How selective access to financial information affects how investors learn

ABSTRACT

In this study, we compare learning in two common settings in financial markets. One in which investors can observe the outcome of an investment alternative only if they invest in it, and another one in which they always can observe the outcome —even if they do not invest in it. We provide empirical evidence that investors' beliefs are, on average, 5% closer to the objective Bayesian beliefs given the observed information when investors are in a setting in which they have access to the financial information because of endogenous choice. Then we are able to describe the mechanism that explains our findings. We show that the endogenous creation of the sample of information triggers different cognitive processes. These alternative processes cause better information processing and are of enough magnitude to help overcome the effect of sampling errors.

JEL classification: G11, G41.

Keywords: Investor's Learning, Belief Elicitation, Limited Cognition, Sampling Error

Investment environments, by their nature, directly affect the way information is sampled, and thus, experienced by investors. There are many important investment environments in which it is impossible to learn about the outcome of an investment unless the investment is made. As a result, the sample of information that investors to evaluate investment alternatives is endogenously created by their own choices. They are, what the financial decision-making literature calls, selective feedback environments.

Examples of this type of environment are financial markets traded over the counter, such as most private equity, structured financial instruments, natural resources exploration, or foreign direct investment alternatives for which the risk/reward data is not available in an actionable time-frame and investors can only learn about the risk/reward trade-off if they invest in the alternatives. Other examples of this type of feedback can be found in other managerial and financial domains, for instance, a potential entrepreneur can only be certain about the performance of her potential start-up if she decides to pursue the venture, an employer can only be certain about the performance of a new employee in her company if the employee is hired, or a CEO can only be certain about the outcome of an investment project if that project is carried forward in her company.

However, not all relevant financial environments have this characteristic. There are other environments in which investors can easily learn about the outcomes of an investment alternative —even if they do not choose it. They are what the literature calls full feedback environments. For instance, in the stock market, an investor can always learn about the past or present prices of traded companies; in recruitment decisions, a manager generally has easy access to information about the performance of an employee already under her supervision or in corporate financial decisions CEO's can, in most cases, learn about the return of a realized investment alternatives.

Experimental evidence in finance and economics suggests that full feedback and selective feedback environments differ in, at least, two important ways that affect learning. First, in the way information is acquired by the investors. Second, in how that information is processed. That information acquisition and information processing components of financial decision making are key components to analyze was suggested by Rangel, Camerer, and Montague (2008). The relevance of this decomposition is underpinned in the neuroscientific findings by O'Doherty, Dayan, Schultz, Deichmann, Friston, and Dolan (2004); Behrens, Woolrich, Walton, and Rushworth (2007) who show that the neural pathways underlying the two cognitive processes can be dissociated.

The third group of effects that we expect to make learning outcomes differ in the two environments is the result of the interaction between information acquisition and information processing. For instance, the different information acquisition strategies mentioned above will make to differ the samples obtained in the two environments. These different samples may affect the sample size or sample proportion, and this has been shown to lead to different information processing outcomes (i.e., Griffin and Tversky (1992)).

To investigate whether learning is different when people face an environment in which they can only learn if they choose an investment alternative relative to when they face an alternative in which they can learn about an alternative regardless of their choice, we recruited adult participants from the U.S. through Amazon's Mechanical Turk online platform, who were proposed to participate in a study that required the completion of a financial decision making task similar to Kuhnen (2015). In our study, however, participants were randomly allocated (50%/50%) to one of two conditions at the beginning of the experiment. Participants could either face the full feedback condition or the partial feedback condition, which was not present in Kuhnen (2015) and is our main intervention. Crucially, the two conditions differed by the way the information regarding the stock payoffs could be accessed. In the selective feedback condition, participants accessed the information about the payoffs only if they chose the stock in that trial. In the full feedback, condition participants accessed the information regarding the payoff of the stock regardless of their choice. More precisely, the steps participants followed in each trial were the following. In either condition, participants had to choose in each trial between a bond or a stock. Those who chose the stock observed the dividend paid by the stock after making their asset choice and then were asked to provide an estimate of the probability that the stock was paying from the good distribution. However, if they chose the bond, only participants in the full feedback condition always observed the dividend paid by the stock and needed to provide the probability estimate. Those in the selective feedback condition neither observed the outcome nor had to state their probability estimate. In either condition, two types of payoff domain—gain or loss—were possible. Subjects were paid based on their investment payoffs and a fixed participation installment.

To deepen our understanding of these two environments, first, we test and measure whether there are any systematic differences in information processing between the two conditions. Here, we provide experimental evidence that participants facing a selective feedback environment, are on average, 5% more accurate in their beliefs compared to the objective Bayesian posterior about the quality of the stock than participants who face the same risky alternative but receive information about it regardless of their choice. This is the first measurement in the literature, of the effect in the belief formation process, of being in a selective versus a full feedback environment.

Next, we measure the effect of information processing and the different information acquisition behaviors resulting from the two learning environments. Note that in the full feedback condition, there is no possible sampling error, but that in the selective feedback condition there is[1]. As a consequence of the two learning environments, we find that the samples of information that investors use in the two environments are systematically different. People in the selective feedback condition gather smaller samples. These smaller samples of information lead to a sampling error that, on average, adds 5% error compared to the fully informed objective Bayesian beliefs[2].

Finally, we measure the combined effect of the two potential sources of error in learning. We find that the better information processing in the selective feedback environment and the increasing sampling error in the same condition lead to an overall null effect on learning outcomes comparing the two environments. Crucially this is the result of a dynamic process that we reveal and measure. Unveiling this process, measuring the size of its distinct components, and explaining the gap between choice behavior and decision outcomes is the main contribution of this empirical work.

Our study is the first one that takes a double approach to analyze the effects of selective feedback environments in investors' learning in the finance field. Here, we quantify both the effects resulting from differences in information processing and the differences arising from information acquisition, and we are able to describe the process that explains our results. Moreover, there is no previous experimental study in finance analyzing the effects of these two learning environments that focus on analyzing investors' beliefs.

Analyzing the beliefs and not focusing only on the value function and choices is important since prior experimental evidence shows that the effects of learning environments can change both the beliefs and the value function. Thanks to this study, we can better understand why previous studies analyzing the effects of foregone outcomes and the effects of active learning had contradictory results. There are counteracting forces, both in information processing and information acquisition, with an effect on investors learning that counterbalance each other. Here we reveal that previously unaccounted effects in information processing also have a role in explaining the differences in learning outcomes and maximization.

Our study can also deal with two possible criticisms of studies that focus on eliciting the beliefs of people. First, that probability errors found in our study are not linked to investors learning. And second, that the subjective beliefs of participants in our study are possibly non-meaningful quantities to study. Kuhnen (2015), in her very similar experimental setting, show that the probability errors reflected by the beliefs of participants are related to the learning capacity outside of the experiment according to two different measures of learning. Then shows that people who were participating in the experimental task acted based on the subjective beliefs stated during the experiment. They are significantly more likely to choose the stock if they believe that the probability of it paying from the good distribution is higher.

Additionally, we have evidence that the experimental task used in this study correlates with real-life investment decisions. Häusler, Kuhnen, Rudorf, and Weber (2018) using fMRI data from an experimental design similar to our study, shows that activity in the anterior insula during the assessment of risky vs. safe choices in an investing task is associated with self-reported real-life active stock trading. Moreover, the authors show that this association remains intact even when they control for financial constraints, education, the understanding of financial matters, and cognitive abilities. Finally, Häusler et al. (2018) using measures of preferences and beliefs about risk-taking show that both measures mediate the association between brain activation in the anterior insula and real-life active stock trading.

The work presented here contributes to the experimental literature on learning in financial markets that have been growing in recent years. For instance, Kluger and Wyatt (2004) show that there is heterogeneity across traders respect their ability to learn according to Bayes's rule. Bruguier, Quartz, and Bossaerts (2010) found that skill in predicting price changes in markets with insiders correlates with scores on two tests that assess the human capacity to discern malicious or benevolent intent and not on the ability to solve complex mathematical problems. Kogan (2008); Carlin, Kogan, and Lowery (2013) analyze both the effects of overconfidence on learning and complexity on trading and found that strategic considerations influence the two.

Payzan-LeNestour and Bossaerts (2014) find that investors that face an environment with investment alternatives that change randomly and with payoffs that are observable only if investors invest in them learn overwhelmingly in a Bayesian way as neoclassical finance assumes. On the contrary, investors stop learning in a Bayesian way and learn in a bounded rational way when not nudged into paying attention to contingency shifts. Asparouhova, Bossaerts, Eguia, and Zame (2015) show that under asymmetric reasoning, prices do not reflect all types of reasoning. Investors unable to produce correct probability computations prefer to hold portfolios with unambiguous returns and do not directly influence asset prices.

Kuhnen (2015) finds that being in the negative domain leads individuals to form overly pessimistic beliefs about available investment options. Kuhnen, Rudorf, and Weber (2017) show that prior portfolio choices influence investors' expectations of asset values and future choices. This is the result of people updating more from information consistent with their prior choices, and this leads to sticky portfolios over time. Banerjee, Das, and Gulati (2017) show that more negative financial outcome experienced histories tended to produce poorer cognitive performance. Payzan-LeNestour (2018) show that people facing tail risk overwhelmingly behaved like Bayesian learners and that this is the best strategy to survive when facing this type of risk. Hartzmark, Hirshman, and Imas (2019) show that people overreact to signals about goods that they own, but that learning is close to Bayesian for non-owned goods.

Studying differences between investment environments is becoming increasingly important. New investment environments are frequently created. With the advent of fintech companies, proptech companies, cryptocurrencies, or peer-to-peer financial platforms, the market architects that build these ecosystems need to be aware of the effects of the choices that they make when they design them. Moreover, most financial markets can be either fit in one of the two investment environments analyzed in this study. Here we show that the way information is provided to the participants on these markets has a systematic effect on the belief formation process of investors and significantly affects their financial decisions.

The remainder of the article is organized as follows. Section I describes the relevant literature. Section II describes the experimental design. Section III analyzes the results. Section IV concludes.

I. Literature Review

A. Information acquisition

A.1. Exploration-exploitation dilemma

Differences in information acquisition strategies are very important to determine the learning outcomes between the two environments. Looking at differences in this aspect between the two environments, we have previous evidence that people, on average, acquire more information in full feedback environments relative to selective feedback ones (Erev and Haruvy (2015)). This results from investors in the selective feedback environment facing the ”exploration-exploitation dilemma” —whereas those in a full feedback environment do not face it. This dilemma refers to the fact that investors in a selective feedback environment to learn about a risky investment alternative —or equivalently in order to explore it—need to choose the alternative. In contrast, in a full feedback environment, that information is available regardless of investors' choices.

This means that, on certain occasions, to learn about investment alternatives, investors may have to choose alternatives with a lower subjective expected value. That is, investors may have to forego the alternative with the highest subjective expected value—generally known as the exploitation option—in order to explore the rest of the alternatives. A key consequence of this is that when learning in environments without access to foregone payoffs, people will tend to use a smaller sample of information to inform their decisions. More precisely, since gathering information can be costly (Selten and Chmura (2008); Shafir, Reich, Tsur, Erev, and Lotem (2008)), investors tend to reduce the size of the samples collected. Moreover, these smaller samples, compared to those of investors in a full feedback environment, will, in most cases, be less representative of the actual distribution of the outcomes of the investment alternatives Fiedler (2000).

A.2. Use of small samples

That investors use unrepresentative samples matters for the quality of their financial decisions. Using these smaller, less representative samples will lead them to make "Sampling error"[3] even if they process information perfectly. Another relevant phenomenon related to information acquisition that arises in a selective feedback environment but not in a full feedback one is that of "Adaptive sampling". "Adaptive sampling" are the terms that we use to refer to the assumption that the adaptive learning models have built-in. That is that decision-makers increase the probability of choosing an alternative after a high outcome and decrease the probability of choosing the alternative after a low outcome[4]. If people evaluate the alternatives following an adaptive behavior. Adaptive sampling can lead investors to collect unrepresentative samples about the alternatives that they are learning from.

A.3. Adaptive sampling

Adaptive sampling has been shown to make risk-neutral decision-makers that use an optimal policy of learning, to behave as risk-averse participants in the gain domain or risk-seeking in the loss domain, or to produce biased impressions of people or social groups (March (1996); Denrell (2005, 2007); Le Mens, Hannan, and Pólos (2011); Le Mens and Denrell (2011)). "Adaptive sampling" has empirical support in the empirical finance literature. Karlsson, Loewenstein, and Seppi (2009) create and test a model which links information acquisition decisions to the hedonic utility of information. The authors provide evidence that individuals monitor and attend to information more actively given preliminary good news but "put their heads in the sand" by avoiding additional information given prior adverse news. They refer to this behavior with the name the "ostrich effect". On another dimension, we know that the use of different samples in the two environments has significant economic implications. Empirical evidence in finance and economics shows that the samples of information that investors directly experience influence key investment outcomes more than other available information that investors' do not directly experience[5]. Experimental data also underpins this statement (Cohn, Engelmann, Fehr, and Maréchal (2015)). Crucially, these empirical studies also show that the different information acquisition attitudes can lead to sub-optimal investment behavior.

B. Information processing

B.1. Access to foregone outcomes

Camerer and Hua Ho (1999) show that foregone payoffs in economic games are weighted less in investors' future choices than payoffs obtained as a result of a direct choice of an alternative. Similar findings are found by Ashby and Rakow (2016) using eye-tracking technology to evaluate decisions from experience[6] in an experimental setting. Their data suggest that vigilance to outcomes decreases as more consecutive choices are made, is greater for obtained than for foregone outcomes, and when options deliver only gains as opposed to losses or a mixture of gains and losses. Furthermore, the authors find that this variation in attentional allocation plays a central role in the apparent inconsistency in choice, with increased attention to foregone outcomes predicting switches to that option on the next choice.

Another difference between the two environments that can arise when given access to foregone outcomes is the result of the phenomena of "selective attention"[7]. Selective attention refers to the proven fact that, in certain situations, investors choose to either avoid paying attention to information or avoid internalizing information concerning the foregone outcomes they are given. This behavior is more likely when the feedback reveals that they have made a mistake than when the feedback reveals that they have made a good choice. This reduction in the attention given to foregone outcomes can have a deep impact on investors' behavior since we have ample evidence that attention influences investment decisions[8]. Theoretical work in finance has also focused on the importance of attention. For example, Hirshleifer and Teoh (2003) model firms' choices between alternative means of presenting information and the effects of different presentations on market prices when investors have limited attention and processing power and are able to rationalize certain behaviors.

A third difference between the two learning environments in information processing that can arise in environments with access to foregone outcomes is that of underweighting of small probabilities. Previous research shows that providing people with information about foregone outcomes in repeated decisions by experience in a laboratory is linked to underweighting of small probabilities by investors (Grosskopf, Erev, and Yechiam (2006)). This underweighting increases the appeal of rare attractive events and thus makes people less risk-averse. That is why foregone payoffs are considered one of the main mechanisms used to encourage participation in casino gambling and state lotteries.

However, interestingly, the literature on the effects of the availability of foregone outcomes reveals that these differences have an important impact on the investment decisions made by investors in the laboratory but not a profound impact on other financial outcomes of interest such as the maximization of rewards (Grosskopf et al. (2006)). Whether having access to foregone payoffs helps people achieve maximization in experimental tasks is not clear. Depending on the environment, this information can either facilitate, impair or have no significant effect on maximization. Furthermore, even though this effect on the maximization of information about foregone payoffs is not apparent, it has been shown to have profound effects on individual choice behavior. This contradiction between no clear effects on maximization and profound effects on choice behavior has been traditionally explained using an information acquisition perspective. According to this view, foregone outcomes have two opposite sign effects on maximization. Foregone outcomes on one side have a positive effect because they increase information about the alternatives that the decision-maker is facing. This information can help avoid "getting stuck" in a sub-optimal alternative. On the other side, foregone outcomes information can lead to counterproductive switching. That is, foregone outcome information can attract people to choose a sub-optimal alternative, for example, one with higher variance but lower expected value.

B.2. Active learning

Another difference in information processing that we can expect between the two environments is the result of "active learning" studied in the psychological learning literature. This literature on "active learning" shows that active control, that is, the opportunity to control the information experienced while learning, improves memory for studied premises as well as transitive inferences involving items that are never experienced. A characteristic pattern that can emerge is that self-directed learning can lead to similar levels of performance with less training even within the same learning environment (Markant and Gureckis (2010); Gureckis and Markant (2012); Markant, Ruggeri, Gureckis, and Xu (2016); Markant (2018)). Related to this idea, in the computer science field, the development of efficient "active learning" algorithms that can select their own training data is an emerging research topic in machine learning. Unlike traditional learning models that involve passively fed training data, this work has explored algorithms that gather their own training data and can be more efficient in certain environments (see: Settles (2009), or Sutton and Barto (2018)). Another relevant fact related to how information is processed by investors is the evidence that shows that access to foregone outcomes is naturally linked to the experience of post-decision regret. Coricelli, Dolan, and Sirigu (2007) using neuropsychological, and neuroimaging data studied the fundamental role of the orbitofrontal cortex in mediating the experience of regret. The patterns in the obtained data reflect learning based on cumulative emotional experience. This suggests that affective consequences can induce specific mechanisms of cognitive control of the choice processes, involving reinforcement or avoidance of the experienced behavior.

In the literature, we also find contradictions regarding the effects of the availability of foregone outcomes. For instance, the literature on the effects of "active learning" has no consensus about this type of learning in the accuracy of learners. Whereas Markant and Gureckis (2010); Gureckis and Markant (2012); Markant et al. (2016); Markant (2018) link "active learning" to positive outcomes in learning accuracy, Waggoner, Smith, and Collins (2009) show that active learners learn with the same accuracy as passive learners. Additional evidence in this direction can be found in Keehner, Hegarty, Cohen, Khooshabeh, and Montello (2008). Here the authors found that learners who could actively manipulate a novel 3D object on a computer were no more accurate in learning its shape than passive learners who saw the same screen displays but were unable to manipulate them.

C. Information acquisition and processing effects

The stated differences in information acquisition can also have an impact on the information processing component. We can find interactions between information processing and information acquisition effects caused by the two learning environments. For instance, Griffin and Tversky (1992) show that people focus on the strength—defined by sample proportion—of the available evidence with insufficient regard for its weight—defined by sample size—and that this leads to substantial violations of Bayes rule. The authors suggest that this behavior can explain both underconfidence and overconfidence in investors' judgments.

II. Experimental Design

One hundred nineteen participants, 65 males, 53 females, were recruited through Amazon's Mechanical Turk online platform to participate in the experiment. Participants had to complete a financial decision-making task similar to Kuhnen (2015). All participants were presented with information regarding two options: a riskless option, called bond, and a risky one, called stock. Participants faced two different conditions: the full feedback condition and the partial feedback condition. Participants were randomly allocated (50%/50%) to one of the two conditions at the beginning of the experiment. In either condition, the Bond paid +\$6 and the Stock either +\$10 or +\$2.

The Stock could be of 2 types: good or bad. Whether the stock was good or bad was decided randomly (50%/50%) at the beginning of each block. The good stock paid +\$10 with 70% probability and +\$2 with 30% probability; the bad stock paid +\$10 with 30% probability and +\$2 with 70% probability. In Figure 1, this information is summarized in a diagram.

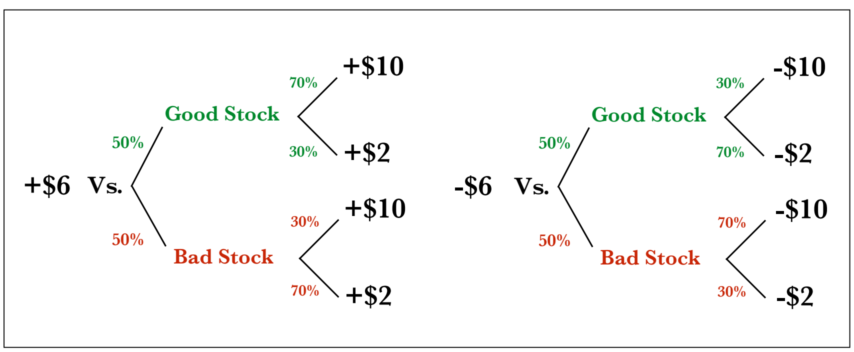

Figure 1. Payoffs and probabilities. This figure describes for the gain domain (left tree) and loss domain (right tree) the: payoffs for the three types of asset, the probabilities of participants facing the good or bad stock, and the probabilities of getting the high or low payoff for each type of stock.

The type of stock that participants faced and its payoffs were generated before the experiment according to the probability distributions mentioned in the previous paragraph. We yoked one participant of each of the two conditions condition to one of the generated sequences. We did this to reduce the variability in the stimuli that participants faced. In total, fifty-nine different sequences were used in the experiment.

Table I

Experimental Design

Each participant had to go through 60 trials. Those trials were split into 10 learning blocks of 6 trials each. In each trial, participants had to choose between a Stock or a Bond. The Stock could be of 2 types: good or bad. Whether the stock was good or bad was decided randomly (50%/50%) at the beginning of each block. The good stock paid the high payoff with 70% probability. The bad stock paid the high payoff with 30% probability. Whether the Stock was good or bad was decided at the beginning of each learning block (with 50%/50% probabilities). In the task, there were 2 conditions: full feedback and selective feedback. Participants faced 10 learning blocks of the same condition, the first 5 blocks in the gain domain and the 5 next blocks in the loss domain. Find below an example of a sequence of full feedback (top table) and selective feedback (bottom table) blocks that a participant may have faced:

Type of Stock	Block Number	Trials	Domain	Condition
Good/Bad	Block 1	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Gain	Full feedback
Good/Bad	Block 2	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Loss	Full feedback
Good/Bad	Block 3	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Gain	Full feedback
Good/Bad	.	.	.	.
Good/Bad	.	.	.	.
Good/Bad	.	.	.	.
Good/Bad	Block 9	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Loss	Full feedback
Good/Bad	Block 10	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Loss	Full feedback

Type of Stock	Block Number	Trials		Condition
Good/Bad	Block 1	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Loss	Selective Feedback
Good/Bad	Block 2	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Loss	Selective Feedback
Good/Bad	Block 3	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Gain	Selective Feedback
Good/Bad	.	.	.	.
Good/Bad	.	.	.	.
Good/Bad	.	.	.	.
Good/Bad	Block 9	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Gain	Selective Feedback
Good/Bad	Block 10	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Gain	Selective Feedback

The task was divided into 10 learning blocks of 6 trials each, the first 5 blocks in the gain domain and the other 5 blocks in the loss domain. Therefore, each participant had to make 60 choices. In Table I, we show a summary of the experimental design and a sequence of loss and gain learning blocks a participant may have faced during the task.

At the beginning of each block, before participants in either condition had possibly observed any payoffs of the stock, we asked them first to estimate the probability the stock they were facing was the good one. Figure 2 shows the screen that participants faced when facing this question.

Then, in each trial of a block, we first asked participants to choose between the stock and the bond. Participants who chose the stock, independently of the condition they were assigned, first observed the payoff of the stock; second, their accumulated payoffs so far for the whole experiment; and third, they were then asked to estimate the probability that the stock they were facing was the good one. Figure 3 shows the timeline of a typical trial in the full feedback and partial feedback conditions in the case participants chose the stock.

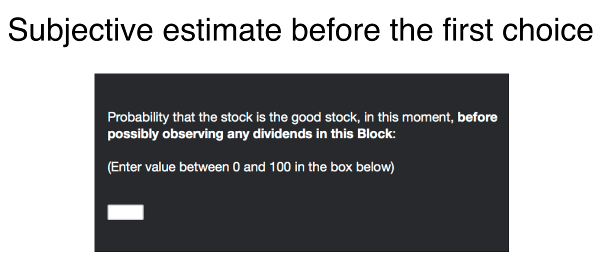

Figure 2. Prior subjective estimate elicitation. This figure describes the payoffs for the three types of asset, the probabilities of participants facing the good or bad stock, and the probabilities of getting the high or low payoff for each type of stock.

If participants chose the bond, the steps they had to follow were different in each condition. In the full feedback condition, they had to follow the same three steps as in the case they chose the stock. However, participants in the partial feedback condition participants only saw their accumulated payoffs. If participants chose the bond and were assigned to the partial feedback condition, they did not observe the payoff of the stock for that period and did not have to estimate the probability of the stock being the good one.

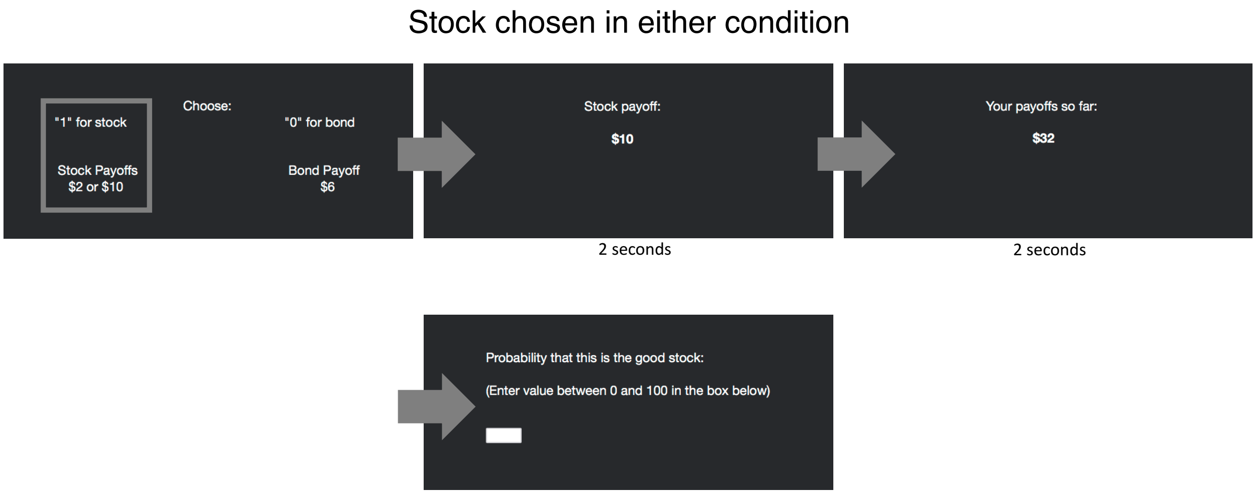

Figure 3. Example of full feedback or partial feedback condition trial in the case the participant chooses the stock. In either condition, the participant first must choose between the stock and the bond. Regardless of the asset choice, then observes the payoff of the stock for that trial. After this, the participant is reminded of the accumulated payoffs for the whole task. Finally, participants are asked to provide an estimate for the probability that the stock is paying from the good dividend distribution and their confidence in this estimate.

Not observing the payoff of the stock is a crucial difference compared to participants assigned in the full feedback condition and the ones in Kuhnen (2015), where all participants were assigned to a full feedback condition and thus observed the payoff of the stock even if they chose the bond. Figure 4 shows the timeline of a typical trial in the full feedback (top timeline) and partial feedback (bottom timeline) conditions for the case that participants chose the bond.

Each participant received a fixed payment of $5 for participating in the experiment and a bonus corresponding to one-tenth of the accumulated payoffs in the whole task.

For this experimental design, the value of the objective Bayesian posterior is easy to calculate. After observing, t high payoffs in n trials in which the payoff of the stock has been observed so far, the Bayesian posterior that the stock is the good one is given by: $\frac{1}{1+\frac{1-p}{p}*(\frac{q}{1-q})^{n-2t}}$ where $p =$ 50% is the prior that the stock is the good one (before any payoffs are observed in that learning block) and $q = 70\%$ is the probability that a good stock pays the high payoff in each trial. In the Appendix, we include all the possible posteriors given all the possible combinations of $\{n, t\}$ in the experiment.

The Bayesian posterior is our benchmark for measuring how close the participants expressed probability estimates are to the objective beliefs. In the full feedback condition, we calculated the Bayesian posterior in each trial; since participants observed the payoff of the stock in all periods. In the partial feedback condition, we calculated the Bayesian posterior only for the trials in which they chose the stock and thus could observe its payoff.

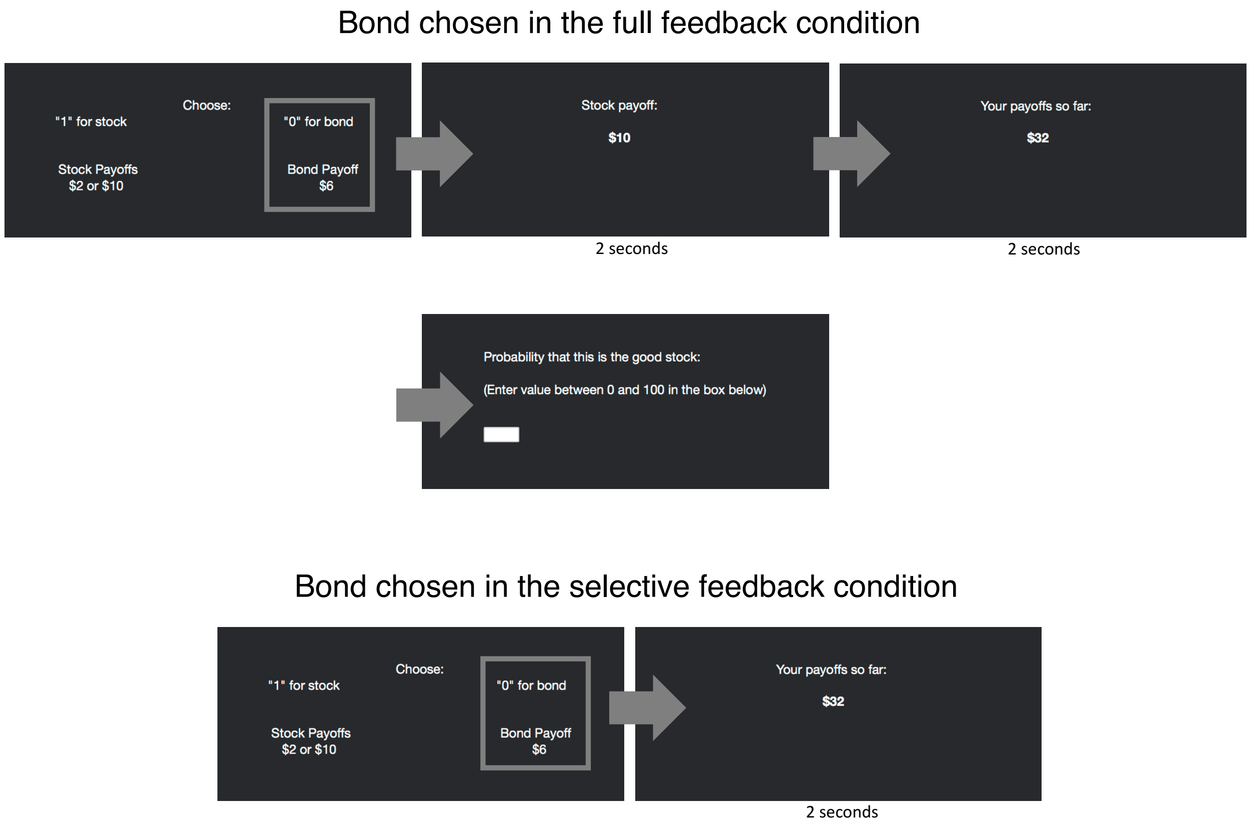

Figure 4. Example of full feedback or partial feedback condition trial if a participant chose the bond. In either type of condition, the participant must first choose between the stock and the bond. Then, participants in the full feedback condition observe the payoff of the stock for that trial, are reminded of the accumulated payoffs for the whole task, and finally, are asked to provide an estimate for the probability that the stock is paying from the good dividend distribution. Participants in the partial feedback condition after choosing the security are only reminded of the accumulated payoffs for the whole task.

We collected measures of financial literacy and risk preferences for all participants. These two measures can be found in the Appendix, but we will also provide a short description here. To assess risk preferences, after each participant completed the financial decision-making task, we asked them to allocate $10,000 into 2 different investment options: a risk-free option, in the form of a savings account, and a risky option, in the form of the stock market. Their choice provided a proxy for risk preferences outside the main task of the experiment. To assess financial literacy, we asked participants to solve a financial problem in which they had to estimate the expected amount of money that their previous choice in the risk preference task would have granted them given the financial conditions of the two types of possible investment, either a risk-free asset or a risky one. This question allowed us to check the knowledge of three concepts: probabilities, the difference between net and gross returns, and the difference between stocks and saving accounts. The answer to this question allowed us to give a financial literacy score from 0 to 3 depending on the number of these three concepts they understood.

III. Empirical Findings

A. Main Results

We find that participants' beliefs regarding the likelihood that the stock pays from the good distribution are different in the selective feedback condition compared to those of the participants in the full feedback condition. Those differences can be summarized in three results, the main one, and two complementary ones. First and main, the subjective beliefs of participants in the selective feedback condition are closer to the objective Bayesian posterior than those of the participants in the full feedback condition. Second, reference point losses in a selective feedback environment, and not only explicit losses, are sufficient to trigger superior adaptive learning by investors. Third, even if we use as a benchmark a Bayesian posterior that is updated in each trial regardless of the participant's choice, the subjective beliefs of participants in the selective feedback condition are as close to the objective Bayesian posterior as those of the participants in the full feedback condition.

In figure 5, we can observe the first and main results. In this figure, in the x-axis, we represent all the Bayesian objective posteriors that participants faced in the experiment. The number of Bayesian objective posteriors that participants faced during the experiment are limited since there is a finite number of outcome historical paths that participants could observe. We list all of them in the Appendix. The y-axis represents the average of the subjective estimates of the probability of the stock being the good one that participants stated after observing the outcome histories that yield each of the Bayesian posteriors on the x-axis. Points outside the 45° line indicate deviations from the objective Bayesian posterior.

Analyzing figure 5, we observe that participants, in both conditions, deviate significantly from what a Bayesian learner would estimate. If we look at the two graphs, the gain domain (on the left) and the loss domain (on the right), there are very clear deviations from the 45° line in most of the points for which we have an observation. Crucially, these deviations vary significantly depending on the condition that participants were assigned. Specifically, subjective posteriors in the selective feedback condition tend to be closer to the objective beliefs than those of the participants in the full feedback condition. We can quantify the differences between the two conditions by looking at

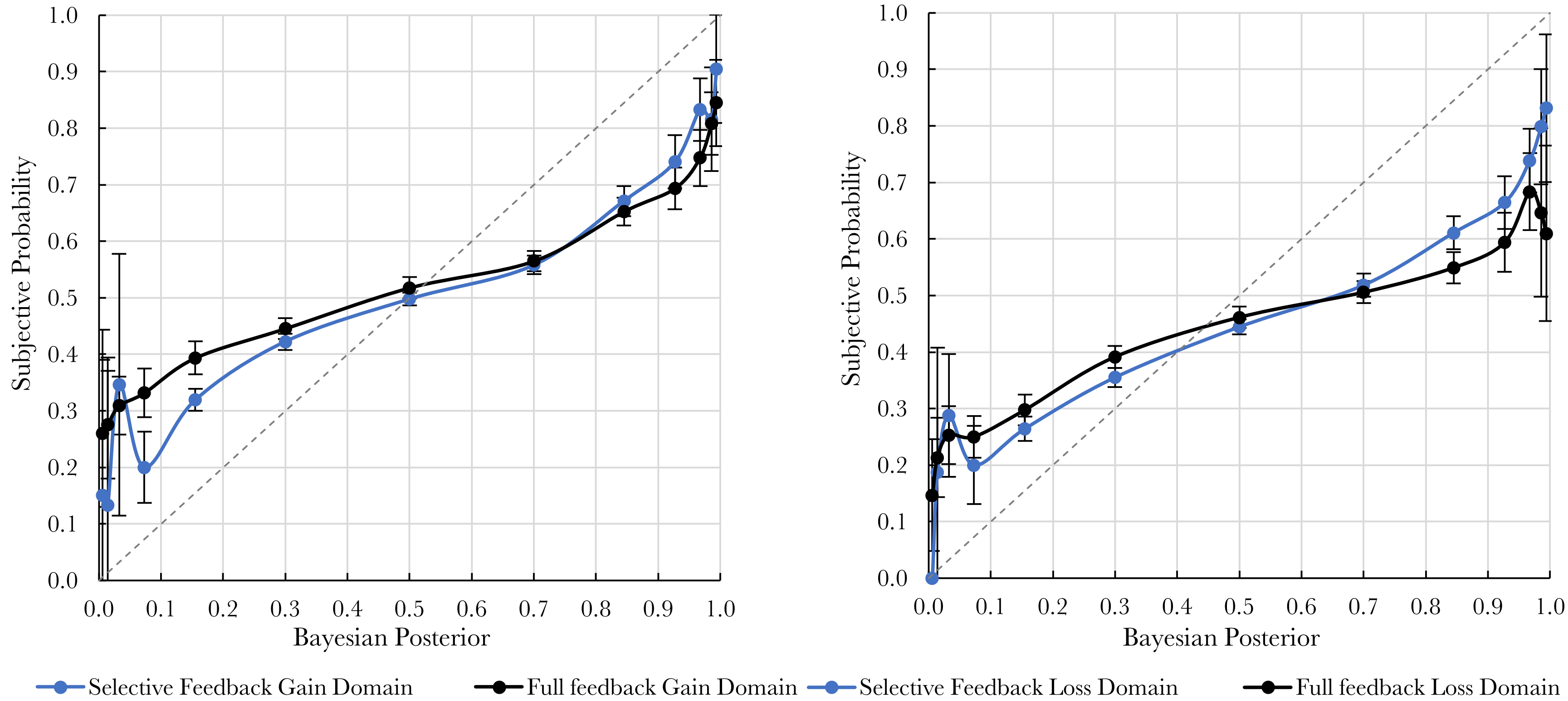

Figure 5. Average subjective estimates for the probability that the stock is the good one, as a function of the Bayesian probability. If participants were Bayesian, all the average subjective estimates would line up in the 45 ° line. Observations outside that line indicate deviations from the objective Bayesian posteriors. All the Bayesian posteriors that were possible in the experiment can be found in the appendix, together with the combinations of high and low payoffs that lead to them. The average subjective estimates for each Bayesian posterior are plotted in black for participants in the full feedback condition and blue for participants in the selective feedback condition. The left panel presents belief data from the Gain domain, while the right panel presents belief data from the Gain domain.

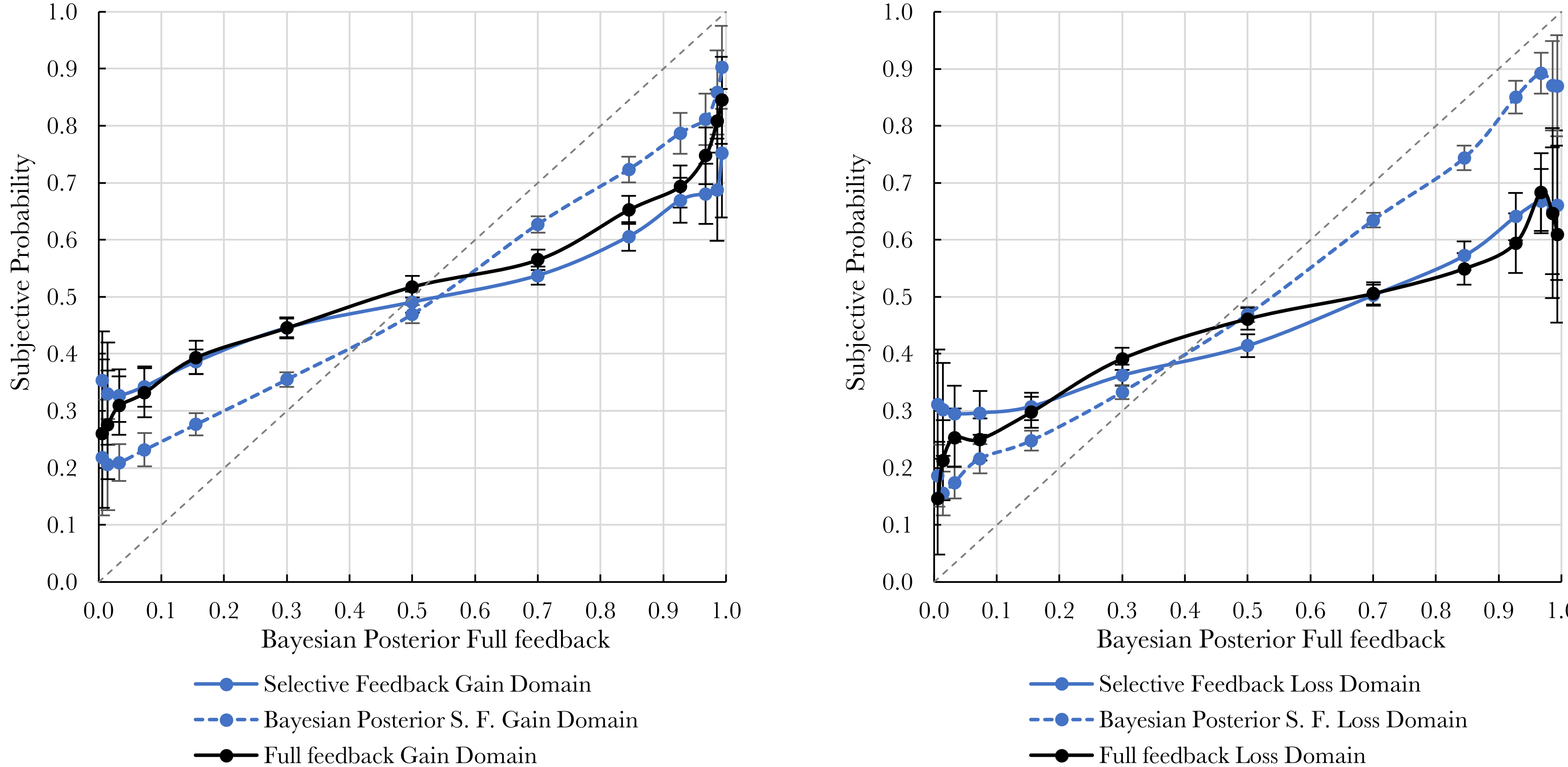

Figure 6. Average subjective estimates for the probability that the stock is the good one, as a function of the Bayesian probability calculated as if participants received full feedback about the payoffs of the stock in each trial. Posteriors in the figure have been updated after each trial as if participants have observed all the payoffs of the stock up to the trial the posterior is calculated. If participants were Bayesian and had observed all the payoffs of the stock up to the trial, the posterior was calculated, all the average subjective estimates would line up in the 45° line. Observations outside that line indicate deviations from the objective Bayesian posteriors with full feedback. All the Bayesian posteriors that were possible in the experiment can be found in the appendix, together with the combinations of high and low payoffs that lead to them. The average subjective estimates for each Bayesian posterior are plotted in black for participants in the full feedback condition and in blue for participants in the selective feedback condition. The average Bayesian posterior of participants in the Selective feedback condition is plotted in blue and is dashed.

the results in Table II (gain domain in Panel A, loss domain in Panel B). According to the column (1) regressions on the table, the probability errors of people in the selective feedback condition are on average 6.32% lower in the gain domain and 4.90% lower in the loss domain than those of people in the full feedback condition (p <0.01). If we look at column (3) and column (5) of Table II, we see that the difference between the two conditions is higher for objective probabilities <50% in the gain domain and for objective probabilities $\geq$ 50% in the loss domain. Specifically, in the gain domain, the average participant in the selective feedback condition was 7.02% closer to the objective beliefs than the average participant in the full feedback condition evaluating objective probabilities <50% (p <0.01). In the loss domain, the average participant in the selective feedback condition was 6.44% closer than the average participant in the full feedback condition to the objective beliefs only evaluating objective probabilities $\geq$ 50% (p <0.01). These six results are robust to the inclusion of trial fixed effects.

A relevant point to asses is in which particular scenarios do participants in the selective feedback condition make less probability estimation error than people in the full feedback condition. The analysis in Table IV presents information that can help us to better understand this, and we use this information as a foundation to explain the second result of this study. In Table IV, we find the average change from trial to trial in the probability estimation error after observing either a high payoff (column (1)) or low payoff (column (1)) in a trial for the selective feedback and full feedback conditions, and the gain (Panel A) and loss (Panel B) domains. In column (2), we observe that after participants have observed a low realization of the stock, those in the selective feedback condition are closer to the objective Bayesian beliefs in both the gain domain and loss domain by respectively 5.87% (p <0.01) and 3.29% (p <0.1). Note that the better performance in the gain domain nearly doubles that of the loss domain and that the better performance in the gain domain is significant at the 1% level of confidence and in the loss domain is only marginally significant. So, up to this point, our analysis suggests that the better performance in the selective feedback, compared to the full feedback, has the largest magnitude after a low realization of the stock rather than a high one. But what happens if we study the effect of the size of the realization, but we differentiate between high and low subjective priors? Columns (3) to (6) add this level of analysis. In column (6), we can see that high subjective prior trials are the main drivers of the effect of low

Table II

Differences in Probability Estimation Errors in the Selective feedback and Full feedback Conditions

This table shows that the probability estimation errors are lower in the selective feedback condition relative to the full feedback condition in both the Gain and the Loss domain. The dependent variable in the regression models below, $Absolute\ Probability\ Error_{\mathrm{it}}$, is the absolute value of the difference between the subjective posterior belief that the stock is the good one that participant i expressed in trial t and the corresponding Objective Bayesian Posterior which is the Bayesian posterior probability that the stock is good, given the information seen by the participant up to trial t in the learning block. The independent variable included is the $Selective\ feedback\ trial_{\mathrm{i}}$ indicator variable, which is equal to one if participant i is in the selective feedback condition and zero if she is in the full feedback condition. Trial fixed effects are included in the second, fourth, and sixth specifications in each panel. Standard errors are robust to heteroskedasticity and are clustered by subject. t-statistics are in parentheses. ***, ** indicate significance at the 1% and 5% level, respectively.

Dependent Variable	$Absolute\ Probability\ Error_{it}$					
Panel A: Gain Domain						
	All Trials	All Trials	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors ≥ 50%	Trials with Objective Posteriors ≥ 50%
$Selective\ Feedback\ Trial_i$	-0.06***	-0.06***	-0.07***	-0.07***	-0.05***	-0.05***
	(-3.83)	(-3.82)	(-3.02)	(-3.11)	(-2.90)	(-2.92)
Constant	0.20***	0.20***	0.23***	0.23***	0.17***	0.17***
	(15.52)	(15.51)	(11.95)	(11.89)	(13.36)	(13.44)
Trial fixed effects	No	Yes	No	Yes	No	Yes
R^2	0.039	0.048	0.045	0.064	0.030	0.045
Observations	3541	3541	1404	1404	2137	2137
Panel B: Loss Domain						
	All Trials	All Trials	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors ≥ 50%	Trials with Objective Posteriors ≥ 50%
$Selective\ Feedback\ Trial_i$	-0.05**	-0.05**	-0.03	-0.03	-0.06**	-0.06**
	(-2.47)	(-2.47)	(-1.50)	(-1.57)	(-2.30)	(-2.30)
Constant	0.21***	0.21***	0.19***	0.19***	0.22***	0.22***
	(13.29)	(13.28)	(12.40)	(12.34)	(10.00)	(10.01)
Trial fixed effects	No	Yes	No	Yes	No	Yes
R^2	0.019	0.030	0.011	0.024	0.026	0.049
Observations	3539	3539	1461	1461	2078	2078

Table III

Differences in Probability Estimation Errors against a Full Feedback Bayesian benchmark in the Selective feedback and Full feedback Conditions

This table shows that the probability estimation errors, using a fully informed Bayesian benchmark, are not significantly different in the selective feedback condition and full feedback conditions in both the Gain and the Loss domain. The dependent variable in the regression models below, *Absolute Probability Error Full Feedback*$_{\text{it}}$, is the absolute value of the difference between the subjective posterior belief that the stock is the good one that participant i expressed in trial t and the corresponding Objective Bayesian Posterior updated with full feedback, which is the Bayesian posterior probability that the stock is good, given the information of all payoffs of the stock up to trial t in the learning block. The independent variable included is the *Selective feedback trial*$_{\text{i}}$ indicator variable, which is equal to one if participant i is in the selective feedback condition and zero if she is in the full feedback condition. Trial fixed effects are included in the second, fourth, and sixth specifications in each panel. Standard errors are robust to heteroskedasticity and are clustered by subject. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5% and level, 10% respectively.

Dependent Variable	*Absolute Probability Error Full Feedback*$_{it}$					
	Panel A: Gain Domain					
	All Trials	All Trials	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors ≥ 50%	Trials with Objective Posteriors ≥ 50%
Selective Feedback Trial$_i$	0.011	0.011	-0.03	-0.03	0.04**	0.04**
	(0.60)	(0.60)	(-1.25)	(-1.43)	(2.02)	(2.02)
Constant	0.20***	0.20***	0.23***	0.24***	0.17***	0.17***
	(15.52)	(15.51)	(11.95)	(11.90)	(13.36)	(13.46)
Trial fixed effects	No	Yes	No	Yes	No	Yes
R^2	0.001	0.025	0.007	0.045	0.014	0.049
Observations	3541	3541	1404	1404	2137	2137
	Panel B: Loss Domain					
	All Trials	All Trials	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors ≥ 50%	Trials with Objective Posteriors ≥ 50%
Selective Feedback Trial$_i$	0.00	0.00	0.01	0.01	0.00	0.00
	(0.16)	(0.16)	(0.43)	(0.29)	(-0.09)	(-0.10)
Constant	0.21***	0.21***	0.19***	0.19***	0.22***	0.22***
	(13.29)	(13.28)	(12.40)	(12.39)	(10.00)	(10.02)
Trial fixed effects	No	Yes	No	Yes	No	Yes
R^2	0.000	0.020	0.001	0.029	0.000	0.032
Observations	3539	3539	1461	1461	2078	2078

Table IV

Mean Probability Estimation Error Updates per Condition and their Difference after Observing a High or Low Payoff

This table shows the average change from trial to trial in the probability estimation error that a participant produced after observing either a high or low payoff in a trial for the selective feedback and full feedback conditions, gain and loss domains, and for high versus low subjective priors. ***, * indicate significance at the 1% and 10% level, respectively.

Dependent Variable	*Absolute Probability Error$_{it}$*					
	Panel A: Gain Domain					
	High Payoff in Trial t	Low Payoff in Trial t	High Payoff in Trial t Subjective estimate t - 1 < 50%	High Payoff in Trial t Subjective estimate t - 1 ≥ 50%	Low Payoff in Trial t Subjective estimate t - 1 < 50%	Low Payoff in Trial t Subjective estimate t - 1 ≥ 50%
Selective feedback condition	0.16	0.15	0.20	0.15	0.16	0.14
Full feedback condition	0.19	0.21	0.22	0.18	0.17	0.23
Difference	-0.03*	-0.06***	-0.02	-0.03*	-0.01	-0.08***
	Panel B: Loss Domain					
Selective feedback condition	0.20	0.15	0.29	0.17	0.17	0.14
Full feedback condition	0.23	0.18	0.30	0.20	0.18	0.18
Difference	-0.04	-0.03*	0.00	-0.03*	-0.01	-0.04*

realizations on the subjective probability error. More precisely, after observing a low realization of the stock, people in the gain domain and the selective feedback are 8.14% ($p < 0.01$) closer to the Bayesian objective posteriors than people in the full feedback condition. So, the analysis of the scenarios indicates that the beliefs of participants in the selective feedback condition are closer to those of participants in the full feedback condition, particularly after a low realization of the stock in the gain domain and, especially when this low realization is preceded by a high subjective prior. Therefore, this allows us to state that reference point losses in a selective feedback environment, not only explicit losses, are sufficient to trigger superior adaptive learning by investors.

Additionally, it is interesting to note that, as shown in column (2) of Table V, our second result can be explained by a larger reaction to a low payoff realization that produces a more aggressive probability updating behavior in the selective feedback relative to the full feedback condition. More precisely, in the gain domain (Panel A), people in the selective feedback condition update their subjective probability after observing a low realization of the stock 2.65% ($p < 0.05$) more than people in the full feedback condition.

In Figure 6, we observe the third result. In the x-axis of this figure, we represent all the Bayesian objective posteriors that a Bayesian learner would have produced if she had received information about all payoffs of the stock up to the corresponding trial. Note that this is a crucial difference for the posteriors of participants in the selective feedback condition, but not for those of the participants in the full feedback condition, which do not change with respect to those in Figure 5. Why does the plot of the selective feedback condition change in Figure 6? Because, when we calculate the posterior for participants in a selective feedback condition, we do not only update it in the trials in which participants have chosen the stock and thus observed the payoff of the stock, but we update it in every period regardless of the asset choice. This is possible thanks to how the experiment was programmed, which allowed us to know whether a participant would have observed a high or low payoff if she had chosen the stock, even if she ended up choosing the bond, and thus, not observing the payoff. In Figure 6, the y-axis represents the average of the subjective estimates of the probability of the stock being the good one that participants stated after having observed, or not –for participants in the selective feedback condition that did not choose the stock in any period– the outcome histories that yield each of the Bayesian posteriors on the x-axis.

Table V

Mean Subjective Probability Updates per Condition and their Difference after Observing a High or Low Payoff

This table shows the average update in the subjective posterior that a participant produced in the selective feedback or full feedback condition after observing a high or low payoff in a trial. In the third and fourth columns, we restrict the observations to those in which participants observed a low payoff and their subjective probabilities in the previous trial were lower than 50% or equal or higher than 50%. *** indicates significance at the 1% level.

Dependent Variable	*Probability Estimate$_{t+1}$ - Probability Estimate$_t$*					
	Panel A: Gain Domain					
	High Payoff in Trial t + 1	Low Payoff in Trial t + 1	High Payoff in Trial t + 1 Subjective estimate < 50%	High Payoff in Trial t + 1 Subjective estimate ≥ 50%	Low Payoff in Trial t + 1 Subjective estimate < 50%	Low Payoff in Trial t + 1 Subjective estimate ≥ 50%
Selective feedback condition	7.27%	-8.09%	10.64%	6.63%	-5.05%	-8.97%
Full feedback condition	5.77%	-5.44%	11.40%	3.85%	-1.42%	-7.72%
Difference	1.51%	-2.65%**	-0.77%	2.78%**	-3.64%	-1.25%
	Panel B: Loss Domain					
Selective feedback condition	6.34%	-9.65%	9.43%	5.41%	-2.73%	-12.58%
Full feedback condition	4.31%	-6.37%	7.21%	2.62%	-1.88%	-10.13%
Difference	2.03%	-3.28%***	2.22%	2.79%	-0.84%	-2.45%

Analyzing Figure 6, we observe a clear pattern. Subjective beliefs of participants in both conditions deviate significantly from the objective Bayesian posterior calculated as if participants in both conditions received full feedback. This is not surprising for the full feedback condition plot since this is the same plot as we observed in Figure 5, but we do indeed get new information for the selective feedback condition. Contrary to Figure 5, we observe that participants' beliefs in the selective feedback condition do not significantly deviate from those in the full feedback one. And, as reported in column (1) of Table III, this is true for both the gain domain (1.06%, $p > 0.1$) and the loss domain (0.30%, $p > 0.1$) (gain domain in Panel A, loss domain in Panel B).

Apart from the subjective beliefs, in Figure 6, we have another plot. This plot is the objective Bayesian posterior that participants in the selective feedback condition could calculate if they were Bayesian learners, as a function of the Bayesian posterior, calculated as if participants had observed the payoff of the stock in all trials up to the moment the Bayesian posterior is calculated. The first posterior is the one that participants would produce if they were Bayesian learners, given the information they observed about the payoffs of the stock; the second one is the one that they would have produced if they were Bayesian learners and had observed all the payoff of the stock so far in the experiment. The difference between the 45° line and this plot is the average Sampling error that participants made for each point in which we have an observation. The sampling error can only exist in the selective feedback condition since in the full feedback condition; the objective Bayesian benchmark is always updated regardless of the asset choice made by participants. Here, we observe that the Sampling error exists across the whole range of objective probabilities and that it is higher in the extremes for very high and very low probabilities. Crucially, columns (1) of Table III shows that the sampling error is responsible for completely erasing the better processing of information in the selective feedback condition that was reflected in the gain and loss domains in column (1) in Table II, and this allows us to quantify its size of about 5% in each condition.

B. *Alternative Explanations*

In figure 5 and Table II, we have shown that participants in the selective feedback condition are close to the objective Bayesian beliefs in the two domains than participants in the full feedback condition. We suggest that this outcome is the product of a different learning process between the two learning environments. Moreover, we suggest that this result is caused by already known effects of access to foregone outcomes.

Table VI

Mean Subjective Probability Updates in the Full feedback Condition when Stock Chosen or Sampled and their Difference after Observing a High or Low Payoff

This table shows the average update in the subjective posterior that a participant produced in the full feedback condition, after choosing the stock, or after passively observing the outcome of the stock, for high or low payoff trials. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

	Dependent Variable	
	Probability Estimate$_{t+1}$ - *Probability Estimate*$_{t}$	*Absolute Probability Error*$_{it}$
	Panel A: Gain Domain	
Stock selected	0.52%	20.35%
Stock sampled	-0.23%	19.17%
Difference	0.75%	1.19%
	Panel B: Loss Domain	
Stock selected	-0.97%	22.34%
Stock sampled	-1.13%	18.55%
Difference	0.16%	3.79%***

The first known effect of foregone outcomes that could cause the different learning outcomes is the documented difference in the weight given in a full feedback setting to selected information and passively observed one. In the context of our experiment, if participants treated these two different sources of information differently, we would observe differences in probability updating and in probability estimation errors between payoffs observed as a result of selected stocks or payoffs observed as a result of sampled stocks[9]. According to the literature, we would expect that selected stocks would be given more weight in probability updating and that probability errors would also be lower after a stock selection. To test this, we constructed Table VI. Analyzing the first column of the table, we observe that there are no significant differences in probability updates between selected and sampled stocks neither in the gain domain (0.75%, p >0.1) nor in the loss domain (0.16%, p >0.1). Analyzing the second column of the table, we observe that there are no significant differences in probability estimation errors in the gain domain (0.01, p >0.1), but there are in the loss domain (0.04, p <0.01). However, this significant difference is against the suggested results in the literature and cannot explain the better processing of information in the selective feedback condition. This could have been a factor if sampled stocks were the origin of higher probability estimation errors.

Table VII

Mean Subjective Probability Updates and Mean Probability Estimation Error Updates in the First Trial of the Selective and Full feedback Conditions by Asset Selection

This table shows the average update in the subjective posterior that a participant produced in the full feedback condition, after choosing the stock, or after passively observing the outcome of the stock, for high or low payoff trials. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

	Dependent Variable	
	Probability Estimate$_{t+1}$ - *Probability Estimate*$_t$	*Absolute Probability Error*$_{it}$
	Panel A: Stock chosen	
Selective feedback condition	-2.81%	0.16
Full feedback condition	-1.65%	0.18
Difference	-1.16%	-0.03***
	Panel B: Bond chosen	
Selective feedback condition	0.00%	0.07
Full feedback condition	-1.74%	0.15
Difference	1.74%	-0.09***

A second effect of having access to foregone outcomes cited in the literature refers to the fact that participants in a full feedback environment will get more conflicting information than those in a selective feedback environment. That participants in the full feedback condition will observe more conflicting information about the quality of the stock is also expected in our experiment. This is because participants in the full feedback condition will observe all the payoffs of the stock and will not miss any, as most participants in the selective feedback will. The more conflicting information that participants in the full feedback condition will receive could affect their information processing.

To test this, we analyze whether there are differences between the two conditions in probability updating and probability estimation errors after the first trial. We choose to measure those two outcomes at this point because this allows us to eliminate potential confounds related to conflicting information since in our test, we will measure differences in outcomes after having made the same choices and where no conflicting information from previous trials is possible. Analyzing column 1 in Table VII, we observe that there are no significant differences in probability updates between the selective feedback and full feedback condition after the stock having been chosen in trial 1 (-1.16%, p >0.1), nor after the bond is chosen in the same trial (1.74%, p >0.1). However, if we compare probability errors at that stage, we observe that differences already exist at that point, and moreover, the differences match the sign of our main result. More precisely, in the second column of Table VII, we observe that the probability errors are already 3% lower in the selective feedback condition compared to the full feedback condition after the stock has been chosen (p <0.01) and 9% lower after the bond has been chosen (p <0.01).

The third effect of foregone outcomes that could explain differential learning is that of the underweighting of small probabilities that access to foregone outcomes produces, according to the literature. To test this, we can look at columns 3, 4, 5, and 6 of Table II. There we observe that the differential learning is not only produced when the objective Bayesian posteriors are lower than 50%, but this is also produced for Bayesian posteriors higher than 50%.

C. Learning in the last trial

Given that learning is a dynamic process that should help participants to improve results with the experience, we analyze the learning outcomes also in the sixth trial of the experimental task, which is the last trial that participants faced in each block of decisions. We can quantify the differences between the two conditions by looking at the results in Table VIII (gain domain in Panel A, loss domain in Panel B). According to the column (1) regressions on the table, the probability errors of people in the selective feedback condition are on average 6.96% lower in the gain domain and 6.32% lower in the loss domain than those of people in the full feedback condition (both p <0.01). If we look at column (3) and column (5) of Table VIII, we see that the difference between the two conditions is higher for objective probabilities $<50\%$ in the gain domain and for objective probabilities $\geq 50\%$ in the loss domain. Specifically, in the gain domain, the average participant in the selective feedback condition was 11.58% closer to the objective beliefs than the average participant in the full feedback condition evaluating objective probabilities $<50\%$ ($p < 0.01$). In the loss domain, the average participant in the selective feedback condition was 7.87% closer than the average participant in the full feedback condition to the objective beliefs only evaluating objective probabilities $\geq 50\%$ ($p < 0.01$). These six results are robust to the inclusion of trial fixed effects.

Probability errors are another learning measure of interest. We obtained them using as a benchmark the Bayesian objective posteriors that a Bayesian learner would have produced if she had received information about all payoffs of the stock up to the corresponding trial. We can quantify the differences between the two conditions according to this measure looking at the results in Table IX (gain domain in Panel A, loss domain in Panel B). According to the column (1) regressions on the table, the probability errors against a fully informed benchmark of people in the selective feedback condition are no significantly different than those of people in the full feedback condition neither in the gain domain (0.04, $p > 0.1$) nor in the loss domain (0.01, $p > 0.1$). If we look at column (3) of Table IX, we observe that there are also no significant differences between the two conditions for objective probabilities $<50\%$ neither in the gain domain (-0.02, $p > 0.1$), nor in the loss domain (0.04, $p > 0.1$). In column (5), we observe the results for objective probabilities $\geq 50\%$. For the gain domain, we observe that participants in the selective feedback condition produced 8.09% significantly higher error updates than participants in the full feedback condition ($p < 0.01$). However, participants in the loss domain produced no significantly different error updates between the two conditions (-0.01, $p > 0.1$). These six results are robust to the inclusion of trial fixed effects.

D. Choices

We proceed now to the analysis of other important learning outcomes. More precisely, now we will analyze differences in choice behavior dynamics in the selective and full feedback condition by the type of stock that the participants faced and by the domain of the payoffs of the decision block. In figure 7, we have plotted the proportion of stock choices per trial for each condition.

Table VIII

Differences in Probability Estimation Errors in the Selective feedback and Full feedback Conditions in Trial 6

This table shows that the probability estimation errors, using a fully informed Bayesian benchmark, are not significantly different in the selective feedback condition and full feedback conditions in both the Gain and the Loss domain in the sixth and last trial of each block. The dependent variable in the regression models below, *Absolute Probability Error Full Feedback*$_{\mathrm{it}}$, is the absolute value of the difference between the subjective posterior belief that the stock is the good one that participant i expressed in trial t and the corresponding Objective Bayesian Posterior updated with full feedback, which is the Bayesian posterior probability that the stock is good, given the information of all payoffs of the stock up to trial t in the learning block. The independent variable included is the *Selective feedback trial*$_{\mathrm{i}}$ indicator variable, which is equal to one if participant i is in the selective feedback condition and zero if she is in the full feedback condition. Trial fixed effects are included in the second, fourth, and sixth specifications in each panel. Standard errors are robust to heteroskedasticity and are clustered by subject. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5% and level, 10% respectively.

Dependent Variable	*Absolute Probability Error*$_{it}$					
			Panel A: Gain Domain			
	All Trials	All Trials	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors ≥ 50%	Trials with Objective Posteriors ≥ 50%
Selective Feedback Trial$_i$	-0.07***	-0.07***	-0.11***	-0.11***	-0.05*	-0.05*
	(-3.17)	(-3.17)	(-3.17)	(-3.17)	(-1.72)	(-1.72)
Constant	0.22***	0.22***	0.27***	0.27***	0.18***	0.18***
	(12.51)	(12.51)	(9.28)	(9.28)	(9.74)	(9.74)
Trial fixed effects	No	Yes	No	Yes	No	Yes
R^2	0.034	0.034	0.072	0.072	0.016	0.016
Observations	590	590	248	248	342	342
			Panel B: Loss Domain			
	All Trials	All Trials	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors ≥ 50%	Trials with Objective Posteriors ≥ 50%
Selective Feedback Trial$_i$	-0.06**	-0.06**	-0.04	-0.04	-0.08**	-0.08**
	(-2.39)	(-2.39)	(-1.43)	(-1.43)	(-2.09)	(-2.09)
Constant	0.24***	0.24***	0.20***	0.20***	0.27***	0.27***
	(11.12)	(11.12)	(8.06)	(8.06)	(8.99)	(8.99)
Trial fixed effects	No	Yes	No	Yes	No	Yes
R^2	0.024	0.024	0.017	0.017	0.028	0.028
Observations	590	590	251	251	339	339

Table IX

Differences in Probability Estimation Errors against a Full Feedback Bayesian benchmark in the Selective feedback and Full feedback Conditions in Trial 6

This table shows that the probability estimation errors are lower in the selective feedback condition relative to the full feedback condition in the sixth trial in both the Gain and the Loss domain. The dependent variable in the regression models below, *Absolute Probability Error Full Feedback*$_{\text{it}}$, is the absolute value of the difference between the subjective posterior belief that the stock is the good one that participant i expressed in trial t and the corresponding Objective Bayesian Posterior updated with full feedback, which is the Bayesian posterior probability that the stock is good, given the information of all payoffs of the stock up to trial t in the learning block. The independent variable included is the *Selective feedback trial*$_{\text{i}}$ indicator variable, which is equal to one if participant i is in the selective feedback condition and zero if she is in the full feedback condition. Trial fixed effects are included in the second, fourth, and sixth specifications in each panel. Standard errors are robust to heteroskedasticity and are clustered by subject. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5% and level, 10% respectively.

Dependent Variable	*Absolute Probability Error Full Feedback*$_{it}$					
Panel A: Gain Domain						
	All Trials	All Trials	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors ≥ 50%	Trials with Objective Posteriors ≥ 50%
Selective Feedback Trial$_i$	0.04	0.04	-0.02	-0.02	0.08***	0.08***
	(1.58)	(1.58)	(-0.68)	(-0.68)	(2.81)	(2.81)
Constant	0.22***	0.22***	0.27***	0.27***	0.18***	0.18***
	(12.51)	(12.51)	(9.28)	(9.28)	(9.74)	(9.74)
Trial fixed effects	No	Yes	No	Yes	No	Yes
R^2	0.009	0.009	0.003	0.003	0.040	0.040
Observations	590	590	248	248	342	342
Panel B: Loss Domain						
	All Trials	All Trials	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors < 50%	Trials with Objective Posteriors ≥ 50%	Trials with Objective Posteriors ≥ 50%
Selective Feedback Trial$_i$	0.01	0.01	0.04	0.04	-0.01	-0.01
	(0.45)	(0.45)	(1.26)	(1.26)	(-0.14)	(-0.14)
Constant	0.24***	0.24***	0.20***	0.20***	0.27***	0.27***
	(11.12)	(11.12)	(8.06)	(8.06)	(8.99)	(8.99)
Trial fixed effects	No	Yes	No	Yes	No	Yes
R^2	0.001	0.001	0.011	0.011	0.001	0.001
Observations	590	590	251	251	339	339

First, we observe in all four graphs that the proportion of stock choices is always higher in the first two trials in the selective feedback condition. This is the result of the exploration-exploitation trade-off. Since the expected payoffs if participants are facing the good stock of choosing that asset is higher than if they choose the bond, they have an incentive to explore the risky alternative to learn about it. Participants in the selective feedback condition, apart from the value of the payoff, get value from the information that the payoff of the stock reveals. However, participants of the full feedback condition will be able to observe the outcome of the stock regardless of their choice, so choosing the stock will not carry that information value. This higher exploration in the selective feedback condition helps participants to choose the best alternative in terms of expected payoff (the stock) when facing the good stock but hinders participants' maximization when facing the bad stock (since the asset with the higher expected value is the bond in that case).

Second, we observe that the slope of the selective feedback condition plot in the graphs in the second column (when participants faced a bad stock either in the gain or loss domain) is more inclined relative to the same plots in the graphs of the left column (when participants faced a good stock). The negativity bias that adaptive sampling predicts is found here. The negativity bias, produced by facing lower than expected payoffs when choosing the stock, leads participants in the selective feedback condition to make the same proportion of stock choices as participants in the full feedback condition when facing the bad stock. In this case, the negativity bias helps participants to choose the best alternative in terms of expected payoff (the bond). However, if we look at the left column graphs, we observe that at least for the gain domain, the absence of a high negativity bias leads participants in the selective feedback condition to make a significantly lower proportion of stock choices (the maximizing option) than participants in the full feedback condition. The effect for the loss domain would be in the same direction if participants in the full feedback condition facing the loss domain would not have incurred in higher loss aversion in that domain relative to the gain domain, as can be seen comparing the full feedback plots of the left column top and bottom graphs.

Finally, and most important of all, overall, we observe that the learning outcomes that we observed in the previous section match the ones that we find in this one. In the last trial of each block, there is no significant difference in choice behavior as a result of learning in a selective or a full feedback setting.

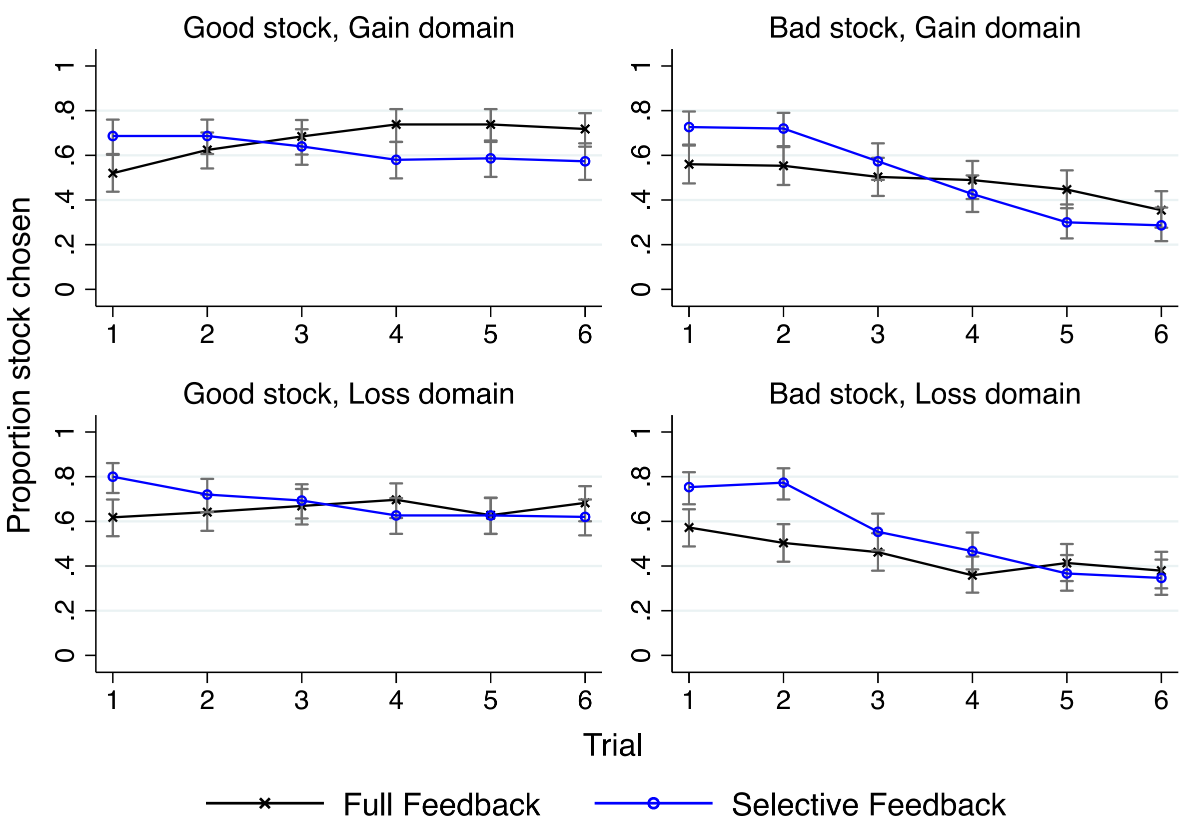

Figure 7. Proportion of stock choices per trial for the selective feedback and full feedback condition by type of stock and domain. The proportion of stock choices for the selective feedback condition are plotted in a blue line, while the proportion of stock choices for the full feedback condition are plotted in black. In light grey are plotted the 95% confidence intervals for the population proportion in either condition. The top row graphs are produced using only trials in which participants faced payoffs in the gain domain. The bottom row graphs are produced using only trials in which participants faced payoffs in the loss domain. The left column graphs are produced using only trials in which participants faced a good stock. The right column graphs are produced using only trials in which participants faced a bad stock.

IV. Discussion and Implications

A. Main Results

As our main finding, we uncover and measure the elements of the process that explains why and how learning differs between selective feedback and full feedback environments. This process is composed of two principal elements. The first one is the better processing of information produced by investors in a selective feedback environment compared to those in a full feedback environment. The elicited beliefs of participants in the selective feedback environment are on average 5% closer to the beliefs that a perfect Bayesian rational learner would have given the available information. We find that investors in a selective feedback environment enter a distinct learning mode that allows them to process the available information in a better way, thus reducing the cognitive error that they make.

As per the second element, we find that the better processing of information in the selective feedback environment is powerful enough to even offset sampling errors. Sampling errors, in our experimental task, on average amount to 5% of additional error. Despite investors in the selective feedback condition having access on average to less information, the better processing of information allows them to offset this sampling error. Sampling errors in our experimental task are generated by the missed information as a result of investors in the selective feedback condition, not choosing the stock, and thus missing the information about its outcome. Therefore we should expect sampling error in a trial, not to change if the stock is sampled, or to necessarily increase if the stock is not chosen. If the latter case happens, the new sampling error will add to the potential new cognitive error and the preexisting cognitive and sampling errors. All these elements combined will produce the total error made by the investor. For these reasons, we expected the error of participants in the selective feedback condition to be higher than that of participants in the full feedback condition.

However, here we show that the better processing of information in a selective feedback environment can, in certain circumstances, eliminate this impairment to investors' learning. This is the result of a dynamic process that we just described and summarized in the following few lines. First, the better processing of information helps participants in the selective feedback condition to make less cognitive error. Second, compared to the investors in a full feedback condition, those in the selective feedback condition, as they decide not to choose the risky alternative, face a cumulative sampling error. In our particular experimental study, we find that these two opposite forces end up perfectly counterbalancing each other.

Additionally, we show that reference point losses in the gain domain, and not only explicit losses, are sufficient to trigger adaptive learning by investors in the selective feedback condition compared to those in the full feedback condition. After observing a low payoff in the gain domain, participants in the selective feedback condition, on average, produce beliefs about the quality of the stock that are 6% closer to the objective Bayesian beliefs than those of the people of the full feedback condition. This result is mainly driven by the observations in which participants believed that the likelihood that they were facing the good stock was higher than 50%. Thus, this difference is mainly driven by data points in which participants were more optimistic about the type of stock they were facing and then received negative information—a low outcome.

B. Method

To study whether people learn differently in a selective feedback setting, compared to a full feedback one—in which investors can learn about the outcomes of an investment alternative regardless of their choice—we choose an experimental approach. This methodological choice is based on three main advantages of this method. The first one is that using conventional archival data sources, beliefs cannot be directly observed, but they can be elicited in an experimental setting. The second one is that an experimental approach allows controlling two key aspects for studying human learning. First, we can set known objective priors from which investors should update when confronted with new information. Second, we can precisely control the information that participants can access. And, moreover, we can even control the information they would have accessed if they had chosen the investment alternative, even if the participant decided not to choose the alternative. The third advantage is that in the few available survey-based archival data sources in which investors' beliefs are elicited, it is impossible to analyze both the beliefs and the choices. Still, we can effectively do so with an experimental approach.

C. Contribution

Our contribution, other than the main result already discussed, is sixfold. First, we focus on eliciting and analyzing investors' beliefs and not only on studying their choices. This is valuable since prior experimental studies analyzing the effects of foregone outcomes have focused on choices rather than beliefs. In those studies from the choices, then researchers fitted model parameters (i.e., Grosskopf et al. (2006); Camerer and Hua Ho (1999)). But we know that using this approach, we can be led astray when we are forced to infer the value of parameters using observable proxies for variables previously thought to be unobservable (Nyarko and Schotter (2002)). Second, thanks to our experimental design, we can precisely measure and isolate two sources of error. The Cognitive error, caused by incorrect processing of information, and the Sampling error, caused by using a smaller sample of information. This is the first study that can measure the two sources, following a belief approach.

Third, Kuhnen (2015) work shows that investors in a full feedback environment, who face outcomes only in the loss domain, make on average higher probability errors than people facing the same environment in the gain domain. Here we show an opposite result, reference point losses—perceived losses relative to the guaranteed payment provided by the riskless alternative—in the selective feedback environment in the gain domain, and not explicit losses, trigger superior adaptive learning by participants relative to those of people in the same domain observing the same outcome. Our findings provide new evidence of the effects of regret in learning. Having access to foregone outcomes is naturally linked to the experience of post-decision regret (Inman, Dyer, and Jia (1997); Ritov and Baron (1995); Taylor (1997)).

The feeling of regret has been linked to important effects in decision making and has sparked the creation of Regret theory (Loomes and Sugden (1982)) and has inspired experimental studies that have revealed that regret can have a profound influence on the decisions people make—for instance increasing the switching behavior between the different alternatives—and can promote both risk-averse as well as risk-seeking choices (Zeelenberg (1999)). Coricelli et al. (2007) using neuropsychological, and neuroimaging data studied the fundamental role of the orbitofrontal cortex in mediating the experience of regret. Their data indicates reactivation of activity within the orbitofrontal cortex and amygdala occurring during the phase of choice when the brain is anticipating possible future consequences of decisions and that this characterizes the anticipation of regret. These patterns reflect learning based on cumulative emotional experience. This suggests that affective consequences can induce specific mechanisms of cognitive control of the choice processes, involving reinforcement or avoidance of the experienced behavior. This reaction caused by post-decision regret could explain the beneficial effect of reference point losses on learning outcomes.

Our findings align with the recent literature on the adaptive role of losses. In tasks ranging from simple economic decisions to meta perception, previous studies have generally shown positive effects of losses on performance (as in, Costantini and Hoving (1973); Denes-Raj and Epstein (1994); Bereby-Meyer and Erev (1998); Dawson, Gilovich, and Regan (2002)). Additionally, a recent stream of literature (e.g., Yechiam and Hochman (2014)) suggests that losses may be treated as signals of attention and not only as signals of avoidance. Our results complement previous findings showing that losses induce more controlled processing than comparable gains (Dunegan (1993)) and are associated with some of the physiological indices of attention (Yechiam and Hochman (2013)).

Fourth, when we compare the sizes of the probability updates performed by investors, in the selective feedback and full feedback condition, given the same outcome observed, we find that the same outcome in the selective feedback condition is given a larger probability update. Moreover, we are able to test whether this probability update affects choice behavior accordingly.

Fifth, traditional models to study simultaneous experienced based learning and decision, like the Bayesian Sequential Risk-Taking model or the Expectancy valence model, making use of maximum likelihood methods, or Bayesian methods that give as a result a fixed set of parameters that account for the choice behavior of participants. Our experimental design allows us to measure the dynamic process of each of the modeled features at each moment of time, thus acting as a new viewpoint to better understand participant's behavior step by step.

Finally, the evidence presented here provides new insights that can explain why access to foregone feedback has a great influence on choice but not on maximization. Using a different perspective than the traditional explanations, which take an information-gathering approach, we provide evidence that the information processing view also plays an important role in thoroughly understanding learning in selective feedback environments. This role is related to the better processing of information in selective feedback environments compared to that of full feedback environments. The better processing, we find, can help overcome the loss of information, and thus if the more accurate beliefs translate into more optimal choices, help maximization.

D. Implications

The empirical findings provided here are related to investors' relevant behaviors outside the laboratory. For instance, recent empirical work in finance highlights the role of the personal experiences of investors. They show that those experiences shape their attitudes towards risky alternatives and financial decisions. We know that whether an investor has experienced the sample of information available matters for economic outcomes of interest and can lead investors to make sub-optimal investment decisions.

For instance, Malmendier and Nagel (2011) show that households that witness bad economic times both become reluctant to invest in equities and have more pessimistic beliefs about future stock returns. More recently, Necker and Ziegelmeyer (2016), and Guiso, Sapienza, and Zingales (2018) prove that individuals become more risk-averse after a financial crisis, and additionally Shigeoka (2019) shows that these effects on risk aversion triggered by personal experience are long-lasting. Effects of personal experience have also been linked to investment behavior in the insurance market or corporate financial decisions. Froot (2001) showed that after floods or earthquakes, people are more likely to buy insurance against such events even though the probability of occurrence of such events does not change; Dittmar and Duchin (2016) show that firms run by CEO's who have experienced distress have less debt, save more cash, and invest less than other firms. More recently Liu and Zuo (2019) have studied the effects of being exposed to an environment with an average risk aversion parameter different than that of your natal environment. The authors have used this setting to explain the existence of the gender gap in risk aversion, and they find that after spending time in a new environment with the majority of riskier averse children, less risk averse children change their risk preferences and adopt the risk preferences of the majority.

The effect of personal experience in such a high stakes decision as saving for retirement has also been documented. Choi, Laibson, Madrian, and Metrick (2009) show that individual investors over-extrapolate from their personal experience when making savings decisions. Investors who experience particularly rewarding outcomes from 401(k) saving—a high average and/or low variance return—increase their 401(k) savings rate more than investors who have less rewarding experiences. The idea that endogenously chosen samples of information have more impact than other available information is related to the realization utility empirical findings (Barberis and Xiong (2012); Ingersoll and Jin (2013); Imas (2016)). According to this view, trading and its resulting realized gains and losses cause greater utility swings than paper gains and losses.

Here, we provide evidence that experiencing information that comes as a result of your own choice affects your beliefs differently than other available information. This, for instance, could help explain the presented findings by Dittmar and Duchin (2016) related to behaviors of managers that have experienced financial distress and why those decisions have impacted later on in their life as financiers. Our findings speak to the role of the effect of information that comes from endogenous choices of agents and not as a result of an exogenous event. Here, we find that the sample of information that comes as a result of endogenous choices helps participants learn more similarly to a Bayesian learner.

Our findings complement those of Hartzmark et al. (2019). In their experimental study show that people overreact to signals about goods that they own but that learning is close to Bayesian for non-owned goods. Moreover, they show that the endowment effect increases in response to positive information and disappears with negative information. Ownership, according to their findings, increases attention to recent signals about owned goods, exacerbating over-extrapolation. Here we find a different channel that affects learning. Learning is not only impacted by ownership but also by the way information is accessed. More precisely, information that comes as a result of an endogenous choice is treated differently in the belief formation process than the information available in the environment.

Our research also speaks to the theoretical literature in finance, which approaches investors' behavior from a bounded rationality approach and uses a non-classical view of the formation of beliefs of economic agents[10]. In this literature, investors are believed to learn as Bayesian learners using a possibly incorrect prior belief. Here we show how investors learn from an objective prior when facing different environments that vary in the way information is sampled, thus adding to the knowledge of how people process new information in different environments and quantifying the effect of lost information.

Another of the channels in information processing that can explain the effect of personal experiences on investment outcomes is the attention paid to the available information. Empirical evidence in the Finance field suggests that the attention investors pay to the financial information influences their financial decisions. Barber, Odean, and Zheng (2005) and Barber and Odean (2007) find that individual investors are net buyers of attention-grabbing stocks and mutual funds. In a study of American households' investment behavior, they find that mutual funds purchases mainly occur in the top quintile of past annual returns and show that many investors consider purchasing only stocks that have first caught their attention. Da, Engelberg, and Gao (2011) using search frequency in Google, as a measure of investors' attention find that an increase in Google searches predicts higher stock prices in the next 2 weeks and an eventual price reversal within the year.

Dellavigna and Pollet (2009) compare the response to earnings announcements on Friday, when investor inattention is more likely, to the response on other weekdays. They find that Friday announcements have a 15% lower immediate response and a 70% higher delayed response. These findings support explanations of post-earnings announcement drift based on underreaction to information caused by limited attention. Sicherman, Loewenstein, Seppi, and Utkus (2015) show how aggregate and individual household trading behavior are related to investor attention. Hartzmark (2014) document that both retail traders and mutual fund managers are more likely to sell the extreme winning and extreme losing positions in their portfolio (what they call "the rank effect"). This effect is not driven by firm-specific information, holding period, or the level of returns itself, but is associated with the salience of extreme portfolio positions. Stango and Zinman (2014) find that conditional on selection into surveys, individuals who face overdraft-related questions are less likely to incur a fee in the survey month. Moreover, taking multiple overdraft surveys builds a "stock" of attention that reduces overdrafts for up to two years. Our study highlights the special role that attention has on attitude formation towards investment alternatives. Our study shows that different market environments affect the attention that investors pay to information. Moreover, we show that being in a setting with information accessed only by endogenous choice can help investors process that information better.

On the theoretical side, the literature analyzing economic games has proposed three alternative modeling approaches to explain how foregone outcomes can be processed by people. Our empirical findings provide evidence that could be incorporated into more realistic models of investor learning. Standard belief-based rational Bayesian models assume that investors consider all information available about the investment alternative whether it has been obtained as a result of their choice or as a result of others' choices (See: Brown and Koopmans (1951); Cournot (1960); Fudenberg, Levine, Drew, K, Levine, Levine, and of Technology (1998)). However, pure reinforcement learning models completely disregard information not directly experienced by investors (See: Erev and Roth (1998)). In the middle ground between the previous two, there are models that take a mixed approach. For instance, Camerer and Hua Ho (1999) produce a hybrid model that combines reinforcement learning and belief learning and situates each as a special case. But none of these models incorporate our main finding. The better processing of information if investors learn in an environment in which they can gather information only as a result of their endogenous choice.

In the financial decision-making literature, the evidence about the weight given to foregone values is also mixed. Experimental and eye-tracking data shows that people do give weight to foregone outcomes (for a review, see: Plonsky and Teodorescu (2020)). Other studies find that people are as sensitive to foregone outcomes as obtained outcomes (Yechiam, Stout, Busemeyer, Rock, and Finn (2005); Yechiam and Rakow (2012)). While, further research finds that people are even more sensitive to foregone outcomes (Yechiam et al. (2005); Yechiam and Rakow (2012)) than experienced ones. More recently, an eye-tracking study has found evidence that people are less sensitive to foregone than to obtained outcomes in line with the findings of the literature in economic games Ashby and Rakow (2016). Here we provide new evidence, using a belief approach, that captures the effects of availability of both: foregone outcomes and outcomes that come as a result of endogenous choice. We show that the probability updates that come as a result of the combination of the two types of outcome are, on average lower than the probability updates produced only as a result of endogenous choice.

The learning by doing management literature has also analyzed experiential learning. The typical finding is that experiential learning leads to biased inferences. Levitt and March (1988) find that experiential learning is hampered by the turnover of personnel and the passage of time. Moreover, learning is further complicated by the ecological structure of the simultaneously adapting behavior of other organizations and by an endogenously changing environment. A similar view is held by Levinthal and March (1993), who suggest a certain conservatism in expectations about the outcomes of organizational learning. This conservatism of expectations about the potential benefits of organizational learning is due to the challenges and difficulties that maintaining exploration in the face of a tendency to overinvest in exploitation presents. On another level, Lejarraga (2010); Lejarraga and Gonzalez (2011) presented research that tackled the description-experience duality in organizational behavior. This duality refers to the fact that managers can have good descriptions of investment alternatives but also evaluate them after they have some experience with their outcomes. The authors find that although descriptive information may be objective, individuals prefer to rely on experience, which provides rougher information but is easier to interpret. The reliance on experience can even be higher when facing complex decisions, which are very common in the organizational environment. In our study, we provide a more positive view of the results of organizational learning in selective feedback environments. We find that, although the challenges of balancing the information acquisition problem are significant and affect learning, the better information processing of information can help learners that rely on experience.

Elucidating the influence of selective feedback environments in investor's learning can shed light on the importance of environments for human learning. Our research goes in line with the reviewed findings in Erev and Roth (2014). We add to their observation that "highlight conditions under which experience does not guarantee the highest efficiency, and also suggest that small modifications of the environment can increase efficiency". The new knowledge obtained in this research can be incorporated into new theoretical models of learning that will help us predict the future choices and behavior of investors in new environments. The new insights can also be used to inform investors of the expected errors that they could make when facing such environments and help them avoid costly mistakes. Application of these new insights can also be employed in many other domains. There are many environments in life in which people cannot learn about the outcome of risky alternatives unless they choose them.

V. Conclusion

In many relevant investment environments, investors only have access to the outcomes of an investment alternative if they choose it. Therefore, the sample of information they use to evaluate the alternative is endogenously created by their own choices. They are in, what the literature calls, selective feedback environments. In this study, we find evidence that investors, on average, learn better about the quality of a risky investment alternative given the information they have observed in a selective feedback environment rather than in a full feedback environment. There is a better processing of information in environments in which the only route to obtaining information about an investment alternative is by endogenous choice, compared to environments in which investors can learn about the outcomes of an investment alternative even if they do not choose the alternative.

The evidence shows that investors' beliefs in a selective feedback environment are closer to a rational benchmark than those of investors in a full feedback environment. This is particularly the case after both receiving negative information about the quality of the investment alternative and when investors beliefs about the quality of the alternative are optimistic before receiving the negative information. Here we show that even in the gain domain, experiencing an outcome lower than the expected value of the investment is sufficient to trigger superior adaptive learning by investors in a selective feedback environment compared to those in a comparable full feedback one. The more aggressive update in the selective feedback environment after receiving negative information seems to be explained in part, the better learning in that environment compared to a full feedback one.

Moreover, if we compare the deviations of participants' beliefs about the quality of the asset in a condition with limited feedback to the objective Bayesian beliefs a perfect Bayesian learner would have produced if she had access to all the outcomes of the investment alternative, we find that there was no significant difference in learning. That is, in our particular experimental task, the better processing of information in the condition with limited feedback completely overcomes the sampling error generated by the loss of access to financial information and makes participants in the limited feedback condition learn, as well, as participants with access to full information about the outcomes of the stock.

The evidence presented supports that investors that find themselves in a selective feedback investment environment trigger different cognitive processes that will help them be closer to the objective, rational beliefs (given the information that they have seen) and not be necessarily farther away from objective beliefs than investors with full information even if they did not have access to the full information set. We consider this empirical finding and the unveiling of the mechanism that generates it our main contribution in this empirical work. The empirical findings that we reveal add another step to allow us to understand why the effects of foregone outcomes on maximization are not clear. Although the information effects of the missed information in selective feedback environments have traditionally been considered, the better processing of information that a more active learning style sparks were previously unaccounted for.

Finally, we have shown that the measures on which we base our main findings are related to important financial decisions outside the laboratory. Our findings contribute to the growing empirical literature on the effects of personal experience and attention into determining the choices and preferences of CEOs, asset managers, and individual investors. Here we show a channel that explains why personally experienced information influences financial decisions more than other available information. Moreover, our findings reveal how the features of learning environments, and not only the information available in them, affect decision making, not only in the financial domain but in all domains in life.

Appendix A. Participant Instructions Full feedback Condition

Welcome to our financial decision making study!

In this study you will work on an investment task. In this task you will repeatedly invest in one of two securities: a risky security (i.e., a stock with risky payoffs) and a riskless security (i.e., a bond with a known payoff), and will provide estimates as to how good an investment the risky security is.

In either task, there are two types of conditions you can face: the GAIN and the LOSS conditions. In the GAIN condition, the two securities will only provide POSITIVE payoffs. In the LOSS condition, the two securities will only provide NEGATIVE payoffs.

Specific details for the GAIN condition:

In the GAIN condition, on any trial, if you choose to invest in the bond, you get a payoff of $6 for sure at the end of the trial. If you choose to invest in the stock, you will receive a dividend which can be either $10 or $2.

The stock can either be good or bad, and this will determine the likelihood of its dividend being high or low. If the stock is good then the probability of receiving the $10 dividend is 70% and the probability of receiving the $2 dividend is 30%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is good, then on each trial the odds of the dividend being $10 are 70%, and the odds of it being $2 are 30%. If the stock is bad then the probability of receiving the $10 dividend is 30% and the probability of receiving the $2 dividend is 70%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is bad, then on each trial the odds of the dividend being $10 are 30%, and the odds of it being $2 are 70%.

Specific details for the LOSS condition:

In the LOSS condition, on any trial, if you choose to invest in the bond, you get a payoff of –$6 for sure at the end of the trial. If you choose to invest in the stock, you will receive a dividend which can be either –$10 or –$2.

The stock can either be good or bad, and this will determine the likelihood of its dividend being high or low. If the stock is good then the probability of receiving the –$10 dividend is 30% and the probability of receiving the –$2 dividend is 70%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is good, then on each trial the odds of the dividend being –$10 are 30%, and the odds of it being –$2 are 70%. If the stock is bad then the probability of receiving the –$10 dividend is 70% and the probability of receiving the –$2 dividend is 30%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is bad, then on each trial the odds of the dividend being –$10 are 70%, and the odds of it being –$2 are 30%.

In both the GAIN and LOSS conditions:

In each condition, at the beginning of each block of six trials, you do not know which type of stock the computer selected for that block. You may be facing the good stock, or the bad stock, with equal probability.

On each trial in the block you will decide whether you want to invest in the stock for that trial and accumulate the dividend paid by the stock, or invest in the riskless security and add the known payoff to your task earnings.

You will then see the dividend paid by the stock, no matter if you chose the stock or the bond.

You will then have to tell us what you think is the probability that the stock is the good one (the answer must be a number between 0 and 100 – do not add the % sign, just type in the value).

You will also have to tell us the same thing at the beginning of each block before making any choice.

There is always an objective, correct, probability that the stock is good, which depends on the history of dividends paid by the stock already. For instance, at the beginning of each block of trials, the probability that the stock is good is exactly 50%, and there is no doubt about this value. As you observe the dividends paid by the stock you will update your belief whether or not the stock is good. It may be that after a series of good dividends, you think the probability of the stock being good is 75%. However, how much you trust your ability to calculate this probability could vary. Sometimes you may not be too confident in the probability estimate you calculated and sometimes you may be highly confident in this estimate. For instance, at the very beginning of each block, the probability of the stock being good is 50% and you should be highly confident in this number because you are told that the computer just picked at random the type of stock you will see in the block, and nothing else has happened since then.

Throughout the task you will be told how much you have accumulated through dividends paid by the stock or bond you chose up to that point.

Your final pay for completing the investment tasks will be:

\$5 + 1/10 x Investment Payoffs, where Investment Payoffs = Dividends of securities you chose in the experiment.

Thank you!

Appendix B. Participant Instructions Selective feedback Condition

Welcome to our financial decision making study!

In this study you will work on an investment task. In this task you will repeatedly invest in one of two securities: a risky security (i.e., a stock with risky payoffs) and a riskless security (i.e., a bond with a known payoff), and will provide estimates as to how good an investment the risky security is.

In either task, there are two types of conditions you can face: the GAIN and the LOSS conditions. In the GAIN condition, the two securities will only provide POSITIVE payoffs. In the LOSS condition, the two securities will only provide NEGATIVE payoffs.

Specific details for the GAIN condition: In the GAIN condition, on any trial, if you choose to invest in the bond, you get a payoff of \$6 for sure at the end of the trial. If you choose to invest in the stock, you will receive a dividend which can be either \$10 or \$2.

The stock can either be good or bad, and this will determine the likelihood of its dividend being high or low. If the stock is good then the probability of receiving the \$10 dividend is 70% and the probability of receiving the \$2 dividend is 30%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is good, then on each trial the odds of the dividend being \$10 are 70%, and the odds of it being \$2 are 30%. If the stock is bad then the probability of receiving the \$10 dividend is 30% and the probability of receiving the \$2 dividend is 70%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is bad, then on each trial the odds of the dividend being \$10 are 30%, and the odds of it being \$2 are 70%.

Specific details for the LOSS condition:

In the LOSS condition, on any trial, if you choose to invest in the bond, you get a payoff of –\$6 for sure at the end of the trial. If you choose to invest in the stock, you will receive a dividend which can be either –\$10 or –\$2.

The stock can either be good or bad, and this will determine the likelihood of its dividend being high or low. If the stock is good then the probability of receiving the –\$10 dividend is 30% and the probability of receiving the –\$2 dividend is 70%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is good, then on each trial the odds of the dividend being –\$10 are 30%, and the odds of it being –\$2 are 70%. If the stock is bad then the probability of receiving the –\$10 dividend is 70% and the probability of receiving the –\$2 dividend is 30%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is bad, then on each trial the odds of the dividend being –\$10 are 70%, and the odds of it being –\$2 are 30%.

In both the GAIN and LOSS conditions:

In each condition, at the beginning of each block of six trials, you do not know which type of stock the computer selected for that block. You may be facing the good stock, or the bad stock, with equal probability.

On each trial in the block you will decide whether you want to invest in the stock for that trial and accumulate the dividend paid by the stock, or invest in the riskless security and add the known payoff to your task earnings.

You will only see the dividend paid by the stock if you select it.

At one or several stages in each block of six trials, you will have to tell us what you think is the probability that the stock is the good one (the answer must be a number between 0 and 100 – do not add the % sign, just type in the value).

There is always an objective, correct, probability that the stock is good, which depends on the history of dividends paid by the stock already. For instance, at the beginning of each block of trials, the probability that the stock is good is exactly 50%, and there is no doubt about this value. As you observe the dividends paid by the stock you will update your belief whether or not the stock is good. It may be that after a series of good dividends, you think the probability of the stock being good is 75%. However, how much you trust your ability to calculate this probability could vary. Sometimes you may not be too confident in the probability estimate you calculated and sometimes you may be highly confident in this estimate. For instance, at the very beginning of each block, the probability of the stock being good is 50% and you should be highly confident in this number because you are told that the computer just picked at random the type of stock you will see in the block, and nothing else has happened since then.

Throughout the task you will be told how much you have accumulated through dividends paid by the stock or bond you chose up to that point.

Your final pay for completing the investment tasks will be:

\$5 + 1/10 Investment Payoffs, where Investment Payoffs = Dividends of securities you chose in the experiment.

Thank you!

Appendix C. Quiz for the Full feedback Condition

How many conditions are there in the task? What is their name?

o 2 conditions called HIGH and LOW

o 2 conditions called GOOD and BAD

o 2 conditions called LOSS and GAIN

How many securities are there in the task? Which is the risky one and which the riskless?

o There are 2 securities. The Stock which is the risky security and the Bond which is the riskless security

o There are 2 securities. The Stock which is the riskless security and the Bond which is the risky security

o There are 3 securities. The Stock which is the riskless security, the Bond which is the risky security and the Option which the very risky security

In the GAIN condition if I choose a Bond I will get... / In the GAIN condition if I choose the Stock I will get...

o ... a payoff of \$6 for sure / ...a dividend which can be \$2 or \$10

o ... a payoff of \$2 for sure / ...a dividend which can be \$6 or \$10

o ... a payoff of \$6 for sure / ...a dividend which can be \$3 or \$10

In the LOSS condition if I choose a Bond I will get... / In the LOSS condition if I choose the Stock I will get...

o ... a payoff of –\$6 for sure / ...a dividend which can be –\$2 or –\$10

o ... a payoff of –\$2 for sure / ...a dividend which can be –\$6 or –\$10

o ... a payoff of –\$6 for sure / ...a dividend which can be –\$3 or –\$10

How many types of Stocks are there in the GAIN condition?

o 2 types, the high Stock and the low Stock

o 2 types, the good Stock and the bad Stock

o 3 types, the good Stock, the bad Stock and the neutral Stock

How many types of Stocks are there in the LOSS condition?

o 2 types, the high Stock and the low Stock

o 2 types, the good Stock and the bad Stock

o 3 types, the good Stock, the bad Stock and the neutral Stock

In the GAIN condition, the good Stock pays $10 with which probability? And $2?

o Pays $10 with 70% probability and $2 with 30%

o Pays $10 with 30% probability and $2 with 70%

o Pays $10 with 50% probability and $2 with 50%

In the LOSS condition, the good Stock pays –$10 with which probability? And –$2?

o Pays –$10 with 70% probability and –$2 with 30%

o Pays –$10 with 30% probability and –$2 with 70%

o Pays –$10 with 50% probability and –$2 with 50%

In the GAIN condition, the bad Stock pays $10 with which probability? And $2?

o Pays $10 with 70% probability and $2 with 30%

o Pays $10 with 30% probability and $2 with 70%

o Pays $10 with 50% probability and $2 with 50%

In the LOSS condition, the bad Stock pays –$10 with which probability? And –$2?

o Pays –$10 with 70% probability and –$2 with 30%

o Pays –$10 with 30% probability and –$2 with 70%

o Pays –\$10 with 50% probability and –\$2 with 50%

At the beginning of each Block... (1)

o I know if I am facing the good or the bad Stock

o I do not know if I am facing the good or the bad Stock

o I will be told which type of Stock do I face

At the beginning of each Block... (2)

o There is a 50% chance that I face the good Stock and a 50% chance that I face the bad Stock

o There is a 70% chance that I face the good Stock and a 30% chance that I face the bad Stock

o There is a 30% chance that I face the good Stock and a 70% chance that I face the bad Stock

At the beginning of each Block... (3)

o I know I will be facing the same type of Stock (good or bad) for the next 6 Trials

o I know I will be facing a different type of Stock (good or bad) in each of the next 6 Trials

o I know I will be facing a different type of Stock (good or bad) in each of the next 10 Trials

At the beginning of each Block... (4)

o I know that the dividends paid by the Stock are independent from Trial to Trial

o I know that the dividends paid by the Stock are dependent from Trial to Trial

o I know that the dividends paid by the Stock are independent from Block to Block

On each Trial of the Block you will see the dividend paid by the Stock, no matter if you chose the Stock or the Bond.

o True

o False

Before the first choice in each block, and after each choice in any trial we ask you: what do you think is the probability that the Stock is the...

o Good one

o Bad one

o High

Is there an objective, correct probability the Stock is the good one?

o Yes, and it depends on the history of dividends paid by the Stock already

o No

o Yes, and it does not depend on the history of dividends paid by the Stock already

What is the objective probability of the Stock being the good one at the beginning of each Block, when you still have not possibly seen any dividend from the Stock?

o 50%

o 30%

o 70%

What is the objective probability of the Stock being the good one at the beginning of each Block, before the first choice, when you still have not possibly seen any dividend from the Stock?

o 50% with no doubt about its value

o 50% but could be slightly different

o 70% or 30%

Which is the high dividend in the GAIN condition? and the low one?

o $2 is the high and $10 is the low

o $10 is the high and $2 is the low

o $6 is the high and $2 is the low

Which is the high dividend in the LOSS condition? and the low one?

o –\$2 is the high and –\$10 is the low

o –\$10 is the high and –\$2 is the low

o –\$6 is the high and –\$2 is the low

If after some trials since you began a Block you see that the Stock has always given high dividends, your estimation of the probability that the Stock is the good one should be?

o Higher than 50%

o Lower than 50%

o Still 50%

If after some trials since you began a Block you see that the Stock has always given low dividends, your estimation of the probability that the Stock is the good one should be?

o Higher than 50%

o Lower than 50%

o Still 50%

Your final payoff will be calculated according to the following formula:

o \$5 + 1/10 Investment Payoffs, where Investment Payoffs = Dividends of securities you chose in the experiment.

o 1/10 Investment Payoffs, where Investment Payoffs = Dividends of securities you chose in the experiment.

o \$5 + 1/100 Investment Payoffs, where Investment Payoffs = Dividends of securities you chose in the experiment.

Appendix D. Quiz for the Selective feedback Condition

How many conditions are there in the task? What is their name?

o 2 conditions called HIGH and LOW

o 2 conditions called GOOD and BAD

o 2 conditions called LOSS and GAIN

How many securities are in the task? Which is the risky one and which the riskless?

o There are 2 securities. The Stock which is the risky security and the Bond which is the riskless security

o There are 2 securities. The Stock which is the riskless security and the Bond which is the risky security

o There are 3 securities. The Stock which is the riskless security, the Bond which is the risky security and the Option which the very risky security

In the GAIN condition if I choose a Bond I will get... / In the GAIN condition if I choose the Stock I will get...

o ... a payoff of \$6 for sure / ...a dividend which can be \$2 or \$10

o ... a payoff of \$2 for sure / ...a dividend which can be \$6 or \$10

o ... a payoff of \$6 for sure / ...a dividend which can be \$3 or \$10

In the LOSS condition if I choose a Bond I will get... / In the LOSS condition if I choose the Stock I will get...

o ... a payoff of –\$6 for sure / ...a dividend which can be –\$2 or –\$10

o ... a payoff of –\$2 for sure / ...a dividend which can be –\$6 or –\$10

o ... a payoff of –\$6 for sure / ...a dividend which can be –\$3 or –\$10

How many types of Stocks are there in the GAIN condition?

o 2 types, the high Stock and the low Stock

o 2 types, the good Stock and the bad Stock

o 3 types, the good Stock, the bad Stock and the neutral Stock

How many types of Stocks are there in the LOSS condition?

o 2 types, the high Stock and the low Stock

o 2 types, the good Stock and the bad Stock

o 3 types, the good Stock, the bad Stock and the neutral Stock

In the GAIN condition, the good Stock pays $10 with which probability? And $2?

o Pays $10 with 70% probability and $2 with 30%

o Pays $10 with 30% probability and $2 with 70%

o Pays $10 with 50% probability and $2 with 50%

In the LOSS condition, the good Stock pays –$10 with which probability? And –$2?

o Pays –$10 with 70% probability and –$2 with 30%

o Pays –$10 with 30% probability and –$2 with 70%

o Pays –$10 with 50% probability and –$2 with 50%

In the GAIN condition, the bad Stock pays $10 with which probability? And $2?

o Pays $10 with 70% probability and $2 with 30%

o Pays $10 with 30% probability and $2 with 70%

o Pays $10 with 50% probability and $2 with 50%

In the LOSS condition, the bad Stock pays –$10 with which probability? And –$2?

o Pays –$10 with 70% probability and –$2 with 30%

o Pays –$10 with 30% probability and –$2 with 70%

o Pays –\$10 with 50% probability and –\$2 with 50%

At the beginning of each Block... (1)

o I know if I am facing the good or the bad Stock

o I do not know if I am facing the good or the bad Stock

o I will be told which type of Stock do I face

At the beginning of each Block... (2)

o There is a 50% chance that I face the good Stock and a 50% chance that I face the bad Stock

o There is a 70% chance that I face the good Stock and a 30% chance that I face the bad Stock

o There is a 30% chance that I face the good Stock and a 70% chance that I face the bad Stock

At the beginning of each Block... (3)

o I know I will be facing the same type of Stock (good or bad) for the next 6 Trials

o I know I will be facing a different type of Stock (good or bad) in each of the next 6 Trials

o I know I will be facing a different type of Stock (good or bad) in each of the next 10 Trials

At the beginning of each Block... (4)

o I know that the dividends paid by the Stock are independent from Trial to Trial

o I know that the dividends paid by the Stock are dependent from Trial to Trial

o I know that the dividends paid by the Stock are independent from Block to Block

On each Trial of the Block you will see the dividend paid by the Stock, no matter if you chose the Stock or the Bond.

o True, I will see the dividend paid by the stock regardless of my choice.

o False, I will only see the dividend paid by the stock if I select it.

At one or several stages during the study we ask you: what do you think is the probability that the Stock is the...

o Good one

o Bad one

o High

Is there an objective, correct probability the Stock is the good one?

o Yes, and it depends on the history of dividends paid by the Stock already

o No

o Yes, and it does not depend on the history of dividends paid by the Stock already

What is the objective probability of the Stock being the good one at the beginning of each Block, when you still have not possibly seen any dividend from the Stock?

o 50%

o 30%

o 70%

What is the objective probability of the Stock being the good one at the beginning of each Block, before the first choice, when you still have not possibly seen any dividend from the Stock?

o 50% with no doubt about its value

o 50% but could be slightly different

o 70% or 30%

Which is the high dividend in the GAIN condition? and the low one?

o $2 is the high and $10 is the low

o $10 is the high and $2 is the low

o $6 is the high and $2 is the low

Which is the high dividend in the LOSS condition? and the low one?

o –\$2 is the high and –\$10 is the low

o –\$10 is the high and –\$2 is the low

o –\$6 is the high and –\$2 is the low

If after some trials since you began a Block you see that the Stock has always given high dividends, your estimation of the probability that the Stock is the good one should be?

o Higher than 50%

o Lower than 50%

o Still 50%

If after some trials since you began a Block you see that the Stock has always given low dividends, your estimation of the probability that the Stock is the good one should be?

o Higher than 50%

o Lower than 50%

o Still 50%

Your final payoff will be calculated according to the following formula:

o \$5 + 1/10 Investment Payoffs, where Investment Payoffs = Dividends of securities you chose in the experiment.

o 1/10 Investment Payoffs, where Investment Payoffs = Dividends of securities you chose in the experiment.

o \$5 + 1/100 Investment Payoffs, where Investment Payoffs = Dividends of securities you chose in the experiment.

Appendix E. Objective Bayesian Posterior Beliefs

The table below provides all possible values for the objectively correct Bayesian posterior that the stock is paying from the good dividend distribution, starting with a 50% to 50% prior, and after observing each possible dividend history path in a learning block. Every trial a new dividend (high or low) is revealed. There are six trials in each learning block. The value of the objective Bayesian posterior that the stock is paying from the good distribution can be easily calculated. Specifically, after observing t high outcomes in n trials so far, the Bayesian posterior that the stock is the good one is given by: $\frac{1}{1+\frac{1-p}{p}*(\frac{q}{1-q})^{n-2t}}$ where $p = 50\%$ is the prior that the stock is the good one (before any payoffs are observed in that learning block) and $q = 70\%$ is the probability that a good stock pays the high payoff (rather than low) in each trial.

n Trials So Far	t High Outcomes So Far	Probability {stock is good | t high outcomes in n trials}
1	0	30.00%
1	1	70.00%
2	0	15.52%
2	1	50.00%
2	2	84.48%
3	0	7.30%
3	1	30.00%
3	2	70.00%
3	3	92.70%
4	0	3.26%
4	1	15.52%
4	2	50.00%
4	3	84.48%
4	4	96.74%
5	0	1.43%
5	1	7.30%
5	2	30.00%
5	3	70.00%
5	4	92.70%
5	5	98.57%
6	0	0.62%
6	1	3.26%
6	2	15.52%
6	3	50.00%
6	4	84.48%
6	5	96.74%
6	6	99.38%

Appendix F. Measures of Financial Literacy

To get measures of financial literacy and risk preferences, each participant was asked the following questions after the completion of the experimental tasks: "Imagine you have saved \$10,000. You can now invest this money over the next year using two investment options: a U.S. stock index mutual fund, which tracks the performance of the U.S. stock market, and a savings account. The annual return per dollar invested in the stock index fund will be either +40% or –20%, with equal probability. In other words, it is equally likely that for each dollar you invest in the stock market, at the end of the one year investment period, you will have either gained 40 cents, or lost 20 cents. For the savings account, the known and certain rate of return for a one year investment is 5%. In other words, for each dollar you put in the savings account today, for sure you will gain 5 cents at the end of the one year investment period. We assume that whatever amount you do not invest in stocks will be invested in the savings account and will earn the risk-free rate of return. Given this information, how much of the \$10,000 will you invest in the U.S. stock index fund? Choose an answer that you would be comfortable with if this was a real-life investment decision. The answer should be a number between \$0 and \$10,000." After each participant wrote their answer to this question, they were asked the following: "Let's say that when you answered the prior question you decided to invest x dollars out of the \$10,000 amount in the U.S. stock index fund, and therefore you put (10,000 – x) dollars in the savings account. Recall that over the next year the rate of return on the stock index fund will be +40% or –20%, with equal probability. For the savings account, the rate of return is 5% for sure. What is the amount of money you expect to have at the end of this one year investment period? Please choose one of the answers below. If you choose the correct answer, you will get a \$1 bonus added to your pay for this experiment. [A] 0.5 (0.4 x – 0.2 x) + 0.05 (10,000 – x); [B] 1.4 x + 0.8 x + 1.05 (10,000 – x); [C] 0.4 (10,000 – x) – 0.2 (10,000 – x) + 0.05 x; [D] 0.5 [0.4 (10,000 – x) – 0.2 (10,000 – x)] + 0.05 x; [E] 0.4 x – 0.2 x + 0.05 (10,000 – x); [F] 0.5 (1.4 x + 0.8 x) + 1.05 (10,000 – x); [G] 1.4 (10,000 – x) + 0.8 (10,000 – x) + 1.05 x; [H] 0.5 [1.4 (10,000 – x) + 0.8 (10,000 – x)] + 1.05 x." The correct answer to this question is [F]. The actual choices (if other than [F]) made by participants indicate three different types of errors that can occur when calculating the expected value of their portfolio holdings: a lack of understanding of statements regarding probabilities (answers [B], [C], [E], [G]); a lack of understanding of the difference between net and gross returns (answers [A], [C], [D], and [E]); and confusing the stock versus risk-free asset investments (answers [C], [D], [G], and [H]). Therefore, a financial knowledge score varying between zero and three can be constructed, based on the number of different types of errors contained in the answer provided by each participant (i.e., zero errors for answer [F], one error for answers [A], [B], and [H], two errors for answers [D], [E], and [G], and three for answer [C]). Hence a financial knowledge score of three indicates a perfect answer, while a score of zero indicates that the participant's answer included all three possible types of errors.

Appendix G. Payoff Sequences

Block	1						2						3						4						5					
Trial	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Sequence 1	10	10	2	2	2	10	2	10	2	2	10	10	2	2	2	2	10	2	10	2	10	2	2	2	10	2	2	2	10	2
Sequence 2	2	2	2	10	10	10	2	2	2	10	2	2	10	10	2	10	10	10	10	10	2	2	2	2	-2	-10	-10	-10	-10	-2
Sequence 3	-2	-2	-2	-2	-2	-2	2	10	2	2	2	2	-10	-2	-2	-2	-10	-10	-2	-2	-10	-2	-2	-2	-2	-2	-10	-2	-2	-2
Sequence 4	-2	-2	-2	-2	-2	-2	-2	-2	-2	-10	-10	-2	-10	-2	-10	-10	-10	-2	10	2	2	2	10	10	2	10	2	10	2	2
Sequence 5	10	2	2	10	10	10	2	2	2	10	10	2	10	10	10	10	10	10	-2	-2	-2	-2	-10	-10	2	2	2	2	10	10
Sequence 6	2	10	10	10	10	10	10	10	10	2	2	10	2	10	2	10	2	2	2	10	10	10	2	2	2	2	10	2	2	2
Sequence 7	2	2	2	2	2	2	10	2	10	2	2	2	2	10	10	2	10	10	10	10	2	2	2	2	2	2	2	10	10	2
Sequence 8	10	2	10	2	2	2	2	10	10	2	10	10	10	10	10	10	10	10	10	10	2	2	10	2	10	2	2	10	2	2
Sequence 9	2	10	2	10	2	2	2	10	2	2	2	2	10	10	10	2	2	10	2	2	10	2	10	10	10	10	2	2	2	2
Sequence 10	10	10	2	10	10	2	10	10	10	2	10	2	10	10	10	10	10	10	2	2	10	10	10	2	10	2	2	10	2	10
Sequence 11	2	10	2	2	2	2	10	2	2	2	2	10	10	2	10	2	2	10	2	10	10	2	2	10	10	2	10	2	2	2
Sequence 12	10	10	10	10	10	10	2	2	2	10	2	2	2	10	10	10	10	10	10	2	10	2	10	10	10	10	10	10	2	10
Sequence 13	2	2	10	2	2	2	10	2	10	10	10	2	2	2	10	2	10	10	10	10	10	10	2	10	2	10	10	2	2	2
Sequence 14	10	10	2	2	2	10	2	2	2	10	2	10	10	2	2	10	10	10	10	10	10	10	10	2	10	2	2	2	10	2
Sequence 15	10	10	10	10	10	2	10	10	10	10	10	2	2	2	10	10	2	2	2	10	10	10	10	10	2	10	2	10	10	10
Sequence 16	2	2	10	2	2	2	2	2	2	2	2	2	10	10	10	2	10	10	10	10	10	2	10	10	2	10	10	2	2	2
Sequence 17	10	2	10	10	10	10	10	2	10	10	2	10	2	10	10	10	10	10	2	2	2	2	2	2	2	2	10	10	10	10
Sequence 18	2	2	10	10	2	2	10	10	10	2	10	10	10	2	2	2	10	2	2	2	2	2	2	2	10	10	2	2	10	10
Sequence 19	2	2	2	2	10	10	10	10	10	2	10	10	10	10	10	10	10	10	10	10	10	10	2	2	2	2	2	10	2	2
Sequence 20	2	2	10	2	2	2	2	2	2	2	10	2	10	2	10	10	2	10	10	2	10	10	2	2	10	10	10	10	10	10
Sequence 21	2	2	10	10	10	10	10	10	2	10	2	10	2	2	10	2	2	10	2	2	2	2	10	2	10	2	2	2	10	2
Sequence 22	10	10	10	2	2	10	10	2	10	10	2	2	10	2	10	10	10	2	2	10	10	2	10	10	10	10	2	10	10	10
Sequence 23	2	2	2	10	2	2	2	2	2	2	2	10	10	2	2	10	2	10	2	2	2	10	2	2	2	2	2	2	10	2
Sequence 24	10	2	2	10	10	2	2	10	2	10	10	10	10	2	2	10	2	10	2	10	2	2	10	2	10	2	2	2	10	2
Sequence 25	2	2	10	2	2	10	2	2	2	2	10	2	10	10	2	10	10	10	10	10	10	10	10	10	2	2	2	2	10	10
Sequence 26	2	10	10	10	10	10	10	2	10	10	10	2	2	2	10	10	2	10	10	10	10	10	10	10	2	2	2	2	10	2
Sequence 27	10	10	2	10	2	2	10	10	10	10	10	2	10	10	10	2	10	2	10	2	2	2	2	2	10	10	10	10	10	10
Sequence 28	2	2	10	2	2	2	10	10	2	10	2	10	2	2	2	2	10	2	10	10	2	2	10	10	2	2	10	2	10	2
Sequence 29	10	10	2	2	2	2	10	2	10	10	2	10	2	10	2	2	2	2	10	2	10	10	10	2	10	2	2	2	2	2
Sequence 30	2	10	10	10	2	10	2	10	10	10	2	10	2	10	2	10	10	10	10	2	2	2	10	2	2	10	2	2	2	2

Block	6						7						8						9						10					
Trial	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Sequence 1	-2	-10	-2	-10	-10	-10	-10	-2	-10	-2	-10	-2	-10	-2	-2	-10	-2	-10	-10	-10	-2	-10	-2	-10	-2	-2	-2	-2	-2	-2
Sequence 2	-2	-2	-2	-2	-10	-2	10	2	2	10	10	2	-2	-10	-2	-2	-10	-2	-10	-10	-2	-2	-2	-2	-2	-2	-2	-10	-2	-2
Sequence 3	10	10	10	10	10	10	-2	-10	-2	-2	-2	-2	10	2	10	2	2	2	10	10	10	10	10	10	2	2	2	2	2	10
Sequence 4	2	2	2	2	10	10	-10	-10	-10	-10	-2	-2	-2	-2	-2	-2	-2	-2	10	10	10	2	10	10	2	2	10	2	10	2
Sequence 5	2	10	10	10	10	10	-10	-2	-2	-10	-10	-10	-10	-2	-10	-2	-10	-10	-2	-10	-10	-10	-2	-10	-10	-10	-10	-10	-2	-2
Sequence 6	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-2	-2	-10	-2	-2	-2	-2	-2	-10	-10	-2	-2
Sequence 7	-2	-2	-2	-10	-2	-2	-10	-2	-2	-2	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-2	-10	-10	-2	-10	-10	-10	-10	-10	-10
Sequence 8	-2	-2	-2	-2	-2	-2	-10	-2	-10	-10	-2	-10	-10	-2	-10	-2	-10	-10	-2	-2	-10	-2	-2	-2	-2	-2	-2	-10	-2	-10
Sequence 9	-10	-2	-10	-10	-2	-10	-10	-10	-10	-10	-2	-2	-10	-10	-2	-10	-10	-2	-2	-10	-2	-10	-2	-2	-2	-10	-10	-10	-10	-10
Sequence 10	-2	-2	-2	-2	-2	-2	-2	-2	-10	-2	-2	-2	-2	-10	-10	-2	-2	-10	-10	-2	-2	-2	-10	-10	-2	-2	-2	-10	-10	-10
Sequence 11	-2	-10	-2	-2	-2	-2	-2	-10	-2	-2	-2	-10	-2	-2	-10	-2	-2	-2	-2	-10	-2	-2	-10	-2	-2	-2	-2	-2	-10	-10
Sequence 12	-10	-2	-10	-10	-10	-2	-10	-10	-10	-2	-10	-2	-10	-2	-10	-2	-10	-2	-10	-2	-2	-2	-2	-10	-10	-10	-10	-10	-10	-2
Sequence 13	-10	-2	-2	-2	-10	-10	-10	-2	-2	-2	-2	-2	-10	-2	-2	-2	-10	-10	-2	-10	-10	-10	-2	-10	-2	-2	-2	-2	-2	-10
Sequence 14	-10	-10	-2	-10	-2	-10	-2	-10	-10	-10	-10	-10	-2	-2	-10	-10	-10	-10	-2	-2	-2	-2	-10	-2	-10	-10	-10	-10	-10	-2
Sequence 15	-2	-2	-2	-10	-10	-2	-2	-10	-10	-2	-10	-10	-2	-10	-2	-2	-10	-2	-10	-10	-2	-2	-10	-2	-2	-10	-2	-10	-10	-2
Sequence 16	-2	-2	-10	-2	-10	-10	-2	-2	-10	-10	-10	-10	-2	-2	-2	-10	-10	-2	-10	-10	-10	-10	-10	-10	-10	-10	-10	-2	-10	-10
Sequence 17	-2	-10	-10	-10	-10	-10	-2	-10	-2	-10	-10	-10	-10	-10	-2	-2	-2	-2	-2	-10	-2	-2	-10	-10	-10	-2	-2	-10	-10	-2
Sequence 18	-2	-10	-10	-10	-2	-10	-2	-10	-2	-2	-10	-10	-10	-10	-2	-10	-10	-10	-2	-2	-10	-10	-10	-10	-2	-10	-10	-10	-10	-10
Sequence 19	-2	-10	-2	-2	-2	-10	-10	-10	-10	-10	-10	-10	-2	-10	-10	-2	-10	-2	-10	-10	-2	-10	-10	-2	-2	-2	-2	-10	-10	-10
Sequence 20	-2	-2	-10	-10	-2	-10	-10	-2	-2	-10	-2	-10	-10	-2	-10	-10	-10	-2	-10	-10	-10	-10	-10	-10	-2	-2	-10	-10	-2	-2
Sequence 21	-2	-2	-10	-10	-2	-2	-10	-2	-10	-2	-10	-10	-2	-2	-10	-2	-2	-2	-2	-10	-10	-10	-2	-2	-10	-2	-2	-2	-2	-10
Sequence 22	-2	-2	-2	-10	-10	-2	-2	-10	-2	-2	-10	-2	-2	-2	-2	-2	-2	-2	-2	-10	-10	-2	-10	-10	-10	-10	-10	-10	-10	-10
Sequence 23	-10	-10	-2	-10	-2	-10	-2	-2	-2	-2	-2	-10	-10	-2	-2	-2	-10	-2	-10	-2	-10	-10	-10	-10	-10	-10	-10	-10	-2	-10
Sequence 24	-10	-2	-10	-2	-2	-10	-10	-10	-2	-2	-10	-2	-10	-10	-10	-10	-10	-10	-10	-2	-10	-2	-2	-10	-10	-2	-2	-2	-2	-10
Sequence 25	-10	-10	-2	-10	-10	-2	-10	-2	-2	-10	-10	-10	-10	-10	-2	-10	-2	-2	-10	-10	-10	-10	-10	-2	-10	-10	-10	-10	-2	-10
Sequence 26	-10	-10	-2	-2	-2	-2	-10	-2	-10	-2	-10	-2	-2	-10	-2	-2	-2	-2	-2	-2	-10	-2	-2	-10	-2	-2	-10	-10	-2	-2
Sequence 27	-2	-10	-2	-2	-10	-2	-2	-10	-10	-10	-2	-10	-10	-10	-10	-2	-2	-10	-2	-2	-2	-2	-10	-2	-2	-2	-2	-10	-2	-2
Sequence 28	-10	-2	-2	-2	-2	-10	-10	-2	-10	-10	-2	-2	-10	-2	-2	-10	-2	-2	-2	-10	-2	-10	-2	-2	-10	-10	-10	-2	-10	-10
Sequence 29	-2	-2	-2	-10	-10	-10	-2	-2	-2	-2	-2	-2	-10	-2	-2	-10	-10	-2	-10	-10	-10	-10	-10	-10	-2	-2	-2	-2	-2	-2
Sequence 30	-10	-10	-2	-2	-2	-10	-2	-10	-10	-10	-10	-2	-2	-2	-2	-2	-2	-2	-10	-10	-10	-10	-2	-10	-10	-10	-2	-10	-10	-2

Block	1						2						3						4						5					
Trial	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Sequence 31	2	10	2	2	2	2	2	2	2	2	10	2	10	2	10	10	10	10	2	2	10	10	2	2	2	2	10	10	10	10
Sequence 32	10	10	10	2	2	10	2	10	2	2	2	2	10	10	10	10	2	2	10	10	10	2	10	2	10	10	10	10	2	10
Sequence 33	10	10	10	10	10	2	10	2	2	2	10	10	2	10	2	2	2	2	2	10	2	2	2	2	10	10	10	10	10	10
Sequence 34	2	10	10	2	10	10	10	10	10	2	2	10	2	10	10	10	10	10	10	10	10	2	10	10	2	2	2	2	2	2
Sequence 35	2	10	2	10	2	2	10	10	10	10	10	2	10	2	2	10	2	2	10	10	10	10	10	10	2	2	2	2	10	2
Sequence 36	10	10	2	10	10	2	2	2	2	2	10	2	10	2	2	10	10	2	10	2	10	10	10	10	10	10	2	2	10	2
Sequence 37	10	10	2	2	10	2	2	10	10	2	2	2	2	2	2	10	10	10	10	2	2	10	2	10	2	10	2	10	2	2
Sequence 38	2	2	2	2	2	2	2	2	10	10	10	2	2	10	2	10	10	10	2	2	10	2	10	2	2	10	2	2	10	2
Sequence 39	2	2	10	2	10	2	2	2	2	2	2	10	10	10	2	10	10	2	2	2	10	2	2	2	10	10	2	10	10	2
Sequence 40	2	2	2	2	2	2	2	2	10	10	10	2	10	10	2	10	10	10	10	10	10	10	2	2	10	10	10	10	10	10
Sequence 41	2	10	2	10	10	10	2	2	10	10	2	2	2	10	10	2	2	2	10	2	2	10	10	2	10	2	10	2	2	2
Sequence 42	2	10	10	2	10	2	2	10	2	2	10	10	2	2	2	10	10	10	10	2	10	2	10	10	10	2	2	2	2	10
Sequence 43	10	10	2	10	10	2	10	10	10	2	2	2	10	10	10	10	10	10	10	2	10	10	2	2	10	2	2	2	2	10
Sequence 44	2	2	10	10	2	10	10	2	2	10	10	2	2	10	2	2	2	10	10	2	10	2	10	10	2	10	10	10	10	10
Sequence 45	2	2	2	2	10	10	2	2	2	10	2	2	10	10	10	10	10	10	2	10	2	2	2	10	2	2	2	2	2	2
Sequence 46	10	10	10	2	10	10	10	10	10	10	10	10	2	2	2	2	2	2	10	10	10	10	10	2	2	10	2	2	2	2
Sequence 47	2	2	2	10	10	2	2	2	10	2	2	2	2	2	10	10	10	10	2	2	2	2	2	2	10	10	2	2	2	10
Sequence 48	2	10	2	2	2	2	2	2	2	2	2	10	10	10	2	2	10	2	10	2	2	10	2	10	2	2	2	2	2	2
Sequence 49	2	10	10	10	2	10	2	10	2	10	10	2	10	2	10	2	10	2	10	2	10	2	10	2	10	10	2	10	10	10
Sequence 50	2	10	10	10	10	10	2	10	2	2	10	10	2	2	10	2	10	10	2	10	10	10	2	2	10	2	10	10	10	2
Sequence 51	10	2	10	2	2	10	10	2	10	10	10	2	10	2	10	10	2	10	2	10	10	10	10	2	2	2	2	2	2	10
Sequence 52	10	10	10	10	10	10	10	2	2	2	2	2	10	10	10	2	10	10	2	10	2	2	10	2	10	10	10	10	2	2
Sequence 53	10	10	2	10	2	10	2	10	10	2	2	2	2	10	2	2	2	10	10	10	10	10	2	10	2	10	2	10	2	2
Sequence 54	2	2	2	2	10	2	10	2	10	2	2	10	2	2	2	2	2	10	2	2	10	10	10	10	2	2	10	2	2	10
Sequence 55	2	10	2	2	2	2	10	10	10	2	10	2	2	2	2	10	2	2	10	2	2	2	2	2	2	10	10	10	10	10
Sequence 56	2	2	10	2	10	2	2	2	10	2	10	10	10	10	10	10	2	10	10	10	2	10	2	10	-2	-2	-10	-10	-10	-10
Sequence 57	2	2	2	2	2	2	2	2	10	10	10	10	2	2	10	2	10	2	-10	-10	-10	-10	-10	-10	-2	-10	-2	-10	-2	-10
Sequence 58	-10	-10	-2	-2	-2	-2	-2	-10	-2	-10	-10	-10	-2	-2	-10	-2	-10	-10	10	2	2	2	2	2	-10	-10	-2	-10	-10	-2
Sequence 59	-10	-10	-10	-10	-10	-2	-10	-10	-10	-2	-10	-10	-10	-2	-2	-2	-2	-2	2	2	10	2	2	10	-10	-10	-10	-10	-10	-2
Sequence 60	-2	-2	-2	-2	-2	-2	2	10	2	2	10	10	2	2	10	10	10	10	-10	-10	-2	-2	-10	-10	-2	-10	-10	-10	-2	-10

Block	6						7						8						9						10					
Trial	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Sequence 31	-2	-10	-10	-10	-2	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-2	-10	-10	-10	-10	-2	-10	-10	-10	-2	-10	-2	-10	-10
Sequence 32	-10	-10	-10	-10	-10	-10	-2	-10	-2	-2	-2	-10	-10	-2	-2	-2	-2	-10	-2	-2	-10	-2	-10	-2	-2	-2	-2	-10	-2	-2
Sequence 33	-2	-2	-2	-2	-2	-2	-10	-10	-10	-10	-2	-2	-10	-10	-2	-10	-2	-2	-2	-2	-2	-2	-10	-2	-2	-2	-10	-10	-2	-2
Sequence 34	-10	-2	-2	-2	-2	-2	-10	-2	-2	-10	-10	-2	-2	-10	-10	-10	-10	-2	-10	-10	-10	-10	-10	-2	-10	-10	-2	-10	-2	-10
Sequence 35	-10	-10	-2	-10	-10	-10	-2	-2	-2	-2	-2	-2	-2	-10	-2	-2	-2	-2	-10	-2	-10	-10	-2	-2	-10	-10	-2	-10	-10	-2
Sequence 36	-10	-10	-10	-10	-10	-2	-10	-10	-10	-2	-10	-10	-2	-2	-2	-2	-2	-2	-2	-10	-10	-2	-2	-2	-10	-10	-2	-10	-10	-10
Sequence 37	-2	-10	-10	-10	-10	-10	-2	-2	-10	-2	-2	-2	-10	-2	-10	-2	-2	-10	-10	-2	-2	-2	-2	-2	-10	-2	-2	-10	-10	-10
Sequence 38	-10	-10	-2	-2	-2	-2	-10	-2	-10	-2	-10	-2	-10	-2	-2	-10	-10	-10	-2	-10	-2	-2	-2	-10	-2	-2	-2	-2	-2	-2
Sequence 39	-10	-2	-10	-2	-2	-10	-2	-2	-2	-2	-10	-2	-10	-2	-10	-10	-10	-2	-10	-10	-10	-10	-2	-2	-2	-2	-2	-2	-10	-2
Sequence 40	-2	-10	-10	-2	-2	-10	-2	-10	-10	-2	-10	-10	-10	-10	-10	-10	-2	-10	-2	-2	-10	-2	-2	-10	-2	-2	-10	-2	-2	-2
Sequence 41	-2	-2	-2	-10	-10	-10	-10	-2	-10	-10	-10	-10	-2	-10	-10	-2	-2	-10	-10	-2	-2	-2	-10	-2	-2	-2	-10	-2	-2	-10
Sequence 42	-10	-2	-2	-10	-10	-10	-10	-2	-2	-2	-10	-2	-2	-2	-2	-2	-2	-2	-2	-10	-2	-10	-10	-10	-2	-2	-2	-2	-2	-2
Sequence 43	-10	-10	-2	-2	-10	-2	-10	-10	-10	-10	-2	-2	-10	-2	-10	-2	-2	-2	-10	-2	-10	-10	-2	-2	-10	-10	-10	-2	-2	-2
Sequence 44	-10	-10	-10	-10	-10	-2	-10	-10	-10	-10	-2	-10	-2	-10	-10	-10	-10	-10	-2	-2	-10	-2	-2	-2	-10	-10	-10	-2	-2	-2
Sequence 45	-10	-2	-2	-2	-2	-10	-10	-2	-2	-10	-10	-10	-2	-2	-10	-2	-10	-2	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10
Sequence 46	-2	-10	-2	-2	-10	-2	-2	-10	-2	-2	-2	-2	-10	-10	-2	-2	-2	-2	-2	-10	-10	-2	-2	-2	-2	-2	-2	-2	-2	-2
Sequence 47	-2	-2	-10	-10	-2	-2	-2	-2	-2	-10	-2	-2	-2	-2	-2	-2	-10	-2	-2	-2	-10	-2	-10	-2	-2	-10	-10	-10	-10	-2
Sequence 48	-2	-2	-2	-2	-2	-2	-10	-10	-10	-10	-10	-10	-10	-10	-2	-2	-10	-10	-10	-10	-10	-10	-10	-2	-2	-10	-10	-10	-2	-2
Sequence 49	-10	-2	-10	-2	-2	-2	-2	-2	-10	-2	-10	-2	-2	-10	-2	-2	-2	-10	-2	-2	-2	-10	-2	-2	-10	-10	-10	-2	-2	-10
Sequence 50	-10	-2	-10	-2	-10	-2	-10	-10	-2	-10	-2	-10	-10	-2	-2	-10	-2	-2	-10	-10	-10	-10	-10	-2	-2	-2	-10	-10	-10	-10
Sequence 51	-10	-2	-10	-10	-10	-2	-2	-2	-10	-2	-10	-2	-2	-2	-2	-10	-10	-2	-10	-2	-10	-2	-2	-10	-2	-2	-2	-10	-10	-2
Sequence 52	-2	-10	-2	-10	-2	-2	-10	-2	-10	-10	-10	-10	-2	-2	-2	-2	-2	-2	-2	-10	-10	-10	-10	-2	-2	-10	-2	-10	-10	-10
Sequence 53	-2	-2	-2	-2	-2	-10	-10	-2	-10	-10	-10	-10	-10	-2	-10	-10	-2	-10	-10	-2	-10	-2	-2	-10	-2	-10	-10	-10	-10	-10
Sequence 54	-10	-2	-10	-10	-10	-10	-10	-2	-10	-2	-2	-2	-10	-2	-2	-2	-2	-2	-2	-2	-10	-10	-2	-10	-2	-2	-2	-10	-2	-2
Sequence 55	-10	-2	-10	-10	-2	-2	-10	-10	-10	-10	-10	-2	-10	-2	-10	-2	-2	-10	-10	-2	-2	-2	-2	-2	-10	-10	-10	-10	-2	-10
Sequence 56	-10	-2	-2	-10	-2	-2	2	10	10	2	2	10	-10	-10	-2	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-2	-2	-10	-10	-10
Sequence 57	-10	-2	-2	-10	-2	-2	-2	-10	-2	-2	-10	-2	-10	-2	-2	-10	-10	-2	10	10	2	10	10	10	10	2	10	2	2	10
Sequence 58	2	2	2	2	2	2	-10	-10	-10	-10	-2	-2	10	10	10	10	10	10	10	10	10	10	2	10	10	10	10	2	10	10
Sequence 59	-2	-10	-10	-2	-10	-10	10	10	10	2	2	2	10	2	2	2	2	2	10	2	2	2	2	2	10	2	2	10	10	10
Sequence 60	2	2	2	2	2	2	-2	-2	-10	-2	-2	-10	10	10	10	10	10	10	10	10	2	10	10	2	-2	-2	-10	-10	-2	-2

Appendix H. Type of Stock Sequences

For any trial in a block a 1 in the table represents that a participant was confronting the good stock, a 0 that the participant was confronting the bad stock. Whether the stock was good or bad was decided randomly at the beginning of each block, with each state having 50% probability.

Block	1						2						3						4						5					
Trial	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Sequence 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 2	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 3	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 4	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 5	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 6	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 7	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 8	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 9	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 10	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 11	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 12	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 13	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 14	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 15	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 16	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 18	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 19	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 20	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 21	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 22	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 24	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 25	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 26	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 27	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 29	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 30	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Block	6						7						8						9						10					
Trial	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Sequence 1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 3	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 4	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 5	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 7	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 8	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 10	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 11	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 13	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 15	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 16	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 17	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 18	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 19	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 20	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 21	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 23	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 24	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 25	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 26	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 27	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 28	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 29	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 30	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0

Block	1						2						3						4						5					
Trial	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Sequence 31	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 32	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 33	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 34	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 35	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 36	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 37	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 38	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 39	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 40	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 41	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 42	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 43	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 44	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 45	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 46	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 47	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 48	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 49	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 50	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 51	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 52	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 53	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 54	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 56	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 57	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 58	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 59	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 60	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0

Block	6						7						8						9						10					
Trial	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Sequence 31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 32	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 33	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 34	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 35	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 36	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 37	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 38	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 39	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 40	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 41	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 42	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 45	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 46	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 47	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 48	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 49	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 50	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 51	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 52	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1
Sequence 53	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 54	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 56	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 57	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
Sequence 58	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sequence 59	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sequence 60	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

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Notes

[1]In the full feedback condition participants have available the full sample of realized outcomes at each point in time, while participants in the selective feedback condition can miss some of that information if they do not choose the stock in any trial

[2]The Bayesian beliefs calculated using all potential information available to investors whether this information has been accessed because the investor has chosen the alternative or not

[3]Sampling error is the fruit of using unrepresentative samples of information to make inferences about the payoff distributions of the alternatives

[4]Adaptive learning agents base their behavior on Thorndike (1927) law of effect, which states that any behavior is followed by favorable consequences is likely to be repeated, and any behavior that is followed by negative consequences is unlikely to be repeated

[5]See Froot (2001); Choi et al. (2009); Malmendier and Nagel (2011); Barberis and Xiong (2012); Ingersoll and Jin (2013); Imas (2016); Dittmar and Duchin (2016); Necker and Ziegelmeyer (2016); Guiso et al. (2018); Shigeoka (2019); Liu and Zuo (2019)

[6]Decisions by experience here means decisions in which participants in the experimental task do not have prior knowledge about the outcome distribution of the investment alternatives they are facing

[7]See Ehrlich, Guttman, Schönbach, and Mills (1957); Frey and Stahlberg (1986); Witte (1996); Caplin and Eliaz (2003); Kőszegi (2003, 2010); Thornton (2008); Oster, Shoulson, and Dorsey (2013); Golman, Hagmann, and Loewenstein (2017)

[8]See Barber et al. (2005); Barber and Odean (2007); Dellavigna and Pollet (2009); Da et al. (2011); Hartzmark (2014); Stango and Zinman (2014); Sicherman et al. (2015)

[9]By sampled we referred that the payoffs are observed as a result of choosing the bond

[10]Barberis, Shleifer, and Vishny (1998); Bossaerts (2004); Brunnermeier and Parker (2005);

Gabaix, Laibson, Moloche, and Weinberg (2006); Van Nieuwerburgh and Veldkamp (2010); Gennaioli and Shleifer (2010)