+1}, s_{f,t+1} | y_t, s_{p,t}).$$

The transition of the past peak is fully defined by the future price: if $y_{t+1} \geq s_{p,t}$ then $s_{p,t+1} = y_{t+1}$ and $s_{p,t+1} = s_{p,t}$ otherwise. For clarity, consider the following example: given the information available at period $t < T$, the expected utility from keeping the asset one period longer, in the Info condition, is given by

$$\mathbb{E}[u(x_{t+1}) | x_t] = \sum_{y_{t+1}} [\mathbb{1}_{\{y_{t+1} \geq s_{p,t}\}} u(y_{t+1}, y_{t+1}, g(\cdot)) + \mathbb{1}_{\{y_{t+1} < s_{p,t}\}} u(y_{t+1}, \max_{\tau \leq t} y_\tau, g(\cdot))] f(y_{t+1} | y_t).$$

Finally, the transition of the expected future peak is completely determined by the price and time according to the function $g(y_t, t)$.

⁷ $g(\cdot)$ is not strictly monotonic in the two arguments because of the discretization imposed to the data.

I Additional Estimations of the Structural Model

In this section, we propose a series of robustness checks employing different specifications of the utility function compared to that in the main text (see Section 4) to study how ω , α , and λ affect decisions.

I.1 No Future Regret in No Info Condition

Here we estimate several models where we assume that participants do not experience future regret in the No Info condition. Suppose that the per-period utility function

$$u(y_t, s_{p,t}, s_{f,t}) = \pi U(y_t) - R(s_{p,t}, s_{f,t}) \quad (\text{I.1})$$

includes a regret function $R(\cdot, \cdot)$ defined by

$$R(s_{p,t}, s_{f,t}) = \mathbb{1}_{\{\text{No Info}\}} \omega_{NI} s_{p,t} + \mathbb{1}_{\{\text{Info}\}} (\omega_I s_{p,t} + \alpha_I s_{f,t}). \quad (\text{I.2})$$

The arguments of the regret function are the past and expected future peaks and the market conditions are denoted by the subscripts “NI” for No Info and “I” for Info. The indicator function distinguishes the utility derived in one condition from the other. If ω_{NI} , ω_I , and α_I are not significantly different from zero, the participants are categorized as regret neutral.

The results from estimating (5.3) are shown in the first three columns of Table I4 and are obtained by nonlinear least squares on the dataset including periods $t \in \{16, \dots, 48\}$.⁸ The results are robust across different designs and discount factors.

	Estimation of (I.2)			Estimation of (I.3)		
	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$
$\hat{\pi}$	1.892*** (0.011)	1.890*** (0.011)	1.888*** (0.011)	1.884*** (0.011)	1.882*** (0.011)	1.880*** (0.011)
$\hat{\omega}_{NI}$	0.313* (0.188)	0.379* (0.185)	0.464* (0.180)	0.364* (0.188)	0.428** (0.185)	0.508*** (0.181)
$\hat{\omega}_I$	-0.073 (0.195)	0.033 (0.192)	0.145 (0.188)	1.539*** (0.400)	1.636*** (0.359)	1.712*** (0.326)
$\hat{\alpha}_I$	0.174** (0.076)	0.221** (0.075)	0.262*** (0.074)	1.488*** (0.295)	1.552*** (0.262)	1.595*** (0.238)
$\hat{\lambda}_I$				-0.206*** (0.045)	-0.215*** (0.041)	-0.221*** (0.038)
N	111,613	111,613	111,613	111,613	111,613	111,613

Table I4: The estimation of (5.3) with the regret terms as in (I.2) and (I.3) in periods 16 to 48 for different values of the discount factor β . The utility is assumed linear. Standard errors are in parenthesis.

***, **, * denote statistical significance at the 1, 5 and 10 percent level.

The estimation of (I.2) in Table I4 shows that participants are both past and future regret averse. In particular, in the specification (I.2) past regret is significant in the No Info condition, while future regret

⁸For consistency period 49 is dropped because choices taken in this period are directly affected by the fact that participants are *forced* to sell in period 50. This marginally shrinks the dataset from 112,137 to 111,613 observations. Including period 49 does not change the results. Note that the CCP must still be computed for period 49.

is significant in the Info condition which means that our participants are also influenced by future regret avoidance. Notice that past regret is not significant in the estimation of (I.2). The absence of the effect of the past peak is surprising given the discussion in Section 3 and the regression analysis in Tables 1, E2, and E3, which shows the centrality of the $s_{p,t}$ term for both conditions. The reason for this might be that the model is missing an important interaction between the past and the future regret: they might reinforce or inhibit each other. Such an interaction was previously exposed in the discussion of Figure 4B and regression E2 in Section 3 when we compared the decisions to sell early and late in the two conditions. Its presence was also used to explain changes in the probability of selling the asset with different values of the past and future peak in Figure 6 in Section 6.1. To our knowledge, no one in the literature pointed out the importance of this interaction. To account for it we reformulate the regret function to include an interaction term in the Info condition as in (4.1):

$$R(s_{p,t}, s_{f,t}) = \mathbb{1}_{\{\text{No Info}\}} \omega_{NI} s_{p,t} + \mathbb{1}_{\{\text{Info}\}} (\omega_I s_{p,t} + \alpha_I s_{f,t} + \lambda_I s_{p,t} s_{f,t}). \quad (\text{I.3})$$

The interaction term captures the cross-partial derivative of the regret function, which allows us to understand the degree of complementarity or substitutability of the two peaks. The last three columns of Table I4 display the results of the estimation of (5.3) with the regret term (I.3). The results confirm that participants are averse to past regret in both conditions and to future regret in the Info condition. In addition, it indicates a pattern of substitution between the two reference points, as $\hat{\lambda}_I < 0$. Notice also that the estimate of the coefficient on the consumption utility is higher than either the coefficient on past or future regret in the Info condition. As we will see below this implies that participants care more about consumption than regret.⁹

I.2 Regret and Risk Preferences

This section reports estimates for several models displaying different parameterization of the regret-averse utility function and risk-aversion. All estimations are consistent with the findings displayed in Section 6. The tables below show NLS estimates assuming the following discount rates: $\beta \in \{99.65\%, 99.60\%, 99.55\%\}$. The objective function is (5.3) in Section 5. We modify (I.1) to allow for risk aversion

$$u(y_t, s_{p,t}, s_{f,t}) = \pi U(y_t; \rho) - R(s_{p,t}, s_{f,t}; \rho),$$

where $U(y_t; \rho)$ represents either a risk-neutral agent ($\rho = 0$) or CRRA with risk aversion parameter ρ (e.g., $\frac{y^{1-\rho}-1}{1-\rho}$), and $R(\cdot, \cdot; \rho)$ is the regret function. The dataset is discretized over 400 points according to the procedure laid out in Section G.

The following utility function (Model 1) is estimated in Table I5

$$u(y_t, s_{p,t}, s_{f,t}; \rho) = \pi U(y_t; \rho) - \omega U(s_{p,t}; \rho) - \alpha U(s_{f,t}; \rho).$$

The first three columns refer to the linear utility case while the remaining part of the table reports estimates for the CRRA case.

Table I6 includes different coefficients for the two conditions and an interaction term as shown in (I.3).

⁹At this point we should mention that the results of the estimations are very similar in all models if we assume CRRA utility function instead of the linear one. In this case the regret term becomes $R(s_{p,t}, s_{f,t}; \rho) = \mathbb{1}_{\{\text{No Info}\}} \omega_{NI} U(s_{p,t}; \rho) + \mathbb{1}_{\{\text{Info}\}} (\omega_I U(s_{p,t}; \rho) + \alpha_I U(s_{f,t}; \rho) + \lambda_I U(s_{p,t}; \rho) U(s_{f,t}; \rho))$, where ρ is a risk preference parameter in $U(y; \rho) = (y^{1-\rho} - 1)/(1 - \rho)$. The same estimation as in Table I4, only with an additional parameter ρ , is presented in Table I7 in Appendix I.2, which also contains several other model specifications. Overall, the estimated risk preferences are close to risk neutrality in all alternative models and the coefficients on the rest of the parameters stay similar.

Two models are reported with different interaction terms. In Model 2 the regret term is specified as

$$R = \mathbb{1}_{\{\text{No Info}\}}\omega_{NI}U(s_{p,t};\rho) + \mathbb{1}_{\{\text{Info}\}}(\omega_I U(s_{p,t};\rho) + \alpha_I U(s_{f,t};\rho) + \lambda_I U(s_{p,t} \times s_{f,t};\rho))$$

while in Model 3 the regret term is:

$$R = \mathbb{1}_{\{\text{No Info}\}}\omega_{NI}U(s_{p,t};\rho) + \mathbb{1}_{\{\text{Info}\}}(\omega_I U(s_{p,t};\rho) + \alpha_I U(s_{f,t};\rho) + \lambda_I s_{p,t} \times s_{f,t}).$$

The last two equations assume CRRA utility because in the linear case they would produce the same estimate as those in the rightmost columns of Table I4.

Table I7 replicates the results of Table I4. The estimates show that the utility function is almost linear the regret parameters stay qualitatively unchanged.

Finally, Table I8 estimates $\pi U(y_t;\rho) - R(s_{p,t}, s_{f,t};\rho)$ where the regret term is defined as

$$R(s_{p,t}, s_{f,t};\rho) = \mathbb{1}_{\{\text{No Info}\}}(\omega_{NI}U(s_{p,t};\rho) + \alpha_{NI}U(s_{f,t};\rho) + \lambda_{NI}U(s_{p,t};\rho)U(s_{f,t};\rho)) \\ + \mathbb{1}_{\{\text{Info}\}}(\omega_I U(s_{p,t};\rho) + \alpha_I U(s_{f,t};\rho) + \lambda_I U(s_{p,t};\rho)U(s_{f,t};\rho))$$

in Model 4 and

$$R(s_{p,t}, s_{f,t};\rho) = \mathbb{1}_{\{\text{No Info}\}}(\omega_{NI}U(s_{p,t};\rho) + \alpha_{NI}U(s_{f,t};\rho) + \lambda_{NI}U(s_{p,t} \times s_{f,t};\rho)) \\ + \mathbb{1}_{\{\text{Info}\}}(\omega_I U(s_{p,t};\rho) + \alpha_I U(s_{f,t};\rho) + \lambda_I U(s_{p,t} \times s_{f,t};\rho))$$

in Model 5, where $U(\cdot;\rho)$ is a CRRA utility function (the estimates report very mild risk-seeking preferences, while the regret parameters do not change substantially). Overall, the results are very similar across all tables, and corroborate our conclusions outlined in Section 7.

Section I.3 estimates a similar model allowing for loss aversion.

	Model 1					
	Linear Utility			CRRA Utility		
	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$
$\hat{\rho}$				0.061*** (0.017)	0.061*** (0.017)	0.062*** (0.017)
$\hat{\pi}$	1.892*** (0.011)	1.890*** (0.011)	1.887*** (0.011)	2.068*** (0.052)	2.068*** (0.052)	2.069*** (0.052)
$\hat{\omega}$	0.128 (0.144)	0.213 (0.142)	0.313* (0.139)	0.235 (0.170)	0.308* (0.170)	0.400** (0.169)
$\hat{\alpha}$	0.176*** (0.076)	0.219** (0.075)	0.255*** (0.073)	0.122 (0.086)	0.161* (0.085)	0.196** (0.083)
N	111,613	111,613	111,613	111,613	111,613	111,613

Table I5: The estimation of (5.3) with the regret terms as in Model 1, specified in Appendix I.2 in periods 16 to 48 for different values of the discount factor β . The CCP are defined as in (6.1), maintaining the coefficient for the future regret term (β_3) equal to zero in the No Info condition. Standard errors are in parenthesis.

***, **, * denote statistical significance at the 1, 5 and 10 percent level.

	Model 2			Model 3		
	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$
CRRA Utility						
$\hat{\rho}$	0.070*** (0.017)	0.074*** (0.017)	0.072*** (0.017)	0.074*** (0.017)	0.075*** (0.017)	0.076*** (0.017)
$\hat{\pi}$	2.089*** (0.053)	2.094*** (0.053)	2.091*** (0.053)	2.099*** (0.054)	2.101*** (0.054)	2.103*** (0.054)
$\hat{\omega}_{NI}$	0.548** (0.225)	0.743*** (0.217)	0.662*** (0.221)	0.567** (0.227)	0.616*** (0.226)	0.683*** (0.223)
$\hat{\omega}_I$	2.234*** (0.588)	2.516*** (0.448)	2.441*** (0.484)	2.272*** (0.570)	2.368*** (0.511)	2.442*** (0.465)
$\hat{\alpha}_I$	1.965*** (0.450)	2.136*** (0.337)	2.098*** (0.364)	1.947*** (0.424)	2.008*** (0.376)	2.046*** (0.340)
$\hat{\lambda}_I$	-0.317*** (0.080)	-0.349*** (0.065)	-0.341*** (0.068)	-0.241*** (0.054)	-0.248*** (0.049)	-0.253** (0.045)
N	111,613	111,613	111,613	111,613	111,613	111,613

Table I6: The estimation of (5.3) with the regret terms as in Models 2 and 3, specified in Appendix I.2 in periods 16 to 48 for different values of the discount factor β . The CCP are defined as in (6.1), maintaining the coefficient for the future regret term (β_3) equal to zero in the No Info condition. Standard errors are in parenthesis.

***, **, * denote statistical significance at the 1, 5 and 10 percent level.

	Estimation of (I.2)			Estimation of (I.3)		
	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$
CRRA Utility						
$\hat{\rho}$	0.060*** (0.017)	0.060*** (0.017)	0.062*** (0.017)	0.070*** (0.017)	0.071*** (0.017)	0.073*** (0.017)
$\hat{\pi}$	2.066*** (0.052)	2.066*** (0.052)	2.068*** (0.052)	2.089*** (0.053)	2.090*** (0.053)	2.092*** (0.053)
$\hat{\omega}_{NI}$	0.454** (0.219)	0.499** (0.218)	0.567*** (0.215)	0.548** (0.225)	0.596** (0.224)	0.662** (0.221)
$\hat{\omega}_I$	-0.008 (0.224)	0.091 (0.223)	0.202 (0.221)	1.917*** (0.515)	2.020*** (0.464)	2.100*** (0.424)
$\hat{\alpha}_I$	0.120 (0.086)	0.169** (0.085)	0.212** (0.084)	1.647*** (0.374)	1.714*** (0.331)	1.757*** (0.300)
$\hat{\lambda}_I$				-0.295*** (0.072)	-0.307*** (0.066)	-0.317*** (0.061)
N	111,613	111,613	111,613	111,613	111,613	111,613

Table I7: The estimation of (5.3) with the regret terms as in (I.2) and (I.3) in periods 16 to 48 for different values of the discount factor β . The CCP are defined as in (6.1), maintaining the coefficient for the future regret term (β_3) equal to zero in the No Info condition. Standard errors are in parenthesis.

***, **, * denote statistical significance at the 1, 5 and 10 percent level.

	Model 4			Model 5		
	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$
	CRRA Utility					
$\hat{\rho}$	-0.134*** (0.022)	-0.133*** (0.022)	-0.131*** (0.022)	-0.134*** (0.022)	-0.133*** (0.022)	-0.131*** (0.022)
$\hat{\tau}$	1.474*** (0.048)	1.476*** (0.048)	1.478*** (0.048)	1.474*** (0.048)	1.476*** (0.048)	1.478*** (0.048)
$\hat{\omega}_{NI}$	0.431 (0.435)	0.633 (0.393)	0.784** (0.360)	0.415 (0.470)	0.635 (0.425)	0.799** (0.388)
$\hat{\omega}_I$	1.526*** (0.459)	1.601*** (0.415)	1.650*** (0.380)	1.670*** (0.499)	1.751*** (0.451)	1.803*** (0.413)
$\hat{\alpha}_{NI}$	-0.236 (0.314)	-0.075 (0.278)	0.042 (0.250)	-0.251 (0.351)	-0.073 (0.311)	0.057 (0.280)
$\hat{\alpha}_I$	1.188*** (0.329)	1.230*** (0.291)	1.252*** (0.262)	1.332*** (0.371)	1.380*** (0.329)	1.406*** (0.297)
$\hat{\lambda}_{NI}$	0.018 (0.043)	-0.002 (0.039)	-0.017 (0.036)	0.016 (0.038)	-0.002 (0.035)	-0.015 (0.032)
$\hat{\lambda}_I$	-0.163*** (0.048)	-0.170*** (0.044)	-0.174*** (0.040)	-0.144*** (0.043)	-0.150*** (0.040)	-0.153** (0.037)
N	111,613	111,613	111,613	111,613	111,613	111,613

Table I8: The estimation of (5.3) with the regret terms as as in Model 4 and 5, specified in Appendix I.2 in periods 16 to 48 for different values of the discount factor β . The CCP are defined as in (6.1) for both conditions. Standard errors are in parenthesis.

***, **, * denote statistical significance at the 1, 5 and 10 percent level.

I.3 Loss Aversion

Table I9 reports estimates for the model in (6.2) allowing for loss aversion. Loss aversion is defined as the utility loss due to selling at a price below the entry price. The regret function including loss aversion, $\tilde{R}(s_{p,t}, s_{f,t})$ is defined as:

$$\mathbb{1}_{\{\text{No Info}\}}(\omega_{NI}s_{p,t} + \alpha_{NI}s_{f,t} + \lambda_{NI}s_{p,t} \times s_{f,t}) + \mathbb{1}_{\{\text{Info}\}}(\omega_I s_{p,t} + \alpha_I s_{f,t} + \lambda_I s_{p,t} \times s_{f,t}) + \psi \mathbb{1}_{\{y_t < \text{entry price}\}}(y_t - \text{entry price})$$

Table I10 shows the same analysis allowing for CRRA risk preferences. In both models the coefficient ψ multiplies the negative loss. Define $\tilde{R}(s_{p,t}, s_{f,t}; \rho, \psi)$ to include both regret and loss aversion as:

1. $\mathbb{1}_{\{\text{No Info}\}}(\omega_{NI}U(s_{p,t}; \rho) + \alpha_{NI}U(s_{f,t}; \rho) + \lambda_{NI}U(s_{p,t}; \rho) \times U(s_{p,t}; \rho))$
 $+ \mathbb{1}_{\{\text{Info}\}}(\omega_I U(s_{p,t}; \rho) + \alpha_I U(s_{f,t}; \rho) + \lambda_I U(s_{p,t}; \rho) \times U(s_{f,t}; \rho)) + \psi \mathbb{1}_{\{y_t < \text{entry price}\}}(y_t - \text{entry price})$
2. $\mathbb{1}_{\{\text{No Info}\}}(\omega_{NI}U(s_{p,t}; \rho) + \alpha_{NI}U(s_{f,t}; \rho) + \lambda_{NI}U(s_{p,t} \times s_{f,t}; \rho))$
 $+ \mathbb{1}_{\{\text{Info}\}}(\omega_I U(s_{p,t}; \rho) + \alpha_I U(s_{f,t}; \rho) + \lambda_I U(s_{p,t} \times s_{f,t}; \rho)) + \psi \mathbb{1}_{\{y_t < \text{entry price}\}}(y_t - \text{entry price})$

In these tables ψ is constrained to be non-negative, as participants would enjoy a loss otherwise.

Parameter	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$
Linear Utility			
$\hat{\pi}$	1.832*** (0.022)	1.830*** (0.022)	1.829*** (0.022)
$\hat{\omega}_{NI}$	1.075*** (0.464)	1.255*** (0.416)	1.386*** (0.378)
$\hat{\omega}_I$	2.195*** (0.477)	2.240*** (0.427)	2.266*** (0.388)
$\hat{\alpha}_{NI}$	0.070 (0.341)	0.214 (0.303)	0.316 (0.274)
$\hat{\alpha}_I$	1.665*** (0.348)	1.680*** (0.309)	1.681*** (0.281)
$\hat{\lambda}_{NI}$	-0.030 (0.051)	-0.050 (0.046)	-0.064 (0.043)
$\hat{\lambda}_I$	-0.244*** (0.053)	-0.247*** (0.048)	-0.249*** (0.044)
$\hat{\psi}$	0.000 (0.024)	0.000 (0.024)	0.000 (0.024)
N	111,613	111,613	111,613

Table I9: Estimation of regret and loss-aversion parameter in the risk-neutral case. Periods: 16 to 48. Standard errors are in parenthesis. $\hat{\psi}$ is the estimated coefficient of loss aversion.

***, **, * denote statistical significance at the 1, 5 and 10 percent level.

Parameter	$\beta = 99.65\%$	$\beta = 99.60\%$	$\beta = 99.55\%$
Model 1			
$\hat{\rho}$	-0.051*** (0.024)	-0.053** (0.024)	-0.049** (0.024)
$\hat{\pi}$	1.698*** (0.070)	1.690*** (0.069)	1.699*** (0.070)
$\hat{\omega}_{NI}$	0.505 (0.492)	0.696 (0.441)	0.862** (0.405)
$\hat{\omega}_I$	1.664*** (0.517)	1.714*** (0.464)	1.768*** (0.426)
$\hat{\alpha}_{NI}$	-0.246 (0.355)	-0.079 (0.312)	0.033 (0.282)
$\hat{\alpha}_I$	1.323*** (0.371)	1.354*** (0.327)	1.364*** (0.296)
$\hat{\lambda}_{NI}$	0.019 (0.055)	-0.004 (0.050)	-0.020 (0.046)
$\hat{\lambda}_I$	-0.204*** (0.061)	-0.208*** (0.055)	-0.211*** (0.052)
$\hat{\psi}$	0.000 (0.027)	0.000 (0.027)	0.000 (0.027)
Model 2			
$\hat{\rho}$	-0.063** (0.024)	-0.051* (0.024)	-0.055** (0.024)
$\hat{\pi}$	1.667*** (0.069)	1.698*** (0.070)	1.683*** (0.069)
$\hat{\omega}_{NI}$	0.505 (0.529)	0.747 (0.486)	0.936** (0.440)
$\hat{\omega}_I$	1.520*** (0.557)	1.958*** (0.515)	2.107*** (0.469)
$\hat{\alpha}_{NI}$	-0.210 (0.398)	-0.045 (0.360)	0.102 (0.322)
$\hat{\alpha}_I$	1.254*** (0.417)	1.583*** (0.381)	1.679*** (0.343)
$\hat{\lambda}_{NI}$	0.011 (0.050)	-0.008 (0.048)	-0.026 (0.043)
$\hat{\lambda}_I$	-0.155*** (0.056)	-0.202*** (0.055)	-0.214*** (0.051)
$\hat{\psi}$	0.000 (0.027)	0.000 (0.027)	0.000 (0.027)
N	111,613	111,613	111,613

Table I10: Estimation of models 1 and 2. Periods: 16 to 48. Standard errors are in parenthesis. $\hat{\psi}$ is the estimated coefficient of loss aversion.

***, **, * denote statistical significance at the 1, 5 and 10 percent level.

J Instructions (English)

J.1 Market Task

J.1.1 General Instructions

Dear Participants,

You are participating in a decision making experiment which consists of a main part and a questionnaire. If you follow the instructions carefully, you can earn a considerable amount of money depending on your decisions and random events. Your earnings will be paid to you at the end of the experiment.

During the experiment you are not allowed to communicate with anybody. In case of questions, please raise your hand. Then we will come to your seat and answer your questions. Any violation of this rule excludes you immediately from the experiment and all payments.

In the end of the experiment the payment will be made in **CASH**.

J.1.2 The Task

In this experiment you will make decisions in 48 different tasks. Each task is separate and does not depend on the previous tasks in any way. At the beginning of each task you receive 10 Euro. You can earn or lose money depending on your choices. This money will be added or subtracted from 10 Euro.

J.1.3 Structure of the Task

Imagine that you are participating in a financial market and that you should decide at each market (trial) when to sell an object. At the beginning of each market (trial) you observe the price of an object for 15 periods (each period lasts 0.8 seconds). During these periods you can see how the price of the object evolves before you enter the market which means that you cannot make any decisions during these 15 periods. The picture on the right shows the example of the price of the object varying during this starting phase. When you see a vertical red line drawn across the graph, this means that the starting phase of price observation is over. The current price of the object at this point corresponds to the price at which you enter the market. On the top of the screen you can see the current price displayed in each period (between €0 and €10).



J.1.4 The Process Guiding the Value

In every market the value changes according to the following process. If the value in the current period is V , then the value in the next period depends on 1) the current value V and 2) the randomly generated number S . In particular, the value in the next period is equal to $0.6V + S$, where S is a number between 0 and 4. This means that in each period any number between 0 and 4 (for example, 2.1789 or 3.51) has equal probability of being chosen and will contribute to the future value. Therefore, any number in the interval between $0.6V$ and $0.6V + 4$ has equal probability to be the value of the object in the next period. The table below shows some examples. Notice also that in each period the current value cannot be higher than € 10 and lower than € 0.

CURRENT VALUE	INTERVAL FOR THE VALUE IN THE NEXT PERIOD	
	MINIMAL VALUE	MAXIMAL VALUE
€2	€1.2	€5.2
€4	€2.4	€6.4
€6	€3.6	€7.6
€8	€4.8	€8.8

J.1.5 Entering the Market

After you have observed the evolution of the value for 15 periods the market stops at the red vertical line and the button ENTRATA (ENTER) appears at the bottom of the screen (see top figure). When you press the button you enter the market. This means that you “buy” the object at the current value and spend €2.59 as indicated at the top of the screen. You do not have a choice at which price to buy the object. Once you press the button three things happen: 1) the Valore di entrata (Entry price) appears on top of the screen in red (see bottom figure); 2) the value starts to change again and 3) the button changes to USCITA (EXIT).



J.1.6 Exiting the Market

The choice you make in the market is when to exit. This is the point at which you “sell” the object and obtain the amount of money equal to the current value. Your profit in the market is the amount you received at the exit minus the amount you paid when you entered. For example, if you entered at the value of €2.59 and exited at the value of €2.68 your profit is $2.68 - 2.59 = 0.09$, or 9 cents. If you entered at the value of €2.59 and exited at the value of €2.45 your profit is $2.45 - 2.59 = -0.14$, or minus 14 cents. Thus, **YOUR PROFIT CAN BE NEGATIVE**. If you do not choose to exit before the closure of the market at period 50, your profit will be calculated using the last period value of the object.

J.1.7 Observed and Unobserved Future

There are two possible scenarios, which can happen after you press the USCITA (EXIT) button, or sell the object. In one scenario you will observe the evolution of the value of the object until the market closure (after period 50). In the other case you will not observe the evolution of the value. You will be informed about which scenario you are in **BEFORE** the opening of each market. Before each market you will observe a screen with two possible phrases: "INFO DOPO l'uscita" (Information after exit) or "NO INFO al'uscita" (No information after exit) (see figures). The former indicates that the market which you will choose in next is the one with observable future value and the latter – the market with non-observable future value. To make sure that you remember which scenario you are in, the "INFO DOPO" and "NO INFO" signs will appear in the top left corner of the screen while the market is evolving.

INFO DOPO l'uscita

NO INFO all'uscita

J.1.8 After Exiting the Market

After you exit the market, or press USCITA (EXIT) button, you will be provided with the information on your profit. Top figure illustrates the scenario with observable future and the bottom figure – with non-observable future. In both cases, you will see the “Valore di uscita” (exit value) in blue and profit in green (if positive) or red (if negative). In case of non-observable future you will be also asked to wait until the market closure which is the same time it would have taken the market to reach closure if you could have observed the future value. When the market closes you can press PROSEGUI (CONTINUE) button to proceed to the next market.



J.1.9 Payment

Your payment in the experiment is determined as follows. Before the experiment you are given an endowment of €10. After you finish choosing in all 50 markets, one of them will be chosen at random and the profit that you made in that market will be added to your endowment. So, if you earned €3 in the chosen market, your total payment will be €10 + €3 = €13. If your profit was -€3, your total payment will be €10 - €3 = €7. Notice that your profit can change between -€10 and €10. Thus you can earn minimum of €0 and maximum of €20.

J.1.10 Trial Markets

Before the beginning of the task you will have an opportunity to familiarize yourself with the interface in 6 trial markets which will look exactly the same as the actual markets but with TRIAL DI PROVA (TRIAL MARKET) written on the screen. **You will not be paid for your decisions in trial markets.**

K Instructions (Italian)

K.1 Market Task

K.1.1 Informazioni Generali

Gentile partecipante,

Prenderai parte ad un esperimento comprendente due compiti decisionali e un questionario. Se segui le istruzioni attentamente potrai guadagnare una considerevole somma di denaro, che dipenderà dalle decisioni che prenderai durante l'esperimento. La somma da te guadagnata ti verrà pagata al termine dell'esperimento.

Ti chiediamo per favore di non comunicare con gli altri partecipanti durante l'esperimento. Nel caso tu abbia delle domande, chiedi allo sperimentatore alzando la mano. A quel punto lo sperimentatore verrà alla tua postazione e risponderà alle tue domande.

Al termine dell'esperimento il pagamento verrà effettuato in **CONTANTI**.

K.1.2 Compito di Scelta

In questo compito ti verrà chiesto di prendere una decisione in 48 diversi problemi. Ogni problema è a se stante e non dipende dall'esito ottenuto nei problemi precedenti. All'inizio del compito riceverai una somma di partenza pari a 10 euro. In ogni problema potrai guadagnare o perdere un certo ammontare di denaro, il quale verrà sommato o sottratto a questi 10 euro.

K.1.3 Struttura di Campito di Scelta

Immagina di essere all'interno di un mercato finanziario e di dover decidere, ad ogni trial, quando incassare l'ammontare investito. Ogni mercato (trial) inizia osservando il valore dell'oggetto del tuo investimento per 15 periodi (ogni period dura 0.8 secondi). Durante questa prima fase, vedrai come il valore dell'oggetto si è evoluto nei precedenti 15 periodi del mercato. Durante questi 15 periodi non potrai prendere nessuna decisione. La figura a destra ti mostra un esempio di come il valore dell'oggetto può variare durante questa prima fase. Quando la linea verticale rossa verrà raggiunta, significa che i 15 periodi della fase di osservazione saranno terminati. A quel punto il valore corrente dell'oggetto corrisponderà al tuo valore d'entrata nel mercato. La dicitura **"Valore corrente"** in alto ti mostra il valore dell'oggetto in ogni periodo (tra €0 e €10).



K.1.4 Il Processo Che Stabilisce il Valore

In ogni mercato il prezzo cambia seguendo un particolare processo. Dato il valore corrente in un periodo del mercato, V , il valore nel periodo successivo (all'interno dello stesso mercato) dipende da 1) il valore corrente, V , e 2) un numero generato in maniera random, S . In particolare, il valore nel periodo seguente è uguale a $0.6V + S$, dove S è un numero tra 0 e 4. Ciò significa che in ogni periodo qualunque numero tra 0 e 4 (per es. 2.1789 o 3.51) ha la stessa probabilità di essere scelto e di contribuire al valore futuro. Perciò ogni numero nell'intervallo tra $0.6V$ e $0.6V + 4$ ha la stessa probabilità di essere il valore dell'oggetto nel prossimo periodo. La tabella qui di seguito riporta alcuni esempi. Nota che in ogni periodo il valore corrente non può essere maggiore di €10 né minore di €0.

VALORE CORRENTE	INTERVALLO DEL VALORE NEL PERIODO SUCCESSIVO	
	VALORE MINIMO	VALORE MASSIMO
€2	€1.2	€5.2
€4	€2.4	€6.4
€6	€3.6	€7.6
€8	€4.8	€8.8

K.1.5 Entrare nel Mercato

Dopo aver osservato 15 periodi il mercato si fermerà alla linea verticale rossa e il pulsante “ENTRATA” apparirà in basso (vedi la figura in alto a destra). A questo punto per entrare nel mercato dovrai premere il tasto “ENTRATA.” Questo significa che effettivamente tu compri l’oggetto al valore corrente. Nell’esempio indicato nella figura in alto spenderesti €2.59. Non ti sarà possibile evitare di entrare nel mercato e non potrai scegliere tu stesso a quale prezzo comprare l’oggetto. Una volta premuto il pulsante “ENTRATA” il valore dell’oggetto comincerà a variare nuovamente e ti compariranno tre nuove informazioni a schermo (figura in basso a destra): 1) il “Valore di entrata” in rosso in alto a sinistra; 2) il valore attuale dell’oggetto; 3) il pulsante “USCITA.”



K.1.6 Uscire dal Mercato (Uscita)

L’unica scelta a tua disposizione in ogni mercato sarà quando uscire. Questa scelta corrisponde al momento in cui decidi di vendere l’oggetto e intascare la somma di denaro pari al “Valore corrente.” Il tuo guadagno nel mercato sarà la differenza tra il “Valore corrente” al momento di vendita dell’oggetto e il “Valore di entrata.” Ad esempio, se tu entri quando l’oggetto vale €2.59 ed esci al valore di €2.68 il tuo guadagno sarà pari a $€2.68 - €2.59 = €0.09$, o 9 centesimi. Se invece entri al “Valore di entrata” pari a €2.59 ed esci quando il “Valore corrente” è €2.45, il tuo guadagno sarà di $€2.45 - €2.59 = €-0.14$, o un guadagno negativo di 14 centesimi. Perciò, **IL TUO GUADAGNO NEL MERCATO PUO’ ESSERE NEGATIVO.** Se non esci prima della fine del mercato, che dura 50 periodi, il tuo guadagno sarà calcolato usando il valore corrente nell’ultimo periodo.

K.1.7 Futuro Osservato o non Osservato

Ci sono due possibili scenari alternativi che si possono realizzare dopo che hai cliccato sul pulsante “USCITA,” ovvero venduto l’oggetto. In uno scenario ti verrà mostrata l’evoluzione del valore dell’oggetto fino alla chiusura del mercato (50esimo periodo). Nell’altro caso, dopo la vendita dell’oggetto non osserverai nulla, e un nuovo mercato inizierà. Sarai informato riguardo allo scenario in cui ti trovi **PRIMA** dell’inizio di ogni mercato. Prima di ogni mercato, osserverai una schermata con due possibili frasi: “**INFO DOPO l’uscita**” o “**NO INFO all’uscita**” (vedi le figure a destra). La prima dicitura indica che ti trovi in un mercato in cui l’evoluzione del valore dopo la vendita è osservabile, mentre la seconda dicitura ti informa che il futuro valore dell’oggetto non è osservabile. Per ricordarti in quale scenario ti trovi, le diciture “INFO DOPO” e “NO INFO” sono mostrate in alto a sinistra della schermata in cui vedi l’evoluzione del mercato.

INFO DOPO l'uscita

NO INFO all'uscita

K.1.8 Dopo Essere Usciti dal Mercato

Dopo la tua uscita dal mercato, o dopo aver premuto il pulsante “USCITA,” riceverai informazioni sul tuo guadagno. La figura in alto a destra ti mostra lo scenario “INFO DOPO,” dove il futuro è osservabile, mentre la figura in basso ti mostra lo scenario “NO INFO,” dove il futuro non è osservabile. In entrambi i casi, in alto a destra visualizzerai il “Valore di uscita” in blu, ed il tuo “Guadagno” in verde se positivo e in rosso se negativo. Inoltre, nello scenario Info Dopo dovrai attendere il termine del mercato, che corrisponde al tempo che il mercato avrebbe impiegato per raggiungere la sua naturale conclusione (50 periodi) se tu non avessi venduto l’oggetto prima. Raggiunto l’ultimo periodo potrai esaminare la tua prova; per accedere al prossimo mercato dovrai cliccare sul pulsante “Prosegui.”



K.1.9 Pagamento

Il tuo guadagno nell’esperimento viene calcolato come segue. Prima dell’esperimento ti vengono dati € 10 a disposizione. Quando hai finito di scegliere in tutti i 48 mercati, uno di questi verrà scelta in modo casuale e il guadagno che tu fai in quel mercato sarà sommato ai € 10 di partenza. Perciò, se tu guadagni € 3 nel mercato scelto, il tuo pagamento totale sarà € 10 + € 3 = € 13. Nel caso di un guadagno negativo, ad esempio -€ 3, il tuo pagamento totale sarà € 10 - € 3 = € 7. Nota che il tuo guadagno può variare tra -€ 10 e +€ 10, perciò il tuo pagamento totale varia tra un minimo di € 0 e un massimo di € 20.

K.1.10 Mercati di Prova

Prima dell’inizio del compito ti viene data l’opportunità di familiarizzare con l’interfaccia in 6 mercati di prova che assomigliano in tutto e per tutto ai mercati reali a cui parteciperai successivamente, con l’unica differenza che in questi mercati la dicitura TRIAL DI PROVA compare sullo schermo. **Non verrai pagato per le tue decisioni nei mercati di prova.**

K.2 Holt and Laury Task (Italian)

DESCRIZIONE DELLA SECONDA PARTE DELL'ESPERIMENTO

In questa parte dell'esperimento ti verranno presentate 10 coppie di lotterie. Ogni lotteria ti garantisce di ottenere, con una certa probabilità, una tra due possibili vincite. Per ogni coppia di lotterie, il tuo compito sarà quello di scegliere la lotteria che preferisci giocare. Di seguito ti verrà presentata una descrizione dettagliata del compito. Premere il pulsante OK per continuare.

DESCRIZIONE DEL COMPITO

Nella parte destra dello schermo sono riportate le 10 coppie di lotterie. Ci sono 10 righe che corrispondono alle 10 scelte che dovrai effettuare. Ogni riga rappresenta una scelta tra due lotterie.

Per effettuare le tue scelte sarà sufficiente cliccare in corrispondenza della lotteria che preferisci. Una volta che avrai scelto una lotteria, essa diventerà di colore rosso.

Dopo che avrai effettuato le tue 10 scelte, il computer selezionerà in modo casuale una delle 10 righe. Infine, la lotteria da te scelta verrà giocata dal computer e tu riceverai la vincita corrispondente all'esito della lotteria. La tua vincita ti verrà mostrata a schermo dopo che avrai completato e validato tutte le tue scelte.

Ricorda, l'ammontare di denaro rappresentato nelle diverse lotterie è reale, perciò sarai pagato/a in base alle scelte che effettuerai e secondo le regole appena descritte.

Se hai qualche dubbio sulla procedura ed il metodo di pagamento sentiti libero/a di chiedere chiarimenti allo sperimentatore.

1	10% prob. vincere €2.30 90% prob. vincere €1.60	OPPURE	10% prob. vincere €4.00 90% prob. vincere €0.20
2	20% prob. vincere €2.30 80% prob. vincere €1.60	OPPURE	20% prob. vincere €4.00 80% prob. vincere €0.20
3	30% prob. vincere €2.30 70% prob. vincere €1.60	OPPURE	30% prob. vincere €4.00 70% prob. vincere €0.20
4	40% prob. vincere €2.30 60% prob. vincere €1.60	OPPURE	40% prob. vincere €4.00 60% prob. vincere €0.20
5	50% prob. vincere €2.30 50% prob. vincere €1.60	OPPURE	50% prob. vincere €4.00 50% prob. vincere €0.20
6	60% prob. vincere €2.30 40% prob. vincere €1.60	OPPURE	60% prob. vincere €4.00 40% prob. vincere €0.20
7	70% prob. vincere €2.30 30% prob. vincere €1.60	OPPURE	70% prob. vincere €4.00 30% prob. vincere €0.20
8	80% prob. vincere €2.30 20% prob. vincere €1.60	OPPURE	80% prob. vincere €4.00 20% prob. vincere €0.20
9	90% prob. vincere €2.30 10% prob. vincere €1.60	OPPURE	90% prob. vincere €4.00 10% prob. vincere €0.20
10	100% prob. vincere €2.30 0% prob. vincere €1.60	OPPURE	100% prob. vincere €4.00 0% prob. vincere €0.20

OK

References

- ABBRING, J. H. (2010). Identification of dynamic discrete choice models. *Annual Review of Economics*, **2** (1), 367–394.
- AGUIRREGABIRIA, V. and MAGESAN, A. (2016). Solution and estimation of dynamic discrete choice structural models using Euler equations, Mimeo, University of Toronto and University of Calgary.
- and MIRA, P. (2010). Dynamic discrete choice structural models: a survey. *Journal of Econometrics*, **156** (1), 38–67.
- EIJKELENBOOM, G., ROHDE, I. and VOSTROKNUTOV, A. (2016). The impact of the level of responsibility on choices under risk: The role of blame, Mimeo, Maastricht University and University of Trento.
- FISCHBACHER, U. (2007). z-tree: Zurich Toolbox for ready-made economic experiments. *Experimental Economics*, **10** (2), 171–178.
- HOLT, C. A. and LAURY, S. K. (2002). Risk aversion and incentive effects. *The American Economic Review*, **92** (5), 1644–1655.
- MAGNAC, T. and THESMAR, D. (2002). Identifying dynamic discrete decision processes. *Econometrica: Journal of the Econometric Society*, **70** (2), 801–816.
- POTUSCHAK, H. and MULLER, W. G. (2009). More on the distribution of the sum of uniform random variables. *Statistical Papers*, **50** (1), 177–183.
- TAUCHEN, G. (1986). Finite state Markov-chain approximations to univariate and vector autoregressions. *Economics Letters*, **20**, 177–181.