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Fostering the adoption of robo-advisors: a 3-weeks online stock-trading experiment

Abstract

We consider how to increase the take-up of robo-advisors to help investors cope with the disposition effect. In a 3-weeks online stock-trading experiment, participants traded freely in week 1, were assisted by trading algorithms in week 2, and chose whether to be assisted in week 3. Passive algorithms prevented trading, active ones traded according to Bayesian rules. Participants could override algorithm choices in some treatments. Only a minority adopted robo-advisors in week 3, with the worst performers being the least likely to do so. Algorithm aversion was reduced if the algorithm traded actively and could be overridden.

Keywords: disposition effect, commitment devices, robo-advisors, sophisticated investors, trading, algorithm aversion

JEL: G11, G40

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1 Introduction

Making use of artificial intelligence to guide and replace human activity is an exciting, promising but also slightly disturbing undertaking. Already, increasingly clever applications help us manage our time, make decisions and keep our commitments, to ourselves and others. In particular, new technologies are changing the way we seek and receive advice. For example, applications make use of artificial intelligence to help users correct their eating habits (e.g. Weight Watchers), choose a suitable dating mate (e.g. Tinder) and adjust their sports training strategies (e.g. Nike+ Running).

This is the case also for financial advice, where robo-advisors that give automated and personalized portfolio management advice have rapidly entered the field. Robo-advisors can help investors select investments and correct for the impact of irrational factors in their trading decisions (Foerster et al. 2017, Uhl and Rohner 2018, Bhatia, Chandani, and Chhateja 2020). This allows them to obtain better balanced and diversified portfolios (D'Acunto, Prabhala, and Rossi, 2019). Moreover, robo-advisors are particularly attractive compared to human advisors because of their low cost, permanent availability and ease of access via user-friendly interfaces. Indeed, robo-advisors could be particularly helpful for households with relatively low incomes and capital, as they could not profitably be advised by human advisers (D'Acunto and Rossi, 2020). Robo-advisors can also reduce moral hazard problems in the relation between advisor and the investor, as they can be verifiably designed to unambiguously serve the interests of the investor rather than those of the advisor (Brenner and Meyll, 2020).

In this project, we consider how robo-advisors can be designed to be attractive to those who need them. We consider a particular issue where robo-advisers can be of help, namely in overcoming the disposition effect, i.e. the tendency to sell rising stocks too early and keep losing ones too long. Specifically, we compare different types of robo-advisers and see which ones are the most helpful and the most likely to be adopted.

The disposition effect is one of the best documented of various market trading anomalies (see Pleßner 2017 for a review). This trading bias leads to portfolios that are overweighted in loss positions, thus reducing investor performance. Neural tests show that individuals experience regret due to this behaviour (Frydman and Camerer, 2016). This means that investors who are subject to the disposition effect consider this behavior to be sub-optimal ex-post. Remedying the disposition effect is therefore a valid target for behavioral interventions (Thaler and Sunstein, 2008). However, as with nudges, we want individuals to choose themselves to be helped. We cannot simply impose robo-advisers, even if that is efficient. We need to get people to voluntarily adopt them.

While the disposition effect is a robust and well documented empirical phenomenon, less attention has been devoted to finding ways to help individuals cope with it. We rely on the limited existing research to investigate how individuals who are subject to the disposition effect can be encouraged to restrict their own freedom of action, such as by committing to trade less often or by letting an algorithm (i.e. a robo-advisor) decide how to trade. Our objective is not to design the best performing robo-advisors. Rather, our objective is to see what features make them more likely to be adopted, especially by those who need them the most and who paradoxically may be the least ready to use them — as we will see.

At that point, the issue we face is that humans are averse to delegating decisions to automated agents. This is a phenomenon called algorithm aversion (Chugunova and Sele 2020, Dietvorst, Simmons, and Massey 2015). Yet, other studies have shown that humans sometimes prefer automated advice to human advice, a phenomenon called algorithm appreciation (Chugunova and Sele 2020). Those contradictory findings indicate that the issue of the acceptability of algorithmic advice is badly understood. We will see how it depends on how the algorithm works, how it is presented, and on the characteristics of the investors, such as their level of experience or their preferences.

To understand which characteristics make algorithms more appealing, we conduct a three-weeks online experiment. Individuals choose in the third week whether to adopt the algorithm which was made available to them in one of the previous two weeks (see Figure A1). We focus on two main differences that may affect acceptance, namely how *active* the algorithm is, and whether it can be *overridden*. Along the first dimension, we offered some participants a robo-adviser that prevented them from trading (*Blocked*), while other participants had access to an algorithm (*Bayesian*) that traded depending on the likelihood a stock would go up or down. Along the second dimension, participants had to follow the algorithm in some treatments (*Hard*), while they were allowed to override the choices of the algorithm in other treatments (*Soft*). Choosing a "hard" robo-advisers means making a strong commitment to following it. These treatments reflect the distinction that Bryan, Karlan, and Nelson (2010) make between hard and soft *commitment devices*: if the incentives are primarily psychological, then the device is soft, otherwise, it is hard.

Varying the degree of commitment imposed by the algorithm (soft, with override, vs. hard, with no override), along with its level of activity (blocked or bayesian trading), allows us to explore two promising ways to improve the *take-up rate* of algorithms by those who normally would not adopt them. We hypothesize that both soft commitments, and limited activity by the robo-adviser, will make them more likely to be adopted. However, both of those characteristics make them less efficient. The question is then whether a potentially higher take-up rate justifies sacrifices in terms of efficiency. This is not necessarily the case. In a related study, Fischbacher, Hoffmann, and Schudy (2017) found that using only simple reminders (i.e. reminders of price limits at which participants wanted to sell the assets) did not reduce the disposition effects. Stricter enforcement of commitments was necessary.

Our intuition is that offering sub-optimal algorithms may be worth the cost because the least able traders may also be the most reluctant to adopt algorithms. This means that even a relatively bad adviser still helps them. This is a corollary of the Dunning-Kruger effect (Kruger and Dunning, 1999). Indeed, while those who do worst do not understand that they do so, they are also those who would benefit the most from advice. The issue is that not understanding that one is doing badly may also mean not understanding how robo-advisers might help. In our case, the best performing investors may also be the most self-aware, that is, the ones who understand not only that the adviser is on average better than them, but also that they might be tempted to override its choices (Bryan, Karlan, and Nelson 2010). They would thus opt for hard commitments. Less sophisticated investors may not anticipate this temptation and would thus reject hard commitments (Beshears, Choi, Laibson, et al. 2018; Dupas and Robinson 2013; Royer, Stehr, and Sydnor 2015; Beshears, Choi, Harris, et al. 2015; Burke, Luoto, and Perez-Arce 2018; Duckworth, Gendler, and Gross 2016;Bryan, Karlan, and Nelson 2010). Offering a soft algorithm would solve this issue. The same reasoning applies to less active algorithms: because they do not trade, they may be perceived as less of a threat.

The results from our experiment show that participants achieve better performance with the help of robo-advisers. They performed significantly better in the week when they had to get help from an algorithm than in the week when they had no help, both in terms of disposition effect and earnings. However, only a small minority of participants decided to rely on algorithms after having tried them, meaning that they either did not notice the performance improvement or this improvement did not compensate for psychological issues in relinquishing some control on their decisions. The majority of our participants preferred to avoid any type of constraint on their own behavior. This was especially so for those who would have benefited the most from such constraints. Indeed, there was a correlation between susceptibility to the disposition effect and unwillingness to adopt algorithms. Encouragingly, however, we observed larger take-up rates for soft algorithms, i.e. the ones that participants can override, and low rates of overriding in this case. Soft algorithms thus still reduced the level of the disposition effect. Surprisingly, we also found that investors preferred active robo-advisers, those that trade on their own, rather than robo-advisers that simply prevent trading.

2 The disposition effect

2.1 Definition

The disposition effect has been the subject of both empirical and experimental research (see Pleßner 2017 for a review). A variety of theories have also been proposed to explain it: prospect theory (e.g. Li and Yang 2013); regret minimisation (e.g. Bleichrodt, Cillo, and Diecidue 2010); realisation utility (e.g Frydman, Barberis, et al. 2014; Barberis and Xiong 2009). While the underlying causes of the disposition effect are still debated, the evidence on this phenomenon is extremely robust. In particular, household investors are more affected by the disposition effect than professional investors, and the disposition effect is greater for females, older people and team investors (Dhar and Zhu 2006, Cueva et al. 2019, Rau 2015). National culture also seems to play a role. Indeed, populations that are more focused on the long-term and less bound by strict social norms have lower average levels of the disposition effect (Breitmayer, Hasso, and Pelster 2019).

While the disposition effect is well documented, less attention has been devoted to mechanisms that would allow investors to cope with it. Frydman and Rangel (2014) show that it is possible to reduce the disposition effect by decreasing the saliency with which the purchasing price is disclosed. Similarly, Fischbacher, Hoffmann, and Schudy (2017) show that automatic selling devices (i.e. stop-loss and take-gain orders) causally reduce the disposition effect by helping investors to realize their losses whereas reminders about selling plans are ineffective.

2.2 Measures

In line with previous research, we measure the disposition effect as in the original work of Odean (1998) that assigns trading decisions to four categories:

- ***realised gain***: a stock that is sold at a price that is higher than the purchasing price;
- ***paper gain***: a stock that is *not* sold but whose price is higher than the purchasing price;
- ***realised loss***: a stock that is sold at a price that is lower than the purchasing price;
- ***paper loss***: a stock that is *not* sold but whose price is lower than the purchasing price;

The disposition effect is computed as *Diff*, the difference between the proportion of realised gains (PGR) and losses (PLR), that is:

$$Diff = \frac{\#RealizedGains}{\#(RealizedGains + PaperGains)} - \frac{\#RealizedLoss}{\#(RealizedLoss + PaperLoss)} \tag{1}$$

In this paper, we also consider *Diff_Amount*, which takes account of the magnitude of the gains and losses:

$$Diff\ Amount = \frac{ECURealizedGains}{ECURealizedGains + ECUPaperGains} - \frac{ECURealizedLoss}{ECURealizedLoss + ECUPaperLoss} \tag{2}$$

Both indicators have a theoretical range going from -1 to +1, where +1 is the value for an investor that sells all his winning positions and holds all losing ones, -1 is the value for an investor that sells all losing positions and holds all winning ones, and 0 is the value for an investor who behaves the same in both cases. The higher the values of these indicators, the more an individual is subject to the disposition effects. In our experiment, the optimal strategy results in both indicators being negative. As a result, a positive value for these indicators unequivocally identifies a distorted - i.e. non optimal - behaviour.

3 Experimental Design

The set-up of our experiment closely resembles Frydman, Barberis, et al. (2014) and Frydman and Rangel (2014). However, we introduce an important change by moving the experiment from the laboratory, where participants stay for a limited time in a specific room, to the field, where participants take part in the experiment while going on with their usual activity. We programmed our experiment with *oTree* (Chen, Schonger, and Wickens 2016), which allowed us to put the experiment online so that each one of our participants had a personalised weblink to access their portfolio and trade. We used *GMass* to send them a personalised email every 8 hours at the start of each new market sessions.

This move outside the physical laboratory thus allows us to increase the interval between consecutive trading periods from seconds to hours (and days). This gives participants the time to develop their understanding of the market and devise their own strategies in a more reflective fashion than they have in the usual experiment. This is important as financial choices are affected both by an instinctive-affective mechanism (System 1), which may drive short-term decisions, such as what stock to buy or sell, and a deliberative-cognitive mechanism (System 2), which may drive longer-term decisions, such as the way in which one manages one's money (Kahneman 2002, Hirshleifer 2015, Ploner 2017). Our design, therefore, allows us to further test the robustness of the disposition effect to experience by assessing it over a long time period, and to achieve higher external validity in terms of the decision to adopt new trading habits, such as getting help from third parties.

Another difference from Frydman, Barberis, et al. (2014) and Frydman and Rangel (2014) is that our participants could buy and sell simultaneously up to 3 stocks per round, while in their setting participants could buy and sell only one stock at a time. This made it more worth for participants to log in every trading period, and also increased the amount of data collected. Specifically, in each round, each one of the three stocks (A, B, C) had its price randomly updated. The price path of each stock was independently governed by a two-state Markov chain, with a good state and a bad state. If the stock i was in the good state, its price increased with probability 0.70 while it decreased with probability 0.30. If the stock was instead in a bad state, its price increased with probability 0.30 and it decreased with probability 0.70. Independently of the direction of the price change, the magnitude of the price variation was uniformly drawn from {5, 10, 15}. In subsequent rounds, the (good or bad) state of each stock remained the same with probabilities 0.80, while it switched state with probability 0.20. To make comparisons easier across participants and treatments, we predetermined 6 series of price realisations, the same across treatments. The beginning state was good with probability 50%.

Each subject could hold a maximum of one share of each stock and a minimum of zero (i.e. short-selling was not allowed). The trading decision was therefore reduced to deciding whether to sell a stock (conditional on holding it) or buying a stock (conditional on not holding it). As in Frydman and Rangel (2014) and Frydman, Barberis, et al. (2014), each stock thus exhibits positive autocorrelation. In other words, a stock that performed well in the last round was likely to be in a good state in the subsequent round.

The experiment lasted 21 days, with each day having 3 trading rounds, each lasting 8 hours. In the first 7 days (i.e. the first week), participants played the base-game without an algorithm to support their choice (i.e without any type of robo-advisors). In the following 7 days (i.e. the second week), a new start was made and participants had access to an adviser (see the timeline in Figure A1). To control for possible order effect, we ran treatments in which participants played with one of the four advisers in the first week while they play freely in the second. As in the standard treatments, participants needed to choose at the beginning of the third week whether they preferred to play as in the second week or as in the first week.

Algorithms differed in their activity (i.e. either *Block* or *Bayesian* trading) and in the flexibility of the commitment to use them (i.e. *Soft* vs *Hard*). Specifically, the blocked trading algorithm committed participants to trade only every two rounds, while the Bayesian algorithm traded every two rounds according to the probability of the stock being in a good state. If the algorithm was of a soft-type, participants were free to override the algorithm's choice, while they could not do so if the algorithm was of the hard-type.

We denote treatments with the "standard" order (robo-adviser in second week) as follows:

1. **Hard Blocked:** participants have to let an algorithm (advisor) make decisions every two rounds, and this decision is not to trade;

2. **Soft Blocked:** participants rely on the same algorithm as above, but they can override that decision on a period by period basis;

3. **Hard Bayes:** participants have to let an algorithm trade every two rounds according to a Bayesian updating of probability, i.e. sell/not buy a stock whenever the probability of that stock is in a bad state is above 50% (and vice-versa);

4. **Soft Bayes:** participants rely on the same algorithm as above, but they can override that decision on a period by period basis;

We denote treatments with a reverted order (robo-adviser in the first week) as **Hard Blocked reverted, Soft Blocked reverted, Hard Bayes reverted** and **Soft Bayes reverted.**

Participants were paid the value of their portfolio at the end of one of the 3 weeks selected at random. Figure (A1) gives the timeline in the case where the use of the algorithm (i.e. robo-advisor) is imposed in the second week.

3.1 Optimal strategy

As in the paper of Frydman, Barberis, et al. (2014) and Frydman and Camerer (2016), our set-up induces positive autocorrelation in stock price changes, which implies that a risk-neutral rational trader ought to sell losing stocks more often than winning stocks, thereby exhibiting the *opposite* of the disposition effect. In particular, the optimal trading strategy for a subject is to sell (or not to buy) a stock when he believes that it is more likely to be in a bad state than in a good state, and to buy (or hold) a stock when he believes that it is more likely to be in good state. Since the three stocks are uncorrelated in our experiment, it is rational for the participants to consider each stock individually.

We can define optimal trading more precisely. Let p_{it} be the price of stock i in round t and let $q_{it} = Pr(p_{it}, p_{i,t-1}, ...p_{i1})$ be the probability, from the point of view of a rational (Bayesian) investor, that stock i is in the good state. Let $z_{it} = 1$ indicates a price increase for the stock i, and $z_{it} = -1$ indicates a price decrease. Then, we have

$$q_{i,t}(q_{i,t-1}, z_{it}) = \frac{Pr(s_{it} = good)Pr(q_{it})}{Pr(s_{it} = good)Pr(q_{it}) + Pr(s_{it} = bad)Pr(q_{it})}$$

$$= \frac{(0.5 + 0.2z_{it})(0.8q_{i,t-1} + 0.2(1 - q_{i,t-1}))}{(0.5 + 0.2z_{it})(0.8q_{i,t-1} + 0.2(1 - q_{i,t-1})) + (0.5 - 0.2z_{it})(0.8(1 - q_{i,t-1}) + 0.2q_{i,t-1})}$$

The optimal strategy is to sell (if holding) or not to buy (if not holding) a stock i when $q_{i,t} < 0.5$, and to keep (if holding) or buy (if not holding) otherwise. The strategy of the Bayes adviser is based on this probability. Similar to previous experiments (Frydman, Barberis, et al. 2014, Frydman and Rangel 2014), it is difficult for participants to exactly compute this probability. However, it is possible to approximate this optimal strategy with a simple rule of thumb: *i.e. "hold on stocks that have recently performed well, sell stocks that have recently performed poorly".*

Optimal (Bayesian) trading leads to an average level of $Diff = -0.5$. Indeed, a stock that is in a good state remains so with probability 80% and goes up with probability 70%, in which case the stock is kept ($Diff = 0$), and goes down with probability 30% in which case the stock is sold so $Diff = -1$. It switches to a bad state with probability 20%, in which case it goes up with probability 30%, whereby $Diff = 0$, and down with probability 70%, whereby $Diff = -1$. On average therefore, as stock that is in a good state has $Diff = (0.8 \times 0.3 + 0.2 \times 0.7) \times (-1) = -0.38$. A stock that is in a bad state has $Diff = (0.8 \times 0.7 + 0.2 \times 0.3) = -0.62$. Since we assigned stocks randomly to a bad or good state in the first period of trading, the optimal Bayesian trader will have an average level of $Diff = 0.5 \times -0.38 + 0.5 \times -0.62 = -0.5$.

3.2 Hypotheses

Based on our review of the literature, and with reference to our experimental design, we make the following four hypotheses:

1. Participants are subject to the disposition effect in the week where they have to trade on their own (week 2 in the "standard" treatments, week 1 in the "reverted" ones). That is, both $Diff$ and *Diff Amount* will be significantly greater than 0.

2. The level of the disposition effect will be lower in the week where participants have to rely on a robo-adviser than in the week where they have to trade on their own.

3. In the third week, participants who experienced *soft* and less active algorithms (*Block*) will be more likely to adopt them compared to those who experienced *hard* and more active (*Bayes*) algorithms.

4. Participants that are the most affected by the disposition effect are also the least likely to adopt robo-advisers in the third week.

This last hypothesis is partially grounded on the Dunning-Kruger effect, i.e. knowing that one needs advice requires knowing that one is doing badly, which a person who does badly may not be able to recognize. It is however also grounded on the simple observation that our robo-advisers correspond to traders with low disposition effect. The Block algorithm has $Diff = 0$ while the Bayes algorithm has an average $Diff = -0.5$. Therefore, they deviate the most from the behavior of traders that are most subject to the disposition effect. Those traders therefore experience the most discrepancy between the trades by the robo-adviser and the trades they would like to make. This discrepancy is felt every round where the robo-adviser trades, while the benefit of using the robo-adviser is harder to see. Indeed, some trades by the robo-adviser turn out to be "bad" ex-post, e.g. selling a stock that goes up next period, and the benefits appear only in the long-term, that is in comparison with the overall evolution of the market, and even then, not always. In other words, an individual's performance in the market is affected more by chance (the market is doing well) than by good trading decisions (I do better than the market). However, an individual notices the overall performance rather than the relative performance. Furthermore, he notices more "mistakes" by the robo-adviser than his own mistakes. All this means that the immediate discrepancy between one's preferred decisions and those of the adviser will have more of an effect on adoption than objective, relative assessment of performance vs. what one would have achieved on one's own.

3.3 Participants and experimental protocol

Data collection started in June 2020 (right after the end of Covid19 lockdown restrictions in Italy) and ended in Mid-August 2020, before the start of a new round of restrictions. Therefore, all our data was collected while the public health situation in Italy was quite stable.[1] Participants were randomly selected out of a pool of about 3000 students from 20 departments of the University of Pisa. Participants were invited to the LES laboratory online with *Microsoft Teams* where they received instructions and a *personal weblink* they could use to play (either on their computer or on their mobile phone). There was a trial session with two periods of trading and participants could ask for clarifications. Although always available online, instructions were also read aloud on *Teams* during the explanatory session. Participants also received instructions in a PDF version (see the English Translation in Appendix at

[1] Having collected the entire data during the same health conditions is important. Indeed Ben-David and Sade (2021) observed a change in take-up rate after Covid-19 compared to pre-Covid-19 period.

the end of the paper). In addition to having a general description of the experimental market, participants were told that at the end of the second and third week they would receive additional information about variations that would be introduced in the game (see Figure A2).

In addition, participants received every 8 hours an email reminding of them the beginning of a new trading session, as well as their personal link to play. They were finally told that, at the end of the third week, one randomly selected week would be selected for payment. At this time, they needed to write an email to the experimenter in order to receive their payment by bank transfer.

4 Results

As stated above, data collection started in June 2020 (right after the end of lockdown restrictions in Italy) and ended in Mid-August. Slightly more than 450 participants, students from the University of Pisa, took part in the online experiments. A large majority were studying engineering or economics. The average age was 25, and 46% of participants were male. The average payment for participation was 17.80 Euro, including a show-up fee of 5 Euro.

We collected information about participants' cognitive ability and level of concern for the future, as well as their financial literacy, locus of control and risk-aversion. Results are shown in Table (A2) in the Appendix. There are no significant differences across treatments. On average, participants were able to answer correctly two out of three logical questions (Cognitive Reflection Test, Frederick 2005), slightly more than two out of three basic financial literacy questions (Lusardi and Mitchell 2007; Lusardi and Mitchell 2011), and scored about 37 (min 0, max 94) in the consideration of future of consequence scale (Consideration Future Consequences, 12-item scale developed by Strathman et al. 1994). Participants scored 2.6 on average on a 4-level Likert scale of general risk-aversion.

The drop out rate was low (about 9%), resulting in a sample of 409 participants who went through all phases, i.e. played all three weeks and claimed payment at the end of the experiment. We exclude from our sample 5 participants who did not actively play at any time during the experiment but did claim payment at the end, as was their right.

Conditional on being in the sample, participants' activity rate was quite high and stable during all three weeks (see Table A1 in the Appendix). Participants actively traded (i.e. either sold or bought at least one stock) in about 57% to 74% of all possible trading periods, i.e. on average about twice per day. We did not observe significant differences in activity levels across treatments.

4.1 Do people suffer from the disposition effect and do they benefit from using an algorithm?

We test our first two hypotheses in this part. As stated in section 3.1, our setting implies that a risk-neutral expected value maximizer would exhibit the opposite of the disposition effect – that is, negative *Diff* values. We report the average disposition effect for our participants in Table (A5) in the Appendix, looking at both the number and value of stocks sold and bought, and excluding trades made with the help of the robo-advisor(*Diff* and *Diff_Amount* cf. equations 1 and 2).

As Table (A5) highlights, the value of *Diff* and *Diff_Amount* was relatively high, positive and statistically greater than zero in the weeks without robo-advisers in almost all treatments. This is less so in reverted treatments, where participants had been helped every two periods by an adviser in the previous week. The disposition effect was lower in almost all treatments in the second week. Indeed, the difference between the first and second week (i.e. the Δ column in Table A5) is always positive, and statistically significantly so in some cases. One reason for this reduction may be that participants learned over time to trade better.

Looking now at the average disposition effect including trades made with the help of the robo-adviser (Table A6 in the Appendix), we see a strong effect of getting assistance from an algorithm. The disposition effect (*Diff*) is significantly higher in the first week than in the second week in "standard" treatments, while the opposite happens in "reverted" treatment. The disposition effect (*Diff*) is particularly low when trade is helped by a Bayesian algorithm, which is because of $Diff = -0.5$ on average for such an algorithm. We also find that *Diff* is not very different between soft and hard treatments, meaning, as we will later check, that participants did not generally override algorithm choices when that was possible.

To get a better sense of the effect of each type of algorithm on the level of the disposition effect in the first two weeks of our experiment, we run the following regression

$$Diff = \beta_1 Algorithm + \beta_2 Reverted + \beta_3 Bayes + \beta_4 Soft + \gamma' Controls + \epsilon \tag{3}$$

where the dependent variable *Diff* is the amount of disposition effect computed as described in equations (1) and (2), while *Algorithm* is a dummy equal to one if the individual had to rely on an algorithm (and 0 otherwise). The dummy *Soft* is equal to one if the individual could override the algorithm (and 0 otherwise), while the dummy *Bayes* denotes the type of adviser, i.e. equal to 1 if the algorithm was Bayesian. The dummy *Reverted* equals 1 if the individual was in reverted treatments (and 0 otherwise). We also include the set of individual characteristics collected through the questionnaire, i.e. financial literacy, future attitude (*CFC*) and cognitive Ability (*CRT*), locus of control (*Control)* and risk aversion, as well as individual engagement in the experiment during the weeks (*Average activity*).

Results are reported in Table (1), both including and excluding the choice made by the algorithm itself. In column (*a*) we observe that *Diff* was lower in weeks where participants had the help of an algorithm (-0.142, significant at 1% level). This difference is not only

Table 1: DETERMINANTS OF THE DISPOSITION EFFECT, WITH AND WITHOUT ALGORITHMIC CHOICES

	Including Algorithm choices				*Excluding Algorithm choices*			
	Diff	Diff_amount	Diff vs Opt	Diff_amount vs Opt	Diff	Diff_amount	Diff vs Opt	Diff_amount vs Opt
	(a)	*(b)*	*(c)*	*(d)*	*(e)*	*(f)*	*(g)*	*(h)*
Algorithm	-0.142***	-0.174***	-0.142***	-0.156***	0.022	0.017	0.021	0.034
	(0.022)	(0.026)	(0.027)	(0.028)	(0.023)	(0.025)	(0.027)	(0.028)
Reverted	-0.104***	-0.118***	-0.094***	-0.134***	-0.102***	-0.117***	-0.094**	-0.134***
	(0.031)	(0.035)	(0.033)	(0.035)	(0.036)	(0.041)	(0.038)	(0.040)
Bayes	-0.169***	-0.205***	-0.183***	-0.153***	-0.004	-0.003	-0.018	0.051
	(0.030)	(0.034)	(0.031)	(0.033)	(0.035)	(0.039)	(0.036)	(0.038)
Soft	0.065**	0.069**	0.053*	0.046	0.004	0.000	-0.010	-0.024
	(0.030)	(0.034)	(0.032)	(0.033)	(0.035)	(0.039)	(0.036)	(0.038)
Average activity	-0.080	-0.074	-0.121**	-0.016	-0.267***	-0.294***	-0.304***	-0.222***
	(0.055)	(0.060)	(0.059)	(0.062)	(0.070)	(0.077)	(0.074)	(0.076)
CRT	-0.033**	-0.027	-0.031*	-0.015	-0.023	-0.016	-0.022	-0.006
	(0.015)	(0.017)	(0.016)	(0.017)	(0.018)	(0.020)	(0.018)	(0.019)
CFC	0.002	0.002	0.001	-0.001	0.001	0.000	-0.000	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Financial Literacy	-0.011	-0.018	-0.003	-0.025	-0.021	-0.028	-0.013	-0.033
	(0.025)	(0.028)	(0.027)	(0.028)	(0.028)	(0.031)	(0.030)	(0.032)
Locus of control	0.005	0.005	0.005	-0.000	0.004	0.004	0.003	0.000
	(0.009)	(0.010)	(0.010)	(0.010)	(0.011)	(0.012)	(0.011)	(0.011)
Risk aversion	-0.010	-0.009	-0.010	-0.007	-0.005	-0.005	-0.004	-0.000
	(0.019)	(0.021)	(0.020)	(0.021)	(0.023)	(0.025)	(0.024)	(0.025)
Constant	-0.084***	-0.098***	-0.096***	-0.203***	-0.114***	-0.132***	-0.125***	-0.237***
	(0.023)	(0.027)	(0.028)	(0.029)	(0.024)	(0.026)	(0.028)	(0.029)
2nd week	0.219	0.288	0.823***	1.141***	0.370*	0.439*	0.975***	1.260***
	(0.167)	(0.190)	(0.175)	(0.194)	(0.201)	(0.230)	(0.208)	(0.226)
ll	-353	-461	-445	-480	-429	-513	-494	-523
N	818	818	818	818	804	804	804	804

The dependent variable in columns *(a)*, *(b)*, is the amount of disposition effect in week 1 and 2 computed as described in equation (1) and (2), section 2.1, respectively. The same applies to columns *(e)*, *(f)*, although algorithm choices where excluded. The dependent variables with the "opt" term in columns (*c*), (*d*), (*g*) and (*h*) are the same variables computed as a difference with the respect to the value of the optimal strategy. *Algorithm* is a dummy equal to 1 if the individual opted for an algorithm in week 3. *Reverted* is a dummy equal to 1 in reverted treatments, while *Bayes* is a dummy equal to 1 for treatment in which the algorithm is based on the bayes probability of being in a good or bad state, and *Soft* is a dummy equal to 1 in treatments in which participants can override algorithm choices. The variable *Average activity* measure the individual activities in the week. The other characteristics are describe in Tab (A3). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

statistically but also economically significant, as the average level of the disposition effect in the sample in the first two weeks is 0.016 (see Table A4). The disposition effect was significantly lower in reverted treatments (-0.104). Relying on a Bayesian algorithm is also associated with a significantly lower disposition effect (about -0.169, significant at 1% level). On the contrary, having the possibility to override an algorithm choice, leads to an increase of 0.065 in the level of the disposition effect (significant a 5% level). Among individual characteristics, only the level of cognitive ability significantly reduces the level of the disposition effects. However, this result is not confirmed when using our second measure of the disposition effects (column *b*), while the other results remain robust. In columns (c) and (d) we check the robustness of our results, by considering the difference between actual *Diff* and optimal *Diff* every period. We confirm our main results.

Another point we examine is whether participants who relied on an algorithm also made better choices even without the algorithm itself (i.e. learned from their use). Thus, in Table (1) - column *e*, *f*, *g, h* - we repeat the previous regressions but removing from the individual performances the choices made by the algorithm itself. In that case, we cannot observe any significant differences depending on the type of algorithms. The only effect we observe is the one derived from being in a reverted treatment and from being a relatively more active trader. In other words, participants did benefit from algorithms, but learning appeared only in the second week when exposed to them in the first week. However, we cannot establish this result for sure, as we do not know how participants would have performed in the second week on their own if they had also been on their own in the first week.

4.2 What algorithms do people prefer, and who chooses them?

We test our hypotheses 3 and 4 in this section. In the third and last week of our experiment, participants could decide in which way to play the remaining rounds of the game, i.e. whether to play with the assistance of an algorithm or not.

In that situation, we know from the experimental literature that at least a fraction of individuals will behave in a sophisticated way. These individuals are not free from present bias (i.e. the tendency to experience benefits right away and to postpone the realisation of losses as much as possible) but they are aware this bias hurts them. Therefore, they will be willing to use commitment devices so as to impose the behaviour they planned now for the future on their "future self".

Not all subjects are that sophisticated, though. Most subjects display *naive* behaviour - they are subject to the disposition effect and unaware of being so. As a result, they will not want to make use of any commitment device.

Indeed, on average, the take-up rate is quite low, as only about 37% of our participants decided to rely on a trading algorithm (see Table 2) while 51% of them suffered from the disposition effect (as measured with *DE,* a dummy variable equal to 1 if average individual *Diff* is more than 0, see Table A3 and A4 in the Appendix). Specifically, we can observe that individuals in the first and second quartiles of *Diff* - i.e those with lower levels of the disposition effect - were more likely to adopt an algorithm than those in the third and fourth quartiles of *Diff* (39% and 42% vs 32% respectively, see table A4). Table (2) also shows that adoption of *Baye*s advisers was higher than that of *Block* advisers, both for their Soft and *Hard* versions, while adoption of *Soft* advisers was higher than that of their *Hard* version, both for the *Block* and *Bayes* variety.

Table 2: ROBO-ADVISER ADOPTION, BY TREATMENT.

	Block		**Bayes**		Total
	HARD	SOFT	HARD	SOFT	
No Advisor	77	68	58	56	259
Advisor	29	40	38	43	150
Total	106	108	96	99	409
Take-up	27%	37%	39%	43%	37%

We get a synthetic view of the effect of each variable on the take-up rate by running a logistic regression as follows:

$$Logit(Algorithm) = \beta_1 Diff + \beta_2 Reverted + \beta_3 Bayes + \beta_4 Soft + \gamma' controls + \epsilon$$

where the dependent variable is the dummy *Algorithm* equal to 1 if an individual opted for getting assistance from an algorithm in the third week (and zero otherwise) and *Diff*, as described above, is our measure of the disposition effect. *Soft* is a dummy variable equal to 1 if an individual could opt for a soft algorithm (and zero otherwise). *Reverted* is a dummy variable equal to 1 if the individual played with an algorithm in the first week (and zero otherwise). *Bayes* is a dummy equal to one if the algorithm was Bayesian (and zero otherwise). The vector *controls* include a series of individual controls we mainly collected through the entry and exit questionnaire. In particular, we control for: the level of the individual average level of activity during the first two weeks (*Average activity)*, individual cognitive reflection ability (*CRT*), financial literacy (*Financial Literacy*), consideration for future consequences (*CFC*), locus of control (*Locus*), and risk aversion (*Risk Aversion*).

Results (marginal effects) are reported in Table (3), in column (a) we observe that being subject to the disposition effect decreases the probability of taking up the algorithm by 8.4%, and this is economically and statistically significant. Although soft algorithms seem to be preferred (+7.0%) the effect is not statistically significant. The more sophisticated type of algorithm (i.e. *Bayes)* is also preferred (+8.9%) although the effect is only significant at 10% level. The average level of weekly activity (column *b*) does not affect the likelihood that a participant will take-up an algorithm in the third week. Among individual characteristics (column *c*), the attitude towards future consequences (CFC) plays a marginal role, decreasing the probability to take-up an algorithm by almost 0.1% for an increase by 1 in the scale. The level of risk aversion (column *d*) increases significantly the probability to take-up the algorithm by 8.1% for an increase of 1 point in the scale of risk-aversion.

In column *(e),* we also introduce the variable *Overconfidence,* which is a dummy variable

Table 3: DETERMINANTS OF TAKE-UP RATE IN THE THIRD WEEK

	(a)	*(b)*	*(c)*	*(d)*	*(e)*	*(f)*	*(g)*
Diff$_{[week\,1,2]}$	-0.084**	-0.082**	-0.083**	-0.078**	-0.052	-0.083***	-0.082**
	(0.033)	(0.033)	(0.032)	(0.033)	(0.041)	(0.029)	(0.033)
Reverted	0.028	0.029	0.029	0.016	0.001	0.018	0.045
	(0.048)	(0.047)	(0.049)	(0.055)	(0.056)	(0.054)	(0.061)
Soft	0.070	0.069	0.064	0.064	0.059	0.066	0.096*
	(0.047)	(0.047)	(0.045)	(0.047)	(0.046)	(0.047)	(0.052)
Bayes	0.089*	0.087*	0.077	0.078	0.087*	0.076	0.084*
	(0.049)	(0.048)	(0.047)	(0.050)	(0.047)	(0.047)	(0.047)
Average activity		-0.083	-0.066	-0.091	-0.093	-0.090	
		(0.086)	(0.080)	(0.072)	(0.086)	(0.070)	
CRT			0.014	0.013	0.012	0.012	0.012
			(0.026)	(0.025)	(0.026)	(0.026)	(0.026)
CFC			-0.009*	-0.008	-0.008	-0.008	-0.008
			(0.005)	(0.006)	(0.007)	(0.006)	(0.006)
Financial Literacy			-0.054	-0.050	-0.056	-0.050	-0.051
			(0.045)	(0.045)	(0.045)	(0.044)	(0.045)
Locus of control				-0.006	-0.008	-0.005	-0.006
				(0.015)	(0.016)	(0.014)	(0.015)
Risk aversion				0.081***	0.087***	0.082***	0.078***
				(0.016)	(0.015)	(0.016)	(0.017)
Overconfidence					0.006		
					(0.061)		
Algorithm better						-0.041	
						(0.095)	
Overrode algorithm							-0.064
							(0.059)
ll	-265	-264	-261	-257	-247	-257	-257
N	409	409	409	409	395	409	409

*p<0.10,** p<0.05, ***p<0.01

The dependent variable is a dummy equal to 1 if the individual opted for an algorithm in the third week. The variable DE instead is a dummy equal to 1 if the individual suffered from disposition effect in the week he could freely trade. *Reverted* is a dummy equal to 1 in reverted treatments, while *Bayes* is a dummy equal to 1 for treatment in which the algorithm is based on the bayes probability of being in a good or bad state, and *Soft* is a dummy equal to 1 in treatments in which participants can override algorithm choices. The variable *Average activity* measure the individual average number of active periods in the previous two weeks, while the variable *Overrode algorithm* is a dummy equal to 1 if the individual overrode the algorithm in the previous two weeks. The variable *Algorithm better* is a dummy equal to 1 if the individual's payoff was higher in the week with the algorithm. This latter variable has a number of missing observations as not all subjects completed the exit questionnaire. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

equal to 1 if the individual said they thought their performance was above that of the majority of other participants in our exit-post questionnaire. This variable is not statistically significant. In column *(f)* we also include a variable *Algorithm better*, which is equal to 1 if an individual's portfolio performance was better in the week when the individual traded with the assistance of an algorithm than in the week where he traded alone. The effect is negative but neither stastistically or economically significant. Finally, in column *(g)* we include a variable *Overrode algorithm,* which captures a different type of activity compared to *Average activity.* Indeed this variable is equal to 1 if the individual (*intended* to) override the choice made by the soft algorithm in the first two weeks.[2] This variable captures unease with the choices of the algorithm. Although this variable alone is not statistically significant, its introduction helps to reduce a bit the noise of our regression: while the previous results remain robust, the coefficient of the *Soft* dummy becomes statistically significant at the 10% level. The take-up rate of softer types of algorithms is thus higher than that of hard algorithms if we also take into account differences in individual tendency to override the algorithm.

To check the robustness of our results and for non-linearities in the data, we replicate the analysis of Tab (3) by replacing the variable *Diff* with a dummy variable DE (equal to 1 if the individual suffers from the disposition effect, i.e. $Diff > 0$) and with four dummy variables capturing the quartile for the disposition effect (i.e. the *Diff* quartiles) to which an individual belongs. The results are substantially analogous, see Table (A7) and Table (A8). Interestingly, if we replace the variable *Diff* with the dummy DE the preference for softer algorithm becomes stronger, while if we replace the variable *Diff* with the four quartile dummies in Table (A8), we can see that the likelihood that an individual in the third quartile will adopt an algorithm is about 12% lower (significant at 1% level) than that of an individual in the first quartile (i.e. the base category). A *t*-test also confirms that the likelihood is also statistically lower compared to the second quartile (significant at 1% level). There is also some evidence that the difference between the second and fourth quartile is negative (at 10% level). [3] Finally, we also control whether individual characteristics, such as age and sex, determined the take-up rate of the algorithm. In line with previous work (see for example D'Acunto, Prabhala, and Rossi 2019), no significant effect emerged.

Overall these results suggest that individuals who were less affected by the disposition effect were also more aware of their weaknesses and of the advantages of adopting the algorithm. Among those who suffered heavily from the disposition, it appears that those who had very poor performance were more able to recognize their weaknesses, thereby opting more often for the algorithm compared, although this difference is not significant from a statistical point of view. Participants also prefer soft and active trading algorithms.

[2] More precisely, we check whether the individual pressed the button to change the choice of the algorithm. Thus, this variable does not distinguish whether the individuals in the end actually re-enter the same choice made by the algorithm or another one.

[3] We also checked the robustness of our results by constructing a dummy variable equal to 1 if the individual were above or below the median level of the disposition effect in either the standard or reverted treatment. Results are analogous even in this case.

4.3 Do people opting for the algorithm benefit from it?

Finally, we are interested in whether individuals who autonomously decided to rely on an algorithm in the third week performed better than individuals who did not. We therefore replicate the regression (3) as in Table (1) but relying only on choices in week 3.

Table (4), column (*a*), highlights once again that - when including algorithm choices - individuals that opted for an algorithm had lower levels in their disposition effect compared to individuals who did opt for playing freely. This impact is even larger than the previous one (-0.195, significant at 1% level). Once again, relying on a more sophisticated type of algorithm, i.e. Bayes, notably reduces the level of the disposition effect (-0.191, significant at 1% level), while being in the reverted treatments did not turn out to be relevant.

Importantly, participants who adopted soft algorithms in the third week had significantly higher levels of the disposition effect (+0.083, significant a 5% level). However, they still perform better than those who choose to trade on their own.

Finally if we look at participants' characteristics we observe positive differences (in terms of reduction of the disposition effect) due to weekly rate of activity (a 10% higher activity rate was associated with a -0.272 lower disposition effect), and a very marginal effect of the attitude towards future consequences. In line with previous research, other individual characteristics does not seem to play any significant role. The results are analogous if we look at our second indicator of the disposition effect (Diff_amount, see column *b*) and if we compare actual and optimal *Diff* and *Diff_amount* (see column *c* and *d).*

A final point is to check whether participants who decided to rely on an algorithm also made better choice on their own, i.e. even without the algorithm itself. Thus, in Table (4) - column *e*, *f*, *g, h* - we again run again the previous set of regressions removing from the individual performance the choices made by the algorithm itself. We do not observe any significant differences depending on the type of algorithms, although there are some indications of a learning effect arising from having access to a Bayes advisor. The only effect we observe is the one from being in a reverted treatment and from being an active trader. In other words, participants did benefit from trades made by algorithms, but did not seem to learn from their use unless exposed to them in the first week and left on their own in the second.

5 Discussion and conclusion

The results from our research shed light on how individuals may be helped in coping with the disposition effect. In particular, our experimental analysis, conducted online over 3 weeks, clearly highlights that there are - as expected - two types of investors: sophisticated and naive. The first category of investors is smaller in number and comprises those individuals who are subject to the disposition effect but appear to be aware of it, whereby they adopt measures to combat it. They are willing to restrict their freedom to trade in order to achieve better outcomes. The second category is more numerous and comprises those in-

Table 4: 3RD WEEK DETERMINANTS OF THE DISPOSITION EFFECT, WITH AND WITHOUT ALGORITHMIC CHOICES

	Including Algorithm choices				*Excluding Algorithm choices*			
	Diff	Diff_amount	Diff vs Opt	Diff_amount vs Opt	Diff	Diff_amount	Diff vs Opt	Diff_amount vs Opt
	(a)	*(b)*	*(c)*	*(d)*	*(e)*	*(f)*	*(g)*	*(h)*
Algorithm	-0.195***	-0.236***	-0.230***	-0.183***	-0.046	-0.049	-0.087	0.004
	(0.043)	(0.048)	(0.050)	(0.058)	(0.048)	(0.053)	(0.054)	(0.061)
Reverted	-0.045	-0.037	-0.057	-0.031	-0.098**	-0.108**	-0.107**	-0.097*
	(0.043)	(0.049)	(0.050)	(0.056)	(0.046)	(0.052)	(0.053)	(0.058)
Bayes	-0.191***	-0.187***	-0.240***	-0.201***	-0.077*	-0.060	-0.117**	-0.063
	(0.043)	(0.048)	(0.050)	(0.057)	(0.046)	(0.051)	(0.053)	(0.058)
Soft	0.083**	0.079*	0.087*	0.089	0.030	0.031	0.033	0.038
	(0.042)	(0.047)	(0.049)	(0.057)	(0.045)	(0.050)	(0.052)	(0.058)
Average activity	-0.272***	-0.258***	-0.387***	-0.057	-0.371***	-0.389***	-0.493***	-0.224*
	(0.080)	(0.088)	(0.090)	(0.103)	(0.093)	(0.102)	(0.103)	(0.115)
CRT	-0.014	-0.034	-0.004	0.002	-0.024	-0.040	-0.015	0.000
	(0.021)	(0.024)	(0.024)	(0.028)	(0.024)	(0.027)	(0.027)	(0.029)
CFC	0.012**	0.012**	0.012**	0.004	0.013**	0.013**	0.013**	0.005
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Financial Literacy	-0.022	-0.023	-0.024	-0.049	-0.029	-0.027	-0.032	-0.062
	(0.036)	(0.039)	(0.039)	(0.044)	(0.038)	(0.041)	(0.042)	(0.045)
Locus of control	-0.001	-0.001	0.007	0.019	-0.010	-0.011	-0.006	0.013
	(0.012)	(0.014)	(0.014)	(0.016)	(0.014)	(0.015)	(0.015)	(0.017)
Risk aversion	-0.017	-0.021	-0.005	-0.051	-0.026	-0.033	-0.013	-0.063
	(0.029)	(0.031)	(0.033)	(0.038)	(0.031)	(0.033)	(0.035)	(0.040)
Constant	-0.099	-0.087	0.405	0.666**	0.057	0.113	0.623**	0.857***
	(0.235)	(0.236)	(0.268)	(0.273)	(0.277)	(0.277)	(0.305)	(0.296)
ll	-215	-261	-273	-333	-226	-265	-273	-320
N	409	409	404	409	390	390	385	390

The dependent variable in columns *(a)*, *(b)*, is the amount of disposition effect in week 3 computed as described in equation (1) and (2), section 2.1, respectively. The same applies to columns *(e)*, *(f)*, although algorithm choices where excluded. The dependent variables with the "opt" term in columns (*c*), (*d*), (*g*) and (*h*) are the same variables computed as a difference with the respect to the value of the optimal strategy. *Algorithm* is a dummy equal to 1 if the individual opted for an algorithm in week 3. *Reverted* is a dummy equal to 1 in reverted treatments, while *Bayes* is a dummy equal to 1 for treatment in which the algorithm is based on the bayes probability of being in a good or bad state, and *Soft* is a dummy equal to 1 in treatments in which participants can override algorithm choices. The variable *Average activity* measure the individual activities in the week. The other characteristics are describe in Tab (A3). $^{*}p < 0.10,^{**}\ p < 0.05,^{***}\ p < 0.01$

vestors who do not realise that relying on a simple commitment device that let them make decisions only in a restricted set of periods (as implemented in the hard robo treatment) would allow them to improve their performance. Our results also suggest that individuals prefer more active robo-advisers, those that trade for them rather than simply do nothing. They also prefer soft commitment devices, that is, those algorithms that can be overridden. In this sense, leaving the possibility to the individual to override the algorithm encourages take-up by some who would not adopt them if no overrides were allowed. However, overrides reduce (although not entirely) the benefits of having a robo-advisor. Individuals in our experiment disregarded the comparison in performance with and without an adviser when choosing whether to adopt it or not. In line with previous evidence (e.g. D'Acunto, Prabhala, and Rossi 2019), we also find that individual characteristics are similarly irrelevant in this choice, the only exception being the level of risk aversion: more risk-averse individuals are more willing to adopt an algorithm in the final week of our experiment.

Our research, together with evidence emerging from previous related studies, also suggests important directions for improving the adoption of commitment devices. In line with other research (Tse, Nobuyuki, and Mao 2021), it may be helpful to make the benefits of robo-advisors more obvious for the investors who perform worst on the stock market, as they otherwise do not realize how much they could benefit from the use of an adviser. This means that they should not only get trading experience both with and without a robo-adviser, but the differences in performance should be conveyed to them in very simple and transparent terms. Second, it is important to give people the ability to override the adviser. Simply offering the option to not approve trades by the robo-adviser is a simple and effective way to enhance the feeling of being in control of decisions, and thus overcome algorithm aversion, and it does not result in losing too much in terms of performance.

Finally, further research could look into whether adoption is encouraged by giving people more leeway in the design of their advisers, that is, by letting them determine by themselves what algorithm to use, rather than simply whether to adopt the one they are offered. For example, it would be interesting to let them vary the strength of their commitment to follow the adviser, e.g. by putting a price on overrides.

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A Appendix

Figure A1: Timeline when algorithm imposed in the second week (standard treatments). Always optional in third week.

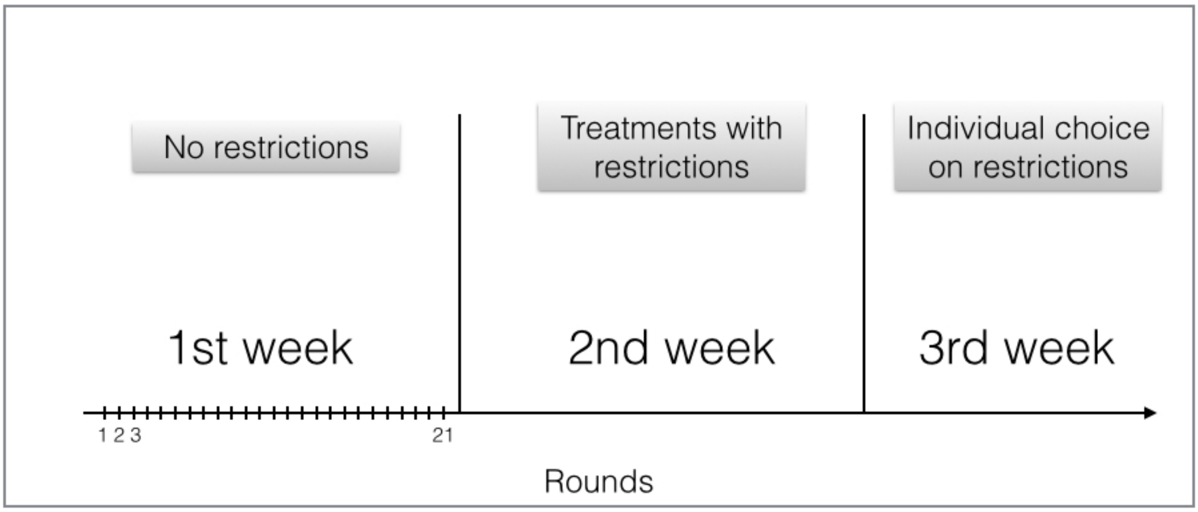

Figure A2: Overview of the experimental treatments over three weeks

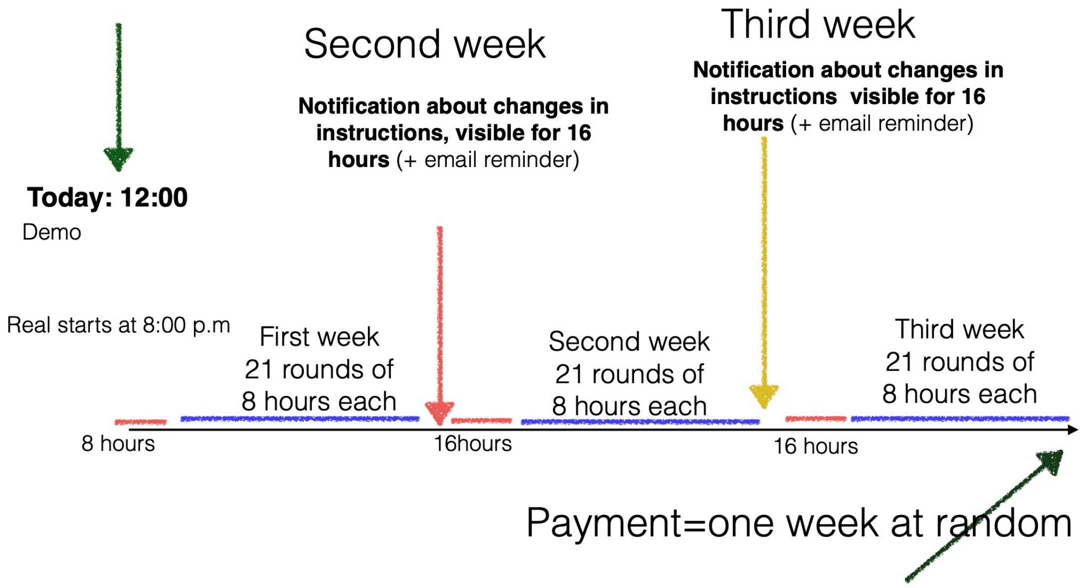

Table A1: SHARE OF ACTIVE TRADING PERIODS, PER WEEK AND TREATMENT

	1^{st} week	2^{nd} week	3^{rd}week	# obs(participants)
Hard Blocked	0.78	**0.69**	0.65	
Hard Bayes	0.74	**0.52**	0.53	
Soft Blocked	0.75	**0.59**	0.55	
Soft Bayes	0.68	**0.54**	0.40	
Hard Blocked reverted	**0.77**	0.73	0.71	
Hard Bayes reverted	**0.70**	0.60	0.60	
Soft Blocked reverted	**0.73**	0.64	0.55	
Soft Bayes reverted	**0.77**	0.51	0.60	
Total	0.74	0.60	0.57	

Active periods refer to periods in which a participant has made an active choice (i.e. either buying or selling a stock). Periods in which the algorithms were in place are excluded. The week with algorithm is in bold.

Table A2: PARTICIPANTS' CHARACTERISTICS

	MEAN	SD	RANGE	OBS
Age	24.95	4.03	19-49	409
Male	0.46		0-1	409
CRT	2.01	1.08	0-3	409
Future Attitude (CFC)	36.69	4.44	23-46	409
Financial Literacy	2.39	0.72	0-3	409
Locus of Control	8.21	1.74	3-12	409
Risk Aversion	2.62	0.82	1-4	409

Table A3: SUMMARY STATISTISTICS

	MEAN	RANGE	DESCRIPTION	OBS
DE	0.51	0-1	Dummy variable equal to 1 if Diff<0 in own trades in the first two weeks, and zero otherwise.	409
Algorithm	0.37	0-1	Dummy variable equal to 1 if the individual adopted the algorithm in the third week, and zero otherwise.	409
Reverted	0.48	0-1	Dummy variable equal to 1 if the individual is in a reverted treatment, and zero otherwise.	409
Soft	0.51	0-1	Dummy variable equal to 1 if the individual is in a soft treatment, and zero otherwise.	409
Bayes	0.48	0-1	Dummy variable equal to 1 if the individual is in a bayes treatment, and zero otherwise.	409
Overrode algorithm	0.26	0-1	Dummy variable equal to 1 if the individual ovverode the soft algorithm, and zero otherwise.	409
Overconfidence	0.19	0-1	Dummy variable equal to 1 if the individual answer yes to the following question "Do you believe to have performed better than the average participants?", and zero otherwise	395
Algorithm better	0.68	0-1	Dummy variable equal to 1 if the individual earned more in the week with the algorithm than the other in the previous two weeks, and zero otherwise	409

Table A4: QUARTILE OF DISPOSITION EFFECT AND ALGORITHM TAKE-UP

QUANTILE	MEAN DIFF	DE	ALGORITHM
1	-0.551	0.26	0.39
2	-0.079	0.36	0.42
3	0.138	0.71	0.32
4	0.566	0.73	0.32
MEAN	0.016	0.51	0.37

This table represents for each quartile of the variable *Diff*, the mean level of *Diff* in the group, the share of individuals suffering from the disposition effect (i.e. *Diff>0* thus having $DE = 1$), the share of individuals adopting an algorithm (i.e. having $Algorithm = 1$).

Table A5: AVERAGE DISPOSITION EFFECT EXCLUDING ALGORITHM CHOICES

TREATMENT	*Diff*			*Diff_Amount*			Obs	Obs
	Week 1	Week 2	Δ	Week 1	Week 2	Δ	Week 1	Week 2
Hard Block	0.146***	**0.145*****	0.001	0.175***	**0.156*****	0.019	58	58
Hard Bayes	0.092*	**0.028**	0.065	0.118**	**0.029**	0.089	51	48
Soft Block	0.159***	**0.111****	0.048	0.197***	**0.116****	0.081	57	55
Soft Bayes	0.142***	**-0.011**	0.153**	0.165***	**0.014**	0.151**	46	41
Hard Block Reverted	**-0.027**	-0.142***	0.114*	**-0.019**	-0.124**	0.105	48	48
Hard Bayes reverted	**0.128***	-0.056	0.185**	**0.142***	-0.050	0.192*	45	44
Soft Block Reverted	**-0.014**	-0.079*	0.065	**-0.013**	-0.104**	0.091	50	50
Soft Bayes reverted	**0.087***	0.021	0.066	**0.104***	0.027	0.077	53	52

The variable *Diff* and *Diff_Amount* computes the disposition effect as described in equation (1) and (2), section 1.1, respectively. Choices made by the algorithm are *excluded*, while the week in which the algorithm is in place are in bold.

Table A6: AVERAGE DISPOSITION EFFECT INCLUDING ALGORITHM CHOICES

TREATMENT	*Diff*			*Diff_Amount*			Obs	Obs
	Week 1	Week 2	Δ	Week 1	Week 2	Δ	Week 1	Week 2
Hard Block	0.146***	**0.145*** **	0.001	0.175***	**0.156*** **	0.019	58	58
Hard Bayes	0.092*	**-0.389*** **	0.482***	0.118**	**-0.467**	0.585***	51	51
Soft Block	0.159***	**0.110** **	0.049	0.197***	**0.147*** **	0.050	57	55
Soft Bayes	0.142***	**-0.240*** **	0.382***	0.165***	**-0.294*** **	0.458***	46	46
Hard Block reverted	**-0.027**	-0.142***	0.114*	**-0.019**	-0.124**	0.105	48	48
Hard Bayes reverted	**-0.381*** **	-0.056	-0.325***	**-0.428*** **	-0.050	-0.378***	45	44
Soft Block reverted	**0.020**	-0.079*	0.099*	**0.032**	-0.104**	0.136**	51	50
Soft Bayes reverted	**-0.153*** **	0.021	-0.174**	**-0.194*** **	0.027	-0.221***	53	52

The variable *Diff* and *Diff_Amount* computes the disposition effect as described in equation (1) and (2), section 2.1, respectively. Choices made by the algorithm are *included*, while the week in which the algorithm is in place are in bold.

Instructions

Welcome! This experiment today will last about 30 minutes e you will receive 5 Euro for your participation. If you want, you can then participate in a second phase of the experiment that will last 21 days. Depending on the choices you will make during these 21 days, you can earn other euros.

Please read this instructions carefully. This first phase will take place in this virtual room (including the demo). At the end of this, the real experiment will began, taking place on your device and lasting 21 days.

IMPORTANT: We remind you that your participation will remain anonymous to the other participants as well as to the experiments. You will receive an identification number, automatically assigned by the computer, and it will be used for payments.

<u>DESCRIPTIONS OF THE GAME</u>

In this experiment you will be given 350 ECU to invest in three different stocks. One ECU corresponds to 0.04 Euro (that is 50 ECU= 2 Euro).

Your job is to choose when to buy and sell each stock, so that you earn the most money by the end of the experiment. Throughout the experiment, you will see the price of each stock changing (more detail below), and you will use this information to decide when to buy and sell. When you sell a stock, you receive an amount of cash equal to the price of the stock. When you buy a stock, you receive one unit of the stock, but you must give up an amount of cash equal to the current price of the stock.

The three stocks you can buy or sell are simply called Stock A, Stock B, and Stock C. At the begin the experiment each one of three stocks will be automatically assigned to you and each one costs 100 ECU. Therefore, at the beginning of the experiment you will have the following situation:

Stock	**Quantity**	**Current Price**	ECU Value	Euro Value
A	1	100	100	4
B	1	100	100	4
C	1	100	100	4
Cash		50	50	2
Total value			350	14

For the entire duration of the experiment, you can hold **one unity at most of each stock.** You cannot hold negative quantity (that is you cannot sell stocks that are not at your disposal). Nevertheless, you might have a negativa amount of cash. That will happen should you buy a stock at a price that is higher than the amount of cash you have at the moment of the purchase. This negative amount will be detracted from your earnings at the end of the experiment.

Structure of the market

In this experiment, every day you will be able to buy and sell stocks in three different time window that will call "sessions of the market":

1. **Morning session**: from 4:00 a.m. to 12:00 p.m;
2. **Afternoon session**: from 12:00 p.m. to 8:00 p.m;
3. **Night session**: from 8:00 p.m. to 4:00 a.m.

In particular, during each market sessions,

- the **price of each stock will be updated** and you will be informed whether the price increased or decreased, and of which amount;
- at the new price you will have the possibility to sell each stock (should you hold it) or buy it (should you not).

You will be able to make your choice at any moment during the opening of the market sessions but you can not make a choice once the session is closed.

Structure of the game during 21 days

The game will be equally repeated with each three market sessions over 21 days, with little variations that will be introduced after 7 and 14 days e that will be notified directly to your screen as well as by email (see further below "**Earnings"**).

In particular, **at the beginning of the second and third week you will receive a notification of the changes that will intervene during each week.** This notification will remain visible on your screen for at least 16 hours. Only this time expires, you will be able to play again. You will receive a remainder to your email as well.

How the stock price changes

Each stock changes price according to the exact same rule. Each stock is either in a **good state** or in a **bad state**. In the **good state**, the stock goes up with 70% chance, and it goes down with 30% chance. In the bad state, the stock goes down with 70% chance and it goes up with 30% chance.

Once it is determined whether the price will go up or down, the *size* of the change is always random, and will either be ECU 5, ECU 10, or ECU 15. For example, in the bad state, the stock will go down with 70% chance, and the amount it goes down by is ECU 5, ECU 10, or ECU 15 with equal chance. Similarly, the good stock will go up with 70% chance, and the amount it goes up by will either be ECU 5, ECU 10, or ECU15.

The stocks will all randomly start in either the good state or bad state, and after each price update, there is a 20% chance the stock switches state.

The tables below summarise these information

Price changes

	Good state	*Bad state*
+ (UP)	70%	30%
- (DOWN)	30%	70%

State changes

	Good state today	*Bad state today*
Good state tomorrow	80%	20%
Bad state tomorrow	20%	80%

<u>Earnings</u>

You will play this game 21 days in total, divided into three phases of each 7 days each. In particular, at the beginning of each new phase (i.e. after 7 and 14 days) you will be able to buy again each stock at 100 ECU and the state of each stocks will be restarted, i.e. randomly drawn again as at the beginning of the experiment.

You earnings will be restarted as well at the beginning of each new phase (i.e. after 7 and 14 days) and will be computed for each phase at the end of the experiment. More precisely, the earnings corresponding to each phase will be equal to the amount of cash you accrued over the two scanning sessions from buying and selling stocks, plus the current price of any stocks that you own.

Earnings=cash + price A(Hold A) + Price B*(Hold B) + Price C*(Hold C)*

Finally, one phase of 7 days out of three will be randomly selected for payment (i.e. you will be paid according to the total earning of a randomly selected week).

Your final earnings will be converted in Euro at the exchange rate of 1 ECU= 0.04 Euro.

For payment you will have two options:

1) **by IBAN**
2) **by cash at the Department of Economics (but only if compatible with the actual normative)**

In any case, you will have to send an email to caterina.giannetti@gmail.com

Table A7: DETERMINANTS OF TAKE-UP RATE IN THE THIRD WEEK

	(a)	*(b)*	*(c)*	*(d)*	*(e)*	*(f)*	*(g)*
DE	-0.083**	-0.078**	-0.075**	-0.071**	-0.061	-0.073**	-0.080**
	(0.034)	(0.036)	(0.032)	(0.036)	(0.037)	(0.033)	(0.033)
Reverted	0.027	0.028	0.029	0.016	-0.001	0.018	0.045
	(0.048)	(0.046)	(0.049)	(0.054)	(0.055)	(0.054)	(0.059)
Soft	0.074	0.073	0.068	0.068	0.063	0.070	0.102**
	(0.046)	(0.047)	(0.045)	(0.047)	(0.046)	(0.047)	(0.052)
Bayes	0.083	0.081	0.073	0.074	0.082*	0.071	0.079
	(0.052)	(0.051)	(0.050)	(0.052)	(0.049)	(0.050)	(0.049)
Average activity		-0.060	-0.044	-0.070	-0.073	-0.068	
		(0.089)	(0.083)	(0.076)	(0.090)	(0.073)	
CRT			0.014	0.013	0.012	0.012	0.012
			(0.025)	(0.025)	(0.025)	(0.026)	(0.025)
CFC			-0.009*	-0.008	-0.008	-0.008	-0.008
			(0.005)	(0.006)	(0.007)	(0.006)	(0.006)
Financial Literacy			-0.054	-0.050	-0.056	-0.049	-0.050
			(0.045)	(0.045)	(0.045)	(0.044)	(0.045)
Locus of control				-0.005	-0.008	-0.004	-0.005
				(0.014)	(0.016)	(0.013)	(0.015)
Risk aversion				0.081***	0.087***	0.082***	0.079***
				(0.015)	(0.015)	(0.015)	(0.016)
Overconfidence					0.006		
					(0.061)		
Algorithm better						-0.038	
						(0.095)	
Overrode algorithm							-0.068
							(0.060)
ll	-264	-264	-261	-257	-247	-256	-257
N	409	409	409	409	395	409	409

The dependent variable is a dummy equal to 1 if the individual opted for an algorithm in the third week. The variable DE instead is a dummy equal to 1 if the individual suffered from disposition effect in the week he could freely trade. *Reverted* is a dummy equal to 1 in reverted treatments, while *Bayes* is a dummy equal to 1 for treatment in which the algorithm is based on the bayes probability of being in a good or bad state, and *Soft* is a dummy equal to 1 in treatments in which participants can override algorithm choices. The variable *Average activity* measure the individual average number of active periods in the previous two weeks, while the variable *Overrode algorithm* is a dummy equal to 1 if the individual overrode the algorithm in the previous two weeks. The variable *Algorithm better* is a dummy equal to 1 if the individual's payoff was higher in the week with the algorithm. This latter variable has a number of missing observations as not all subjects completed the exit questionnaire. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A8: DETERMINANTS OF TAKE-UP RATE IN THE THIRD WEEK (QUARTILE)

	(a)	*(b)*	*(c)*	*(d)*	*(e)*	*(f)*	*(g)*
2^{nd} quartile *Diff*	0.073	0.068	0.072	0.078	0.074	0.081	0.080
	(0.052)	(0.055)	(0.051)	(0.056)	(0.050)	(0.058)	(0.054)
3^{rd} quartile *Diff*	-0.118**	-0.118**	-0.106**	-0.090**	-0.096**	-0.090**	-0.093**
	(0.046)	(0.047)	(0.044)	(0.045)	(0.039)	(0.045)	(0.044)
4^{th} quartile *Diff*	-0.071	-0.078	-0.074	-0.063	-0.077	-0.062	-0.058
	(0.105)	(0.104)	(0.096)	(0.098)	(0.089)	(0.099)	(0.102)
Reverted	0.033	0.033	0.036	0.023	0.002	0.026	0.051
	(0.047)	(0.046)	(0.047)	(0.052)	(0.052)	(0.052)	(0.057)
Soft	0.054	0.053	0.050	0.051	0.047	0.052	0.081
	(0.045)	(0.044)	(0.042)	(0.044)	(0.043)	(0.043)	(0.053)
Bayes	0.081*	0.079*	0.070*	0.072*	0.079*	0.069*	0.077*
	(0.043)	(0.043)	(0.042)	(0.043)	(0.041)	(0.041)	(0.041)
Average activity		-0.080	-0.063	-0.087	-0.088	-0.085	
		(0.081)	(0.074)	(0.066)	(0.085)	(0.066)	
CRT			0.013	0.013	0.012	0.012	0.012
			(0.025)	(0.024)	(0.024)	(0.025)	(0.025)
CFC			-0.007	-0.006	-0.007	-0.006	-0.007
			(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
Financial Literacy			-0.061	-0.057	-0.063	-0.056	-0.057
			(0.038)	(0.039)	(0.040)	(0.039)	(0.038)
Locus of control				-0.009	-0.011	-0.008	-0.009
				(0.015)	(0.016)	(0.014)	(0.015)
Risk aversion				0.074***	0.080***	0.075***	0.072***
				(0.015)	(0.014)	(0.014)	(0.016)
Overconfidence					0.003		
					(0.065)		
Algorithm better						-0.044	
						(0.096)	
Overrode algorithm							-0.062
							(0.055)
ll	-260	-260	-257	-253	-242	-253	-253
N	408	408	408	408	394	408	408

The dependent variable is a dummy equal to 1 if the individual opted for an algorithm in the third week. The variable $2^{nd}, 3^{rd}, 4^{th}$*quartile Diff* dummy variables for quartiles of *Diff* (see Tab A4). *Reverted* is a dummy equal to 1 in reverted treatments, while *Bayes* is a dummy equal to 1 for treatment in which the algorithm is based on the bayes probability of being in a good or bad state, and *Soft* is a dummy equal to 1 in treatments in which participants can override algorithm choices. The variable *Average activity* measure the individual average number of active periods in the previous two weeks, while the variable *Overrode algorithm* is a dummy equal to 1 if the individual overrode the algorithm in the previous two weeks. The variable *Algorithm better* is a dummy equal to 1 if the individual's payoff was higher in the week with the algorithm. This latter variable has a number of missing observations as not all subjects completed the exit questionnaire. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$